PyTorch Warm Up

Deep Learning and Practice @ MediaTek Inc.

Department of Computer Science, NCTU

Some slides are from Stanford CS231n

Frameworks

- **C++**
  - Caffe
- **Python**
  - Caffe2, TensorFlow, PyTorch, Theano, Keras, MXNet

    It died.
- **Lua**
  - Torch7
- **Matlab**
  - MatConvNet

Google:
TensorFlow

"One framework to rule them all"

Facebook:
PyTorch +Caffe2

Research

Production

Future Homework

- Do your homework using PyTorch

Install PyTorch

- http://pytorch.org/

Get Started.

Select your preferences, then run the PyTorch install command.

Please ensure that you are on the latest pip and numpy packages.
Anaconda is our recommended package manager

OS	Linux	OSX	
Package Manager	conda	pip	Source
Python	2.7	3.5	3.6
CUDA	7.5	8.0	None

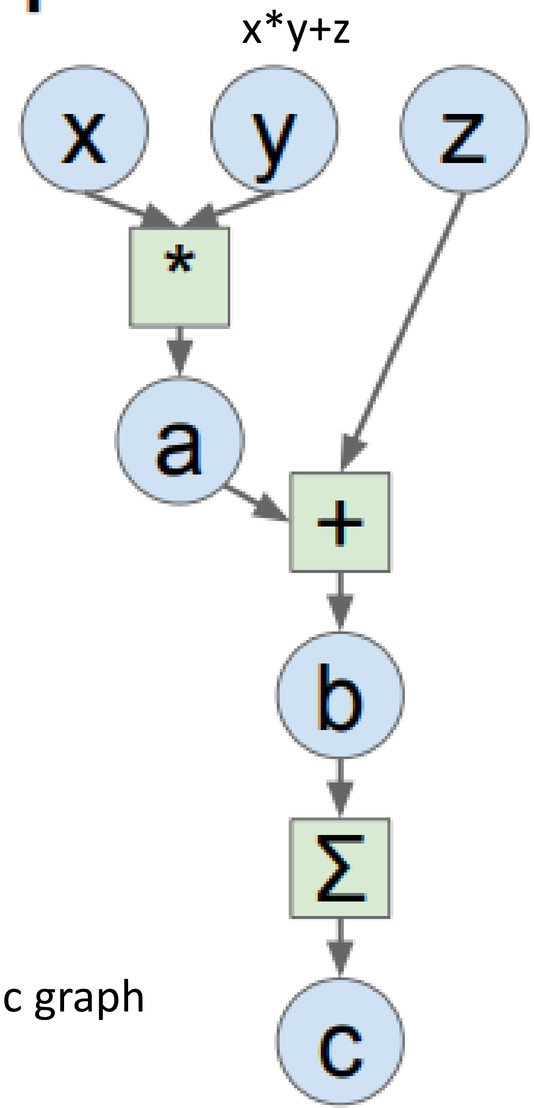
Run this command:

```
pip install http://download.pytorch.org/whl/cu80/torch-0.1.12.post2-cp27-none-linux_x86_64.whl
pip install torchvision
```

Computational Graphs

Numpy

```
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)
```



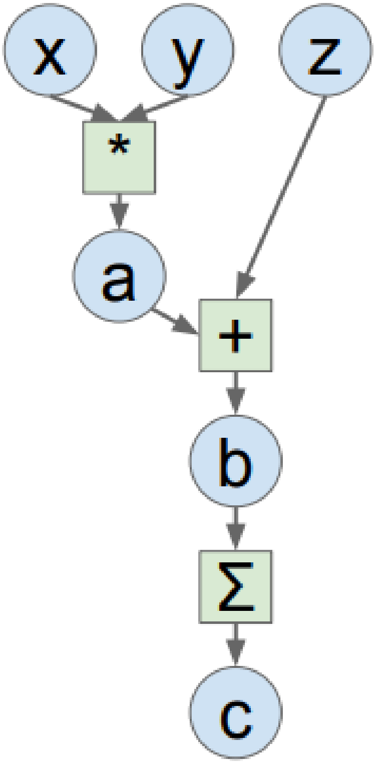
Neural network can be denoted as a directed acyclic graph

Computational Graphs

Numpy

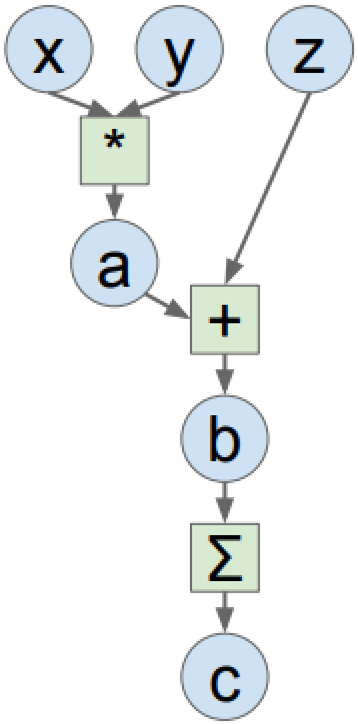
```
import numpy as np
np.random.seed(0)

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
```

compute gradients



Problems:
- Can't run on GPU
- Have to compute our own gradients

Computational Graphs



PyTorch

```python
import torch
from torch.autograd import Variable

N, D = 3, 4
```

Define Variable to start building graph

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

Forward Pass

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

Compute gradient

```python
c.backward()

print(x.grad.data)
print(y.grad.data)
print(z.grad.data)
```

PyTorch: Three Levels of Abstraction

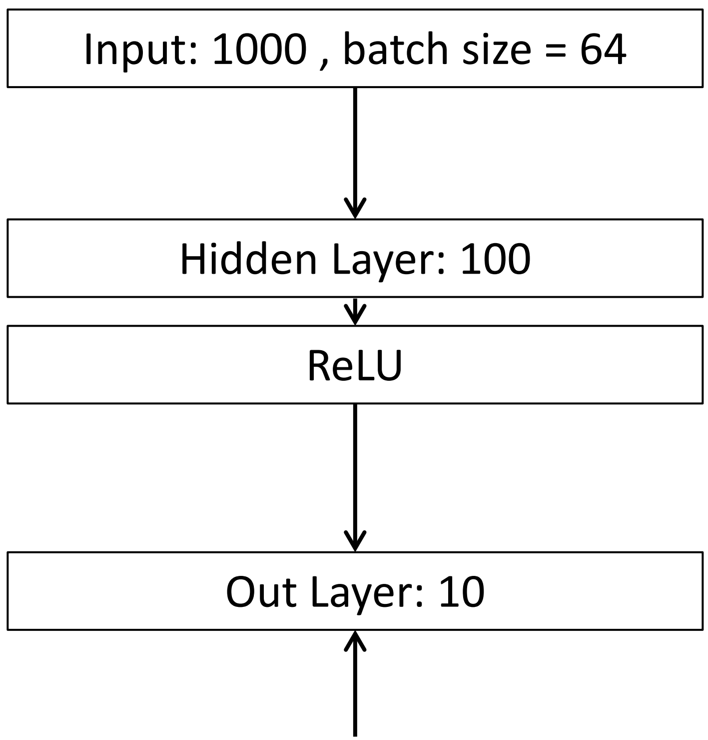
Tensor: Imperative ndarray, but runs on GPU

Variable: Node in a computational graph; stores data and gradient

Module: A neural network layer; may store state or learnable weights

Example

- A 2-layer ReLU 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

y:64×10

Loss: sum of square error $\sum(y - \hat{y})^2$

PyTorch: Autograd

A PyTorch **Variable** is a node in a computational graph

x.data is a Tensor

x.grad is a Variable of gradients (same shape as x.data)

x.grad.data is a Tensor of gradients

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in), requires_grad=False)
y = Variable(torch.randn(N, D_out), requires_grad=False)
w1 = Variable(torch.randn(D_in, H), requires_grad=True)
w2 = Variable(torch.randn(H, D_out), requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    if w1.grad: w1.grad.data.zero_()
    if w2.grad: w2.grad.data.zero_()
    loss.backward() compute gradient

    w1.data -= learning_rate * w1.grad.data apply gradient
    w2.data -= learning_rate * w2.grad.data
```

PyTorch: Autograd

We will not want gradients (of loss) with respect to data

Do want gradients with respect to weights

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in), requires_grad=False)
y = Variable(torch.randn(N, D_out), requires_grad=False)
w1 = Variable(torch.randn(D_in, H), requires_grad=True)
w2 = Variable(torch.randn(H, D_out), requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    if w1.grad: w1.grad.data.zero_()
    if w2.grad: w2.grad.data.zero_()
    loss.backward()

    w1.data -= learning_rate * w1.grad.data
    w2.data -= learning_rate * w2.grad.data
```

PyTorch: Autograd

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in), requires_grad=False)
y = Variable(torch.randn(N, D_out), requires_grad=False)
w1 = Variable(torch.randn(D_in, H), requires_grad=True)
w2 = Variable(torch.randn(H, D_out), requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    if w1.grad: w1.grad.data.zero_()
    if w2.grad: w2.grad.data.zero_()
    loss.backward()

    w1.data -= learning_rate * w1.grad.data
    w2.data -= learning_rate * w2.grad.data
```

Forward pass looks exactly the same as the Tensor version, but everything is a variable now

PyTorch: nn

Higher-level wrapper for working with neural nets

Similar to Keras and friends … but only one, and it's good =)

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

PyTorch: nn

Define our model as a sequence of layers

nn also defines common loss functions

```
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from torch.autograd import Variable

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model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

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for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

PyTorch: nn

```python
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from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

Forward pass: feed data to model, and prediction to loss function

PyTorch: nn

Backward pass:
compute all gradients

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10
x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    model.zero_grad()
    loss.backward()

    for param in model.parameters():
        param.data -= learning_rate * param.grad.data
```

PyTorch: optim

Use an **optimizer** for different update rules

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    optimizer.zero_grad()
    loss.backward()

    optimizer.step()
```

PyTorch: optim

```
import torch
from torch.autograd import Variable

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))
loss_fn = torch.nn.MSELoss(size_average=False)

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for t in range(500):
    y_pred = model(x)
    loss = loss_fn(y_pred, y)

    optimizer.zero_grad()
    loss.backward()

    optimizer.step()
```

Update all parameters after computing gradients

PyTorch: nn
Define new Modules

A PyTorch **Module** is a neural net layer; it inputs and outputs Variables

Modules can contain weights (as Variables) or other Modules

You can define your own Modules using autograd!

```
import torch
from torch.autograd import Variable

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

PyTorch: nn
Define new Modules

Define our whole model as a single Module

```
import torch
from torch.autograd import Variable

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

PyTorch: nn
Define new Modules

Initializer sets up two children (Modules can contain modules)

```python
import torch
from torch.autograd import Variable

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

PyTorch: nn
Define new Modules

Define forward pass using child modules and autograd ops on Variables

No need to define backward - autograd will handle it

```
import torch
from torch.autograd import Variable

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

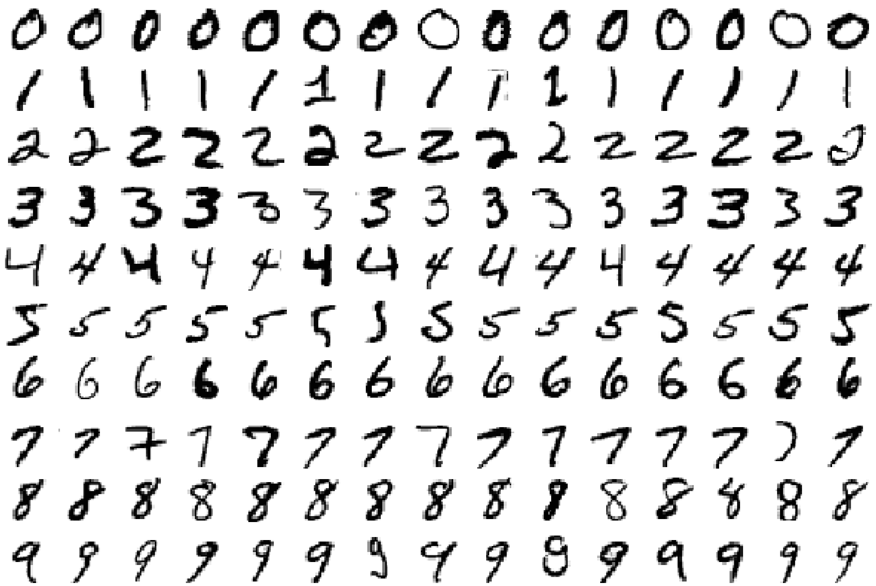
PyTorch: nn
Define new Modules

Construct and train an instance of our model

```
import torch
from torch.autograd import Variable

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10

x = Variable(torch.randn(N, D_in))
y = Variable(torch.randn(N, D_out), requires_grad=False)

model = TwoLayerNet(D_in, H, D_out)

criterion = torch.nn.MSELoss(size_average=False)
optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Real Application

- MNIST example for PyTorch



- git clone https://github.com/2017-fall-DL-training-program/PyTorchWarmUp.git

CNN_MNIST_pytorch.py

Build and train a CNN classifier

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

Set hypermeters

```
# Training settings
parser = argparse.ArgumentParser(description='PyTorch MNIST Example')
parser.add_argument('--batch-size', type=int, default=128, metavar='N',
                    help='input batch size for training (default: 128)')
parser.add_argument('--epochs', type=int, default=20, metavar='N',
                    help='number of epochs to train (default: 164)')
parser.add_argument('--lr', type=float, default=0.1, metavar='LR',
                    help='learning rate (default: 0.1)')
parser.add_argument('--momentum', type=float, default=0.9, metavar='M',
                    help='SGD momentum (default: 0.9)')
parser.add_argument('--no-cuda', action='store_true', default=False,
                    help='disables CUDA training')
parser.add_argument('--seed', type=int, default=1, metavar='S',
                    help='random seed (default: 1)')

args = parser.parse_args()
```

Data Loader

- Pytorch offers data loaders for popular dataset

The following datasets are available:

Datasets

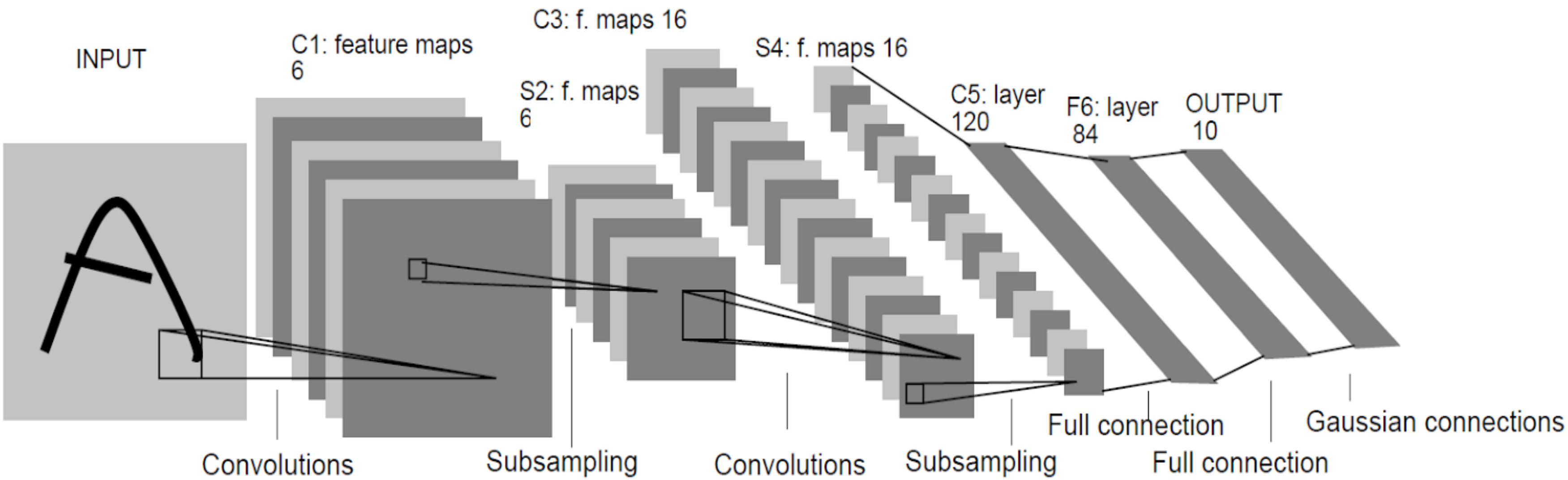
- MNIST
- COCO
  - Captions
  - Detection
- LSUN
- ImageFolder
- Imagenet-12
- CIFAR
- STL10
- SVHN
- PhotoTour

Data Loader

```
import torch
from torchvision import datasets, transforms

# Dataloader
train_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=True, download=True,
                   transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
    batch_size=args.batch_size, shuffle=True,num_workers = 2)

test_loader = torch.utils.data.DataLoader(
    datasets.MNIST('../data', train=False, transform=transforms.Compose([
                       transforms.ToTensor(),
                       transforms.Normalize((0.1307,), (0.3081,))
                   ])),
    batch_size=args.batch_size, shuffle=True,num_workers = 2)
```

Define Network

- LeNet



Define Network

```
#Define Network, we implement LeNet here
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, kernel_size=(5,5),stride=1, padding=0)
        self.conv2 = nn.Conv2d(6, 16, kernel_size=(5,5),stride=1, padding=0)
        self.fc1 = nn.Linear(16*4*4, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        out = F.relu(self.conv1(x))
        out = F.max_pool2d(out, 2)
        out = F.relu(self.conv2(out))
        out = F.max_pool2d(out, 2)
        out = out.view(out.size(0), -1) #flatten
        out = F.relu(self.fc1(out))
        out = F.relu(self.fc2(out))
        out = self.fc3(out)
        return out

model = Net()
if args.cuda:
    model.cuda()
```

Define Optimizer/Loss function

- Cross Entropy Loss
- Stochastic Gradient Descent

```
#define optimizer/loss function
Loss = nn.CrossEntropyLoss()
optimizer = optim.SGD(model.parameters(), lr=args.lr, momentum=args.momentum)
```

Learning rate scheduling

- 20 epochs
- LR decay at 10 and 15 epoch

```python
#learning rate scheduling
def adjust_learning_rate(optimizer, epoch):

    if epoch < 10:
        lr = 0.01
    elif epoch < 15:
        lr = 0.001
    else:
        lr = 0.0001

    for param_group in optimizer.param_groups:
        param_group['lr'] = lr
```

Training

```
#training function
def train(epoch):
    model.train()
    adjust_learning_rate(optimizer, epoch)

    for batch_idx, (data, target) in enumerate(train_loader):
        if args.cuda:
            data, target = data.cuda(), target.cuda()
        data, target = Variable(data), Variable(target)
        optimizer.zero_grad()
        output = model(data)
        loss = Loss(output, target)
        loss.backward()
        optimizer.step()
        print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
                epoch, batch_idx * len(data), len(train_loader.dataset),
                100. * batch_idx / len(train_loader), loss.data[0]))
```

Set model to training mode

Clean gradient

Backward gradient

Update weight

Testing

```
#Testing function
def test(epoch):
    model.eval()
    test_loss = 0
    correct = 0
    for batch_idx, (data, target) in enumerate(test_loader):
        if args.cuda:
            data, target = data.cuda(), target.cuda()
        data, target = Variable(data, volatile=True), Variable(target)
        output = model(data)
        test_loss += Loss(output, target).data[0]
        pred = output.data.max(1)[1] # get the index of the max log-probability
        correct += pred.eq(target.data).cpu().sum()

    test_loss = test_loss
    test_loss /= len(test_loader) # loss function already averages over batch size
    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

```
#run and save model
for epoch in range(1, args.epochs + 1):
    train(epoch)
    test(epoch)
    savefilename = 'LeNet_'+str(epoch)+'.tar'
    torch.save({
            'epoch': epoch,
            'state_dict': model.state_dict(),
        }, savefilename)
```

You can achieve ~99.1% test accuracy.

Exercise

- Deeper: add more convolution layer
  - insert two 3x3 conv layer between conv1 and conv2 (stride=1,pad=1)
  - Hint: define new conv layer, and forward
  - Notice the *spatial* dimension
- Wider: add more neuron
  - Make your net 2x wider
  - Notice the *in/out* dimension
- Other Optimizer
  - Try Adam/RMSprop
- More epochs, New learning rate schedule, ….