Poutyne

An Easy and Flexible Deep Learning Framework for PyTorch

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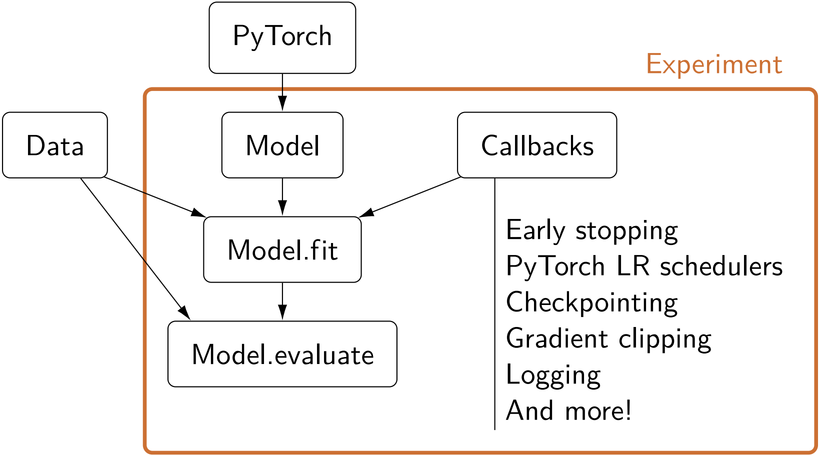
What Is Poutyne?

- Framework for training neural networks with PyTorch
- Includes checkpointing and logging mechanisms
- Allows to setup experiments quickly

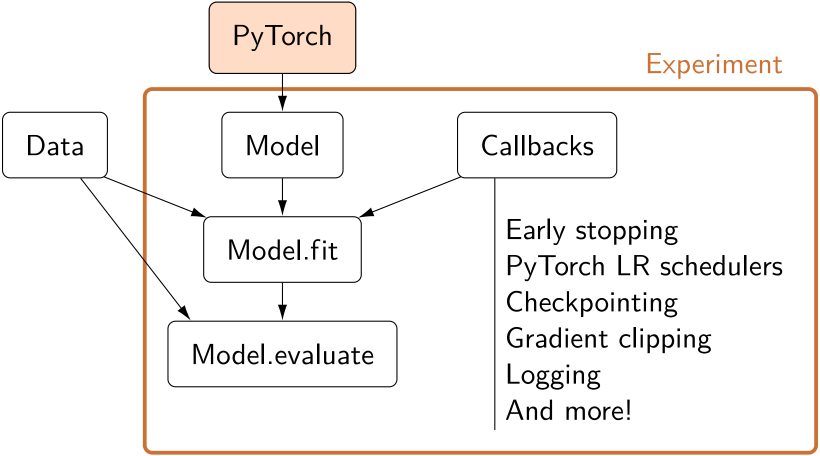
Core Principles

- Easy to use for simple use cases
- Flexible enough for more complex use cases
- Callbacks are your friends

Poutyne Flow



Poutyne Flow



PyTorch

- Automatic differentiation Python library
- For every differentiable operation done in the "forward" pass, backpropagation is done in the "backward" pass.

```
from torch import nn

class MnistLogistic(nn.Module):
    def __init__(self):
        super().__init__()
        self.weights = nn.Parameter(torch.randn(784, 10) /
                                    math.sqrt(784)) # W
        self.bias = nn.Parameter(torch.zeros(10)) # b

    def forward(self, xb):
        return xb.matmul(self.weights) + self.bias # xW + b
```

Usual Code for Training With PyTorch

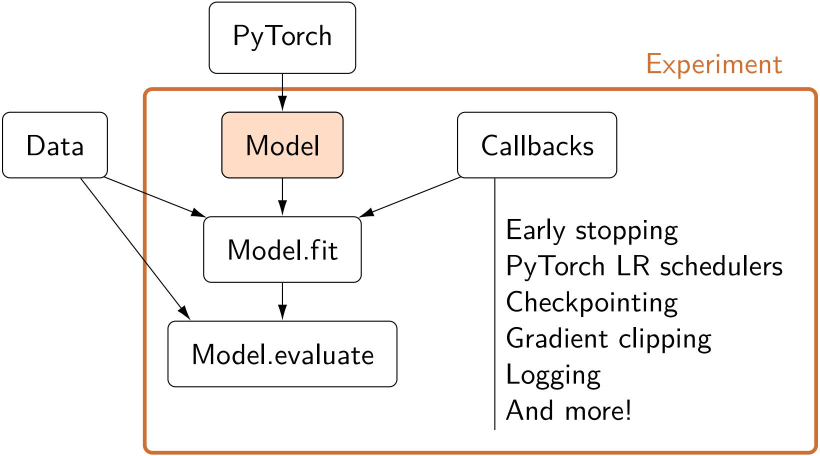
```python
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import TensorDataset, DataLoader

net = nn.Sequential(
    nn.Linear(100, 64),
    nn.ReLU(),
    nn.Linear(64, 10)
)

num_features = 100
num_classes = 10

train_dataset = TensorDataset(x_train, y_train)
train_loader = DataLoader(train_dataset, batch_size=32)

test_dataset = TensorDataset(x_test, y_test)
test_loader = DataLoader(test_dataset, batch_size=32)

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

```python
for epoch in range(5):  # loop over the dataset multiple times
    running_loss = 0.0
    for i, data in enumerate(train_loader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999:    # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' % (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0


correct = 0
total = 0
with torch.no_grad():
    for data in test_loader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (100 * correct / total))
```

Equivalent Code for Training With Poutyne

```
import torch.nn as nn
import torch.optim as optim
from poutyne.framework import Model

net = nn.Sequential(
    nn.Linear(100, 64),
    nn.ReLU(),
    nn.Linear(64, 10)
)

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)

model = Model(net, optimizer, criterion, batch_metrics=['accuracy'])
model.fit(x_train, y_train, epochs=5,  batch_size=32)
loss, accuracy = model.evaluate(x_test, y_test, batch_size=32)
```

Poutyne Flow

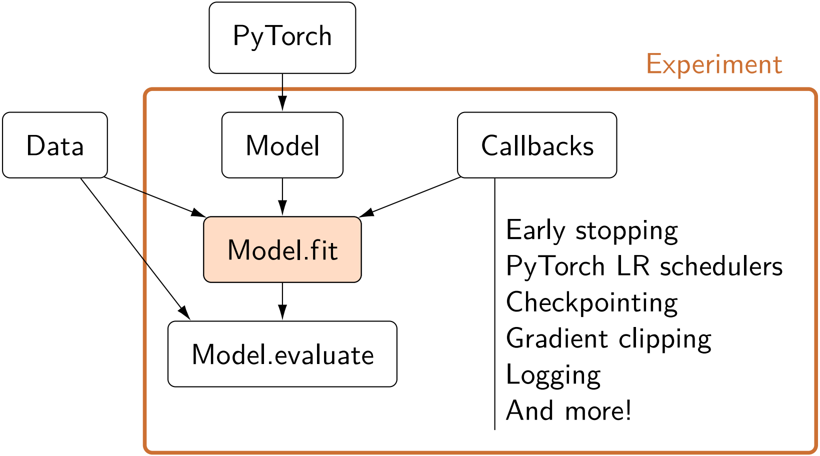


Model Class

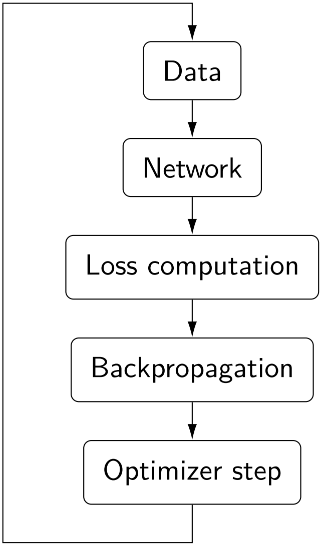
- Main class of the framework
- Plays well with Numpy
- No restrictions on the input or the output format of the network
- Manages devices (GPUs)

```
from poutyne.framework import Model

model = Model(network, optimizer, loss_function)
model.to(device)

model.fit_generator(train_loader, valid_loader,
                    epochs=num_epochs, callbacks=callbacks)

test_loss = model.evaluate_generator(test_loader)
```

Poutyne Flow



Poutyne Training Flow



Poutyne Training Flow

for n epochs **do**

for each drawn batch (x, y) in training dataset **do**

$$\hat{y} = f(x; \theta)$$
$$\ell = \mathcal{L}(\hat{y}, y)$$
$$g = \nabla_\theta \ell$$

Update θ with g using chosen optimizer.
Compute and accumulate metrics with $\hat{y}$ and y.

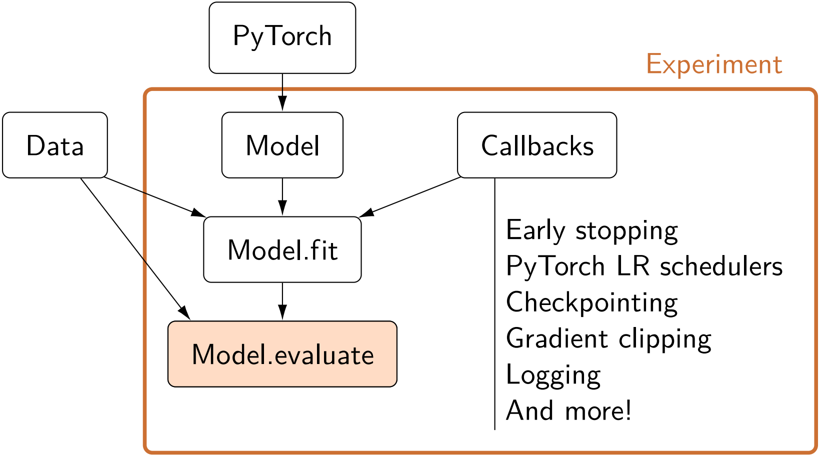
end for
Compute loss and metrics on validation dataset.

end for

Poutyne Training Flow

for n epochs **do**
    Callback on epoch begin
    for each drawn batch (x, y) in training dataset **do**
        Callback on batch begin
        $\hat{y} = f(x; \theta)$
        $\ell = \mathcal{L}(\hat{y}, y)$
        $g = \nabla_\theta \ell$
        Callback on backward end
        Update θ with g using chosen optimizer.
        Compute and accumulate metrics with $\hat{y}$ and y.
        Callback on batch end
    end for
    Compute loss and metrics on validation dataset.
    Callback on epoch end
end for

Poutyne Flow



Evaluation Metrics

Using metrics with Poutyne allows easy early stopping, checkpointing and logging.

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  - Provide a scikit-learn wrapper

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  - Non-decomposable metrics (e.g. F1, AUC ROC, etc.)
  - Provide a scikit-learn wrapper

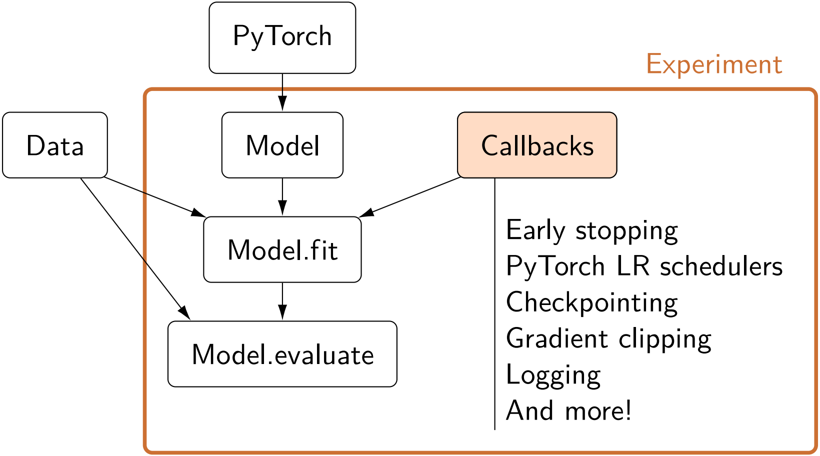
```python
from poutyne.framework import Model

model = Model(network, 'sgd', 'cross_entropy',
                batch_metrics=['accuracy'], epoch_metrics=['f1'])
model.to(device)

model.fit_generator(train_loader, valid_loader,
                    epochs=num_epochs, callbacks=callbacks)

test_loss, (test_acc, test_f1) = model.evaluate_generator(test_loader)
print(f'Test: Loss: {test_loss}, Accuracy: {test_acc}, F1: {test_f1}')
```

Poutyne Flow



Callbacks

```python
class Callback:
    def on_train_begin(self, logs: dict): ...
    def on_train_end(self, logs: dict): ...

    def on_epoch_begin(self, epoch_number: int, logs: dict): ...
    def on_epoch_end(self, epoch_number: int, logs: dict): ...

    def on_train_batch_begin(self, batch_number: int, logs: dict): ...
    def on_train_batch_end(self, batch_number: int, logs: dict): ...

    def on_backward_end(self, batch_number: int): ...

    def on_test_batch_begin(self, batch_number: int, logs: dict): ...
    def on_test_batch_end(self, batch_number: int, logs: dict): ...

    def on_test_begin(self, logs: dict): ...
    def on_test_end(self, logs: dict): ...

    self.params = {...} # Contains 'epochs' and 'steps_per_epoch'
    self.model = ... # Poutyne Model
```

Callbacks

```
from poutyne.framework import Model, ModelCheckpoint, CSVLogger

callbacks = [
    ModelCheckpoint('last_epoch.ckpt'),
    ModelCheckpoint('best_epoch.ckpt', save_best_only=True,
                    monitor='val_acc', mode='max'),
    CSVLogger('log.csv'),
]

model = Model(network, 'sgd', 'cross_entropy',
              batch_metrics=['accuracy'], epoch_metrics=['f1'])
model.to(device)

model.fit_generator(train_loader, valid_loader,
                    epochs=num_epochs, callbacks=callbacks)

test_loss, (test_acc, test_f1) = model.evaluate_generator(test_loader)
print(f'Test: Loss: {test_loss}, Accuracy: {test_acc}, F1: {test_f1}')
```

Checkpointing

- ModelCheckpoint
- OptimizerCheckpoint
- LRSchedulerCheckpoint

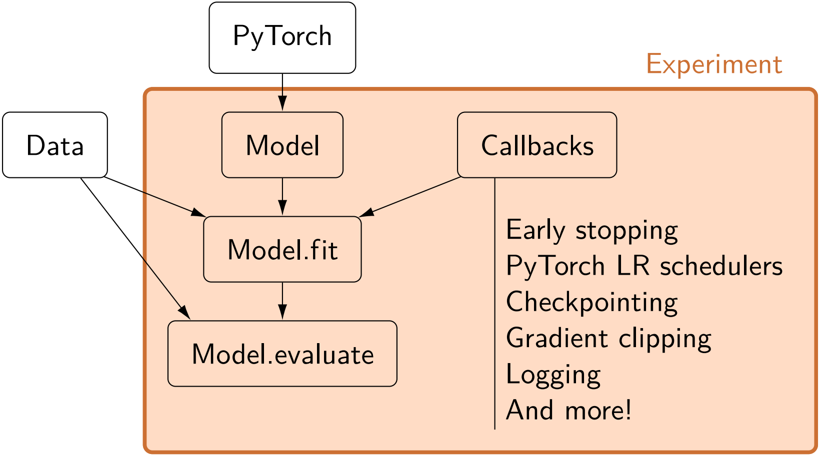
Early Stopping and LR Scheduling

- EarlyStopping
- Any PyTorch LR scheduler
- FastAI-like learning rate policies

Playing With Gradient

- Use PyTorch's respective functions
  - ClipNorm
  - ClipGrad
- TensorBoardGradientTracker

Poutyne Flow



Experiment Class

- Allows stopping and resuming optimization any time
- Saves and logs everything in a single directory
- Integration with Tensorboard

```
from poutyne.framework import Experiment

# Instead of `task`, you can provide your own loss function and metrics.
expt = Experiment('my_directory', network,
                  task='classifier', optimizer='sgd')
expt.train(train_loader, valid_loader,
           epochs=epochs,
           callbacks=callbacks,
           seed=42)
expt.test(test_loader)
```

Experiment Class

- Saves the last checkpoint and every “best” checkpoint (ModelCheckpoint).
- Saves the last states of the optimizer and LR schedulers (OptimizerCheckpoint, LRSchedulerCheckpoint).
- Logs training and validation loss and metrics into CSV and Tensorboard (CSVLogger, TensorBoardLogger).

Related Works

PyTorch Lightning:

- Flexible
- Couples network with training
  - Requires inherting from a special class
  - Everything training related is inside the network
- Add boilerplate where it should not (e.g. adding LR schedulers seems awkward)

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FastAI:

- Lots of features
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AllenNLP:

- Specialized for NLP
- Experiment framework
- Trainer not flexible enough (everything in `__init__`)

Demo Time

Fine-tuning with dataset:
`http://www.vision.caltech.edu/visipedia/CUB-200.html`

Future Works

- Add tqdm and colors for progression.
- Add tutorial pages to website.
- Integrate multi-GPU.
- Add a simpler way to add regularizer to the loss function.
- Add utilities to simplify parameters initialization.
- Integrate an experiment library such as MLFlow.

Obtain Poutyne

Install via pip

`pip install poutyne`

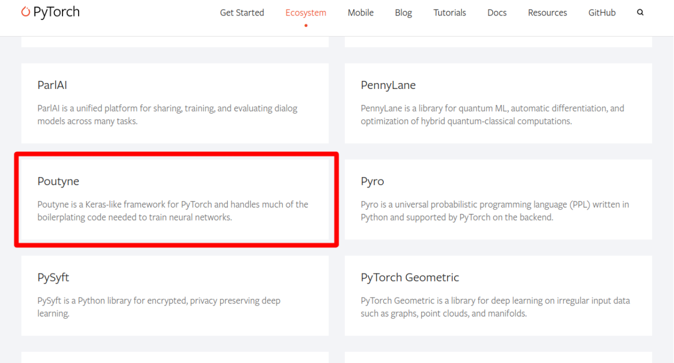
Documentation and examples available!

`https://poutyne.org`

GRAAL-Research/poutyne

Poutyne in the PyTorch Ecosystem

https://pytorch.org/ecosystem/



The end.

Questions?