Deep Learning with PyTorch

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Outline



Popular Deep Learning Frameworks

Imperative-style programs execute the computation immediately.

```
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
d = c + 1
```

 Symbolic-style programs trace the computation graph first, and then execute it later.

```
A = Variable('A')
B = Variable('B')
C = B * A
D = C + Constant(1)
# compiles the function
f = compile(D)
d = f(A=np.ones(10), B=np.ones(10)*2)
```

PyTorch: Levels of Abstraction

Tensor:

- A multidimensional high-performance array.
- Can run on GPU.
- Same behavior as numpy ndarrays for the most part.

Autograd:

- A tensor also acts as a node in a computation graph.
- Tensor C = A + B retains information about how it was created.
- Autograd uses this information to compute gradients automatically.

Module:

- Generic neural network building blocks.
- Linear layer, convolutional layer, etc.

PyTorch: Tensors

```
x = torch.rand(5, 3)
print(x)
```

PyTorch: Tensors

PyTorch: Tensors

- Acts as a multi-dimensional array.
- Ex:
 - o [[0, 1, 2], [3, 4, 5]]
 - o torch.tensor([[0, 1, 2], [3, 4, 5]])
 - Represent the same data.

All tensors track their computation paths and compute their own gradients!

```
x = torch.ones(2, 2, requires_grad=True)
print(x)
```

All tensors track their computation paths and compute their own gradients!

```
y = x + 2
print(y)
```

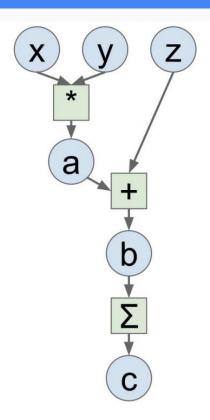
All tensors track their computation paths and compute their own gradients!

```
print(y.grad_fn)
```

<AddBackward0 object at 0x7f429cdbd588>

Numpy

```
import numpy as np
np.random.seed(0)
N, D = 3, 4
x = np.random.randn(N, D)
y = np.random.randn(N, D)
z = np.random.randn(N, D)
a = x * y
b = a + z
c = np.sum(b)
grad c = 1.0
grad_b = grad_c * np.ones((N, D))
grad a = grad b.copy()
grad z = grad b.copy()
grad x = grad a * y
grad y = grad a * x
```



- c.backward()
- x.grad, y.grad, z.grad all automatically computed!

- Neural network layer class.
- Neural networks are composed functions:

```
 \begin{array}{ll} \circ & a = f(x) \\ \circ & b = g(a) \\ \circ & c = h(b) \\ \circ & c = h(g(f(x))) \end{array}
```

Modules are classes that define one of these composable functions.

- Convolution layers

Conv1d

Conv2d

Conv3d

ConvTranspose1d

ConvTranspose2d

ConvTranspose3d

Unfold

Fold

- Pooling layers

MaxPool1d

MaxPool2d

MaxPool3d

MaxUnpool1d

MaxUnpool2d

MaxUnpool3d

AvgPool1d

AvgPool2d AvgPool3d

FractionalMaxPool2d

LPPool1d

LPPool2d

AdaptiveMaxPool1d

AdaptiveMaxPool2d

AdaptiveMaxPool3d

AdaptiveAvgPool1d

AdaptiveAvgPool2d

AdaptiveAvgPool3d

 Non-linear activations (weighted sum, nonlinearity)

ELU

Hardshrink

Hardtanh

LeakyReLU LogSigmoid

MultiheadAttention

PReLU

ReLU

ReLU6

RReLU

SELU

Sigmoid

Softplus

Softshrink

Softsign

Tanh

Tanhshrink

Threshold

- Recurrent layers

RNN

LSTM

GRU

RNNCell LSTMCell

GRUCell

- Loss functions

L1Loss

MSELoss

CrossEntropyLoss

CTCLoss

NLLLoss

PoissonNLLLoss

KLDivLoss BCFLoss

BCEWithLogitsLoss

MarginRankingLoss

HingeEmbeddingLoss

MultiLabel MarginLoss

SmoothL1Loss

SoftMarginLoss

MultiLabelSoftMarginLoss

CosineEmbeddingLoss

MultiMarginLoss

TripletMarginLoss

```
Convolutional
                           Convolutional
                                          Fully-
connected
                                 laver 2
                    layer
        Input layer
class Net(nn.Module):
    def init (self):
        super(Net, self). init ()
        self.conv1 = nn.Conv2d(1, 10, kernel size=5)
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
        self.mp = nn.MaxPool2d(2)
        self.fc = nn.Linear(320, 10) # 320 -> 10
    def forward(self, x):
        in size = x.size(0)
        x = F.relu(self.mp(self.conv1(x)))
        x = F.relu(self.mp(self.conv2(x)))
        x = x.view(in size, -1) # flatten the tensor
        x = self.fc(x)
        return F.log_softmax(x)
```

