PYTORCH

- a pythonic DL framework

>>> 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

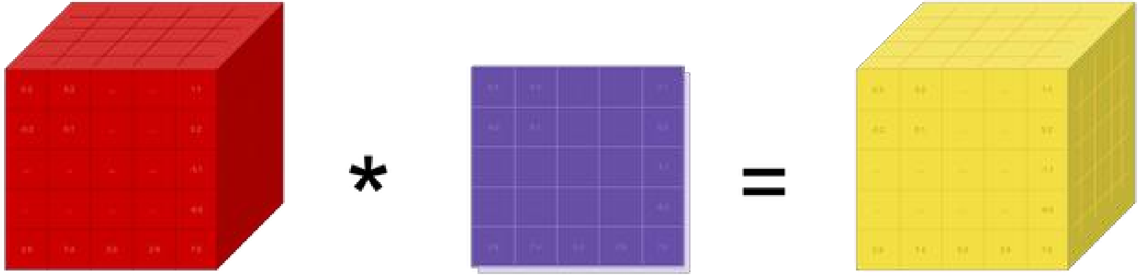
>>> Installation

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* Anaconda (RECOMMEND for new hands): easy to install and run; out-of-date; automatically download dependencies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:

```
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
```

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()
```

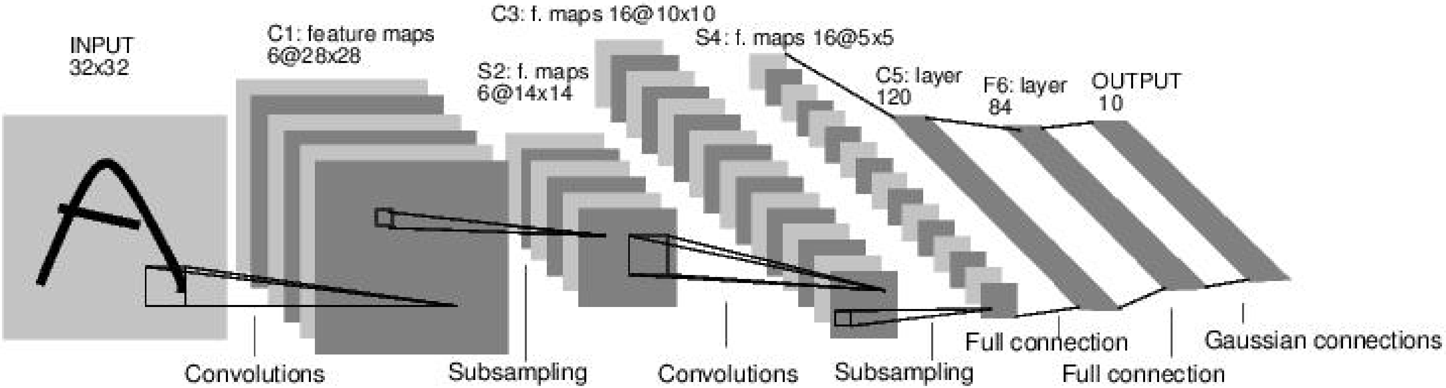
>>> Autograd

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 forward function, backward function is automatically defined.

```
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)

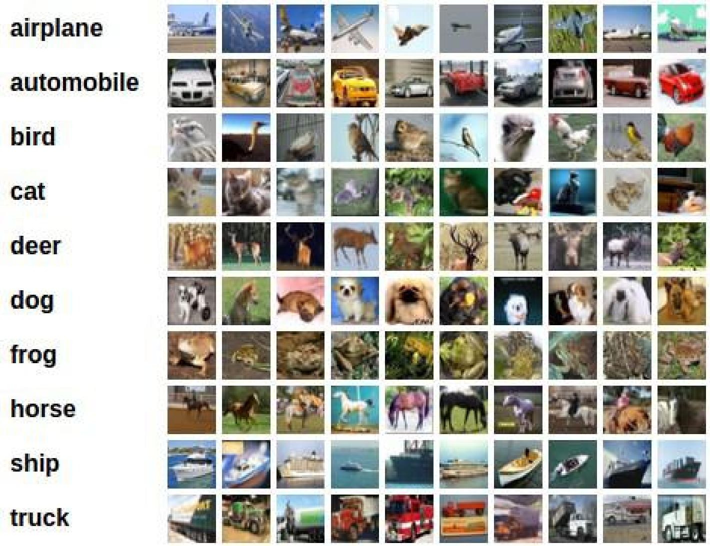
Set up an update rule such as SGD, Adam, *etc*, by using torch.optim package.

```
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 data:

```
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 prediction:

```python
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 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/