PyTorch

>>> ELEG5491: Introduction to Deep Learning
>>> PyTorch Tutorials

Name: GE Yixiao†

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†yxge@link.cuhk.edu.hk

>>> WHAT IS PYTORCH?

It’s a Python-based scientific computing package targeted at two sets of audiences:

* A replacement for NumPy to use the power of GPUs
* A deep learning research platform that provides maximum flexibility and speed

>>> Outline[1]

1. Installation
2. Basic Concepts
3. Autograd: Automatic Differentiation
4. Neural Networks
5. Example: An Image Classifier
6. Further

[1] Refer to https://pytorch.org/tutorials/beginner/deep_learning_60min_blitz.html

>>> Installation

PyTorch Build	Stable (1.0)	Preview (Nightly)			
Your OS	Linux	Mac	Windows		
Package	Conda	Pip	LibTorch	Source	
Language	Python 2.7	Python 3.5	Python 3.6	Python 3.7	C++
CUDA	8.0	9.0	10.0	None	
Run this Command:	`conda install pytorch torchvision cudatoolkit=9.0 -c pytorch`				

https://pytorch.org/

* Anaconda (RECOMMEND for new hands): easy to install and run; out-of-date; automatically download dependencies
* Source install (a great choice for the experienced): latest version; some new features

>>> Tensors

Tensors are similar to NumPy's ndarrays. Start with:

```python
import torch
```

>>> Tensors

Initialize tensors:

```
# Construct a 5x3 matrix, uninitialized
x = torch.empty(5, 3)
# Construct a randomly initialized matrix
x = torch.rand(5, 3)
# Construct a matrix filled zeros and of dtype long
x = torch.zeros(5, 3, dtype=torch.long)
# Construct a tensor directly from data
x = torch.tensor([5.5, 3])
```

>>> Operations

Addition operation:

```
x = torch.rand(5, 3)
y = torch.rand(5, 3)
# Syntax 1
z = x + y
# Syntax 2
z = torch.empty(5, 3)
torch.add(x, y, out=z)

# In-place addition, adds x to y
y.add_(x)
```

Explore the subtraction operation(*torch.sub*), multiplication operation(*torch.mul*), *etc.*

>>> Torch Tensor & NumPy Array

Convert Torch Tensor to NumPy Array:

```
a = torch.ones(5) # Torch Tensor
b = a.numpy() # NumPy Array
```

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```

Convert NumPy Array to Torch Tensor:

```
import numpy as np
a = np.ones(5) # NumPy Array
b = torch.from_numpy(a) # Torch Tensor
```

>>> CUDA Tensors

Tensors can be moved onto any device using the *.to* method.

```
# move the tensor to GPU
x = x.to("cuda")
# or
x = x.cuda()

# directly create a tensor on GPU
device = torch.device("cuda")
y = torch.ones_like(x, device=device)

# move the tensor to CPU
x = x.to("cpu")
# or
x = x.cpu()
```

>>> Autograd

Track all operations by setting Tensors' attribute *.requires_grad* as True:

```
x = torch.ones(2, 2, requires_grad=True)
# or
x = torch.ones(2, 2)
x.requires_grad_(True) # in-place
```

Do operations:

```
y = x + 2
z = y * y * 3
out = z.mean()
```

Let' s backpropagate:

```
out.backward()
```

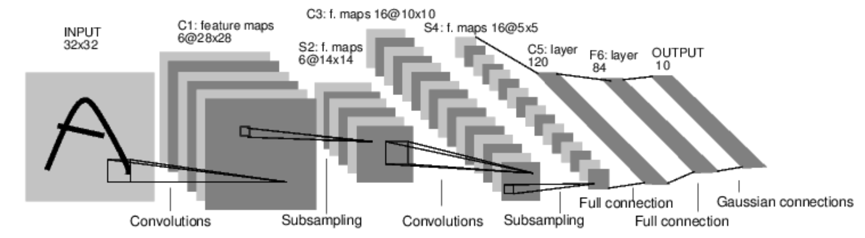
>>> Autograd

Stop autograd on Tensors with *.requires_grad=True* by:

```
>>> print(x.requires_grad)
>>> True

with torch.no_grad():
    # Do operations on x
```

>>> Training procedure



1. Define the neural network that has some learnable parameters/weights
2. Process input through the network
3. Compute the loss (how far is the output from being correct)
4. Propagate gradients back into the network' s parameters, and update the weights of the network, typically using a simple update rule: *weight = weight - learning_rate * gradient*

Repeat step 2-4 by iterating over a dataset of inputs.

>>> Define the network (step 1)

Only need to define the forward function, and the backward function is automatically defined.

```python
import torch
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

>>> Define the network (step 1)

View the network structure:

```
>>> net = Net()
>>> print(net)
>>> Net(
      (conv1): Conv2d(1, 6, kernel_size=(5, 5), stride=(1, 1))
      (conv2): Conv2d(6, 16, kernel_size=(5, 5), stride=(1, 1))
      (fc1): Linear(in_features=400, out_features=120, bias=True)
      (fc2): Linear(in_features=120, out_features=84, bias=True)
      (fc3): Linear(in_features=84, out_features=10, bias=True)
    )
```

The learnable parameters of a model are returned by `net.parameters()`.

>>> Process inputs (step 2)

Try a random input:

```
input = torch.randn(1, 1, 32, 32)
out = net(input)
```

>>> Compute the loss (step 3)

Example: nn.MSELoss which computes the mean-squared error between the input and the target.

```
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)
```

Look into several different loss functions by https://pytorch.org/docs/stable/nn.html.

>>> Backprop and update the weights (step 4)

Set up an update rule such as SGD, Adam, *etc*, by using torch.optim package.

```
import torch.optim as optim

optimizer = optim.SGD(net.parameters(), lr=0.01)
```

>>> Backprop and update the weights (step 4)

Set up an update rule such as SGD, Adam, *etc*, by using torch.optim package.

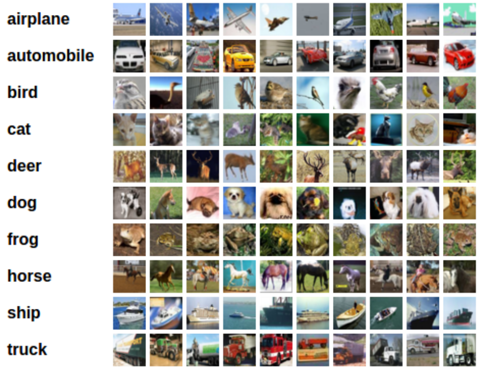
```
import torch.optim as optim

optimizer = optim.SGD(net.parameters(), lr=0.01)
```

Then backpropagate the error and update the weights:

```
optimizer.zero_grad() # zero the gradient buffers
loss = criterion(output, target)
loss.backward()
optimizer.step() # Does the update
```

>>> Training an image classifier



1. Load and normalizing the training and test datasets.
2. Define a Convolutional Neural Network
3. Define a loss function
4. Train the network on the training data
5. Test the network on the test data

>>> Load data

Deal with images,

1. load data into a numpy array by packages such as Pillow, OpenCV
2. convert this array into a torch.*Tensor
3. normalize data by torchvision.transforms
4. assign mini batches by torch.utils.data.DataLoader

Exist data loaders for common datasets such as Imagenet, CIFAR10, MNIST, *etc* in torchvision.datasets (replace step 1-2).

>>> Load data (step 1)

Example: Loading and normalizing CIFAR10

```
import torch
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)

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)
```

>>> Define the network (step 2)

Same as before:

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = F.max_pool2d(F.relu(self.conv1(x)), (2, 2))
        x = F.max_pool2d(F.relu(self.conv2(x)), 2)
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

net = Net()
```

>>> Define a loss function and optimizer (step 3)

Use Cross-Entropy loss and SGD with momentum:

```
import torch.optim as optim

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

>>> Train the network (step 4)

Loop over our data iterator:

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

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0
```

\>>> Train the network (step 4)

Out:

```
[1, 2000] loss: 2.258
[1, 4000] loss: 1.877
[1, 6000] loss: 1.699
[1, 8000] loss: 1.594
[1, 10000] loss: 1.533
[1, 12000] loss: 1.475
[2, 2000] loss: 1.425
[2, 4000] loss: 1.380
[2, 6000] loss: 1.350
[2, 8000] loss: 1.347
[2, 10000] loss: 1.332
[2, 12000] loss: 1.277
```

>>> Test the network (step 5)

Check by prediction:

```
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

>>> Test the network (step 5)

Check by prediction:

```
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

Out:

```
Accuracy of the network on the 10000 test images: 54 %
```

\>>> Option: training on GPU

Transfer the network and tensors onto the GPU:

```
device = torch.device("cuda:0")
# training on the first cuda device

net.to(device)

inputs, labels = inputs.to(device), labels.to(device)
```

>>> Option: training on multiple GPUs

You can easily run your operations on multiple GPUs by making your model run parallelly using:

```
net = nn.DataParallel(net)
```

Advantages: larger batch size, higher speed, *etc*.

\>>> More Adventures

* Tutorials https://github.com/pytorch/tutorials
* Examples https://github.com/pytorch/examples
* Docs http://pytorch.org/docs/
* Discussions https://discuss.pytorch.org/