Practices in Visual Computing II
Spring 2023

Lab #1: PyTorch Review

Deep Learning Frameworks / PyTorch

- What is a deep learning framework?
  - abstract certain things away to faster develop and test new ideas.
  - automatically compute gradients!
  - run it on efficiently on a GPU
  - Frameworks: PyTorch, TensorFlow, MXNet, CNTK, ...
- Why PyTorch?
  - very similar to Numpy, hence, beginner friendly.
  - great for fast and flexible development.

Basic Computations

Tensor

- Construct a Tensor

```python
x = torch.zeros(8, 3)
print(x)
```

```
tensor([[0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.],
        [0., 0., 0.]])
```

```python
x = torch.rand(8, 3)
print(x)
```

```
tensor([[0.0984, 0.3671, 0.2543],
        [0.5016, 0.8017, 0.0918],
        [0.5081, 0.6020, 0.0867],
        [0.5313, 0.4571, 0.1624],
        [0.4231, 0.3993, 0.2713],
        [0.8978, 0.6039, 0.8519],
        [0.4829, 0.6648, 0.8295],
        [0.9060, 0.2132, 0.4110]])
```

Basic Computations

Operations

- Multiple syntaxes, e.g. Addition

```
y = torch.rand(8, 3)
print(x + y)
```

```
print(torch.add(x, y))
```

```
# providing an output tensor as argument
result = torch.empty(8, 3)
torch.add(x, y, out=result)
print(result)
```

```
# adds x to y
y.add_(x)
print(y)
```

- Other operations including transposing, indexing, slicing, linear algebra etc. at `https://pytorch.org/docs/stable/torch.html`

Basic Computations

Bridge to Numpy

- PyTorch $\rightarrow$ Numpy

```
a = torch.ones(5)
b = a.numpy()
```

- Numpy $\rightarrow$ PyTorch

```
a = np.ones(5)
b = torch.from_numpy(a)
```

- Tensors can only be converted to Numpy when they are on CPU

Basic Computations

Difference to Numpy

- GPU acceleration

```
if torch.cuda.is_available():
    x = x.cuda()
    y = y.cuda()
    z = x + y
    print(z)
    print(z.cpu())        # ``.to`` can change dtype
```

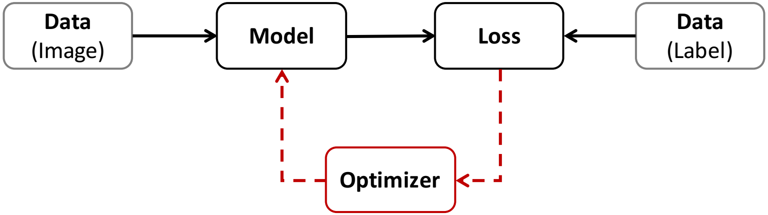
```
tensor([2.9218], device='cuda:0')
tensor([2.9218], dtype=torch.float64)
```

Autograd Demo

Calculate the derivative of $Q = 3a^3 - b^2$ **in** $a = 2,\ b = 6$

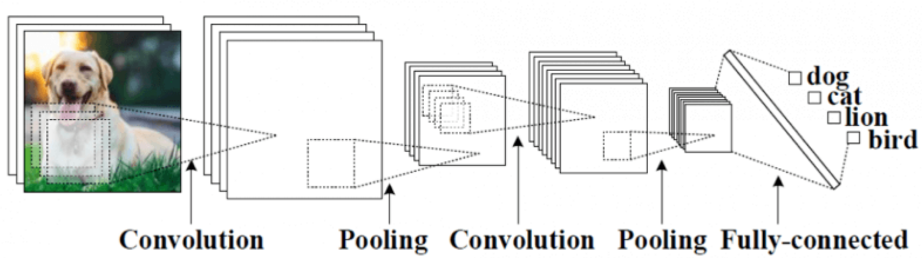
Neural Networks

- Model → `torch.nn.Module`
- Loss → `torch.nn.Module.Loss`
- Optimizer → `torch.optim`
- Data → `torch.utils.data`



Neural Networks

Model



Neural Networks

Model

- Define a model as a class that inherits from `torch.nn.Module`

```
class Net(nn.Module):
```

- Define layers in the `__init__()` method

```
    def __init__(self):
        ...
```

- Define computation flow given an input `x` in the `forward()` method

```
    def forward(self, x):
        ...
```

- `backward()` is automatically defined

Neural Networks

Model

```
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)

    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)
        return x
```

https://pytorch.org/tutorials/beginner/blitz/neural_networks_tutorial.html#define-the-network

Neural Networks

Model

- PyTorch contains a bunch of standard layers which are also subclasses of `torch.nn.Module`:
  - Convolution layers — `nn.Conv2d(`C_{in}`, `C_{out}`, `K`)`
  - Pooling layers — `nn.MaxPool2d(`K`)`
  - Non-linear activations — `nn.ReLU()`
  - Normalization layers — `nn.BatchNorm2d(`N`)`
  - Linear layers — `nn.Linear(`C_{in}`,`C_{out}`)`
  - ... — ...
- It is also easy to implement custom layers: `https://pytorch.org/docs/stable/notes/extending.html#extending-torch-nn`

Neural Networks

Loss

- Loss function returns a non-negative value J measuring the distance between network estimation and the ground truth
- PyTorch contains a branch of loss functions which are also subclasses of `torch.nn.Module`:
  - L1Loss
  - MSELoss
  - CrossEntroyLoss
  - NLLLoss
  - SmoothL1Loss
  - ...

Loss

- Example of using a loss function

```
loss = nn.CrossEntropyLoss()
input = torch.randn(3, 5, requires_grad=True)
target = torch.empty(3, dtype=torch.long).random_(5)
output = loss(input, target)
output.backward()
```

Optimizer

- Optimizer decides how to update the parameters in the model, e.g.
  $\theta = \theta - \eta \nabla J(\theta)$
- PyTorch implements a set of optimization algorithms in `torch.optim`:
  - SGD
  - SGD + Momentum
  - Adam
  - ...

Neural Networks

Optimizer

- 1. Construct an Optimizer

```
optimizer = optim.SGD(model.parameters(), lr = 0.01, momentum=0.9)
```

- 2. Take an optimization step for every batch/sample

```
for input, target in dataset:
    # clear saved gradients before computing gradient for the new batch
    optimizer.zero_grad()

    output = model(input)
    loss = loss_fn(output, target)

    loss.backward()

    # update parameters in model
    optimizer.step()
```

Neural Networks

Data

- PyTorch provides `Dataset`,`DataLoader` in `torch.utils.data` that allows batching data, shuffling data and load data with multiple processes.
- For small scale of dataset it is fine to implement your own data loader.

Neural Networks

Saving Models

- Save/Load `state_dict` (Recommended)

```
# save
torch.save(model.state_dict(), PATH)
# load
model = TheModelClass(*args, **kwargs)
model.load_state_dict(torch.load(PATH))
model.eval()
```

- Save/Load entire model

```
# save
torch.save(model, PATH)
# load
# Model class must be defined somewhere
model = torch.load(PATH)
model.eval()
```

MNIST Classification

Upload the `lab1.ipynb` to Google Colab.

Tasks:

[1] Calculate the normalization constants for MNIST

[2] Build a Pytorch dataloader

[3] Implement the MLP class

[4] Implement the device

[5] Implement the training loop.

[6] Implement the optimizer

[7] Reach a test accuracy of > 95 % on MNIST with an MLP

[8] Implement the CNN class

[9] Reach a test accuracy of > 97 % on MNIST with a CNN

References

- PyTorch official tutorials:
  `https://pytorch.org/tutorials/`
- Stanford Course on Deep Learning for Computer Vision:
  `http://cs231n.stanford.edu/slides/2018/cs231n_2018_lecture08.pdf`
- PyTorch tutorial with code examples:
  `https://github.com/MorvanZhou/PyTorch-Tutorial`