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Applied Accelerated Al

Introduction to PyTorch

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What is PyTorch

- Open source machine learning library
- Developed by Facebook's AI Research lab
- It leverages the power of GPUs
- Automatic computation of gradients
- Makes it easier to test and develop new ideas.





Other libraries





PyTorch Tensor

- Similar to NumPy arrays
- They can also be used on a GPU
 - Faster computation

Random matrix

```
import torch
```

```
x=torch.rand(2,3)
y=torch.rand(3,3)
```

print x print y



PyTorch Tensor

- Similar to NumPy arrays
- They can also be used on a GPU
 - Faster computation
- All zeros
- Directly from data
- Size of a tensor

```
import torch

x = torch.zeros(5, 3)

x = torch.tensor([5.5, 3])

print x.size()
```



Operations

- Adding tensors
- Indexing

```
x = torch.randn(4, 4)
y = torch.randn(4, 4)
print(torch.add(x, y))
print(x[:, 1])
```



Operations

- Resizing
 - If you want to resize/reshape tensor

```
• x = torch.randn(4, 4)
     = x.view(16)
           x.view(-1,
                          8)
•print(x.size(), y.size(),
z.size())
• Output:
• torch.Size([4, 4])
•torch.Size([16])
```

• torch.Size([2, 8])



```
x = torch.randn(1, 4, 32, 24)
y = x.view(8, 2, -1, 3, 8)
print(y.size())
```

Output shape?



Torch tensor vs NumPy array

- NumPy array
 - CPU
- Torch tensor
 - GPU

```
a = torch.ones(5)
tensor([1., 1., 1., 1., 1.])
b = a.numpy()

a = numpy.ones(5)
b = torch.from numpy(a)
```



Matrix Multiplication in PyTorch

```
import torch
mat1=torch.randn(2,3)
mat2=torch.randn(3,3)
res=torch.mm (mat1, mat2)
print res.size()
Output: (2L, 3L)
```



Batch Matrix Multiplication in PyTorch

```
import torch
batch1=torch.randn(10,3,4)
batch2=torch.randn(10,4,5)
res=torch.bmm (batch1, batch2)
print res.size()
Output: (10L, 3L, 5L)
```



Many Tensor operations in PyTorch...

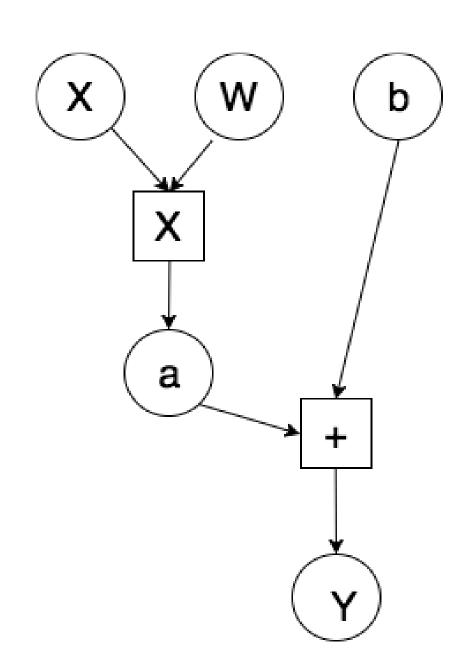
- torch.mm
- Matrix multiplication
- torch.bmm
- Batch matrix multiplication
- torch.cat
- Tensor Concatenation
- torch.sqeueeze/torch.unsqueeze
- Change Tensor dimensions
- •
- Check documentation at http://pytorch.org/docs/master/torch.html#tensors



Computational Graphs

```
import torch

x = torch.ones(2,2)
y = torch.ones(2,1)
w = torch.randn(2,1,requires_grad=True)
b = torch.randn(1,requires_grad=True)
```



Computational Graphs

```
p = torch.sigmoid(torch.mm(x, w) + b) #
prediction
loss = -y*torch.log(p)-(1-y)*torch.log(1-p)
cross-entropy loss
cost = loss.mean()
# the cost to minimize
```



Automatic Gradient Computation

```
p = torch.sigmoid(torch.mm(x, w) + b)

loss = -y*torch.log(p) - (1-y)*torch.log(1-p)
cost = loss.mean()

cost.backward()

print w.grad
print b.grad
```



Training procedure

- Define the neural network
- Iterate over a dataset of inputs
- Process input through the network
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Build Neural Networks using PyTorch

Neural networks can be constructed using the torch.nn package.

- Forward
 - An nn.Module contains layers, and
 - A method forward(input) that returns the output
 - You can use any of the Tensor operations in the forward function
- Backward
 - nn depends on autograd
 - You just have to define the forward function



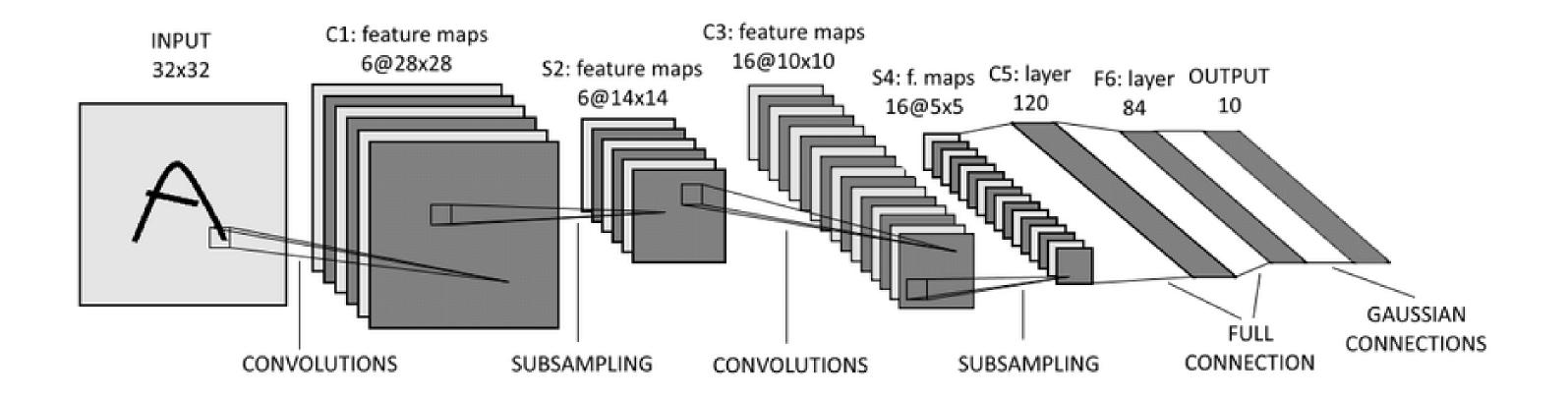
Define a Network Class

```
import torch
import torch.nn as nn
class Net(nn.Module):
  def init (self):
     super (Net, self). init ()
     # create layers
  def forward(self, x):
     # define feed-forward function
```

You don't need to define a backward function!



CNN for MNIST: A Full Example





```
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels, 5x5 square convolutio
        # kernel
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
   def forward(self, x):
        # Max pooling over a (2, 2) window
       x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
       # If the size is a square you can only specify a single number
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
       x = x.view(-1, self.num_flat_features(x))
       x = F.relu(self.fc1(x))
       x = F.relu(self.fc2(x))
       x = self.fc3(x)
        return x
    def num_flat_features(self, x):
        size = x.size()[1:] # all dimensions except the batch dimension
        num_features = 1
        for s in size:
            num_features *= s
        return num_features
```

```
def init (self):
    super(Net, self).__init__()

# 1 input image channel, 6 output channels,
5x5 square convolution kernel

self.conv1 = nn.Conv2d(1, 6, 5)
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```
def forward(self, x):
    # Max pooling over a (2, 2) window
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    #square you can only specify a single number
    x = F.max_pool2d(F.relu(self.conv2(x)), 2)
    x = x.view(-1, self.num_flat_features(x))
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
```



```
def num_flat_features(self, x):
    size = x.size()[1:] # all dimensions except the batch dimension
    num_features = 1
    for s in size:
        num_features *= s
return num_features
```



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Data

- For images
 - Pillow, OpenCV are useful
- For audio
 - Scipy and librosa
- For text
 - NLTK and SpaCy are useful
- Load data into memory as NumPy array
 - Then convert to tensor for GPU



Loading data - torchvision

- Torchvision
 - it's extremely easy to load existing datasets

```
import torchvision
import torchvision.transforms as transforms
```



Loading data - torchvision

```
import torchvision
import torchvision.transforms as transforms

transform = transforms.Compose([transforms.ToTensor(),
transforms.Normalize((0.5,0.5,0.5), (0.5,0.5,0.5))])

trainset = torchvision.datasets.CIFAR10(root='./data',
train=True, download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset,
batch_size=4, shuffle=True, num_workers=2)
```



Loading data - torchvision

```
import torchvision
import torchvision.transforms as transforms

transform = transforms.Compose([transforms.ToTensor(),
   transforms.Normalize((0.5,0.5,0.5), (0.5,0.5,0.5))])

testset = torchvision.datasets.CIFAR10(root='./data',
   train=False, download=True, transform=transform)

testloader = torch.utils.data.DataLoader(testset,
   batch_size=4, shuffle=False, num_workers=2)
```



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Feed-forward

```
def forward(self, x):
    # Max pooling over a (2, 2) window
    x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
    # If the size is a square you can only specify a
single number
    x = F.max_pool2d(F.relu(self.conv2(x)), 2)
    x = x.view(-1, self.num_flat_features(x))
    x = F.relu(self.fc1(x))
    x = F.relu(self.fc2(x))
    x = self.fc3(x)
```



Training procedure

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Loss function

- A loss function takes the (output, target) pair of inputs
- Computes a value that estimates how far away the output is from the target.
- There are several different loss functions under the nn package.
- A simple loss can be
 - nn.MSELoss
 - It computes the mean-squared error between the input and the target.



Loss function

```
output = net(input)
target = torch.randn(10)
# a dummy target, for example
target = target.view(1, -1)
# make it the same shape as output

criterion = nn.MSELoss()

loss = criterion(output, target)
```



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Gradient computation

```
output = net(input)
loss = criterion(output, target)
loss.backward()
```



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Update parameters

```
# create your optimizer
optimizer = optim.SGD(net.parameters(), lr=0.01)
# in your training loop:
optimizer.zero_grad()
output = net(input)
loss = criterion(output, target)
loss.backward()
optimizer.step() # Does the update
```



- Total training samples = 80000 Batch-size = 50
- Each iteration takes 30 seconds
- How many hours for 3 epochs of training?





```
for epoch in range(2):
# loop over the dataset multiple times

running_loss = 0.0
for i, data in enumerate(trainloader, 0):
    # training code for each batch

print('Finished Training')
```



```
for epoch in range(2):
    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs;
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()
        ...
```







```
for epoch in range(2):
# loop over the dataset multiple times

# training code for each batch
print('Finished Training')

PATH = './cifar_net.pth'
torch.save(net.state_dict(), PATH)
```



Testing

```
dataiter = iter(testloader)
images, labels = dataiter.next()

net = Net()
net.load_state_dict(torch.load(PATH))
outputs = net(images)

_, predicted = torch.max(outputs, 1)
```



Training on GPU

• Let's first define our device

```
device = torch.device("cuda:0" if
torch.cuda.is_available() else "cpu")

net.to(device)

inputs, labels = data[0].to(device),
data[1].to(device)
```



References

• Sources for this lecture include materials from pytorch.org

Thank You