

---

**hexia**

*Release 0.0.1*

**Jun 30, 2019**



---

## Tutorials

---

<b>1 Quickstart</b>	<b>3</b>
<b>2 Indices and tables</b>	<b>9</b>



This is **Hexia**. A **PyTorch** based framework for building visual question answering models. Hexia provides a mid-level API for seamless integration of your VQA models with pre-defined data, image preprocessing and natural language preprocessing pipelines.



**Author:** Ali Gholami

In this section, we'll walk through general examples that help you get hexia up and running with your own vqa models.

## 1.1 Installation

1. Clone the repository and enter it:

```
git clone https://github.com/aligholami/hexia && cd hexia
```

1. Run the **setup.py** to install dependencies:

```
python3 setup.py install --user
```

## 1.2 Examples

### 1.2.1 Preparing Images

Image preprocessing with a custom CNN architecture:

```
import torch.nn as nn
from hexia.backend.cnn.resnet import resnet
from hexia.preprocessing.vision import Vision
from hexia.tests import config

# define your own image feature extractor which inherits pytorch nn module
class myCNN(nn.Module):

    def __init__(self):
```

(continues on next page)

(continued from previous page)

```

super(myCNN, self).__init__()
self.model = resnet.resnet101(pretrained=True)

def save_output(module, input, output):
    self.buffer = output

self.model.layer4.register_forward_hook(save_output)

def forward(self, x):
    self.model(x)
    return self.buffer

# perform image preprocessing with your custom CNN
my_cnn = myCNN().cuda()
visual_preprocessor = Vision(
    transforms_to_apply=['none'],
    cnn_to_use=myCNN,
    path_to_save=config.preprocessed_path,
    path_to_train_images=config.train_path,
    path_to_val_images=config.val_path,
    batch_size=config.preprocess_batch_size,
    image_size=config.image_size,
    keep_central_fraction=config.central_fraction,
    num_threads_to_use=8
)
visual_preprocessor.initiate_visual_preprocessing()

```

The above code will load your defined model (either pre-trained or from scratch) and saves the extracted features to **path\_to\_save**.

## 1.2.2 Preparing Questions and Answers

Text preprocessing with one of the available models (GloVe or Word2Vec):

```

from hexia.preprocessing.language import Language
from hexia.tests import config

language_preprocessor = Language(
    max_answers=config.max_answers,
    save_vocab_to=config.vocabulary_path
)
language_preprocessor.initiate_vocab_extraction()

# Remove this line if you want to use Word2Vec embeddings
language_preprocessor.extract_glove_embeddings(
    dims=50,
    path_to_pretrained_embeddings=config.glove_embeddings,
    save_vectors_to=config.glove_processed_vectors,
    save_words_to=config.glove_words,
    save_ids_to=config.glove_ids
)

```

The above code will tokenize the VQA dataset and saves extracted GloVe vectors to **save\_vectors\_to**. If you want to use random Word2Vec embeddings, simply remove the call to **extract\_glove\_embeddings**; the framework will automatically switch to randomly initialized Word2Vec embeddings.



## 1.2.3 Training, Validation and Checkpointing

Model training, validation and checkpointing:

```
import torch
import torch.nn as nn
import torch.optim as optim
from tensorboardX import SummaryWriter
import os
from hexia.backend.utilities import utils
from hexia.tests import config
from hexia.backend.monitoring.tracker import Tracker
from hexia.runtime.train_val import TrainValidation
from hexia.vqa.models.joint import M_Resnet18_randw2v_NoAtt_Concat as model

# Prepare dataset
train_loader, val_loader = utils.prepare_data_loaders(path_to_feature_maps=config.
↳preprocessed_path,
                                                    batch_size=config.batch_size,
↳num_workers=config.data_workers)

# Build the model
net = nn.DataParallel(model.Net(train_loader.dataset.num_tokens)).cuda()
optimizer = optim.Adam([p for p in net.parameters() if p.requires_grad])
tracker = Tracker()
train_writer = SummaryWriter(config.visualization_dir + 'train')
val_writer = SummaryWriter(config.visualization_dir + 'val')

# Separate objects for train and validation (enables auto-resume on valid path,
↳settings)
vqa_trainer = TrainValidation(net, train_loader, optimizer, tracker, train_writer,
↳train=True, prefix='train',
                               latest_vqa_results_path=config.latest_vqa_results_path)
vqa_validator = TrainValidation(net, val_loader, optimizer, tracker, val_writer,
↳train=False, prefix='val', latest_vqa_results_path=None)

best_loss = 10.0
best_accuracy = 0.1
for epoch in range(config.num_epochs):
    _ = vqa_trainer.run_single_epoch()
    r = vqa_validator.run_single_epoch()

train_writer.close()
val_writer.close()
```

The above code will create two separate data loaders for train and validation (with their respective image paths). Then you may use **Tracker** and **TensorboardX.SummaryWriter** classes to track and visualize the training and validation process. Note that it is important to use the parameter **latest\_vqa\_results\_path** only once among all objects. To enable **auto\_resume** functionality while re-running the code, you can add the following to your higher-level training and validation loop:

```
if r['epoch_accuracy'] > best_accuracy and r['epoch_loss'] < best_loss:
    # Update best accuracy and loss
    best_accuracy = r['epoch_accuracy']
    best_loss = r['epoch_loss']
```

(continues on next page)

(continued from previous page)

```

# Clear path from previous saved models and pre-evaluation files
try:
    os.remove(config.best_vqa_weights_path)
    os.remove(config.best_vqa_answers_to_eval)
except FileNotFoundError as fe:
    pass

# Save the new model weights
weights = net.state_dict()
torch.save(weights, config.best_vqa_weights_path)

# Save ans, idxs and qids for later evaluation
utils.save_for_vqa_evaluation(r['answ'], r['ids'], r['qids'])

checkpoint = {
    'epoch': r['epoch'],
    'model_state_dict': net.state_dict(),
    'optimizer_state_dict': optimizer.state_dict(),
    'tracker': tracker.to_dict(),
    'vocab': train_loader.dataset.vocab,
    'train_iters': r['train_iters'],
    'val_iters': r['val_iters'],
    'prefix': r['prefix'],
    'train': r['train'],
    'loader': r['loader']
}

torch.save(checkpoint, config.latest_vqa_results_path)

```

In this code, variable `r` contains crucial information about the last training and validation step, writer, tracker and optimizable model parameters status.

Note: If you would like to use your custom VQA model, you may import it as a replacement of this line:

```
from hexia.vqa.models.joint import M_Resnet18_randw2v_NoAtt_Concat as model
```

your model should inherit the `nn.Module` and its overridden forward function should look like this:

```
def forward(self, v, q, q_len):
    # your vqa logic to compute an answer
    return answer
```

## 1.2.4 Model Evaluation

Evaluating the trained model (based on official evaluation class):

```

# Import the evaluation module
from hexia.vqa.evaluation.evaluator import VQAEvaluator

v_evaluator = VQAEvaluator(
    data_directory=config.data_directory,
    best_model_results_directory=config.best_vqa_answers_to_eval)

```

(continues on next page)

(continued from previous page)

```
v_evaluator.evaluate_best_vqa_model()
```

Parameter **data\_directory** specifies the directory of data (make sure its according to the official format), and **best\_model\_results\_directory** is the path to the generated JSON file as the answers to the best model.



## CHAPTER 2

---

### Indices and tables

---

- `genindex`
- `modindex`
- `search`