

Introduction to Deep Learning (CS474)

Lecture 17

Outline

- **Module 2**
 - Discussion on building a simple ConvNet using PyTorch

Introduction

- I hope that you remember our discussion on CIFAR-10 dataset!
- With the building blocks which was discussed in our earlier lectures, we can now proceed to build our convolutional neural network in PyTorch for detecting birds and airplanes.
- Look into the following code snippet for *model* building!

```
nn.Conv2d(3, 16, kernel_size=3, padding=1),  
nn.Tanh(),  
nn.MaxPool2d(2),  
nn.Conv2d(16, 8, kernel_size=3, padding=1),  
nn.Tanh(),  
nn.MaxPool2d(2)
```

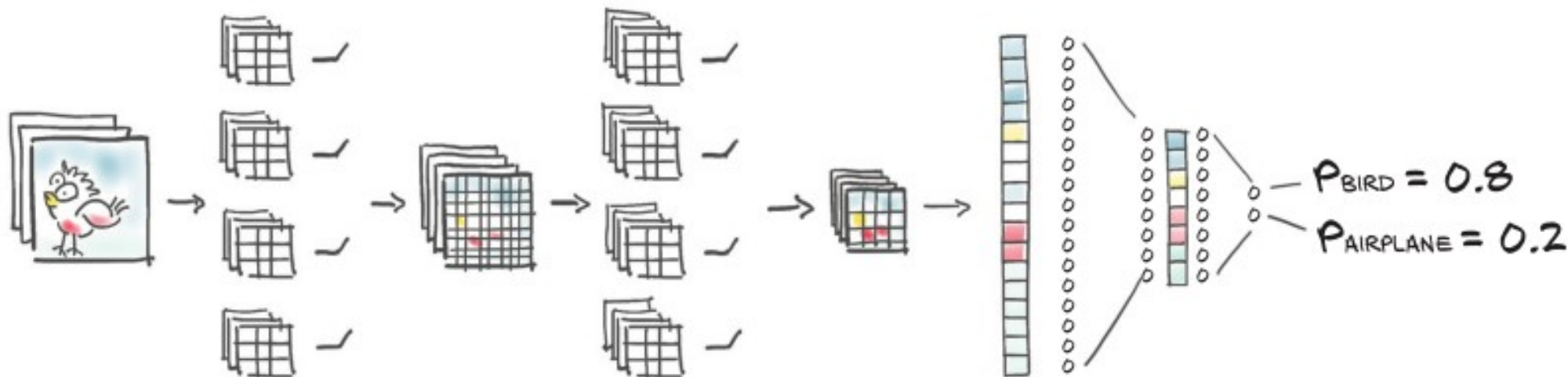
Putting it all together

- The first **convolution** takes us from 3 RGB channels to 16, thereby giving the network a chance to generate 16 independent features that operate to (hopefully) *discriminate* **low-level features** of birds and airplanes.
- Then we apply the **Tanh activation function**.
- The resulting 16-channel 32×32 image is **pooled** to a 16-channel 16×16 image by the first MaxPool .
- At this point, the downsampled image undergoes another convolution that generates an 8-channel 16×16 output.
- With any luck, this output will consist of **higher-level features**.
- Again, we apply a **Tanh** activation and then **pool** to an 8-channel 8×8 output.

Putting it all together

- Where does this end?
- After the input image has been reduced to a set of 8×8 features, we expect to be able to output some probabilities from the network.
- However, probabilities are a pair of numbers in a 1D vector (one for airplane, one for bird), but here we're still dealing with multi-channel 2D features.
- we already know what we need to do: turn the 8-channel 8×8 image into a 1D vector and complete our network with a set of fully connected layers.

Putting it all together



Subclassing nn.Module

- At some point in developing neural networks, we will find ourselves in a situation where we want to compute something that the *premade* modules do not cover..
- we learn how to make our own `nn.Module` subclasses that we can then use just like the prebuilt ones or `nn.Sequential`.
- When we want to build models that do more complex things than just applying one layer after another, we need to leave `nn.Sequential` for something that gives us added flexibility.
- **PyTorch** allows us to use any computation in our model by subclassing `nn.Module`.

Subclassing `nn.Module`

- In order to subclass `nn.Module`, at a minimum we need to define a **forward** function that takes the inputs to the module and returns the output.
- With **PyTorch**, if we use standard torch operations, *autograd* will take care of the backward pass automatically; and indeed, an `nn.Module` never comes with a backward.
- Typically, our computation will use other modules—**premade** like convolutions or customized.
- To include these submodules, we typically define them in the constructor `__init__` and assign them to self for use in the forward function.

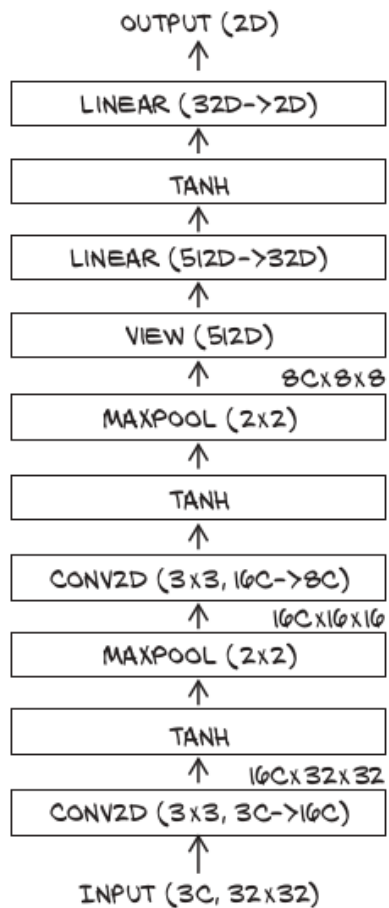
Subclassing nn.Module (example)

```
import torch
import torch.nn as nn

class Net(nn.Module):
    def __init__(self):
        super().__init__()
        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, padding=1)
        self.act1 = nn.Tanh()
        self.pool1 = nn.MaxPool2d(2)
        self.conv2 = nn.Conv2d(16, 8, kernel_size=3, padding=1)
        self.act2 = nn.Tanh()
        self.pool2 = nn.MaxPool2d(2)
        self.fc1 = nn.Linear(8 * 8 * 8, 32)
        self.act3 = nn.Tanh()
        self.fc2 = nn.Linear(32, 2)

    def forward(self, x):
        out = self.pool1(self.act1(self.conv1(x)))
        out = self.pool2(self.act2(self.conv2(out)))
        out = out.view(-1, 8 * 8 * 8) # <1>
        out = self.act3(self.fc1(out))
        out = self.fc2(out)
        return out
```

Subclassing nn.Module (example)



References

- All the contents present in the slides are taken from various online resources. Due credit is given in the respective slides. These slides are used for *academic* purposes only.