Deep Learning

Lab0: PyTorch Warm-up

Department of Computer Science, NYCU

TA 劉子齊 Jonathan

Reference: Stanford CS231n

Frameworks

TensorFlow

PyTorch

PaddlePaddle

Microsoft CNTK

Keras

torch

Chainer

Caffe2

DL4J

mxnet

Caffe

And others……

Frameworks

Most people use these

TensorFlow

PyTorch

PaddlePaddle

Microsoft CNTK

Keras

torch

Chainer

Caffe2

DL4J

mxnet

Caffe

And others……

Frameworks

We will focus on this

PyTorch

TensorFlow

PaddlePaddle

Microsoft CNTK

Keras

torch

Chainer

Caffe2

DL4J

mxnet

Caffe

And others……

Advantages of DL frameworks

- Developing and testing new ideas are quickly
- Computing gradients automatically
- Running model structures on GPU is efficiently

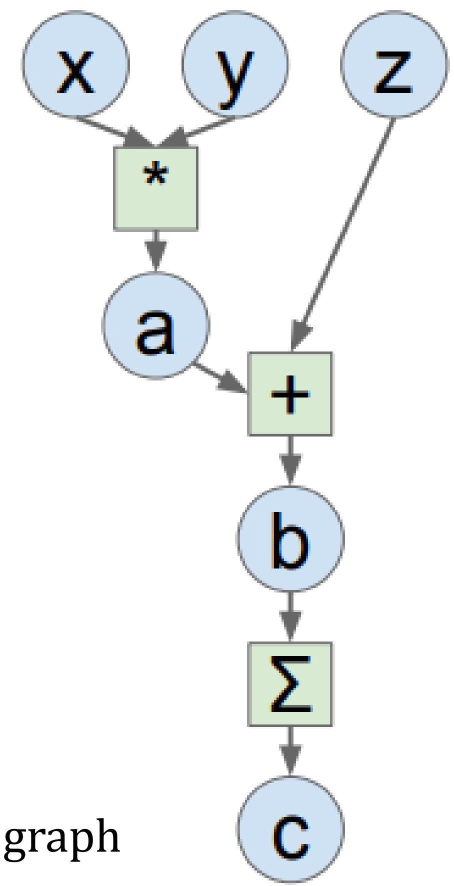
Please use PyTorch
to complete all your assignments !!

PyTorch PyTorch PyTorch

Computational Graphs

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)
```

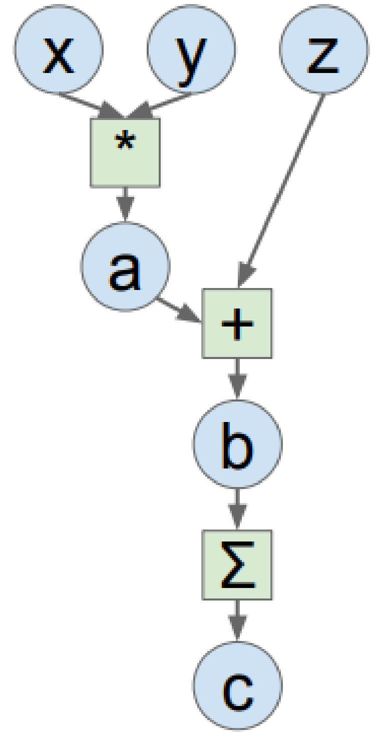
$$x \times y + z$$



Neural network can be denoted as a directed acyclic graph

Computational Graphs

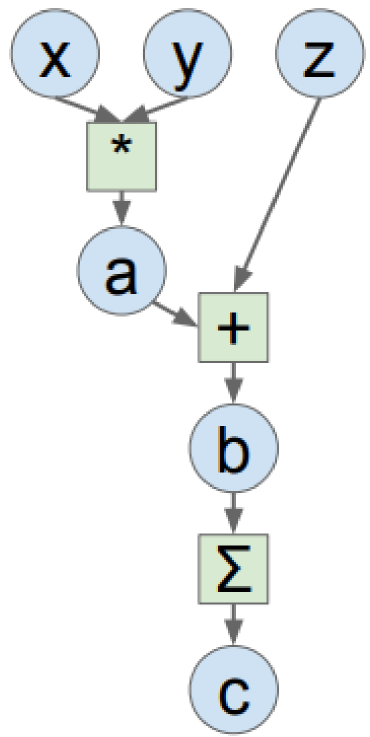
```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```



Problems:
- **Can't run on GPU**
- **Have to compute gradients ourself**

Computational Graphs

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```




```python
import torch

N, D = 3, 4

x = torch.randn(N, D)
y = torch.randn(N, D)
z = torch.randn(N, D)

a = x * y
b = a + z
c = torch.sum(b)
```

Looks exactly like numpy

Computational Graphs

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```

```python
import torch

N, D = 3, 4

x = torch.randn(N, D, requires_grad=True)
y = torch.randn(N, D)
z = torch.randn(N, D)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()
print(x.grad)
```

PyTorch handles gradients for us.

.backward() calculates the gradient

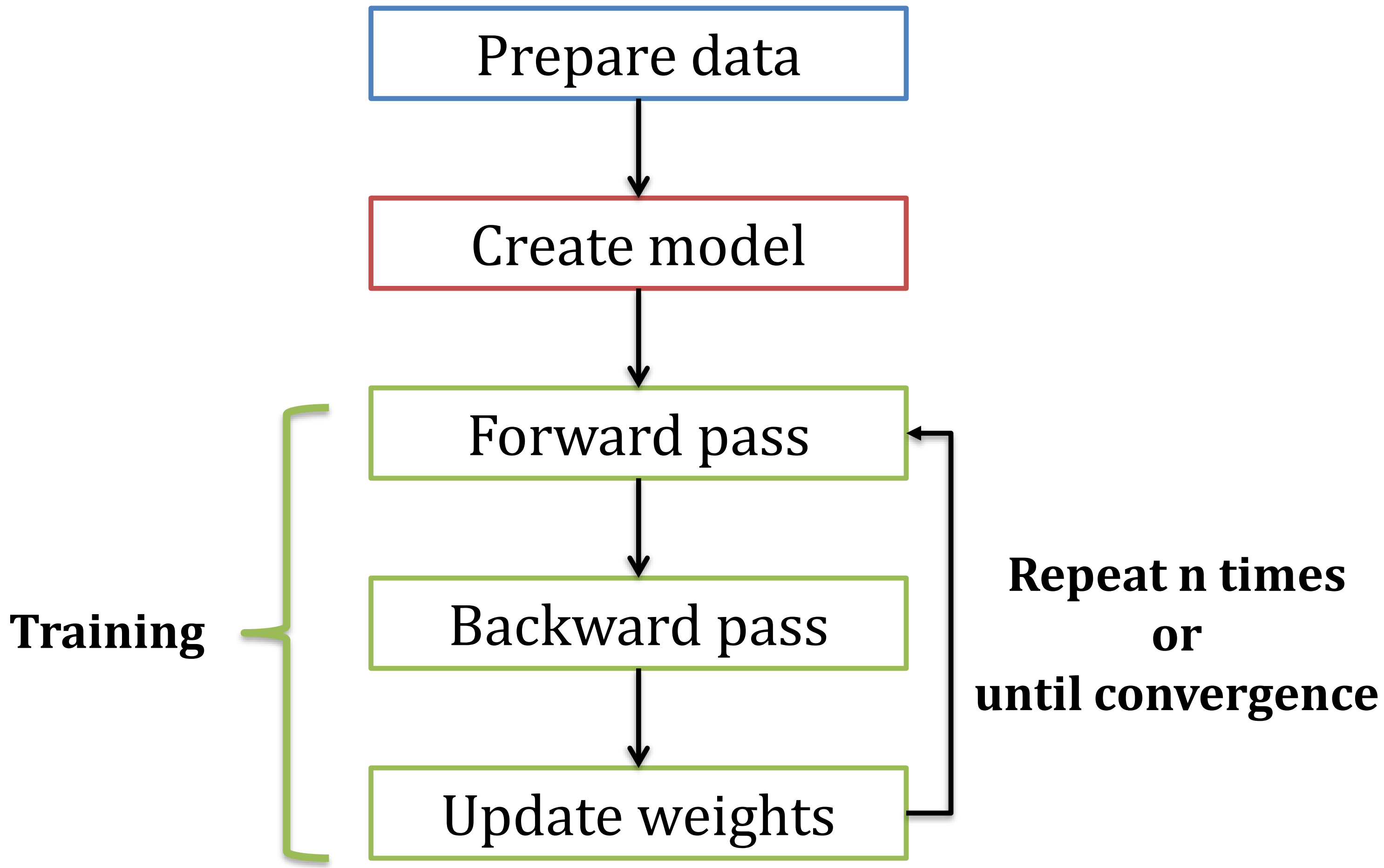
Computational Graphs

```python
import numpy as np
np.random.seed(0)

N, D = 3, 4

x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)

a = x * y
b = a + z
c = np.sum(b)

grad_c = 1.0
grad_b = grad_c * np.ones((N, D))
grad_a = grad_b.copy()
grad_z = grad_b.copy()
grad_x = grad_a * y
grad_y = grad_a * x
```

```python
import torch

device = 'cuda:0'
N, D = 3, 4

x = torch.randn(N, D, device=device,
                requires_grad=True)
y = torch.randn(N, D, device=device)
z = torch.randn(N, D, device=device)

a = x * y
b = a + z
c = torch.sum(b)

c.backward()
print(x.grad)
```

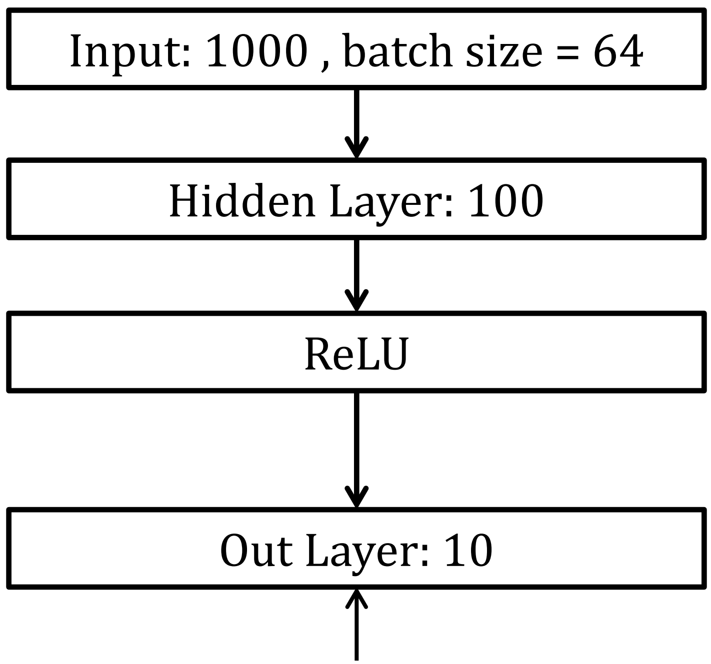
Trivial to run on GPU
- just construct arrays on a different device

Flow Chart


Prepare data
Create model
Forward pass
Backward pass
Update weights
Training
Repeat n times
or
until convergence

Example

- 2-layer network



x: 64×1000

w1: 1000×100

$$ReLU(x) = \begin{cases} x \ if \ x > 0 \\ 0 \ if \ x \leq 0 \end{cases}$$

w2: 100×10

Loss : sum of square error

$$\sum (\boldsymbol{y} - \widehat{\boldsymbol{y}})^{\mathbf{2}}$$

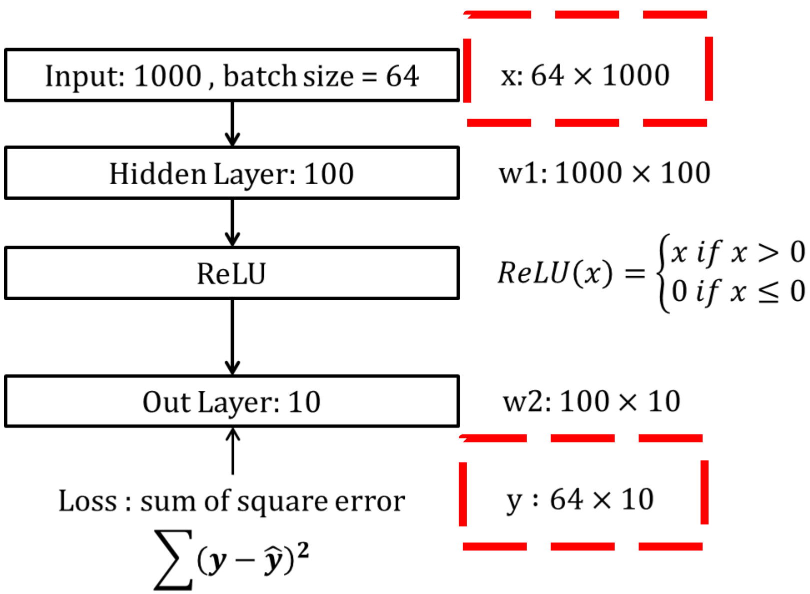
y : 64×10

Step1. Prepare Data
PyTorch Tensors

Create random tensors as input and ground truth

To run on GPU, just use a different device, like a following:

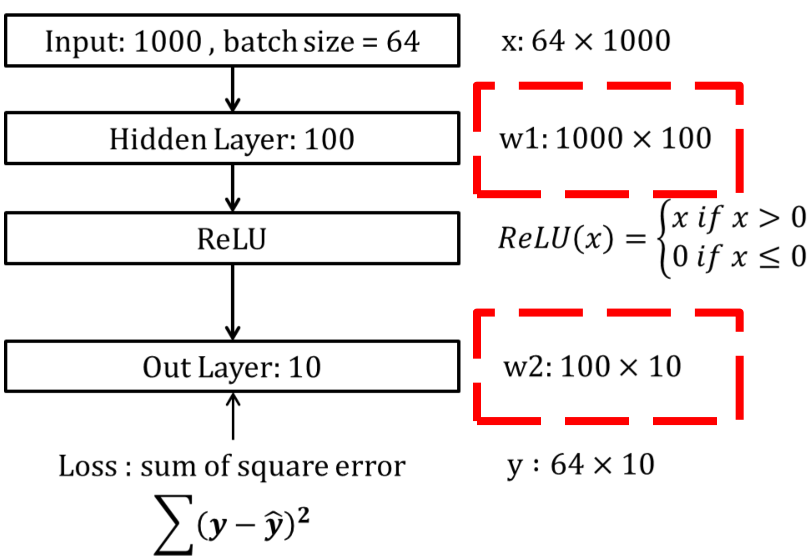
```
device = torch.device('cuda:0')
```




```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

Step2. Create Model
PyTorch Tensors

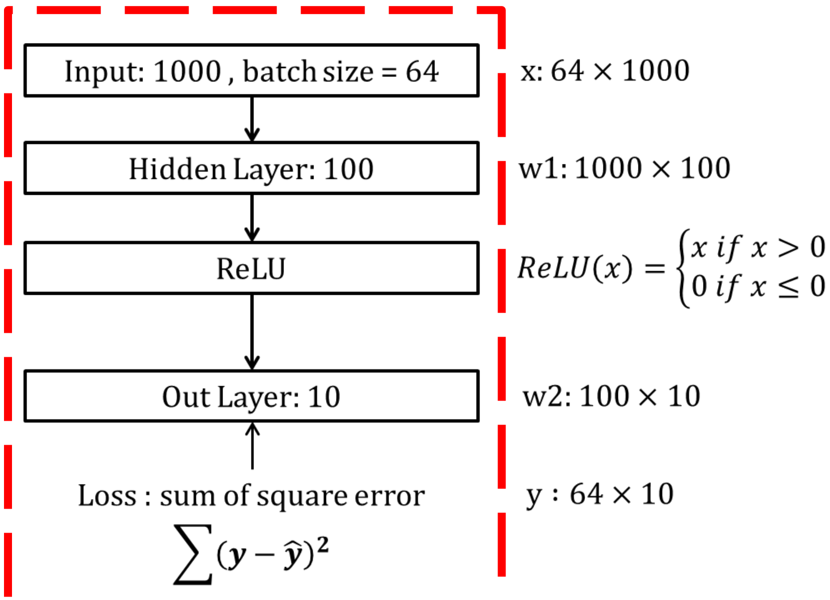
Create random tensors as layer weights




```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

Step3. Forward pass
PyTorch Tensors

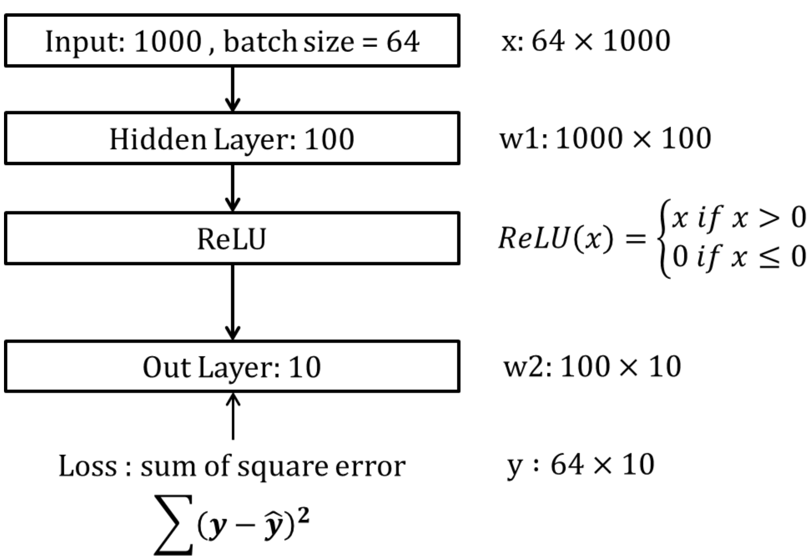
Compute predictions and loss




```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

Step4. Backward pass
PyTorch Tensors

Manually compute gradients

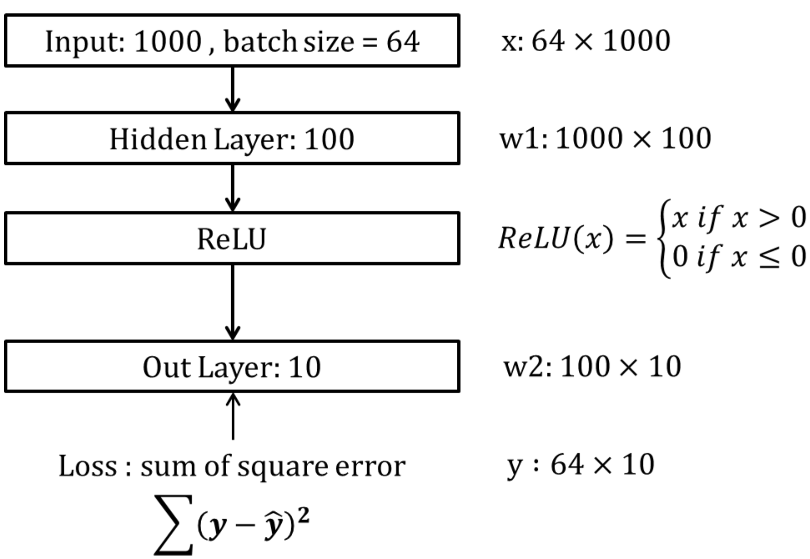



```python
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

Step5. Update Weights

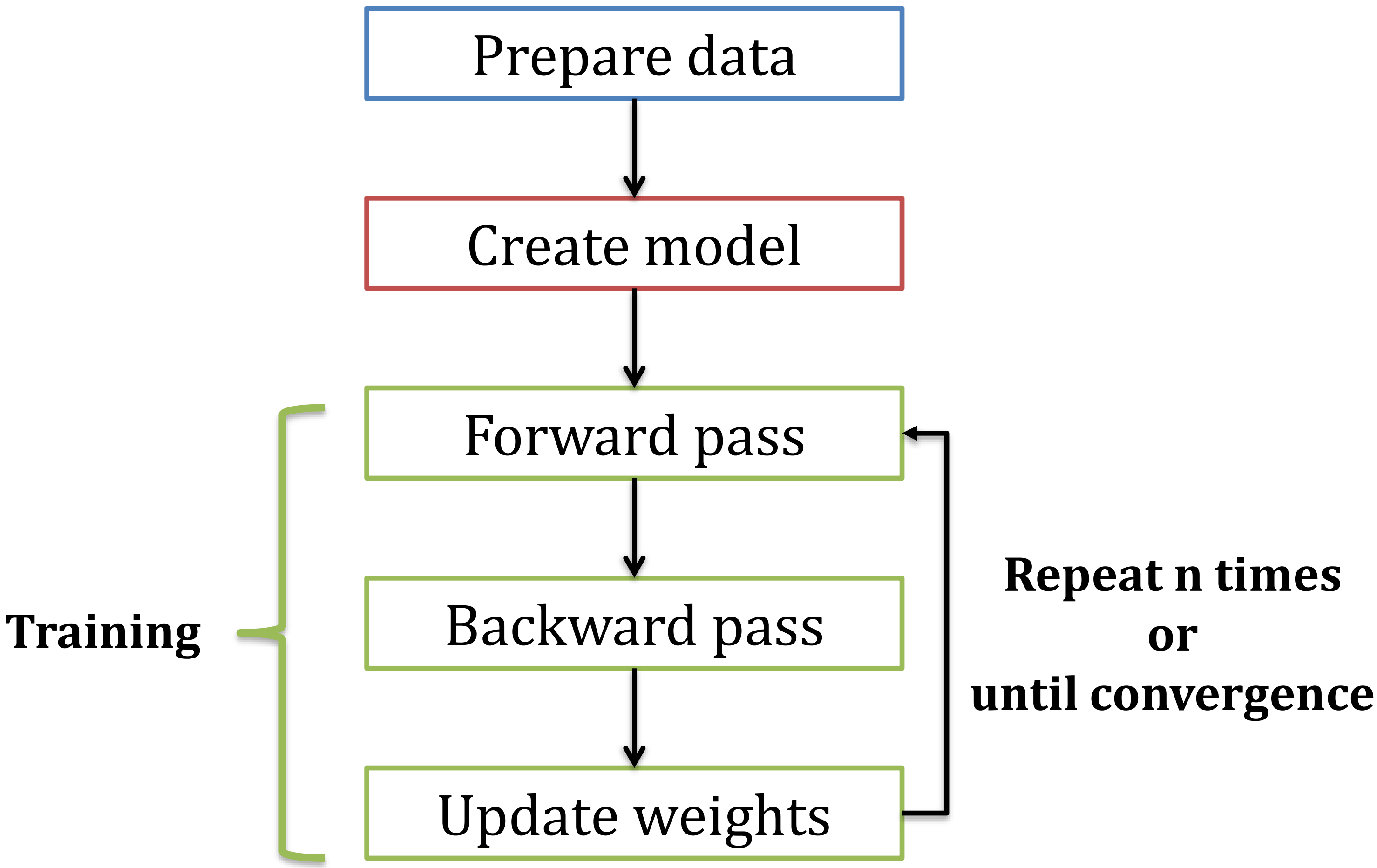
PyTorch Tensors

Gradient descent step on weights




```
import torch

device = torch.device('cpu')
learning_rate = 1e-6

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)

w1 = torch.randn(1000, 100, device=device)
w2 = torch.randn(100, 10, device=device)

for t in range(300):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y)

    grad_y_pred = 2.0 * loss
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h<0] = 0
    grad_w1 = x.t().mm(grad_h)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2

    print(loss.pow(2).sum())
```

Flow Chart


Prepare data
Create model
Forward pass
Backward pass
Update weights
Training
Repeat n times
or
until convergence

Easily implement your own deep learning model by using **PyTorch**

Step1. Prepare Data
PyTorch.utils.data

DataLoader wraps a **Dataset** and provides mini-batches, shuffling, multithreading for you

When you need to load custom data, just write your own Dataset class

Iterate over loader to form mini-batches

https://github.com/utkuozbulak/pytorch-custom-dataset-examples

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step2. Create Model
PyTorch.nn

Higher-level wrapper for working with neural nets

This will make your life A LOT easier

A PyTorch Module is a neural net layer; it can contain weights or other modules

Define your whole model as a single module

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step2. Create Model
PyTorch.nn

Initializer sets up two children (Module can contain Modules)

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step2. Create Model
PyTorch.nn

Define forward pass using child modules

Only need to define forward pass

Autograd will handle the rest of it

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step3. Forward pass

PyTorch.nn

Define forward pass using child modules

Pass data to the model and compute the loss

nn.functional has useful helpers like loss functions

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step4. Backward pass
PyTorch.autograd

Forward pass looks exactly the same as before, but we don't need to track intermediate values

PyTorch keeps track of them for us in the computational graph

Compute gradient of loss with respect to all model weights (they have requires_grad=True)

```python
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Step5. Update Weights
PyTorch.optim

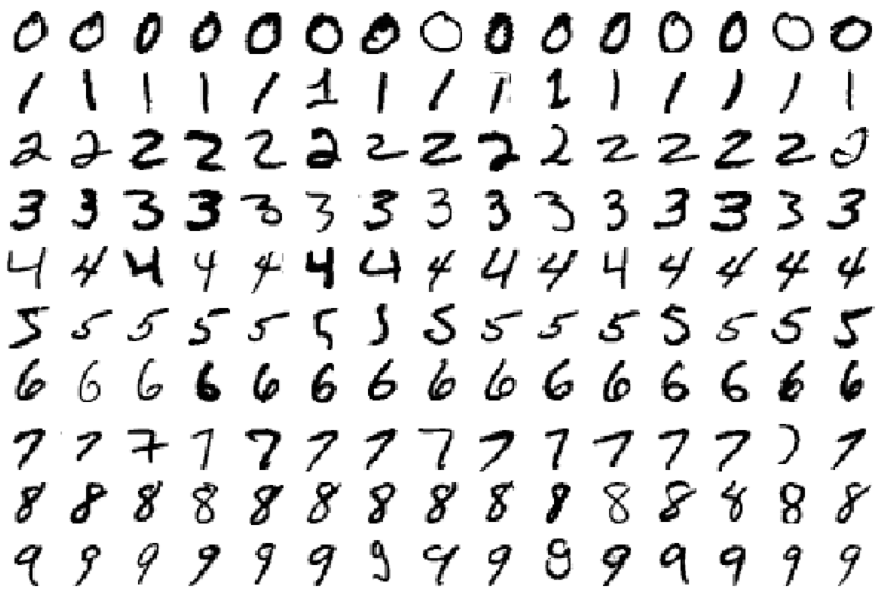
Use an **optimizer** for different update rules

After computing gradients, use optimizer to update each model parameters and reset gradients

```
import torch
from torch.utils.data import TensorDataset, DataLoader

device = torch.device('cpu')
learning_rate = 1e-2

x = torch.randn(64, 1000, device=device)
y = torch.randn(64, 10, device=device)
loader = DataLoader(TensorDataset(x, y), batch_size=8)

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear_1 = torch.nn.Linear(D_in, H)
        self.linear_2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h = self.linear_1(x)
        h_relu = torch.nn.functional.relu(h)
        y_pred = self.linear_2(h_relu)
        return y_pred

model = TwoLayerNet(D_in=1000, H=100, D_out=10)
model = model.to(device)

optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for epochs in range(50):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred,
                                            y_batch)
        print(loss.item())

        loss.backward()

        optimizer.step()
        optimizer.zero_grad()
```

Real Application

MNIST example for PyTorch



https://github.com/pytorch/examples/tree/master/mnist

Build and train a CNN classifier

- Data Loader
- Define Network
- Define Optimizer/Loss function
- Learning rate scheduling
- Training
- Testing
- Run and Save model

Set hyperparameters

```python
    # Training settings
    parser = argparse.ArgumentParser(description='PyTorch MNIST Example')
    parser.add_argument('--batch-size', type=int, default=64, metavar='N',
                        help='input batch size for training (default: 64)')
    parser.add_argument('--test-batch-size', type=int, default=1000, metavar='N',
                        help='input batch size for testing (default: 1000)')
    parser.add_argument('--epochs', type=int, default=14, metavar='N',
                        help='number of epochs to train (default: 14)')
    parser.add_argument('--lr', type=float, default=1.0, metavar='LR',
                        help='learning rate (default: 1.0)')
    parser.add_argument('--gamma', type=float, default=0.7, metavar='M',
                        help='Learning rate step gamma (default: 0.7)')
    parser.add_argument('--no-cuda', action='store_true', default=False,
                        help='disables CUDA training')
    parser.add_argument('--dry-run', action='store_true', default=False,
                        help='quickly check a single pass')
    parser.add_argument('--seed', type=int, default=1, metavar='S',
                        help='random seed (default: 1)')
    parser.add_argument('--log-interval', type=int, default=10, metavar='N',
                        help='how many batches to wait before logging training status')
    parser.add_argument('--save-model', action='store_true', default=False,
                        help='For Saving the current Model')
    args = parser.parse_args()
```

Data Loader

Pytorch offers data loaders for popular dataset

The following datasets are available:

Datasets

- MNIST
- COCO
  - Captions
  - Detection
- LSUN
- ImageFolder
- Imagenet-12
- CIFAR
- STL10
- SVHN
- PhotoTour

Data Loader

```
transform=transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.1307,), (0.3081,))
    ])
dataset1 = datasets.MNIST('../data', train=True, download=True,
                   transform=transform)
dataset2 = datasets.MNIST('../data', train=False,
                   transform=transform)
train_loader = torch.utils.data.DataLoader(dataset1,**train_kwargs)
test_loader = torch.utils.data.DataLoader(dataset2, **test_kwargs)
```

Define Network

```python
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.dropout1 = nn.Dropout(0.25)
        self.dropout2 = nn.Dropout(0.5)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)
```

```python

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)
        x = self.dropout1(x)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.dropout2(x)
        x = self.fc2(x)
        output = F.log_softmax(x, dim=1)
        return output
```

Define Optimizer/Loss function

- Negative log-likelihood loss

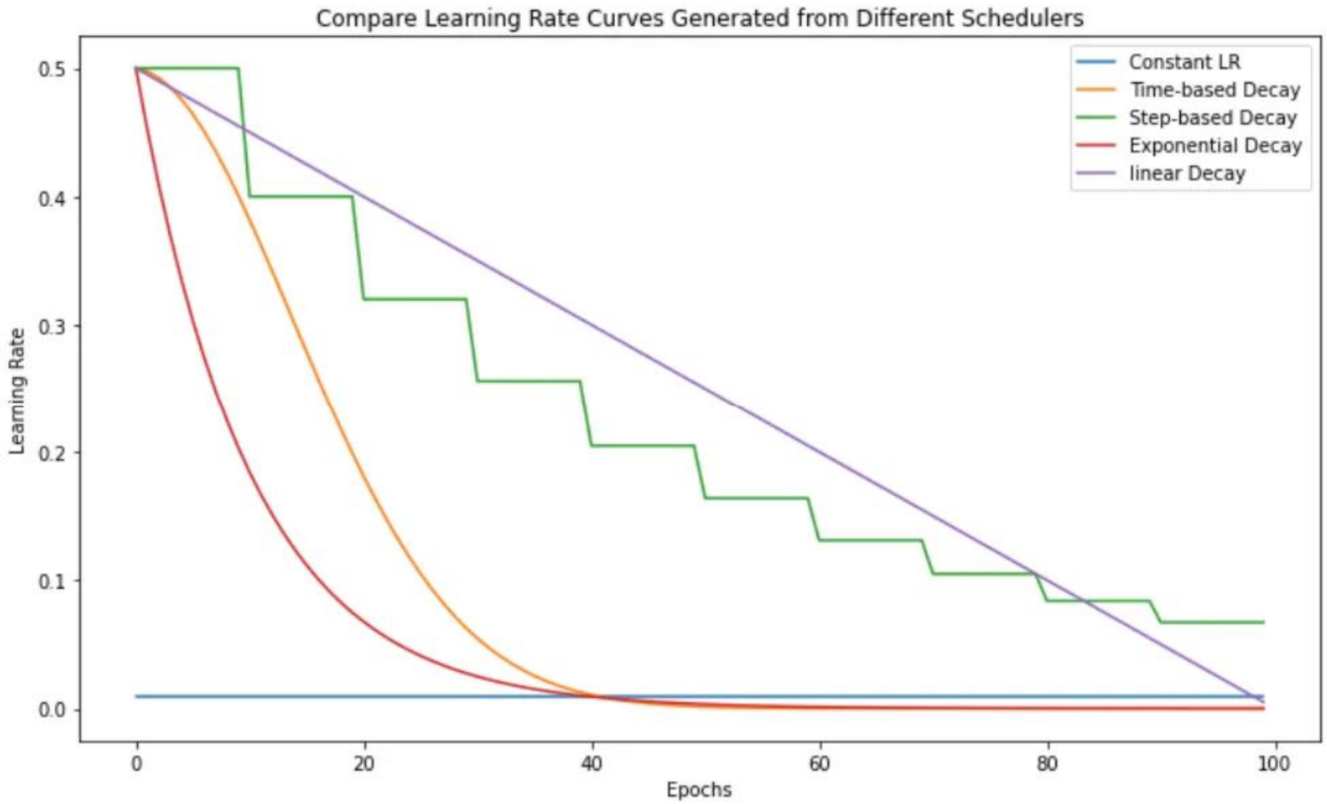
```
loss = F.nll_loss(output, target)
```

- Adadelta

```
optimizer = optim.Adadelta(model.parameters(), lr=args.lr)
```

Learning rate scheduling

```
scheduler = StepLR(optimizer, step_size=1, gamma=args.gamma)
```



Ref: [StepLR | CloudFactory Computer Vision Wiki]

Training

```python
def train(args, model, device, train_loader, optimizer, epoch):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output = model(data)
        loss = F.nll_loss(output, target)
        loss.backward()
        optimizer.step()
        if batch_idx % args.log_interval == 0:
            print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.item()))
            if args.dry_run:
                break
```

Testing

```
def test(model, device, test_loader):
    model.eval()
    test_loss = 0
    correct = 0
    with torch.no_grad():
        for data, target in test_loader:
            data, target = data.to(device), target.to(device)
            output = model(data)
            test_loss += F.nll_loss(output, target, reduction='sum').item()  # sum up batch loss
            pred = output.argmax(dim=1, keepdim=True)  # get the index of the max log-probability
            correct += pred.eq(target.view_as(pred)).sum().item()

    test_loss /= len(test_loader.dataset)

    print('\nTest set: Average loss: {:.4f}, Accuracy: {}/{} ({:.0f}%)\n'.format(
        test_loss, correct, len(test_loader.dataset),
        100. * correct / len(test_loader.dataset)))
```

Run and Save model

```python
    for epoch in range(1, args.epochs + 1):
        train(args, model, device, train_loader, optimizer, epoch)
        test(model, device, test_loader)
        scheduler.step()

    if args.save_model:
        torch.save(model.state_dict(), "mnist_cnn.pt")
```

Deep Learning

Lab0: PyTorch Warm-up

Department of Computer Science, NYCU

TA 劉子齊 Jonathan

Reference: Stanford CS231n