LightGBM

Release 4.6.0.99

Microsoft Corporation

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CONTENTS:

LightGBM is a gradient boosting framework that uses tree based learning algorithms. It is designed to be distributed and efficient with the following advantages:

- Faster training speed and higher efficiency.
- Lower memory usage.
- Better accuracy.
- Support of parallel, distributed, and GPU learning.
- Capable of handling large-scale data.

For more details, please refer to Features.

CHAPTER

ONE

INSTALLATION GUIDE

1.1 Versioning

LightGBM releases use a 3-part version number, with this format:

```
{major}.{minor}.{patch}
```

This version follows a scheme called Intended Effort Versioning ("Effver" for short). Changes to a component of the version indicate how much effort it will likely take to update code using a previous version.

- `major` = updating will require significant effort
- `minor` = some effort
- `patch` = no or very little effort

This means that **new minor versions can contain breaking changes**, but these are typically small or limited to less-frequently-used parts of the project.

For more details on why LightGBM uses EffVer instead of other schemes like semantic versioning, see https://jacobtomlinson.dev/effver/.

1.2 Nightly Packages

When built from source on an unreleased commit, the package version takes the following form:

```
{major}.{minor}.{patch}.99
```

That `.99` is added to ensure that a version built from an unreleased commit is considered "newer" than all previous releases, and "older" than all future releases.

To download such artifacts, run the following from the root of this repository.

```
bash .ci/download-artifacts.sh ${COMMIT_ID}
```

Where `COMMIT_ID` is the full commit SHA pointing to a commit on `master`. The artifacts can then be found in the `release-artifacts/` directory.

For the Python package, nightly packages are also available via installers like `pip`. See the python-package documentation for details.

1.3 General Installation Notes

All instructions below are aimed at compiling the 64-bit version of LightGBM. It is worth compiling the 32-bit version only in very rare special cases involving environmental limitations. The 32-bit version is slow and untested, so use it at your own risk and don't forget to adjust some of the commands below when installing.

By default, instructions below will use **VS Build Tools** or **make** tool to compile the code. It it possible to use Ninja tool instead of make on all platforms, but VS Build Tools cannot be replaced with Ninja. You can add `-G Ninja` to CMake flags to use Ninja.

By default, instructions below will produce a shared library file and an executable file with command-line interface. You can add `-DBUILD_CLI=OFF` to CMake flags to disable the executable compilation.

If you need to build a static library instead of a shared one, you can add `-DBUILD_STATIC_LIB=ON` to CMake flags.

By default, instructions below will place header files into system-wide folder. You can add `-DINSTALL_HEADERS=OFF` to CMake flags to disable headers installation.

By default, on macOS, CMake is looking into Homebrew standard folders for finding dependencies (e.g. OpenMP). You can add `-DUSE_HOMEBREW_FALLBACK=OFF` to CMake flags to disable this behaviour.

Users who want to perform benchmarking can make LightGBM output time costs for different internal routines by adding `-DUSE_TIMETAG=ON` to CMake flags.

It is possible to build LightGBM in debug mode. In this mode all compiler optimizations are disabled and LightGBM performs more checks internally. To enable debug mode you can add `-DUSE_DEBUG=ON` to CMake flags or choose `Debug_*` configuration (e.g. `Debug_DLL`, `Debug_mpi`) in Visual Studio depending on how you are building LightGBM.

In addition to the debug mode, LightGBM can be built with compiler sanitizers. To enable them add `-DUSE_SANITIZER=ON -DENABLED_SANITIZERS="address;leak;undefined"` to CMake flags. These values refer to the following supported sanitizers:

- `address` - AddressSanitizer (ASan);
- `leak` - LeakSanitizer (LSan);
- `undefined` - UndefinedBehaviorSanitizer (UBSan);
- `thread` - ThreadSanitizer (TSan).

Please note, that ThreadSanitizer cannot be used together with other sanitizers. For more info and additional sanitizers' parameters please refer to the following docs. It is very useful to build *C++ unit tests* with sanitizers.

1.4 Windows

On Windows, LightGBM can be built using

- **Visual Studio**;
- **CMake** and **VS Build Tools**;
- **CMake** and **MinGW**.

1.4.1 Visual Studio (or VS Build Tools)

With GUI

1. Install Visual Studio.
2. Navigate to one of the releases at https://github.com/lightgbm-org/LightGBM/releases, download `LightGBM-complete_source_code_zip.zip`, and unzip it.
3. Go to `LightGBM-complete_source_code_zip/windows` folder.

4. Open `LightGBM.sln` file with **Visual Studio**, choose `Release` configuration if you need executable file or `DLL` configuration if you need shared library and click `Build -> Build Solution (Ctrl+Shift+B)`.

   If you have errors about **Platform Toolset**, go to `Project -> Properties -> Configuration Properties -> General` and select the toolset installed on your machine.

   If you have errors about **Windows SDK Version**, go to `Project -> Properties -> Configuration Properties -> General` and select the SDK installed on your machine.

The `.exe` file will be in `LightGBM-complete_source_code_zip/windows/x64/Release` folder. The `.dll` file will be in `LightGBM-complete_source_code_zip/windows/x64/DLL` folder.

From Command Line

1. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is already installed).
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -A x64
cmake --build build --target ALL_BUILD --config Release
```

The `.exe` and `.dll` files will be in `LightGBM/Release` folder.

1.4.2 MinGW-w64

1. Install Git for Windows, CMake and MinGW-w64.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -G "MinGW Makefiles"
cmake --build build -j4
```

The `.exe` and `.dll` files will be in `LightGBM/` folder.

Note: You may need to run the `cmake -B build -S . -G "MinGW Makefiles"` one more time or add `-DCMAKE_SH=CMAKE_SH-NOTFOUND` to CMake flags if you encounter the `sh.exe was found in your PATH` error.

It is recommended that you use **Visual Studio** since it has better multithreading efficiency in **Windows** for many-core systems (see Question 4 and Question 8).

1.5 Linux

On Linux, LightGBM can be built using

- **CMake** and **gcc**;
- **CMake** and **Clang**.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

1.5.1 gcc

1. Install CMake and **gcc**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S .
cmake --build build -j4
```

1.5.2 Clang

1. Install CMake, **Clang** and **OpenMP**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S .
cmake --build build -j4
```

1.6 macOS

On macOS, LightGBM can be installed using

- **Homebrew**;
- **MacPorts**;

or can be built using

- **CMake** and **Apple Clang**;
- **CMake** and **gcc**.

1.6.1 Install Using `Homebrew`

```
brew install lightgbm
```

Refer to https://formulae.brew.sh/formula/lightgbm for more details.

1.6.2 Install Using `MacPorts`

```
sudo port install LightGBM
```

Refer to https://ports.macports.org/port/LightGBM for more details.

Note: Port for LightGBM is not maintained by LightGBM's maintainers.

1.6.3 Build from GitHub

After compilation the executable and `.dylib` files will be in `LightGBM/` folder.

Apple Clang

1. Install CMake and **OpenMP**:

```
brew install cmake libomp
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S .
cmake --build build -j4
```

gcc

1. Install CMake and **gcc**:

```
brew install cmake gcc
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=g++-7 CC=gcc-7  # replace "7" with version of gcc installed on your␣
↪machine
cmake -B build -S .
cmake --build build -j4
```

1.7 Docker

Refer to Docker folder.

1.8 Build Threadless Version (not Recommended)

The default build version of LightGBM is based on OpenMP. You can build LightGBM without OpenMP support but it is **strongly not recommended**.

1.8.1 Windows

On Windows, a version of LightGBM without OpenMP support can be built using

- **Visual Studio**;
- **CMake** and **VS Build Tools**;
- **CMake** and **MinGW**.

Visual Studio (or VS Build Tools)

With GUI

1. Install Visual Studio.
2. Navigate to one of the releases at https://github.com/lightgbm-org/LightGBM/releases, download `LightGBM-complete_source_code_zip.zip`, and unzip it.

3. Go to `LightGBM-complete_source_code_zip/windows` folder.
4. Open `LightGBM.sln` file with **Visual Studio**, choose `Release` configuration if you need executable file or `DLL` configuration if you need shared library.
5. Go to `Project -> Properties -> Configuration Properties -> C/C++ -> Language` and change the `OpenMP Support` property to `No (/openmp-)`.
6. Get back to the project's main screen and click `Build -> Build Solution (Ctrl+Shift+B)`.

   If you have errors about **Platform Toolset**, go to `Project -> Properties -> Configuration Properties -> General` and select the toolset installed on your machine.

   If you have errors about **Windows SDK Version**, go to `Project -> Properties -> Configuration Properties -> General` and select the SDK installed on your machine.

The `.exe` file will be in `LightGBM-complete_source_code_zip/windows/x64/Release` folder. The `.dll` file will be in `LightGBM-complete_source_code_zip/windows/x64/DLL` folder.

From Command Line

1. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is already installed).
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -A x64 -DUSE_OPENMP=OFF
cmake --build build --target ALL_BUILD --config Release
```

The `.exe` and `.dll` files will be in `LightGBM/Release` folder.

MinGW-w64

1. Install Git for Windows, CMake and MinGW-w64.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -G "MinGW Makefiles" -DUSE_OPENMP=OFF
cmake --build build -j4
```

The `.exe` and `.dll` files will be in `LightGBM/` folder.

Note: You may need to run the `cmake -B build -S . -G "MinGW Makefiles" -DUSE_OPENMP=OFF` one more time or add `-DCMAKE_SH=CMAKE_SH-NOTFOUND` to CMake flags if you encounter the `sh.exe was found in your PATH` error.

1.8.2 Linux

On Linux, a version of LightGBM without OpenMP support can be built using

- **CMake** and **gcc**;
- **CMake** and **Clang**.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

gcc

1. Install CMake and **gcc**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_OPENMP=OFF
cmake --build build -j4
```

Clang

1. Install CMake and **Clang**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_OPENMP=OFF
cmake --build build -j4
```

1.8.3 macOS

On macOS, a version of LightGBM without OpenMP support can be built using

- **CMake** and **Apple Clang**;
- **CMake** and **gcc**.

After compilation the executable and `.dylib` files will be in `LightGBM/` folder.

Apple Clang

1. Install CMake:

```
brew install cmake
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_OPENMP=OFF
cmake --build build -j4
```

gcc

1. Install CMake and **gcc**:

```
brew install cmake gcc
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=g++-7 CC=gcc-7  # replace "7" with version of gcc installed on your␣
↪machine
cmake -B build -S . -DUSE_OPENMP=OFF
cmake --build build -j4
```

1.9 Build MPI Version

The default build version of LightGBM is based on socket. LightGBM also supports MPI. MPI is a high performance communication approach with RDMA support.

If you need to run a distributed learning application with high performance communication, you can build the LightGBM with MPI support.

1.9.1 Windows

On Windows, an MPI version of LightGBM can be built using

- **MS MPI** and **Visual Studio**;
- **MS MPI**, **CMake** and **VS Build Tools**.

Note: Building MPI version by **MinGW** is not supported due to the miss of MPI library in it.

With GUI

1. You need to install MS MPI first. Both `msmpisdk.msi` and `msmpisetup.exe` are needed.
2. Install Visual Studio.
3. Navigate to one of the releases at https://github.com/lightgbm-org/LightGBM/releases, download `LightGBM-complete_source_code_zip.zip`, and unzip it.
4. Go to `LightGBM-complete_source_code_zip/windows` folder.
5. Open `LightGBM.sln` file with **Visual Studio**, choose `Release_mpi` configuration and click `Build -> Build Solution (Ctrl+Shift+B)`.

   If you have errors about **Platform Toolset**, go to `Project -> Properties -> Configuration Properties -> General` and select the toolset installed on your machine.

   If you have errors about **Windows SDK Version**, go to `Project -> Properties -> Configuration Properties -> General` and select the SDK installed on your machine.

The `.exe` file will be in `LightGBM-complete_source_code_zip/windows/x64/Release_mpi` folder.

From Command Line

1. You need to install MS MPI first. Both `msmpisdk.msi` and `msmpisetup.exe` are needed.
2. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is already installed).
3. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
```

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```
cmake -B build -S . -A x64 -DUSE_MPI=ON
cmake --build build --target ALL_BUILD --config Release
```

The `.exe` and `.dll` files will be in `LightGBM/Release` folder.

1.9.2 Linux

On Linux, an MPI version of LightGBM can be built using

- **CMake**, **gcc** and **Open MPI**;
- **CMake**, **Clang** and **Open MPI**.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

gcc

1. Install CMake, **gcc** and Open MPI.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_MPI=ON
cmake --build build -j4
```

Clang

1. Install CMake, **Clang**, **OpenMP** and Open MPI.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_MPI=ON
cmake --build build -j4
```

1.9.3 macOS

On macOS, an MPI version of LightGBM can be built using

- **CMake**, **Open MPI** and **Apple Clang**;
- **CMake**, **Open MPI** and **gcc**.

After compilation the executable and `.dylib` files will be in `LightGBM/` folder.

Apple Clang

1. Install CMake, **OpenMP** and Open MPI:

```
brew install cmake libomp open-mpi
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_MPI=ON
cmake --build build -j4
```

gcc

1. Install CMake, Open MPI and **gcc**:

   ```
   brew install cmake open-mpi gcc
   ```

2. Run the following commands:

   ```
   git clone --recursive https://github.com/lightgbm-org/LightGBM
   cd LightGBM
   export CXX=g++-7 CC=gcc-7  # replace "7" with version of gcc installed on your␣
   ↪machine
   cmake -B build -S . -DUSE_MPI=ON
   cmake --build build -j4
   ```

1.10 Build GPU Version

1.10.1 Windows

On Windows, a GPU version of LightGBM (`device_type=gpu`) can be built using

- **OpenCL**, **Boost**, **CMake** and **VS Build Tools**;
- **OpenCL**, **Boost**, **CMake** and **MinGW**.

If you use **MinGW**, the build procedure is similar to the build on Linux.

Following procedure is for the **MSVC** (Microsoft Visual C++) build.

1. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is installed).
2. Install **OpenCL** for Windows. The installation depends on the brand (NVIDIA, AMD, Intel) of your GPU card.
   - For running on Intel, get Intel SDK for OpenCL.
   - For running on AMD, get AMD APP SDK.
   - For running on NVIDIA, get CUDA Toolkit.

   Further reading and correspondence table: GPU SDK Correspondence and Device Targeting Table.
3. Install Boost Binaries.

   Note: Match your Visual C++ version:

   Visual Studio 2017 -> `msvc-14.1-64.exe`,

   Visual Studio 2019 -> `msvc-14.2-64.exe`,

   Visual Studio 2022 -> `msvc-14.3-64.exe`.
4. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -A x64 -DUSE_GPU=ON -DBOOST_ROOT=C:/local/boost_1_63_0 -DBOOST_
↪LIBRARYDIR=C:/local/boost_1_63_0/lib64-msvc-14.3
# if you have installed NVIDIA CUDA to a customized location, you should specify␣
↪paths to OpenCL headers and library like the following:
# cmake -B build -S . -A x64 -DUSE_GPU=ON -DBOOST_ROOT=C:/local/boost_1_63_0 -
↪DBOOST_LIBRARYDIR=C:/local/boost_1_63_0/lib64-msvc-14.3 -DOpenCL_LIBRARY="C:/
↪Program Files/NVIDIA GPU Computing Toolkit/CUDA/v10.0/lib/x64/OpenCL.lib" -
↪DOpenCL_INCLUDE_DIR="C:/Program Files/NVIDIA GPU Computing Toolkit/CUDA/v10.0/
↪include"
cmake --build build --target ALL_BUILD --config Release
```

Note: `C:/local/boost_1_63_0` and `C:/local/boost_1_63_0/lib64-msvc-14.3` are locations of your **Boost** binaries (assuming you've downloaded 1.63.0 version for Visual Studio 2022).

The `.exe` and `.dll` files will be in `LightGBM/Release` folder.

1.10.2 Linux

On Linux, a GPU version of LightGBM (`device_type=gpu`) can be built using

- **CMake**, **OpenCL**, **Boost** and **gcc**;
- **CMake**, **OpenCL**, **Boost** and **Clang**.

OpenCL headers and libraries are usually provided by GPU manufacture. The generic OpenCL ICD packages (for example, Debian packages `ocl-icd-libopencl1`, `ocl-icd-opencl-dev`, `pocl-opencl-icd`) can also be used.

Required **Boost** libraries (Boost.Align, Boost.System, Boost.Filesystem, Boost.Chrono) should be provided by the following Debian packages: `libboost-dev`, `libboost-system-dev`, `libboost-filesystem-dev`, `libboost-chrono-dev`.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

gcc

1. Install CMake, **gcc**, **OpenCL** and **Boost**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_GPU=ON
# if you have installed NVIDIA CUDA to a customized location, you should specify␣
↪paths to OpenCL headers and library like the following:
# cmake -B build -S . -DUSE_GPU=ON -DOpenCL_LIBRARY=/usr/local/cuda/lib64/libOpenCL.
↪so -DOpenCL_INCLUDE_DIR=/usr/local/cuda/include/
cmake --build build -j4
```

Clang

1. Install CMake, **Clang**, **OpenMP**, **OpenCL** and **Boost**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_GPU=ON
# if you have installed NVIDIA CUDA to a customized location, you should specify␣
↪paths to OpenCL headers and library like the following:
# cmake -B build -S . -DUSE_GPU=ON -DOpenCL_LIBRARY=/usr/local/cuda/lib64/libOpenCL.
↪so -DOpenCL_INCLUDE_DIR=/usr/local/cuda/include/
cmake --build build -j4
```

1.10.3 macOS

The GPU version is not supported on macOS.

1.10.4 Docker

Refer to GPU Docker folder.

1.11 Build CUDA Version

The *original GPU version* of LightGBM (`device_type=gpu`) is based on OpenCL, and only computes histograms on GPUs, with other parts of training in CPUs.

The CUDA-based version (`device_type=cuda`) is a separate implementation that runs significantly faster by putting all the training process on GPUs. It also supports multi-GPU, and multi-node multi-GPU training. Use this version in Linux environments with an NVIDIA GPU with compute capability 6.0 or higher.

1.11.1 Windows

The CUDA version is not supported on Windows. Use the *GPU version* (`device_type=gpu`) for GPU acceleration on Windows.

1.11.2 Linux

On Linux, a CUDA version of LightGBM can be built using

- **CMake**, **gcc** and **CUDA**;
- **CMake**, **Clang** and **CUDA**.

Please refer to this detailed guide for **CUDA** libraries installation.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

Note

By default, the library will be built with support for a hard-coded list of GPU architectures based on the detected CUDA Toolkit version.

To build the library with support for more architectures, set `CMAKE_CUDA_ARCHITECTURES`.

```
# example: all Blackwell arches, including DGX Spark
cmake -B build -S . -DUSE_CUDA=ON -DCMAKE_CUDA_ARCHITECTURES="100;120;121-real;121-
↪virtual"

# example: just the local GPU
cmake -B build -S . -DUSE_CUDA=ON -DCMAKE_CUDA_ARCHITECTURES="native"
```

gcc

1. Install CMake, **gcc** and **CUDA**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_CUDA=ON
cmake --build build -j4
```

Clang

1. Install CMake, **Clang**, **OpenMP** and **CUDA**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_CUDA=ON
cmake --build build -j4
```

1.11.3 macOS

The CUDA version is not supported on macOS.

1.12 Build ROCm Version

The *original GPU version* of LightGBM (`device_type=gpu`) is based on OpenCL.

The ROCm-based version (`device_type=cuda`) is a separate implementation. Yes, the ROCm version reuses the `device_type=cuda` as a convenience for users. Use this version in Linux environments with an AMD GPU.

1.12.1 Windows

The ROCm version is not supported on Windows. Use the *GPU version* (`device_type=gpu`) for GPU acceleration on Windows.

1.12.2 Linux

On Linux, a ROCm version of LightGBM can be built using

- **CMake**, **gcc** and **ROCm**;
- **CMake**, **Clang** and **ROCm**.

Please refer to the ROCm docs for **ROCm** libraries installation.

After compilation the executable and `.so` files will be in `LightGBM/` folder.

gcc

1. Install CMake, **gcc** and **ROCm**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_ROCM=ON
cmake --build build -j4
```

Clang

1. Install CMake, **Clang**, **OpenMP** and **ROCm**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_ROCM=ON
cmake --build build -j4
```

1.12.3 macOS

The ROCm version is not supported on macOS.

1.13 Build Java Wrapper

Using the following instructions you can generate a JAR file containing the LightGBM C API wrapped by **SWIG**.

After compilation the `.jar` file will be in `LightGBM/build` folder.

1.13.1 Windows

On Windows, a Java wrapper of LightGBM can be built using

- **Java**, **SWIG**, **CMake** and **VS Build Tools**;
- **Java**, **SWIG**, **CMake** and **MinGW**.

VS Build Tools

1. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is already installed).
2. Install SWIG and **Java** (also make sure that `JAVA_HOME` environment variable is set properly).
3. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -A x64 -DUSE_SWIG=ON
cmake --build build --target ALL_BUILD --config Release
```

MinGW-w64

1. Install Git for Windows, CMake and MinGW-w64.
2. Install SWIG and **Java** (also make sure that `JAVA_HOME` environment variable is set properly).
3. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -G "MinGW Makefiles" -DUSE_SWIG=ON
cmake --build build -j4
```

Note: You may need to run the `cmake -B build -S . -G "MinGW Makefiles" -DUSE_SWIG=ON` one more time or add `-DCMAKE_SH=CMAKE_SH-NOTFOUND` to CMake flags if you encounter the `sh.exe was found in your PATH` error.

It is recommended to use **VS Build Tools (Visual Studio)** since it has better multithreading efficiency in **Windows** for many-core systems (see Question 4 and Question 8).

1.13.2 Linux

On Linux, a Java wrapper of LightGBM can be built using

- **CMake**, **gcc**, **Java** and **SWIG**;
- **CMake**, **Clang**, **Java** and **SWIG**.

gcc

1. Install CMake, **gcc**, SWIG and **Java** (also make sure that `JAVA_HOME` environment variable is set properly).
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_SWIG=ON
cmake --build build -j4
```

Clang

1. Install CMake, **Clang**, **OpenMP**, SWIG and **Java** (also make sure that `JAVA_HOME` environment variable is set properly).
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DUSE_SWIG=ON
cmake --build build -j4
```

1.13.3 macOS

On macOS, a Java wrapper of LightGBM can be built using

- **CMake**, **Java**, **SWIG** and **Apple Clang**;
- **CMake**, **Java**, **SWIG** and **gcc**.

Apple Clang

1. Install CMake, **Java** (also make sure that `JAVA_HOME` environment variable is set properly), SWIG and **OpenMP**:

```
brew install cmake openjdk swig libomp
export JAVA_HOME="$(brew --prefix openjdk)/libexec/openjdk.jdk/Contents/Home/"
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_SWIG=ON
cmake --build build -j4
```

gcc

1. Install CMake, **Java** (also make sure that `JAVA_HOME` environment variable is set properly), SWIG and **gcc**:

```
brew install cmake openjdk swig gcc
export JAVA_HOME="$(brew --prefix openjdk)/libexec/openjdk.jdk/Contents/Home/"
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=g++-7 CC=gcc-7  # replace "7" with version of gcc installed on your␣
↪machine
cmake -B build -S . -DUSE_SWIG=ON
cmake --build build -j4
```

1.14 Build Python-package

Refer to the python-package documentation.

1.15 Build R-package

Refer to R-package folder.

1.16 Build C++ Unit Tests

1.16.1 Windows

On Windows, C++ unit tests of LightGBM can be built using

- **CMake** and **VS Build Tools**;
- **CMake** and **MinGW**.

VS Build Tools

1. Install Git for Windows, CMake and VS Build Tools (**VS Build Tools** is not needed if **Visual Studio** is already installed).
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -A x64 -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm --config Debug
```

The `.exe` file will be in `LightGBM/Debug` folder.

MinGW-w64

1. Install Git for Windows, CMake and MinGW-w64.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -G "MinGW Makefiles" -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm -j4
```

The `.exe` file will be in `LightGBM/` folder.

Note: You may need to run the `cmake -B build -S . -G "MinGW Makefiles" -DBUILD_CPP_TEST=ON` one more time or add `-DCMAKE_SH=CMAKE_SH-NOTFOUND` to CMake flags if you encounter the `sh.exe was found in your PATH` error.

1.16.2 Linux

On Linux, a C++ unit tests of LightGBM can be built using

- **CMake** and **gcc**;
- **CMake** and **Clang**.

After compilation the executable file will be in `LightGBM/` folder.

gcc

1. Install CMake and **gcc**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm -j4
```

Clang

1. Install CMake, **Clang** and **OpenMP**.
2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=clang++-14 CC=clang-14  # replace "14" with version of Clang installed␣
↪on your machine
cmake -B build -S . -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm -j4
```

1.16.3 macOS

On macOS, a C++ unit tests of LightGBM can be built using

- **CMake** and **Apple Clang**;
- **CMake** and **gcc**.

After compilation the executable file will be in `LightGBM/` folder.

Apple Clang

1. Install CMake and **OpenMP**:

```
brew install cmake libomp
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm -j4
```

gcc

1. Install CMake and **gcc**:

```
brew install cmake gcc
```

2. Run the following commands:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
export CXX=g++-7 CC=gcc-7  # replace "7" with version of gcc installed on your␣
↪machine
cmake -B build -S . -DBUILD_CPP_TEST=ON
cmake --build build --target testlightgbm -j4
```

CHAPTER

TWO

QUICK START

This is a quick start guide for LightGBM CLI version.

Follow the Installation Guide to install LightGBM first.

List of other helpful links

- Parameters
- Parameters Tuning
- Python-package Quick Start
- Python API

2.1 Training Data Format

LightGBM supports input data files with CSV, TSV and LibSVM (zero-based) formats.

Files could be both with and without headers.

Label column could be specified both by index and by name.

Some columns could be ignored.

2.1.1 Categorical Feature Support

LightGBM can use categorical features directly (without one-hot encoding). The experiment on Expo data shows about 8x speed-up compared with one-hot encoding.

For the setting details, please refer to the `categorical_feature` parameter.

2.1.2 Weight and Query/Group Data

LightGBM also supports weighted training, it needs an additional weight data. And it needs an additional query data for ranking task.

Also, weight and query data could be specified as columns in training data in the same manner as label.

2.2 Parameters Quick Look

The parameters format is `key1=value1 key2=value2 ...`.

Parameters can be set both in config file and command line. If one parameter appears in both command line and config file, LightGBM will use the parameter from the command line.

The most important parameters which new users should take a look at are located into Core Parameters and the top of Learning Control Parameters sections of the full detailed list of LightGBM's parameters.

2.3 Run LightGBM

```
lightgbm config=your_config_file other_args ...
```

Parameters can be set both in the config file and command line, and the parameters in command line have higher priority than in the config file. For example, the following command line will keep `num_trees=10` and ignore the same parameter in the config file.

```
lightgbm config=train.conf num_trees=10
```

2.4 Examples

- Binary Classification
- Regression
- Lambdarank
- Distributed Learning

CHAPTER

THREE

PYTHON-PACKAGE INTRODUCTION

This document gives a basic walk-through of LightGBM Python-package.

List of other helpful links

- Python Examples
- Python API
- Parameters Tuning

3.1 Install

The preferred way to install LightGBM is via pip:

```
pip install lightgbm
```

Refer to Python-package folder for the detailed installation guide.

To verify your installation, try to `import lightgbm` in Python:

```
import lightgbm as lgb
```

3.2 Data Interface

The LightGBM Python module can load data from:

- LibSVM (zero-based) / TSV / CSV format text file
- NumPy 2D array(s), SciPy sparse matrix
- pandas DataFrame, polars DataFrame, pyarrow Table
- LightGBM binary file
- LightGBM `Sequence` object(s)

The data is stored in a `Dataset` object.

Many of the examples in this page use functionality from `numpy`. To run the examples, be sure to import `numpy` in your session.

```
import numpy as np
```

To load a LibSVM (zero-based) text file or a LightGBM binary file into Dataset:

```
train_data = lgb.Dataset('train.svm.bin')
```

To load a numpy array into Dataset:

```
rng = np.random.default_rng()
data = rng.uniform(size=(500, 10))  # 500 entities, each contains 10 features
label = rng.integers(low=0, high=2, size=(500, ))  # binary target
train_data = lgb.Dataset(data, label=label)
```

To load a scipy.sparse.csr_matrix array into Dataset:

```
import scipy
csr = scipy.sparse.csr_matrix((dat, (row, col)))
train_data = lgb.Dataset(csr)
```

Load from Sequence objects:

We can implement `Sequence` interface to read binary files. The following example shows reading HDF5 file with `h5py`.

```
import h5py

class HDFSequence(lgb.Sequence):
    def __init__(self, hdf_dataset, batch_size):
        self.data = hdf_dataset
        self.batch_size = batch_size

    def __getitem__(self, idx):
        return self.data[idx]

    def __len__(self):
        return len(self.data)

f = h5py.File('train.hdf5', 'r')
train_data = lgb.Dataset(HDFSequence(f['X'], 8192), label=f['Y'][:])
```

Features of using `Sequence` interface:

- Data sampling uses random access, thus does not go through the whole dataset
- Reading data in batch, thus saves memory when constructing `Dataset` object
- Supports creating `Dataset` from multiple data files

Please refer to `Sequence` API doc.

dataset_from_multi_hdf5.py is a detailed example.

Saving Dataset into a LightGBM binary file will make loading faster:

```
train_data = lgb.Dataset('train.svm.txt')
train_data.save_binary('train.bin')
```

Create validation data:

```
validation_data = train_data.create_valid('validation.svm')
```

or

```
validation_data = lgb.Dataset('validation.svm', reference=train_data)
```

In LightGBM, the validation data should be aligned with training data.

Specific feature names and categorical features:

```
train_data = lgb.Dataset(data, label=label, feature_name=['c1', 'c2', 'c3'], categorical_
↪feature=['c3'])
```

LightGBM can use categorical features as input directly. It doesn't need to convert to one-hot encoding, and is much faster than one-hot encoding (about 8x speed-up).

Note: You should convert your categorical features to `int` type before you construct `Dataset`.

Weights can be set when needed:

```
rng = np.random.default_rng()
w = rng.uniform(size=(500, ))
train_data = lgb.Dataset(data, label=label, weight=w)
```

or

```
train_data = lgb.Dataset(data, label=label)
rng = np.random.default_rng()
w = rng.uniform(size=(500, ))
train_data.set_weight(w)
```

And you can use `Dataset.set_init_score()` to set initial score, and `Dataset.set_group()` to set group/query data for ranking tasks.

Memory efficient usage:

The `Dataset` object in LightGBM is very memory-efficient, it only needs to save discrete bins. However, Numpy/Array/Pandas object is memory expensive. If you are concerned about your memory consumption, you can save memory by:

1. Set `free_raw_data=True` (default is `True`) when constructing the `Dataset`
2. Explicitly set `raw_data=None` after the `Dataset` has been constructed
3. Call `gc`

3.3 Setting Parameters

LightGBM can use a dictionary to set Parameters. For instance:

- Booster parameters:

  ```
  param = {'num_leaves': 31, 'objective': 'binary'}
  param['metric'] = 'auc'
  ```

- You can also specify multiple eval metrics:

  ```
  param['metric'] = ['auc', 'binary_logloss']
  ```

3.4 Training

Training a model requires a parameter list and data set:

```
num_round = 10
bst = lgb.train(param, train_data, num_round, valid_sets=[validation_data])
```

After training, the model can be saved:

```
bst.save_model('model.txt')
```

The trained model can also be dumped to JSON format:

```
json_model = bst.dump_model()
```

A saved model can be loaded:

```
bst = lgb.Booster(model_file='model.txt')  # init model
```

3.5 CV

Training with 5-fold CV:

```
lgb.cv(param, train_data, num_round, nfold=5)
```

3.6 Early Stopping

If you have a validation set, you can use early stopping to find the optimal number of boosting rounds. Early stopping requires at least one set in `valid_sets`. If there is more than one, it will use all of them except the training data:

```
bst = lgb.train(param, train_data, num_round, valid_sets=valid_sets, callbacks=[lgb.
↪early_stopping(stopping_rounds=5)])
bst.save_model('model.txt', num_iteration=bst.best_iteration)
```

The model will train until the validation score stops improving. Validation score needs to improve at least every `stopping_rounds` to continue training.

The index of iteration that has the best performance will be saved in the `best_iteration` field if early stopping logic is enabled by setting `early_stopping` callback. Note that `train()` will return a model from the best iteration.

This works with both metrics to minimize (L2, log loss, etc.) and to maximize (NDCG, AUC, etc.). Note that if you specify more than one evaluation metric, all of them will be used for early stopping. However, you can change this behavior and make LightGBM check only the first metric for early stopping by passing `first_metric_only=True` in `early_stopping` callback constructor.

3.7 Prediction

A model that has been trained or loaded can perform predictions on datasets:

```
# 7 entities, each contains 10 features
rng = np.random.default_rng()
data = rng.uniform(size=(7, 10))
ypred = bst.predict(data)
```

If early stopping is enabled during training, you can get predictions from the best iteration with `bst.best_iteration`:

```
ypred = bst.predict(data, num_iteration=bst.best_iteration)
```

CHAPTER

FOUR

FEATURES

This is a conceptual overview of how LightGBM works[1]. We assume familiarity with decision tree boosting algorithms to focus instead on aspects of LightGBM that may differ from other boosting packages. For detailed algorithms, please refer to the citations or source code.

4.1 Optimization in Speed and Memory Usage

Many boosting tools use pre-sort-based algorithms[2, 3] (e.g. default algorithm in xgboost) for decision tree learning. It is a simple solution, but not easy to optimize.

LightGBM uses histogram-based algorithms[4, 5, 6], which bucket continuous feature (attribute) values into discrete bins. This speeds up training and reduces memory usage. Advantages of histogram-based algorithms include the following:

- **Reduced cost of calculating the gain for each split**
  - Pre-sort-based algorithms have time complexity `O(#data)`
  - Computing the histogram has time complexity `O(#data)`, but this involves only a fast sum-up operation. Once the histogram is constructed, a histogram-based algorithm has time complexity `O(#bins)`, and `#bins` is far smaller than `#data`.
- **Use histogram subtraction for further speedup**
  - To get one leaf's histograms in a binary tree, use the histogram subtraction of its parent and its neighbor
  - So it needs to construct histograms for only one leaf (with smaller `#data` than its neighbor). It then can get histograms of its neighbor by histogram subtraction with small cost (`O(#bins)`)
- **Reduce memory usage**
  - Replaces continuous values with discrete bins. If `#bins` is small, can use small data type, e.g. uint8_t, to store training data
  - No need to store additional information for pre-sorting feature values
- **Reduce communication cost for distributed learning**

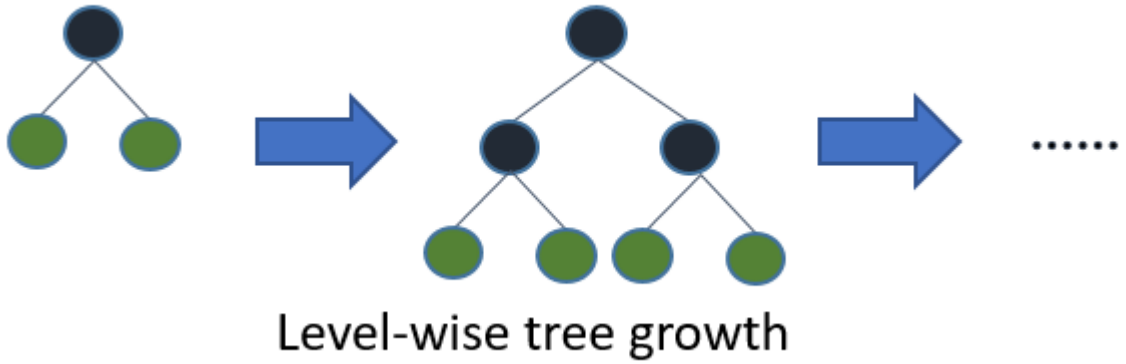
4.2 Sparse Optimization

- Need only `O(2 * #non_zero_data)` to construct histogram for sparse features

4.3 Optimization in Accuracy

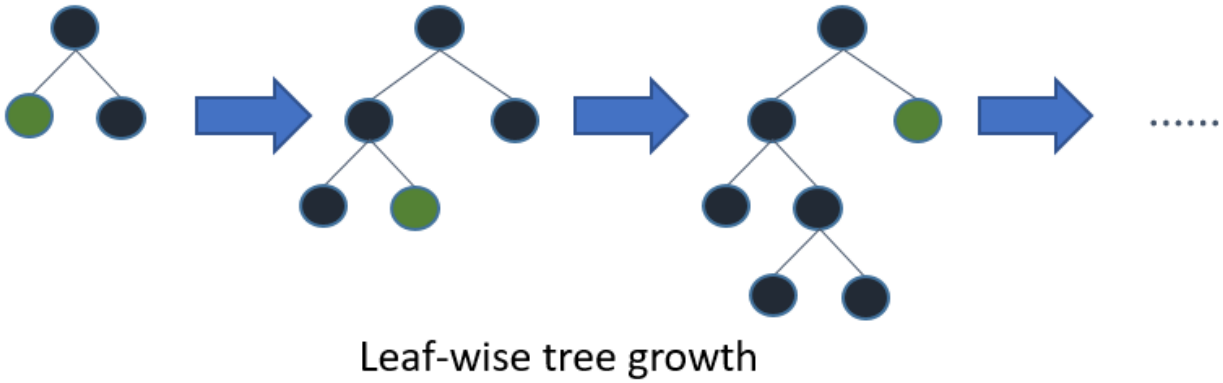
4.3.1 Leaf-wise (Best-first) Tree Growth

Most decision tree learning algorithms grow trees by level (depth)-wise, like the following image:



LightGBM grows trees leaf-wise (best-first)*[7]*. It will choose the leaf with max delta loss to grow. Holding `#leaf` fixed, leaf-wise algorithms tend to achieve lower loss than level-wise algorithms.

Leaf-wise may cause over-fitting when `#data` is small, so LightGBM includes the `max_depth` parameter to limit tree depth. However, trees still grow leaf-wise even when `max_depth` is specified.



4.3.2 Optimal Split for Categorical Features

It is common to represent categorical features with one-hot encoding, but this approach is suboptimal for tree learners. Particularly for high-cardinality categorical features, a tree built on one-hot features tends to be unbalanced and needs to grow very deep to achieve good accuracy.

Instead of one-hot encoding, the optimal solution is to split on a categorical feature by partitioning its categories into 2 subsets. If the feature has `k` categories, there are `2^(k-1) - 1` possible partitions. But there is an efficient solution for regression trees*[8]*. It needs about `O(k * log(k))` to find the optimal partition.

The basic idea is to sort the categories according to the training objective at each split. More specifically, LightGBM sorts the histogram (for a categorical feature) according to its accumulated values (`sum_gradient / sum_hessian`) and then finds the best split on the sorted histogram.

4.4 Optimization in Network Communication

It only needs to use some collective communication algorithms, like "All reduce", "All gather" and "Reduce scatter", in distributed learning of LightGBM. LightGBM implements state-of-the-art algorithms[9]. These collective communication algorithms can provide much better performance than point-to-point communication.

4.5 Optimization in Distributed Learning

LightGBM provides the following distributed learning algorithms.

4.5.1 Feature Parallel

Traditional Algorithm

Feature parallel aims to parallelize the "Find Best Split" in the decision tree. The procedure of traditional feature parallel is:

1. Partition data vertically (different machines have different feature set).
2. Workers find local best split point {feature, threshold} on local feature set.
3. Communicate local best splits with each other and get the best one.
4. Worker with best split to perform split, then send the split result of data to other workers.
5. Other workers split data according to received data.

The shortcomings of traditional feature parallel:

- Has computation overhead, since it cannot speed up "split", whose time complexity is `O(#data)`. Thus, feature parallel cannot speed up well when `#data` is large.
- Need communication of split result, which costs about `O(#data / 8)` (one bit for one data).

Feature Parallel in LightGBM

Since feature parallel cannot speed up well when `#data` is large, we make a little change: instead of partitioning data vertically, every worker holds the full data. Thus, LightGBM doesn't need to communicate for split result of data since every worker knows how to split data. And `#data` won't be larger, so it is reasonable to hold the full data in every machine.

The procedure of feature parallel in LightGBM:

1. Workers find local best split point {feature, threshold} on local feature set.
2. Communicate local best splits with each other and get the best one.
3. Perform best split.

However, this feature parallel algorithm still suffers from computation overhead for "split" when `#data` is large. So it will be better to use data parallel when `#data` is large.

4.5.2 Data Parallel

Traditional Algorithm

Data parallel aims to parallelize the whole decision learning. The procedure of data parallel is:

1. Partition data horizontally.
2. Workers use local data to construct local histograms.

3. Merge global histograms from all local histograms.
4. Find best split from merged global histograms, then perform splits.

The shortcomings of traditional data parallel:

- High communication cost. If using point-to-point communication algorithm, communication cost for one machine is about `O(#machine * #feature * #bin)`. If using collective communication algorithm (e.g. "All Reduce"), communication cost is about `O(2 * #feature * #bin)` (check cost of "All Reduce" in chapter 4.5 at *[9]*).

Data Parallel in LightGBM

We reduce communication cost of data parallel in LightGBM:

1. Instead of "Merge global histograms from all local histograms", LightGBM uses "Reduce Scatter" to merge histograms of different (non-overlapping) features for different workers. Then workers find the local best split on local merged histograms and sync up the global best split.
2. As aforementioned, LightGBM uses histogram subtraction to speed up training. Based on this, we can communicate histograms only for one leaf, and get its neighbor's histograms by subtraction as well.

All things considered, data parallel in LightGBM has time complexity `O(0.5 * #feature * #bin)`.

4.5.3 Voting Parallel

Voting parallel further reduces the communication cost in *Data Parallel* to constant cost. It uses two-stage voting to reduce the communication cost of feature histograms*[10]*.

4.6 GPU Support

Thanks @huanzhang12 for contributing this feature. Please read *[11]* to get more details.

- GPU Installation
- GPU Tutorial

4.7 Applications and Metrics

LightGBM supports the following applications:

- regression, the objective function is L2 loss
- binary classification, the objective function is logloss
- multi classification
- cross-entropy, the objective function is logloss and supports training on non-binary labels
- LambdaRank, the objective function is LambdaRank with NDCG

LightGBM supports the following metrics:

- L1 loss
- L2 loss
- Log loss
- Classification error rate
- AUC

- NDCG
- MAP
- Multi-class log loss
- Multi-class error rate
- AUC-mu `(new in v3.0.0)`
- Average precision `(new in v3.1.0)`
- Fair
- Huber
- Poisson
- Quantile
- MAPE
- Kullback-Leibler
- Gamma
- Tweedie

For more details, please refer to Parameters.

4.8 Other Features

- Limit `max_depth` of tree while grows tree leaf-wise
- DART
- L1/L2 regularization
- Bagging
- Column (feature) sub-sample
- Continued train with input GBDT model
- Continued train with the input score file
- Weighted training
- Validation metric output during training
- Multiple validation data
- Multiple metrics
- Early stopping (both training and prediction)
- Prediction for leaf index

For more details, please refer to Parameters.

4.9 References

[1] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, Tie-Yan Liu. "LightGBM: A Highly Efficient Gradient Boosting Decision Tree." Advances in Neural Information Processing Systems 30 (NIPS 2017), pp. 3149-3157.

[2] Mehta, Manish, Rakesh Agrawal, and Jorma Rissanen. "SLIQ: A fast scalable classifier for data mining." International Conference on Extending Database Technology. Springer Berlin Heidelberg, 1996.

[3] Shafer, John, Rakesh Agrawal, and Manish Mehta. "SPRINT: A scalable parallel classifier for data mining." Proc. 1996 Int. Conf. Very Large Data Bases. 1996.

[4] Ranka, Sanjay, and V. Singh. "CLOUDS: A decision tree classifier for large datasets." Proceedings of the 4th Knowledge Discovery and Data Mining Conference. 1998.

[5] Machado, F. P. "Communication and memory efficient parallel decision tree construction." (2003).

[6] Li, Ping, Qiang Wu, and Christopher J. Burges. "Mcrank: Learning to rank using multiple classification and gradient boosting." Advances in Neural Information Processing Systems 20 (NIPS 2007).

[7] Shi, Haijian. "Best-first decision tree learning." Diss. The University of Waikato, 2007.

[8] Walter D. Fisher. "On Grouping for Maximum Homogeneity." Journal of the American Statistical Association. Vol. 53, No. 284 (Dec., 1958), pp. 789-798.

[9] Thakur, Rajeev, Rolf Rabenseifner, and William Gropp. "Optimization of collective communication operations in MPICH." International Journal of High Performance Computing Applications 19.1 (2005), pp. 49-66.

[10] Qi Meng, Guolin Ke, Taifeng Wang, Wei Chen, Qiwei Ye, Zhi-Ming Ma, Tie-Yan Liu. "A Communication-Efficient Parallel Algorithm for Decision Tree." Advances in Neural Information Processing Systems 29 (NIPS 2016), pp. 1279-1287.

[11] Huan Zhang, Si Si and Cho-Jui Hsieh. "GPU Acceleration for Large-scale Tree Boosting." SysML Conference, 2018.

CHAPTER

FIVE

EXPERIMENTS

5.1 Comparison Experiment

For the detailed experiment scripts and output logs, please refer to this repo.

5.1.1 History

08 Mar, 2020: update according to the latest master branch (1b97eaf for XGBoost, bcad692 for LightGBM). (`xgboost_exact` is not updated for it is too slow.)

27 Feb, 2017: first version.

5.1.2 Data

We used 5 datasets to conduct our comparison experiments. Details of data are listed in the following table:

Data	Task	Link	#Train_Set	#Feature	Comments
Higgs	Binary classification	link	10,500,000	28	last 500,000 samples were used as test set
Yahoo LTR	Learning to rank	link	473,134	700	set1.train as train, set1.test as test
MS LTR	Learning to rank	link	2,270,296	137	{S1,S2,S3} as train set, {S5} as test set
Expo	Binary classification	link	11,000,000	700	last 1,000,000 samples were used as test set
Allstate	Binary classification	link	13,184,290	4228	last 1,000,000 samples were used as test set

5.1.3 Environment

We ran all experiments on a single Linux server (Azure ND24s) with the following specifications:

OS	CPU	Memory
Ubuntu 16.04 LTS	2 * E5-2690 v4	448GB

5.1.4 Baseline

We used xgboost as a baseline.

Both xgboost and LightGBM were built with OpenMP support.

5.1.5 Settings

We set up total 3 settings for experiments. The parameters of these settings are:

1. xgboost:

```
eta = 0.1
max_depth = 8
num_round = 500
nthread = 16
tree_method = exact
min_child_weight = 100
```

2. xgboost_hist (using histogram based algorithm):

```
eta = 0.1
num_round = 500
nthread = 16
min_child_weight = 100
tree_method = hist
grow_policy = lossguide
max_depth = 0
max_leaves = 255
```

3. LightGBM:

```
learning_rate = 0.1
num_leaves = 255
num_trees = 500
num_threads = 16
min_data_in_leaf = 0
min_sum_hessian_in_leaf = 100
```

xgboost grows trees depth-wise and controls model complexity by `max_depth`. LightGBM uses a leaf-wise algorithm instead and controls model complexity by `num_leaves`. So we cannot compare them in the exact same model setting. For the tradeoff, we use xgboost with `max_depth=8`, which will have max number leaves to 255, to compare with LightGBM with `num_leaves=255`.

Other parameters are default values.

5.1.6 Result

Speed

We compared speed using only the training task without any test or metric output. We didn't count the time for IO. For the ranking tasks, since XGBoost and LightGBM implement different ranking objective functions, we used `regression` objective for speed benchmark, for the fair comparison.

The following table is the comparison of time cost:

Data	xgboost	xgboost_hist	LightGBM
Higgs	3794.34 s	165.575 s	**130.094 s**
Yahoo LTR	674.322 s	131.462 s	**76.229 s**
MS LTR	1251.27 s	98.386 s	**70.417 s**
Expo	1607.35 s	137.65 s	**62.607 s**
Allstate	2867.22 s	315.256 s	**148.231 s**

LightGBM ran faster than xgboost on all experiment data sets.

Accuracy

We computed all accuracy metrics only on the test data set.

Data	Metric	xgboost	xgboost_hist	LightGBM
Higgs	AUC	0.839593	0.845314	**0.845724**
Yahoo LTR	$NDCG_1$	0.719748	0.720049	**0.732981**
	$NDCG_3$	0.717813	0.722573	**0.735689**
	$NDCG_5$	0.737849	0.740899	**0.75352**
	$NDCG_{10}$	0.78089	0.782957	**0.793498**
MS LTR	$NDCG_1$	0.483956	0.485115	**0.517767**
	$NDCG_3$	0.467951	0.47313	**0.501063**
	$NDCG_5$	0.472476	0.476375	**0.504648**
	$NDCG_{10}$	0.492429	0.496553	**0.524252**
Expo	AUC	0.756713	0.776224	**0.776935**
Allstate	AUC	0.607201	**0.609465**	0.609072

Memory Consumption

We monitored RES while running training task. And we set `two_round=true` (this will increase data-loading time and reduce peak memory usage but not affect training speed or accuracy) in LightGBM to reduce peak memory usage.

Data	xgboost	xgboost_hist	LightGBM (col-wise)	LightGBM (row-wise)
Higgs	4.853GB	7.335GB	**0.897GB**	1.401GB
Yahoo LTR	1.907GB	4.023GB	**1.741GB**	2.161GB
MS LTR	5.469GB	7.491GB	**0.940GB**	1.296GB
Expo	1.553GB	2.606GB	**0.555GB**	0.711GB
Allstate	6.237GB	12.090GB	**1.116GB**	1.755GB

5.2 Parallel Experiment

5.2.1 History

27 Feb, 2017: first version.

5.2.2 Data

We used a terabyte click log dataset to conduct parallel experiments. Details are listed in following table:

Data	Task	Link	#Data	#Feature
Criteo	Binary classification	link	1,700,000,000	67

This data contains 13 integer features and 26 categorical features for 24 days of click logs. We statisticized the click-through rate (CTR) and count for these 26 categorical features from the first ten days. Then we used next ten days' data, after replacing the categorical features by the corresponding CTR and count, as training data. The processed training data have a total of 1.7 billions records and 67 features.

5.2.3 Environment

We ran our experiments on 16 Windows servers with the following specifications:

OS	CPU	Memory	Network Adapter
Windows Server 2012	2 * E5-2670 v2	DDR3 1600Mhz, 256GB	Mellanox ConnectX-3, 54Gbps, RDMA support

5.2.4 Settings

```
learning_rate = 0.1
num_leaves = 255
num_trees = 100
num_thread = 16
tree_learner = data
```

We used data parallel here because this data is large in `#data` but small in `#feature`. Other parameters were default values.

5.2.5 Results

#Machine	Time per Tree	Memory Usage(per Machine)
1	627.8 s	176GB
2	311 s	87GB
4	156 s	43GB
8	80 s	22GB
16	42 s	11GB

The results show that LightGBM achieves a linear speedup with distributed learning.

5.3 GPU Experiments

Refer to GPU Performance.

CHAPTER

SIX

PARAMETERS

This page contains descriptions of all parameters in LightGBM.

List of other helpful links

- Python API
- Parameters Tuning

6.1 Parameters Format

Parameters are merged together in the following order (later items overwrite earlier ones):

1. LightGBM's default values
2. special files for `weight`, `init_score`, `query`, and `positions` (see *Others*)
3. (CLI only) configuration in a file passed like `config=train.conf`
4. (CLI only) configuration passed via the command line
5. (Python, R) special keyword arguments to some functions (e.g. `num_boost_round` in `train()`)
6. (Python, R) `params` function argument (including `**kwargs` in Python and `...` in R)
7. (C API) `parameters` or `params` function argument

Many parameters have "aliases", alternative names which refer to the same configuration.

Where a mix of the primary parameter name and aliases are given, the primary parameter name is always preferred to any aliases.

For example, in Python:

```
# use learning rate of 0.07, because 'learning_rate'
# is the primary parameter name
lgb.train(
   params={
      "learning_rate": 0.07,
      "shrinkage_rate": 0.12
   },
   train_set=dtrain
)
```

Where multiple aliases are given, and the primary parameter name is not, the first alias appearing in the lists returned by `Config::parameter2aliases()` in the C++ library is used. Those lists are hard-coded in a fairly arbitrary way... wherever possible, avoid relying on this behavior.

For example, in Python:

```
# use learning rate of 0.12, LightGBM has a hard-coded preference for 'shrinkage_rate'
# over any other aliases, and 'learning_rate' is not provided
lgb.train(
   params={
      "eta": 0.19,
      "shrinkage_rate": 0.12
   },
   train_set=dtrain
)
```

CLI

The parameters format is `key1=value1 key2=value2 ...`. Parameters can be set both in config file and command line. By using command line, parameters should not have spaces before and after =. By using config files, one line can only contain one parameter. You can use # to comment.

Python

Any parameters that accept multiple values should be passed as a Python list.

```
params = {
   "monotone_constraints": [-1, 0, 1]
}
```

R

Any parameters that accept multiple values should be passed as an R list.

```
params <- list(
   monotone_constraints = c(-1, 0, 1)
)
```

6.2 Core Parameters

- `config` , default = "", type = string, aliases: `config_file`
  - path of config file
  - **Note**: can be used only in CLI version
- `task` , default = `train`, type = enum, options: `train`, `predict`, `convert_model`, `refit`, aliases: `task_type`
  - `train`, for training, aliases: `training`
  - `predict`, for prediction, aliases: `prediction`, `test`
  - `convert_model`, for converting model file into if-else format, see more information in *Convert Parameters*
  - `refit`, for refitting existing models with new data, aliases: `refit_tree`
  - `save_binary`, load train (and validation) data then save dataset to binary file. Typical usage: `save_binary` first, then run multiple `train` tasks in parallel using the saved binary file
  - **Note**: can be used only in CLI version; for language-specific packages you can use the correspondent functions
- `objective` , default = `regression`, type = enum, options: `regression`, `regression_l1`, `huber`, `fair`, `poisson`, `quantile`, `mape`, `gamma`, `tweedie`, `binary`, `multiclass`, `multiclassova`, `cross_entropy`, `cross_entropy_lambda`, `lambdarank`, `rank_xendcg`, aliases: `objective_type`, `app`, `application`, `loss`

  - regression application
    - `regression`, L2 loss, aliases: `regression_l2`, `l2`, `mean_squared_error`, `mse`, `l2_root`, `root_mean_squared_error`, `rmse`
    - `regression_l1`, L1 loss, aliases: `l1`, `mean_absolute_error`, `mae`
    - `huber`, Huber loss
    - `fair`, Fair loss
    - `poisson`, Poisson regression
    - `quantile`, Quantile regression
    - `mape`, MAPE loss, aliases: `mean_absolute_percentage_error`
    - `gamma`, Gamma regression with log-link. It might be useful, e.g., for modeling insurance claims severity, or for any target that might be gamma-distributed
    - `tweedie`, Tweedie regression with log-link. It might be useful, e.g., for modeling total loss in insurance, or for any target that might be tweedie-distributed
  - binary classification application
    - `binary`, binary log loss classification (or logistic regression)
    - requires labels in {0, 1}; see `cross-entropy` application for general probability labels in [0, 1]
  - multi-class classification application
    - `multiclass`, softmax objective function, aliases: `softmax`
    - `multiclassova`, One-vs-All binary objective function, aliases: `multiclass_ova`, `ova`, `ovr`
    - `num_class` should be set as well
  - cross-entropy application
    - `cross_entropy`, objective function for cross-entropy (with optional linear weights), aliases: `xentropy`
    - `cross_entropy_lambda`, alternative parameterization of cross-entropy, aliases: `xentlambda`
    - label is anything in interval [0, 1]
  - ranking application
    - `lambdarank`, lambdarank objective. *label_gain* can be used to set the gain (weight) of `int` label and all values in `label` must be smaller than number of elements in `label_gain`
    - `rank_xendcg`, XE_NDCG_MART ranking objective function, aliases: `xendcg`, `xe_ndcg`, `xe_ndcg_mart`, `xendcg_mart`
    - `rank_xendcg` is faster than and achieves the similar performance as `lambdarank`
    - label should be `int` type, and larger number represents the higher relevance (e.g. 0:bad, 1:fair, 2:good, 3:perfect)
  - custom objective function (gradients and hessians not computed directly by LightGBM)
    - `custom`
    - must be passed through parameters explicitly in the C API
    - **Note**: cannot be used in CLI version

- `boosting` , default = `gbdt`, type = enum, options: `gbdt`, `rf`, `dart`, aliases: `boosting_type`, `boost`

  - gbdt, traditional Gradient Boosting Decision Tree, aliases: gbrt
  - rf, Random Forest, aliases: random_forest
  - dart, Dropouts meet Multiple Additive Regression Trees
    - **Note**: internally, LightGBM uses gbdt mode for the first 1 / learning_rate iterations
- data_sample_strategy , default = bagging, type = enum, options: bagging, goss
  - bagging, Randomly Bagging Sampling
    - **Note**: bagging is only effective when bagging_freq > 0 and bagging_fraction < 1.0
  - goss, Gradient-based One-Side Sampling
  - *New in version 4.0.0*
- data , default = "", type = string, aliases: train, train_data, train_data_file, data_filename
  - path of training data, LightGBM will train from this data
  - **Note**: can be used only in CLI version
- valid , default = "", type = string, aliases: test, valid_data, valid_data_file, test_data, test_data_file, valid_filenames
  - path(s) of validation/test data, LightGBM will output metrics for these data
  - support multiple validation data, separated by ,
  - **Note**: can be used only in CLI version
- num_iterations , default = 100, type = int, aliases: num_iteration, n_iter, num_tree, num_trees, num_round, num_rounds, nrounds, num_boost_round, n_estimators, max_iter, constraints: num_iterations >= 0
  - number of boosting iterations
  - **Note**: internally, LightGBM constructs num_class * num_iterations trees for multi-class classification problems
- learning_rate , default = 0.1, type = double, aliases: shrinkage_rate, eta, constraints: learning_rate > 0.0
  - shrinkage rate
  - in dart, it also affects on normalization weights of dropped trees
- num_leaves , default = 31, type = int, aliases: num_leaf, max_leaves, max_leaf, max_leaf_nodes, constraints: 1 < num_leaves <= 131072
  - max number of leaves in one tree
- tree_learner , default = serial, type = enum, options: serial, feature, data, voting, aliases: tree, tree_type, tree_learner_type
  - serial, single machine tree learner
  - feature, feature parallel tree learner, aliases: feature_parallel
  - data, data parallel tree learner, aliases: data_parallel
  - voting, voting parallel tree learner, aliases: voting_parallel
  - refer to Distributed Learning Guide to get more details
- num_threads , default = 0, type = int, aliases: num_thread, nthread, nthreads, n_jobs

  - used only in `train`, `prediction` and `refit` tasks or in correspondent functions of language-specific packages
  - number of threads for LightGBM
  - `0` means default number of threads in OpenMP
  - for the best speed, set this to the number of **real CPU cores**, not the number of threads (most CPUs use hyper-threading to generate 2 threads per CPU core)
  - do not set it too large if your dataset is small (for instance, do not use 64 threads for a dataset with 10,000 rows)
  - be aware a task manager or any similar CPU monitoring tool might report that cores not being fully utilized. **This is normal**
  - for distributed learning, do not use all CPU cores because this will cause poor performance for the network communication
  - **Note**: please **don't** change this during training, especially when running multiple jobs simultaneously by external packages, otherwise it may cause undesirable errors
- `device_type` , default = `cpu`, type = enum, options: `cpu`, `gpu`, `cuda`, aliases: `device`
  - device for the tree learning
  - `cpu` supports all LightGBM functionality and is portable across the widest range of operating systems and hardware
  - `cuda` offers faster training than `gpu` or `cpu`, but only works on GPUs supporting CUDA or ROCm
  - `gpu` can be faster than `cpu` and works on a wider range of GPUs than CUDA
  - **Note**: it is recommended to use the smaller `max_bin` (e.g. 63) to get the better speed up
  - **Note**: for the faster speed, GPU uses 32-bit float point to sum up by default, so this may affect the accuracy for some tasks. You can set `gpu_use_dp=true` to enable 64-bit float point, but it will slow down the training
  - **Note**: refer to Installation Guide to build LightGBM with GPU, CUDA, or ROCm support
- `seed` , default = `None`, type = int, aliases: `random_seed`, `random_state`
  - this seed is used to generate other seeds, e.g. `data_random_seed`, `feature_fraction_seed`, etc.
  - by default, this seed is unused in favor of default values of other seeds
  - this seed has lower priority in comparison with other seeds, which means that it will be overridden, if you set other seeds explicitly
- `deterministic` , default = `false`, type = bool
  - used only with `cpu` device type
  - setting this to `true` should ensure the stable results when using the same data and the same parameters (and different `num_threads`)
  - when you use the different seeds, different LightGBM versions, the binaries compiled by different compilers, or in different systems, the results are expected to be different
  - you can raise issues in LightGBM GitHub repo when you meet the unstable results
  - **Note**: setting this to `true` may slow down the training
  - **Note**: to avoid potential instability due to numerical issues, please set `force_col_wise=true` or `force_row_wise=true` when setting `deterministic=true`

6.3 Learning Control Parameters

- `force_col_wise` , default = `false`, type = bool
  - used only with `cpu` device type
  - set this to `true` to force col-wise histogram building
  - enabling this is recommended when:
    - the number of columns is large, or the total number of bins is large
    - `num_threads` is large, e.g. `> 20`
    - you want to reduce memory cost
  - **Note**: when both `force_col_wise` and `force_row_wise` are `false`, LightGBM will firstly try them both, and then use the faster one. To remove the overhead of testing set the faster one to `true` manually
  - **Note**: this parameter cannot be used at the same time with `force_row_wise`, choose only one of them
- `force_row_wise` , default = `false`, type = bool
  - used only with `cpu` device type
  - set this to `true` to force row-wise histogram building
  - enabling this is recommended when:
    - the number of data points is large, and the total number of bins is relatively small
    - `num_threads` is relatively small, e.g. `<= 16`
    - you want to use small `bagging_fraction` or `goss` sample strategy to speed up
  - **Note**: setting this to `true` will double the memory cost for Dataset object. If you have not enough memory, you can try setting `force_col_wise=true`
  - **Note**: when both `force_col_wise` and `force_row_wise` are `false`, LightGBM will firstly try them both, and then use the faster one. To remove the overhead of testing set the faster one to `true` manually
  - **Note**: this parameter cannot be used at the same time with `force_col_wise`, choose only one of them
- `histogram_pool_size` , default = `-1.0`, type = double, aliases: `hist_pool_size`
  - max cache size in MB for historical histogram
  - `< 0` means no limit
- `max_depth` , default = `-1`, type = int
  - limit the max depth for tree model. This is used to deal with over-fitting when `#data` is small. Tree still grows leaf-wise
  - `<= 0` means no limit
- `min_data_in_leaf` , default = `20`, type = int, aliases: `min_data_per_leaf`, `min_data`, `min_child_samples`, `min_samples_leaf`, constraints: `min_data_in_leaf >= 0`
  - minimal number of data in one leaf. Can be used to deal with over-fitting
  - **Note**: this is an approximation based on the Hessian, so occasionally you may observe splits which produce leaf nodes that have less than this many observations
- `min_sum_hessian_in_leaf` , default = `1e-3`, type = double, aliases: `min_sum_hessian_per_leaf`, `min_sum_hessian`, `min_hessian`, `min_child_weight`, constraints: `min_sum_hessian_in_leaf >= 0.0`
  - minimal sum hessian in one leaf. Like `min_data_in_leaf`, it can be used to deal with over-fitting

- `bagging_fraction` , default = `1.0`, type = double, aliases: `sub_row`, `subsample`, `bagging`, constraints: `0.0 < bagging_fraction <= 1.0`
  - like `feature_fraction`, but this will randomly select part of data without resampling
  - can be used to speed up training
  - can be used to deal with over-fitting
  - **Note**: to enable bagging, `bagging_freq` should be set to a non zero value as well
- `pos_bagging_fraction` , default = `1.0`, type = double, aliases: `pos_sub_row`, `pos_subsample`, `pos_bagging`, constraints: `0.0 < pos_bagging_fraction <= 1.0`
  - used only in `binary` application
  - used for imbalanced binary classification problem, will randomly sample `#pos_samples * pos_bagging_fraction` positive samples in bagging
  - should be used together with `neg_bagging_fraction`
  - set this to `1.0` to disable
  - **Note**: to enable this, you need to set `bagging_freq` and `neg_bagging_fraction` as well
  - **Note**: if both `pos_bagging_fraction` and `neg_bagging_fraction` are set to `1.0`, balanced bagging is disabled
  - **Note**: if balanced bagging is enabled, `bagging_fraction` will be ignored
- `neg_bagging_fraction` , default = `1.0`, type = double, aliases: `neg_sub_row`, `neg_subsample`, `neg_bagging`, constraints: `0.0 < neg_bagging_fraction <= 1.0`
  - used only in `binary` application
  - used for imbalanced binary classification problem, will randomly sample `#neg_samples * neg_bagging_fraction` negative samples in bagging
  - should be used together with `pos_bagging_fraction`
  - set this to `1.0` to disable
  - **Note**: to enable this, you need to set `bagging_freq` and `pos_bagging_fraction` as well
  - **Note**: if both `pos_bagging_fraction` and `neg_bagging_fraction` are set to `1.0`, balanced bagging is disabled
  - **Note**: if balanced bagging is enabled, `bagging_fraction` will be ignored
- `bagging_freq` , default = `0`, type = int, aliases: `subsample_freq`
  - frequency for bagging
  - `0` means disable bagging; `k` means perform bagging at every `k` iteration. Every `k`-th iteration, LightGBM will randomly select `bagging_fraction * 100%` of the data to use for the next `k` iterations
  - **Note**: bagging is only effective when `0.0 < bagging_fraction < 1.0`
- `bagging_seed` , default = `3`, type = int, aliases: `bagging_fraction_seed`
  - random seed for bagging
- `bagging_by_query` , default = `false`, type = bool
  - whether to do bagging sample by query
  - *New in version 4.6.0*

- feature_fraction , default = 1.0, type = double, aliases: sub_feature, colsample_bytree, constraints: 0.0 < feature_fraction <= 1.0
  - LightGBM will randomly select a subset of features on each iteration (tree) if feature_fraction is smaller than 1.0. For example, if you set it to 0.8, LightGBM will select 80% of features before training each tree
  - can be used to speed up training
  - can be used to deal with over-fitting
- feature_fraction_bynode , default = 1.0, type = double, aliases: sub_feature_bynode, colsample_bynode, constraints: 0.0 < feature_fraction_bynode <= 1.0
  - LightGBM will randomly select a subset of features on each tree node if feature_fraction_bynode is smaller than 1.0. For example, if you set it to 0.8, LightGBM will select 80% of features at each tree node
  - can be used to deal with over-fitting
  - **Note**: unlike feature_fraction, this cannot speed up training
  - **Note**: if both feature_fraction and feature_fraction_bynode are smaller than 1.0, the final fraction of each node is feature_fraction * feature_fraction_bynode
- feature_fraction_seed , default = 2, type = int
  - random seed for feature_fraction
- extra_trees , default = false, type = bool, aliases: extra_tree
  - use extremely randomized trees
  - if set to true, when evaluating node splits LightGBM will check only one randomly-chosen threshold for each feature
  - can be used to speed up training
  - can be used to deal with over-fitting
- extra_seed , default = 6, type = int
  - random seed for selecting thresholds when extra_trees is true
- early_stopping_round , default = 0, type = int, aliases: early_stopping_rounds, early_stopping, n_iter_no_change
  - will stop training if one metric of one validation data doesn't improve in last early_stopping_round rounds
  - <= 0 means disable
  - can be used to speed up training
- early_stopping_min_delta , default = 0.0, type = double, constraints: early_stopping_min_delta >= 0.0
  - when early stopping is used (i.e. early_stopping_round > 0), require the early stopping metric to improve by at least this delta to be considered an improvement
  - *New in version 4.4.0*
- first_metric_only , default = false, type = bool
  - LightGBM allows you to provide multiple evaluation metrics. Set this to true, if you want to use only the first metric for early stopping
- max_delta_step , default = 0.0, type = double, aliases: max_tree_output, max_leaf_output

  - used to limit the max output of tree leaves
  - <= 0 means no constraint
  - the final max output of leaves is learning_rate * max_delta_step
- lambda_l1 , default = 0.0, type = double, aliases: reg_alpha, l1_regularization, constraints: lambda_l1 >= 0.0
  - L1 regularization
- lambda_l2 , default = 0.0, type = double, aliases: reg_lambda, lambda, l2_regularization, constraints: lambda_l2 >= 0.0
  - L2 regularization
- linear_lambda , default = 0.0, type = double, constraints: linear_lambda >= 0.0
  - linear tree regularization, corresponds to the parameter lambda in Eq. 3 of Gradient Boosting with Piece-Wise Linear Regression Trees
- min_gain_to_split , default = 0.0, type = double, aliases: min_split_gain, constraints: min_gain_to_split >= 0.0
  - the minimal gain to perform split
  - can be used to speed up training
- drop_rate , default = 0.1, type = double, aliases: rate_drop, constraints: 0.0 <= drop_rate <= 1.0
  - used only in dart
  - dropout rate: a fraction of previous trees to drop during the dropout
- max_drop , default = 50, type = int
  - used only in dart
  - max number of dropped trees during one boosting iteration
  - <=0 means no limit
- skip_drop , default = 0.5, type = double, constraints: 0.0 <= skip_drop <= 1.0
  - used only in dart
  - probability of skipping the dropout procedure during a boosting iteration
- xgboost_dart_mode , default = false, type = bool
  - used only in dart
  - set this to true, if you want to use XGBoost DART mode
- uniform_drop , default = false, type = bool
  - used only in dart
  - set this to true, if you want to use uniform drop
- drop_seed , default = 4, type = int
  - used only in dart
  - random seed to choose dropping models
- top_rate , default = 0.2, type = double, constraints: 0.0 <= top_rate <= 1.0
  - used only in goss

  - the retain ratio of large gradient data

- `other_rate` , default = `0.1`, type = double, constraints: `0.0 <= other_rate <= 1.0`
  - used only in `goss`
  - the retain ratio of small gradient data

- `min_data_per_group` , default = `100`, type = int, constraints: `min_data_per_group > 0`
  - used for the categorical features
  - minimal number of data per categorical group

- `max_cat_threshold` , default = `32`, type = int, constraints: `max_cat_threshold > 0`
  - used for the categorical features
  - limit number of split points considered for categorical features. See the documentation on how LightGBM finds optimal splits for categorical features for more details
  - can be used to speed up training

- `cat_l2` , default = `10.0`, type = double, constraints: `cat_l2 >= 0.0`
  - used for the categorical features
  - L2 regularization in categorical split

- `cat_smooth` , default = `10.0`, type = double, constraints: `cat_smooth >= 0.0`
  - used for the categorical features
  - this can reduce the effect of noises in categorical features, especially for categories with few data

- `max_cat_to_onehot` , default = `4`, type = int, constraints: `max_cat_to_onehot > 0`
  - used for the categorical features
  - when number of categories of one feature smaller than or equal to `max_cat_to_onehot`, one-vs-other split algorithm will be used

- `top_k` , default = `20`, type = int, aliases: `topk`, constraints: `top_k > 0`
  - used only in `voting` tree learner, refer to Voting parallel
  - set this to larger value for more accurate result, but it will slow down the training speed

- `monotone_constraints` , default = `None`, type = multi-int, aliases: `mc`, `monotone_constraint`, `monotonic_cst`
  - used for constraints of monotonic features
  - `1` means increasing, `-1` means decreasing, `0` means non-constraint
  - you need to specify all features in order. For example, `mc=-1,0,1` means decreasing for the 1st feature, non-constraint for the 2nd feature and increasing for the 3rd feature

- `monotone_constraints_method` , default = `basic`, type = enum, options: `basic`, `intermediate`, `advanced`, aliases: `monotone_constraining_method`, `mc_method`
  - used only if `monotone_constraints` is set
  - monotone constraints method
    - `basic`, the most basic monotone constraints method. It does not slow down the training speed at all, but over-constrains the predictions

    - `intermediate`, a more advanced method, which may slow down the training speed very slightly. However, this method is much less constraining than the basic method and should significantly improve the results
    - `advanced`, an even more advanced method, which may slow down the training speed. However, this method is even less constraining than the intermediate method and should again significantly improve the results

- `monotone_penalty` , default = `0.0`, type = double, aliases: `monotone_splits_penalty`, `ms_penalty`, `mc_penalty`, constraints: `monotone_penalty >= 0.0`
  - used only if `monotone_constraints` is set
  - monotone penalty: a penalization parameter X forbids any monotone splits on the first X (rounded down) level(s) of the tree. The penalty applied to monotone splits on a given depth is a continuous, increasing function the penalization parameter
  - if `0.0` (the default), no penalization is applied
- `feature_contri` , default = `None`, type = multi-double, aliases: `feature_contrib`, `fc`, `fp`, `feature_penalty`
  - used to control feature's split gain, will use `gain[i] = max(0, feature_contri[i]) * gain[i]` to replace the split gain of i-th feature
  - you need to specify all features in order
- `forcedsplits_filename` , default = `""`, type = string, aliases: `fs`, `forced_splits_filename`, `forced_splits_file`, `forced_splits`
  - path to a `.json` file that specifies splits to force at the top of every decision tree before best-first learning commences
  - `.json` file can be arbitrarily nested, and each split contains `feature`, `threshold` fields, as well as `left` and `right` fields representing subsplits
  - categorical splits are forced in a one-hot fashion, with `left` representing the split containing the feature value and `right` representing other values
  - **Note**: the forced split logic will be ignored, if the split makes gain worse
  - see this file as an example
- `refit_decay_rate` , default = `0.9`, type = double, constraints: `0.0 <= refit_decay_rate <= 1.0`
  - decay rate of `refit` task, will use `leaf_output = refit_decay_rate * old_leaf_output + (1.0 - refit_decay_rate) * new_leaf_output` to refit trees
  - used only in `refit` task in CLI version or as argument in `refit` function in language-specific package
- `cegb_tradeoff` , default = `1.0`, type = double, constraints: `cegb_tradeoff >= 0.0`
  - cost-effective gradient boosting multiplier for all penalties
- `cegb_penalty_split` , default = `0.0`, type = double, constraints: `cegb_penalty_split >= 0.0`
  - cost-effective gradient-boosting penalty for splitting a node
- `cegb_penalty_feature_lazy` , default = `0,0,...,0`, type = multi-double
  - cost-effective gradient boosting penalty for using a feature
  - applied per data point
- `cegb_penalty_feature_coupled` , default = `0,0,...,0`, type = multi-double
  - cost-effective gradient boosting penalty for using a feature

  - applied once per forest

- `path_smooth` , default = `0`, type = double, constraints: `path_smooth >= 0.0`
  - controls smoothing applied to tree nodes
  - helps prevent overfitting on leaves with few samples
  - if `0.0` (the default), no smoothing is applied
  - if `path_smooth > 0` then `min_data_in_leaf` must be at least `2`
  - larger values give stronger regularization
    - the weight of each node is `w * (n / path_smooth) / (n / path_smooth + 1) + w_p / (n / path_smooth + 1)`, where `n` is the number of samples in the node, `w` is the optimal node weight to minimise the loss (approximately `-sum_gradients / sum_hessians`), and `w_p` is the weight of the parent node
    - note that the parent output `w_p` itself has smoothing applied, unless it is the root node, so that the smoothing effect accumulates with the tree depth
- `interaction_constraints` , default = `""`, type = string
  - controls which features can appear in the same branch
  - by default interaction constraints are disabled, to enable them you can specify
    - for CLI, lists separated by commas, e.g. `[0,1,2],[2,3]`
    - for Python-package, list of lists, e.g. `[[0, 1, 2], [2, 3]]`
    - for R-package, list of character or numeric vectors, e.g. `list(c("var1", "var2", "var3"), c("var3", "var4"))` or `list(c(1L, 2L, 3L), c(3L, 4L))`. Numeric vectors should use 1-based indexing, where `1L` is the first feature, `2L` is the second feature, etc.
  - any two features can only appear in the same branch only if there exists a constraint containing both features
- `verbosity` , default = `1`, type = int, aliases: `verbose`
  - controls the level of LightGBM's verbosity
  - `< 0`: Fatal, `= 0`: Error (Warning), `= 1`: Info, `> 1`: Debug
- `input_model` , default = `""`, type = string, aliases: `model_input`, `model_in`
  - filename of input model
  - for `prediction` task, this model will be applied to prediction data
  - for `train` task, training will be continued from this model
  - **Note**: can be used only in CLI version
- `output_model` , default = `LightGBM_model.txt`, type = string, aliases: `model_output`, `model_out`
  - filename of output model in training
  - **Note**: can be used only in CLI version
- `saved_feature_importance_type` , default = `0`, type = int
  - the feature importance type in the saved model file
  - `0`: count-based feature importance (numbers of splits are counted); `1`: gain-based feature importance (values of gain are counted)
  - **Note**: can be used only in CLI version

- `snapshot_freq` , default = `-1`, type = int, aliases: `save_period`
  - frequency of saving model file snapshot
  - set this to positive value to enable this function. For example, the model file will be snapshotted at each iteration if `snapshot_freq=1`
  - **Note**: can be used only in CLI version
- `use_quantized_grad` , default = `false`, type = bool
  - whether to use gradient quantization when training
  - enabling this will discretize (quantize) the gradients and hessians into bins of `num_grad_quant_bins`
  - with quantized training, most arithmetics in the training process will be integer operations
  - gradient quantization can accelerate training, with little accuracy drop in most cases
  - **Note**: works only with `cpu` and `cuda` device type
  - *New in version 4.0.0*
- `num_grad_quant_bins` , default = `4`, type = int
  - used only if `use_quantized_grad=true`
  - number of bins to quantization gradients and hessians
  - with more bins, the quantized training will be closer to full precision training
  - **Note**: works only with `cpu` and `cuda` device type
  - *New in version 4.0.0*
- `quant_train_renew_leaf` , default = `false`, type = bool
  - used only if `use_quantized_grad=true`
  - whether to renew the leaf values with original gradients when quantized training
  - renewing is very helpful for good quantized training accuracy for ranking objectives
  - **Note**: works only with `cpu` and `cuda` device type
  - *New in version 4.0.0*
- `stochastic_rounding` , default = `true`, type = bool
  - used only if `use_quantized_grad=true`
  - whether to use stochastic rounding in gradient quantization
  - **Note**: works only with `cpu` and `cuda` device type
  - *New in version 4.0.0*

6.4 IO Parameters

6.4.1 Dataset Parameters

- `linear_tree` , default = `false`, type = bool, aliases: `linear_trees`
  - fit piecewise linear gradient boosting tree
  - tree splits are chosen in the usual way, but the model at each leaf is linear instead of constant
  - the linear model at each leaf includes all the numerical features in that leaf's branch

  - the first tree has constant leaf values
  - categorical features are used for splits as normal but are not used in the linear models
  - missing values should not be encoded as `0`. Use `np.nan` for Python, `NA` for the CLI, and `NA`, `NA_real_`, or `NA_integer_` for R
  - it is recommended to rescale data before training so that features have similar mean and standard deviation
  - **Note**: works only with `cpu`, `gpu` device type and `serial` tree learner
  - **Note**: `regression_l1` objective is not supported with linear tree boosting
  - **Note**: setting `linear_tree=true` significantly increases the memory use of LightGBM
  - **Note**: if you specify `monotone_constraints`, constraints will be enforced when choosing the split points, but not when fitting the linear models on leaves

- `max_bin` , default = `255`, type = int, aliases: `max_bins`, constraints: `max_bin > 1`
  - max number of bins that feature values will be bucketed in
  - small number of bins may reduce training accuracy but may increase general power (deal with over-fitting)
  - LightGBM will auto compress memory according to `max_bin`. For example, LightGBM will use `uint8_t` for feature value if `max_bin=255`
- `max_bin_by_feature` , default = `None`, type = multi-int
  - max number of bins for each feature
  - if not specified, will use `max_bin` for all features
- `min_data_in_bin` , default = `3`, type = int, constraints: `min_data_in_bin > 0`
  - minimal number of data inside one bin
  - use this to avoid one-data-one-bin (potential over-fitting)
- `bin_construct_sample_cnt` , default = `200000`, type = int, aliases: `subsample_for_bin`, constraints: `bin_construct_sample_cnt > 0`
  - number of data that sampled to construct feature discrete bins
  - setting this to larger value will give better training result, but may increase data loading time
  - set this to larger value if data is very sparse
  - **Note**: don't set this to small values, otherwise, you may encounter unexpected errors and poor accuracy
- `data_random_seed` , default = `1`, type = int, aliases: `data_seed`
  - random seed for sampling data to construct histogram bins
- `is_enable_sparse` , default = `true`, type = bool, aliases: `is_sparse`, `enable_sparse`, `sparse`
  - used to enable/disable sparse optimization
- `enable_bundle` , default = `true`, type = bool, aliases: `is_enable_bundle`, `bundle`
  - set this to `false` to disable Exclusive Feature Bundling (EFB), which is described in LightGBM: A Highly Efficient Gradient Boosting Decision Tree
  - **Note**: disabling this may cause the slow training speed for sparse datasets
- `use_missing` , default = `true`, type = bool
  - set this to `false` to disable the special handle of missing value
- `zero_as_missing` , default = `false`, type = bool

  - set this to `true` to treat all zero as missing values (including the unshown values in LibSVM / sparse matrices)
  - set this to `false` to use `na` for representing missing values

- `feature_pre_filter` , default = `true`, type = bool
  - set this to `true` (the default) to tell LightGBM to ignore the features that are unsplittable based on `min_data_in_leaf`
  - as dataset object is initialized only once and cannot be changed after that, you may need to set this to `false` when searching parameters with `min_data_in_leaf`, otherwise features are filtered by `min_data_in_leaf` firstly if you don't reconstruct dataset object
  - **Note**: setting this to `false` may slow down the training

- `pre_partition` , default = `false`, type = bool, aliases: `is_pre_partition`
  - used for distributed learning (excluding the `feature_parallel` mode)
  - `true` if training data are pre-partitioned, and different machines use different partitions

- `two_round` , default = `false`, type = bool, aliases: `two_round_loading`, `use_two_round_loading`
  - set this to `true` if data file is too big to fit in memory
  - by default, LightGBM will map data file to memory and load features from memory. This will provide faster data loading speed, but may cause run out of memory error when the data file is very big
  - **Note**: works only in case of loading data directly from text file

- `header` , default = `false`, type = bool, aliases: `has_header`
  - set this to `true` if input data has header
  - **Note**: works only in case of loading data directly from text file

- `label_column` , default = "", type = int or string, aliases: `label`
  - used to specify the label column
  - use number for index, e.g. `label=0` means column_0 is the label
  - add a prefix `name:` for column name, e.g. `label=name:is_click`
  - if omitted, the first column in the training data is used as the label
  - **Note**: works only in case of loading data directly from text file

- `weight_column` , default = "", type = int or string, aliases: `weight`
  - used to specify the weight column
  - use number for index, e.g. `weight=0` means column_0 is the weight
  - add a prefix `name:` for column name, e.g. `weight=name:weight`
  - **Note**: works only in case of loading data directly from text file
  - **Note**: index starts from `0` and it doesn't count the label column when passing type is `int`, e.g. when label is column_0, and weight is column_1, the correct parameter is `weight=0`
  - **Note**: weights should be non-negative

- `group_column` , default = "", type = int or string, aliases: `group`, `group_id`, `query_column`, `query`, `query_id`
  - used to specify the query/group id column

  - use number for index, e.g. `query=0` means column_0 is the query id
  - add a prefix `name:` for column name, e.g. `query=name:query_id`
  - **Note**: works only in case of loading data directly from text file
  - **Note**: data should be grouped by query_id, for more information, see *Query Data*
  - **Note**: index starts from `0` and it doesn't count the label column when passing type is `int`, e.g. when label is column_0 and query_id is column_1, the correct parameter is `query=0`

- `ignore_column` , default = "", type = multi-int or string, aliases: `ignore_feature`, `blacklist`
  - used to specify some ignoring columns in training
  - use number for index, e.g. `ignore_column=0,1,2` means column_0, column_1 and column_2 will be ignored
  - add a prefix `name:` for column name, e.g. `ignore_column=name:c1,c2,c3` means c1, c2 and c3 will be ignored
  - **Note**: works only in case of loading data directly from text file
  - **Note**: index starts from `0` and it doesn't count the label column when passing type is `int`
  - **Note**: despite the fact that specified columns will be completely ignored during the training, they still should have a valid format allowing LightGBM to load file successfully

- `categorical_feature` , default = "", type = multi-int or string, aliases: `cat_feature`, `categorical_column`, `cat_column`, `categorical_features`
  - used to specify categorical features
  - use number for index, e.g. `categorical_feature=0,1,2` means column_0, column_1 and column_2 are categorical features
  - add a prefix `name:` for column name, e.g. `categorical_feature=name:c1,c2,c3` means c1, c2 and c3 are categorical features
  - **Note**: all values will be cast to `int32` (integer codes will be extracted from pandas categoricals in the Python-package)
  - **Note**: index starts from `0` and it doesn't count the label column when passing type is `int`
  - **Note**: all values should be less than `Int32.MaxValue` (2147483647)
  - **Note**: using large values could be memory consuming. Tree decision rule works best when categorical features are presented by consecutive integers starting from zero
  - **Note**: all negative values will be treated as **missing values**
  - **Note**: the output cannot be monotonically constrained with respect to a categorical feature
  - **Note**: floating point numbers in categorical features will be rounded towards 0

- `forcedbins_filename` , default = "", type = string
  - path to a `.json` file that specifies bin upper bounds for some or all features
  - `.json` file should contain an array of objects, each containing the word `feature` (integer feature index) and `bin_upper_bound` (array of thresholds for binning)
  - see this file as an example

- `save_binary` , default = `false`, type = bool, aliases: `is_save_binary`, `is_save_binary_file`
  - if `true`, LightGBM will save the dataset (including validation data) to a binary file. This speed ups the data loading for the next time

  - **Note**: `init_score` is not saved in binary file
  - **Note**: can be used only in CLI version; for language-specific packages you can use the correspondent function
- `precise_float_parser` , default = `false`, type = bool
  - use precise floating point number parsing for text parser (e.g. CSV, TSV, LibSVM input)
  - **Note**: setting this to `true` may lead to much slower text parsing
- `parser_config_file` , default = "", type = string
  - path to a `.json` file that specifies customized parser initialized configuration
  - see lightgbm-transform for usage examples
  - **Note**: `lightgbm-transform` is not maintained by LightGBM's maintainers. Bug reports or feature requests should go to issues page
  - *New in version 4.0.0*

6.4.2 Predict Parameters

- `start_iteration_predict` , default = `0`, type = int
  - used only in `prediction` task
  - used to specify from which iteration to start the prediction
  - `<= 0` means from the first iteration
- `num_iteration_predict` , default = `-1`, type = int
  - used only in `prediction` task
  - used to specify how many trained iterations will be used in prediction
  - `<= 0` means no limit
- `predict_raw_score` , default = `false`, type = bool, aliases: `is_predict_raw_score`, `predict_rawscore`, `raw_score`
  - used only in `prediction` task
  - set this to `true` to predict only the raw scores
  - set this to `false` to predict transformed scores
- `predict_leaf_index` , default = `false`, type = bool, aliases: `is_predict_leaf_index`, `leaf_index`
  - used only in `prediction` task
  - set this to `true` to predict with leaf index of all trees
- `predict_contrib` , default = `false`, type = bool, aliases: `is_predict_contrib`, `contrib`
  - used only in `prediction` task
  - set this to `true` to estimate SHAP values, which represent how each feature contributes to each prediction
  - produces `#features + 1` values where the last value is the expected value of the model output over the training data
  - **Note**: if you want to get more explanation for your model's predictions using SHAP values like SHAP interaction values, you can install shap package
  - **Note**: unlike the shap package, with `predict_contrib` we return a matrix with an extra column, where the last column is the expected value

  - **Note**: this feature is not implemented for linear trees

- `predict_disable_shape_check` , default = `false`, type = bool
  - used only in `prediction` task
  - control whether or not LightGBM raises an error when you try to predict on data with a different number of features than the training data
  - if `false` (the default), a fatal error will be raised if the number of features in the dataset you predict on differs from the number seen during training
  - if `true`, LightGBM will attempt to predict on whatever data you provide. This is dangerous because you might get incorrect predictions, but you could use it in situations where it is difficult or expensive to generate some features and you are very confident that they were never chosen for splits in the model
  - **Note**: be very careful setting this parameter to `true`
- `pred_early_stop` , default = `false`, type = bool
  - used only in `prediction` task
  - used only in `classification` and `ranking` applications
  - used only for predicting normal or raw scores
  - if `true`, will use early-stopping to speed up the prediction. May affect the accuracy
  - **Note**: cannot be used with `rf` boosting type or custom objective function
- `pred_early_stop_freq` , default = `10`, type = int
  - used only in `prediction` task and if `pred_early_stop=true`
  - the frequency of checking early-stopping prediction
- `pred_early_stop_margin` , default = `10.0`, type = double
  - used only in `prediction` task and if `pred_early_stop=true`
  - the threshold of margin in early-stopping prediction
- `output_result` , default = `LightGBM_predict_result.txt`, type = string, aliases: `predict_result`, `prediction_result`, `predict_name`, `prediction_name`, `pred_name`, `name_pred`
  - used only in `prediction` task
  - filename of prediction result
  - **Note**: can be used only in CLI version

6.4.3 Convert Parameters

- `convert_model_language` , default = `""`, type = string
  - used only in `convert_model` task
  - only `cpp` is supported yet; for conversion model to other languages consider using m2cgen utility
  - if `convert_model_language` is set and `task=train`, the model will be also converted
  - **Note**: can be used only in CLI version
- `convert_model` , default = `gbdt_prediction.cpp`, type = string, aliases: `convert_model_file`
  - used only in `convert_model` task
  - output filename of converted model

  - **Note**: can be used only in CLI version

6.5 Objective Parameters

- `objective_seed` , default = `5`, type = int
  - used only in `rank_xendcg` objective
  - random seed for objectives, if random process is needed
- `num_class` , default = `1`, type = int, aliases: `num_classes`, constraints: `num_class > 0`
  - used only in `multi-class` classification application
- `is_unbalance` , default = `false`, type = bool, aliases: `unbalance`, `unbalanced_sets`
  - used only in `binary` and `multiclassova` applications
  - set this to `true` if training data are unbalanced
  - **Note**: while enabling this should increase the overall performance metric of your model, it will also result in poor estimates of the individual class probabilities
  - **Note**: this parameter cannot be used at the same time with `scale_pos_weight`, choose only **one** of them
- `scale_pos_weight` , default = `1.0`, type = double, constraints: `scale_pos_weight > 0.0`
  - used only in `binary` and `multiclassova` applications
  - weight of labels with positive class
  - **Note**: while enabling this should increase the overall performance metric of your model, it will also result in poor estimates of the individual class probabilities
  - **Note**: this parameter cannot be used at the same time with `is_unbalance`, choose only **one** of them
- `sigmoid` , default = `1.0`, type = double, constraints: `sigmoid > 0.0`
  - used only in `binary` and `multiclassova` classification and in `lambdarank` applications
  - parameter for the sigmoid function
- `boost_from_average` , default = `true`, type = bool
  - used only in `regression`, `binary`, `multiclassova` and `cross-entropy` applications
  - adjusts initial score to the mean of labels for faster convergence
- `reg_sqrt` , default = `false`, type = bool
  - used only in `regression` application
  - used to fit `sqrt(label)` instead of original values and prediction result will be also automatically converted to `prediction^2`
  - might be useful in case of large-range labels
- `alpha` , default = `0.9`, type = double, constraints: `alpha > 0.0`
  - used only in `huber` and `quantile` `regression` applications
  - parameter for Huber loss and Quantile regression
- `fair_c` , default = `1.0`, type = double, constraints: `fair_c > 0.0`
  - used only in `fair` `regression` application
  - parameter for Fair loss

- `poisson_max_delta_step` , default = `0.7`, type = double, constraints: `poisson_max_delta_step > 0.0`
  - used only in `poisson regression` application
  - parameter for Poisson regression to safeguard optimization
- `tweedie_variance_power` , default = `1.5`, type = double, constraints: `1.0 <= tweedie_variance_power < 2.0`
  - used only in `tweedie regression` application
  - used to control the variance of the tweedie distribution
  - set this closer to `2` to shift towards a **Gamma** distribution
  - set this closer to `1` to shift towards a **Poisson** distribution
- `lambdarank_truncation_level` , default = `30`, type = int, constraints: `lambdarank_truncation_level > 0`
  - used only in `lambdarank` application
  - controls the number of top-results to focus on during training, refer to "truncation level" in the Sec. 3 of LambdaMART paper
  - this parameter is closely related to the desirable cutoff `k` in the metric **NDCG@k** that we aim at optimizing the ranker for. The optimal setting for this parameter is likely to be slightly higher than `k` (e.g., `k + 3`) to include more pairs of documents to train on, but perhaps not too high to avoid deviating too much from the desired target metric **NDCG@k**
- `lambdarank_norm` , default = `true`, type = bool
  - used only in `lambdarank` application
  - set this to `true` to normalize the lambdas for different queries, and improve the performance for unbalanced data
  - set this to `false` to enforce the original lambdarank algorithm
- `label_gain` , default = `0,1,3,7,15,31,63,...,2^30-1`, type = multi-double
  - used only in `lambdarank` application
  - relevant gain for labels. For example, the gain of label `2` is `3` in case of default label gains
  - separate by `,`
- `lambdarank_position_bias_regularization` , default = `0.0`, type = double, constraints: `lambdarank_position_bias_regularization >= 0.0`
  - used only in `lambdarank` application when positional information is provided and position bias is modeled
  - larger values reduce the inferred position bias factors
  - *New in version 4.1.0*

6.6 Metric Parameters

- `metric` , default = "", type = multi-enum, aliases: `metrics`, `metric_types`
  - metric(s) to be evaluated on the evaluation set(s)
    - "" (empty string or not specified) means that metric corresponding to specified `objective` will be used (this is possible only for pre-defined objective functions, otherwise no evaluation metric will be added)

    - "None" (string, **not** a None value) means that no metric will be registered, aliases: na, null, custom
    - l1, absolute loss, aliases: mean_absolute_error, mae, regression_l1
    - l2, square loss, aliases: mean_squared_error, mse, regression_l2, regression
    - rmse, root square loss, aliases: root_mean_squared_error, l2_root
    - quantile, Quantile regression
    - mape, MAPE loss, aliases: mean_absolute_percentage_error
    - huber, Huber loss
    - fair, Fair loss
    - poisson, negative log-likelihood for Poisson regression
    - gamma, negative log-likelihood for **Gamma** regression
    - gamma_deviance, residual deviance for **Gamma** regression
    - tweedie, negative log-likelihood for **Tweedie** regression
    - ndcg, NDCG, aliases: lambdarank, rank_xendcg, xendcg, xe_ndcg, xe_ndcg_mart, xendcg_mart
    - map, MAP, aliases: mean_average_precision
    - auc, AUC
    - average_precision, average precision score
    - r2, R-squared
    - binary_logloss, log loss, aliases: binary
    - binary_error, for one sample: 0 for correct classification, 1 for error classification
    - auc_mu, AUC-mu
    - multi_logloss, log loss for multi-class classification, aliases: multiclass, softmax, multiclassova, multiclass_ova, ova, ovr
    - multi_error, error rate for multi-class classification
    - cross_entropy, cross-entropy (with optional linear weights), aliases: xentropy
    - cross_entropy_lambda, "intensity-weighted" cross-entropy, aliases: xentlambda
    - kullback_leibler, Kullback-Leibler divergence, aliases: kldiv
  - support multiple metrics, separated by ,

- metric_freq , default = 1, type = int, aliases: output_freq, constraints: metric_freq > 0
  - frequency for metric output
  - **Note**: can be used only in CLI version

- is_provide_training_metric , default = false, type = bool, aliases: training_metric, is_training_metric, train_metric
  - set this to true to output metric result over training dataset
  - **Note**: can be used only in CLI version

- eval_at , default = 1,2,3,4,5, type = multi-int, aliases: ndcg_eval_at, ndcg_at, map_eval_at, map_at
  - used only with ndcg and map metrics

  - NDCG and MAP evaluation positions, separated by `,`

- `multi_error_top_k` , default = 1, type = int, constraints: `multi_error_top_k > 0`
  - used only with `multi_error` metric
  - threshold for top-k multi-error metric
  - the error on each sample is `0` if the true class is among the top `multi_error_top_k` predictions, and `1` otherwise
    - more precisely, the error on a sample is `0` if there are at least `num_classes - multi_error_top_k` predictions strictly less than the prediction on the true class
  - when `multi_error_top_k=1` this is equivalent to the usual multi-error metric
- `auc_mu_weights` , default = `None`, type = multi-double
  - used only with `auc_mu` metric
  - list representing flattened matrix (in row-major order) giving loss weights for classification errors
  - list should have `n * n` elements, where `n` is the number of classes
  - the matrix co-ordinate `[i, j]` should correspond to the `i * n + j`-th element of the list
  - if not specified, will use equal weights for all classes

6.7 Network Parameters

- `num_machines` , default = `1`, type = int, aliases: `num_machine`, constraints: `num_machines > 0`
  - the number of machines for distributed learning application
  - this parameter is needed to be set in both **socket** and **MPI** versions
- `local_listen_port` , default = `12400 (random for Dask-package)`, type = int, aliases: `local_port`, `port`, constraints: `local_listen_port > 0`
  - TCP listen port for local machines
  - **Note**: don't forget to allow this port in firewall settings before training
- `time_out` , default = `120`, type = int, constraints: `time_out > 0`
  - socket time-out in minutes
- `machine_list_filename` , default = `""`, type = string, aliases: `machine_list_file`, `machine_list`, `mlist`
  - path of file that lists machines for this distributed learning application
  - each line contains one IP and one port for one machine. The format is `ip port` (space as a separator)
  - **Note**: can be used only in CLI version
- `machines` , default = `""`, type = string, aliases: `workers`, `nodes`
  - list of machines in the following format: `ip1:port1,ip2:port2`

6.8 GPU Parameters

- `gpu_platform_id` , default = `-1`, type = int
  - used only with `gpu` device type
  - OpenCL platform ID. Usually each GPU vendor exposes one OpenCL platform

  - `-1` means the system-wide default platform
  - **Note**: refer to GPU Targets for more details

- `gpu_device_id` , default = `-1`, type = int
  - OpenCL device ID in the specified platform or CUDA device ID. Each GPU in the selected platform has a unique device ID
  - `-1` means the default device in the selected platform
  - in multi-GPU case (`num_gpu`>1) means ID of the master GPU
  - **Note**: refer to GPU Targets for more details

- `gpu_device_id_list` , default = `""`, type = string
  - list of CUDA device IDs
  - **Note**: can be used only in CUDA implementation (`device_type="cuda"`) and when `num_gpu`>1
  - if empty, the devices with the smallest IDs will be used

- `gpu_use_dp` , default = `false`, type = bool
  - set this to `true` to use double precision math on GPU (by default single precision is used)
  - **Note**: can be used only in OpenCL implementation (`device_type="gpu"`), in CUDA implementation only double precision is currently supported

- `num_gpu` , default = 1, type = int, constraints: `num_gpu > 0`
  - number of GPUs used for training in this node
  - **Note**: can be used only in CUDA implementation (`device_type="cuda"`)
  - if `0`, only 1 GPU will be used
  - used in both single-machine and distributed learning applications
  - in distributed learning application, each machine can use different number of GPUs

6.9 Others

6.9.1 Continued Training with Input Score

LightGBM supports continued training with initial scores. It uses an additional file to store these initial scores, like the following:

```
0.5
-0.1
0.9
...
```

It means the initial score of the first data row is `0.5`, second is `-0.1`, and so on. The initial score file corresponds with data file line by line, and has per score per line.

If the name of data file is `train.txt`, the initial score file should be named as `train.txt.init` and placed in the same folder as the data file. In this case, LightGBM will auto load initial score file if it exists.

If binary data files exist for raw data file `train.txt`, for example in the name `train.txt.bin`, then the initial score file should be named as `train.txt.bin.init`.

6.9.2 Weight Data

LightGBM supports weighted training. It uses an additional file to store weight data, like the following:

```
1.0
0.5
0.8
...
```

It means the weight of the first data row is `1.0`, second is `0.5`, and so on. Weights should be non-negative.

The weight file corresponds with data file line by line, and has per weight per line.

And if the name of data file is `train.txt`, the weight file should be named as `train.txt.weight` and placed in the same folder as the data file. In this case, LightGBM will load the weight file automatically if it exists.

Also, you can include weight column in your data file. Please refer to the `weight_column` *parameter* in above.

6.9.3 Query Data

For learning to rank, it needs query information for training data.

LightGBM uses an additional file to store query data, like the following:

```
27
18
67
...
```

For wrapper libraries like in Python and R, this information can also be provided as an array-like via the Dataset parameter `group`.

```
[27, 18, 67, ...]
```

For example, if you have a 112-document dataset with `group = [27, 18, 67]`, that means that you have 3 groups, where the first 27 records are in the first group, records 28-45 are in the second group, and records 46-112 are in the third group.

Note: data should be ordered by the query.

If the name of data file is `train.txt`, the query file should be named as `train.txt.query` and placed in the same folder as the data file. In this case, LightGBM will load the query file automatically if it exists.

Also, you can include query/group id column in your data file. Please refer to the `group_column` *parameter* in above.

CHAPTER

SEVEN

PARAMETERS TUNING

This page contains parameters tuning guides for different scenarios.

List of other helpful links

- Parameters
- Python API
- FLAML for automated hyperparameter tuning
- Optuna for automated hyperparameter tuning

7.1 Tune Parameters for the Leaf-wise (Best-first) Tree

LightGBM uses the leaf-wise tree growth algorithm, while many other popular tools use depth-wise tree growth. Compared with depth-wise growth, the leaf-wise algorithm can converge much faster. However, the leaf-wise growth may be over-fitting if not used with the appropriate parameters.

To get good results using a leaf-wise tree, these are some important parameters:

1. `num_leaves`. This is the main parameter to control the complexity of the tree model. Theoretically, we can set `num_leaves = 2^(max_depth)` to obtain the same number of leaves as depth-wise tree. However, this simple conversion is not good in practice. A leaf-wise tree is typically much deeper than a depth-wise tree for a fixed number of leaves. Unconstrained depth can induce over-fitting. Thus, when trying to tune the `num_leaves`, we should let it be smaller than `2^(max_depth)`. For example, when the `max_depth=7` the depth-wise tree can get good accuracy, but setting `num_leaves` to `127` may cause over-fitting, and setting it to `70` or `80` may get better accuracy than depth-wise.

2. `min_data_in_leaf`. This is a very important parameter to prevent over-fitting in a leaf-wise tree. Its optimal value depends on the number of training samples and `num_leaves`. Setting it to a large value can avoid growing too deep a tree, but may cause under-fitting. In practice, setting it to hundreds or thousands is enough for a large dataset.

3. `max_depth`. You also can use `max_depth` to limit the tree depth explicitly. If you set `max_depth`, also explicitly set `num_leaves` to some value `<= 2^max_depth`.

7.2 For Faster Speed

7.2.1 Add More Computational Resources

On systems where it is available, LightGBM uses OpenMP to parallelize many operations. The maximum number of threads used by LightGBM is controlled by the parameter `num_threads`. By default, this will defer to the default behavior of OpenMP (one thread per real CPU core or the value in environment variable `OMP_NUM_THREADS`, if it is set). For best performance, set this to the number of **real** CPU cores available.

You might be able to achieve faster training by moving to a machine with more available CPU cores.

Using distributed (multi-machine) training might also reduce training time. See the Distributed Learning Guide for details.

7.2.2 Use a GPU-enabled version of LightGBM

You might find that training is faster using a GPU-enabled build of LightGBM. See the GPU Tutorial for details.

7.2.3 Grow Shallower Trees

The total training time for LightGBM increases with the total number of tree nodes added. LightGBM comes with several parameters that can be used to control the number of nodes per tree.

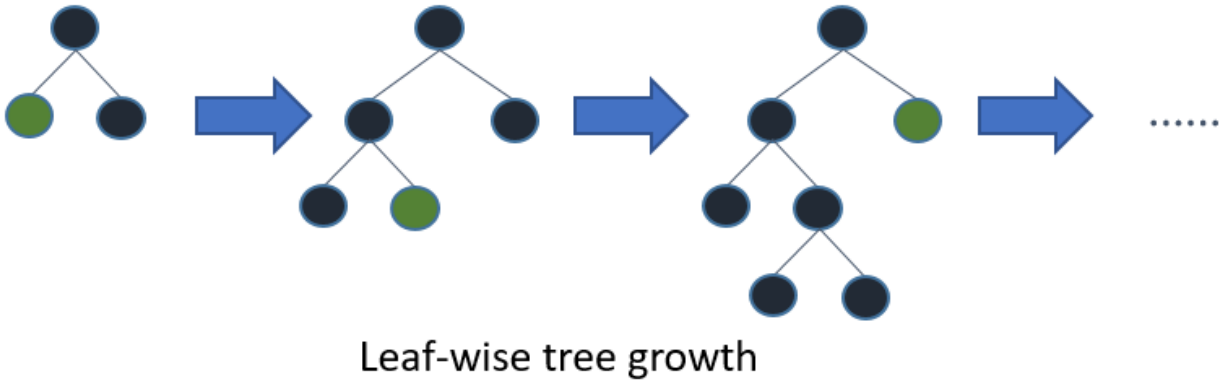
The suggestions below will speed up training, but might hurt training accuracy.

Decrease `max_depth`

This parameter is an integer that controls the maximum distance between the root node of each tree and a leaf node. Decrease `max_depth` to reduce training time.

Decrease `num_leaves`

LightGBM adds nodes to trees based on the gain from adding that node, regardless of depth. This figure from the feature documentation illustrates the process.



Because of this growth strategy, it isn't straightforward to use `max_depth` alone to limit the complexity of trees. The `num_leaves` parameter sets the maximum number of nodes per tree. Decrease `num_leaves` to reduce training time.

Increase `min_gain_to_split`

When adding a new tree node, LightGBM chooses the split point that has the largest gain. Gain is basically the reduction in training loss that results from adding a split point. By default, LightGBM sets `min_gain_to_split` to 0.0, which means "there is no improvement that is too small". However, in practice you might find that very small improvements in the training loss don't have a meaningful impact on the generalization error of the model. Increase `min_gain_to_split` to reduce training time.

Increase `min_data_in_leaf` and `min_sum_hessian_in_leaf`

Depending on the size of the training data and the distribution of features, it's possible for LightGBM to add tree nodes that only describe a small number of observations. In the most extreme case, consider the addition of a tree node that only a single observation from the training data falls into. This is very unlikely to generalize well, and probably is a sign of overfitting.

This can be prevented indirectly with parameters like `max_depth` and `num_leaves`, but LightGBM also offers parameters to help you directly avoid adding these overly-specific tree nodes.

- `min_data_in_leaf`: Minimum number of observations that must fall into a tree node for it to be added.
- `min_sum_hessian_in_leaf`: Minimum sum of the Hessian (second derivative of the objective function evaluated for each observation) for observations in a leaf. For some regression objectives, this is just the minimum number of records that have to fall into each node. For classification objectives, it represents a sum over a distribution of probabilities. See this Stack Overflow answer for a good description of how to reason about values of this parameter.

7.2.4 Grow Less Trees

Decrease `num_iterations`

The `num_iterations` parameter controls the number of boosting rounds that will be performed. Since LightGBM uses decision trees as the learners, this can also be thought of as "number of trees".

If you try changing `num_iterations`, change the `learning_rate` as well. `learning_rate` will not have any impact on training time, but it will impact the training accuracy. As a general rule, if you reduce `num_iterations`, you should increase `learning_rate`.

Choosing the right value of `num_iterations` and `learning_rate` is highly dependent on the data and objective, so these parameters are often chosen from a set of possible values through hyperparameter tuning.

Decrease `num_iterations` to reduce training time.

Use Early Stopping

If early stopping is enabled, after each boosting round the model's training accuracy is evaluated against a validation set that contains data not available to the training process. That accuracy is then compared to the accuracy as of the previous boosting round. If the model's accuracy fails to improve for some number of consecutive rounds, LightGBM stops the training process.

That "number of consecutive rounds" is controlled by the parameter `early_stopping_round`. For example, `early_stopping_round=1` says "the first time accuracy on the validation set does not improve, stop training".

Set `early_stopping_round` and provide a validation set to possibly reduce training time.

7.2.5 Consider Fewer Splits

The parameters described in previous sections control how many trees are constructed and how many nodes are constructed per tree. Training time can be further reduced by reducing the amount of time needed to add a tree node to the model.

The suggestions below will speed up training, but might hurt training accuracy.

Enable Feature Pre-Filtering When Creating Dataset

By default, when a LightGBM `Dataset` object is constructed, some features will be filtered out based on the value of `min_data_in_leaf`.

For a simple example, consider a 1000-observation dataset with a feature called `feature_1`. `feature_1` takes on only two values: 25.0 (995 observations) and 50.0 (5 observations). If `min_data_in_leaf = 10`, there is no split for this feature which will result in a valid split at least one of the leaf nodes will only have 5 observations.

Instead of reconsidering this feature and then ignoring it every iteration, LightGBM filters this feature out at before training, when the `Dataset` is constructed.

If this default behavior has been overridden by setting `feature_pre_filter=False`, set `feature_pre_filter=True` to reduce training time.

Decrease `max_bin` or `max_bin_by_feature` When Creating Dataset

LightGBM training buckets continuous features into discrete bins to improve training speed and reduce memory requirements for training. This binning is done one time during `Dataset` construction. The number of splits considered when adding a node is `O(#feature * #bin)`, so reducing the number of bins per feature can reduce the number of splits that need to be evaluated.

`max_bin` is controls the maximum number of bins that features will bucketed into. It is also possible to set this maximum feature-by-feature, by passing `max_bin_by_feature`.

Reduce `max_bin` or `max_bin_by_feature` to reduce training time.

Increase `min_data_in_bin` When Creating Dataset

Some bins might contain a small number of observations, which might mean that the effort of evaluating that bin's boundaries as possible split points isn't likely to change the final model very much. You can control the granularity of the bins by setting `min_data_in_bin`.

Increase `min_data_in_bin` to reduce training time.

Decrease `feature_fraction`

By default, LightGBM considers all features in a `Dataset` during the training process. This behavior can be changed by setting `feature_fraction` to a value `> 0` and `<= 1.0`. Setting `feature_fraction` to `0.5`, for example, tells LightGBM to randomly select `50%` of features at the beginning of constructing each tree. This reduces the total number of splits that have to be evaluated to add each tree node.

Decrease `feature_fraction` to reduce training time.

Decrease `max_cat_threshold`

LightGBM uses a custom approach for finding optimal splits for categorical features. In this process, LightGBM explores splits that break a categorical feature into two groups. These are sometimes called "k-vs.-rest" splits. Higher `max_cat_threshold` values correspond to more split points and larger possible group sizes to search.

Decrease `max_cat_threshold` to reduce training time.

7.2.6 Use Less Data

Use Bagging

By default, LightGBM uses all observations in the training data for each iteration. It is possible to instead tell LightGBM to randomly sample the training data. This process of training over multiple random samples without replacement is called "bagging".

Set `bagging_freq` to an integer greater than 0 to control how often a new sample is drawn. Set `bagging_fraction` to a value `> 0.0` and `< 1.0` to control the size of the sample. For example, `{"bagging_freq": 5, "bagging_fraction": 0.75}` tells LightGBM "re-sample without replacement every 5 iterations, and draw samples of 75% of the training data".

Decrease `bagging_fraction` to reduce training time.

7.2.7 Save Constructed Datasets with `save_binary`

This only applies to the LightGBM CLI. If you pass parameter `save_binary`, the training dataset and all validations sets will be saved in a binary format understood by LightGBM. This can speed up training next time, because binning and other work done when constructing a `Dataset` does not have to be re-done.

7.3 For Better Accuracy

- Use large `max_bin` (may be slower)
- Use small `learning_rate` with large `num_iterations`
- Use large `num_leaves` (may cause over-fitting)
- Use bigger training data
- Try `dart`

7.4 Deal with Over-fitting

- Use small `max_bin`
- Use small `num_leaves`
- Use `min_data_in_leaf` and `min_sum_hessian_in_leaf`
- Use bagging by set `bagging_fraction` and `bagging_freq`
- Use feature sub-sampling by set `feature_fraction`
- Use bigger training data
- Try `lambda_l1`, `lambda_l2` and `min_gain_to_split` for regularization
- Try `max_depth` to avoid growing deep tree
- Try `extra_trees`
- Try increasing `path_smooth`

CHAPTER

EIGHT

C API

Copyright

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Note

To avoid type conversion on large data, the most of our exposed interface supports both float32 and float64, except the following:

1. gradient and Hessian;
2. current score for training and validation data.

The reason is that they are called frequently, and the type conversion on them may be time-cost.

Defines

C_API_DTYPE_FLOAT32 (0)

float32 (single precision float).

C_API_DTYPE_FLOAT64 (1)

float64 (double precision float).

C_API_DTYPE_INT32 (2)

int32.

C_API_DTYPE_INT64 (3)

int64.

C_API_FEATURE_IMPORTANCE_GAIN (1)

Gain type of feature importance.

C_API_FEATURE_IMPORTANCE_SPLIT (0)

Split type of feature importance.

C_API_MATRIX_TYPE_CSC (1)

CSC sparse matrix type.

C_API_MATRIX_TYPE_CSR (0)

CSR sparse matrix type.

C_API_PREDICT_CONTRIB (3)

Predict feature contributions (SHAP values).

C_API_PREDICT_LEAF_INDEX (2)

Predict leaf index.

C_API_PREDICT_NORMAL (0)

Normal prediction, with transform (if needed).

C_API_PREDICT_RAW_SCORE (1)

Predict raw score.

INLINE_FUNCTION inline

Inline specifier.

LIGHTGBM_DEPRECATED(msg) /*!< \brief Deprecated function. */

Deprecated function.

THREAD_LOCAL thread_local

Thread local specifier.

Typedefs

typedef void ***BoosterHandle**

Handle of booster.

typedef void ***ByteBufferHandle**

Handle of ByteBuffer.

typedef void ***DatasetHandle**

Handle of dataset.

typedef void ***FastConfigHandle**

Handle of FastConfig.

Functions

static char ***LastErrorMsg**()

Handle of error message.

Returns

Error message

LIGHTGBM_C_EXPORT int **LGBM_BoosterAddValidData**(*BoosterHandle* handle, const *DatasetHandle* valid_data)

Add new validation data to booster.

Parameters

- **handle** – Handle of booster
- **valid_data** – Validation dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterCalcNumPredict**(*BoosterHandle* handle, int num_row, int predict_type, int start_iteration, int num_iteration, int64_t *out_len)

Get number of predictions.

Parameters

- **handle** – Handle of booster
- **num_row** – Number of rows
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **out_len** – **[out]** Length of prediction

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterCreate**(const *DatasetHandle* train_data, const char *parameters, *BoosterHandle* *out)

Create a new boosting learner.

Parameters

- **train_data** – Training dataset
- **parameters** – Parameters in format 'key1=value1 key2=value2'
- **out** – **[out]** Handle of created booster

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterCreateFromModelfile**(const char *filename, int *out_num_iterations, *BoosterHandle* *out)

Load an existing booster from model file.

Parameters

- **filename** – Filename of model

- **out_num_iterations** – **[out]** Number of iterations of this booster
- **out** – **[out]** Handle of created booster

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterDumpModel**(*BoosterHandle* handle, int start_iteration, int num_iteration, int feature_importance_type, int64_t buffer_len, int64_t *out_len, char *out_str)

Dump model to JSON.

Parameters

- **handle** – Handle of booster
- **start_iteration** – Start index of the iteration that should be dumped
- **num_iteration** – Index of the iteration that should be dumped, <= 0 means dump all
- **feature_importance_type** – Type of feature importance, can be *C_API_FEATURE_IMPORTANCE_SPLIT* or *C_API_FEATURE_IMPORTANCE_GAIN*
- **buffer_len** – String buffer length, if `buffer_len < out_len`, you should re-allocate buffer
- **out_len** – **[out]** Actual output length
- **out_str** – **[out]** JSON format string of model, should pre-allocate memory

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterFeatureImportance**(*BoosterHandle* handle, int num_iteration, int importance_type, double *out_results)

Get model feature importance.

Parameters

- **handle** – Handle of booster
- **num_iteration** – Number of iterations for which feature importance is calculated, <= 0 means use all
- **importance_type** – Method of importance calculation:
  - *C_API_FEATURE_IMPORTANCE_SPLIT*: result contains numbers of times the feature is used in a model;
  - *C_API_FEATURE_IMPORTANCE_GAIN*: result contains total gains of splits which use the feature
- **out_results** – **[out]** Result array with feature importance

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterFree**(*BoosterHandle* handle)

Free space for booster.

Parameters

- **handle** – Handle of booster to be freed

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterFreePredictSparse**(void *indptr, int32_t *indices, void *data, int indptr_type, int data_type)

Method corresponding to *LGBM_BoosterPredictSparseOutput* to free the allocated data.

Parameters

- **indptr** – Pointer to output row headers or column headers to be deallocated
- **indices** – Pointer to sparse indices to be deallocated
- **data** – Pointer to sparse data space to be deallocated
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetCurrentIteration**(*BoosterHandle* handle, int *out_iteration)

Get index of the current boosting iteration.

Parameters

- **handle** – Handle of booster
- **out_iteration** – **[out]** Index of the current boosting iteration

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetEval**(*BoosterHandle* handle, int data_idx, int *out_len, double *out_results)

Get evaluation for training data and validation data.

Note

a. You should call *LGBM_BoosterGetEvalNames* first to get the names of evaluation metrics.

b. You should pre-allocate memory for `out_results`, you can get its length by *LGBM_BoosterGetEvalCounts*.

Parameters

- **handle** – Handle of booster
- **data_idx** – Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- **out_len** – **[out]** Length of output result
- **out_results** – **[out]** Array with evaluation results

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetEvalCounts**(*BoosterHandle* handle, int *out_len)

Get number of evaluation metrics.

Parameters

- **handle** – Handle of booster
- **out_len** – **[out]** Total number of evaluation metrics

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetEvalNames**(*BoosterHandle* handle, const int len, int *out_len, const size_t buffer_len, size_t *out_buffer_len, char **out_strs)

Get names of evaluation metrics.

Parameters

- **handle** – Handle of booster
- **len** – Number of `char*` pointers stored at `out_strs`. If smaller than the max size, only this many strings are copied
- **out_len** – **[out]** Total number of evaluation metrics
- **buffer_len** – Size of pre-allocated strings. Content is copied up to `buffer_len - 1` and null-terminated
- **out_buffer_len** – **[out]** String sizes required to do the full string copies
- **out_strs** – **[out]** Names of evaluation metrics, should pre-allocate memory

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetFeatureNames**(*BoosterHandle* handle, const int len, int *out_len, const size_t buffer_len, size_t *out_buffer_len, char **out_strs)

Get names of features.

Parameters

- **handle** – Handle of booster
- **len** – Number of `char*` pointers stored at `out_strs`. If smaller than the max size, only this many strings are copied
- **out_len** – **[out]** Total number of features
- **buffer_len** – Size of pre-allocated strings. Content is copied up to `buffer_len - 1` and null-terminated
- **out_buffer_len** – **[out]** String sizes required to do the full string copies
- **out_strs** – **[out]** Names of features, should pre-allocate memory

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLeafValue**(*BoosterHandle* handle, int tree_idx, int leaf_idx, double *out_val)

Get leaf value.

Parameters

- **handle** – Handle of booster
- **tree_idx** – Index of tree

- **leaf_idx** – Index of leaf
- **out_val** – **[out]** Output result from the specified leaf

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLinear**(*BoosterHandle* handle, int *out)

Get int representing whether booster is fitting linear trees.

Parameters

- **handle** – Handle of booster
- **out** – **[out]** The address to hold linear trees indicator

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLoadedParam**(*BoosterHandle* handle, int64_t buffer_len, int64_t *out_len, char *out_str)

Get parameters as JSON string.

Parameters

- **handle** – Handle of booster
- **buffer_len** – Allocated space for string
- **out_len** – **[out]** Actual size of string
- **out_str** – **[out]** JSON string containing parameters

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetLowerBoundValue**(*BoosterHandle* handle, double *out_results)

Get model lower bound value.

Parameters

- **handle** – Handle of booster
- **out_results** – **[out]** Result pointing to min value

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumClasses**(*BoosterHandle* handle, int *out_len)

Get number of classes.

Parameters

- **handle** – Handle of booster
- **out_len** – **[out]** Number of classes

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumFeature**(*BoosterHandle* handle, int *out_len)

Get number of features.

Parameters

- **handle** – Handle of booster

- **out_len** – **[out]** Total number of features

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetNumPredict**(*BoosterHandle* handle, int data_idx, int64_t *out_len)

Get number of predictions for training data and validation data (this can be used to support customized evaluation functions).

Parameters

- **handle** – Handle of booster
- **data_idx** – Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- **out_len** – **[out]** Number of predictions

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetPredict**(*BoosterHandle* handle, int data_idx, int64_t *out_len, double *out_result)

Get prediction for training data and validation data.

> **Note**
>
> You should pre-allocate memory for `out_result`, its length is equal to `num_class * num_data`.

Parameters

- **handle** – Handle of booster
- **data_idx** – Index of data, 0: training data, 1: 1st validation data, 2: 2nd validation data and so on
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterGetUpperBoundValue**(*BoosterHandle* handle, double *out_results)

Get model upper bound value.

Parameters

- **handle** – Handle of booster
- **out_results** – **[out]** Result pointing to max value

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterLoadModelFromString**(const char *model_str, int *out_num_iterations, *BoosterHandle* *out)

Load an existing booster from string.

Parameters

- **model_str** – Model string
- **out_num_iterations** – **[out]** Number of iterations of this booster
- **out** – **[out]** Handle of created booster

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterMerge**(*BoosterHandle* handle, *BoosterHandle* other_handle)

Merge model from `other_handle` into `handle`.

Parameters

- **handle** – Handle of booster, will merge another booster into this one
- **other_handle** – Other handle of booster

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterNumberOfTotalModel**(*BoosterHandle* handle, int *out_models)

Get number of weak sub-models.

Parameters

- **handle** – Handle of booster
- **out_models** – **[out]** Number of weak sub-models

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterNumModelPerIteration**(*BoosterHandle* handle, int *out_tree_per_iteration)

Get number of trees per iteration.

Parameters

- **handle** – Handle of booster
- **out_tree_per_iteration** – **[out]** Number of trees per iteration

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForArrow**(*BoosterHandle* handle, int64_t n_chunks, struct ArrowArray *chunks, struct ArrowSchema *schema, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset.

Deprecated:
This function is deprecated in favor of *LGBM_BoosterPredictForArrowStream*.

< Deprecated function.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **n_chunks** – The number of Arrow arrays passed to this function
- **chunks** – Pointer to the list of Arrow arrays
- **schema** – Pointer to the schema of all Arrow arrays
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForArrowStream**(*BoosterHandle* handle, struct ArrowArrayStream *stream, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **stream** – Arrow stream pointer
- **predict_type** – What should be predicted

  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSC**(*BoosterHandle* handle, const void *col_ptr, int col_ptr_type, const int32_t *indices, const void *data, int data_type, int64_t ncol_ptr, int64_t nelem, int64_t num_row, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset in CSC format.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **col_ptr** – Pointer to column headers
- **col_ptr_type** – Type of `col_ptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to row indices
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **ncol_ptr** – Number of columns in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_row** – Number of rows
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);

  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSR**(*BoosterHandle* handle, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset in CSR format.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **indptr** – Pointer to row headers
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_col** – Number of columns
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;

  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSRSingleRow**(*BoosterHandle* handle, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset in CSR format. This method re-uses the internal predictor structure from previous calls and is optimized for single row invocation.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **indptr** – Pointer to row headers
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_col** – Number of columns
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);

  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSRSingleRowFast**(*FastConfigHandle* fastConfig_handle, const void *indptr, const int indptr_type, const int32_t *indices, const void *data, const int64_t nindptr, const int64_t nelem, int64_t *out_len, double *out_result)

Faster variant of *LGBM_BoosterPredictForCSRSingleRow*.

Score single rows after setup with *LGBM_BoosterPredictForCSRSingleRowFastInit*.

By removing the setup steps from this call extra optimizations can be made like initializing the config only once, instead of once per call.

Note

Setting up the number of threads is only done once at *LGBM_BoosterPredictForCSRSingleRowFastInit* instead of at each prediction. If you use a different number of threads in other calls, you need to start the setup process over, or that number of threads will be used for these calls as well.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **fastConfig_handle** – FastConfig object handle returned by *LGBM_BoosterPredictForCSRSingleRowFastInit*
- **indptr** – Pointer to row headers
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices

- **data** – Pointer to the data space
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForCSRSingleRowFastInit**(*BoosterHandle* handle, const int predict_type, const int start_iteration, const int num_iteration, const int data_type, const int64_t num_col, const char *parameter, *FastConfigHandle* *out_fastConfig)

Initialize and return a *FastConfigHandle* for use with *LGBM_BoosterPredictForCSRSingleRowFast*.

Release the FastConfig by passing its handle to *LGBM_FastConfigFree* when no longer needed.

Parameters

- **handle** – Booster handle
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **data_type** – Type of data pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **num_col** – Number of columns
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_fastConfig** – **[out]** FastConfig object with which you can call *LGBM_BoosterPredictForCSRSingleRowFast*

Returns
0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForFile**(*BoosterHandle* handle, const char *data_filename, int data_has_header, int predict_type, int start_iteration, int num_iteration, const char *parameter, const char *result_filename)

Make prediction for file.

Parameters

- **handle** – Handle of booster
- **data_filename** – Filename of file with data
- **data_has_header** – Whether file has header or not
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **result_filename** – Filename of result file in which predictions will be written

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMat**(*BoosterHandle* handle, const void *data, int data_type, int32_t nrow, int32_t ncol, int is_row_major, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number of columns
- **is_row_major** – 1 for row-major, 0 for column-major
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;

- *C_API_PREDICT_LEAF_INDEX*: leaf index;
- *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)

- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMats**(*BoosterHandle* handle, const void **data, int data_type, int32_t nrow, int32_t ncol, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset presented in a form of array of pointers to rows.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number columns
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result

- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMatSingleRow**(*BoosterHandle* handle, const void *data, int data_type, int ncol, int is_row_major, int predict_type, int start_iteration, int num_iteration, const char *parameter, int64_t *out_len, double *out_result)

Make prediction for a new dataset. This method re-uses the internal predictor structure from previous calls and is optimized for single row invocation.

Note

You should pre-allocate memory for `out_result`:

- for normal and raw score, its length is equal to `num_class * num_data`;
- for leaf index, its length is equal to `num_class * num_data * num_iteration`;
- for feature contributions, its length is equal to `num_class * num_data * (num_feature + 1)`.

Parameters

- **handle** – Handle of booster
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **ncol** – Number columns
- **is_row_major** – 1 for row-major, 0 for column-major
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iteration for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMatSingleRowFast**(*FastConfigHandle* fastConfig_handle, const void *data, int64_t *out_len, double *out_result)

Faster variant of *LGBM_BoosterPredictForMatSingleRow*.

Score a single row after setup with *LGBM_BoosterPredictForMatSingleRowFastInit*.

By removing the setup steps from this call extra optimizations can be made like initializing the config only once, instead of once per call.

> **Note**
>
> Setting up the number of threads is only done once at *LGBM_BoosterPredictForMatSingleRowFastInit* instead of at each prediction. If you use a different number of threads in other calls, you need to start the setup process over, or that number of threads will be used for these calls as well.

Parameters

- **fastConfig_handle** – FastConfig object handle returned by *LGBM_BoosterPredictForMatSingleRowFastInit*
- **data** – Single-row array data (no other way than row-major form).
- **out_len** – **[out]** Length of output result
- **out_result** – **[out]** Pointer to array with predictions

Returns

0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictForMatSingleRowFastInit**(*BoosterHandle* handle, const int predict_type, const int start_iteration, const int num_iteration, const int data_type, const int32_t ncol, const char *parameter, *FastConfigHandle* *out_fastConfig)

Initialize and return a *FastConfigHandle* for use with *LGBM_BoosterPredictForMatSingleRowFast*.

Release the `FastConfig` by passing its handle to *LGBM_FastConfigFree* when no longer needed.

Parameters

- **handle** – Booster handle
- **predict_type** – What should be predicted
  - *C_API_PREDICT_NORMAL*: normal prediction, with transform (if needed);
  - *C_API_PREDICT_RAW_SCORE*: raw score;
  - *C_API_PREDICT_LEAF_INDEX*: leaf index;
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **ncol** – Number of columns

- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **out_fastConfig** – **[out]** FastConfig object with which you can call *LGBM_BoosterPredictForMatSingleRowFast*

Returns

0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterPredictSparseOutput**(*BoosterHandle* handle, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col_or_row, int predict_type, int start_iteration, int num_iteration, const char *parameter, int matrix_type, int64_t *out_len, void **out_indptr, int32_t **out_indices, void **out_data)

Make sparse prediction for a new dataset in CSR or CSC format. Currently only used for feature contributions.

Note

The outputs are pre-allocated, as they can vary for each invocation, but the shape should be the same:

- for feature contributions, the shape of sparse matrix will be `num_class * num_data * (num_feature + 1)`. The output indptr_type for the sparse matrix will be the same as the given input indptr_type. Call *LGBM_BoosterFreePredictSparse* to deallocate resources.

Parameters

- **handle** – Handle of booster
- **indptr** – Pointer to row headers for CSR or column headers for CSC
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices for CSR or row indices for CSC
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of entries in `indptr`
- **nelem** – Number of nonzero elements in the matrix
- **num_col_or_row** – Number of columns for CSR or number of rows for CSC
- **predict_type** – What should be predicted, only feature contributions supported currently
  - *C_API_PREDICT_CONTRIB*: feature contributions (SHAP values)
- **start_iteration** – Start index of the iteration to predict
- **num_iteration** – Number of iterations for prediction, <= 0 means no limit
- **parameter** – Other parameters for prediction, e.g. early stopping for prediction
- **matrix_type** – Type of matrix input and output, can be *C_API_MATRIX_TYPE_CSR* or *C_API_MATRIX_TYPE_CSC*

- **out_len** – **[out]** Length of output data and output indptr (pointer to an array with two entries where to write them)
- **out_indptr** – **[out]** Pointer to output row headers for CSR or column headers for CSC
- **out_indices** – **[out]** Pointer to sparse column indices for CSR or row indices for CSC
- **out_data** – **[out]** Pointer to sparse data space

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterRefit**(*BoosterHandle* handle, const int32_t *leaf_preds, int32_t nrow, int32_t ncol)

Refit the tree model using the new data (online learning).

Parameters

- **handle** – Handle of booster
- **leaf_preds** – Pointer to predicted leaf indices
- **nrow** – Number of rows of `leaf_preds`
- **ncol** – Number of columns of `leaf_preds`

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterResetParameter**(*BoosterHandle* handle, const char *parameters)

Reset config for booster.

Parameters

- **handle** – Handle of booster
- **parameters** – Parameters in format 'key1=value1 key2=value2'

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterResetTrainingData**(*BoosterHandle* handle, const *DatasetHandle* train_data)

Reset training data for booster.

Parameters

- **handle** – Handle of booster
- **train_data** – Training dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterRollbackOneIter**(*BoosterHandle* handle)

Rollback one iteration.

Parameters

- **handle** – Handle of booster

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterSaveModel**(*BoosterHandle* handle, int start_iteration, int num_iteration, int feature_importance_type, const char *filename)

Save model into file.

Parameters

- **handle** – Handle of booster
- **start_iteration** – Start index of the iteration that should be saved
- **num_iteration** – Index of the iteration that should be saved, <= 0 means save all
- **feature_importance_type** – Type of feature importance, can be *C_API_FEATURE_IMPORTANCE_SPLIT* or *C_API_FEATURE_IMPORTANCE_GAIN*
- **filename** – The name of the file

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterSaveModelToString**(*BoosterHandle* handle, int start_iteration, int num_iteration, int feature_importance_type, int64_t buffer_len, int64_t *out_len, char *out_str)

Save model to string.

Parameters

- **handle** – Handle of booster
- **start_iteration** – Start index of the iteration that should be saved
- **num_iteration** – Index of the iteration that should be saved, <= 0 means save all
- **feature_importance_type** – Type of feature importance, can be *C_API_FEATURE_IMPORTANCE_SPLIT* or *C_API_FEATURE_IMPORTANCE_GAIN*
- **buffer_len** – String buffer length, if `buffer_len < out_len`, you should re-allocate buffer
- **out_len** – **[out]** Actual output length
- **out_str** – **[out]** String of model, should pre-allocate memory

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterSetLeafValue**(*BoosterHandle* handle, int tree_idx, int leaf_idx, double val)

Set leaf value.

Parameters

- **handle** – Handle of booster
- **tree_idx** – Index of tree
- **leaf_idx** – Index of leaf
- **val** – Leaf value

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterShuffleModels**(*BoosterHandle* handle, int start_iter, int end_iter)

Shuffle models.

Parameters

- **handle** – Handle of booster
- **start_iter** – The first iteration that will be shuffled
- **end_iter** – The last iteration that will be shuffled

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterUpdateOneIter**(*BoosterHandle* handle, int *produced_empty_tree)

Update the model for one iteration.

Parameters

- **handle** – Handle of booster
- **produced_empty_tree** – **[out]** 1 means the tree(s) produced by this iteration did not have any splits. This usually means that training is "finished" (calling this function again will not change the model's predictions). However, that is not always the case. For example, if you have added any randomness (like column sampling by setting `feature_fraction_bynode < 1.0`), it is possible that another call to this function would produce a non-empty tree.

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterUpdateOneIterCustom**(*BoosterHandle* handle, const float *grad, const float *hess, int *produced_empty_tree)

Update the model by specifying gradient and Hessian directly (this can be used to support customized loss functions).

Note

The length of the arrays referenced by `grad` and `hess` must be equal to `num_class * num_train_data`, this is not verified by the library, the caller must ensure this.

Parameters

- **handle** – Handle of booster
- **grad** – The first order derivative (gradient) statistics
- **hess** – The second order derivative (Hessian) statistics
- **produced_empty_tree** – **[out]** 1 means the tree(s) produced by this iteration did not have any splits. This usually means that training is "finished" (calling this function again will not change the model's predictions). However, that is not always the case. For example, if you have added any randomness (like column sampling by setting `feature_fraction_bynode < 1.0`), it is possible that another call to this function would produce a non-empty tree.

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_BoosterValidateFeatureNames**(*BoosterHandle* handle, const char **data_names, int data_num_features)

Check that the feature names of the data match the ones used to train the booster.

Parameters

- **handle** – Handle of booster
- **data_names** – Array with the feature names in the data
- **data_num_features** – Number of features in the data

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_ByteBufferFree**(*ByteBufferHandle* handle)

Free space for byte buffer.

Parameters

- **handle** – Handle of byte buffer to be freed

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_ByteBufferGetAt**(*ByteBufferHandle* handle, int32_t index, uint8_t *out_val)

Get a ByteBuffer value at an index.

Parameters

- **handle** – Handle of byte buffer to be read
- **index** – Index of value to return
- **out_val** – **[out]** Byte value at index to return

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetAddFeaturesFrom**(*DatasetHandle* target, *DatasetHandle* source)

Add features from `source` to `target`.

Parameters

- **target** – The handle of the dataset to add features to
- **source** – The handle of the dataset to take features from

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateByReference**(const *DatasetHandle* reference, int64_t num_total_row, *DatasetHandle* *out)

Allocate the space for dataset and bucket feature bins according to reference dataset.

Parameters

- **reference** – Used to align bin mapper with other dataset
- **num_total_row** – Number of total rows
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromArrow**(int64_t n_chunks, struct ArrowArray *chunks, struct ArrowSchema *schema, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create dataset from Arrow.

Deprecated:

This function is deprecated in favor of *LGBM_DatasetCreateFromArrowStream*.

< Deprecated function.

Parameters

- **n_chunks** – The number of Arrow arrays passed to this function
- **chunks** – Pointer to the list of Arrow arrays
- **schema** – Pointer to the schema of all Arrow arrays
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromArrowStream**(struct ArrowArrayStream *stream, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create dataset from Arrow stream.

Parameters

- **stream** – Arrow stream pointer
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromCSC**(const void *col_ptr, int col_ptr_type, const int32_t *indices, const void *data, int data_type, int64_t ncol_ptr, int64_t nelem, int64_t num_row, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create a dataset from CSC format.

Parameters

- **col_ptr** – Pointer to column headers
- **col_ptr_type** – Type of `col_ptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to row indices
- **data** – Pointer to the data space

- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **ncol_ptr** – Number of columns in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_row** – Number of rows
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromCSR**(const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create a dataset from CSR format.

Parameters

- **indptr** – Pointer to row headers
- **indptr_type** – Type of `indptr`, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_col** – Number of columns
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromCSRFunc**(void *get_row_funptr, int num_rows, int64_t num_col, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create a dataset from CSR format through callbacks.

Parameters

- **get_row_funptr** – Pointer to `std::function<void(int idx, std::vector<std::pair<int, double>>& ret)>` (called for every row and expected to clear and fill `ret`)
- **num_rows** – Number of rows

- **num_col** – Number of columns
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromFile**(const char *filename, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Load dataset from file (like LightGBM CLI version does).

Parameters

- **filename** – The name of the file
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** A loaded dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromMat**(const void *data, int data_type, int32_t nrow, int32_t ncol, int is_row_major, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create dataset from dense matrix.

Parameters

- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number of columns
- **is_row_major** – 1 for row-major, 0 for column-major
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromMats**(int32_t nmat, const void **data, int data_type, int32_t *nrow, int32_t ncol, int *is_row_major, const char *parameters, const *DatasetHandle* reference, *DatasetHandle* *out)

Create dataset from array of dense matrices.

Parameters

- **nmat** – Number of dense matrices

- **data** – Pointer to the data space
- **data_type** – Type of data pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number of columns
- **is_row_major** – Pointer to the data layouts. 1 for row-major, 0 for column-major
- **parameters** – Additional parameters
- **reference** – Used to align bin mapper with other dataset, nullptr means isn't used
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromSampledColumn**(double **sample_data, int **sample_indices, int32_t ncol, const int *num_per_col, int32_t num_sample_row, int32_t num_local_row, int64_t num_dist_row, const char *parameters, *DatasetHandle* *out)

Allocate the space for dataset and bucket feature bins according to sampled data.

Parameters

- **sample_data** – Sampled data, grouped by the column
- **sample_indices** – Indices of sampled data
- **ncol** – Number of columns
- **num_per_col** – Size of each sampling column
- **num_sample_row** – Number of sampled rows
- **num_local_row** – Total number of rows local to machine
- **num_dist_row** – Number of total distributed rows
- **parameters** – Additional parameters
- **out** – **[out]** Created dataset

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetCreateFromSerializedReference**(const void *ref_buffer, int32_t ref_buffer_size, int64_t num_row, int32_t num_classes, const char *parameters, *DatasetHandle* *out)

Allocate the space for dataset and bucket feature bins according to serialized reference dataset.

Parameters

- **ref_buffer** – A binary representation of the dataset schema (feature groups, bins, etc.)
- **ref_buffer_size** – The size of the reference array in bytes

- **num_row** – Number of total rows the dataset will contain
- **num_classes** – Number of classes (will be used only in case of multiclass and specifying initial scores)
- **parameters** – Additional parameters
- **out** – **[out]** Created dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetDumpText**(*DatasetHandle* handle, const char *filename)

Save dataset to text file, intended for debugging use only.

Parameters

- **handle** – Handle of dataset
- **filename** – The name of the file

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetFree**(*DatasetHandle* handle)

Free space for dataset.

Parameters

- **handle** – Handle of dataset to be freed

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetFeatureNames**(*DatasetHandle* handle, const int len, int *num_feature_names, const size_t buffer_len, size_t *out_buffer_len, char **feature_names)

Get feature names of dataset.

Parameters

- **handle** – Handle of dataset
- **len** – Number of `char*` pointers stored at `out_strs`. If smaller than the max size, only this many strings are copied
- **num_feature_names** – **[out]** Number of feature names
- **buffer_len** – Size of pre-allocated strings. Content is copied up to `buffer_len - 1` and null-terminated
- **out_buffer_len** – **[out]** String sizes required to do the full string copies
- **feature_names** – **[out]** Feature names, should pre-allocate memory

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetFeatureNumBin**(*DatasetHandle* handle, int feature, int *out)

Get number of bins for feature.

Parameters

- **handle** – Handle of dataset
- **feature** – Index of the feature

- **out** – **[out]** The address to hold number of bins

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetField**(*DatasetHandle* handle, const char *field_name, int *out_len, const void **out_ptr, int *out_type)

Get info vector from dataset.

Parameters

- **handle** – Handle of dataset
- **field_name** – Field name
- **out_len** – **[out]** Used to set result length
- **out_ptr** – **[out]** Pointer to the result
- **out_type** – **[out]** Type of result pointer, can be *C_API_DTYPE_INT32*, *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetNumData**(*DatasetHandle* handle, int *out)

Get number of data points.

Parameters

- **handle** – Handle of dataset
- **out** – **[out]** The address to hold number of data points

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetNumFeature**(*DatasetHandle* handle, int *out)

Get number of features.

Parameters

- **handle** – Handle of dataset
- **out** – **[out]** The address to hold number of features

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetGetSubset**(const *DatasetHandle* handle, const int32_t *used_row_indices, int32_t num_used_row_indices, const char *parameters, *DatasetHandle* *out)

Create subset of a data.

Parameters

- **handle** – Handle of full dataset
- **used_row_indices** – Indices used in subset
- **num_used_row_indices** – Length of `used_row_indices`
- **parameters** – Additional parameters
- **out** – **[out]** Subset of data

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetInitStreaming**(*DatasetHandle* dataset, int32_t has_weights, int32_t has_init_scores, int32_t has_queries, int32_t nclasses, int32_t nthreads, int32_t omp_max_threads)

Initialize the Dataset for streaming.

Parameters

- **dataset** – Handle of dataset
- **has_weights** – Whether the dataset has Metadata weights
- **has_init_scores** – Whether the dataset has Metadata initial scores
- **has_queries** – Whether the dataset has Metadata queries/groups
- **nclasses** – Number of initial score classes
- **nthreads** – Number of external threads that will use the PushRows APIs
- **omp_max_threads** – Maximum number of OpenMP threads (-1 for default)

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetMarkFinished**(*DatasetHandle* dataset)

Mark the Dataset as complete by calling `dataset->FinishLoad`.

Parameters

- **dataset** – Handle of dataset

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRows**(*DatasetHandle* dataset, const void *data, int data_type, int32_t nrow, int32_t ncol, int32_t start_row)

Push data to existing dataset, if `nrow + start_row == num_total_row`, will call `dataset->FinishLoad`.

Parameters

- **dataset** – Handle of dataset
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number of columns
- **start_row** – Row start index

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRowsByCSR**(*DatasetHandle* dataset, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t num_col, int64_t start_row)

Push data to existing dataset, if `nrow + start_row == num_total_row`, will call `dataset->FinishLoad`.

Parameters

- **dataset** – Handle of dataset
- **indptr** – Pointer to row headers
- **indptr_type** – Type of indptr, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices
- **data** – Pointer to the data space
- **data_type** – Type of data pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **num_col** – Number of columns
- **start_row** – Row start index

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRowsByCSRWithMetadata**(*DatasetHandle* dataset, const void *indptr, int indptr_type, const int32_t *indices, const void *data, int data_type, int64_t nindptr, int64_t nelem, int64_t start_row, const float *label, const float *weight, const double *init_score, const int32_t *query, int32_t tid)

Push CSR data to existing dataset. (See *LGBM_DatasetPushRowsWithMetadata* for more details.).

Parameters

- **dataset** – Handle of dataset
- **indptr** – Pointer to row headers
- **indptr_type** – Type of indptr, can be *C_API_DTYPE_INT32* or *C_API_DTYPE_INT64*
- **indices** – Pointer to column indices
- **data** – Pointer to the data space
- **data_type** – Type of data pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nindptr** – Number of rows in the matrix + 1
- **nelem** – Number of nonzero elements in the matrix
- **start_row** – Row start index
- **label** – Pointer to array with nindptr-1 labels
- **weight** – Optional pointer to array with nindptr-1 weights
- **init_score** – Optional pointer to array with (nindptr-1)*nclasses initial scores, in column format
- **query** – Optional pointer to array with nindptr-1 query values
- **tid** – The id of the calling thread, from 0...N-1 threads

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetPushRowsWithMetadata**(*DatasetHandle* dataset, const void *data, int data_type, int32_t nrow, int32_t ncol, int32_t start_row, const float *label, const float *weight, const double *init_score, const int32_t *query, int32_t tid)

Push data to existing dataset. The general flow for a streaming scenario is:

a. create Dataset "schema" (e.g. *LGBM_DatasetCreateFromSampledColumn*)
b. init them for thread-safe streaming (*LGBM_DatasetInitStreaming*)
c. push data (*LGBM_DatasetPushRowsWithMetadata* or *LGBM_DatasetPushRowsByCSRWithMetadata*)
d. call *LGBM_DatasetMarkFinished*

Parameters

- **dataset** – Handle of dataset
- **data** – Pointer to the data space
- **data_type** – Type of `data` pointer, can be *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*
- **nrow** – Number of rows
- **ncol** – Number of feature columns
- **start_row** – Row start index, i.e., the index at which to start inserting data
- **label** – Pointer to array with nrow labels
- **weight** – Optional pointer to array with nrow weights
- **init_score** – Optional pointer to array with nrow*nclasses initial scores, in column format
- **query** – Optional pointer to array with nrow query values
- **tid** – The id of the calling thread, from 0...N-1 threads

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSaveBinary**(*DatasetHandle* handle, const char *filename)

Save dataset to binary file.

Parameters

- **handle** – Handle of dataset
- **filename** – The name of the file

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSerializeReferenceToBinary**(*DatasetHandle* handle, *ByteBufferHandle* *out, int32_t *out_len)

Create a dataset schema representation as a binary byte array (excluding data).

Parameters

- **handle** – Handle of dataset
- **out** – **[out]** The output byte array
- **out_len** – **[out]** The length of the output byte array (returned for convenience)

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSetFeatureNames**(*DatasetHandle* handle, const char **feature_names, int num_feature_names)

Save feature names to dataset.

Parameters

- **handle** – Handle of dataset
- **feature_names** – Feature names
- **num_feature_names** – Number of feature names

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSetField**(*DatasetHandle* handle, const char *field_name, const void *field_data, int num_element, int type)

Set vector to a content in info.

Note

- *group* only works for *C_API_DTYPE_INT32*;
- *label* and *weight* only work for *C_API_DTYPE_FLOAT32*;
- *init_score* only works for *C_API_DTYPE_FLOAT64*.

Parameters

- **handle** – Handle of dataset
- **field_name** – Field name, can be *label*, *weight*, *init_score*, *group*
- **field_data** – Pointer to data vector
- **num_element** – Number of elements in `field_data`
- **type** – Type of `field_data` pointer, can be *C_API_DTYPE_INT32*, *C_API_DTYPE_FLOAT32* or *C_API_DTYPE_FLOAT64*

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSetFieldFromArrow**(*DatasetHandle* handle, const char *field_name, int64_t n_chunks, struct ArrowArray *chunks, struct ArrowSchema *schema)

Set vector to a content in info.

Deprecated:

This function is deprecated in favor of *LGBM_DatasetSetFieldFromArrowStream*.

< Deprecated function.

Note

- *group* converts input datatype into `int32`;
- *label* and *weight* convert input datatype into `float32`;
- *init_score* converts input datatype into `float64`.

Parameters

- **handle** – Handle of dataset
- **field_name** – Field name, can be *label*, *weight*, *init_score*, *group*
- **n_chunks** – The number of Arrow arrays passed to this function
- **chunks** – Pointer to the list of Arrow arrays
- **schema** – Pointer to the schema of all Arrow arrays

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSetFieldFromArrowStream**(*DatasetHandle* handle, const char *field_name, struct ArrowArrayStream *stream)

Set vector to a content in info.

Note

- *group* converts input datatype into `int32`;
- *label* and *weight* convert input datatype into `float32`;
- *init_score* converts input datatype into `float64`.

Parameters

- **handle** – Handle of dataset
- **field_name** – Field name, can be *label*, *weight*, *init_score*, *group*
- **stream** – Arrow stream pointer

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetSetWaitForManualFinish**(*DatasetHandle* dataset, int wait)

Set whether or not the Dataset waits for a manual MarkFinished call or calls FinishLoad on itself automatically. Set to 1 for streaming scenario, and use *LGBM_DatasetMarkFinished* to manually finish the Dataset.

Parameters

- **dataset** – Handle of dataset
- **wait** – Whether to wait or not (1 or 0)

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DatasetUpdateParamChecking**(const char *old_parameters, const char *new_parameters)

Raise errors for attempts to update dataset parameters.

Parameters

- **old_parameters** – Current dataset parameters
- **new_parameters** – New dataset parameters

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_DumpParamAliases**(int64_t buffer_len, int64_t *out_len, char *out_str)

Dump all parameter names with their aliases to JSON.

Parameters

- **buffer_len** – String buffer length, if `buffer_len < out_len`, you should re-allocate buffer
- **out_len** – **[out]** Actual output length
- **out_str** – **[out]** JSON format string of parameters, should pre-allocate memory

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_FastConfigFree**(*FastConfigHandle* fastConfig)

Release FastConfig object.

Parameters

- **fastConfig** – Handle to the FastConfig object acquired with a `*FastInit()` method.

Returns

0 when it succeeds, -1 when failure happens

LIGHTGBM_C_EXPORT const char ***LGBM_GetLastError**()

Get string message of the last error.

Returns

Error information

LIGHTGBM_C_EXPORT int **LGBM_GetMaxThreads**(int *out)

Get current maximum number of threads used by LightGBM routines in this process.

Parameters

- **out** – **[out]** current maximum number of threads used by LightGBM. -1 means defaulting to omp_get_num_threads().

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_GetSampleCount**(int32_t num_total_row, const char *parameters, int *out)

Get number of samples based on parameters and total number of rows of data.

Parameters

- **num_total_row** – Number of total rows
- **parameters** – Additional parameters, namely, `bin_construct_sample_cnt` is used to calculate returned value
- **out** – **[out]** Number of samples. This value is used to pre-allocate memory to hold sample indices when calling *LGBM_SampleIndices*

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_NetworkFree**()

Finalize the network.

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_NetworkInit**(const char *machines, int local_listen_port, int listen_time_out, int num_machines)

Initialize the network.

Parameters

- **machines** – List of machines in format 'ip1:port1,ip2:port2'
- **local_listen_port** – TCP listen port for local machines
- **listen_time_out** – Socket time-out in minutes
- **num_machines** – Total number of machines

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_NetworkInitWithFunctions**(int num_machines, int rank, void *reduce_scatter_ext_fun, void *allgather_ext_fun)

Initialize the network with external collective functions.

Parameters

- **num_machines** – Total number of machines
- **rank** – Rank of local machine
- **reduce_scatter_ext_fun** – The external reduce-scatter function
- **allgather_ext_fun** – The external allgather function

Returns

0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_RegisterLogCallback**(void (*callback)(const char*))

Register a callback function for log redirecting.

Parameters

- **callback** – The callback function to register

Returns
0 when succeed, -1 when failure happens

LIGHTGBM_C_EXPORT int **LGBM_SampleIndices**(int32_t num_total_row, const char *parameters, void *out, int32_t *out_len)

Create sample indices for total number of rows.

> **Note**
>
> You should pre-allocate memory for `out`, you can get its length by *LGBM_GetSampleCount*.

Parameters

- **num_total_row** – Number of total rows
- **parameters** – Additional parameters, namely, `bin_construct_sample_cnt` and `data_random_seed` are used to produce the output
- **out** – **[out]** Created indices, type is int32_t
- **out_len** – **[out]** Number of indices

Returns
0 when succeed, -1 when failure happens

inline void **LGBM_SetLastError**(const char *msg)

Set string message of the last error.

> **Note**
>
> This will call unsafe `sprintf` when compiled using C standards before C99.

Parameters

- **msg** – Error message

LIGHTGBM_C_EXPORT int **LGBM_SetMaxThreads**(int num_threads)

Set maximum number of threads used by LightGBM routines in this process.

Parameters

- **num_threads** – maximum number of threads used by LightGBM. -1 means defaulting to omp_get_num_threads().

Returns
0 when succeed, -1 when failure happens

CHAPTER

NINE

PYTHON API

9.1 Data Structure API

Dataset(data[, label, reference, weight, ...])	Dataset in LightGBM.
Booster([params, train_set, model_file, ...])	Booster in LightGBM.
CVBooster([model_file])	CVBooster in LightGBM.
Sequence()	Generic data access interface.

9.1.1 lightgbm.Dataset

class lightgbm.**Dataset**(*data*, *label=None*, *reference=None*, *weight=None*, *group=None*, *init_score=None*, *feature_name='auto'*, *categorical_feature='auto'*, *params=None*, *free_raw_data=True*, *position=None*)

Bases: `object`

Dataset in LightGBM.

LightGBM does not train on raw data. It discretizes continuous features into histogram bins, tries to combine categorical features, and automatically handles missing and infinite values.

This class handles that preprocessing, and holds that alternative representation of the input data.

__init__(*data*, *label=None*, *reference=None*, *weight=None*, *group=None*, *init_score=None*, *feature_name='auto'*, *categorical_feature='auto'*, *params=None*, *free_raw_data=True*, *position=None*)

Initialize Dataset.

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, scipy.sparse, Sequence, list of Sequence, list of numpy array, pyarrow Table or polars DataFrame*) – Data source of Dataset. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM) or a LightGBM Dataset binary file.
- **label** (*list, numpy 1-D array, pandas Series / one-column DataFrame, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Label of the data.
- **reference** (*Dataset or None, optional (default=None)*) – If this is Dataset for validation, training data should be used as reference.

- **weight** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Weight for each instance. Weights should be non-negative.
- **group** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **init_score** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None, optional (default=None)*) – Init score for Dataset.
- **feature_name** (*list of str, or 'auto', optional (default="auto")*) – Feature names. If 'auto' and data is pandas DataFrame, pyarrow Table, or polars DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default="auto")*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- **params** (*dict or None, optional (default=None)*) – Other parameters for Dataset.
- **free_raw_data** (*bool, optional (default=True)*) – If True, raw data is freed after constructing inner Dataset.
- **position** (*numpy 1-D array, pandas Series or None, optional (default=None)*) – Position of items used in unbiased learning-to-rank task.

Methods

__init__(data[, label, reference, weight, ...])	Initialize Dataset.
add_features_from(other)	Add features from other Dataset to the current Dataset.
construct()	Lazy init.
create_valid(data[, label, weight, group, ...])	Create validation data align with current Dataset.
feature_num_bin(feature)	Get the number of bins for a feature.
get_data()	Get the raw data of the Dataset.
get_feature_name()	Get the names of columns (features) in the Dataset.
get_field(field_name)	Get property from the Dataset.
get_group()	Get the group of the Dataset.
get_init_score()	Get the initial score of the Dataset.
get_label()	Get the label of the Dataset.
get_params()	Get the used parameters in the Dataset.

continues on next page

Table 2 – continued from previous page

get_position()	Get the position of the Dataset.
get_ref_chain([ref_limit])	Get a chain of Dataset objects.
get_weight()	Get the weight of the Dataset.
num_data()	Get the number of rows in the Dataset.
num_feature()	Get the number of columns (features) in the Dataset.
save_binary(filename)	Save Dataset to a binary file.
set_categorical_feature(categorical_feature)	Set categorical features.
set_feature_name(feature_name)	Set feature name.
set_field(field_name, data)	Set property into the Dataset.
set_group(group)	Set group size of Dataset (used for ranking).
set_init_score(init_score)	Set init score of Booster to start from.
set_label(label)	Set label of Dataset.
set_position(position)	Set position of Dataset (used for ranking).
set_reference(reference)	Set reference Dataset.
set_weight(weight)	Set weight of each instance.
subset(used_indices[, params])	Get subset of current Dataset.

add_features_from(*other*)

Add features from other Dataset to the current Dataset.

Both Datasets must be constructed before calling this method.

Parameters

other (Dataset) – The Dataset to take features from.

Returns

self – Dataset with the new features added.

Return type

Dataset

construct()

Lazy init.

Returns

self – Constructed Dataset object.

Return type

Dataset

create_valid(*data*, *label=None*, *weight=None*, *group=None*, *init_score=None*, *params=None*, *position=None*)

Create validation data align with current Dataset.

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, scipy.sparse, Sequence, list of Sequence, list of numpy array, pyarrow Table or polars DataFrame*) – Data source of Dataset. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM) or a LightGBM Dataset binary file.
- **label** (*list, numpy 1-D array, pandas Series / one-column DataFrame, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Label of the data.

- **weight** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Weight for each instance. Weights should be non-negative.
- **group** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **init_score** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None, optional (default=None)*) – Init score for Dataset.
- **params** (*dict or None, optional (default=None)*) – Other parameters for validation Dataset.
- **position** (*numpy 1-D array, pandas Series or None, optional (default=None)*) – Position of items used in unbiased learning-to-rank task.

Returns
valid – Validation Dataset with reference to self.

Return type
Dataset

`feature_num_bin`(*feature*)

Get the number of bins for a feature.

Added in version 4.0.0.

Parameters
feature (*int or str*) – Index or name of the feature.

Returns
number_of_bins – The number of constructed bins for the feature in the Dataset.

Return type
int

`get_data`()

Get the raw data of the Dataset.

Returns
data – Raw data used in the Dataset construction.

Return type
str, pathlib.Path, numpy array, pandas DataFrame, scipy.sparse, *Sequence*, list of *Sequence*, list of numpy array, pyarrow Table, polars DataFrame, or None

`get_feature_name`()

Get the names of columns (features) in the Dataset.

Returns
feature_names – The names of columns (features) in the Dataset.

Return type
list of str

`get_field`(*field_name*)

Get property from the Dataset.

Can only be run on a constructed Dataset.

Unlike `get_group()`, `get_init_score()`, `get_label()`, `get_position()`, and `get_weight()`, this method ignores any raw data passed into `lgb.Dataset()` on the Python side, and will only read data from the constructed C++ `Dataset` object.

Parameters
field_name (*str*) – The field name of the information.

Returns
info – A numpy array with information from the Dataset.

Return type
numpy array or None

`get_group`()

Get the group of the Dataset.

Returns
group – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc. For a constructed `Dataset`, this will only return `None` or a numpy array.

Return type
list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None

`get_init_score`()

Get the initial score of the Dataset.

Returns
init_score – Init score of Booster. For a constructed `Dataset`, this will only return `None` or a numpy array.

Return type
list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None

`get_label`()

Get the label of the Dataset.

Returns
label – The label information from the Dataset. For a constructed `Dataset`, this will only return a numpy array.

Return type
list, numpy 1-D array, pandas Series / one-column DataFrame, pyarrow ChunkedArray, polars Series or None

`get_params`()

Get the used parameters in the Dataset.

Returns
params – The used parameters in this Dataset object.

Return type
dict

`get_position`()

Get the position of the Dataset.

Returns
position – Position of items used in unbiased learning-to-rank task. For a constructed `Dataset`, this will only return `None` or a numpy array.

Return type
numpy 1-D array, pandas Series or None

`get_ref_chain`(*ref_limit=100*)

Get a chain of Dataset objects.

Starts with r, then goes to r.reference (if exists), then to r.reference.reference, etc. until we hit `ref_limit` or a reference loop.

Parameters
ref_limit (*int, optional (default=100)*) – The limit number of references.

Returns
ref_chain – Chain of references of the Datasets.

Return type
set of *Dataset*

`get_weight`()

Get the weight of the Dataset.

Returns
weight – Weight for each data point from the Dataset. Weights should be non-negative. For a constructed `Dataset`, this will only return `None` or a numpy array.

Return type
list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None

`num_data`()

Get the number of rows in the Dataset.

Returns
number_of_rows – The number of rows in the Dataset.

Return type
int

`num_feature`()

Get the number of columns (features) in the Dataset.

Returns
number_of_columns – The number of columns (features) in the Dataset.

Return type
int

`save_binary`(*filename*)

Save Dataset to a binary file.

> **Note**
>
> Please note that *init_score* is not saved in binary file. If you need it, please set it again after loading Dataset.

Parameters
filename (*str or pathlib.Path*) – Name of the output file.

Returns
self – Returns self.

Return type
Dataset

set_categorical_feature(*categorical_feature*)

Set categorical features.

Parameters
categorical_feature (*list of str or int, or 'auto'*) – Names or indices of categorical features.

Returns
self – Dataset with set categorical features.

Return type
Dataset

set_feature_name(*feature_name*)

Set feature name.

Parameters
feature_name (*list of str*) – Feature names.

Returns
self – Dataset with set feature name.

Return type
Dataset

set_field(*field_name*, *data*)

Set property into the Dataset.

Parameters

- **field_name** (*str*) – The field name of the information.
- **data** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None*) – The data to be set.

Returns
self – Dataset with set property.

Return type
Dataset

set_group(*group*)

Set group size of Dataset (used for ranking).

Parameters

group (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

Returns

self – Dataset with set group.

Return type

Dataset

`set_init_score`(*init_score*)

Set init score of Booster to start from.

Parameters

init_score (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None*) – Init score for Booster.

Returns

self – Dataset with set init score.

Return type

Dataset

`set_label`(*label*)

Set label of Dataset.

Parameters

label (*list, numpy 1-D array, pandas Series / one-column DataFrame, pyarrow ChunkedArray, polars Series or None*) – The label information to be set into Dataset.

Returns

self – Dataset with set label.

Return type

Dataset

`set_position`(*position*)

Set position of Dataset (used for ranking).

Parameters

position (*numpy 1-D array, pandas Series or None, optional (default=None)*) – Position of items used in unbiased learning-to-rank task.

Returns

self – Dataset with set position.

Return type

Dataset

`set_reference`(*reference*)

Set reference Dataset.

Parameters

reference (`Dataset`) – Reference that is used as a template to construct the current Dataset.

Returns
self – Dataset with set reference.

Return type
Dataset

`set_weight`(*weight*)

Set weight of each instance.

Parameters
weight (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None*) – Weight to be set for each data point. Weights should be non-negative.

Returns
self – Dataset with set weight.

Return type
Dataset

`subset`(*used_indices*, *params=None*)

Get subset of current Dataset.

Parameters

- **used_indices** (*list of int*) – Indices used to create the subset.
- **params** (*dict or None, optional (default=None)*) – These parameters will be passed to Dataset constructor.

Returns
subset – Subset of the current Dataset.

Return type
Dataset

9.1.2 lightgbm.Booster

`class lightgbm.Booster`(*params=None*, *train_set=None*, *model_file=None*, *model_str=None*)

Bases: `object`

Booster in LightGBM.

`__init__`(*params=None*, *train_set=None*, *model_file=None*, *model_str=None*)

Initialize the Booster.

Parameters

- **params** (*dict or None, optional (default=None)*) – Parameters for Booster.
- **train_set** (*Dataset or None, optional (default=None)*) – Training dataset.
- **model_file** (*str, pathlib.Path or None, optional (default=None)*) – Path to the model file.
- **model_str** (*str or None, optional (default=None)*) – Model will be loaded from this string.

Methods

__init__([params, train_set, model_file, ...])	Initialize the Booster.
add_valid(data, name)	Add validation data.
current_iteration()	Get the index of the current iteration.
dump_model([num_iteration, start_iteration, ...])	Dump Booster to JSON format.
eval(data, name[, feval])	Evaluate for data.
eval_train([feval])	Evaluate for training data.
eval_valid([feval])	Evaluate for validation data.
feature_importance([importance_type, iteration])	Get feature importances.
feature_name()	Get names of features.
free_dataset()	Free Booster's Datasets.
free_network()	Free Booster's network.
get_leaf_output(tree_id, leaf_id)	Get the output of a leaf.
get_split_value_histogram(feature[, bins, ...])	Get split value histogram for the specified feature.
lower_bound()	Get lower bound value of a model.
model_from_string(model_str)	Load Booster from a string.
model_to_string([num_iteration, ...])	Save Booster to string.
num_feature()	Get number of features.
num_model_per_iteration()	Get number of models per iteration.
num_trees()	Get number of weak sub-models.
predict(data[, start_iteration, ...])	Make a prediction.
refit(data, label[, decay_rate, reference, ...])	Refit the existing Booster by new data.
reset_parameter(params)	Reset parameters of Booster.
rollback_one_iter()	Rollback one iteration.
save_model(filename[, num_iteration, ...])	Save Booster to file.
set_leaf_output(tree_id, leaf_id, value)	Set the output of a leaf.
set_network(machines[, local_listen_port, ...])	Set the network configuration.
set_train_data_name(name)	Set the name to the training Dataset.
shuffle_models([start_iteration, end_iteration])	Shuffle models.
trees_to_dataframe()	Parse the fitted model and return in an easy-to-read pandas DataFrame.
update([train_set, fobj])	Update Booster for one iteration.
upper_bound()	Get upper bound value of a model.

add_valid(*data*, *name*)

Add validation data.

Parameters

- **data** (Dataset) – Validation data.
- **name** (*str*) – Name of validation data.

Returns

self – Booster with set validation data.

Return type

Booster

current_iteration()

Get the index of the current iteration.

Returns

cur_iter – The index of the current iteration.

Return type
int

dump_model(*num_iteration=None*, *start_iteration=0*, *importance_type='split'*, *object_hook=None*)

Dump Booster to JSON format.

Parameters

- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be dumped. If None, if the best iteration exists, it is dumped; otherwise, all iterations are dumped. If <= 0, all iterations are dumped.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be dumped.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be dumped. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.
- **object_hook** (*callable or None, optional (default=None)*) – If not None, `object_hook` is a function called while parsing the json string returned by the C API. It may be used to alter the json, to store specific values while building the json structure. It avoids walking through the structure again. It saves a significant amount of time if the number of trees is huge. Signature is `def object_hook(node: dict) -> dict`. None is equivalent to `lambda node: node`. See documentation of `json.loads()` for further details.

Returns
json_repr – JSON format of Booster.

Return type
dict

eval(*data*, *name*, *feval=None*)

Evaluate for data.

Parameters

- **data** (`Dataset`) – Data for the evaluating.
- **name** (*str*) – Name of the data.
- **feval** (*callable, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, eval_data, and return (metric_name, metric_value, maximize) or list of such tuples.

  preds
  [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes]. If custom objective function is used, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

  eval_data
  [Dataset] A `Dataset` to evaluate.

  metric_name
  [str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

  metric_value
  [float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

Returns
result – List with (dataset_name, metric_name, metric_value, maximize) tuples.

Return type
list

`eval_train`(*feval=None*)

Evaluate for training data.

Parameters
feval (*callable, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, eval_data, and return (metric_name, metric_value, maximize) or list of such tuples.

preds
[numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes]. If custom objective function is used, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

eval_data
[Dataset] The training dataset.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

Returns
result – List with (train_dataset_name, metric_name, metric_value, maximize) tuples.

Return type
list

`eval_valid`(*feval=None*)

Evaluate for validation data.

Parameters
feval (*callable, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, eval_data, and return (metric_name, metric_value, maximize) or list of such tuples.

preds
[numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes]. If custom objective function is used, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

eval_data
[Dataset] The validation dataset.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

Returns
result – List with (validation_dataset_name, metric_name, metric_value, maximize) tuples.

Return type
list

`feature_importance`(*importance_type='split'*, *iteration=None*)

Get feature importances.

Parameters

- **importance_type** (*str, optional (default="split")*) – How the importance is calculated. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.
- **iteration** (*int or None, optional (default=None)*) – Limit number of iterations in the feature importance calculation. If None, if the best iteration exists, it is used; otherwise, all trees are used. If <= 0, all trees are used (no limits).

Returns
result – Array with feature importances.

Return type
numpy array

`feature_name`()

Get names of features.

Returns
result – List with names of features.

Return type
list of str

`free_dataset`()

Free Booster's Datasets.

Returns
self – Booster without Datasets.

Return type
Booster

`free_network`()

Free Booster's network.

Returns
self – Booster with freed network.

Return type
Booster

`get_leaf_output`(*tree_id*, *leaf_id*)

Get the output of a leaf.

Parameters

- **tree_id** (*int*) – The index of the tree.
- **leaf_id** (*int*) – The index of the leaf in the tree.

Returns

result – The output of the leaf.

Return type

float

`get_split_value_histogram`(*feature*, *bins=None*, *xgboost_style=False*)

Get split value histogram for the specified feature.

Parameters

- **feature** (*int or str*) – The feature name or index the histogram is calculated for. If int, interpreted as index. If str, interpreted as name.

  Warning

  Categorical features are not supported.

- **bins** (*int, str or None, optional (default=None)*) – The maximum number of bins. If None, or int and > number of unique split values and `xgboost_style=True`, the number of bins equals number of unique split values. If str, it should be one from the list of the supported values by `numpy.histogram()` function.
- **xgboost_style** (*bool, optional (default=False)*) – Whether the returned result should be in the same form as it is in XGBoost. If False, the returned value is tuple of 2 numpy arrays as it is in `numpy.histogram()` function. If True, the returned value is matrix, in which the first column is the right edges of non-empty bins and the second one is the histogram values.

Returns

- **result_tuple** (*tuple of 2 numpy arrays*) – If `xgboost_style=False`, the values of the histogram of used splitting values for the specified feature and the bin edges.
- **result_array_like** (*numpy array or pandas DataFrame (if pandas is installed)*) – If `xgboost_style=True`, the histogram of used splitting values for the specified feature.

`lower_bound`()

Get lower bound value of a model.

Returns

lower_bound – Lower bound value of the model.

Return type

float

`model_from_string`(*model_str*)

Load Booster from a string.

Parameters

model_str (*str*) – Model will be loaded from this string.

Returns
self – Loaded Booster object.

Return type
Booster

model_to_string(*num_iteration=None*, *start_iteration=0*, *importance_type='split'*)

Save Booster to string.

Parameters

- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If None, if the best iteration exists, it is saved; otherwise, all iterations are saved. If <= 0, all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be saved. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.

Returns
str_repr – String representation of Booster.

Return type
str

num_feature()

Get number of features.

Returns
num_feature – The number of features.

Return type
int

num_model_per_iteration()

Get number of models per iteration.

Returns
model_per_iter – The number of models per iteration.

Return type
int

num_trees()

Get number of weak sub-models.

Returns
num_trees – The number of weak sub-models.

Return type
int

predict(*data*, *start_iteration=0*, *num_iteration=None*, *raw_score=False*, *pred_leaf=False*, *pred_contrib=False*, *data_has_header=False*, *validate_features=False*, ***kwargs*)

Make a prediction.

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, scipy.sparse, pyarrow Table or polars DataFrame*) – Data source for prediction. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM).
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **data_has_header** (*bool, optional (default=False)*) – Whether the data has header. Used only if data is str.
- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

result – Prediction result. Can be sparse or a list of sparse objects (each element represents predictions for one class) for feature contributions (when `pred_contrib=True`).

Return type

numpy array, scipy.sparse or list of scipy.sparse

refit(*data*, *label*, *decay_rate=0.9*, *reference=None*, *weight=None*, *group=None*, *init_score=None*, *feature_name='auto'*, *categorical_feature='auto'*, *dataset_params=None*, *free_raw_data=True*, *validate_features=False*, ***kwargs*)

Refit the existing Booster by new data.

Parameters

- **data** (*str, pathlib.Path, numpy array, pandas DataFrame, scipy.sparse, Sequence, list of Sequence, list of numpy array, pyarrow Table or polars DataFrame*) – Data source for refit. If str or pathlib.Path, it represents the path to a text file (CSV, TSV, or LibSVM).
- **label** (*list, numpy 1-D array, pandas Series / one-column DataFrame, pyarrow ChunkedArray, polars Series or None*) – Label for refit.

- **decay_rate** (*float, optional (default=0.9)*) – Decay rate of refit, will use `leaf_output = decay_rate * old_leaf_output + (1.0 - decay_rate) * new_leaf_output` to refit trees.
- **reference** (*Dataset or None, optional (default=None)*) – Reference for `data`.

  Added in version 4.0.0.
- **weight** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Weight for each `data` instance. Weights should be non-negative.

  Added in version 4.0.0.
- **group** (*list, numpy 1-D array, pandas Series, pyarrow ChunkedArray, polars Series or None, optional (default=None)*) – Group/query size for `data`. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

  Added in version 4.0.0.
- **init_score** (*list, list of lists (for multi-class task), numpy array, pandas Series, pandas DataFrame (for multi-class task), pyarrow ChunkedArray, pyarrow Table (for multi-class task), polars Series, polars DataFrame (for multi-class task) or None, optional (default=None)*) – Init score for `data`.

  Added in version 4.0.0.
- **feature_name** (*list of str, or 'auto', optional (default="auto")*) – Feature names for `data`. If 'auto' and data is pandas DataFrame, data columns names are used.

  Added in version 4.0.0.
- **categorical_feature** (*list of str or int, or 'auto', optional (default="auto")*) – Categorical features for `data`. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.

  Added in version 4.0.0.
- **dataset_params** (*dict or None, optional (default=None)*) – Other parameters for Dataset `data`.

  Added in version 4.0.0.
- **free_raw_data** (*bool, optional (default=True)*) – If True, raw data is freed after constructing inner Dataset for `data`.

  Added in version 4.0.0.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to refit the model match the original ones. Used only if data is pandas DataFrame.

  Added in version 4.0.0.

- ****kwargs** – Other parameters for refit. These parameters will be passed to `predict` method.

Returns
result – Refitted Booster.

Return type
Booster

reset_parameter(*params*)

Reset parameters of Booster.

Parameters
params (*dict*) – New parameters for Booster.

Returns
self – Booster with new parameters.

Return type
Booster

rollback_one_iter()

Rollback one iteration.

Returns
self – Booster with rolled back one iteration.

Return type
Booster

save_model(*filename*, *num_iteration=None*, *start_iteration=0*, *importance_type='split'*)

Save Booster to file.

Parameters

- **filename** (*str or pathlib.Path*) – Filename to save Booster.
- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If None, if the best iteration exists, it is saved; otherwise, all iterations are saved. If <= 0, all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be saved. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.

Returns
self – Returns self.

Return type
Booster

set_leaf_output(*tree_id*, *leaf_id*, *value*)

Set the output of a leaf.

Added in version 4.0.0.

Parameters

- **tree_id** (*int*) – The index of the tree.
- **leaf_id** (*int*) – The index of the leaf in the tree.
- **value** (*float*) – Value to set as the output of the leaf.

Returns
self – Booster with the leaf output set.

Return type
Booster

set_network(*machines*, *local_listen_port=12400*, *listen_time_out=120*, *num_machines=1*)

Set the network configuration.

Parameters

- **machines** (*list, set or str*) – Names of machines.
- **local_listen_port** (*int, optional (default=12400)*) – TCP listen port for local machines.
- **listen_time_out** (*int, optional (default=120)*) – Socket time-out in minutes.
- **num_machines** (*int, optional (default=1)*) – The number of machines for distributed learning application.

Returns
self – Booster with set network.

Return type
Booster

set_train_data_name(*name*)

Set the name to the training Dataset.

Parameters
name (*str*) – Name for the training Dataset.

Returns
self – Booster with set training Dataset name.

Return type
Booster

shuffle_models(*start_iteration=0*, *end_iteration=-1*)

Shuffle models.

Parameters

- **start_iteration** (*int, optional (default=0)*) – The first iteration that will be shuffled.
- **end_iteration** (*int, optional (default=-1)*) – The last iteration that will be shuffled. If <= 0, means the last available iteration.

Returns
self – Booster with shuffled models.

Return type
Booster

`trees_to_dataframe()`

Parse the fitted model and return in an easy-to-read pandas DataFrame.

The returned DataFrame has the following columns.

- `tree_index` : int64, which tree a node belongs to. 0-based, so a value of `6`, for example, means "this node is in the 7th tree".
- `node_depth` : int64, how far a node is from the root of the tree. The root node has a value of `1`, its direct children are `2`, etc.
- `node_index` : str, unique identifier for a node.
- `left_child` : str, `node_index` of the child node to the left of a split. `None` for leaf nodes.
- `right_child` : str, `node_index` of the child node to the right of a split. `None` for leaf nodes.
- `parent_index` : str, `node_index` of this node's parent. `None` for the root node.
- `split_feature` : str, name of the feature used for splitting. `None` for leaf nodes.
- `split_gain` : float64, gain from adding this split to the tree. `NaN` for leaf nodes.
- `threshold` : float64, value of the feature used to decide which side of the split a record will go down. `NaN` for leaf nodes.
- `decision_type` : str, logical operator describing how to compare a value to `threshold`. For example, `split_feature = "Column_10", threshold = 15, decision_type = "<="` means that records where `Column_10 <= 15` follow the left side of the split, otherwise follows the right side of the split. `None` for leaf nodes.
- `missing_direction` : str, split direction that missing values should go to. `None` for leaf nodes.
- `missing_type` : str, describes what types of values are treated as missing.
- `value` : float64, predicted value for this leaf node, multiplied by the learning rate.
- `weight` : float64 or int64, sum of Hessian (second-order derivative of objective), summed over observations that fall in this node.
- `count` : int64, number of records in the training data that fall into this node.

Returns
result – Returns a pandas DataFrame of the parsed model.

Return type
pandas DataFrame

`update`(*train_set=None*, *fobj=None*)

Update Booster for one iteration.

Parameters

- **train_set** (Dataset *or None, optional (default=None)*) – Training data. If None, last training data is used.
- **fobj** (*callable or None, optional (default=None)*) – Customized objective function. Should accept two parameters: preds, train_data, and return (grad, hess).

  preds
  [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data
[Dataset] The training dataset.

grad
[numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of preds for each sample point.

hess
[numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of preds for each sample point.

For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Returns
produced_empty_tree – `True` if the tree(s) produced by this iteration did not have any splits. This usually means that training is "finished" (calling `update()` again will not change the model's predictions). However, that is not always the case. For example, if you have added any randomness (like column sampling by setting `feature_fraction_bynode < 1.0`), it is possible that another call to `update()` would produce a non-empty tree.

Return type
bool

`upper_bound()`

Get upper bound value of a model.

Returns
upper_bound – Upper bound value of the model.

Return type
float

9.1.3 lightgbm.CVBooster

`class lightgbm.CVBooster(model_file=None)`

Bases: `object`

CVBooster in LightGBM.

Auxiliary data structure to hold and redirect all boosters of `cv()` function. This class has the same methods as Booster class. All method calls, except for the following methods, are actually performed for underlying Boosters and then all returned results are returned in a list.

- `model_from_string()`
- `model_to_string()`
- `save_model()`

`boosters`

The list of underlying fitted models.

Type
list of *Booster*

best_iteration

The best iteration of fitted model.

Type
int

__init__(*model_file=None*)

Initialize the CVBooster.

Parameters
model_file (*str, pathlib.Path or None, optional (default=None)*) – Path to the CVBooster model file.

Methods

__init__([model_file])	Initialize the CVBooster.
model_from_string(model_str)	Load CVBooster from a string.
model_to_string([num_iteration, ...])	Save CVBooster to JSON string.
save_model(filename[, num_iteration, ...])	Save CVBooster to a file as JSON text.

model_from_string(*model_str*)

Load CVBooster from a string.

Parameters
model_str (*str*) – Model will be loaded from this string.

Returns
self – Loaded CVBooster object.

Return type
CVBooster

model_to_string(*num_iteration=None*, *start_iteration=0*, *importance_type='split'*)

Save CVBooster to JSON string.

Parameters

- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If None, if the best iteration exists, it is saved; otherwise, all iterations are saved. If <= 0, all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be saved. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.

Returns
str_repr – JSON string representation of CVBooster.

Return type
str

save_model(*filename*, *num_iteration=None*, *start_iteration=0*, *importance_type='split'*)

Save CVBooster to a file as JSON text.

Parameters

- **filename** (*str or pathlib.Path*) – Filename to save CVBooster.
- **num_iteration** (*int or None, optional (default=None)*) – Index of the iteration that should be saved. If None, if the best iteration exists, it is saved; otherwise, all iterations are saved. If <= 0, all iterations are saved.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration that should be saved.
- **importance_type** (*str, optional (default="split")*) – What type of feature importance should be saved. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.

Returns
self – Returns self.

Return type
CVBooster

9.1.4 lightgbm.Sequence

class lightgbm.**Sequence**

Bases: ABC

Generic data access interface.

Object should support the following operations:

```
# Get total row number.
>>> len(seq)
# Random access by row index. Used for data sampling.
>>> seq[10]
# Range data access. Used to read data in batch when constructing Dataset.
>>> seq[0:100]
# Optionally specify batch_size to control range data read size.
>>> seq.batch_size
```

- With random access, **data sampling does not need to go through all data**.
- With range data access, there's **no need to read all data into memory thus reduce memory usage**.

Added in version 3.3.0.

batch_size

Default size of a batch.

Type
int

__init__()

Methods

__init__()

Attributes

batch_size

9.2 Training API

train(params, train_set[, num_boost_round, ...])	Perform the training with given parameters.
cv(params, train_set[, num_boost_round, ...])	Perform the cross-validation with given parameters.

9.2.1 lightgbm.train

lightgbm.**train**(*params*, *train_set*, *num_boost_round=100*, *valid_sets=None*, *valid_names=None*, *feval=None*, *init_model=None*, *keep_training_booster=False*, *callbacks=None*)

Perform the training with given parameters.

Parameters

- **params** (*dict*) – Parameters for training. Values passed through `params` take precedence over those supplied via arguments.
- **train_set** (Dataset) – Data to be trained on.
- **num_boost_round** (*int, optional (default=100)*) – Number of boosting iterations.
- **valid_sets** (*list of* Dataset*, or None, optional (default=None)*) – List of data to be evaluated on during training.
- **valid_names** (*list of str, or None, optional (default=None)*) – Names of `valid_sets`.
- **feval** (*callable, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, eval_data, and return (metric_name, metric_value, maximize) or list of such tuples.

  preds
  [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes]. If custom objective function is used, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

  eval_data
  [Dataset] A `Dataset` to evaluate.

  metric_name
  [str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

  metric_value
  [float] Value of the evaluation metric.

  maximize
  [bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

To ignore the default metric corresponding to the used objective, set the `metric` parameter to the string `"None"` in `params`.

- **init_model** (*str, pathlib.Path, Booster or None, optional (default=None)*) – Filename of LightGBM model or Booster instance used for continue training.
- **keep_training_booster** (*bool, optional (default=False)*) – Whether the returned Booster will be used to keep training. If False, the returned value will be converted into _InnerPredictor before returning. This means you won't be able to use `eval`, `eval_train` or `eval_valid` methods of the returned Booster. When your model is very large and cause the memory error, you can try to set this param to `True` to avoid the model conversion performed during the internal call of `model_to_string`. You can still use _InnerPredictor as `init_model` for future continue training.
- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.

Note

A custom objective function can be provided for the `objective` parameter. It should accept two parameters: preds, train_data and return (grad, hess).

preds
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data
: [Dataset] The training dataset.

grad
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of preds for each sample point.

hess
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of preds for each sample point.

For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Returns
: **booster** – The trained Booster model.

Return type
: *Booster*

9.2.2 lightgbm.cv

`lightgbm.cv`(*params*, *train_set*, *num_boost_round=100*, *folds=None*, *nfold=5*, *stratified=True*, *shuffle=True*, *metrics=None*, *feval=None*, *init_model=None*, *fpreproc=None*, *seed=0*, *callbacks=None*, *eval_train_metric=False*, *return_cvbooster=False*)

Perform the cross-validation with given parameters.

Parameters

- **params** (*dict*) – Parameters for training. Values passed through `params` take precedence over those supplied via arguments.
- **train_set** (`Dataset`) – Data to be trained on.
- **num_boost_round** (*int, optional (default=100)*) – Number of boosting iterations.
- **folds** (*generator or iterator of (train_idx, test_idx) tuples, scikit-learn splitter object or None, optional (default=None)*) – If generator or iterator, it should yield the train and test indices for each fold. If object, it should be one of the scikit-learn splitter classes (https://scikit-learn.org/stable/modules/classes.html#splitter-classes) and have `split` method. This argument has highest priority over other data split arguments.
- **nfold** (*int, optional (default=5)*) – Number of folds in CV.
- **stratified** (*bool, optional (default=True)*) – Whether to perform stratified sampling.
- **shuffle** (*bool, optional (default=True)*) – Whether to shuffle before splitting data.
- **metrics** (*str, list of str, or None, optional (default=None)*) – Evaluation metrics to be monitored while CV. If not None, the metric in `params` will be overridden.
- **feval** (*callable, list of callable, or None, optional (default=None)*) – Customized evaluation function. Each evaluation function should accept two parameters: preds, eval_data, and return (metric_name, metric_value, maximize) or list of such tuples.

  preds
  [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes]. If custom objective function is used, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

  eval_data
  [Dataset] A `Dataset` to evaluate.

  metric_name
  [str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

  metric_value
  [float] Value of the evaluation metric.

  maximize
  [bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

  To ignore the default metric corresponding to the used objective, set `metrics` to the string `"None"`.
- **init_model** (*str, pathlib.Path, Booster or None, optional (default=None)*) – Filename of LightGBM model or Booster instance used for continue training.
- **fpreproc** (*callable or None, optional (default=None)*) – Preprocessing function that takes (dtrain, dtest, params) and returns transformed versions of those.

- **seed** (*int, optional (default=0)*) – Seed used to generate the folds (passed to numpy.random.seed).
- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **eval_train_metric** (*bool, optional (default=False)*) – Whether to display the train metric in progress. The score of the metric is calculated again after each training step, so there is some impact on performance.
- **return_cvbooster** (*bool, optional (default=False)*) – Whether to return Booster models trained on each fold through `CVBooster`.

Note

A custom objective function can be provided for the `objective` parameter. It should accept two parameters: preds, train_data and return (grad, hess).

preds
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

train_data
: [Dataset] The training dataset.

grad
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of preds for each sample point.

hess
: [numpy 1-D array or numpy 2-D array (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of preds for each sample point.

For multi-class task, preds are numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Returns

eval_results – History of evaluation results of each metric. The dictionary has the following format: {'valid metric1-mean': [values], 'valid metric1-stdv': [values], 'valid metric2-mean': [values], 'valid metric2-stdv': [values], ...}. If `return_cvbooster=True`, also returns trained boosters wrapped in a `CVBooster` object via `cvbooster` key. If `eval_train_metric=True`, also returns the train metric history. In this case, the dictionary has the following format: {'train metric1-mean': [values], 'valid metric1-mean': [values], 'train metric2-mean': [values], 'valid metric2-mean': [values], ...}.

Return type

dict

9.3 Scikit-learn API

LGBMModel(*[, boosting_type, num_leaves, ...])	Implementation of the scikit-learn API for LightGBM.
LGBMClassifier(*[, boosting_type, ...])	LightGBM classifier.
LGBMRegressor(*[, boosting_type, ...])	LightGBM regressor.

continues on next page

Table 8 – continued from previous page

LGBMRanker(*[, boosting_type, num_leaves, ...])	LightGBM ranker.

9.3.1 lightgbm.LGBMModel

class lightgbm.**LGBMModel**(** (Keyword-only parameters separator (PEP 3102))*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Bases: BaseEstimator

Implementation of the scikit-learn API for LightGBM.

__init__(***, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/

stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.

- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.
- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

Warning

**kwargs is not supported in sklearn, it may cause unexpected issues.

Note

A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:

y_true
[numpy 1-D array of shape = [n_samples]] The target values.

y_pred
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

weight
[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.

hess
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.

For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.

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Table 9 – continued from previous page

set_fit_request(*[, callbacks, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
`dict`

property booster_

The underlying Booster of this model.

Type
Booster

property evals_result_

The evaluation results if validation sets have been specified.

Type
`dict`

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type
`array` of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format `Column_0`, `Column_1`, ..., `Column_N`.

Type
`list` of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of `.feature_name_`.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises `AttributeError`.

Added in version 4.5.0.

Type
`array` of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *group=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_class_weight=None*, *eval_init_score=None*, *eval_group=None*, *eval_metric=None*, *feature_name='auto'*, *categorical_feature='auto'*, *callbacks=None*, *init_model=None*, ***, *eval_X=None*, *eval_y=None*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*numpy array, pandas Series, list of int or float, pyarrow ChunkedArray, polars Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*numpy array, pandas DataFrame, pandas Series, list of int or float, list of lists, pyarrow ChunkedArray, pyarrow Table, polars Series, polars DataFrame of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task) or*

shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)) – Init score of training data.

- **group** (*numpy array, pandas Series, pyarrow ChunkedArray, polars Series, list of int or float, or None, optional (default=None)*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (list of array (same types as `sample_weight` supports), or None, optional (default=None)) – Weights of eval data. Weights should be non-negative.
- **eval_class_weight** (*list or None, optional (default=None)*) – Class weights of eval data.
- **eval_init_score** (list of array (same types as `init_score` supports), or None, optional (default=None)) – Init score of eval data.
- **eval_group** (list of array (same types as `group` supports), or None, optional (default=None)) – Group data of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or

LGBMModel instance used for continue training.

- **eval_X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features], or tuple of such inputs, or None, optional (default=None)*) – Feature matrix or tuple thereof, e.g. `(X_val0, X_val1)`, to use as validation sets.
- **eval_y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples], or tuple of such inputs, or None, optional (default=None)*) – Target values or tuple thereof, e.g. `(y_val0, y_val1)`, to use as validation sets.

Returns
self – Returns self.

Return type
LGBMModel

Note

Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):

y_true
[numpy 1-D array of shape = [n_samples]] The target values.

y_pred
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight
[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A MetadataRequest encapsulating routing information.

Return type
MetadataRequest

`get_params`(*deep=True*)

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

`property n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

`property n_features_`

The number of features of fitted model.

Type
`int`

`property n_features_in_`

The number of features of fitted model.

Type
`int`

`property n_iter_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

`property objective_`

The concrete objective used while fitting this model.

Type
`str` or `callable`

`predict`(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or list with n_classes length of such objects*) – If `pred_contrib=True`, the feature contributions for each sample.

set_fit_request(*, *callbacks='$UNCHANGED$'*, *categorical_feature='$UNCHANGED$'*, *eval_X='$UNCHANGED$'*, *eval_class_weight='$UNCHANGED$'*, *eval_group='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *feature_name='$UNCHANGED$'*, *group='$UNCHANGED$'*, *init_model='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **callbacks** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `callbacks` parameter in `fit`.
- **categorical_feature** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `categorical_feature` parameter in `fit`.
- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_class_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_class_weight` parameter in `fit`.
- **eval_group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_group` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.

- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **feature_name** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `feature_name` parameter in `fit`.
- **group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `group` parameter in `fit`.
- **init_model** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_model` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

set_params(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns
self – The updated object.

Return type
object

9.3.2 lightgbm.LGBMClassifier

class lightgbm.**LGBMClassifier**(**, boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=None, importance_type='split', **kwargs*)

Bases: `ClassifierMixin`, *LGBMModel*

LightGBM classifier.

__init__(**, boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=None, importance_type='split', **kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.

- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.
- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

Warning

**kwargs is not supported in sklearn, it may cause unexpected issues.

Note

A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:

y_true
: [numpy 1-D array of shape = [n_samples]] The target values.

y_pred
: [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.

weight
: [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
: [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad
: [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.

hess
: [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.

For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
decision_function(X, *[, start_iteration, ...])	Return the raw margin score for each sample.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
predict_proba(X[, raw_score, ...])	Return the predicted probability for each class for each sample.
score(X, y[, sample_weight])	Return accuracy on provided data and labels.
set_decision_function_request(*[, ...])	Configure whether metadata should be requested to be passed to the `decision_function` method.
set_fit_request(*[, callbacks, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_proba_request(*[, ...])	Configure whether metadata should be requested to be passed to the `predict_proba` method.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.
set_score_request(*[, sample_weight])	Configure whether metadata should be requested to be passed to the `score` method.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*classes_*	The class label array.

continues on next page

Table 12 – continued from previous page

*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_classes_*	The number of classes.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
`dict`

property booster_

The underlying Booster of this model.

Type
Booster

property classes_

The class label array.

Type
`array` of shape = [n_classes]

decision_function(*X*, ***, *start_iteration=0*, *num_iteration=None*, *validate_features=False*, ***kwargs*)

Return the raw margin score for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.

- ****kwargs** – Other parameters forwarded to `predict()`.

Returns
raw_score – The predicted values.

Return type
array-like of shape = [n_samples] or shape = [n_samples, n_classes]

property evals_result_

The evaluation results if validation sets have been specified.

Type
`dict`

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type
`array` of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format `Column_0`, `Column_1`, ..., `Column_N`.

Type
`list` of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of `.feature_name_`.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises `AttributeError`.

Added in version 4.5.0.

Type
`array` of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_class_weight=None*, *eval_init_score=None*, *eval_metric=None*, *feature_name='auto'*, *categorical_feature='auto'*, *callbacks=None*, *init_model=None*, ***, *eval_X=None*, *eval_y=None*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*numpy array, pandas Series, list of int or float, pyarrow ChunkedArray, polars Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*numpy array, pandas DataFrame, pandas Series, list of int or float, list of lists, pyarrow ChunkedArray, pyarrow Table, polars Series, polars DataFrame of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task) or shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)*) – Init score of training data.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (list of array (same types as `sample_weight` supports), or None, optional (default=None)) – Weights of eval data. Weights should be non-negative.
- **eval_class_weight** (*list or None, optional (default=None)*) – Class weights of eval data.
- **eval_init_score** (list of array (same types as `init_score` supports), or None, optional (default=None)) – Init score of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained

with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.

- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.
- **eval_X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features], or tuple of such inputs, or None, optional (default=None)*) – Feature matrix or tuple thereof, e.g. `(X_val0, X_val1)`, to use as validation sets.
- **eval_y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples], or tuple of such inputs, or None, optional (default=None)*) – Target values or tuple thereof, e.g. `(y_val0, y_val1)`, to use as validation sets.

Returns

self – Returns self.

Return type

LGBMClassifier

Note

Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):

y_true

[numpy 1-D array of shape = [n_samples]] The target values.

y_pred

[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight

[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group

[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

metric_name

[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

`property n_classes_`

The number of classes.

Type
`int`

`property n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

`property n_features_`

The number of features of fitted model.

Type
`int`

`property n_features_in_`

The number of features of fitted model.

Type
`int`

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property objective_

The concrete objective used while fitting this model.

Type
`str` or `callable`

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.

- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or list with n_classes length of such objects*) – If `pred_contrib=True`, the feature contributions for each sample.

predict_proba(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted probability for each class for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_probability** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or list with n_classes length of such objects*) – If `pred_contrib=True`, the feature contributions for each sample.

score(*X*, *y*, *sample_weight=None*)

Return accuracy on provided data and labels.

In multi-label classification, this is the subset accuracy which is a harsh metric since you require for each sample that each label set be correctly predicted.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples.
- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True labels for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns

score – Mean accuracy of `self.predict(X)` w.r.t. *y*.

Return type

float

set_decision_function_request(*, *num_iteration='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `decision_function` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `decision_function` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `decision_function`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `decision_function`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `decision_function`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `decision_function`.

Returns

self – The updated object.

Return type
object

set_fit_request(*, *callbacks='$UNCHANGED$'*, *categorical_feature='$UNCHANGED$'*, *eval_X='$UNCHANGED$'*, *eval_class_weight='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *feature_name='$UNCHANGED$'*, *init_model='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **callbacks** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `callbacks` parameter in `fit`.
- **categorical_feature** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `categorical_feature` parameter in `fit`.
- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_class_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_class_weight` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.

- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **feature_name** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `feature_name` parameter in `fit`.
- **init_model** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_model` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

set_params(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_proba_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict_proba` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict_proba` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict_proba`.

- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict_proba`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict_proba`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict_proba`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict_proba`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict_proba`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict_proba`.

Returns
self – The updated object.

Return type
object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns

self – The updated object.

Return type

object

set_score_request(*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `score` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `score` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `score`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

sample_weight (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `score`.

Returns

self – The updated object.

Return type

object

9.3.3 lightgbm.LGBMRegressor

class lightgbm.**LGBMRegressor**(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Bases: `RegressorMixin`, *LGBMModel*

LightGBM regressor.

__init__(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.

- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.
- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains num-

bers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.

- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

> **Warning**
>
> **kwargs is not supported in sklearn, it may cause unexpected issues.

> **Note**
>
> A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **grad**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.
>
> **hess**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.
>
> For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.

continues on next page

Table 13 – continued from previous page

fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
score(X, y[, sample_weight])	Return coefficient of determination on test data.
set_fit_request(*[, callbacks, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.
set_score_request(*[, sample_weight])	Configure whether metadata should be requested to be passed to the `score` method.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
`dict`

property booster_

The underlying Booster of this model.

Type
Booster

property evals_result_

The evaluation results if validation sets have been specified.

Type
dict

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> importance_type attribute is passed to the function to configure the type of importance values to be extracted.

Type
array of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format Column_0, Column_1, ..., Column_N.

Type
list of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of .feature_name_.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises AttributeError.

Added in version 4.5.0.

Type
array of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_init_score=None*, *eval_metric=None*, *feature_name='auto'*, *categorical_feature='auto'*, *callbacks=None*, *init_model=None*, ***, *eval_X=None*, *eval_y=None*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*numpy array, pandas Series, list of int or float, pyarrow ChunkedArray, polars Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.

- **init_score** (*numpy array, pandas DataFrame, pandas Series, list of int or float, list of lists, pyarrow ChunkedArray, pyarrow Table, polars Series, polars DataFrame of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task) or shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)*) – Init score of training data.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (list of array (same types as `sample_weight` supports), or None, optional (default=None)) – Weights of eval data. Weights should be non-negative.
- **eval_init_score** (list of array (same types as `init_score` supports), or None, optional (default=None)) – Init score of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.
- **eval_X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features], or tuple of such inputs, or None, optional (default=None)*) – Feature matrix or tuple thereof, e.g. `(X_val0, X_val1)`, to use as validation sets.
- **eval_y** (*numpy array, pandas DataFrame, pandas Series, list of*

int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples], or tuple of such inputs, or None, optional (default=None)) – Target values or tuple thereof, e.g. `(y_val0, y_val1)`, to use as validation sets.

Returns
self – Returns self.

Return type
LGBMRegressor

Note

Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):

y_true
[numpy 1-D array of shape = [n_samples]] The target values.

y_pred
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight
[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

property n_estimators_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property n_features_

The number of features of fitted model.

Type
`int`

property n_features_in_

The number of features of fitted model.

Type
`int`

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property objective_

The concrete objective used while fitting this model.

Type
`str` or `callable`

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.

- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or list with n_classes length of such objects*) – If `pred_contrib=True`, the feature contributions for each sample.

score(*X*, *y*, *sample_weight=None*)

Return coefficient of determination on test data.

The coefficient of determination, R^2, is defined as $(1 - \frac{u}{v})$, where u is the residual sum of squares `((y_true - y_pred)** 2).sum()` and v is the total sum of squares `((y_true - y_true.mean()) ** 2).sum()`. The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of *y*, disregarding the input features, would get a R^2 score of 0.0.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples. For some estimators this may be a precomputed kernel matrix or a list of generic objects instead with shape `(n_samples, n_samples_fitted)`, where `n_samples_fitted` is the number of samples used in the fitting for the estimator.
- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True values for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns
score – R^2 of `self.predict(X)` w.r.t. y.

Return type
float

Notes

The R^2 score used when calling `score` on a regressor uses `multioutput='uniform_average'` from version 0.23 to keep consistent with default value of `r2_score()`. This influences the `score` method of all the multioutput regressors (except for `MultiOutputRegressor`).

set_fit_request(*, *callbacks='$UNCHANGED$'*, *categorical_feature='$UNCHANGED$'*, *eval_X='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *feature_name='$UNCHANGED$'*, *init_model='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **callbacks** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `callbacks` parameter in `fit`.
- **categorical_feature** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `categorical_feature` parameter in `fit`.
- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.

- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **feature_name** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `feature_name` parameter in `fit`.
- **init_model** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_model` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

set_params(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns

self – The updated object.

Return type

object

set_score_request(*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `score` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `score` if provided. The request is ignored if metadata is not provided.

- `False`: metadata is not requested and the meta-estimator will not pass it to `score`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

sample_weight (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `score`.

Returns

self – The updated object.

Return type

object

9.3.4 lightgbm.LGBMRanker

class lightgbm.**LGBMRanker**(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Bases: *LGBMModel*

LightGBM ranker.

Warning

scikit-learn doesn't support ranking applications yet, therefore this class is not really compatible with the sklearn ecosystem. Please use this class mainly for training and applying ranking models in common sklearnish way.

__init__(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, ***kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.

- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is

picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.

- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.

- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.

- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

> **Warning**
>
> **kwargs is not supported in sklearn, it may cause unexpected issues.

> **Note**
>
> A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

grad
: [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.

hess
: [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.

For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
set_fit_request(*[, callbacks, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
dict

property booster_

The underlying Booster of this model.

Type
Booster

property evals_result_

The evaluation results if validation sets have been specified.

Type
dict

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> importance_type attribute is passed to the function to configure the type of importance values to be extracted.

Type
array of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format Column_0, Column_1, ..., Column_N.

Type
list of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of .feature_name_.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises AttributeError.

Added in version 4.5.0.

Type
array of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *group=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_init_score=None*, *eval_group=None*, *eval_metric=None*, *eval_at=(1, 2, 3, 4, 5)*, *feature_name='auto'*, *categorical_feature='auto'*, *callbacks=None*, *init_model=None*, ***, *eval_X=None*, *eval_y=None*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*numpy array, pandas Series, list of int or float, pyarrow ChunkedArray, polars Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*numpy array, pandas DataFrame, pandas Series, list of int or float, list of lists, pyarrow ChunkedArray, pyarrow Table, polars Series, polars DataFrame of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task) or shape = [n_samples, n_classes] (for multi-class task) or None, optional (default=None)*) – Init score of training data.
- **group** (*numpy array, pandas Series, pyarrow ChunkedArray, polars Series, list of int or float, or None, optional (default=None)*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (list of array (same types as `sample_weight` supports), or None, optional (default=None)) – Weights of eval data. Weights should be non-negative.
- **eval_init_score** (list of array (same types as `init_score` supports), or None, optional (default=None)) – Init score of eval data.
- **eval_group** (list of array (same types as `group` supports), or None, optional (default=None)) – Group data of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.

- **eval_at** (*list or tuple of int, optional (default=(1, 2, 3, 4, 5))*) – The evaluation positions of the specified metric.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- **callbacks** (*list of callable, or None, optional (default=None)*) – List of callback functions that are applied at each iteration. See Callbacks in Python API for more information.
- **init_model** (*str, pathlib.Path, Booster, LGBMModel or None, optional (default=None)*) – Filename of LightGBM model, Booster instance or LGBMModel instance used for continue training.
- **eval_X** (*numpy array, pandas DataFrame, pyarrow Table, polars DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features], or tuple of such inputs, or None, optional (default=None)*) – Feature matrix or tuple thereof, e.g. `(X_val0, X_val1)`, to use as validation sets.
- **eval_y** (*numpy array, pandas DataFrame, pandas Series, list of int or float, pyarrow ChunkedArray or polars Series of shape = [n_samples], or tuple of such inputs, or None, optional (default=None)*) – Target values or tuple thereof, e.g. `(y_val0, y_val1)`, to use as validation sets.

Returns

self – Returns self.

Return type

LGBMRanker

Note

Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):

y_true

[numpy 1-D array of shape = [n_samples]] The target values.

y_pred

[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight
[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

`property n_estimators_`

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

`property n_features_`

The number of features of fitted model.

Type
`int`

property n_features_in_

The number of features of fitted model.

Type
`int`

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property objective_

The concrete objective used while fitting this model.

Type
`str` or `callable`

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.

- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*array-like of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*array-like of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*array-like of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or list with n_classes length of such objects*) – If `pred_contrib=True`, the feature contributions for each sample.

set_fit_request(*, *callbacks='$UNCHANGED$'*, *categorical_feature='$UNCHANGED$'*, *eval_X='$UNCHANGED$'*, *eval_at='$UNCHANGED$'*, *eval_group='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *feature_name='$UNCHANGED$'*, *group='$UNCHANGED$'*, *init_model='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **callbacks** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `callbacks` parameter in `fit`.
- **categorical_feature** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `categorical_feature` parameter in `fit`.
- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_at** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_at` parameter in `fit`.

- **eval_group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_group` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **feature_name** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `feature_name` parameter in `fit`.
- **group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `group` parameter in `fit`.
- **init_model** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_model` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

`set_params`(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns
self – The updated object.

Return type
object

9.4 Dask API

Added in version 3.2.0.

DaskLGBMClassifier(*[, boosting_type, ...])	Distributed version of lightgbm.LGBMClassifier.
DaskLGBMRegressor(*[, boosting_type, ...])	Distributed version of lightgbm.LGBMRegressor.
DaskLGBMRanker(*[, boosting_type, ...])	Distributed version of lightgbm.LGBMRanker.

9.4.1 lightgbm.DaskLGBMClassifier

class lightgbm.**DaskLGBMClassifier**(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, *client=None*, ***kwargs*)

Bases: LGBMClassifier, _DaskLGBMModel

Distributed version of lightgbm.LGBMClassifier.

__init__(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, *client=None*, ***kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing num_leaves to <= 2^max_depth.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use callbacks parameter of fit method to shrink/adapt learning rate in training using reset_parameter callback. Note, that this will ignore the learning_rate argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.

- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.
- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains num-

bers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.

- **client** (*distributed.Client or None, optional (default=None)*) – Dask client. If None, distributed.default_client() will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.
- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

> **Warning**
>
> **kwargs is not supported in sklearn, it may cause unexpected issues.

> **Note**
>
> A custom objective function can be provided for the objective parameter. In this case, it should have the signature objective(y_true, y_pred) -> grad, hess, objective(y_true, y_pred, weight) -> grad, hess or objective(y_true, y_pred, weight, group) -> grad, hess:
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with group = [10, 20, 40, 10, 10, 10], that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **grad**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.
>
> **hess**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.
>
> For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
decision_function(X, *[, start_iteration, ...])	Return the raw margin score for each sample.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
predict_proba(X[, raw_score, ...])	Return the predicted probability for each class for each sample.
score(X, y[, sample_weight])	Return accuracy on provided data and labels.
set_decision_function_request(*[, ...])	Configure whether metadata should be requested to be passed to the `decision_function` method.
set_fit_request(*[, eval_X, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_proba_request(*[, ...])	Configure whether metadata should be requested to be passed to the `predict_proba` method.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.
set_score_request(*[, sample_weight])	Configure whether metadata should be requested to be passed to the `score` method.
to_local()	Create regular version of lightgbm.LGBMClassifier from the distributed version.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*classes_*	The class label array.
*client_*	Dask client.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_classes_*	The number of classes.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type

int

property best_score_

The best score of fitted model.

Type
dict

property booster_

The underlying Booster of this model.

Type
Booster

property classes_

The class label array.

Type
array of shape = [n_classes]

property client_

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type
distributed.Client

decision_function(*X*, *, *start_iteration=0*, *num_iteration=None*, *validate_features=False*, ***kwargs*)

Return the raw margin score for each sample.

Parameters

- **X** (*numpy array, pandas DataFrame, scipy.sparse, list of lists of int or float of shape = [n_samples, n_features]*) – Input features matrix.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters forwarded to `predict()`.

Returns
raw_score – The predicted values.

Return type
array-like of shape = [n_samples] or shape = [n_samples, n_classes]

property evals_result_

The evaluation results if validation sets have been specified.

Type
dict

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type
`array` of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format `Column_0`, `Column_1`, ..., `Column_N`.

Type
`list` of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of `.feature_name_`.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises `AttributeError`.

Added in version 4.5.0.

Type
`array` of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_class_weight=None*, *eval_init_score=None*, *eval_metric=None*, ***, *eval_X=None*, *eval_y=None*, ***kwargs*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*Dask Array, Dask DataFrame or Dask Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*Dask Array or Dask Series of shape = [n_samples] or shape = [n_samples * n_classes] (for multi-class task), or Dask Array or Dask DataFrame of shape = [n_samples, n_classes] (for multi-class task), or None, optional (default=None)*) – Init score of training data.

- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Weights of eval data. Weights should be non-negative.
- **eval_class_weight** (*list or None, optional (default=None)*) – Class weights of eval data.
- **eval_init_score** (*list of Dask Array, Dask Series or Dask DataFrame (for multi-class task), or None, optional (default=None)*) – Init score of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- ****kwargs** – Other parameters passed through to `LGBMClassifier.fit()`.

Returns

self – Returns self.

Return type

lightgbm.DaskLGBMClassifier

Note

Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):

y_true

[numpy 1-D array of shape = [n_samples]] The target values.

y_pred
[numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.

weight
[numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.

group
[numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.

metric_name
[str] Unique identifier for the metric (e.g. "custom_adjusted_mse").

metric_value
[float] Value of the evaluation metric.

maximize
[bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

`property n_classes_`

The number of classes.

Type
`int`

`property n_estimators_`

True number of boosting iterations performed.

This might be less than parameter n_estimators if early stopping was enabled or if boosting stopped early due to limits on complexity like min_gain_to_split.

Added in version 4.0.0.

Type
int

property n_features_

The number of features of fitted model.

Type
int

property n_features_in_

The number of features of fitted model.

Type
int

property n_iter_

True number of boosting iterations performed.

This might be less than parameter n_estimators if early stopping was enabled or if boosting stopped early due to limits on complexity like min_gain_to_split.

Added in version 4.0.0.

Type
int

property objective_

The concrete objective used while fitting this model.

Type
str or callable

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from start_iteration are used (no limits). If <= 0, all iterations from start_iteration are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

> **Note**
>
> If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*Dask Array of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (Dask Array of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or (if multi-class and using sparse inputs) a list of `n_classes` Dask Arrays of shape = [n_samples, n_features + 1]) – If `pred_contrib=True`, the feature contributions for each sample.

predict_proba(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted probability for each class for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.
- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

> **Note**
>
> If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_probability** (*Dask Array of shape = [n_samples] or shape = [n_samples, n_classes]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees] or shape = [n_samples, n_trees * n_classes]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (Dask Array of shape = [n_samples, n_features + 1] or shape = [n_samples, (n_features + 1) * n_classes] or (if multi-class and using sparse inputs) a list of `n_classes` Dask Arrays of shape = [n_samples, n_features + 1]) – If `pred_contrib=True`, the feature contributions for each sample.

score(*X*, *y*, *sample_weight=None*)

Return accuracy on provided data and labels.

In multi-label classification, this is the subset accuracy which is a harsh metric since you require for each sample that each label set be correctly predicted.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples.
- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True labels for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns

score – Mean accuracy of `self.predict(X)` w.r.t. *y*.

Return type

float

set_decision_function_request(*, *num_iteration='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `decision_function` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `decision_function` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `decision_function`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `decision_function`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `decision_function`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `decision_function`.

Returns

self – The updated object.

Return type

object

set_fit_request(*, *eval_X='$UNCHANGED$'*, *eval_class_weight='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_class_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_class_weight` parameter in `fit`.

- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

set_params(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_proba_request(*, num_iteration='$UNCHANGED$', pred_contrib='$UNCHANGED$', pred_leaf='$UNCHANGED$', raw_score='$UNCHANGED$', start_iteration='$UNCHANGED$', validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict_proba` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict_proba` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict_proba`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict_proba`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict_proba`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict_proba`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict_proba`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict_proba`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict_proba`.

Returns

self – The updated object.

Return type

object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.

- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns

self – The updated object.

Return type

object

`set_score_request`(*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `score` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `score` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `score`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

sample_weight (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `score`.

Returns

self – The updated object.

Return type

object

`to_local()`

Create regular version of lightgbm.LGBMClassifier from the distributed version.

Returns

model – Local underlying model.

Return type

lightgbm.LGBMClassifier

9.4.2 lightgbm.DaskLGBMRegressor

`class lightgbm.DaskLGBMRegressor(*, boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=None, importance_type='split', client=None, **kwargs)`

Bases: *LGBMRegressor*, `_DaskLGBMModel`

Distributed version of lightgbm.LGBMRegressor.

`__init__(*, boosting_type='gbdt', num_leaves=31, max_depth=-1, learning_rate=0.1, n_estimators=100, subsample_for_bin=200000, objective=None, class_weight=None, min_split_gain=0.0, min_child_weight=0.001, min_child_samples=20, subsample=1.0, subsample_freq=0, colsample_bytree=1.0, reg_alpha=0.0, reg_lambda=0.0, random_state=None, n_jobs=None, importance_type='split', client=None, **kwargs)`

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.

- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.
- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None`

(the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

Changed in version 4.0.0.

- **`importance_type`** (*`str, optional (default='split')`*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- **`client`** (*`distributed.Client or None, optional (default=None)`*) – Dask client. If `None`, `distributed.default_client()` will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.
- **`**kwargs`** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

> **Warning**
>
> **kwargs is not supported in sklearn, it may cause unexpected issues.

> **Note**
>
> A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **grad**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.
>
> **hess**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples,

n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.

For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.
get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
score(X, y[, sample_weight])	Return coefficient of determination on test data.
set_fit_request(*[, eval_X, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.
set_score_request(*[, sample_weight])	Configure whether metadata should be requested to be passed to the `score` method.
to_local()	Create regular version of lightgbm.LGBMRegressor from the distributed version.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*client_*	Dask client.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
`dict`

property booster_

The underlying Booster of this model.

Type
Booster

property client_

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type
`distributed.Client`

property evals_result_

The evaluation results if validation sets have been specified.

Type
`dict`

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type
`array` of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format `Column_0`, `Column_1`, ..., `Column_N`.

Type
`list` of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of `.feature_name_`.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises `AttributeError`.

Added in version 4.5.0.

Type
array of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_init_score=None*, *eval_metric=None*, *, *eval_X=None*, *eval_y=None*, ***kwargs*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*Dask Array, Dask DataFrame or Dask Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).
- **sample_weight** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Init score of training data.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Weights of eval data. Weights should be non-negative.
- **eval_init_score** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Init score of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.

- ****kwargs** – Other parameters passed through to `LGBMRegressor.fit()`.

Returns
self – Returns self.

Return type
lightgbm.DaskLGBMRegressor

> **Note**
>
> Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **metric_name**
> [str] Unique identifier for the metric (e.g. "custom_adjusted_mse").
>
> **metric_value**
> [float] Value of the evaluation metric.
>
> **maximize**
> [bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

property n_estimators_

True number of boosting iterations performed.

This might be less than parameter n_estimators if early stopping was enabled or if boosting stopped early due to limits on complexity like min_gain_to_split.

Added in version 4.0.0.

Type
int

property n_features_

The number of features of fitted model.

Type
int

property n_features_in_

The number of features of fitted model.

Type
int

property n_iter_

True number of boosting iterations performed.

This might be less than parameter n_estimators if early stopping was enabled or if boosting stopped early due to limits on complexity like min_gain_to_split.

Added in version 4.0.0.

Type
int

property objective_

The concrete objective used while fitting this model.

Type
str or callable

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.

- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*Dask Array of shape = [n_samples]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*Dask Array of shape = [n_samples, n_features + 1]*) – If `pred_contrib=True`, the feature contributions for each sample.

score(*X*, *y*, *sample_weight=None*)

Return coefficient of determination on test data.

The coefficient of determination, R^2, is defined as $(1 - \frac{u}{v})$, where u is the residual sum of squares `((y_true - y_pred)** 2).sum()` and v is the total sum of squares `((y_true - y_true.mean()) ** 2).sum()`. The best possible score is 1.0 and it can be negative (because the model can be arbitrarily worse). A constant model that always predicts the expected value of y, disregarding the input features, would get a R^2 score of 0.0.

Parameters

- **X** (*array-like of shape (n_samples, n_features)*) – Test samples. For some estimators this may be a precomputed kernel matrix or a list of generic objects instead with shape `(n_samples, n_samples_fitted)`, where `n_samples_fitted` is the number of samples used in the fitting for the estimator.
- **y** (*array-like of shape (n_samples,) or (n_samples, n_outputs)*) – True values for *X*.
- **sample_weight** (*array-like of shape (n_samples,), default=None*) – Sample weights.

Returns

score – R^2 of `self.predict(X)` w.r.t. *y*.

Return type

float

Notes

The R^2 score used when calling `score` on a regressor uses `multioutput='uniform_average'` from version 0.23 to keep consistent with default value of `r2_score()`. This influences the `score` method of all the multioutput regressors (except for `MultiOutputRegressor`).

set_fit_request(*, *eval_X='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.

- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns
self – The updated object.

Return type
object

`set_params`(***params*)

Set the parameters of this estimator.

Parameters
****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

`set_predict_request`(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.

- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns
self – The updated object.

Return type
object

`set_score_request`(*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `score` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `score` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `score`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters
sample_weight (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `score`.

Returns
self – The updated object.

Return type
object

`to_local`()

Create regular version of lightgbm.LGBMRegressor from the distributed version.

Returns
model – Local underlying model.

Return type
lightgbm.LGBMRegressor

9.4.3 lightgbm.DaskLGBMRanker

class lightgbm.**DaskLGBMRanker**(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, *client=None*, ***kwargs*)

Bases: *LGBMRanker*, _DaskLGBMModel

Distributed version of lightgbm.LGBMRanker.

__init__(*, *boosting_type='gbdt'*, *num_leaves=31*, *max_depth=-1*, *learning_rate=0.1*, *n_estimators=100*, *subsample_for_bin=200000*, *objective=None*, *class_weight=None*, *min_split_gain=0.0*, *min_child_weight=0.001*, *min_child_samples=20*, *subsample=1.0*, *subsample_freq=0*, *colsample_bytree=1.0*, *reg_alpha=0.0*, *reg_lambda=0.0*, *random_state=None*, *n_jobs=None*, *importance_type='split'*, *client=None*, ***kwargs*)

Construct a gradient boosting model.

Parameters

- **boosting_type** (*str, optional (default='gbdt')*) – 'gbdt', traditional Gradient Boosting Decision Tree. 'dart', Dropouts meet Multiple Additive Regression Trees. 'rf', Random Forest.
- **num_leaves** (*int, optional (default=31)*) – Maximum tree leaves for base learners.
- **max_depth** (*int, optional (default=-1)*) – Maximum tree depth for base learners, <=0 means no limit. If setting this to a positive value, consider also changing `num_leaves` to `<= 2^max_depth`.
- **learning_rate** (*float, optional (default=0.1)*) – Boosting learning rate. You can use `callbacks` parameter of `fit` method to shrink/adapt learning rate in training using `reset_parameter` callback. Note, that this will ignore the `learning_rate` argument in training.
- **n_estimators** (*int, optional (default=100)*) – Number of boosted trees to fit.
- **subsample_for_bin** (*int, optional (default=200000)*) – Number of samples for constructing bins.
- **objective** (*str, callable or None, optional (default=None)*) – Specify the learning task and the corresponding learning objective or a custom objective function to be used (see note below). Default: 'regression' for LGBMRegressor, 'binary' or 'multiclass' for LGBMClassifier, 'lambdarank' for LGBMRanker.
- **class_weight** (*dict, 'balanced' or None, optional (default=None)*) – Weights associated with classes in the form `{class_label: weight}`. Use this parameter only for multi-class classification task; for binary classification task you may use `is_unbalance` or `scale_pos_weight` parameters. Note, that the usage of all these parameters will result in poor estimates of the individual class probabilities. You may want to consider performing probability calibration (https://scikit-learn.org/

stable/modules/calibration.html) of your model. The 'balanced' mode uses the values of y to automatically adjust weights inversely proportional to class frequencies in the input data as `n_samples / (n_classes * np.bincount(y))`. If None, all classes are supposed to have weight one. Note, that these weights will be multiplied with `sample_weight` (passed through the `fit` method) if `sample_weight` is specified.

- **min_split_gain** (*float, optional (default=0.)*) – Minimum loss reduction required to make a further partition on a leaf node of the tree.
- **min_child_weight** (*float, optional (default=1e-3)*) – Minimum sum of instance weight (Hessian) needed in a child (leaf).
- **min_child_samples** (*int, optional (default=20)*) – Minimum number of data needed in a child (leaf).
- **subsample** (*float, optional (default=1.)*) – Subsample ratio of the training instance.
- **subsample_freq** (*int, optional (default=0)*) – Frequency of subsample, <=0 means no enable.
- **colsample_bytree** (*float, optional (default=1.)*) – Subsample ratio of columns when constructing each tree.
- **reg_alpha** (*float, optional (default=0.)*) – L1 regularization term on weights.
- **reg_lambda** (*float, optional (default=0.)*) – L2 regularization term on weights.
- **random_state** (*int, RandomState object or None, optional (default=None)*) – Random number seed. If int, this number is used to seed the C++ code. If RandomState or Generator object (numpy), a random integer is picked based on its state to seed the C++ code. If None, default seeds in C++ code are used.
- **n_jobs** (*int or None, optional (default=None)*) – Number of parallel threads to use for training (can be changed at prediction time by passing it as an extra keyword argument).

  For better performance, it is recommended to set this to the number of physical cores in the CPU.

  Negative integers are interpreted as following joblib's formula (n_cpus + 1 + n_jobs), just like scikit-learn (so e.g. -1 means using all threads). A value of zero corresponds the default number of threads configured for OpenMP in the system. A value of `None` (the default) corresponds to using the number of physical cores in the system (its correct detection requires either the `joblib` or the `psutil` util libraries to be installed).

  Changed in version 4.0.0.
- **importance_type** (*str, optional (default='split')*) – The type of feature importance to be filled into `feature_importances_`. If 'split', result contains numbers of times the feature is used in a model. If 'gain', result contains total gains of splits which use the feature.
- **client** (*distributed.Client or None, optional (default=None)*) – Dask client. If `None`, `distributed.default_client()` will be used at runtime. The Dask client used by this class will not be saved if the model object is pickled.

- ****kwargs** – Other parameters for the model. Check http://lightgbm.readthedocs.io/en/latest/Parameters.html for more parameters.

> **Warning**
>
> **kwargs is not supported in sklearn, it may cause unexpected issues.

> **Note**
>
> A custom objective function can be provided for the `objective` parameter. In this case, it should have the signature `objective(y_true, y_pred) -> grad, hess`, `objective(y_true, y_pred, weight) -> grad, hess` or `objective(y_true, y_pred, weight, group) -> grad, hess`:
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. Predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **grad**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the first order derivative (gradient) of the loss with respect to the elements of y_pred for each sample point.
>
> **hess**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The value of the second order derivative (Hessian) of the loss with respect to the elements of y_pred for each sample point.
>
> For multi-class task, y_pred is a numpy 2-D array of shape = [n_samples, n_classes], and grad and hess should be returned in the same format.

Methods

__init__(*[, boosting_type, num_leaves, ...])	Construct a gradient boosting model.
fit(X, y[, sample_weight, init_score, ...])	Build a gradient boosting model from the training set (X, y).
get_metadata_routing()	Get metadata routing of this object.

continues on next page

Table 22 – continued from previous page

get_params([deep])	Get parameters for this estimator.
predict(X[, raw_score, start_iteration, ...])	Return the predicted value for each sample.
set_fit_request(*[, eval_X, eval_at, ...])	Configure whether metadata should be requested to be passed to the `fit` method.
set_params(**params)	Set the parameters of this estimator.
set_predict_request(*[, num_iteration, ...])	Configure whether metadata should be requested to be passed to the `predict` method.
to_local()	Create regular version of lightgbm.LGBMRanker from the distributed version.

Attributes

*best_iteration_*	The best iteration of fitted model if `early_stopping()` callback has been specified.
*best_score_*	The best score of fitted model.
*booster_*	The underlying Booster of this model.
*client_*	Dask client.
*evals_result_*	The evaluation results if validation sets have been specified.
*feature_importances_*	The feature importances (the higher, the more important).
*feature_name_*	The names of features.
*feature_names_in_*	scikit-learn compatible version of `.feature_name_`.
*n_estimators_*	True number of boosting iterations performed.
*n_features_*	The number of features of fitted model.
*n_features_in_*	The number of features of fitted model.
*n_iter_*	True number of boosting iterations performed.
*objective_*	The concrete objective used while fitting this model.

property best_iteration_

The best iteration of fitted model if `early_stopping()` callback has been specified.

Type
`int`

property best_score_

The best score of fitted model.

Type
`dict`

property booster_

The underlying Booster of this model.

Type
Booster

property client_

Dask client.

This property can be passed in the constructor or updated with `model.set_params(client=client)`.

Type
`distributed.Client`

property evals_result_

The evaluation results if validation sets have been specified.

Type
`dict`

property feature_importances_

The feature importances (the higher, the more important).

> **Note**
>
> `importance_type` attribute is passed to the function to configure the type of importance values to be extracted.

Type
`array` of shape = [n_features]

property feature_name_

The names of features.

> **Note**
>
> If input does not contain feature names, they will be added during fitting in the format `Column_0`, `Column_1`, ..., `Column_N`.

Type
`list` of shape = [n_features]

property feature_names_in_

scikit-learn compatible version of `.feature_name_`.

Only available when training data had feature names (e.g. a pandas DataFrame). When training was done with data without feature names (e.g. a numpy array), accessing this attribute raises `AttributeError`.

Added in version 4.5.0.

Type
`array` of shape = [n_features]

fit(*X*, *y*, *sample_weight=None*, *init_score=None*, *group=None*, *eval_set=None*, *eval_names=None*, *eval_sample_weight=None*, *eval_init_score=None*, *eval_group=None*, *eval_metric=None*, *eval_at=(1, 2, 3, 4, 5)*, ***, *eval_X=None*, *eval_y=None*, ***kwargs*)

Build a gradient boosting model from the training set (X, y).

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input feature matrix.
- **y** (*Dask Array, Dask DataFrame or Dask Series of shape = [n_samples]*) – The target values (class labels in classification, real numbers in regression).

- **sample_weight** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Weights of training data. Weights should be non-negative.
- **init_score** (*Dask Array or Dask Series of shape = [n_samples] or None, optional (default=None)*) – Init score of training data.
- **group** (*Dask Array or Dask Series or None, optional (default=None)*) – Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
- **eval_set** (*list or None, optional (default=None)*) – Deprecated since version 4.7.0: A list of (X, y) tuple pairs to use as validation sets. Use `eval_X` and `eval_y` instead.
- **eval_names** (*list of str, or None, optional (default=None)*) – Unique identifiers for each evaluation dataset. Should be the same length as `eval_set` / `eval_X`.
- **eval_sample_weight** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Weights of eval data. Weights should be non-negative.
- **eval_init_score** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Init score of eval data.
- **eval_group** (*list of Dask Array or Dask Series, or None, optional (default=None)*) – Group data of eval data.
- **eval_metric** (*str, callable, list or None, optional (default=None)*) – If str, it should be a built-in evaluation metric to use. If callable, it should be a custom evaluation metric, see note below for more details. If list, it can be a list of built-in metrics, a list of custom evaluation metrics, or a mix of both. In either case, the `metric` from the model parameters will be evaluated and used as well. Default: 'l2' for LGBMRegressor, 'logloss' for LGBMClassifier, 'ndcg' for LGBMRanker.
- **eval_at** (*list or tuple of int, optional (default=(1, 2, 3, 4, 5))*) – The evaluation positions of the specified metric.
- **feature_name** (*list of str, or 'auto', optional (default='auto')*) – Feature names. If 'auto' and data is pandas DataFrame, data columns names are used.
- **categorical_feature** (*list of str or int, or 'auto', optional (default='auto')*) – Categorical features. If list of int, interpreted as indices. If list of str, interpreted as feature names (need to specify `feature_name` as well). If 'auto' and data is pandas DataFrame, pandas unordered categorical columns are used. All values in categorical features will be cast to int32 and thus should be less than int32 max value (2147483647). Large values could be memory consuming. Consider using consecutive integers starting from zero. All negative values in categorical features will be treated as missing values. The output cannot be monotonically constrained with respect to a categorical feature. Floating point numbers in categorical features will be rounded towards 0.
- ****kwargs** – Other parameters passed through to `LGBMRanker.fit()`.

Returns
self – Returns self.

Return type
lightgbm.DaskLGBMRanker

> **Note**
>
> Custom eval function expects a callable with following signatures: `func(y_true, y_pred)`, `func(y_true, y_pred, weight)` or `func(y_true, y_pred, weight, group)` and returns (metric_name, metric_value, maximize) or list of (metric_name, metric_value, maximize):
>
> **y_true**
> [numpy 1-D array of shape = [n_samples]] The target values.
>
> **y_pred**
> [numpy 1-D array of shape = [n_samples] or numpy 2-D array of shape = [n_samples, n_classes] (for multi-class task)] The predicted values. In case of custom `objective`, predicted values are returned before any transformation, e.g. they are raw margin instead of probability of positive class for binary task in this case.
>
> **weight**
> [numpy 1-D array of shape = [n_samples]] The weight of samples. Weights should be non-negative.
>
> **group**
> [numpy 1-D array] Group/query data. Only used in the learning-to-rank task. sum(group) = n_samples. For example, if you have a 100-document dataset with `group = [10, 20, 40, 10, 10, 10]`, that means that you have 6 groups, where the first 10 records are in the first group, records 11-30 are in the second group, records 31-70 are in the third group, etc.
>
> **metric_name**
> [str] Unique identifier for the metric (e.g. "custom_adjusted_mse").
>
> **metric_value**
> [float] Value of the evaluation metric.
>
> **maximize**
> [bool] Are higher values better? e.g. `True` for AUC and `False` for binary error.

`get_metadata_routing()`

Get metadata routing of this object.

Please check User Guide on how the routing mechanism works.

Returns
routing – A `MetadataRequest` encapsulating routing information.

Return type
MetadataRequest

`get_params(deep=True)`

Get parameters for this estimator.

Parameters
deep (*bool, optional (default=True)*) – If True, will return the parameters for this estimator and contained subobjects that are estimators.

Returns
params – Parameter names mapped to their values.

Return type
dict

property n_estimators_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property n_features_

The number of features of fitted model.

Type
`int`

property n_features_in_

The number of features of fitted model.

Type
`int`

property n_iter_

True number of boosting iterations performed.

This might be less than parameter `n_estimators` if early stopping was enabled or if boosting stopped early due to limits on complexity like `min_gain_to_split`.

Added in version 4.0.0.

Type
`int`

property objective_

The concrete objective used while fitting this model.

Type
`str` or `callable`

predict(*X*, *raw_score=False*, *start_iteration=0*, *num_iteration=None*, *pred_leaf=False*, *pred_contrib=False*, *validate_features=False*, ***kwargs*)

Return the predicted value for each sample.

Parameters

- **X** (*Dask Array or Dask DataFrame of shape = [n_samples, n_features]*) – Input features matrix.
- **raw_score** (*bool, optional (default=False)*) – Whether to predict raw scores.
- **start_iteration** (*int, optional (default=0)*) – Start index of the iteration to predict. If <= 0, starts from the first iteration.

- **num_iteration** (*int or None, optional (default=None)*) – Total number of iterations used in the prediction. If None, if the best iteration exists and start_iteration <= 0, the best iteration is used; otherwise, all iterations from `start_iteration` are used (no limits). If <= 0, all iterations from `start_iteration` are used (no limits).
- **pred_leaf** (*bool, optional (default=False)*) – Whether to predict leaf index.
- **pred_contrib** (*bool, optional (default=False)*) – Whether to predict feature contributions.

  Note

  If you want to get more explanations for your model's predictions using SHAP values, like SHAP interaction values, you can install the shap package (https://github.com/slundberg/shap). Note that unlike the shap package, with `pred_contrib` we return a matrix with an extra column, where the last column is the expected value.

- **validate_features** (*bool, optional (default=False)*) – If True, ensure that the features used to predict match the ones used to train. Used only if data is pandas DataFrame.
- ****kwargs** – Other parameters for the prediction.

Returns

- **predicted_result** (*Dask Array of shape = [n_samples]*) – The predicted values.
- **X_leaves** (*Dask Array of shape = [n_samples, n_trees]*) – If `pred_leaf=True`, the predicted leaf of every tree for each sample.
- **X_SHAP_values** (*Dask Array of shape = [n_samples, n_features + 1]*) – If `pred_contrib=True`, the feature contributions for each sample.

set_fit_request(*, *eval_X='$UNCHANGED$'*, *eval_at='$UNCHANGED$'*, *eval_group='$UNCHANGED$'*, *eval_init_score='$UNCHANGED$'*, *eval_metric='$UNCHANGED$'*, *eval_names='$UNCHANGED$'*, *eval_sample_weight='$UNCHANGED$'*, *eval_set='$UNCHANGED$'*, *eval_y='$UNCHANGED$'*, *group='$UNCHANGED$'*, *init_score='$UNCHANGED$'*, *sample_weight='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `fit` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `fit` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `fit`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **eval_X** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_X` parameter in `fit`.
- **eval_at** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_at` parameter in `fit`.
- **eval_group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_group` parameter in `fit`.
- **eval_init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_init_score` parameter in `fit`.
- **eval_metric** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_metric` parameter in `fit`.
- **eval_names** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_names` parameter in `fit`.
- **eval_sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_sample_weight` parameter in `fit`.
- **eval_set** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_set` parameter in `fit`.
- **eval_y** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `eval_y` parameter in `fit`.
- **group** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `group` parameter in `fit`.
- **init_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `init_score` parameter in `fit`.
- **sample_weight** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `sample_weight` parameter in `fit`.

Returns

self – The updated object.

Return type

object

set_params(***params*)

Set the parameters of this estimator.

Parameters

****params** – Parameter names with their new values.

Returns
self – Returns self.

Return type
object

set_predict_request(*, *num_iteration='$UNCHANGED$'*, *pred_contrib='$UNCHANGED$'*, *pred_leaf='$UNCHANGED$'*, *raw_score='$UNCHANGED$'*, *start_iteration='$UNCHANGED$'*, *validate_features='$UNCHANGED$'*)

Configure whether metadata should be requested to be passed to the `predict` method.

Note that this method is only relevant when this estimator is used as a sub-estimator within a meta-estimator and metadata routing is enabled with `enable_metadata_routing=True` (see `sklearn.set_config()`). Please check the User Guide on how the routing mechanism works.

The options for each parameter are:

- `True`: metadata is requested, and passed to `predict` if provided. The request is ignored if metadata is not provided.
- `False`: metadata is not requested and the meta-estimator will not pass it to `predict`.
- `None`: metadata is not requested, and the meta-estimator will raise an error if the user provides it.
- `str`: metadata should be passed to the meta-estimator with this given alias instead of the original name.

The default (`sklearn.utils.metadata_routing.UNCHANGED`) retains the existing request. This allows you to change the request for some parameters and not others.

Added in version 1.3.

Parameters

- **num_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `num_iteration` parameter in `predict`.
- **pred_contrib** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_contrib` parameter in `predict`.
- **pred_leaf** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `pred_leaf` parameter in `predict`.
- **raw_score** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `raw_score` parameter in `predict`.
- **start_iteration** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `start_iteration` parameter in `predict`.
- **validate_features** (*str, True, False, or None, default=sklearn.utils.metadata_routing.UNCHANGED*) – Metadata routing for `validate_features` parameter in `predict`.

Returns
self – The updated object.

Return type
object

to_local()

Create regular version of lightgbm.LGBMRanker from the distributed version.

Returns
model – Local underlying model.

Return type
lightgbm.LGBMRanker

9.5 Callbacks

early_stopping(stopping_rounds[, ...])	Create a callback that activates early stopping.
log_evaluation([period, show_stdv])	Create a callback that logs the evaluation results.
record_evaluation(eval_result)	Create a callback that records the evaluation history into `eval_result`.
reset_parameter(**kwargs)	Create a callback that resets the parameter after the first iteration.

9.5.1 lightgbm.early_stopping

lightgbm.**early_stopping**(*stopping_rounds*, *first_metric_only=False*, *verbose=True*, *min_delta=0.0*)

Create a callback that activates early stopping.

Activates early stopping. The model will train until the validation score doesn't improve by at least `min_delta`. Validation score needs to improve at least every `stopping_rounds` round(s) to continue training. Requires at least one validation data and one metric. If there's more than one, will check all of them. But the training data is ignored anyway. To check only the first metric set `first_metric_only` to True. The index of iteration that has the best performance will be saved in the `best_iteration` attribute of a model.

Note

If using `boosting_type="dart"`, this callback has no effect and early stopping will not be performed.

Parameters

- **stopping_rounds** (*int*) – The possible number of rounds without the trend occurrence.
- **first_metric_only** (*bool, optional (default=False)*) – Whether to use only the first metric for early stopping.
- **verbose** (*bool, optional (default=True)*) – Whether to log message with early stopping information. By default, standard output resource is used. Use `register_logger()` function to register a custom logger.
- **min_delta** (*float or list of float, optional (default=0.0)*) – Minimum improvement in score to keep training. If float, this single value is used for all metrics. If list, its length should match the total number of metrics.

  Added in version 4.0.0.

Returns
callback – The callback that activates early stopping.

Return type
_EarlyStoppingCallback

9.5.2 lightgbm.log_evaluation

lightgbm.**log_evaluation**(*period=1*, *show_stdv=True*)

Create a callback that logs the evaluation results.

By default, standard output resource is used. Use `register_logger()` function to register a custom logger.

> **Note**
>
> Requires at least one validation data.

Parameters

- **period** (*int, optional (default=1)*) – The period to log the evaluation results. The last boosting stage or the boosting stage found by using `early_stopping` callback is also logged.
- **show_stdv** (*bool, optional (default=True)*) – Whether to log stdv (if provided).

Returns

callback – The callback that logs the evaluation results every `period` boosting iteration(s).

Return type

_LogEvaluationCallback

9.5.3 lightgbm.record_evaluation

lightgbm.**record_evaluation**(*eval_result*)

Create a callback that records the evaluation history into `eval_result`.

Parameters

eval_result (*dict*) – Dictionary used to store all evaluation results of all validation sets. This should be initialized outside of your call to `record_evaluation()` and should be empty. Any initial contents of the dictionary will be deleted.

Example

With two validation sets named 'eval' and 'train', and one evaluation metric named 'logloss' this dictionary after finishing a model training process will have the following structure:

```
{
 'train':
     {
      'logloss': [0.48253, 0.35953, ...]
     },
 'eval':
     {
      'logloss': [0.480385, 0.357756, ...]
     }
}
```

Returns

callback – The callback that records the evaluation history into the passed dictionary.

Return type

_RecordEvaluationCallback

9.5.4 lightgbm.reset_parameter

lightgbm.**reset_parameter**(***kwargs*)

Create a callback that resets the parameter after the first iteration.

> **Note**
>
> The initial parameter will still take in-effect on first iteration.

Parameters

****kwargs** (*value should be list or callable*) – List of parameters for each boosting round or a callable that calculates the parameter in terms of current number of round (e.g. yields learning rate decay). If list lst, parameter = lst[current_round]. If callable func, parameter = func(current_round).

Returns

callback – The callback that resets the parameter after the first iteration.

Return type

_ResetParameterCallback

9.6 Plotting

plot_importance(booster[, ax, height, xlim, ...])	Plot model's feature importances.
plot_split_value_histogram(booster, feature)	Plot split value histogram for the specified feature of the model.
plot_metric(booster[, metric, ...])	Plot one metric during training.
plot_tree(booster[, ax, tree_index, ...])	Plot specified tree.
create_tree_digraph(booster[, tree_index, ...])	Create a digraph representation of specified tree.

9.6.1 lightgbm.plot_importance

lightgbm.**plot_importance**(*booster*, *ax=None*, *height=0.2*, *xlim=None*, *ylim=None*, *title='Feature importance'*, *xlabel='Feature importance'*, *ylabel='Features'*, *importance_type='auto'*, *max_num_features=None*, *ignore_zero=True*, *figsize=None*, *dpi=None*, *grid=True*, *precision=3*, ***kwargs*)

Plot model's feature importances.

Parameters

- **booster** (Booster *or* LGBMModel) – Booster or LGBMModel instance which feature importance should be plotted.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **height** (*float, optional (default=0.2)*) – Bar height, passed to `ax.barh()`.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.
- **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.

- **title** (*str or None, optional (default="Feature importance")*) – Axes title. If None, title is disabled.
- **xlabel** (*str or None, optional (default="Feature importance")*) – X-axis title label. If None, title is disabled. @importance_type@ placeholder can be used, and it will be replaced with the value of `importance_type` parameter.
- **ylabel** (*str or None, optional (default="Features")*) – Y-axis title label. If None, title is disabled.
- **importance_type** (*str, optional (default="auto")*) – How the importance is calculated. If "auto", if `booster` parameter is LGBMModel, `booster.importance_type` attribute is used; "split" otherwise. If "split", result contains numbers of times the feature is used in a model. If "gain", result contains total gains of splits which use the feature.
- **max_num_features** (*int or None, optional (default=None)*) – Max number of top features displayed on plot. If None or <1, all features will be displayed.
- **ignore_zero** (*bool, optional (default=True)*) – Whether to ignore features with zero importance.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- ****kwargs** – Other parameters passed to `ax.barh()`.

Returns

ax – The plot with model's feature importances.

Return type

matplotlib.axes.Axes

9.6.2 lightgbm.plot_split_value_histogram

lightgbm.**plot_split_value_histogram**(*booster*, *feature*, *bins=None*, *ax=None*, *width_coef=0.8*, *xlim=None*, *ylim=None*, *title='Split value histogram for feature with @index/name@ @feature@'*, *xlabel='Feature split value'*, *ylabel='Count'*, *figsize=None*, *dpi=None*, *grid=True*, ***kwargs*)

Plot split value histogram for the specified feature of the model.

Parameters

- **booster** (Booster *or* LGBMModel) – Booster or LGBMModel instance of which feature split value histogram should be plotted.
- **feature** (*int or str*) – The feature name or index the histogram is plotted for. If int, interpreted as index. If str, interpreted as name.
- **bins** (*int, str or None, optional (default=None)*) – The maximum number of bins. If None, the number of bins equals number of unique split values. If str, it should be one from the list of the supported values by `numpy.histogram()` function.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.

- **width_coef** (*float, optional (default=0.8)*) – Coefficient for histogram bar width.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.
- **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.
- **title** (*str or None, optional (default="Split value histogram for feature with @index/name@ @feature@")*) – Axes title. If None, title is disabled. @feature@ placeholder can be used, and it will be replaced with the value of `feature` parameter. @index/name@ placeholder can be used, and it will be replaced with `index` word in case of `int` type `feature` parameter or `name` word in case of `str` type `feature` parameter.
- **xlabel** (*str or None, optional (default="Feature split value")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*str or None, optional (default="Count")*) – Y-axis title label. If None, title is disabled.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.
- ****kwargs** – Other parameters passed to `ax.bar()`.

Returns

ax – The plot with specified model's feature split value histogram.

Return type

matplotlib.axes.Axes

9.6.3 lightgbm.plot_metric

lightgbm.**plot_metric**(*booster*, *metric=None*, *dataset_names=None*, *ax=None*, *xlim=None*, *ylim=None*, *title='Metric during training'*, *xlabel='Iterations'*, *ylabel='@metric@'*, *figsize=None*, *dpi=None*, *grid=True*)

Plot one metric during training.

Parameters

- **booster** (*dict or* `LGBMModel`) – Dictionary returned from `lightgbm.train()` or LGBMModel instance.
- **metric** (*str or None, optional (default=None)*) – The metric name to plot. Only one metric supported because different metrics have various scales. If None, first metric picked from dictionary (according to hashcode).
- **dataset_names** (*list of str, or None, optional (default=None)*) – List of the dataset names which are used to calculate metric to plot. If None, all datasets are used.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **xlim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.xlim()`.

- **ylim** (*tuple of 2 elements or None, optional (default=None)*) – Tuple passed to `ax.ylim()`.
- **title** (*str or None, optional (default="Metric during training")*) – Axes title. If None, title is disabled.
- **xlabel** (*str or None, optional (default="Iterations")*) – X-axis title label. If None, title is disabled.
- **ylabel** (*str or None, optional (default="@metric@")*) – Y-axis title label. If 'auto', metric name is used. If None, title is disabled. @metric@ placeholder can be used, and it will be replaced with metric name.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.
- **grid** (*bool, optional (default=True)*) – Whether to add a grid for axes.

Returns

ax – The plot with metric's history over the training.

Return type

matplotlib.axes.Axes

9.6.4 lightgbm.plot_tree

lightgbm.**plot_tree**(*booster*, *ax=None*, *tree_index=0*, *figsize=None*, *dpi=None*, *show_info=None*, *precision=3*, *orientation='horizontal'*, *example_case=None*, ***kwargs*)

Plot specified tree.

Each node in the graph represents a node in the tree.

Non-leaf nodes have labels like `Column_10 <= 875.9`, which means "this node splits on the feature named "Column_10", with threshold 875.9".

Leaf nodes have labels like `leaf 2: 0.422`, which means "this node is a leaf node, and the predicted value for records that fall into this node is 0.422". The number (`2`) is an internal unique identifier and doesn't have any special meaning.

> **Note**
>
> It is preferable to use `create_tree_digraph()` because of its lossless quality and returned objects can be also rendered and displayed directly inside a Jupyter notebook.

Parameters

- **booster** (`Booster` *or* `LGBMModel`) – Booster or LGBMModel instance to be plotted.
- **ax** (*matplotlib.axes.Axes or None, optional (default=None)*) – Target axes instance. If None, new figure and axes will be created.
- **tree_index** (*int, optional (default=0)*) – The index of a target tree to plot.
- **figsize** (*tuple of 2 elements or None, optional (default=None)*) – Figure size.
- **dpi** (*int or None, optional (default=None)*) – Resolution of the figure.

- **show_info** (*list of str, or None, optional (default=None)*) – What information should be shown in nodes.
  - `'split_gain'` : gain from adding this split to the model
  - `'internal_value'` : raw predicted value that would be produced by this node if it was a leaf node
  - `'internal_count'` : number of records from the training data that fall into this non-leaf node
  - `'internal_weight'` : total weight of all nodes that fall into this non-leaf node
  - `'leaf_count'` : number of records from the training data that fall into this leaf node
  - `'leaf_weight'` : total weight (sum of Hessian) of all observations that fall into this leaf node
  - `'data_percentage'` : percentage of training data that fall into this node
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- **orientation** (*str, optional (default='horizontal')*) – Orientation of the tree. Can be 'horizontal' or 'vertical'.
- **example_case** (*numpy 2-D array, pandas DataFrame or None, optional (default=None)*) – Single row with the same structure as the training data. If not None, the plot will highlight the path that sample takes through the tree.

  Added in version 4.0.0.
- ****kwargs** – Other parameters passed to `Digraph` constructor. Check https://graphviz.readthedocs.io/en/stable/api.html#digraph for the full list of supported parameters.

Returns

ax – The plot with single tree.

Return type

matplotlib.axes.Axes

9.6.5 lightgbm.create_tree_digraph

lightgbm.**create_tree_digraph**(*booster*, *tree_index=0*, *show_info=None*, *precision=3*, *orientation='horizontal'*, *example_case=None*, *max_category_values=10*, ***kwargs*)

Create a digraph representation of specified tree.

Each node in the graph represents a node in the tree.

Non-leaf nodes have labels like `Column_10 <= 875.9`, which means "this node splits on the feature named "Column_10", with threshold 875.9".

Leaf nodes have labels like `leaf 2: 0.422`, which means "this node is a leaf node, and the predicted value for records that fall into this node is 0.422". The number (`2`) is an internal unique identifier and doesn't have any special meaning.

> **Note**
>
> For more information please visit https://graphviz.readthedocs.io/en/stable/api.html#digraph.

Parameters

- **booster** (Booster or LGBMModel) – Booster or LGBMModel instance to be converted.
- **tree_index** (*int, optional (default=0)*) – The index of a target tree to convert.
- **show_info** (*list of str, or None, optional (default=None)*) – What information should be shown in nodes.
  - `'split_gain'` : gain from adding this split to the model
  - `'internal_value'` : raw predicted value that would be produced by this node if it was a leaf node
  - `'internal_count'` : number of records from the training data that fall into this non-leaf node
  - `'internal_weight'` : total weight of all nodes that fall into this non-leaf node
  - `'leaf_count'` : number of records from the training data that fall into this leaf node
  - `'leaf_weight'` : total weight (sum of Hessian) of all observations that fall into this leaf node
  - `'data_percentage'` : percentage of training data that fall into this node
- **precision** (*int or None, optional (default=3)*) – Used to restrict the display of floating point values to a certain precision.
- **orientation** (*str, optional (default='horizontal')*) – Orientation of the tree. Can be 'horizontal' or 'vertical'.
- **example_case** (*numpy 2-D array, pandas DataFrame or None, optional (default=None)*) – Single row with the same structure as the training data. If not None, the plot will highlight the path that sample takes through the tree.

  Added in version 4.0.0.
- **max_category_values** (*int, optional (default=10)*) – The maximum number of category values to display in tree nodes, if the number of thresholds is greater than this value, thresholds will be collapsed and displayed on the label tooltip instead.

  Warning

  Consider wrapping the SVG string of the tree graph with `IPython.display.HTML` when running on JupyterLab to get the tooltip working right.

  Example:

  ```
  from IPython.display import HTML

  graph = lgb.create_tree_digraph(clf, max_category_values=5)
  HTML(graph._repr_image_svg_xml())
  ```

  Added in version 4.0.0.
- ****kwargs** – Other parameters passed to `Digraph` constructor. Check https://graphviz.readthedocs.io/en/stable/api.html#digraph for the full list of supported parameters.

Returns

graph – The digraph representation of specified tree.

Return type
graphviz.Digraph

9.7 Utilities

register_logger(logger[, info_method_name, ...])	Register custom logger.

9.7.1 lightgbm.register_logger

lightgbm.**register_logger**(*logger*, *info_method_name='info'*, *warning_method_name='warning'*)

Register custom logger.

Parameters

- **logger** (*Any*) – Custom logger.
- **info_method_name** (*str, optional (default="info")*) – Method used to log info messages.
- **warning_method_name** (*str, optional (default="warning")*) – Method used to log warning messages.

CHAPTER

TEN

DISTRIBUTED LEARNING GUIDE

This guide describes distributed learning in LightGBM. Distributed learning allows the use of multiple machines to produce a single model.

Follow the Quick Start to know how to use LightGBM first.

10.1 How Distributed LightGBM Works

This section describes how distributed learning in LightGBM works. To learn how to do this in various programming languages and frameworks, please see *Integrations*.

10.1.1 Choose Appropriate Parallel Algorithm

LightGBM provides 3 distributed learning algorithms now.

Parallel Algorithm	How to Use
Data parallel	`tree_learner=data`
Feature parallel	`tree_learner=feature`
Voting parallel	`tree_learner=voting`

These algorithms are suited for different scenarios, which is listed in the following table:

	#data is small	#data is large
#feature is small	Feature Parallel	Data Parallel
#feature is large	Feature Parallel	Voting Parallel

More details about these parallel algorithms can be found in optimization in distributed learning.

10.2 Integrations

This section describes how to run distributed LightGBM training in various programming languages and frameworks. To learn how distributed learning in LightGBM works generally, please see *How Distributed LightGBM Works*.

10.2.1 Apache Spark

Apache Spark users can use SynapseML for machine learning workflows with LightGBM. This project is not maintained by LightGBM's maintainers.

See this SynapseML example for additional information on using LightGBM on Spark.

Note

`SynapseML` is not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to https://github.com/microsoft/SynapseML/issues.

10.2.2 Dask

Added in version 3.2.0.

LightGBM's Python-package supports distributed learning via Dask. This integration is maintained by LightGBM's maintainers.

Warning

Dask integration is only tested on macOS and Linux.

Dask Examples

For sample code using `lightgbm.dask`, see these Dask examples.

Training with Dask

This section contains detailed information on performing LightGBM distributed training using Dask.

Configuring the Dask Cluster

Allocating Threads

When setting up a Dask cluster for training, give each Dask worker process at least two threads. If you do not do this, training might be substantially slower because communication work and training work will block each other.

If you do not have other significant processes competing with Dask for resources, just accept the default `nthreads` from your chosen `dask.distributed` cluster.

```
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=3)
client = Client(cluster)
```

Managing Memory

Use the Dask diagnostic dashboard or your preferred monitoring tool to monitor Dask workers' memory consumption during training. As described in the Dask worker documentation, Dask workers will automatically start spilling data to disk if memory consumption gets too high. This can substantially slow down computations, since disk I/O is usually much slower than reading the same data from memory.

> *At 60% of memory load, [Dask will] spill least recently used data to disk*

To reduce the risk of hitting memory limits, consider restarting each worker process before running any data loading or training code.

```
client.restart()
```

Setting Up Training Data

The estimators in `lightgbm.dask` expect that matrix-like or array-like data are provided in Dask DataFrame, Dask Array, or (in some cases) Dask Series format. See the Dask DataFrame documentation and the Dask Array documentation for more information on how to create such data structures.

While setting up for training, `lightgbm` will concatenate all of the partitions on a worker into a single dataset. Distributed training then proceeds with one LightGBM worker process per Dask worker.

When setting up data partitioning for LightGBM training with Dask, try to follow these suggestions:

- ensure that each worker in the cluster has some of the training data
- try to give each worker roughly the same amount of data, especially if your dataset is small
- if you plan to train multiple models (for example, to tune hyperparameters) on the same data, use `client.persist()` before training to materialize the data one time

Using a Specific Dask Client

In most situations, you should not need to tell `lightgbm.dask` to use a specific Dask client. By default, the client returned by `distributed.default_client()` will be used.

However, you might want to explicitly control the Dask client used by LightGBM if you have multiple active clients in the same session. This is useful in more complex workflows like running multiple training jobs on different Dask clusters.

LightGBM's Dask estimators support setting an attribute `client` to control the client that is used.

```
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster()
client = Client(cluster)

# option 1: keyword argument in constructor
dask_model = lgb.DaskLGBMClassifier(client=client)

# option 2: set_params() after construction
dask_model = lgb.DaskLGBMClassifier()
dask_model.set_params(client=client)
```

Using Specific Ports

At the beginning of training, `lightgbm.dask` sets up a LightGBM network where each Dask worker runs one long-running task that acts as a LightGBM worker. During training, LightGBM workers communicate with each other over TCP sockets. By default, random open ports are used when creating these sockets.

If the communication between Dask workers in the cluster used for training is restricted by firewall rules, you must tell LightGBM exactly what ports to use.

Option 1: provide a specific list of addresses and ports

LightGBM supports a parameter `machines`, a comma-delimited string where each entry refers to one worker (host name or IP) and a port that that worker will accept connections on. If you provide this parameter to the estimators in `lightgbm.dask`, LightGBM will not search randomly for ports.

For example, consider the case where you are running one Dask worker process on each of the following IP addresses:

```
10.0.1.0
10.0.2.0
10.0.3.0
```

You could edit your firewall rules to allow traffic on one additional port on each of these hosts, then provide `machines` directly.

```
import lightgbm as lgb

machines = "10.0.1.0:12401,10.0.2.0:12402,10.0.3.0:15000"
dask_model = lgb.DaskLGBMRegressor(machines=machines)
```

If you are running multiple Dask worker processes on physical host in the cluster, be sure that there are multiple entries for that IP address, with different ports. For example, if you were running a cluster with `nprocs=2` (2 Dask worker processes per machine), you might open two additional ports on each of these hosts, then provide `machines` as follows.

```
import lightgbm as lgb

machines = ",".join([
  "10.0.1.0:16000",
  "10.0.1.0:16001",
  "10.0.2.0:16000",
  "10.0.2.0:16001",
])
dask_model = lgb.DaskLGBMRegressor(machines=machines)
```

Warning

Providing `machines` gives you complete control over the networking details of training, but it also makes the training process fragile. Training will fail if you use `machines` and any of the following are true:

- any of the ports mentioned in `machines` are not open when training begins
- some partitions of the training data are held by machines that that are not present in `machines`
- some machines mentioned in `machines` do not hold any of the training data

Option 2: specify one port to use on every worker

If you are only running one Dask worker process on each host, and if you can reliably identify a port that is open on every host, using `machines` is unnecessarily complicated. If `local_listen_port` is given and `machines` is not, LightGBM will not search for ports randomly, but it will limit the list of addresses in the LightGBM network to those Dask workers that have a piece of the training data.

For example, consider the case where you are running one Dask worker process on each of the following IP addresses:

```
10.0.1.0
10.0.2.0
10.0.3.0
```

You could edit your firewall rules to allow communication between any of the workers over one port, then provide that port via parameter `local_listen_port`.

```
import lightgbm as lgb

dask_model = lgb.DaskLGBMRegressor(local_listen_port=12400)
```

Warning

Providing `local_listen_port` is slightly less fragile than `machines` because LightGBM will automatically figure out which workers have pieces of the training data. However, using this method, training can fail if any of the following are true:

- the port `local_listen_port` is not open on any of the worker hosts
- any machine has multiple Dask worker processes running on it

Using Custom Objective Functions with Dask

Added in version 4.0.0.

It is possible to customize the boosting process by providing a custom objective function written in Python. See the Dask API's documentation for details on how to implement such functions.

Warning

Custom objective functions used with `lightgbm.dask` will be called by each worker process on only that worker's local data.

Follow the example below to use a custom implementation of the `regression_l2` objective.

```
import dask.array as da
import lightgbm as lgb
import numpy as np
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

def custom_l2_obj(y_true, y_pred):
    grad = y_pred - y_true
    hess = np.ones(len(y_true))
    return grad, hess

dask_model = lgb.DaskLGBMRegressor(
    objective=custom_l2_obj
)
dask_model.fit(X, y)
```

Prediction with Dask

The estimators from `lightgbm.dask` can be used to create predictions based on data stored in Dask collections. In that interface, `.predict()` expects a Dask Array or Dask DataFrame, and returns a Dask Array of predictions.

See the Dask prediction example for some sample code that shows how to perform Dask-based prediction.

For model evaluation, consider using the metrics functions from dask-ml. Those functions are intended to provide the same API as equivalent functions in `sklearn.metrics`, but they use distributed computation powered by Dask to compute metrics without all of the input data ever needing to be on a single machine.

Saving Dask Models

After training with Dask, you have several options for saving a fitted model.

Option 1: pickle the Dask estimator

LightGBM's Dask estimators can be pickled directly with `cloudpickle`, `joblib`, or `pickle`.

```
import dask.array as da
import pickle
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

with open("dask-model.pkl", "wb") as f:
    pickle.dump(dask_model, f)
```

A model saved this way can then later be loaded with whichever serialization library you used to save it.

```
import pickle
with open("dask-model.pkl", "rb") as f:
    dask_model = pickle.load(f)
```

> **Note**
>
> If you explicitly set a Dask client (see *Using a Specific Dask Client*), it will not be saved when pickling the estimator. When loading a Dask estimator from disk, if you need to use a specific client you can add it after loading with `dask_model.set_params(client=client)`.

Option 2: pickle the sklearn estimator

The estimators available from `lightgbm.dask` can be converted to an instance of the equivalent class from `lightgbm.sklearn`. Choosing this option allows you to use Dask for training but avoid depending on any Dask libraries at scoring time.

```
import dask.array as da
import joblib
```

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```
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

# convert to sklearn equivalent
sklearn_model = dask_model.to_local()

print(type(sklearn_model))
#> lightgbm.sklearn.LGBMRegressor

joblib.dump(sklearn_model, "sklearn-model.joblib")
```

A model saved this way can then later be loaded with whichever serialization library you used to save it.

```
import joblib

sklearn_model = joblib.load("sklearn-model.joblib")
```

Option 3: save the LightGBM Booster

The lowest-level model object in LightGBM is the `lightgbm.Booster`. After training, you can extract a Booster from the Dask estimator.

```
import dask.array as da
import lightgbm as lgb
from distributed import Client, LocalCluster

cluster = LocalCluster(n_workers=2)
client = Client(cluster)

X = da.random.random((1000, 10), (500, 10))
y = da.random.random((1000,), (500,))

dask_model = lgb.DaskLGBMRegressor()
dask_model.fit(X, y)

# get underlying Booster object
bst = dask_model.booster_
```

From the point forward, you can use any of the following methods to save the Booster:

- serialize with `cloudpickle`, `joblib`, or `pickle`
- `bst.dump_model()`: dump the model to a dictionary which could be written out as JSON
- `bst.model_to_string()`: dump the model to a string in memory
- `bst.save_model()`: write the output of `bst.model_to_string()` to a text file

10.2.3 Kubeflow

Kubeflow users can also use the Kubeflow XGBoost Operator for machine learning workflows with LightGBM. You can see this example for more details.

Kubeflow integrations for LightGBM are not maintained by LightGBM's maintainers.

> **Note**
>
> The Kubeflow integrations for LightGBM are not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to https://github.com/kubeflow/fairing/issues or https://github.com/kubeflow/xgboost-operator/issues.

10.2.4 LightGBM CLI

Preparation

By default, distributed learning with LightGBM uses socket-based communication.

If you need to build distributed version with MPI support, please refer to Installation Guide.

Socket Version

It needs to collect IP of all machines that want to run distributed learning in and allocate one TCP port (assume 12345 here) for all machines, and change firewall rules to allow income of this port (12345). Then write these IP and ports in one file (assume `mlist.txt`), like following:

```
machine1_ip 12345
machine2_ip 12345
```

MPI Version

It needs to collect IP (or hostname) of all machines that want to run distributed learning in. Then write these IP in one file (assume `mlist.txt`) like following:

```
machine1_ip
machine2_ip
```

Note: For Windows users, need to start "smpd" to start MPI service. More details can be found here.

Run Distributed Learning

Socket Version

1. Edit following parameters in config file:

   `tree_learner=your_parallel_algorithm`, edit `your_parallel_algorithm` (e.g. feature/data) here.

   `num_machines=your_num_machines`, edit `your_num_machines` (e.g. 4) here.

   `machine_list_file=mlist.txt`, `mlist.txt` is created in *Preparation section*.

   `local_listen_port=12345`, `12345` is allocated in *Preparation section*.

2. Copy data file, executable file, config file and `mlist.txt` to all machines.

3. Run following command on all machines, you need to change `your_config_file` to real config file.

   For Windows: `lightgbm.exe config=your_config_file`

For Linux: `./lightgbm config=your_config_file`

MPI Version

1. Edit following parameters in config file:

   `tree_learner=your_parallel_algorithm`, edit `your_parallel_algorithm` (e.g. feature/data) here.

   `num_machines=your_num_machines`, edit `your_num_machines` (e.g. 4) here.

2. Copy data file, executable file, config file and `mlist.txt` to all machines.

   Note: MPI needs to be run in the **same path on all machines**.

3. Run following command on one machine (not need to run on all machines), need to change `your_config_file` to real config file.

   For Windows:

   ```
   mpiexec.exe /machinefile mlist.txt lightgbm.exe config=your_config_file
   ```

   For Linux:

   ```
   mpiexec --machinefile mlist.txt ./lightgbm config=your_config_file
   ```

Example

- A simple distributed learning example

10.2.5 Ray

Ray is a Python-based framework for distributed computing. Ray provides LightGBM support through the Ray Train API with `LightGBMTrainer` and the lightgbm_ray project maintained within the official Ray GitHub organization.

For the Ray Train API, see the Ray documentation for usage examples.

For the lightgbm_ray project, see the lightgbm_ray documentation for usage examples.

> **Note**
>
> `lightgbm_ray` and `ray` are not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to https://github.com/ray-project/lightgbm_ray/issues and https://github.com/ray-project/ray/issues respectively.

10.2.6 Mars

Mars is a tensor-based framework for large-scale data computation. LightGBM integration, maintained within the Mars GitHub repository, can be used to perform distributed LightGBM training using `pymars`.

See the mars documentation for usage examples.

> **Note**
>
> `Mars` is not maintained by LightGBM's maintainers. Bug reports or feature requests should be directed to https://github.com/mars-project/mars/issues.

CHAPTER

ELEVEN

LIGHTGBM GPU TUTORIAL

The purpose of this document is to give you a quick step-by-step tutorial on GPU training.

We will use the GPU instance on Microsoft Azure cloud computing platform for demonstration, but you can use any machine with modern AMD or NVIDIA GPUs.

11.1 GPU Setup

You need to launch a `NV` type instance on Azure (available in East US, North Central US, South Central US, West Europe and Southeast Asia zones) and select Ubuntu 16.04 LTS as the operating system.

For testing, the smallest `NV6` type virtual machine is sufficient, which includes 1/2 M60 GPU, with 8 GB memory, 180 GB/s memory bandwidth and 4,825 GFLOPS peak computation power. Don't use the `NC` type instance as the GPUs (K80) are based on an older architecture (Kepler).

First we need to install minimal NVIDIA drivers and OpenCL development environment:

```
sudo apt-get update
sudo apt-get install --no-install-recommends nvidia-375
sudo apt-get install --no-install-recommends nvidia-opencl-icd-375 nvidia-opencl-dev␣
↪opencl-headers
```

After installing the drivers you need to restart the server.

```
sudo init 6
```

After about 30 seconds, the server should be up again.

If you are using an AMD GPU, you should download and install the AMDGPU-Pro driver and also install packages `ocl-icd-libopencl1` and `ocl-icd-opencl-dev`.

11.2 Build LightGBM

Now install necessary building tools and dependencies:

```
sudo apt-get install --no-install-recommends git cmake build-essential libboost-dev␣
↪libboost-system-dev libboost-filesystem-dev
```

The `NV6` GPU instance has a 320 GB ultra-fast SSD mounted at `/mnt`. Let's use it as our workspace (skip this if you are using your own machine):

```
sudo mkdir -p /mnt/workspace
sudo chown $(whoami):$(whoami) /mnt/workspace
cd /mnt/workspace
```

Now we are ready to checkout LightGBM and compile it with GPU support:

```
git clone --recursive https://github.com/lightgbm-org/LightGBM
cd LightGBM
cmake -B build -S . -DUSE_GPU=1
# if you have installed NVIDIA CUDA to a customized location, you should specify paths␣
↪to OpenCL headers and library like the following:
# cmake -B build -S . -DUSE_GPU=1 -DOpenCL_LIBRARY=/usr/local/cuda/lib64/libOpenCL.so -
↪DOpenCL_INCLUDE_DIR=/usr/local/cuda/include/
cmake --build build -j$(nproc)
```

You will see two binaries are generated, `lightgbm` and `lib_lightgbm.so`.

If you are building on macOS, you probably need to remove macro `BOOST_COMPUTE_USE_OFFLINE_CACHE` in `src/treelearner/gpu_tree_learner.h` to avoid a known crash bug in Boost.Compute.

11.3 Install Python Interface (optional)

If you want to use the Python interface of LightGBM, you can install it now (along with some necessary Python-package dependencies):

```
sudo apt-get -y install python3-pip python3-venv
sudo -H pip install numpy scipy scikit-learn -U
sudo sh ./build-python.sh install --precompile
```

You need to set an additional parameter `"device" : "gpu"` (along with your other options like `learning_rate`, `num_leaves`, etc) to use GPU in Python.

You can read our Python-package Examples for more information on how to use the Python interface.

11.4 Dataset Preparation

Using the following commands to prepare the Higgs dataset:

```
git clone https://github.com/guolinke/boosting_tree_benchmarks.git
cd boosting_tree_benchmarks/data
wget "https://archive.ics.uci.edu/ml/machine-learning-databases/00280/HIGGS.csv.gz"
gunzip HIGGS.csv.gz
python higgs2libsvm.py
cd ../..
ln -s boosting_tree_benchmarks/data/higgs.train
ln -s boosting_tree_benchmarks/data/higgs.test
```

Now we create a configuration file for LightGBM by running the following commands (please copy the entire block and run it as a whole):

```
cat > lightgbm_gpu.conf <<EOF
max_bin = 63
num_leaves = 255
```

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```
num_iterations = 50
learning_rate = 0.1
tree_learner = serial
task = train
is_training_metric = false
min_data_in_leaf = 1
min_sum_hessian_in_leaf = 100
ndcg_eval_at = 1,3,5,10
device = gpu
gpu_platform_id = 0
gpu_device_id = 0
EOF
echo "num_threads=$(nproc)" >> lightgbm_gpu.conf
```

GPU is enabled in the configuration file we just created by setting `device=gpu`. In this configuration we use the first GPU installed on the system (`gpu_platform_id=0` and `gpu_device_id=0`). If `gpu_platform_id` or `gpu_device_id` is not set, the default platform and GPU will be selected. You might have multiple platforms (AMD/Intel/NVIDIA) or GPUs. You can use the clinfo utility to identify the GPUs on each platform. On Ubuntu, you can install `clinfo` by executing `sudo apt-get install clinfo`. If you have a discrete GPU by AMD/NVIDIA and an integrated GPU by Intel, make sure to select the correct `gpu_platform_id` to use the discrete GPU.

11.5 Run Your First Learning Task on GPU

Now we are ready to start GPU training!

First we want to verify the GPU works correctly. Run the following command to train on GPU, and take a note of the AUC after 50 iterations:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train valid=higgs.test objective=binary␣
↪metric=auc
```

Now train the same dataset on CPU using the following command. You should observe a similar AUC:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train valid=higgs.test objective=binary␣
↪metric=auc device=cpu
```

Now we can make a speed test on GPU without calculating AUC after each iteration.

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=binary metric=auc
```

Speed test on CPU:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=binary metric=auc␣
↪device=cpu
```

You should observe over three times speedup on this GPU.

The GPU acceleration can be used on other tasks/metrics (regression, multi-class classification, ranking, etc) as well. For example, we can train the Higgs dataset on GPU as a regression task:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=regression_l2 metric=l2
```

Also, you can compare the training speed with CPU:

```
./lightgbm config=lightgbm_gpu.conf data=higgs.train objective=regression_l2 metric=l2␣
↪device=cpu
```

11.6 Further Reading

- GPU Tuning Guide and Performance Comparison
- GPU SDK Correspondence and Device Targeting Table

11.7 Reference

Please kindly cite the following article in your publications if you find the GPU acceleration useful:

Huan Zhang, Si Si and Cho-Jui Hsieh. "GPU Acceleration for Large-scale Tree Boosting." SysML Conference, 2018.

CHAPTER

TWELVE

ADVANCED TOPICS

12.1 Missing Value Handle

- LightGBM enables the missing value handle by default. Disable it by setting `use_missing=false`.
- LightGBM uses NA (NaN) to represent missing values by default. Change it to use zero by setting `zero_as_missing=true`.
- When `zero_as_missing=false` (default), the unrecorded values in sparse matrices (and LightSVM) are treated as zeros.
- When `zero_as_missing=true`, NA and zeros (including unrecorded values in sparse matrices (and LightSVM)) are treated as missing.

12.2 Categorical Feature Support

- LightGBM offers good accuracy with integer-encoded categorical features. LightGBM applies Fisher (1958) to find the optimal split over categories as described here. This often performs better than one-hot encoding.
- Use `categorical_feature` to specify the categorical features. Refer to the parameter `categorical_feature` in Parameters.
- Categorical features will be cast to `int32` (integer codes will be extracted from pandas categoricals in the Python-package) so they must be encoded as non-negative integers (negative values will be treated as missing) less than `Int32.MaxValue` (2147483647). It is best to use a contiguous range of integers started from zero. Floating point numbers in categorical features will be rounded towards 0.
- When using `pandas.DataFrame` inputs with columns of dtype `category`, LightGBM will align categories to those observed during training before converting them to integer values. This ensures consistent encoding between training and prediction without additional preprocessing.
- At `predict()` time, categories not seen during training will be treated as missing values.
- Use `min_data_per_group`, `cat_smooth` to deal with over-fitting (when `#data` is small or `#category` is large).
- For a categorical feature with high cardinality (`#category` is large), it often works best to treat the feature as numeric, either by simply ignoring the categorical interpretation of the integers or by embedding the categories in a low-dimensional numeric space.

12.3 LambdaRank

- The label should be of type `int`, such that larger numbers correspond to higher relevance (e.g. 0:bad, 1:fair, 2:good, 3:perfect).
- Use `label_gain` to set the gain(weight) of `int` label.

- Use `lambdarank_truncation_level` to truncate the max DCG.

12.4 Cost Efficient Gradient Boosting

Cost Efficient Gradient Boosting (CEGB) makes it possible to penalise boosting based on the cost of obtaining feature values. CEGB penalises learning in the following ways:

- Each time a tree is split, a penalty of `cegb_penalty_split` is applied.
- When a feature is used for the first time, `cegb_penalty_feature_coupled` is applied. This penalty can be different for each feature and should be specified as one `double` per feature.
- When a feature is used for the first time for a data row, `cegb_penalty_feature_lazy` is applied. Like `cegb_penalty_feature_coupled`, this penalty is specified as one `double` per feature.

Each of the penalties above is scaled by `cegb_tradeoff`. Using this parameter, it is possible to change the overall strength of the CEGB penalties by changing only one parameter.

12.5 Parameters Tuning

- Refer to Parameters Tuning.

12.6 Distributed Learning

- Refer to Distributed Learning Guide.

12.7 GPU Support

- Refer to GPU Tutorial and GPU Targets.

12.8 Support for Position Bias Treatment

Often the relevance labels provided in Learning-to-Rank tasks might be derived from implicit user feedback (e.g., clicks) and therefore might be biased due to their position/location on the screen when having been presented to a user. LightGBM can make use of positional data.

For example, consider the case where you expect that the first 3 results from a search engine will be visible in users' browsers without scrolling, and all other results for a query would require scrolling.

LightGBM could be told to account for the position bias from results being "above the fold" by providing a `positions` array encoded as follows:

```
0
0
0
1
1
0
0
0
1
...
```

Where `0 = "above the fold"` and `1 = "requires scrolling"`. The specific values are not important, as long as they are consistent across all observations in the training data. An encoding like `100 = "above the fold"` and `17 = "requires scrolling"` would result in exactly the same trained model.

In that way, `positions` in LightGBM's API are similar to a categorical feature. Just as with non-ordinal categorical features, an integer representation is just used for memory and computational efficiency... LightGBM does not care about the absolute or relative magnitude of the values.

Unlike a categorical feature, however, `positions` are used to adjust the target to reduce the bias in predictions made by the trained model.

The position file corresponds with training data file line by line, and has one position per line. And if the name of training data file is `train.txt`, the position file should be named as `train.txt.position` and placed in the same folder as the data file. In this case, LightGBM will load the position file automatically if it exists. The positions can also be specified through the `Dataset` constructor when using Python API. If the positions are specified in both approaches, the `.position` file will be ignored.

Currently, implemented is an approach to model position bias by using an idea of Generalized Additive Models (GAM) to linearly decompose the document score `s` into the sum of a relevance component `f` and a positional component `g`: `s(x, pos) = f(x) + g(pos)` where the former component depends on the original query-document features and the latter depends on the position of an item. During the training, the compound scoring function `s(x, pos)` is fit with a standard ranking algorithm (e.g., LambdaMART) which boils down to jointly learning the relevance component `f(x)` (it is later returned as an unbiased model) and the position factors `g(pos)` that help better explain the observed (biased) labels. Similar score decomposition ideas have previously been applied for classification & pointwise ranking tasks with assumptions of binary labels and binary relevance (a.k.a. "two-tower" models, refer to the papers: Towards Disentangling Relevance and Bias in Unbiased Learning to Rank, PAL: a position-bias aware learning framework for CTR prediction in live recommender systems, A General Framework for Debiasing in CTR Prediction). In LightGBM, we adapt this idea to general pairwise Lerarning-to-Rank with arbitrary ordinal relevance labels. Besides, GAMs have been used in the context of explainable ML (Accurate Intelligible Models with Pairwise Interactions) to linearly decompose the contribution of each feature (and possibly their pairwise interactions) to the overall score, for subsequent analysis and interpretation of their effects in the trained models.

CHAPTER

THIRTEEN

LIGHTGBM FAQ

LightGBM Frequently Asked Questions

Please post questions, feature requests, and bug reports at https://github.com/lightgbm-org/LightGBM/issues.

This project is mostly maintained by volunteers, so please be patient. If your request is time-sensitive or more than a month goes by without a response, please tag the maintainers below for help.

- @guolinke **Guolin Ke**
- @shiyu1994 **Yu Shi**
- @jameslamb **James Lamb**
- @jmoralez **José Morales**
- @borchero **Oliver Borchert**
- @mayer79 **Michael Mayer**

13.1 General LightGBM Questions

13.1.1 1. Where do I find more details about LightGBM parameters?

Take a look at Parameters.

13.1.2 2. On datasets with millions of features, training does not start (or starts after a very long time).

Use a smaller value for `bin_construct_sample_cnt` and a larger value for `min_data`.

13.1.3 3. When running LightGBM on a large dataset, my computer runs out of RAM.

Multiple Solutions: set the `histogram_pool_size` parameter to the MB you want to use for LightGBM (histogram_pool_size + dataset size = approximately RAM used), lower `num_leaves` or lower `max_bin` (see lightgbm-org/LightGBM#562).

13.1.4 4. I am using Windows. Should I use Visual Studio or MinGW for compiling LightGBM?

Visual Studio performs best for LightGBM.

13.1.5 5. When using LightGBM GPU, I cannot reproduce results over several runs.

This is normal and expected behaviour, but you may try to use `gpu_use_dp = true` for reproducibility (see lightgbm-org/LightGBM#560). You may also use the CPU version.

13.1.6 6. Bagging is not reproducible when changing the number of threads.

LightGBM bagging is multithreaded, so its output depends on the number of threads used. There is no workaround currently.

Starting from #2804 bagging result doesn't depend on the number of threads. So this issue should be solved in the latest version.

13.1.7 7. I tried to use Random Forest mode, and LightGBM crashes!

This is expected behaviour for arbitrary parameters. To enable Random Forest, you must use `bagging_fraction` and `feature_fraction` different from 1, along with a `bagging_freq`. This thread includes an example.

13.1.8 8. CPU usage is low (like 10%) in Windows when using LightGBM on very large datasets with many-core systems.

Please use Visual Studio as it may be 10x faster than MinGW especially for very large trees.

13.1.9 9. When I'm trying to specify a categorical column with the `categorical_feature` parameter, I get the following sequence of warnings, but there are no negative values in the column.

```
[LightGBM] [Warning] Met negative value in categorical features, will convert it to NaN
[LightGBM] [Warning] There are no meaningful features, as all feature values are␣
↪constant.
```

The column you're trying to pass via `categorical_feature` likely contains very large values. Categorical features in LightGBM are limited by int32 range, so you cannot pass values that are greater than `Int32.MaxValue` (2147483647) as categorical features (see lightgbm-org/LightGBM#1359). You should convert them to integers ranging from zero to the number of categories first.

13.1.10 10. LightGBM crashes randomly with the error like: `Initializing libiomp5.dylib, but found libomp.dylib already initialized.`

```
OMP: Error #15: Initializing libiomp5.dylib, but found libomp.dylib already initialized.
OMP: Hint: This means that multiple copies of the OpenMP runtime have been linked into␣
↪the program. That is dangerous, since it can degrade performance or cause incorrect␣
↪results. The best thing to do is to ensure that only a single OpenMP runtime is linked␣
↪into the process, e.g. by avoiding static linking of the OpenMP runtime in any library.
↪ As an unsafe, unsupported, undocumented workaround you can set the environment␣
↪variable KMP_DUPLICATE_LIB_OK=TRUE to allow the program to continue to execute, but␣
↪that may cause crashes or silently produce incorrect results. For more information,␣
↪please see http://www.intel.com/software/products/support/.
```

Possible Cause: This error means that you have multiple OpenMP libraries installed on your machine and they conflict with each other. (File extensions in the error message may differ depending on the operating system).

If you are using Python distributed by Conda, then it is highly likely that the error is caused by the `numpy` package from Conda which includes the `mkl` package which in turn conflicts with the system-wide library. In this case you can update the `numpy` package in Conda or replace the Conda's OpenMP library instance with system-wide one by creating a symlink to it in Conda environment folder `$CONDA_PREFIX/lib`.

Solution: Assuming you are using macOS with Homebrew, the command which overwrites OpenMP library files in the current active Conda environment with symlinks to the system-wide library ones installed by Homebrew:

```
ln -sf `ls -d "$(brew --cellar libomp)"/*/lib`/* $CONDA_PREFIX/lib
```

The described above fix worked fine before the release of OpenMP 8.0.0 version. Starting from 8.0.0 version, Homebrew formula for OpenMP includes `-DLIBOMP_INSTALL_ALIASES=OFF` option which leads to that the fix doesn't work anymore. However, you can create symlinks to library aliases manually:

```
for LIBOMP_ALIAS in libgomp.dylib libiomp5.dylib libomp.dylib; do sudo ln -sf "$(brew --
↪cellar libomp)"/*/lib/libomp.dylib $CONDA_PREFIX/lib/$LIBOMP_ALIAS; done
```

Another workaround would be removing MKL optimizations from Conda's packages completely:

```
conda install nomkl
```

If this is not your case, then you should find conflicting OpenMP library installations on your own and leave only one of them.

13.1.11 11. LightGBM hangs when multithreading (OpenMP) and using forking in Linux at the same time.

Use `nthreads=1` to disable multithreading of LightGBM. There is a bug with OpenMP which hangs forked sessions with multithreading activated. A more expensive solution is to use new processes instead of using fork, however, keep in mind it is creating new processes where you have to copy memory and load libraries (example: if you want to fork 16 times your current process, then you will require to make 16 copies of your dataset in memory) (see lightgbm-org/LightGBM#1789).

An alternative, if multithreading is really necessary inside the forked sessions, would be to compile LightGBM with Intel toolchain. Intel compilers are unaffected by this bug.

For C/C++ users, any OpenMP feature cannot be used before the fork happens. If an OpenMP feature is used before the fork happens (example: using OpenMP for forking), OpenMP will hang inside the forked sessions. Use new processes instead and copy memory as required by creating new processes instead of forking (or, use Intel compilers).

Cloud platform container services may cause LightGBM to hang, if they use Linux fork to run multiple containers on a single instance. For example, LightGBM hangs in AWS Batch array jobs, which use the ECS agent to manage multiple running jobs. Setting `nthreads=1` mitigates the issue.

13.1.12 12. Why is early stopping not enabled by default in LightGBM?

Early stopping involves choosing a validation set, a special type of holdout which is used to evaluate the current state of the model after each iteration to see if training can stop.

In `LightGBM`, we have decided to require that users specify this set directly. Many options exist for splitting training data into training, test, and validation sets.

The appropriate splitting strategy depends on the task and domain of the data, information that a modeler has but which `LightGBM` as a general-purpose tool does not.

13.1.13 13. Does LightGBM support direct loading data from zero-based or one-based LibSVM format file?

LightGBM supports loading data from zero-based LibSVM format file directly.

13.1.14 14. Why CMake cannot find the compiler when compiling LightGBM with MinGW?

```
CMake Error: CMAKE_C_COMPILER not set, after EnableLanguage
CMake Error: CMAKE_CXX_COMPILER not set, after EnableLanguage
```

This is a known issue of CMake when using MinGW. The easiest solution is to run again your `cmake` command to bypass the one time stopper from CMake. Or you can upgrade your version of CMake to at least version 3.17.0.

See lightgbm-org/LightGBM#3060 for more details.

13.1.15 15. Where can I find LightGBM's logo to use it in my presentation?

You can find LightGBM's logo in different file formats and resolutions here.

13.1.16 16. LightGBM crashes randomly or operating system hangs during or after running LightGBM.

Possible Cause: This behavior may indicate that you have multiple OpenMP libraries installed on your machine and they conflict with each other, similarly to the `FAQ #10`.

If you are using any Python-package that depends on `threadpoolctl`, you also may see the following warning in your logs in this case:

```
/root/miniconda/envs/test-env/lib/python3.8/site-packages/threadpoolctl.py:546:␣
↪RuntimeWarning:
Found Intel OpenMP ('libiomp') and LLVM OpenMP ('libomp') loaded at
the same time. Both libraries are known to be incompatible and this
can cause random crashes or deadlocks on Linux when loaded in the
same Python program.
Using threadpoolctl may cause crashes or deadlocks. For more
information and possible workarounds, please see
    https://github.com/joblib/threadpoolctl/blob/master/multiple_openmp.md
```

Detailed description of conflicts between multiple OpenMP instances is provided in the following document.

Solution: Assuming you are using LightGBM Python-package and conda as a package manager, we strongly recommend using `conda-forge` channel as the only source of all your Python package installations because it contains built-in patches to workaround OpenMP conflicts. Some other workarounds are listed here under the "Workarounds for Intel OpenMP and LLVM OpenMP case" section.

If this is not your case, then you should find conflicting OpenMP library installations on your own and leave only one of them.

13.1.17 17. Loading LightGBM fails like: `cannot allocate memory in static TLS block`

When loading LightGBM, you may encounter errors like the following.

```
lib/libgomp.so.1: cannot allocate memory in static TLS block
```

This most commonly happens on aarch64 Linux systems.

`gcc`'s OpenMP library (`libgomp.so`) tries to allocate a small amount of static thread-local storage ("TLS") when it's dynamically loaded.

That error can happen when the loader isn't able to find a large enough block of memory.

On aarch64 Linux, processes and loaded libraries share the same pool of static TLS, which makes such failures more likely. See these discussions:

- https://bugzilla.redhat.com/show_bug.cgi?id=1722181#c6
- https://gcc.gcc.gnu.narkive.com/vOXMQqLA/failure-to-dlopen-libgomp-due-to-static-tls-data

If you are experiencing this issue when using the `lightgbm` Python-package, try upgrading to at least `v4.6.0`.

For older versions of the Python-package, or for other LightGBM APIs, this issue can often be avoided by loading `libgomp.so.1`. That can be done directly by setting environment variable `LD_PRELOAD`, like this:

```
export LD_PRELOAD=/root/miniconda3/envs/test-env/lib/libgomp.so.1
```

It can also be done indirectly by changing the order that other libraries are loaded into processes, which varies by programming language and application type.

For more details, see these discussions:

- https://github.com/lightgbm-org/LightGBM/pull/6654#issuecomment-2352014275
- https://github.com/lightgbm-org/LightGBM/issues/6509
- https://maskray.me/blog/2021-02-14-all-about-thread-local-storage
- https://bugzilla.redhat.com/show_bug.cgi?id=1722181#c6

13.2 R-package

13.2.1 1. Any training command using LightGBM does not work after an error occurred during the training of a previous LightGBM model.

In older versions of the R-package (prior to `v3.3.0`), this could happen occasionally and the solution was to run `lgb.unloader(wipe = TRUE)` to remove all LightGBM-related objects. Some conversation about this could be found in lightgbm-org/LightGBM#698.

That is no longer necessary as of `v3.3.0`, and function `lgb.unloader()` has since been removed from the R-package.

13.2.2 2. I used `setinfo()`, tried to print my `lgb.Dataset`, and now the R console froze!

As of at least LightGBM v3.3.0, this issue has been resolved and printing a `Dataset` object does not cause the console to freeze.

In older versions, avoid printing the `Dataset` after calling `setinfo()`.

As of LightGBM v4.0.0, `setinfo()` has been replaced by a new method, `set_field()`.

13.2.3 3. `error in data.table::data.table()...argument 2 is NULL`.

If you are experiencing this error when running `lightgbm`, you may be facing the same issue reported in #2715 and later in #2989. We have seen that in some situations, using `data.table` 1.11.x results in this error. To get around this, you can upgrade your version of `data.table` to at least version 1.12.0.

13.2.4 4. package/dependency 'Matrix' is not available ...

In April 2024, `Matrix==1.7-0` was published to CRAN. That version had a floor of `R (>=4.4.0)`. `{Matrix}` is a hard runtime dependency of `{lightgbm}`, so on any version of R older than `4.4.0`, running `install.packages("lightgbm")` results in something like the following.

```
package 'Matrix' is not available for this version of R
```

To fix that without upgrading to R 4.4.0 or greater, manually install an older version of `{Matrix}`.

```
install.packages('https://cran.r-project.org/src/contrib/Archive/Matrix/Matrix_1.6-5.tar.
↪gz', repos = NULL)
```

13.3 Python-package

13.3.1 1. Error: setup script specifies an absolute path when installing from GitHub using python setup.py install.

Note

As of v4.0.0, `lightgbm` does not support directly invoking `setup.py`. This answer refers only to versions of `lightgbm` prior to v4.0.0.

```
error: Error: setup script specifies an absolute path:
/Users/Microsoft/LightGBM/python-package/lightgbm/../../lib_lightgbm.so
setup() arguments must *always* be /-separated paths relative to the setup.py directory,␣
↪*never* absolute paths.
```

This error should be solved in latest version. If you still meet this error, try to remove `lightgbm.egg-info` folder in your Python-package and reinstall, or check this thread on stackoverflow.

13.3.2 2. Error messages: Cannot ... before construct dataset.

I see error messages like...

```
Cannot get/set label/weight/init_score/group/num_data/num_feature before construct␣
↪dataset
```

but I've already constructed a dataset by some code like:

```
train = lightgbm.Dataset(X_train, y_train)
```

or error messages like

```
Cannot set predictor/reference/categorical feature after freed raw data, set free_raw_
↪data=False when construct Dataset to avoid this.
```

Solution: Because LightGBM constructs bin mappers to build trees, and train and valid Datasets within one Booster share the same bin mappers, categorical features and feature names etc., the Dataset objects are constructed when constructing a Booster. If you set `free_raw_data=True` (default), the raw data (with Python data struct) will be freed. So, if you want to:

- get label (or weight/init_score/group/data) before constructing a dataset, it's same as get `self.label`;
- set label (or weight/init_score/group) before constructing a dataset, it's same as `self.label=some_label_array`;
- get num_data (or num_feature) before constructing a dataset, you can get data with `self.data`. Then, if your data is `numpy.ndarray`, use some code like `self.data.shape`. But do not do this after subsetting the Dataset, because you'll get always `None`;
- set predictor (or reference/categorical feature) after constructing a dataset, you should set `free_raw_data=False` or init a Dataset object with the same raw data.

13.3.3 3. I encounter segmentation faults (segfaults) randomly after installing LightGBM from PyPI using `pip install lightgbm`.

We are doing our best to provide universal wheels which have high running speed and are compatible with any hardware, OS, compiler, etc. at the same time. However, sometimes it's just impossible to guarantee the possibility of usage of LightGBM in any specific environment (see lightgbm-org/LightGBM#1743).

Therefore, the first thing you should try in case of segfaults is **compiling from the source** using `pip install --no-binary lightgbm lightgbm`. For the OS-specific prerequisites see https://github.com/lightgbm-org/LightGBM/blob/master/python-package/README.rst.

Also, feel free to post a new issue in our GitHub repository. We always look at each case individually and try to find a root cause.

13.3.4 4. I would like to install LightGBM from conda. What channel should I choose?

We strongly recommend installation from the `conda-forge` channel and not from the `default` one.

For some specific examples, see this comment.

In addition, as of `lightgbm==4.4.0`, the `conda-forge` package automatically supports CUDA-based GPU acceleration.

13.3.5 5. How do I subclass `scikit-learn` estimators?

For `lightgbm <= 4.5.0`, copy all of the constructor arguments from the corresponding `lightgbm` class into the constructor of your custom estimator.

For later versions, just ensure that the constructor of your custom estimator calls `super().__init__()`.

Consider the example below, which implements a regressor that allows creation of truncated predictions. This pattern will work with `lightgbm > 4.5.0`.

```
import numpy as np
from lightgbm import LGBMRegressor
from sklearn.datasets import make_regression

class TruncatedRegressor(LGBMRegressor):

    def __init__(self, **kwargs):
        super().__init__(**kwargs)

    def predict(self, X, max_score: float = np.inf):
        preds = super().predict(X)
        np.clip(preds, a_min=None, a_max=max_score, out=preds)
        return preds

X, y = make_regression(n_samples=1_000, n_features=4)

reg_trunc = TruncatedRegressor().fit(X, y)

preds = reg_trunc.predict(X)
print(f"mean: {preds.mean():.2f}, max: {preds.max():.2f}")
# mean: -6.81, max: 345.10

preds_trunc = reg_trunc.predict(X, max_score=preds.mean())
print(f"mean: {preds_trunc.mean():.2f}, max: {preds_trunc.max():.2f}")
# mean: -56.50, max: -6.81
```

CHAPTER

FOURTEEN

DEVELOPMENT GUIDE

14.1 Algorithms

Refer to Features for understanding of important algorithms used in LightGBM.

14.2 Classes and Code Structure

14.2.1 Important Classes

Class	Description
`Application`	The entrance of application, including training and prediction logic
`Bin`	Data structure used for storing feature discrete values (converted from float values)
`Boosting`	Boosting interface (GBDT, DART, etc.)
`Config`	Stores parameters and configurations
`Dataset`	Stores information of dataset
`DatasetLoader`	Used to construct dataset
`FeatureGroup`	Stores the data of feature, could be multiple features
`Metric`	Evaluation metrics
`Network`	Network interfaces and communication algorithms
`ObjectiveFunction`	Objective functions used to train
`Tree`	Stores information of tree model
`TreeLearner`	Used to learn trees

14.2.2 Code Structure

Path	Description
./include	Header files
./include/utils	Some common functions
./src/applicatior	Implementations of training and prediction logic
./src/boosting	Implementations of Boosting
./src/io	Implementations of IO related classes, including `Bin`, `Config`, `Dataset`, `DatasetLoader`, `Feature` and `Tree`
./src/metric	Implementations of metrics
./src/network	Implementations of network functions
./src/objective	Implementations of objective functions
./src/treelearner	Implementations of tree learners

14.3 Documents API

Refer to docs README.

14.4 C API

Refer to C API or the comments in c_api.h file, from which the documentation is generated.

14.5 Tests

C++ unit tests are located in the `./tests/cpp_tests` folder and written with the help of Google Test framework. To run tests locally first refer to the Installation Guide for how to build tests and then simply run compiled executable file. It is highly recommended to build tests with sanitizers.

14.6 High Level Language Package

See the implementations at Python-package and R-package.

14.7 Questions

Refer to FAQ.

Also feel free to open issues if you met problems.

CHAPTER

FIFTEEN

GPU TUNING GUIDE AND PERFORMANCE COMPARISON

15.1 How It Works?

In LightGBM, the main computation cost during training is building the feature histograms. We use an efficient algorithm on GPU to accelerate this process. The implementation is highly modular, and works for all learning tasks (classification, ranking, regression, etc). GPU acceleration also works in distributed learning settings. GPU algorithm implementation is based on OpenCL and can work with a wide range of GPUs.

15.2 Supported Hardware

We target AMD Graphics Core Next (GCN) architecture and NVIDIA Maxwell and Pascal architectures. Most AMD GPUs released after 2012 and NVIDIA GPUs released after 2014 should be supported. We have tested the GPU implementation on the following GPUs:

- AMD RX 480 with AMDGPU-pro driver 16.60 on Ubuntu 16.10
- AMD R9 280X (aka Radeon HD 7970) with fglrx driver 15.302.2301 on Ubuntu 16.10
- NVIDIA GTX 1080 with driver 375.39 and CUDA 8.0 on Ubuntu 16.10
- NVIDIA Titan X (Pascal) with driver 367.48 and CUDA 8.0 on Ubuntu 16.04
- NVIDIA Tesla M40 with driver 375.39 and CUDA 7.5 on Ubuntu 16.04

Using the following hardware is discouraged:

- NVIDIA Kepler (K80, K40, K20, most GeForce GTX 700 series GPUs) or earlier NVIDIA GPUs. They don't support hardware atomic operations in local memory space and thus histogram construction will be slow.
- AMD VLIW4-based GPUs, including Radeon HD 6xxx series and earlier GPUs. These GPUs have been discontinued for years and are rarely seen nowadays.

15.3 How to Achieve Good Speedup on GPU

1. You want to run a few datasets that we have verified with good speedup (including Higgs, epsilon, Bosch, etc) to ensure your setup is correct. If you have multiple GPUs, make sure to set `gpu_platform_id` and `gpu_device_id` to use the desired GPU. Also make sure your system is idle (especially when using a shared computer) to get accuracy performance measurements.
2. GPU works best on large scale and dense datasets. If dataset is too small, computing it on GPU is inefficient as the data transfer overhead can be significant. If you have categorical features, use the `categorical_column` option and input them into LightGBM directly; do not convert them into one-hot variables.
3. To get good speedup with GPU, it is suggested to use a smaller number of bins. Setting `max_bin=63` is recommended, as it usually does not noticeably affect training accuracy on large datasets, but GPU training can

be significantly faster than using the default bin size of 255. For some dataset, even using 15 bins is enough (`max_bin=15`); using 15 bins will maximize GPU performance. Make sure to check the run log and verify that the desired number of bins is used.

4. Try to use single precision training (`gpu_use_dp=false`) when possible, because most GPUs (especially NVIDIA consumer GPUs) have poor double-precision performance.

15.4 Performance Comparison

We evaluate the training performance of GPU acceleration on the following datasets:

Data	Task	Link	#Examples	#Features	Comments
Higgs	Binary classification	link1	10,500,000	28	use last 500,000 samples as test set
Epsilon	Binary classification	link2	400,000	2,000	use the provided test set
Bosch	Binary classification	link3	1,000,000	968	use the provided test set
Yahoo LTR	Learning to rank	link4	473,134	700	set1.train as train, set1.test as test
MS LTR	Learning to rank	link5	2,270,296	137	{S1,S2,S3} as train set, {S5} as test set
Expo	Binary classification (Categorical)	link6	11,000,000	700	use last 1,000,000 as test set

We used the following hardware to evaluate the performance of LightGBM GPU training. Our CPU reference is **a high-end dual socket Haswell-EP Xeon server with 28 cores**; GPUs include a budget GPU (RX 480) and a mainstream (GTX 1080) GPU installed on the same server. It is worth mentioning that **the GPUs used are not the best GPUs in the market**; if you are using a better GPU (like AMD RX 580, NVIDIA GTX 1080 Ti, Titan X Pascal, Titan Xp, Tesla P100, etc), you are likely to get a better speedup.

Hardware	Peak FLOPS	Peak Memory BW	Cost (MSRP)
AMD Radeon RX 480	5,161 GFLOPS	256 GB/s	$199
NVIDIA GTX 1080	8,228 GFLOPS	320 GB/s	$499
2x Xeon E5-2683v3 (28 cores)	1,792 GFLOPS	133 GB/s	$3,692

During benchmarking on CPU we used only 28 physical cores of the CPU, and did not use hyper-threading cores, because we found that using too many threads actually makes performance worse. The following shows the training configuration we used:

```
max_bin = 63
num_leaves = 255
num_iterations = 500
learning_rate = 0.1
tree_learner = serial
task = train
is_training_metric = false
min_data_in_leaf = 1
min_sum_hessian_in_leaf = 100
ndcg_eval_at = 1,3,5,10
device = gpu
gpu_platform_id = 0
```

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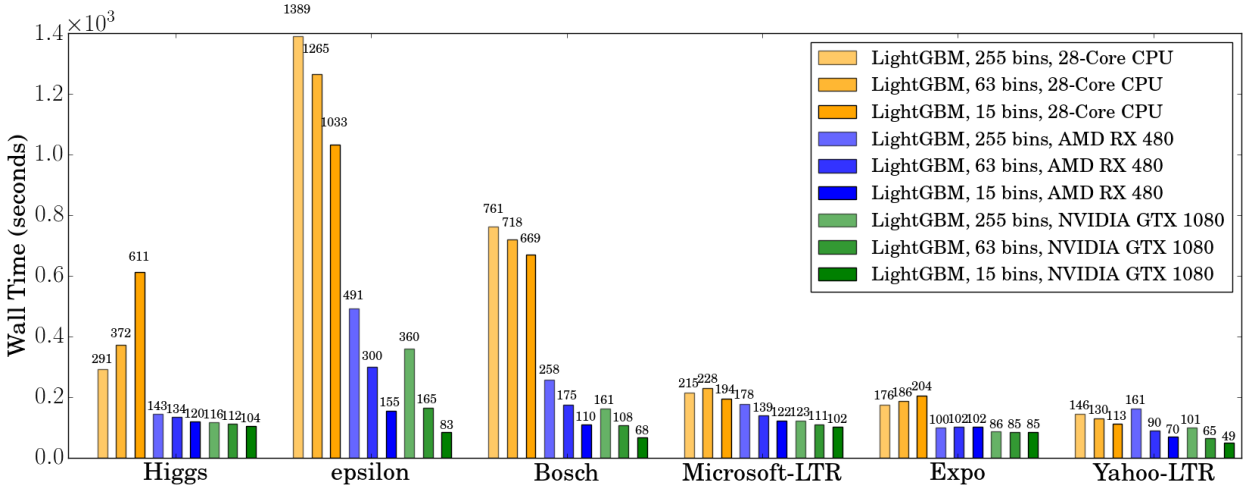
```
gpu_device_id = 0
num_thread = 28
```

We use the configuration shown above, except for the Bosch dataset, we use a smaller `learning_rate=0.015` and set `min_sum_hessian_in_leaf=5`. For all GPU training we vary the max number of bins (255, 63 and 15). The GPU implementation is from commit 0bb4a82 of LightGBM, when the GPU support was just merged in.

The following table lists the accuracy on test set that CPU and GPU learner can achieve after 500 iterations. GPU with the same number of bins can achieve a similar level of accuracy as on the CPU, despite using single precision arithmetic. For most datasets, using 63 bins is sufficient.

	CPU 255 bins	CPU 63 bins	CPU 15 bins	GPU 255 bins	GPU 63 bins	GPU 15 bins
Higgs AUC	0.845612	0.845239	0.841066	0.845612	0.845209	0.840748
Epsilon AUC	0.950243	0.949952	0.948365	0.950057	0.949876	0.948365
Yahoo-LTR $NDCG_1$	0.730824	0.730165	0.729647	0.730936	0.732257	0.73114
Yahoo-LTR $NDCG_3$	0.738687	0.737243	0.736445	0.73698	0.739474	0.735868
Yahoo-LTR $NDCG_5$	0.756609	0.755729	0.754607	0.756206	0.757007	0.754203
Yahoo-LTR $NDCG_{10}$	0.79655	0.795827	0.795273	0.795894	0.797302	0.795584
Expo AUC	0.776217	0.771566	0.743329	0.776285	0.77098	0.744078
MS-LTR $NDCG_1$	0.521265	0.521392	0.518653	0.521789	0.522163	0.516388
MS-LTR $NDCG_3$	0.503153	0.505753	0.501697	0.503886	0.504089	0.501691
MS-LTR $NDCG_5$	0.509236	0.510391	0.507193	0.509861	0.510095	0.50663
MS-LTR $NDCG_{10}$	0.527835	0.527304	0.524603	0.528009	0.527059	0.524722
Bosch AUC	0.718115	0.721791	0.716677	0.717184	0.724761	0.717005

We record the wall clock time after 500 iterations, as shown in the figure below:



When using a GPU, it is advisable to use a bin size of 63 rather than 255, because it can speed up training significantly without noticeably affecting accuracy. On CPU, using a smaller bin size only marginally improves performance, sometimes even slows down training, like in Higgs (we can reproduce the same slowdown on two different machines, with different GCC versions). We found that GPU can achieve impressive acceleration on large and dense datasets like

Higgs and Epsilon. Even on smaller and sparse datasets, a *budget* GPU can still compete and be faster than a 28-core Haswell server.

15.5 Memory Usage

The next table shows GPU memory usage reported by `nvidia-smi` during training with 63 bins. We can see that even the largest dataset just uses about 1 GB of GPU memory, indicating that our GPU implementation can scale to huge datasets over 10x larger than Bosch or Epsilon. Also, we can observe that generally a larger dataset (using more GPU memory, like Epsilon or Bosch) has better speedup, because the overhead of invoking GPU functions becomes significant when the dataset is small.

Datasets	Higgs	Epsilon	Bosch	MS-LTR	Expo	Yahoo-LTR
GPU Memory Usage (MB)	611	901	1067	413	405	291

15.6 Further Reading

You can find more details about the GPU algorithm and benchmarks in the following article:

Huan Zhang, Si Si and Cho-Jui Hsieh. GPU Acceleration for Large-scale Tree Boosting. SysML Conference, 2018.

CHAPTER

SIXTEEN

GPU SDK CORRESPONDENCE AND DEVICE TARGETING TABLE

16.1 GPU Targets Table

OpenCL is a universal massively parallel programming framework that targets multiple backends (GPU, CPU, FPGA, etc). Basically, to use a device from a vendor, you have to install drivers from that specific vendor. Intel's and AMD's OpenCL runtime also include x86 CPU target support. NVIDIA's OpenCL runtime only supports NVIDIA GPU (no CPU support). In general, OpenCL CPU backends are quite slow, and should be used for testing and debugging only.

You can find below a table of correspondence:

SDK	CPU Intel/AMD	GPU Intel	GPU AMD	GPU NVIDIA
Intel SDK for OpenCL	Supported	Supported	Not Supported	Not Supported
AMD APP SDK *	Supported	Not Supported	Supported	Not Supported
PoCL	Supported	Not Supported	Supported	Not Supported
NVIDIA CUDA Toolkit	Not Supported	Not Supported	Not Supported	Supported

Legend:

* AMD APP SDK is deprecated. On Windows, OpenCL is included in AMD graphics driver. On Linux, newer generation AMD cards are supported by the ROCm driver. You can download an archived copy of AMD APP SDK from our GitHub repo (for Linux and for Windows).

16.2 Query OpenCL Devices in Your System

Your system might have multiple GPUs from different vendors ("platforms") installed. Setting up LightGBM GPU device requires two parameters: OpenCL Platform ID (`gpu_platform_id`) and OpenCL Device ID (`gpu_device_id`). Generally speaking, each vendor provides an OpenCL platform, and devices from the same vendor have different device IDs under that platform. For example, if your system has an Intel integrated GPU and two discrete GPUs from AMD, you will have two OpenCL platforms (with `gpu_platform_id=0` and `gpu_platform_id=1`). If the platform 0 is Intel, it has one device (`gpu_device_id=0`) representing the Intel GPU; if the platform 1 is AMD, it has two devices (`gpu_device_id=0`, `gpu_device_id=1`) representing the two AMD GPUs. If you have a discrete GPU by AMD/NVIDIA and an integrated GPU by Intel, make sure to select the correct `gpu_platform_id` to use the discrete GPU as it usually provides better performance.

On Windows, OpenCL devices can be queried using GPUCapsViewer, under the OpenCL tab. Note that the platform and device IDs reported by this utility start from 1. So you should minus the reported IDs by 1.

On Linux, OpenCL devices can be listed using the `clinfo` command. On Ubuntu, you can install `clinfo` by executing `sudo apt-get install clinfo`.

16.3 Examples

We provide test R code below, but you can use the language of your choice with the examples of your choices:

```
library(lightgbm)
data(agaricus.train, package = "lightgbm")
train <- agaricus.train
train$data[, 1] <- 1:6513
dtrain <- lgb.Dataset(train$data, label = train$label)
data(agaricus.test, package = "lightgbm")
test <- agaricus.test
dtest <- lgb.Dataset.create.valid(dtrain, test$data, label = test$label)
valids <- list(test = dtest)

params <- list(objective = "regression",
               metric = "rmse",
               device = "gpu",
               gpu_platform_id = 0,
               gpu_device_id = 0,
               nthread = 1,
               boost_from_average = FALSE,
               num_tree_per_iteration = 10,
               max_bin = 32)
model <- lgb.train(params,
                   dtrain,
                   2,
                   valids,
                   min_data = 1,
                   learning_rate = 1,
                   early_stopping_rounds = 10)
```

Make sure you list the OpenCL devices in your system and set `gpu_platform_id` and `gpu_device_id` correctly. In the following examples, our system has 1 GPU platform (`gpu_platform_id = 0`) from AMD APP SDK. The first device `gpu_device_id = 0` is a GPU device (AMD Oland), and the second device `gpu_device_id = 1` is the x86 CPU backend.

Example of using GPU (`gpu_platform_id = 0` and `gpu_device_id = 0` in our system):

```
> params <- list(objective = "regression",
+                metric = "rmse",
+                device = "gpu",
+                gpu_platform_id = 0,
+                gpu_device_id = 0,
+                nthread = 1,
+                boost_from_average = FALSE,
+                num_tree_per_iteration = 10,
+                max_bin = 32)
> model <- lgb.train(params,
+                    dtrain,
+                    2,
+                    valids,
+                    min_data = 1,
+                    learning_rate = 1,
+                    early_stopping_rounds = 10)
```

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```
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 232
[LightGBM] [Info] Number of data: 6513, number of used features: 116
[LightGBM] [Info] Using GPU Device: Oland, Vendor: Advanced Micro Devices, Inc.
[LightGBM] [Info] Compiling OpenCL Kernel with 16 bins...
[LightGBM] [Info] GPU programs have been built
[LightGBM] [Info] Size of histogram bin entry: 12
[LightGBM] [Info] 40 dense feature groups (0.12 MB) transferred to GPU in 0.004211 secs.␣
↪76 sparse feature groups.
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=16 and depth=8
[1]:    test's rmse:1.10643e-17
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=7 and depth=5
[2]:    test's rmse:0
```

Running on OpenCL CPU backend devices is in generally slow, and we observe crashes on some Windows and macOS systems. Make sure you check the `Using GPU Device` line in the log and it is not using a CPU. The above log shows that we are using `Oland` GPU from AMD and not CPU.

Example of using CPU (`gpu_platform_id = 0`, `gpu_device_id = 1`). The GPU device reported is `Intel(R) Core(TM) i7-4600U CPU`, so it is using the CPU backend rather than a real GPU.

```
> params <- list(objective = "regression",
+                metric = "rmse",
+                device = "gpu",
+                gpu_platform_id = 0,
+                gpu_device_id = 1,
+                nthread = 1,
+                boost_from_average = FALSE,
+                num_tree_per_iteration = 10,
+                max_bin = 32)
> model <- lgb.train(params,
+                    dtrain,
+                    2,
+                    valids,
+                    min_data = 1,
+                    learning_rate = 1,
+                    early_stopping_rounds = 10)
[LightGBM] [Info] This is the GPU trainer!!
[LightGBM] [Info] Total Bins 232
[LightGBM] [Info] Number of data: 6513, number of used features: 116
[LightGBM] [Info] Using requested OpenCL platform 0 device 1
[LightGBM] [Info] Using GPU Device: Intel(R) Core(TM) i7-4600U CPU @ 2.10GHz, Vendor:␣
↪GenuineIntel
[LightGBM] [Info] Compiling OpenCL Kernel with 16 bins...
[LightGBM] [Info] GPU programs have been built
[LightGBM] [Info] Size of histogram bin entry: 12
[LightGBM] [Info] 40 dense feature groups (0.12 MB) transferred to GPU in 0.004540 secs.␣
↪76 sparse feature groups.
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=16 and depth=8
[1]:    test's rmse:1.10643e-17
```

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```
[LightGBM] [Info] No further splits with positive gain, best gain: -inf
[LightGBM] [Info] Trained a tree with leaves=7 and depth=5
[2]:    test's rmse:0
```

Known issues:

- Using a bad combination of `gpu_platform_id` and `gpu_device_id` can potentially lead to a **crash** due to OpenCL driver issues on some machines (you will lose your entire session content). Beware of it.
- On some systems, if you have integrated graphics card (Intel HD Graphics) and a dedicated graphics card (AMD, NVIDIA), the dedicated graphics card will automatically override the integrated graphics card. The workaround is to disable your dedicated graphics card to be able to use your integrated graphics card.

The content of this document was very outdated and is no longer available to avoid any misleadings.

Starting from the `3.2.0` version LightGBM Python packages have been having built-in support of training on GPU devices.

The content of this document was very outdated and is no longer available to avoid any misleadings.

CHAPTER

SEVENTEEN

DOCUMENTATION

Documentation for LightGBM is generated using Sphinx and Breathe, which works on top of Doxygen output.

List of parameters and their descriptions in Parameters.rst is generated automatically from comments in config file by this script.

After each commit on `master`, documentation is updated and published to Read the Docs.

17.1 Build

It is not necessary to re-build this documentation while modifying LightGBM's source code. The HTML files generated using `Sphinx` are not checked into source control. However, you may want to build them locally during development to test changes.

17.1.1 Docker

The most reliable way to build the documentation locally is with Docker, using the same images Read the Docs uses.

Run the following from the root of this repository to pull the relevant image and run a container locally.

```
docker run \
    --rm \
    --user=0 \
    -v $(pwd):/opt/LightGBM \
    --env C_API=true \
    --env CONDA=/opt/miniforge \
    --env READTHEDOCS=true \
    --workdir=/opt/LightGBM/docs \
    --entrypoint="" \
    readthedocs/build:ubuntu-24.04-2024.06.17 \
    /bin/bash build-docs.sh
```

When that code completes, open `docs/_build/html/index.html` in your browser.

Note

The navigation in these locally-built docs does not link to the local copy of the R documentation. To view the local version of the R docs, open `docs/_build/html/R/index.html` in your browser.

17.1.2 Without Docker

You can build the documentation locally without Docker. Just install Doxygen and run in `docs` folder

```
pip install breathe sphinx 'sphinx_rtd_theme>=0.5'
make html
```

Note that this will not build the R documentation. Consider using common R utilities for documentation generation, if you need it. Or use the Docker-based approach described above to build the R documentation locally.

Optionally, you may also install `scikit-learn` and get richer documentation for the classes in `Scikit-learn API`.

If you faced any problems with Doxygen installation or you simply do not need documentation for C code, it is possible to build the documentation without it:

```
pip install sphinx 'sphinx_rtd_theme>=0.5'
export C_API=NO || set C_API=NO
make html
```

CHAPTER

EIGHTEEN

INDICES AND TABLES

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