PyTorch Tutorial

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Outline

- PyTorch Basics
- Automatic Differentiation
- Neural Network Building Blocks
- Datasets and End-to-End Training

What is PyTorch?

- Automatic differentiation package
- Written entirely in Python
- Enables composing high-level DNN APIs with low-level control of individual operations

```python
import torch.nn as nn

class Residual(nn.Module):
    def __init__(self, fn):
        super().__init__()
        self.fn = fn

    def forward(self, x):
        return self.fn(x) + x

def ConvMixer(dim, depth, kernel_size=9, patch_size=7, n_classes=1000):
    return nn.Sequential(
        nn.Conv2d(3, dim, kernel_size=patch_size, stride=patch_size),
        nn.GELU(),
        nn.BatchNorm2d(dim),
        *[nn.Sequential(
                Residual(nn.Sequential(
                    nn.Conv2d(dim, dim, kernel_size, groups=dim, padding="same"),
                    nn.GELU(),
                    nn.BatchNorm2d(dim)
                )),
                nn.Conv2d(dim, dim, kernel_size=1),
                nn.GELU(),
                nn.BatchNorm2d(dim)
        ) for i in range(depth)],
        nn.AdaptiveAvgPool2d((1,1)),
        nn.Flatten(),
        nn.Linear(dim, n_classes)
    )
```

Figure 7: A more readable PyTorch (Paszke et al., 2019) implementation of ConvMixer, where h = dim, d = depth, p = patch_size, k = kernel_size.

Tensors

Initializing a Tensor

Tensors can be initialized in various ways. Take a look at the following examples:

Directly from data

Tensors can be created directly from data. The data type is automatically inferred.

```
data = [[1, 2],[3, 4]]
x_data = torch.tensor(data)
```

From a NumPy array

Tensors can be created from NumPy arrays (and vice versa - see Bridge with NumPy).

```
np_array = np.array(data)
x_np = torch.from_numpy(np_array)
```

From another tensor:

The new tensor retains the properties (shape, datatype) of the argument tensor, unless explicitly overridden.

```
x_ones = torch.ones_like(x_data) # retains the properties of x_data
print(f"Ones Tensor: \n {x_ones} \n")

x_rand = torch.rand_like(x_data, dtype=torch.float) # overrides the datatype of
x_data
print(f"Random Tensor: \n {x_rand} \n")
```

Out:

```
Ones Tensor:
 tensor([[1, 1],
        [1, 1]])

Random Tensor:
 tensor([[0.9765, 0.7175],
        [0.2641, 0.5792]])
```

Attributes and Operations

```python
tensor = torch.rand(3,4)

print(f"Shape of tensor: {tensor.shape}")
print(f"Datatype of tensor: {tensor.dtype}")
print(f"Device tensor is stored on: {tensor.device}")
```

Out:

```
Shape of tensor: torch.Size([3, 4])
Datatype of tensor: torch.float32
Device tensor is stored on: cpu
```

Numpy-Style Operations

Arithmetic operations

```
# This computes the matrix multiplication between two tensors. y1, y2, y3 will have the same value
y1 = tensor @ tensor.T
y2 = tensor.matmul(tensor.T)

y3 = torch.rand_like(y1)
torch.matmul(tensor, tensor.T, out=y3)


# This computes the element-wise product. z1, z2, z3 will have the same value
z1 = tensor * tensor
z2 = tensor.mul(tensor)

z3 = torch.rand_like(tensor)
torch.mul(tensor, tensor, out=z3)
```

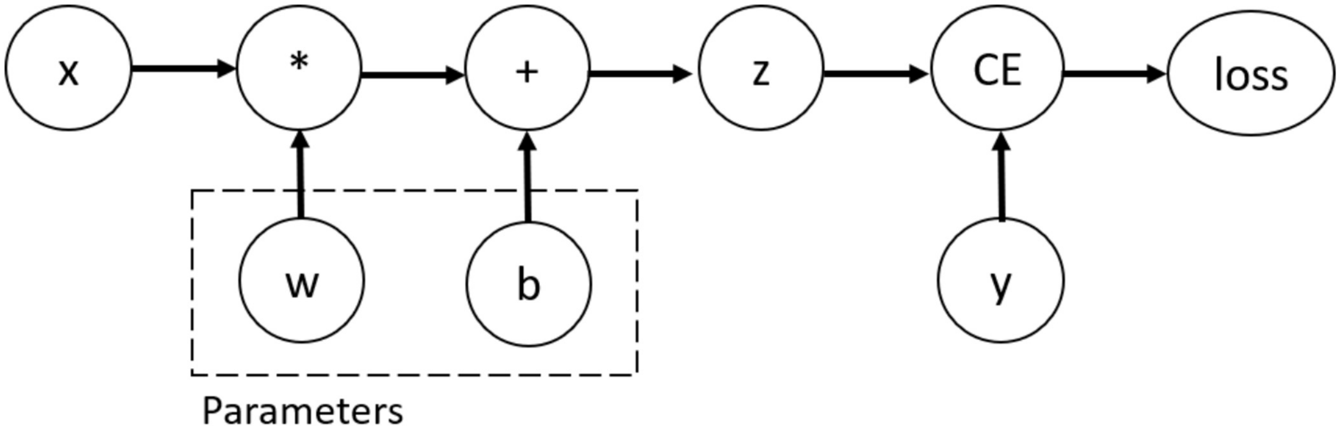
Automatic Differentiation

```python
import torch

x = torch.ones(5)  # input tensor
y = torch.zeros(3)  # expected output
w = torch.randn(5, 3, requires_grad=True)
b = torch.randn(3, requires_grad=True)
z = torch.matmul(x, w)+b
loss = torch.nn.functional.binary_cross_entropy_with_logits(z, y)
```

Tensors, Functions and Computational graph

This code defines the following **computational graph**:



Backward

```
loss.backward()
print(w.grad)
print(b.grad)
```

Out:

```
tensor([[0.3270, 0.0819, 0.0467],
        [0.3270, 0.0819, 0.0467],
        [0.3270, 0.0819, 0.0467],
        [0.3270, 0.0819, 0.0467],
        [0.3270, 0.0819, 0.0467]])
tensor([0.3270, 0.0819, 0.0467])
```

Modules

Base class for all neural network modules.

Your models should also subclass this class.

Modules can also contain other Modules, allowing to nest them in a tree structure. You can assign the submodules as regular attributes:

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

class Model(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(1, 20, 5)
        self.conv2 = nn.Conv2d(20, 20, 5)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        return F.relu(self.conv2(x))
```

Submodules assigned in this way will be registered, and will have their parameters converted too when you call `to()`, etc.

Usage of modules

```
# Construct our loss function and an Optimizer. The call to model.parameters()
# in the SGD constructor will contain the learnable parameters (defined
# with torch.nn.Parameter) which are members of the model.
criterion = torch.nn.MSELoss(reduction='sum')
optimizer = torch.optim.SGD(model.parameters(), lr=1e-6)
for t in range(2000):
    # Forward pass: Compute predicted y by passing x to the model
    y_pred = model(x)

    # Compute and print loss
    loss = criterion(y_pred, y)
    if t % 100 == 99:
        print(t, loss.item())

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

Datasets

```python
import torch
from torch.utils.data import Dataset
from torchvision import datasets
from torchvision.transforms import ToTensor, Lambda
import matplotlib.pyplot as plt


training_data = datasets.FashionMNIST(
    root="data",
    train=True,
    download=True,
    transform=ToTensor()
)

test_data = datasets.FashionMNIST(
    root="data",
    train=False,
    download=True,
    transform=ToTensor()
)
```

Dataloaders

```
from torch.utils.data import DataLoader

train_dataloader = DataLoader(training_data, batch_size=64, shuffle=True)
test_dataloader = DataLoader(test_data, batch_size=64, shuffle=True)
```

```
# Display image and label.
train_features, train_labels = next(iter(train_dataloader))
print(f"Feature batch shape: {train_features.size()}")
print(f"Labels batch shape: {train_labels.size()}")
img = train_features[0].squeeze()
label = train_labels[0]
plt.imshow(img, cmap="gray")
plt.show()
print(f"Label: {label}")
```

Putting it together

Basic pseudocode for training loop

- Declare model as instance of class inheriting from nn.Module()
- Define optimizer containing model parameters
- For (x, y) in dataloader:
    - Zero out the optimizer's accumulated gradients (optimizer.zerograd())
    - Compute loss on (x, y) via loss(net(x), y)
    - loss.backward() - compute the gradients of the loss with respect to each parameter
    - optimizer.step() - take a step in the direction of the gradient (or something fancier)
    - (Optional) evaluate test/validation error

Questions?

- If you’d like a more interactive setup with the same information, check out “Deep Learning with PyTorch: A 60 Minute Blitz”
- Make sure to familiarize yourself with the different types of layers/modules you might need to use