VDL Documentation

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Contents:

This documentation documents how to reproduce the result in the VDL project. The most update-to-date version can be found in the VDL github repository

The final presentation is hosted here. The pdf version can be downloaded from `here`

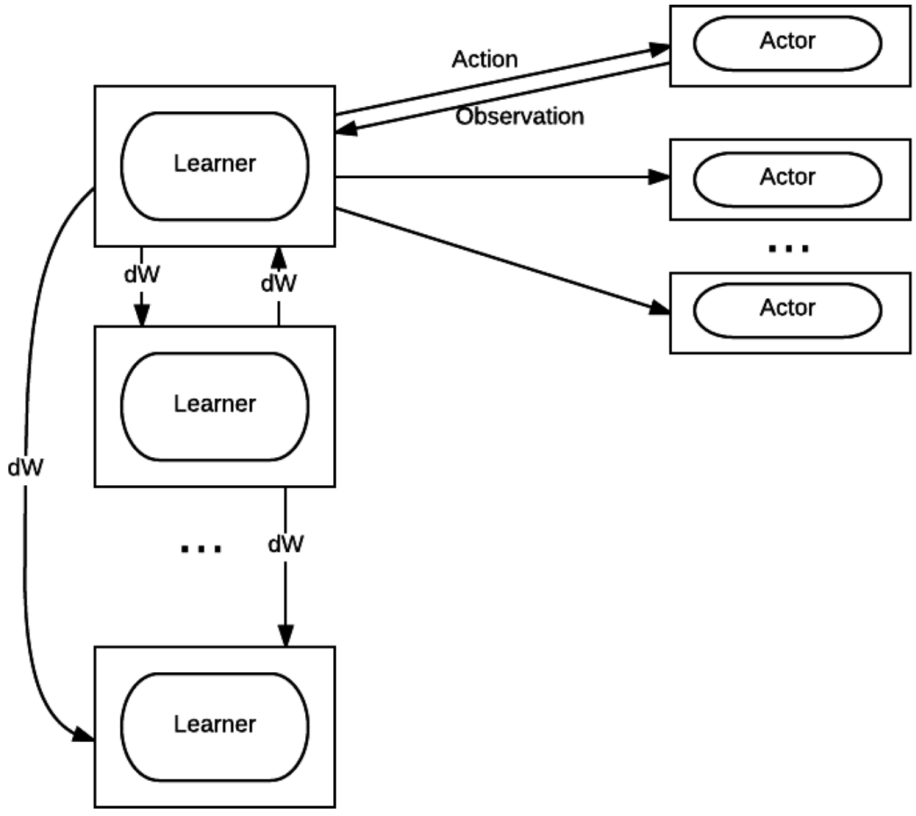


Fig. 1: The architecture with multiple learners and multiple actors

This project implements the distributed learning system as shown in the above figure. How to run and benchmark each component and how to run the complete system are documented in the following sections.

CHAPTER 1

Multiple learners component

1.1 Multiple learners on Tensorflow MNIST

First, please go to *tensorflow_MNIST* folder. To run P2P multi-learner code on Tensorflow MNIST task, you can use either unreliable Python multicast (slightly faster) or reliable Spread mutlicast. To run Python multicast, do:

```
python mnist_mcast_peer.py <num_peers> <my_peer_ID> <batch_size> <num_rounds>
```

For instance, if you want to run 4 parallel learners, each with a data batch size of 100 and 250 rounds each, do on four different machines:

```
python mnist_mcast_peer.py 4 1 100 250
python mnist_mcast_peer.py 4 2 100 250
python mnist_mcast_peer.py 4 3 100 250
python mnist_mcast_peer.py 4 4 100 250
```

To synchronize the training, you also need to run a short script after all 4 learner programs have been started. Do:

```
python start_mcast.py
```

To run Spread mutlicast, do:

```
python mnist_spread_peer.py <num_peers> <my_peer_ID> <batch_size> <num_rounds>
```

The corresponding commands for 4 parallel learners will be:

```
python mnist_spread_peer.py 4 1 100 250
python mnist_spread_peer.py 4 2 100 250
python mnist_spread_peer.py 4 3 100 250
python mnist_spread_peer.py 4 4 100 250
```

Similarly, to synchronize the training, do:

```
python start_spread.py
```

1.2 Multiple learners on Neonrace task

First, please go to *universe-starter-agent* folder. To run P2P multi-learner code on Neonrace task, say for 3 paralell learners for example, do:

```
python run.py --num-workers 3 --log-dir train-log/pong-multi-learners-0 -id 0
python run.py --num-workers 3 --log-dir train-log/pong-multi-learners-1 -id 1
python run.py --num-workers 3 --log-dir train-log/pong-multi-learners-2 -id 2
```

In any machine

```
python start_spread.py
```

To clean up the train log

```
rm train-log/pong-multi-learners* -r
```

CHAPTER 2

Run 5 learners and 10 actors in a cluster

The setup and execution is a complex procedure. If not clear, please report an issue in the issue tracker

2.1 Install dependencies for the code

The complete system requires several dependencies. The dependencies are:

- docker
- **python libraries**
  - OpenAI gym
  - OpenAI universe
  - Tensorflow
- The learning code for neonrace is modified from openai/universe-starter-agent

An installation script is provided in `universe-starter-agent/install/install.sh`

2.2 Modify the cluster configuration

The multiple-learner component is implemented with distributed tensorflow.

The learner configuration is hard coded in `universe-starter-agent/ccv1_cluster_spec.py`. Modify this file according to your cluster spec.

In the following document, the parameter server will be `ccv12`. And the other five machines `ccv11-5` will run learners. The parameter server is responsible for coordinating weights between learners.

2.3 Start the parameter server

In the machine for parameter server, `ccvl2`, start the parameter server with

```
cd universe-starter-agent/
sh run_ps.sh
```

`universe-starter-agent/run_ps.sh` will start `ps_run.py` with proper parameters.

2.4 Start five learners

In each machine from *ccvl1-5*, start the learner with

```
sh run_learner.sh 0
```

The number 0 is the worker id for ccvl1, number 1 will be the id for ccvl2.

The learner will wait until all actors are connected.

2.5 Start all actors and start learning

Start docker which contains the `neonrace` virtual environment. This script will start two docker containers, each running a neonrace virtual environment.

```
sh run_docker.sh
```

Start the actor code with

```
sh run_actor.sh
```

`run_actor.sh` will run `actor.py` with proper parameters.

2.6 Check the learning result

The learning procedure can be visualized by connecting to the docker container through vnc.

Use TurboVNC client to connect to `ccvl1.ccvl.jhu.edu:13000`. Change the url to your own configuration.

The learnt models will be stored in `train-log` folder. Use *tensorboard* to visualize the result, or use the code in `neonrace` to use trained model.

CHAPTER 3

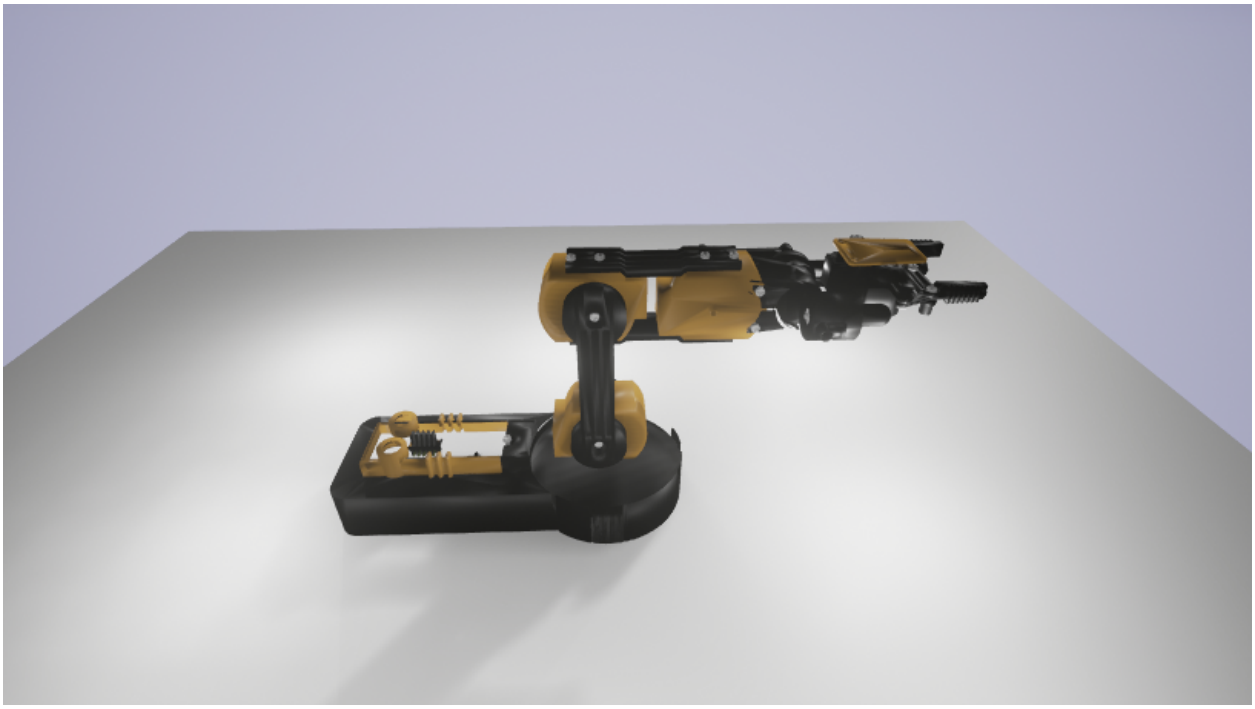
The virtual robot arm

The virtual arm is stored in a different repository qiuwch/UE4VirtualArm. This is because the 3D CAD models are very large. This repository is still in private mode, because we are still finializing the design and will release it together with a publication. If you are interested in this project, please send an email to qiuwch@gmail.com to request access.

A compiled virtual arm binary can be downloaded.

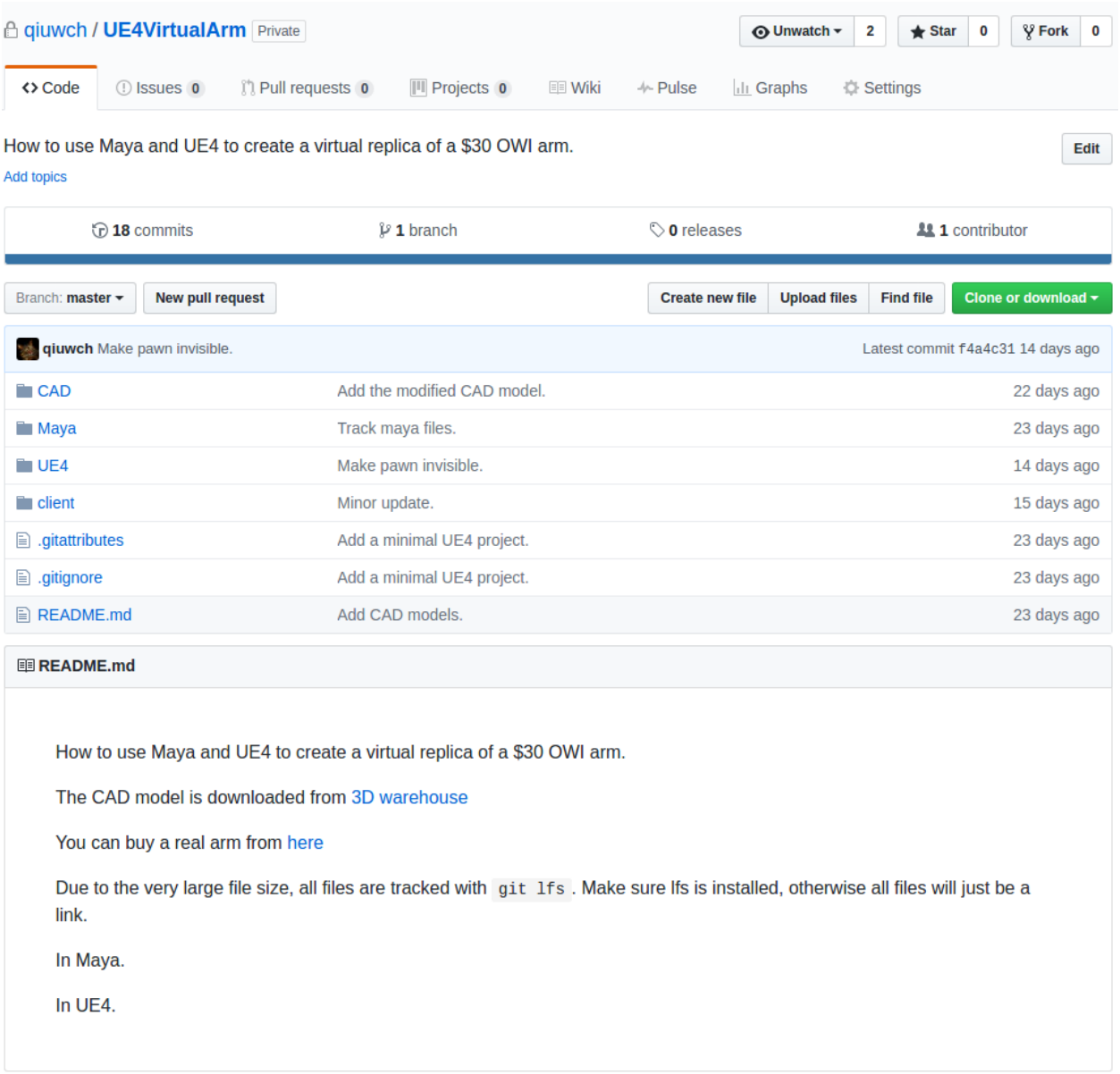
- Windows version
- Linux version

The screenshot of the virtual arm



The arm is placed in an empty environment. If you want to place the arm to a different virtual environment. The access to the source project is required.

This virutal arm can be controlled with the unrealcv project.



CHAPTER 4

Files in this project

```
# Main
docs/                   # Documentation files in reStructuredText format
universe-starter-agent/ # Virtual distributed learning system, the code is
# modified from https://github.com/openai/universe-starter-agent, which
# provides the baseline learning algorithm.

# Components
learner-actor/          # Experiment code for learner-actor communication
tensorflow_MNIST/       # Experiment code for P2P-multi-learner

# Utility
gym-demo/               # Virtual environnment demos to make sure the dev
# boxs are correctly configured.
benchmark/              # Benchmark code to evaluate the network speed and
# speed of different virtual environments
neonrace/               # Code to run trained neonrace auto-driving model
spread/                 # Compiled spread and its python wrapper

# Virtual arm
arm-pose/               # Pose estimation code trained on the virtual arm
# and test on the real arm.
owi-arm/                # Code to control real and the virtual arm
```