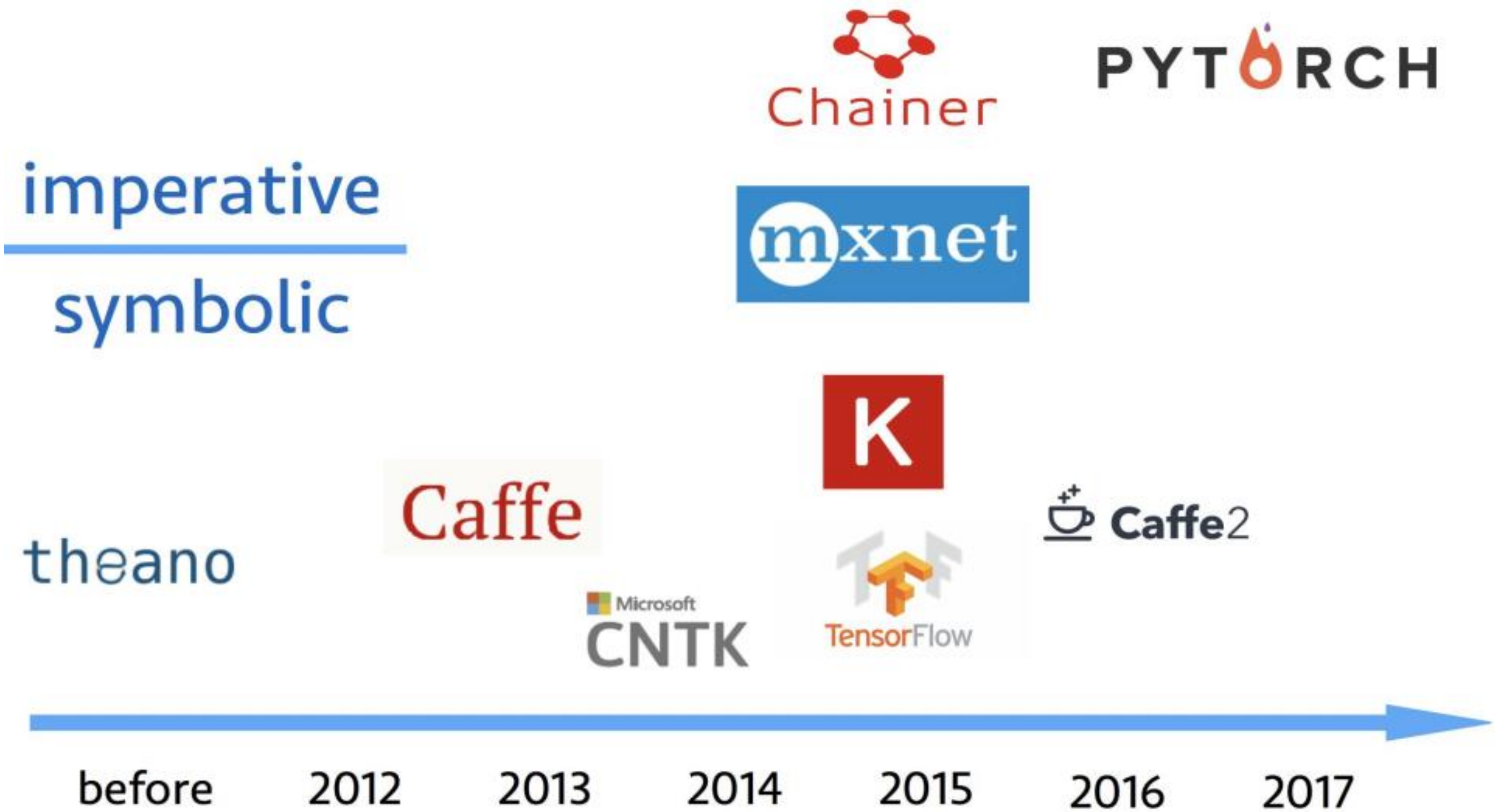
UNT
UNIVERSITY OF NORTH TEXAS

CSCE 5218 & 4930
Deep Learning

PyTorch Tutorial

Slides adapted from Wu et al (ecs289g, UC Davis) and Want et al (cs231n, Stanford)

Popular Deep Learning Frameworks



Gluon: new MXNet interface to accelerate research

Popular Deep Learning Frameworks

Caffe
(UC Berkeley) → Caffe2
(Facebook)

lua Torch
(NYU / Facebook) → PyTorch
(Facebook)

Theano
(U Montreal) → TensorFlow
(Google)

Paddle
(Baidu)

CNTK
(Microsoft)

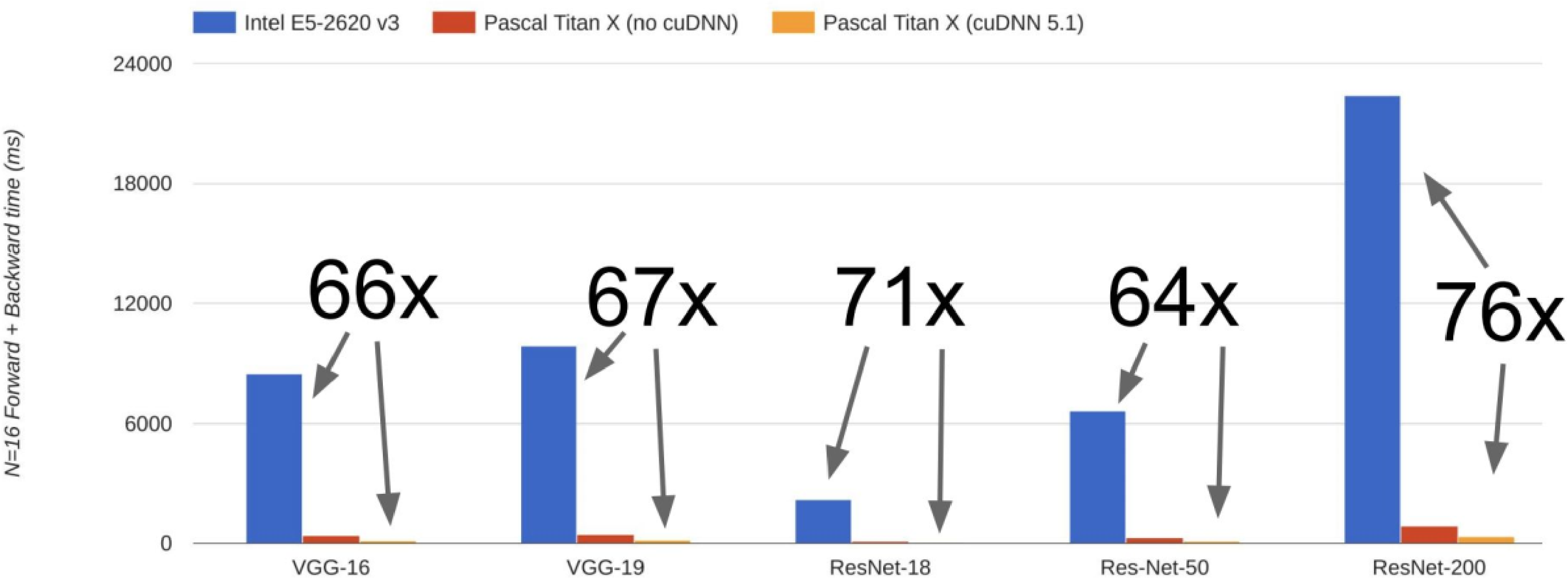
MXNet
(Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc but main framework of choice at AWS

C++, Python, R, Julia, Perl Scala

And others...

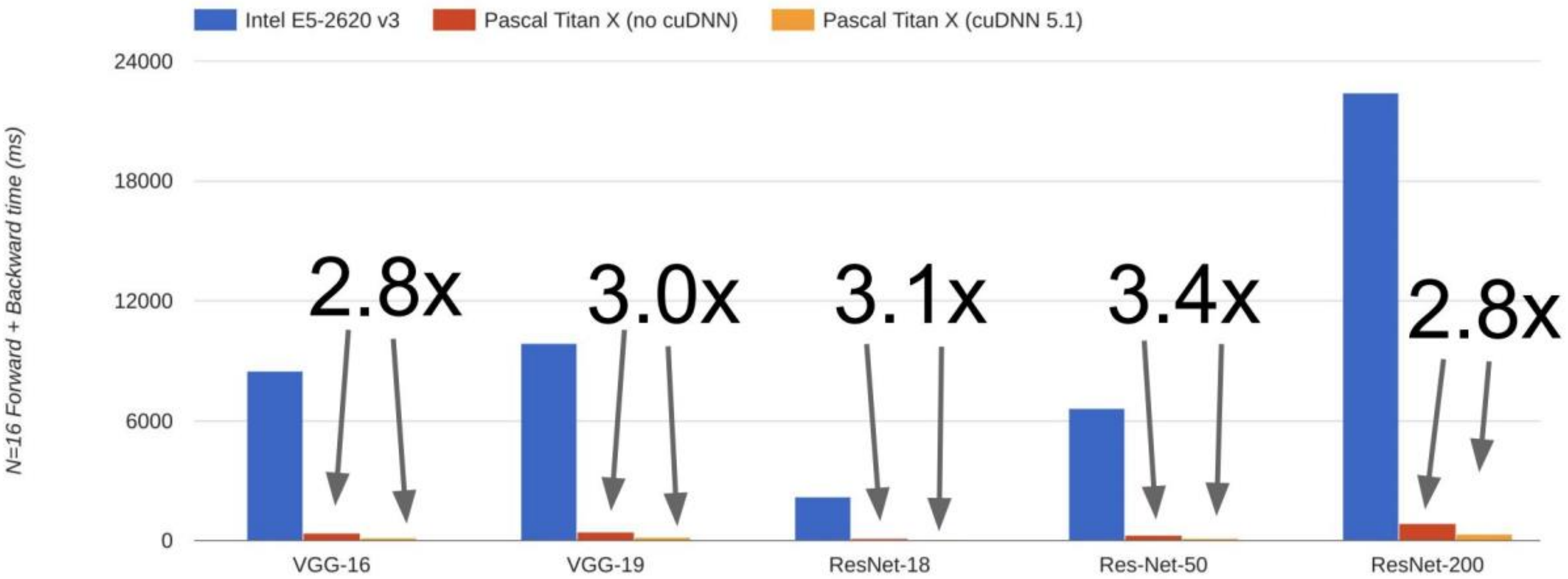
Stanford cs231n.

CPU vs GPU in practice



Stanford cs231n.

CPU vs GPU in practice



Stanford cs231n.

PYTORCH

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

PyTorch: Tensor

PyTorch Tensors are just like numpy arrays, but they can run on GPU.

No built-in notion of computational graph, or gradients, or deep learning.

Here we fit a two-layer net using PyTorch Tensors:

```python
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

PyTorch: Tensor

```python
import numpy as np
import torch

# Task: compute matrix multiplication C = AB
d = 3000

# using numpy
A = np.random.rand(d, d).astype(np.float32)
B = np.random.rand(d, d).astype(np.float32)
C = A.dot(B)

# using torch with gpu
A = torch.rand(d, d).cuda()
B = torch.rand(d, d).cuda()
C = torch.mm(A, B)
```

350 ms

0.1 ms

https://transfer.d2.mpi-inf.mpg.de/rshetty/hlcv/Pytorch_tutorial.pdf

PyTorch: Tensor

```python
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

to run on GPU

```python
import torch

dtype = torch.cuda.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

PyTorch: Tensor

Create random tensors for data and weights

```python
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

PyTorch: Tensor

Forward pass: compute predictions and loss

```
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

PyTorch: Tensor

Backward pass: manually compute gradients

```python
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

PyTorch: Tensor

```python
import torch

dtype = torch.FloatTensor

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

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

    grad_y_pred = 2.0 * (y_pred - y)
    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
```

Gradient descent
step on weights

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

PyTorch: Autograd

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

x.data is a Tensor

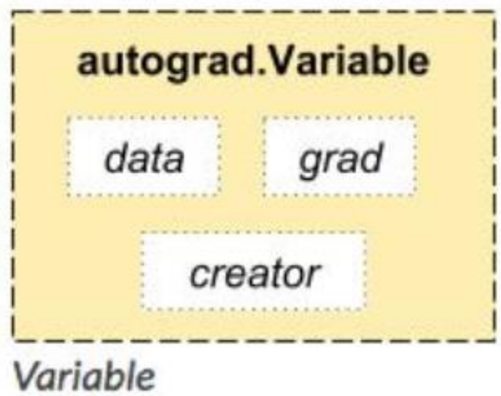
x.grad is a Variable of gradients (same shape as x.data)

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()

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

PyTorch: Variable

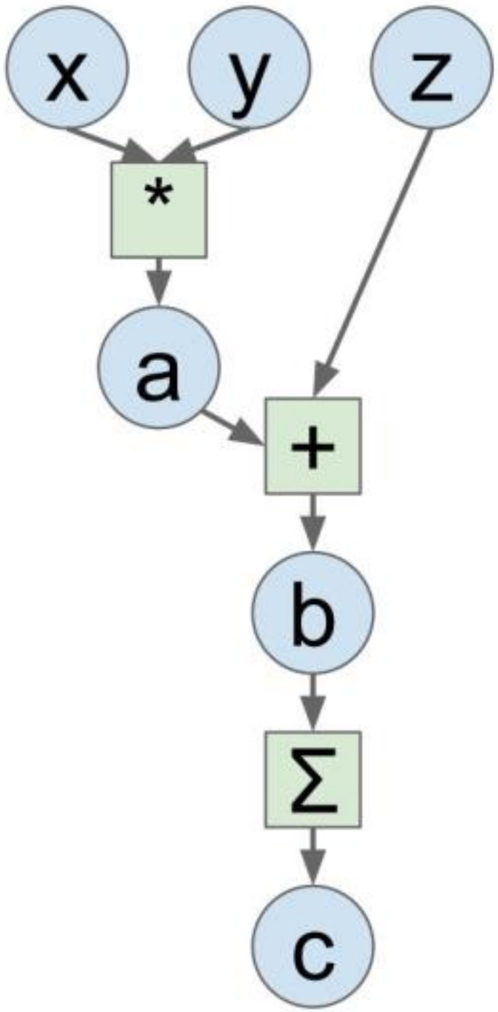
The autograd package provides automatic differentiation for all operations on Tensors.



" autograd.Variable is the central class of the package. It wraps a Tensor, and supports nearly all of operations defined on it.

Once you finish your computation you can call .backward() and have all the gradients computed automatically. "

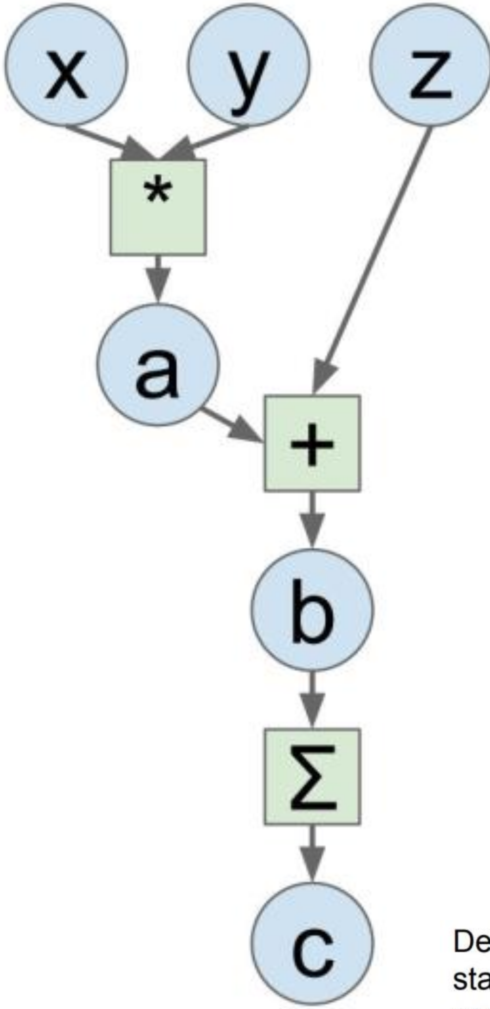
Computational Graphs




```
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
```

Numpy

Computational Graphs

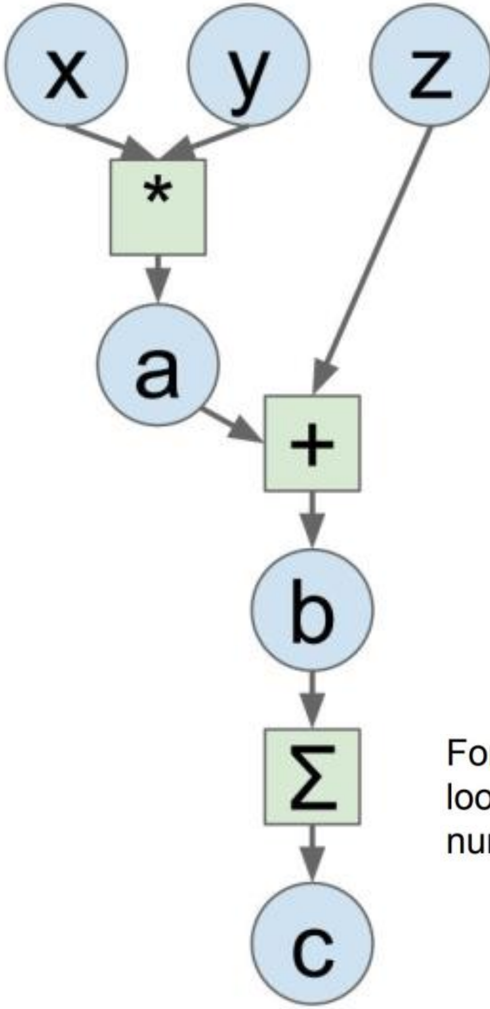



```
import torch
from torch.autograd import Variable

N, D = 3, 4

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)

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

c.backward()

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

Define **Variables** to start building a computational graph

PyTorch

Computational Graphs

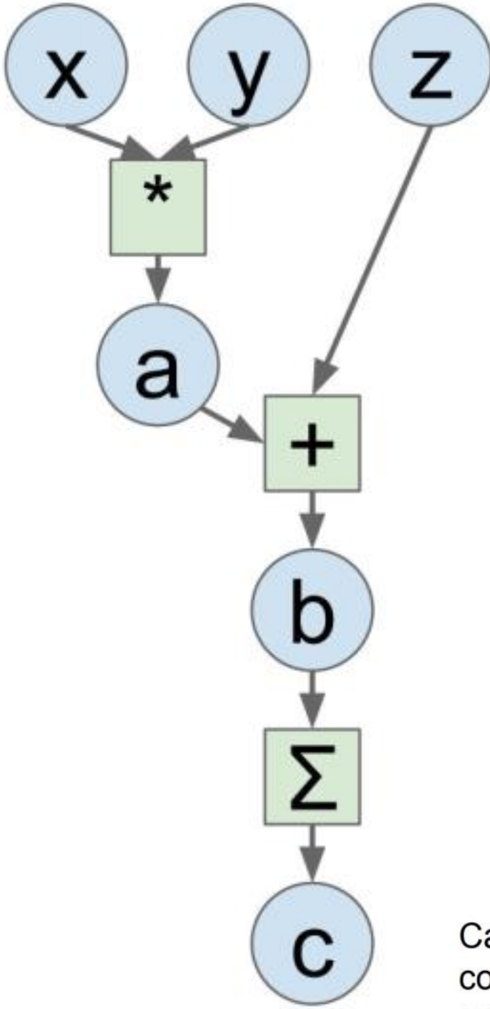


Forward pass looks just like numpy

```
import torch
from torch.autograd import Variable

N, D = 3, 4

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)

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

c.backward()

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

PyTorch

Computational Graphs

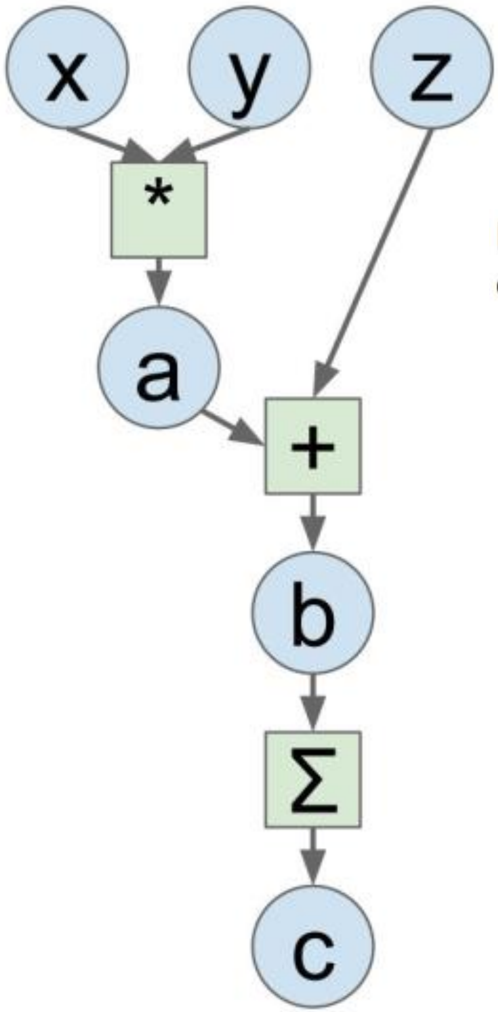



```python
import torch
from torch.autograd import Variable

N, D = 3, 4

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)

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

c.backward()

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

Calling c.backward() computes all gradients

PyTorch

Computational Graphs



Run on GPU by casting to .cuda()

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

N, D = 3, 4

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

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

c.backward()

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

PyTorch

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

Module: Single Layer

⊟ **torch.nn**

- Parameters
- ⊞ Containers
- ⊟ **Convolution Layers**
  - Conv1d
  - Conv2d
  - Conv3d
  - ConvTranspose1d
  - ConvTranspose2d
  - ConvTranspose3d

Other layers:
Dropout, Linear,
Normalization Layer

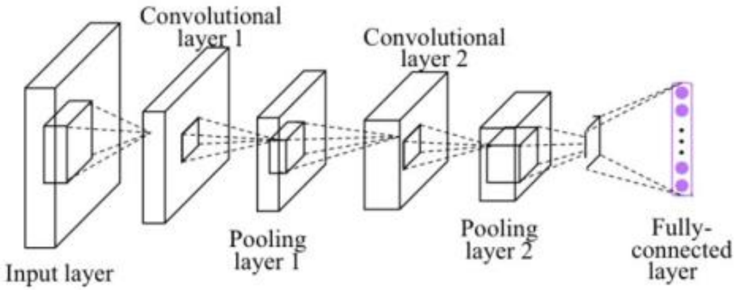
⊟ **torch.nn**

- Parameters
- ⊞ Containers
- ⊞ Convolution Layers
- ⊟ **Pooling Layers**
  - MaxPool1d
  - MaxPool2d
  - MaxPool3d
  - MaxUnpool1d
  - MaxUnpool2d
  - MaxUnpool3d
  - AvgPool1d
  - AvgPool2d
  - AvgPool3d
  - FractionalMaxPool2d
  - LPPool2d
  - AdaptiveMaxPool1d
  - AdaptiveMaxPool2d
  - AdaptiveMaxPool3d
  - AdaptiveAvgPool1d
  - AdaptiveAvgPool2d
  - AdaptiveAvgPool3d

⊟ **Loss functions**

- L1Loss
- MSELoss
- CrossEntropyLoss
- NLLLoss
- PoissonNLLLoss
- KLDivLoss
- BCELoss
- BCEWithLogitsLoss
- MarginRankingLoss
- HingeEmbeddingLoss
- MultiLabelMarginLoss
- SmoothL1Loss
- SoftMarginLoss
- MultiLabelSoftMarginLoss
- CosineEmbeddingLoss
- MultiMarginLoss
- TripletMarginLoss

Module: Network




```
class Net(nn.Module):

    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(320, 10) # 320 -> 10

    def forward(self, x):
        in_size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = F.relu(self.mp(self.conv2(x)))
        x = x.view(in_size, -1) # flatten the tensor
        x = self.fc(x)
        return F.log_softmax(x)
```

Module: Sub-Network

```
VGG (
  (features): Sequential (
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU (inplace)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU (inplace)
    (4): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU (inplace)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU (inplace)
    (9): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU (inplace)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU (inplace)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU (inplace)
    (16): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU (inplace)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU (inplace)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU (inplace)
    (23): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU (inplace)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU (inplace)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU (inplace)
    (30): MaxPool2d (size=(2, 2), stride=(2, 2), dilation=(1, 1))
  )
  (classifier): Sequential (
    (0): Dropout (p = 0.5)
    (1): Linear (25088 -> 4096)
    (2): ReLU (inplace)
    (3): Dropout (p = 0.5)
    (4): Linear (4096 -> 4096)
    (5): ReLU (inplace)
    (6): Linear (4096 -> 1000)
  )
)
```

Feature sub-network

Classification sub-network

VGG-Net, K Simonyan, et al., ICLR'15.

PyTorch: Starting a New Project

- Data preparation
- Model design
- Training strategy
- Save and load model weights

PyTorch: Data Preparation

- Data loading

```
xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
x_data = Variable(torch.from_numpy(xy[:, 0:-1]))
y_data = Variable(torch.from_numpy(xy[:, [-1]]))

...

# Training Loop
for epoch in range(100):
        # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x_data)

    # Compute and print loss
    loss = criterion(y_pred, y_data)
    print(epoch, loss.data[0])

    # Zero gradients, perform a backward pass, and update the weights.
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

PyTorch: Data Preparation

- Data loading

```
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, **kwargs)
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.test_batch_size, shuffle=True, **kwargs)
```

Pytorch, zero to all. HKUST

PyTorch: Data Preparation

- Data loading

```python
class DiabetesDataset(Dataset):
    """ Diabetes dataset."""

    # Initialize your data, download, etc.
    def __init__(self):



    def __getitem__(self, index):
        return

    def __len__(self):
        return


dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

1 download, read data, etc.

2 return one item on the index

3 return the data length

Custom DataLoader

PyTorch: Data Preparation

- Data loading

```
class DiabetesDataset(Dataset):
    """ Diabetes dataset."""

    # Initialize your data, download, etc.
    def __init__(self):
        xy = np.loadtxt('data-diabetes.csv', delimiter=',', dtype=np.float32)
        self.len = xy.shape[0]
        self.x_data = torch.from_numpy(xy[:, 0:-1])
        self.y_data = torch.from_numpy(xy[:, [-1]])

    def __getitem__(self, index):
        return self.x_data[index], self.y_data[index]

    def __len__(self):
        return self.len


dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset,
                          batch_size=32,
                          shuffle=True,
                          num_workers=2)
```

Custom DataLoader

PyTorch: Data Preparation

- Data loading

```
dataset = DiabetesDataset()
train_loader = DataLoader(dataset=dataset, batch_size=32, shuffle=True, num_workers=2)
```

```
# Training Loop
for epoch in range(2):
    for i, data in enumerate(train_loader, 0):
        # get the inputs
        inputs, labels = data

        # wrap them in Variable
        inputs, labels = Variable(inputs), Variable(labels)

        # Forward pass: Compute predicted y by passing x to the model
        y_pred = model(inputs)

        # Compute and print loss
        loss = criterion(y_pred, labels)
        print(epoch, i, loss.data[0])

        # Zero gradients, perform a backward pass, and update the weights.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
```

Using DataLoader

Pytorch, zero to all. HKUST

PyTorch: Data Preparation

- Data processing

Convert numpy to tensor, and normalize data

```
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, **kwargs)
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.test_batch_size, shuffle=True, **kwargs)
```

PyTorch: Data Preparation

- Data augmentation

```
def get_transform(opt, params=None, grayscale=False, method=Image.BICUBIC, convert=True):
    transform_list = []
    if grayscale:
        transform_list.append(transforms.Grayscale(1))
    if 'resize' in opt.preprocess:
        osize = [opt.load_size, opt.load_size]
        transform_list.append(transforms.Resize(osize, method))
    elif 'scale_width' in opt.preprocess:
        transform_list.append(transforms.Lambda(lambda img: __scale_width(img, opt.load_size, opt.crop_size, method)))

    if 'crop' in opt.preprocess:
        if params is None:
            transform_list.append(transforms.RandomCrop(opt.crop_size))
        else:
            transform_list.append(transforms.Lambda(lambda img: __crop(img, params['crop_pos'], opt.crop_size)))

    if opt.preprocess == 'none':
        transform_list.append(transforms.Lambda(lambda img: __make_power_2(img, base=4, method=method)))

    if not opt.no_flip:
        if params is None:
            transform_list.append(transforms.RandomHorizontalFlip())
        elif params['flip']:
            transform_list.append(transforms.Lambda(lambda img: __flip(img, params['flip'])))
```

https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix

PyTorch: Model Design

- Pretrained model

  - AlexNet
  - VGG
  - ResNet
  - SqueezeNet
  - DenseNet
  - Inception v3
  - GoogLeNet
  - ShuffleNet v2
  - MobileNetV2
  - MobileNetV3
  - ResNeXt
  - Wide ResNet
  - MNASNet
  - EfficientNet
  - RegNet

```
import torchvision.models as models
resnet18 = models.resnet18()
alexnet = models.alexnet()
vgg16 = models.vgg16()
squeezenet = models.squeezenet1_0()
densenet = models.densenet161()
inception = models.inception_v3()
googlenet = models.googlenet()
shufflenet = models.shufflenet_v2_x1_0()
mobilenet_v2 = models.mobilenet_v2()
mobilenet_v3_large = models.mobilenet_v3_large()
mobilenet_v3_small = models.mobilenet_v3_small()
resnext50_32x4d = models.resnext50_32x4d()
wide_resnet50_2 = models.wide_resnet50_2()
mnasnet = models.mnasnet1_0()
efficientnet_b0 = models.efficientnet_b0()
efficientnet_b1 = models.efficientnet_b1()
efficientnet_b2 = models.efficientnet_b2()
efficientnet_b3 = models.efficientnet_b3()
efficientnet_b4 = models.efficientnet_b4()
efficientnet_b5 = models.efficientnet_b5()
efficientnet_b6 = models.efficientnet_b6()
efficientnet_b7 = models.efficientnet_b7()
regnet_y_400mf = models.regnet_y_400mf()
regnet_y_800mf = models.regnet_y_800mf()
regnet_y_1_6gf = models.regnet_y_1_6gf()
```

PyTorch: Model Design

- Design your own

We define our neural network by subclassing `nn.Module`, and initialize the neural network layers in `__init__`. Every `nn.Module` subclass implements the operations on input data in the `forward` method.

```
class NeuralNetwork(nn.Module):
    def __init__(self):
        super(NeuralNetwork, self).__init__()
        self.flatten = nn.Flatten()
        self.linear_relu_stack = nn.Sequential(
            nn.Linear(28*28, 512),
            nn.ReLU(),
            nn.Linear(512, 512),
            nn.ReLU(),
            nn.Linear(512, 10),
        )

    def forward(self, x):
        x = self.flatten(x)
        logits = self.linear_relu_stack(x)
        return logits
```

backward is automatic

PyTorch: Model Design

- Design your own

CPU or GPU

We create an instance of `NeuralNetwork`, and move it to the `device`, and print its structure.

```
model = NeuralNetwork().to(device)
print(model)
```

```
NeuralNetwork(
  (flatten): Flatten(start_dim=1, end_dim=-1)
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=784, out_features=512, bias=True)
    (1): ReLU()
    (2): Linear(in_features=512, out_features=512, bias=True)
    (3): ReLU()
    (4): Linear(in_features=512, out_features=10, bias=True)
  )
)
```

PyTorch: Model Design

- Weights initialization: torch.nn.init

```
from torch.nn import init
```

including different initialization methods

```
def weights_init_xavier(m):
    classname = m.__class__.__name__
    # print(classname)
    if classname.find('Conv') != -1:
        init.xavier_normal(m.weight.data, gain=0.02)
    elif classname.find('Linear') != -1:
        init.xavier_normal(m.weight.data, gain=0.02)
    elif classname.find('BatchNorm2d') != -1:
        init.normal(m.weight.data, 1.0, 0.02)
        init.constant(m.bias.data, 0.0)
```

```
def weights_init_orthogonal(m):
    classname = m.__class__.__name__
    print(classname)
    if classname.find('Conv') != -1:
        init.orthogonal(m.weight.data, gain=1)
    elif classname.find('Linear') != -1:
        init.orthogonal(m.weight.data, gain=1)
    elif classname.find('BatchNorm2d') != -1:
        init.normal(m.weight.data, 1.0, 0.02)
        init.constant(m.bias.data, 0.0)
```

```
def weights_init_normal(m):
    classname = m.__class__.__name__
    # print(classname)
    if classname.find('Conv') != -1:
        init.normal(m.weight.data, 0.0, 0.02)
    elif classname.find('Linear') != -1:
        init.normal(m.weight.data, 0.0, 0.02)
    elif classname.find('BatchNorm2d') != -1:
        init.normal(m.weight.data, 1.0, 0.02)
        init.constant(m.bias.data, 0.0)
```

```
def weights_init_kaiming(m):
    classname = m.__class__.__name__
    # print(classname)
    if classname.find('Conv') != -1:
        init.kaiming_normal(m.weight.data, a=0, mode='fan_in')
    elif classname.find('Linear') != -1:
        init.kaiming_normal(m.weight.data, a=0, mode='fan_in')
    elif classname.find('BatchNorm2d') != -1:
        init.normal(m.weight.data, 1.0, 0.02)
        init.constant(m.bias.data, 0.0)
```

PyTorch: Training Strategy

- Loss: torch.nn

Common loss functions include nn.MSELoss (Mean Square Error) for regression tasks, and nn.NLLLoss (Negative Log Likelihood) for classification. nn.CrossEntropyLoss combines `nn.LogSoftmax` and `nn.NLLLoss`.

We pass our model's output logits to `nn.CrossEntropyLoss`, which will normalize the logits and compute the prediction error.

```
>>> # Example of target with class indices
>>> loss = nn.CrossEntropyLoss()
>>> input = torch.randn(3, 5, requires_grad=True)
>>> target = torch.empty(3, dtype=torch.long).random_(5)
>>> output = loss(input, target)
>>> output.backward()
>>>
>>> # Example of target with class probabilities
>>> input = torch.randn(3, 5, requires_grad=True)
>>> target = torch.randn(3, 5).softmax(dim=1)
>>> output = loss(input, target)
>>> output.backward()
```

PyTorch: Training Strategy

- Optimizer: torch.optim

Constructing it

To construct an `Optimizer` you have to give it an iterable containing the parameters (all should be `Variable` s) to optimize. Then, you can specify optimizer-specific options such as the learning rate, weight decay, etc.

```
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
optimizer = optim.Adam([var1, var2], lr=0.0001)
```

Per-parameter options

`Optimizer` s also support specifying per-parameter options. To do this, instead of passing an iterable of `Variable` s, pass in an iterable of `dict` s. Each of them will define a separate parameter group, and should contain a `params` key, containing a list of parameters belonging to it. Other keys should match the keyword arguments accepted by the optimizers, and will be used as optimization options for this group.

```
optim.SGD([
                {'params': model.base.parameters()},
                {'params': model.classifier.parameters(), 'lr': 1e-3}
            ], lr=1e-2, momentum=0.9)
```

PyTorch: Training Strategy

- Optimizer: torch.optim

Inside the training loop, optimization happens in three steps:

- Call `optimizer.zero_grad()` to reset the gradients of model parameters. Gradients by default add up; to prevent double-counting, we explicitly zero them at each iteration.
- Backpropagate the prediction loss with a call to `loss.backwards()`. PyTorch deposits the gradients of the loss w.r.t. each parameter.
- Once we have our gradients, we call `optimizer.step()` to adjust the parameters by the gradients collected in the backward pass.

```
for input, target in dataset:
    optimizer.zero_grad()
    output = model(input)
    loss = loss_fn(output, target)
    loss.backward()
    optimizer.step()
```

PyTorch: Save and load model weights

PyTorch models store the learned parameters in an internal state dictionary, called `state_dict`. These can be persisted via the `torch.save` method:

```
model = models.vgg16(pretrained=True)
torch.save(model.state_dict(), 'model_weights.pth')
```

To load model weights, you need to create an instance of the same model first, and then load the parameters using `load_state_dict()` method.

```
model = models.vgg16() # we do not specify pretrained=True, i.e. do not load default weights
model.load_state_dict(torch.load('model_weights.pth'))
model.eval()
```

PyTorch: Save and load model weights

When loading model weights, we needed to instantiate the model class first, because the class defines the structure of a network. We might want to save the structure of this class together with the model, in which case we can pass `model` (and not `model.state_dict()`) to the saving function:

```
torch.save(model, 'model.pth')
```

We can then load the model like this:

```
model = torch.load('model.pth')
```

A Real Example

[MINIST classification]

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  - Official PyTorch document: https://pytorch.org/tutorials/
  - PyTorch, Zero to All (HKUST): https://www.youtube.com/playlist?list=PLlMkM4tgfjnJ3I-dbhO9JTw7gNty6o_2m