UCF CENTER FOR RESEARCH IN COMPUTER VISION

CAP5415
Computer Vision

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HEC-241

Questions?

PyTorch Tutorial

Lecture 8

Agenda

- PyTorch basics
- Model training

PyTorch Tutorial

Lecture 8

Basics

Deep learning libraries

- Torch (Lua):
  - http://torch.ch/
- PyTorch (Python)
  - http://pytorch.org/
- TensorFlow (Python and C++):
  - https://www.tensorflow.org/
- Theano (Python)
  - http://deeplearning.net/software/theano/
- Keras
  - https://keras.io/

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)

y = x.view(16)
z = x.view(-1, 8)

print(x.size(), y.size(),
z.size())
```

Output:

```
torch.Size([4, 4])
torch.Size([16])
torch.Size([2, 8])
```

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

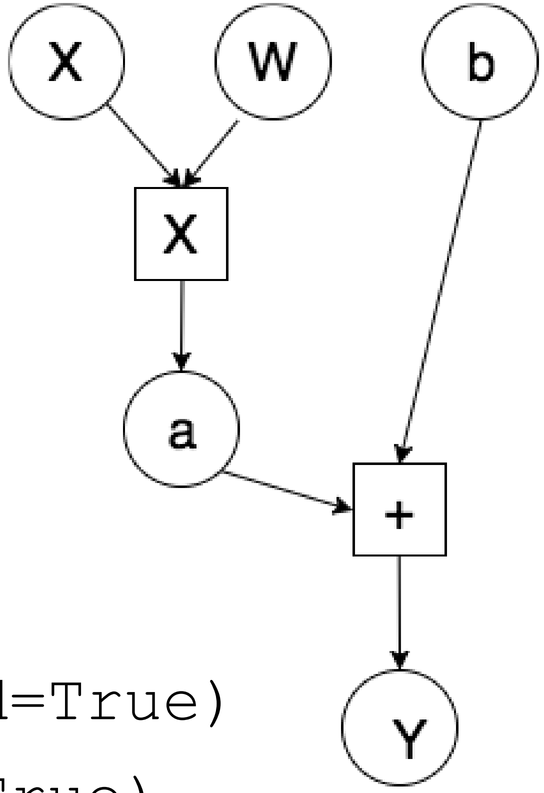
…

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
```

Questions?

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Feedback

- How is it going so far?
- Help with any topic from class?
- Help in assignments?
- Any issues so far?
  - Office hours?
- General comments?

Administrative

- Mid-term
  - Coming soon, Oct 19
  - Zoom/in-person, same time as lecture
  - 20 questions
    - True/False
    - Fill in the blanks
    - Multiple choice
    - Subjective
  - We will release sample questions

Questions?

PyTorch Tutorial

Lecture 8

Model training

Training procedure

- Define the neural network
- Iterate over a dataset of inputs
- Process input through the network
- Compute the loss
- Propagate gradients back into the network's parameters
- Update the weights of 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

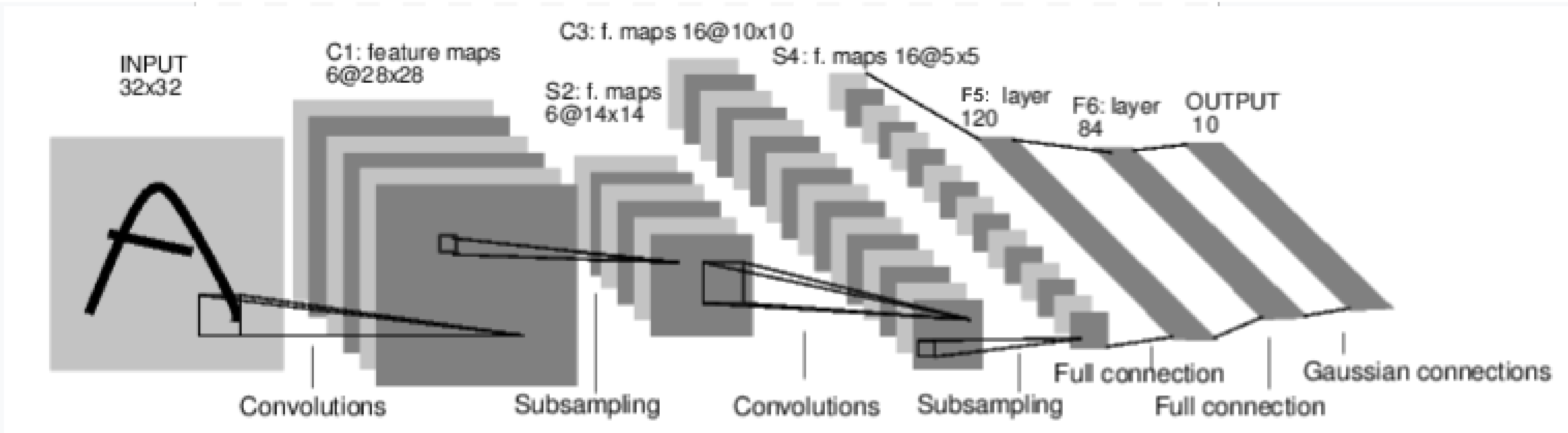
Backward
- nn depends on autograd
- You just have to define the forward function

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



Example from http://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html

Define a CNN Network

```python
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
```

Define a CNN Network

```
def __init__(self):
        super(Net, self).__init__()
        # 1 input image channel, 6 output channels,
3x3 square convolution kernel
        self.conv1 = nn.Conv2d(1, 6, 3)
        self.conv2 = nn.Conv2d(6, 16, 3)
        # an affine operation: y = Wx + b
        self.fc1 = nn.Linear(16 * 6 * 6, 120)  # 6*6
from image dimension
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
```

Define a CNN Network

```
 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
```

Define a CNN Network

```
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
```

Training procedure

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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)
```

Training procedure

- Define the neural network
- Iterate over a dataset of inputs
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- Update the weights of the network

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)

        return x
```

Training procedure

- Define the neural network
- Iterate over a dataset of inputs
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- Update the weights of the network

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)
```

Training procedure

- Define the neural network
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Gradient computation

```
output = net(input)

loss = criterion(output, target)

loss.backward()
```

Training procedure

- Define the neural network
- Iterate over a dataset of inputs
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- Update the weights of the network

Update parameters

```
import torch.optim as optim

# create your optimizer
optimizer = optim.SGD(net.parameters(), lr=0.01)

# in your training loop:
optimizer.zero_grad()   # zero the gradient buffers
output = net(input)
loss = criterion(output, target)
loss.backward()
optimizer.step()    # Does the update
```

Full training

```
net = Net()

trainloader = torch.utils.data.DataLoader
                (trainset, batch_size=4,
                 shuffle=True, num_workers=2)

criterion = nn.CrossEntropyLoss()

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

Full 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')
```

Full 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()
        ...
```

Full training

```
for epoch in range(2):
    for i, data in enumerate(trainloader, 0):
        ...
        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        ...
```

Full training

```
for epoch in range(2):
    for i, data in enumerate(trainloader, 0):
        ...
        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999: # every 2000 batches
            print('[%d, %5d] loss: %.3f' %
            (epoch+1,i+1,running_loss/2000))
            running_loss = 0.0
```

Full 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’)

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)
```

Questions?

Questions?

Sources for this lecture include materials from pytorch.org