Deep Learning with PyTorch

January 15, 2020

Outline

- Tensor
- Autograd
- Modules
- Exercises

Popular Deep Learning Frameworks

- Imperative-style programs execute the computation **immediately**.

```python
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.

```python
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

```
tensor([[0.5683, 0.1334, 0.7669],
        [0.8196, 0.1895, 0.6653],
        [0.3621, 0.8314, 0.6239],
        [0.8716, 0.2269, 0.1005],
        [0.3598, 0.1292, 0.5585]])
```

PyTorch: Tensors

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

PyTorch: Autograd

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

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

PyTorch: Autograd

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

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

PyTorch: Autograd

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

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

```
<AddBackward0 object at 0x7f429cdbd588>
```

PyTorch: Autograd

Numpy

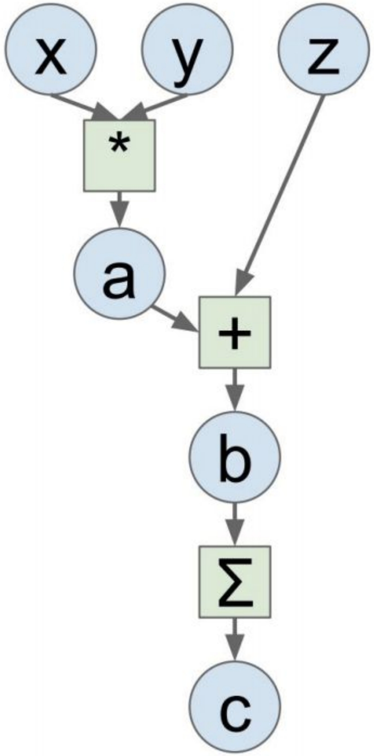
```
import numpy as np
np.random.seed(0)

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
```



PyTorch: Autograd

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

PyTorch: Modules

- Neural network layer class.
- Neural networks are composed functions:
  - a = f(x)
  - b = g(a)
  - c = h(b)
  - c = h(g(f(x)))

- Modules are classes that define one of these composable functions.

PyTorch: Modules

- Convolution layers
  - Conv1d
  - Conv2d
  - Conv3d
  - ConvTranspose1d
  - ConvTranspose2d
  - ConvTranspose3d
  - Unfold
  - Fold

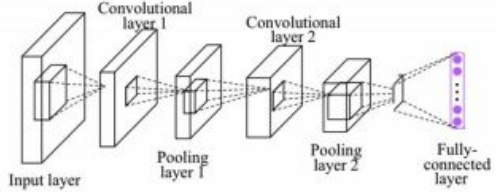
- Pooling layers
  - MaxPool1d
  - MaxPool2d
  - MaxPool3d
  - MaxUnpool1d
  - MaxUnpool2d
  - MaxUnpool3d
  - AvgPool1d
  - AvgPool2d
  - AvgPool3d
  - FractionalMaxPool2d
  - LPPool1d
  - LPPool2d
  - AdaptiveMaxPool1d
  - AdaptiveMaxPool2d
  - AdaptiveMaxPool3d
  - AdaptiveAvgPool1d
  - AdaptiveAvgPool2d
  - AdaptiveAvgPool3d

- Non-linear activations (weighted sum, nonlinearity)
  - ELU
  - Hardshrink
  - Hardtanh
  - LeakyReLU
  - LogSigmoid
  - MultiheadAttention
  - PReLU
  - ReLU
  - ReLU6
  - RReLU
  - SELU
  - CELU
  - Sigmoid
  - Softplus
  - Softshrink
  - Softsign
  - Tanh
  - Tanhshrink
  - Threshold

- Recurrent layers
  - RNN
  - LSTM
  - GRU
  - RNNCell
  - LSTMCell
  - GRUCell

- Loss functions
  - L1Loss
  - MSELoss
  - CrossEntropyLoss
  - CTCLoss
  - NLLLoss
  - PoissonNLLLoss
  - KLDivLoss
  - BCELoss
  - BCEWithLogitsLoss
  - MarginRankingLoss
  - HingeEmbeddingLoss
  - MultiLabelMarginLoss
  - SmoothL1Loss
  - SoftMarginLoss
  - MultiLabelSoftMarginLoss
  - CosineEmbeddingLoss
  - MultiMarginLoss
  - TripletMarginLoss

PyTorch: Modules

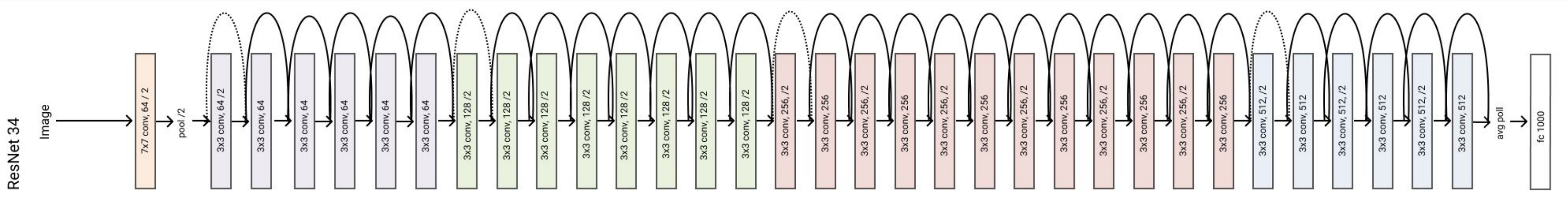



```
class Net(nn.Module):

    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)
```

PyTorch: Modules



Residual Networks: Implementing ResNet in Pytorch