



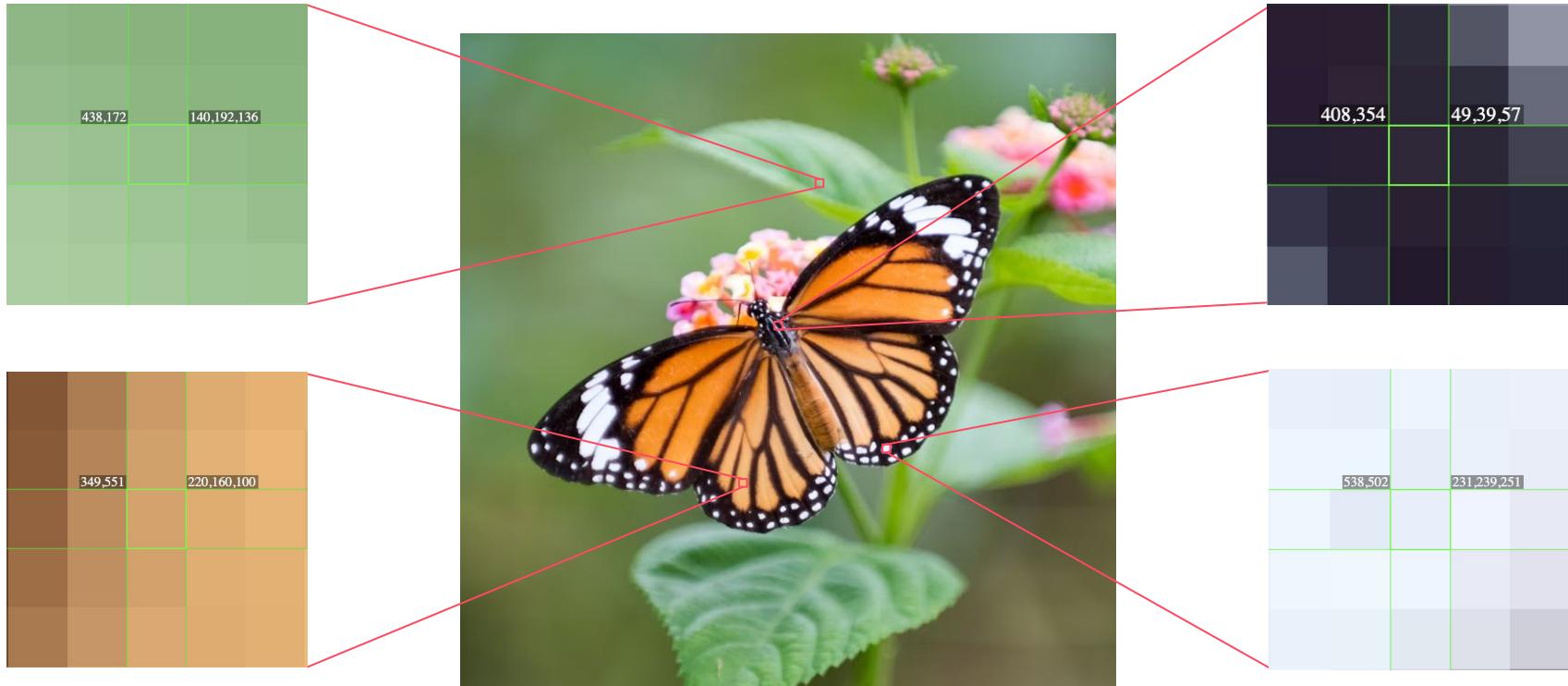
DeepLearning.AI

Convolutional Neural Networks

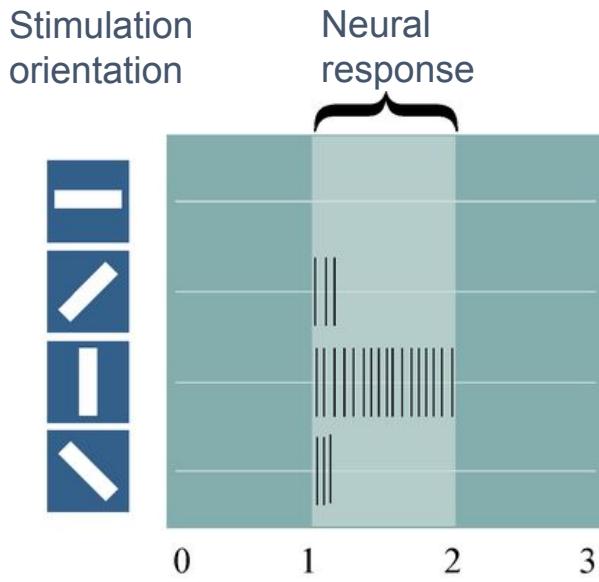
Part 1: Filters, Patterns, and Feature Maps

Core Neural Network Components

Linear layers treat every pixel as independent

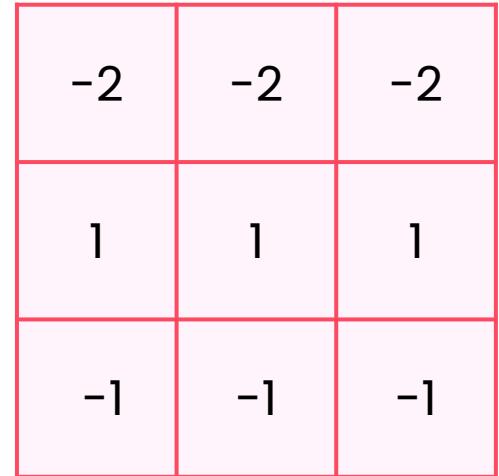
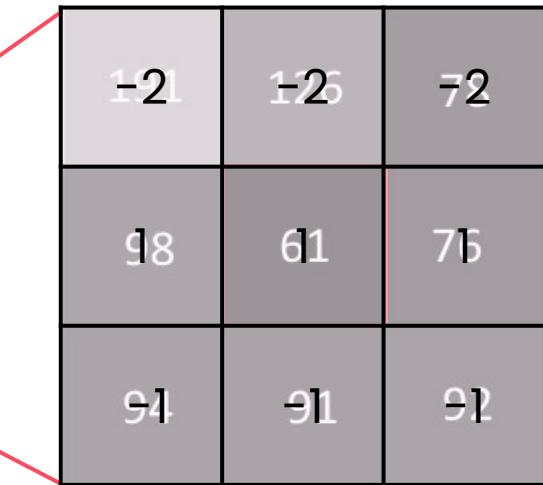


CNNs mimic biological vision

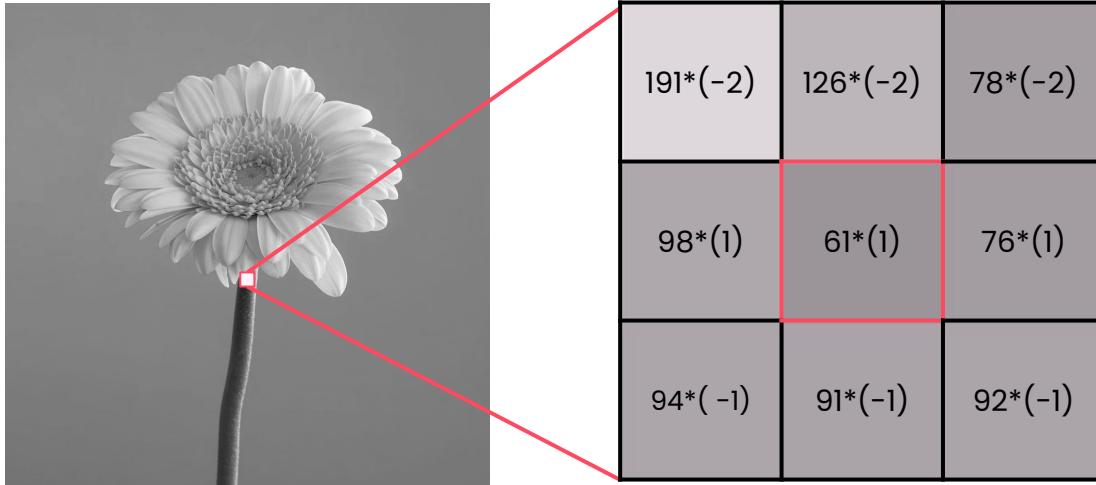


Hubel and Wiesel (1962)

Convolutional Filters



Convolutional Filters

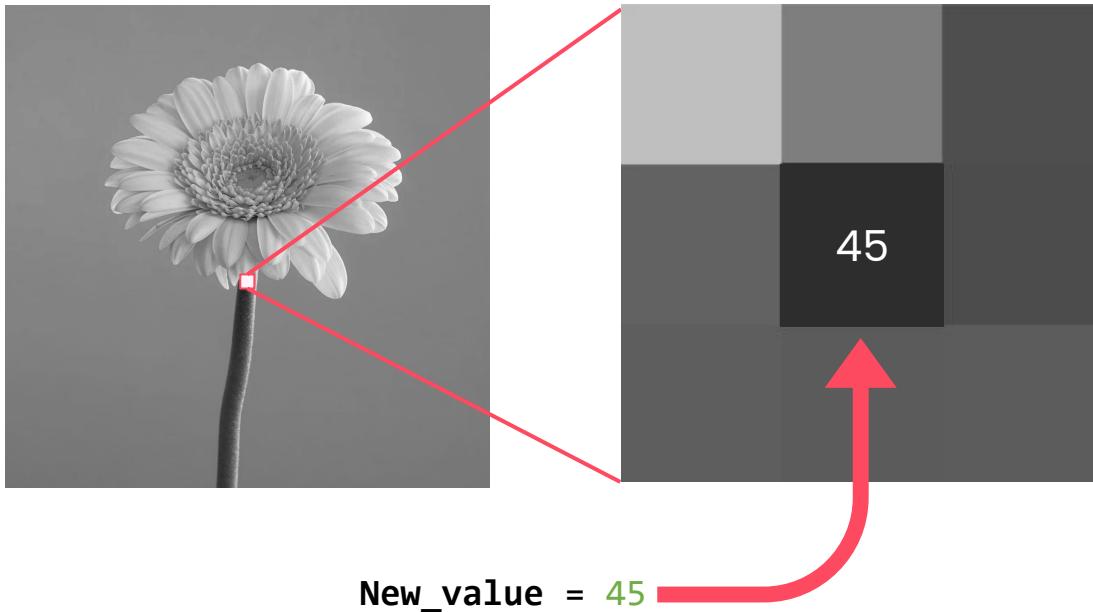


Convolutional Filters

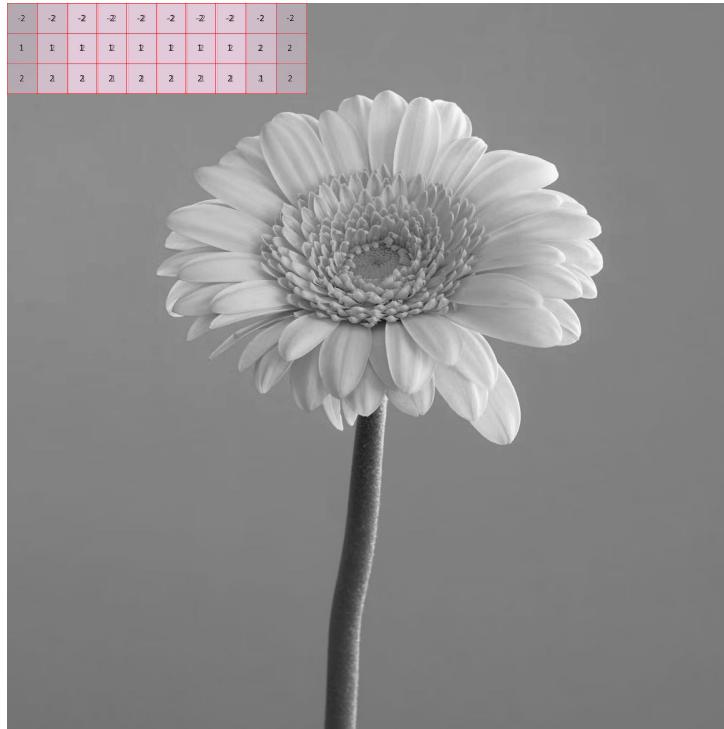


New_value = sum(-382, -252, -156, 98, 122, 152, 188, 91, 184) + bias

Convolutional Filters



How does convolution work?



What does this filter do?



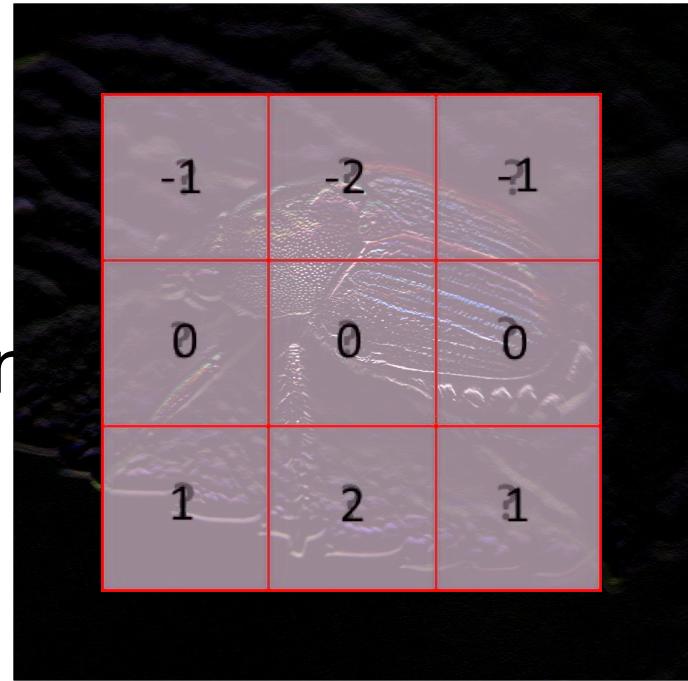
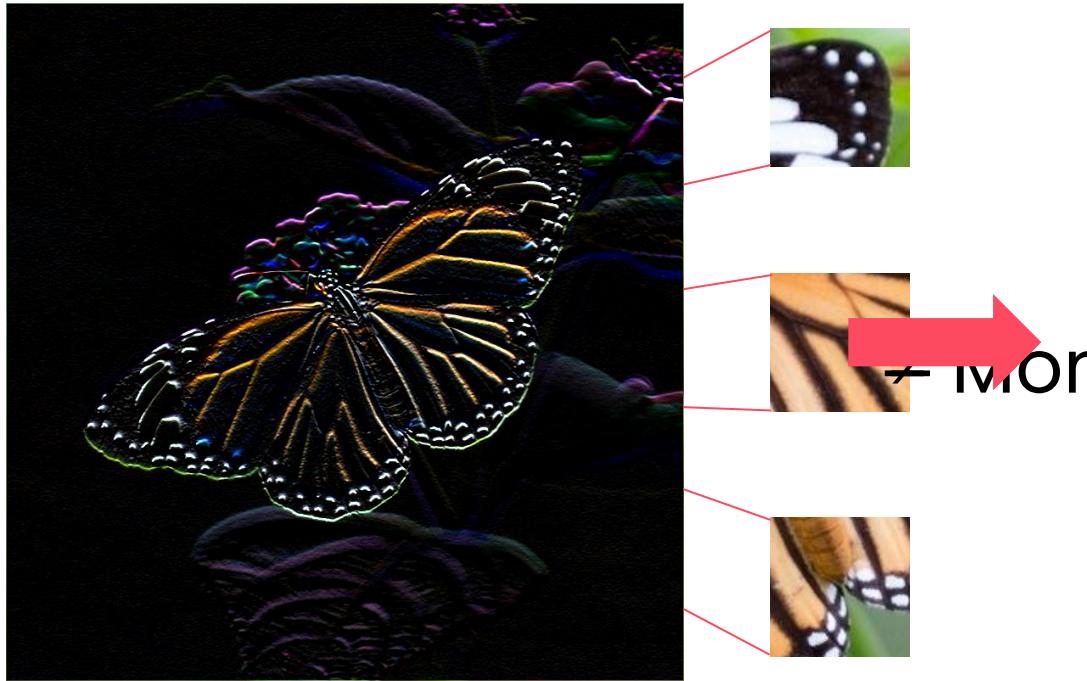
-1	0	1
-2	0	2
-1	0	1



-1	-2	-1
0	0	0
1	2	1



Filters highlight patterns to identify objects



How to create CNNs in PyTorch with nn.Module

```
# Basic convolutional layer
conv_layer = nn.Conv2d(
    in_channels=3,          # Number of input channels (e.g., RGB has 3)
    out_channels=16,         # Number of output channels (number of filters)
    kernel_size=3,           # Size of the convolutional kernel (3x3)
    stride=1,                # Step size of the convolution
    padding=1                 # Zero-padding around the edges
)
```

How to create CNNs in PyTorch with nn.Module

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# Basic convolutional layer
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    out_channels=16,
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    padding=1
)
```

Number of input channels (e.g., RGB has 3)
Number of output channels (number of filters)
Size of the convolutional kernel (3x3)
Step size of the convolution
Zero-padding around the edges

How to create CNNs in PyTorch with nn.Module

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    padding=1)               # Zero-padding around the edges
)
```

How does padding work?

0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	R: 100 G: 100 B: 100	R: 100 G: 99 B: 99	R: 52 G: 97 B: 12	R: 71 G: 114 B: 18	R: 79 G: 121 B: 19	R: 67 G: 110 B: 20	R: 78 G: 124 B: 14	R: 66 G: 109 B: 2	
0	0	R: 100 G: 100 B: 100	R: 100 G: 100 B: 100	R: 61 G: 110 B: 0	R: 91 G: 145 B: 25	R: 107 G: 154 B: 34	R: 61 G: 102 B: 23	R: 80 G: 129 B: 18	R: 57 G: 101 B: 17	
0	0	R:210 G:221 B: 90	R:118 G:147 B: 42	R: 79 G:123 B: 22	R: 79 G:129 B: 4	R:103 G:145 B: 33	R: 61 G: 99 B: 24	R: 62 G: 106 B: 14	R: 90 G:135 B: 32	
0	0	R:111 G:126 B: 28	R:149 G:174 B: 72	R:136 G:172 B: 53	R:104 G:145 B: 0	R:104 G:146 B: 21	R: 83 G: 126 B: 17	R: 62 G: 106 B: 16	R: 77 G:123 B: 18	
0	0	R:118 G:140 B: 40	R:176 G:194 B: 65	R:198 G:216 B: 82	R:152 G:176 B: 55	R:128 G:160 B: 47	R:110 G:148 B: 34	R: 63 G: 110 B: 11	R: 45 G: 97 B: 0	
0	0	R:186 G:196 B:103	R:200 G:201 B: 86	R:214 G:222 B: 82	R:202 G:218 B: 82	R:196 G:203 B: 94	R:175 G:194 B: 65	R: 80 G: 116 B: 6	R: 58 G:109 B: 1	





DeepLearning.AI

Convolutional Neural Networks

Part 2: The Full Architecture

Core Neural Network Components

```
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional layer
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2)

        # Second convolutional layer
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2)

        # Flatten layer (no parameters, just reshaping)
        self.flatten = nn.Flatten()

        # Fully connected layer
        self.fc = nn.Linear(64 * 7 * 7, 10)
```

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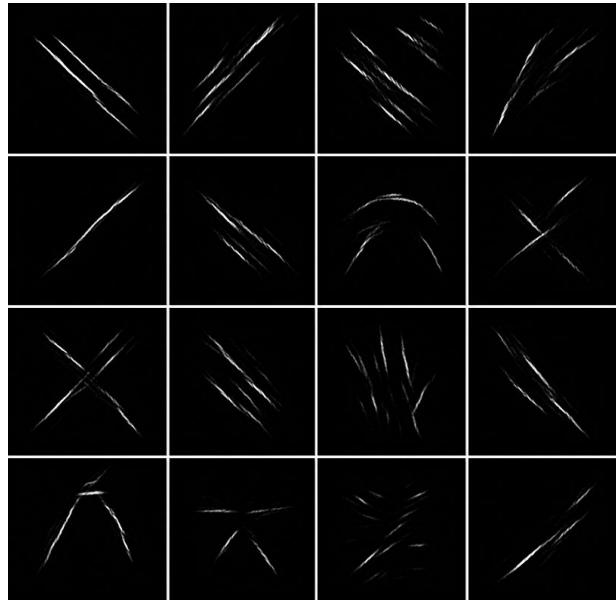
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Feature maps or activation maps



0	64	128	128
48	192	144	144
142	226	168	0
255	0	0	64

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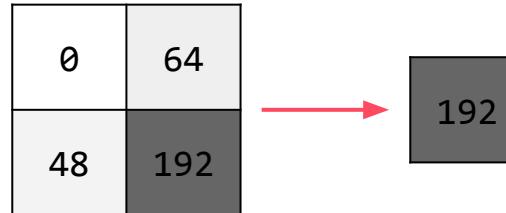
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```

Pooling in action

```
self.pool1 = nn.MaxPool2d(kernel_size=2)
```



A 4x4 input feature map with values:

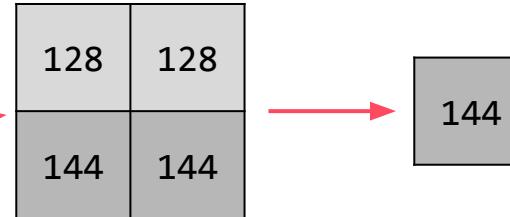
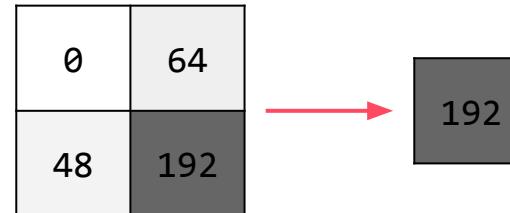
0	64	128	128
48	192	144	144
142	226	168	0
255	0	0	64

The top-left 2x2 subgrid (values 0, 64, 48, 192) is highlighted with a red border. A red arrow points from this subgrid to the 2x2 output grid above.

Pooling in action

```
self.pool1 = nn.MaxPool2d(kernel_size=2)
```

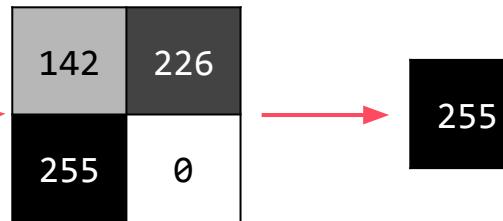
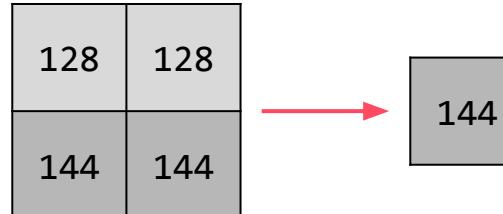
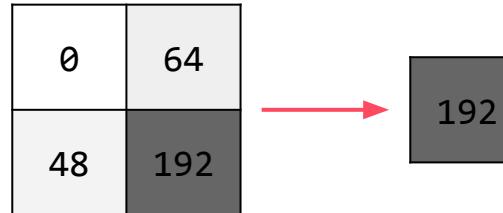
0	64	128	128
48	192	144	144
142	226	168	0
255	0	0	64



Pooling in action

```
self.pool1 = nn.MaxPool2d(kernel_size=2)
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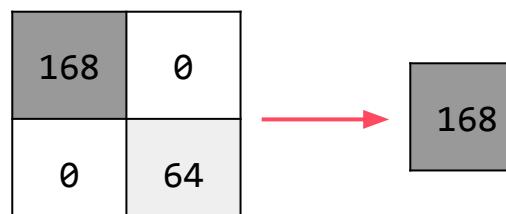
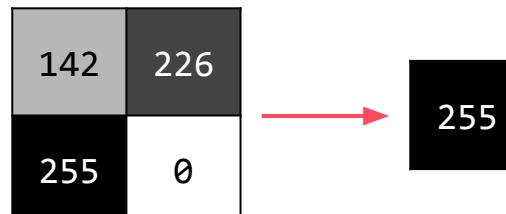
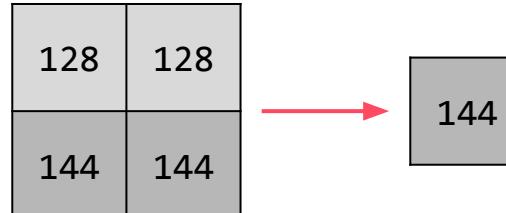
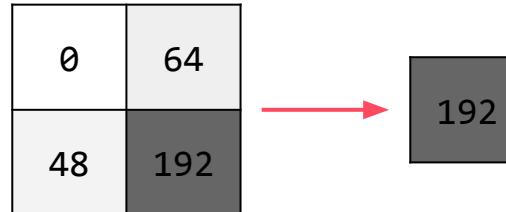
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Pooling in action

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self.pool1 = nn.MaxPool2d(kernel_size=2)
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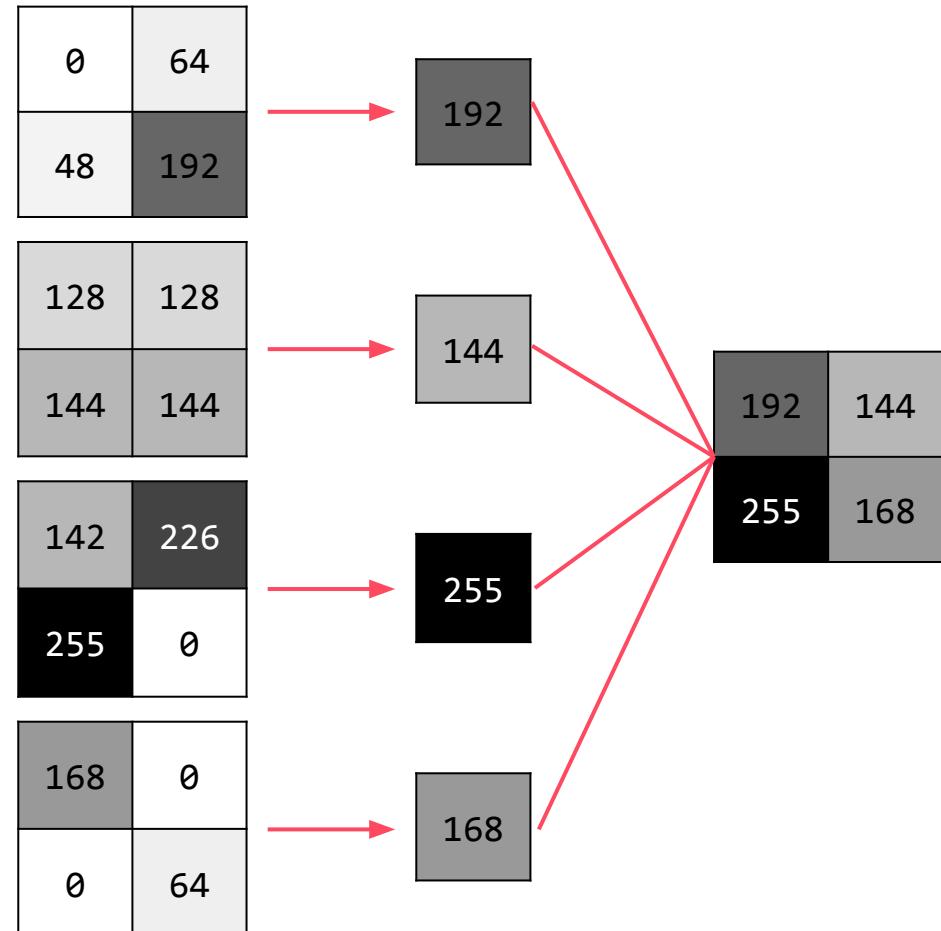
0	64	128	128
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Pooling in action

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self.pool1 = nn.MaxPool2d(kernel_size=2)
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0	64	128	128
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255	0	0	64



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        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2)

        # Second convolutional layer
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
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28x28

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28x28



14x14

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        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2)

        # Flatten layer (no parameters, just reshaping)
        self.flatten = nn.Flatten()

        # Fully connected layer
        self.fc = nn.Linear(64 * 7 * 7, 10)
```

```
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional layer
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2)

        # Second convolutional layer
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2)

        # Flatten layer (no parameters, just reshaping)
        self.flatten = nn.Flatten()

        # Fully connected layer
        self.fc = nn.Linear(64 * 7 * 7, 10)
```

28x28

↓

14x14

↓

7x7

```
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional layer
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2)

        # Second convolutional layer
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2)

        # Flatten layer (no parameters, just reshaping)
        self.flatten = nn.Flatten()

        # Fully connected layer
        self.fc = nn.Linear(64 * 7 * 7, 10)
```

28x28

↓

14x14

↓

7x7

```
def forward(self, x):
    # First conv block
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Second conv block
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Flatten before the fully connected layer
    x = self.flatten(x)

    # Fully connected layer
    x = self.fc(x)
    return x

# Create an instance of our CNN
model = SimpleCNN()
print(model)
```

```
def forward(self, x):
    # First conv block
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Second conv block
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Flatten before the fully connected layer
    x = self.flatten(x)

    # Fully connected layer
    x = self.fc(x)
    return x

# Create an instance of our CNN
model = SimpleCNN()
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```
def forward(self, x):
    # First conv block
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Second conv block
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Flatten before the fully connected layer
    x = self.flatten(x)

    # Fully connected layer
    x = self.fc(x)
    return x
```

```
# Create an instance of our CNN
model = SimpleCNN()
print(model)
```

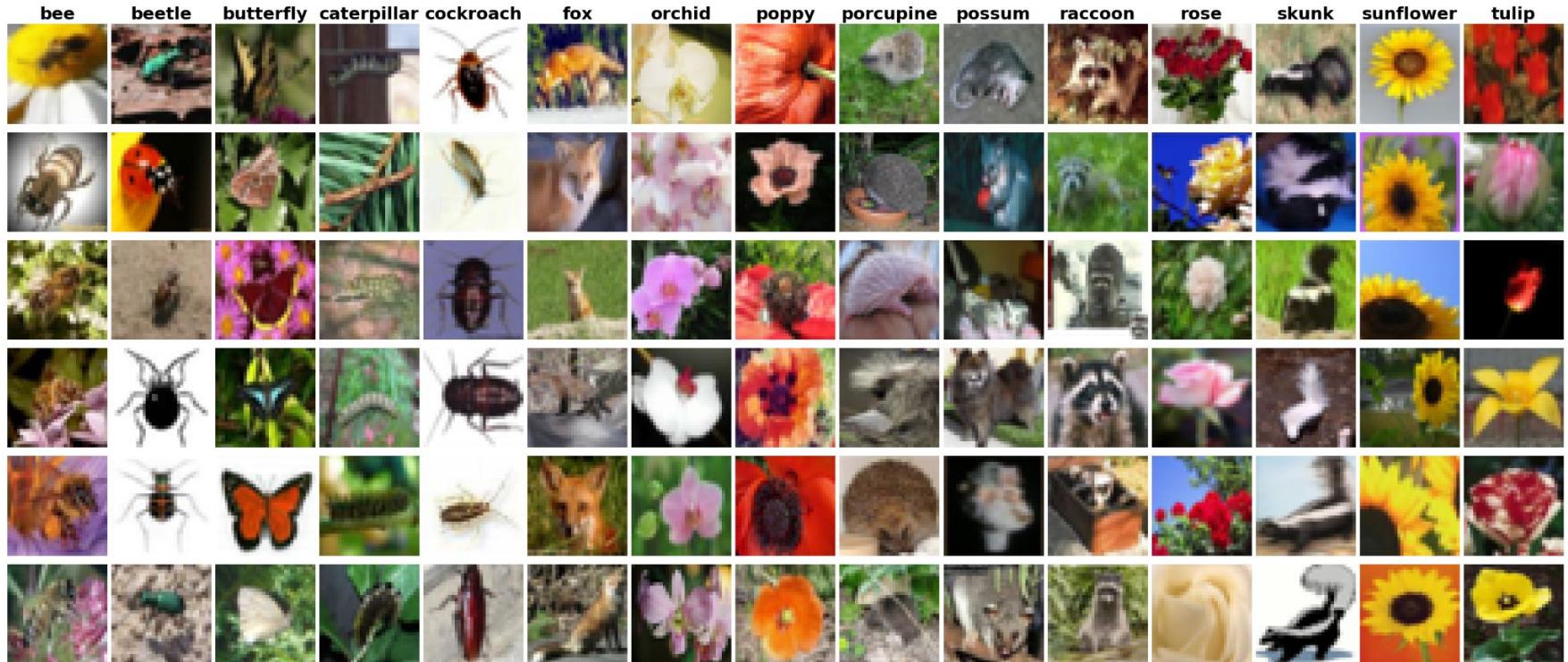


DeepLearning.AI

Train a CNN for Image Classification

Core Neural Network Components

The dataset: 32x32 color images



```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self). init_()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

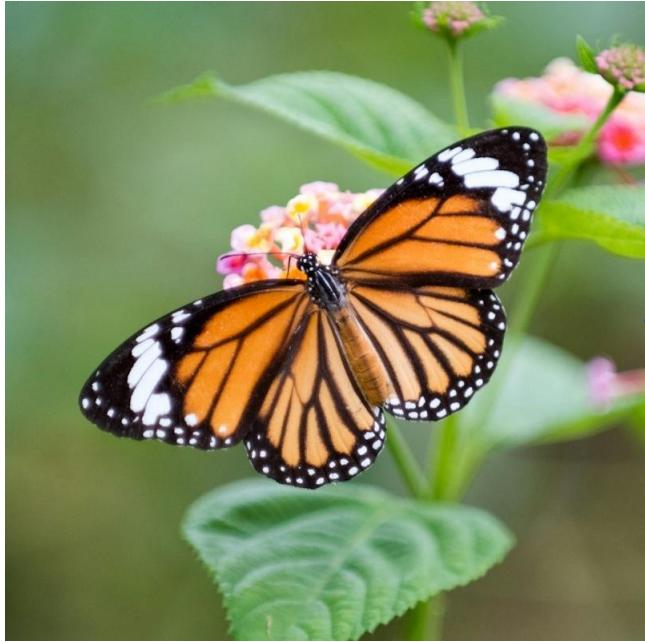
```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

Three input channels: red, green, and blue



```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

    # Fully connected layers
    # Input image is 32x32, after 3 pooling layers: 4x4
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

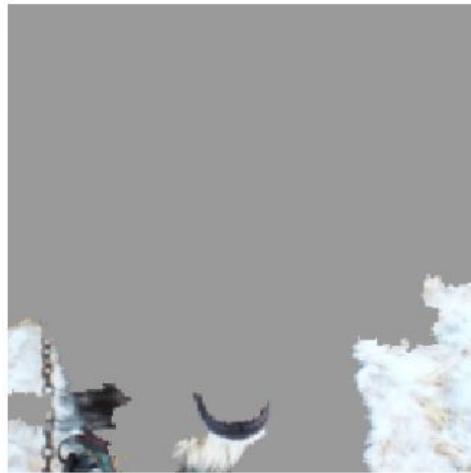
```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU() # This line is highlighted with a red box
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

This husky was misclassified as a wolf. Why?



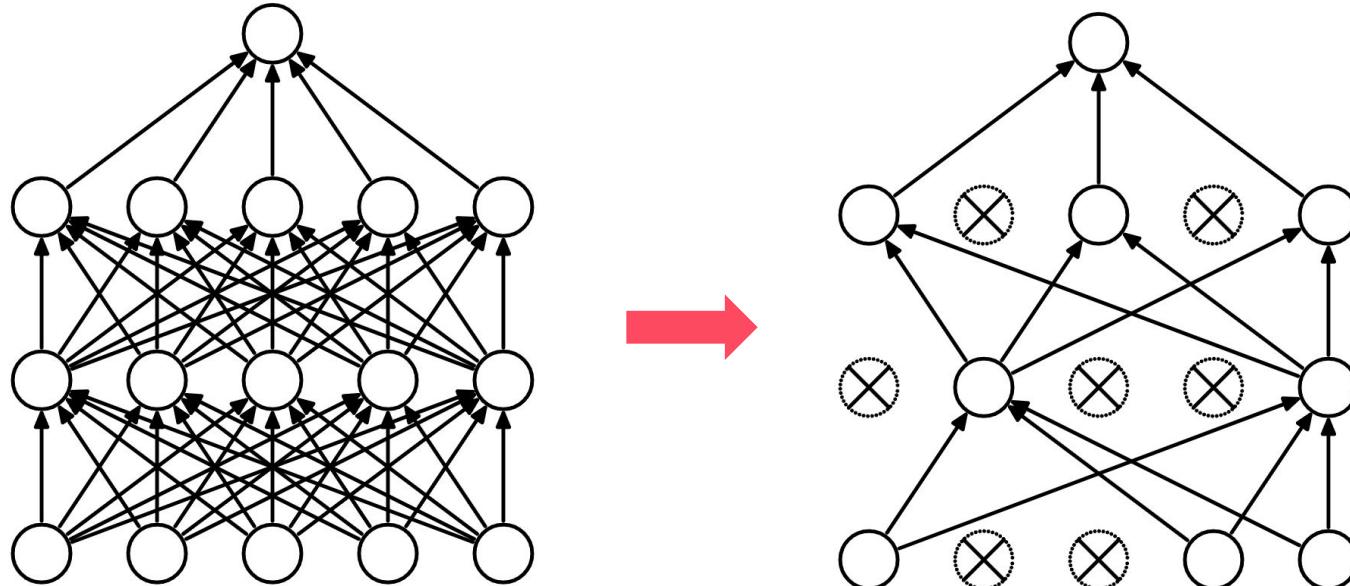
Ribeiro, Singh & Guestrin (2016)

This husky was misclassified as a wolf. Why?



Co-adaptation: neurons learn to rely on shortcuts.

Dropout breaks co-adaptation



Srivastava et al. (2014)

```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

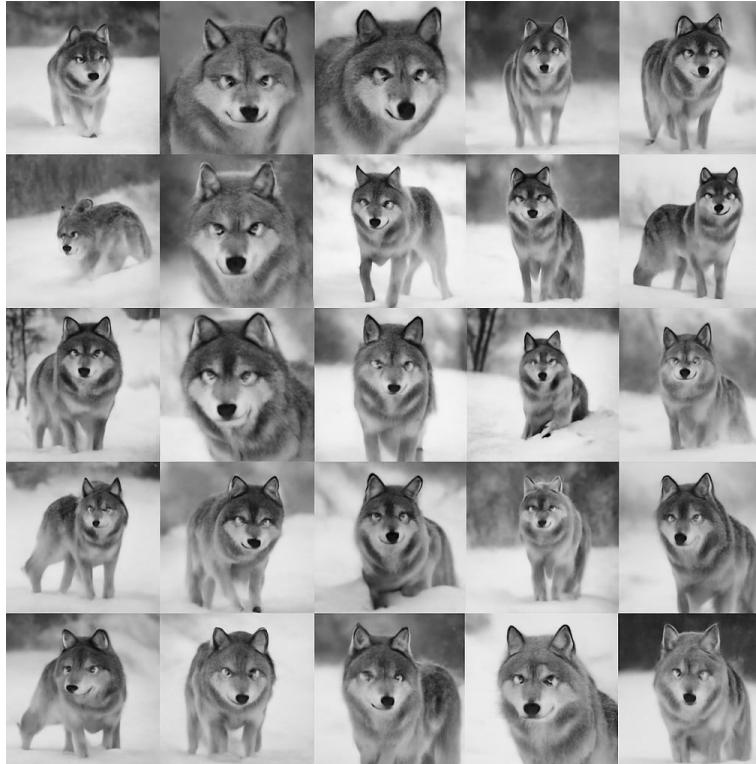
Dataset Problems vs. Co-Adaptation



Dataset Problems vs. Co-Adaptation



Dropout helps learn features that generalize



```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()
        # First convolutional block
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
        self.relu1 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Second convolutional block
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
        self.relu2 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)
        # Third convolutional block
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        self.fc1 = nn.Linear(128 * 4 * 4, 512)
        self.relu4 = nn.ReLU()
        self.dropout = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 15) # 15 classes in the dataset
```

```
# Define the loss function
loss_function = nn.CrossEntropyLoss()

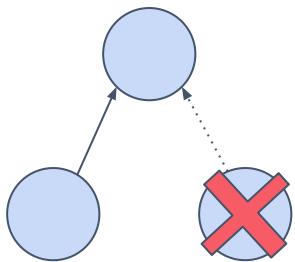
# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.0005, weight_decay=0.0005)
```

```
# Define the loss function
loss_function = nn.CrossEntropyLoss()

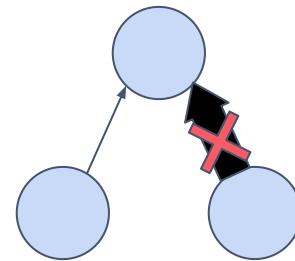
# Define the optimizer
optimizer = optim.Adam(model.parameters(), lr=0.0005, weight_decay=0.0005)
```

Dropout and Weight Decay

Regularization Techniques

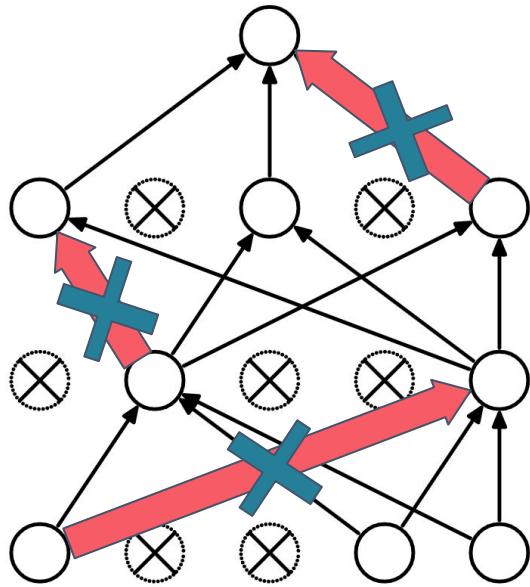


Dropout



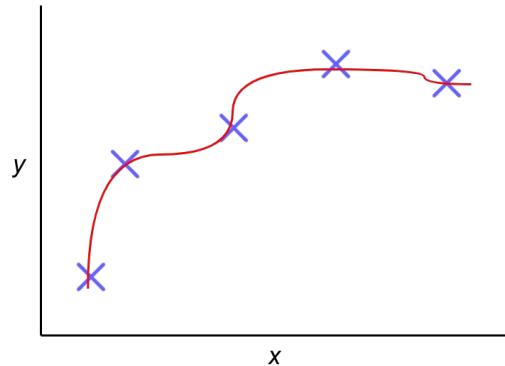
Weight Decay

Regularization Techniques



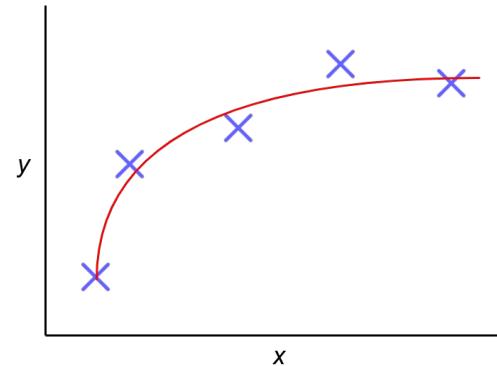
Weight Decay

Penalize large weights



Overfitting

Mahmud (2021)



Just right

Model output:

```
C:>
Input shape: torch.Size([1, 3, 32, 32])
After conv1: torch.Size([1, 32, 32, 32])
After pool1: torch.Size([1, 32, 16, 16])
After conv2: torch.Size([1, 64, 16, 16])
After pool2: torch.Size([1, 64, 8, 8])
After conv3: torch.Size([1, 128, 8, 8])
After pool3: torch.Size([1, 128, 4, 4])
After flatten: torch.Size([1, 2048])
After fc1: torch.Size([1, 512])
Output shape: torch.Size([1, 10])
```

Model output:

```
C:>
Input shape: torch.Size([1, 3, 32, 32])
After conv1: torch.Size([1, 32, 32, 32])
After pool1: torch.Size([1, 32, 16, 16])
After conv2: torch.Size([1, 64, 16, 16])
After pool2: torch.Size([1, 64, 8, 8])
After conv3: torch.Size([1, 128, 8, 8])
After pool3: torch.Size([1, 128, 4, 4])
After flatten: torch.Size([1, 2048])
After fc1: torch.Size([1, 512])
Output shape: torch.Size([1, 10])
```

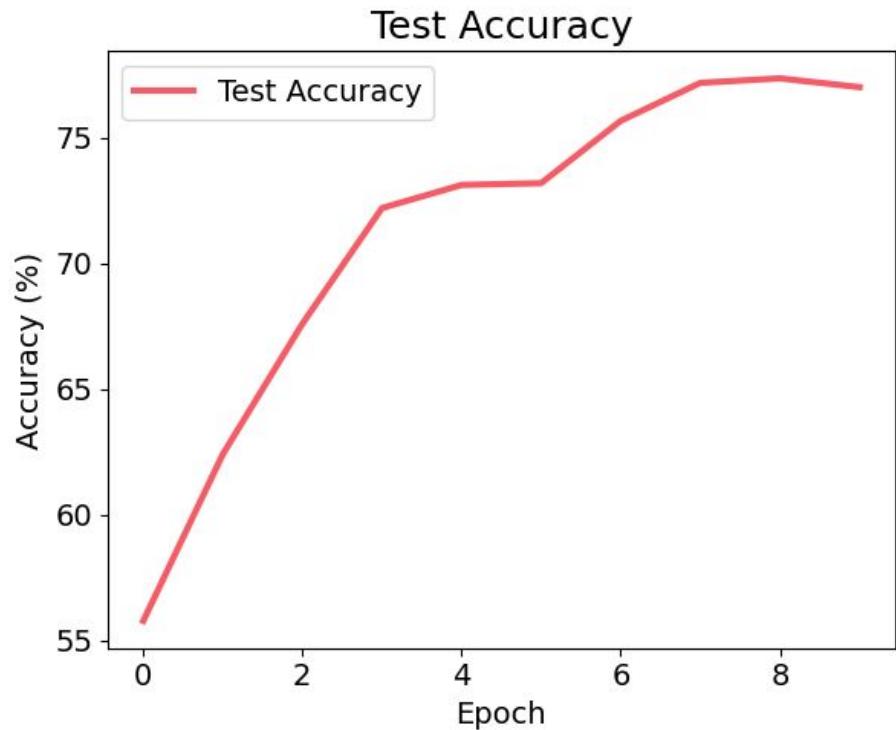
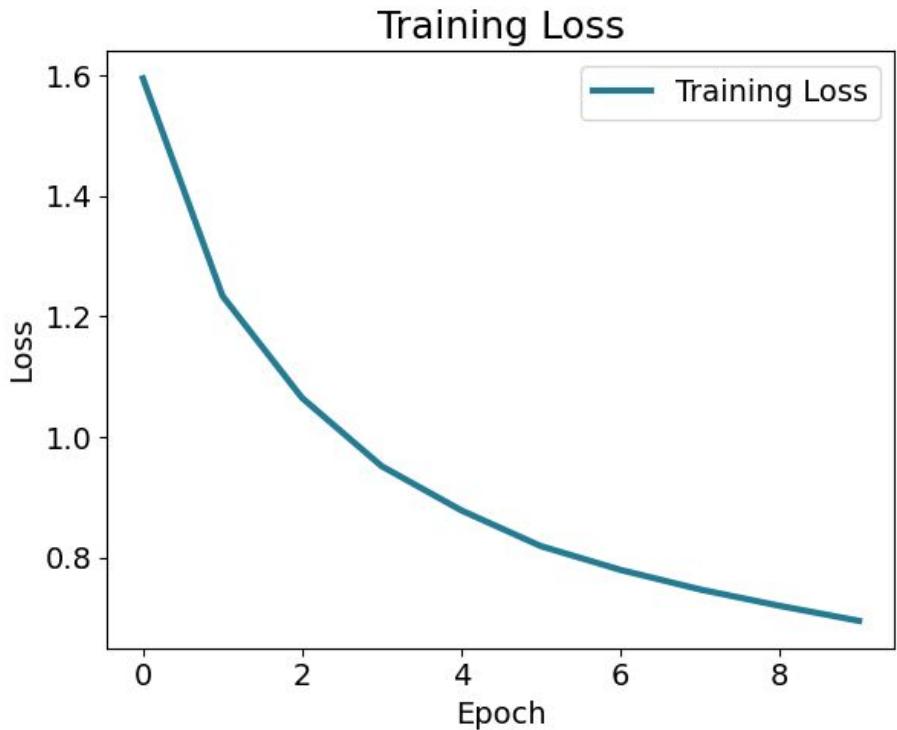
Model output:

```
C:>
Input shape: torch.Size([1, 3, 32, 32])
After conv1: torch.Size([1, 32, 32, 32])
After pool1: torch.Size([1, 32, 16, 16])
After conv2: torch.Size([1, 64, 16, 16])
After pool2: torch.Size([1, 64, 8, 8])
After conv3: torch.Size([1, 128, 8, 8])
After pool3: torch.Size([1, 128, 4, 4])
After flatten: torch.Size([1, 2048])
After fc1: torch.Size([1, 512])
Output shape: torch.Size([1, 15])
```

Model output:

```
C:>
Input shape: torch.Size([1, 3, 32, 32])
After conv1: torch.Size([1, 32, 32, 32])
After pool1: torch.Size([1, 32, 16, 16])
After conv2: torch.Size([1, 64, 16, 16])
After pool2: torch.Size([1, 64, 8, 8])
After conv3: torch.Size([1, 128, 8, 8])
After pool3: torch.Size([1, 128, 4, 4])
After flatten: torch.Size([1, 2048])
After fc1: torch.Size([1, 512])
Output shape: torch.Size([1, 15])
```

Training and testing results



Model predictions accurate!





DeepLearning.AI

Dynamic Graphs

Core Neural Network Components

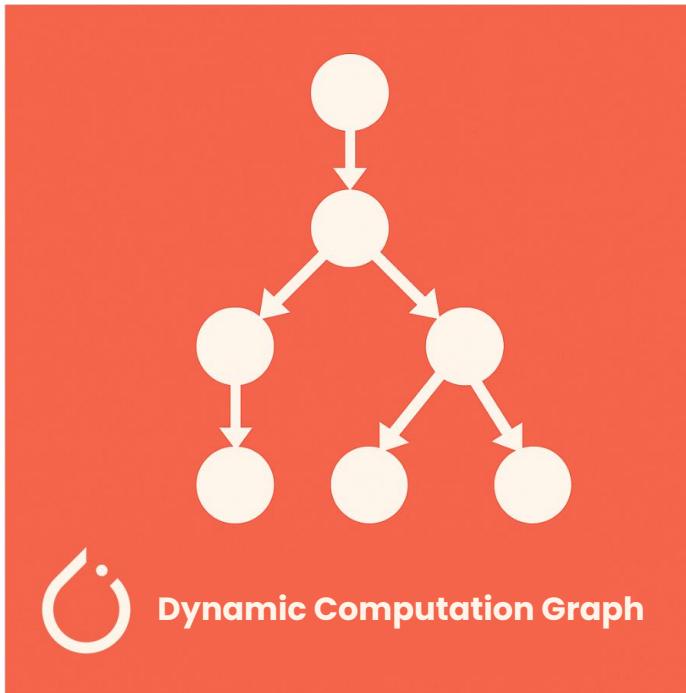
```
# Define a simple CNN with only Conv2d layers
class SimpleCNN(nn.Module):

    def forward(self, x):
        # First convolutional block
        x = self.conv1(x)
        x = self.relu1(x)
        x = self.pool1(x)
        # Second convolutional block
        x = self.conv2(x)
        x = self.relu2(x)
        x = self.pool2(x)
        # Third convolutional block
        x = self.conv3(x)
        x = self.relu3(x)
        x = self.pool3(x)

        # Fully connected layers
        # Input image is 32x32, after 3 pooling layers: 4x4
        x = self.fc1(x)
        x = self.relu4(x)
        x = self.dropout(x)
        x = self.fc2(x)

    return x
```

Dynamic Computation Graph



Early Frameworks

```
# A chain of operations, one feeding into the next
result1 = do_math(input)
result2 = do_math(result1)
result3 = do_math(result2)
result4 = do_math(result3)
result5 = do_math(result4)
# ... and so on, down the line
```

nn.Sequential

```
model = nn.Sequential(  
    nn.Conv2d(3, 32, 3),  
    nn.ReLU(),  
    nn.Conv2d(32, 64, 3),  
    nn.ReLU(),  
    nn.Flatten(),  
    nn.Linear(64 * 26 * 26, 10)  
)
```



~~for a in b:~~
~~if a:~~
~~print()~~

What is a computation graph?

```
model = nn.Sequential(  
    nn.Conv2d(3, 32, 3),  
    nn.ReLU(),  
    nn.Conv2d(32, 64, 3),  
    nn.ReLU(),  
    nn.Flatten(),  
    nn.Linear(64 * 26 * 26, 10)  
)
```

nn.Conv2d()

$$out(N_i, C_{out_j}) = bias(C_{out_j}) + \sum_{k=0}^{C_{in}-1} weight(C_{out_j}, k) \star input(N_i, k)$$

What is a computation graph?

```
model = nn.Sequential(  
    nn.Conv2d(3, 32, 3),  
    nn.ReLU(),  
    nn.Conv2d(32, 64, 3),  
    nn.ReLU(),  
    nn.Flatten(),  
    nn.Linear(64 * 26 * 26, 10)  
)
```

nn.Conv2d()

$$out(N_i, C_{out_j}) = bias(C_{out_j}) + \sum_{k=0}^{C_{in}-1} weight(C_{out_j}, k) \star input(N_i, k)$$

nn.ReLU()

$$ReLU(x) = (x)^+ = \max(0, x)$$

What is a computation graph?

```
model = nn.Sequential(  
    nn.Conv2d(3, 32, 3),  
    nn.ReLU(),  
    nn.Conv2d(32, 64, 3),  
    nn.ReLU(),  
    nn.Flatten(),  
    nn.Linear(64 * 26 * 26, 10)  
)
```

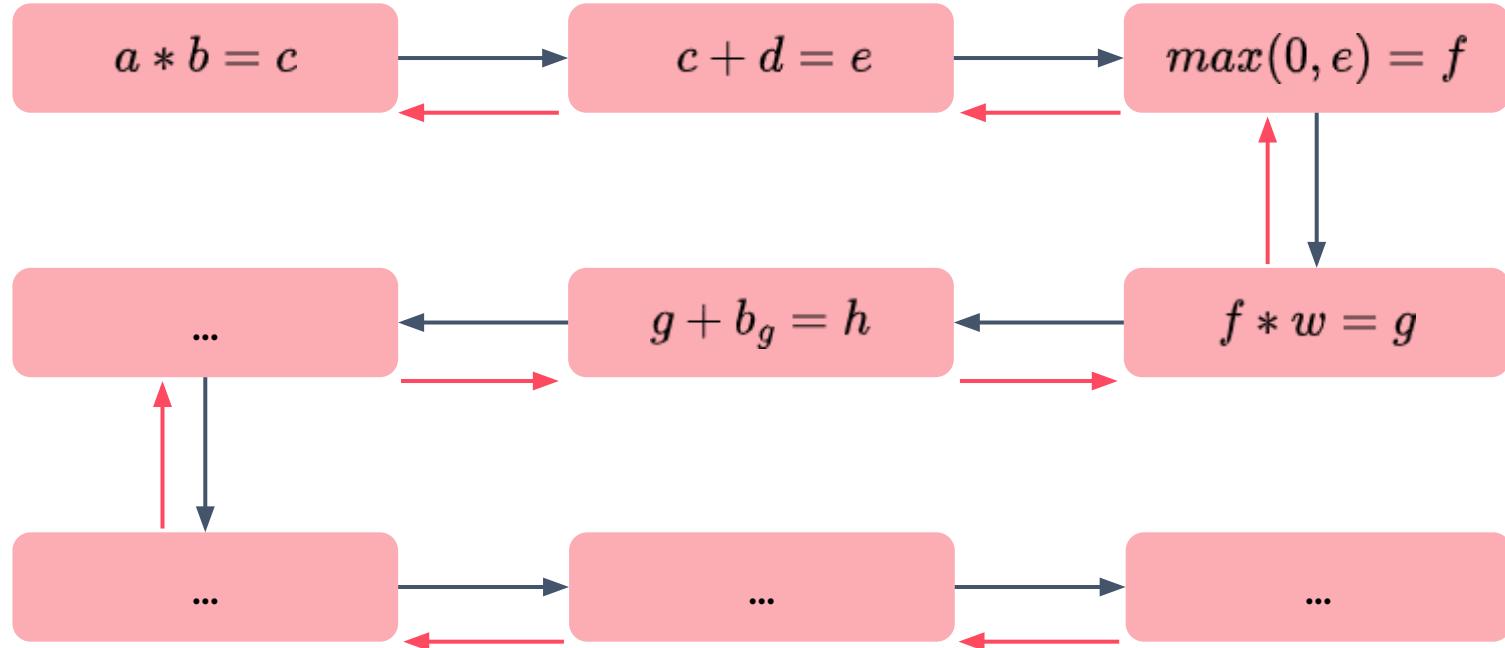
nn.Conv2d()

$$out(N_i, C_{out_j}) = bias(C_{out_j}) + \sum_{k=0}^{C_{in}-1} weight(C_{out_j}, k) \star input(N_i, k)$$

nn.ReLU()

$$ReLU(x) = (x)^+ = \max(0, x)$$

What is a computation graph?



`nn.Sequential` constraints:

- Every operation locked in order.
- No print statements to debug intermediate values.
- No if statements that conditionally branch.
- No loops that adjust to your data.

nn.Sequential tradeoffs:



- Knows all operations ahead of time
- Can optimize aggressively



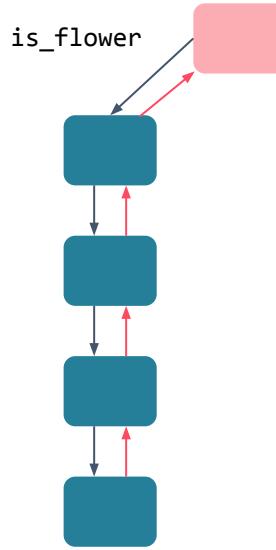
- Lose Python's power
- No debugging with print statements
- No conditional logic
- No experimentation on the fly

Dynamic Graphs

```
def forward(self, x):
    if self.is_flower(x):
        return self.flower_layers(x)
    else:
        return self.butterfly_layers(x)
```

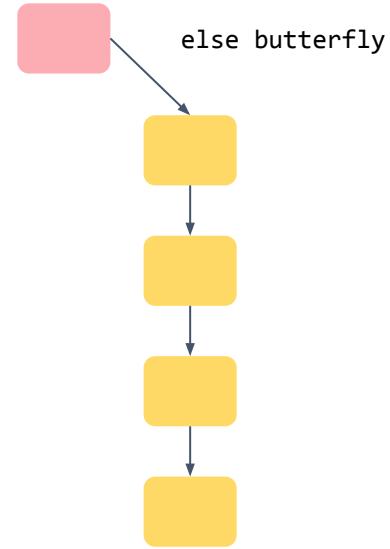
Dynamic Graphs

```
def forward(self, x):
    if self.is_flower(x):
        return self.flower_layers(x)
    else:
        return self.butterfly_layers(x)
```



Dynamic Graphs

```
def forward(self, x):
    if self.is_flower(x):
        return self.flower_layers(x)
    else:
        return self.butterfly_layers(x)
```

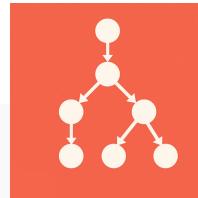


Static vs. Dynamic Frameworks



Static

Spell out every possible execution path.



Dynamic

Adapt as you go.

Dynamic Graphs

```
import torch.nn as nn

class MyModel(nn.Module):

    def __init__(self):
        super().__init__()
        self.fc1 = nn.Linear(784, 128)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x
```

}

Defines Model

}

Defines Flow of Dynamic Graph

Flexible Input Shapes

```
def forward(self, sentences):

    # Graph builds on the fly - no max length required
    for sentence in sentences:
        # sentence might be 3 words
        # sentence might be 50 words
        process(sentence) # Each is processed dynamically
```

Debugging in PyTorch is like regular Python

```
def forward(self, x):
    x = self.conv1(x)

    if x.std() < 0.1:
        print(f"Problem detected! Variance: {x.std()}")

    x = self.conv2(x)
    return x
```

Adaptive Processing

```
def forward(self, x):

    if is_easy_case(x):
        # Easy image - use small network (2 layers)
        return self.small_network(x)
    else:
        # Hard image - use big network (50 layers)
        return self.full_network(x)
```

Adaptive Processing

```
def forward(self, x):  
  
    if is_easy_case(x):  
        # Easy image - use small network (2 layers)  
        return self.small_network(x)  
    else:  
        # Hard image - use big network (50 layers)  
        return self.full_network(x)
```



DeepLearning.AI

Modular Architectures

Core Neural Network Components



```
class SimpleCNN(nn.Module):
    def __init__(self):
        super(SimpleCNN, self).__init__()

    # Block 1
    self.conv1 = nn.Conv2d(in_channels=3, out_channels=32, kernel_size=3, padding=1)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2)

    # Block 2
    self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2)

    # Block 3
    self.conv3 = nn.Conv2d(in_channels=64, out_channels=128, kernel_size=3, padding=1)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

# Block 3
self.conv3 = nn.Conv2d(...)
self.relu3 = nn.ReLU()
self.pool3 = nn.MaxPool2d(...)

# Fully connected layers
self.fc1 = nn.Linear(128 * 4 * 4, 512)
self.relu4 = nn.ReLU()
self.dropout = nn.Dropout(0.5)
self.fc2 = nn.Linear(512, 10)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

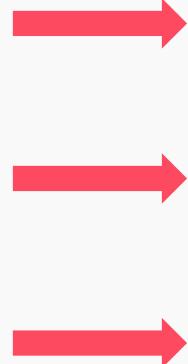
    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```



```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```



`__init__`

Defines Architecture



`forward`

Defines Flow

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Block 4
    self.conv4 = nn.Conv2d(...)
    self.relu4 = nn.ReLU()
    self.pool4 = nn.MaxPool2d(...)
```

```
# Fully connected layers
self.fc1 = nn.Linear(128 * 4 * 4, 512)
self.relu4 = nn.ReLU()
self.dropout = nn.Dropout(0.5)
self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Block 4
    self.conv4 = nn.Conv2d(...)
    self.relu4 = nn.ReLU()
    self.pool4 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Block 4
    self.conv4 = nn.Conv2d(...)
    self.relu5 = nn.ReLU()
    self.pool4 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Block 4
    self.conv4 = nn.Conv2d(...)
    self.relu5 = nn.ReLU()
    self.pool4 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)

    # Block 4
    x = self.conv4(x)
    x = self.relu5(x) # Or was it 4?
    x = self.pool4(x)
```

```
def __init__(self):
    super().__init__()
    # Block 1
    self.conv1 = nn.Conv2d(...)
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(...)

    # Block 2
    self.conv2 = nn.Conv2d(...)
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(...)

    # Block 3
    self.conv3 = nn.Conv2d(...)
    self.relu3 = nn.ReLU()
    self.pool3 = nn.MaxPool2d(...)

    # Block 4
    self.conv4 = nn.Conv2d(...)
    self.relu5 = nn.ReLU()
    self.pool4 = nn.MaxPool2d(...)

    # Fully connected layers
    self.fc1 = nn.Linear(128 * 4 * 4, 512)
    self.relu4 = nn.ReLU()
    self.dropout = nn.Dropout(0.5)
    self.fc2 = nn.Linear(512, 10)
```

```
def forward(self, x):
    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)

    # Block 4
    x = self.conv4(x)
    x = self.relu5(x)
    x = self.pool4(x)
```

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

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

    self.block2 = nn.Sequential(
        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))
```

```
def forward(self, x):

    # Block 1
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Block 2
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Block 3
    x = self.conv3(x)
    x = self.relu3(x)
    x = self.pool3(x)

    # Block 4
    x = self.conv4(x)
    x = self.relu5(x)
    x = self.pool4(x)
```

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

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

    self.block2 = nn.Sequential(
        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))
```

```
def forward(self, x):
    x = self.block1(x)
    x = self.block2(x)
```

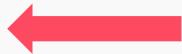
```
def __init__(self):
    super().__init__()

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))
```



```
def forward(self, x):
    x = self.block1(x)
    x = self.block2(x)
```

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

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

    nn.Conv2d(...),
    nn.ReLU(),
    nn.MaxPool2d(...))

self.block2 = nn.Sequential(
    nn.Linear(128 * 4 * 4, 512),
    nn.ReLU(),
    nn.Dropout(0.5),
    nn.Linear(512, 10))
```

```
def forward(self, x):
    x = self.block1(x)
    x = self.block2(x)
```

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

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

```

No branching

No looping

One input / One output

```
def forward(self, x):
    x = self.block1(x)
    y = self.block2(x)

    return x, y
```

```
self.block2 = nn.Sequential(
    nn.Linear(128 * 4 * 4, 512),
    nn.ReLU(),
    nn.Dropout(0.5),
    nn.Linear(512, 10))
```

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

    self.block1 = nn.Sequential(
        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...),

        nn.Conv2d(...),
        nn.ReLU(),
        nn.MaxPool2d(...))

    self.block2 = nn.Sequential(
        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))
```



```
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    super().__init__()

    self.block1 = nn.Sequential(
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        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))
```

```
class ConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()

        self.block = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )

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

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

    self.features = nn.Sequential(
        ConvBlock(3, 32),
        ConvBlock(32, 64),
        ConvBlock(64, 128))

    self.classifier = nn.Sequential(
        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))

def forward(self, x):
    x = self.features(x)
    return self.classifier(x)
```

```
class ConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()

        self.block = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )

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

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

    self.features = nn.Sequential(
        ConvBlock(3, 32),
        ConvBlock(32, 64),
        ConvBlock(64, 128),
        ConvBlock(128, 256),)

    self.classifier = nn.Sequential(
        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
        nn.Dropout(0.5),
        nn.Linear(512, 10))

def forward(self, x):
    x = self.features(x)
    return self.classifier(x)
```

```
class ConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()

        self.block = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
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            nn.MaxPool2d(kernel_size=2, stride=2),
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        nn.Linear(128 * 4 * 4, 512),
        nn.ReLU(),
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        nn.Linear(512, 10))

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    x = self.features(x)
    return self.classifier(x)
```

```
class ConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super().__init__()

        self.block = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, padding=1),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2),
        )

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

Workflow Tips

- Start explicit – write it all out
- Look for patterns
- Refactor



DeepLearning.AI

Model Inspecting and Debugging

Core Neural Network Components

How do you see what's in your model?

```
print(model)
```

Output:

```
SimpleCNN(  
  (conv1): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
  (relu1): ReLU()  
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
```

What's missing?

- How many parameters does each layer have?
- What shapes are the tensors?
- What's actually inside those Sequential blocks?

How many parameters does your model have?

```
print(model.parameters())
```

Output:

```
<generator object Module.parameters at 0x7f8b8c0a5f90>
```

How many parameters does your model have?

```
for param in model.parameters():
    print(param.shape)
```

Output:

```
torch.Size([32, 3, 3, 3])
torch.Size([32])
torch.Size([64, 32, 3, 3])
torch.Size([64])
...
...
```

How many parameters does your model have?

```
total_params = sum(param.numel() for param in model.parameters())
print(f"Total parameters: {total_params}")
```

Output:

```
Total parameters: 1147466
```

How can you see inside each layer?

```
for name, param in model.named_parameters():
    print(f"{name}: {param.shape}")
```

How can you see inside each layer?

```
for name, param in model.named_parameters():
    print(f"{name}: {param.shape}")
```

```
conv1.weight: torch.Size([32, 3, 3, 3])
conv1.bias: torch.Size([32])
conv2.weight: torch.Size([64, 32, 3, 3])
conv2.bias: torch.Size([64])
conv3.weight: torch.Size([128, 64, 3, 3])
conv3.bias: torch.Size([128])
fc1.weight: torch.Size([512, 2048])
fc1.bias: torch.Size([512])
fc2.weight: torch.Size([10, 512])
fc2.bias: torch.Size([10])
...
```

How can you see inside each layer?

```
for name, param in model.named_parameters():
    print(f"{name}: {param.shape}")
```

```
conv1.weight: torch.Size([32, 3, 3, 3])
conv1.bias: torch.Size([32])
conv2.weight: torch.Size([64, 32, 3, 3])
conv2.bias: torch.Size([64])
conv3.weight: torch.Size([128, 64, 3, 3])
conv3.bias: torch.Size([128])
fc1.weight: torch.Size([512, 2048])
fc1.bias: torch.Size([512])
fc2.weight: torch.Size([10, 512])
fc2.bias: torch.Size([10])
...
```

Methods for exploring inside nested blocks:

```
for name, module in model.named_children():
    print(name, module)
```

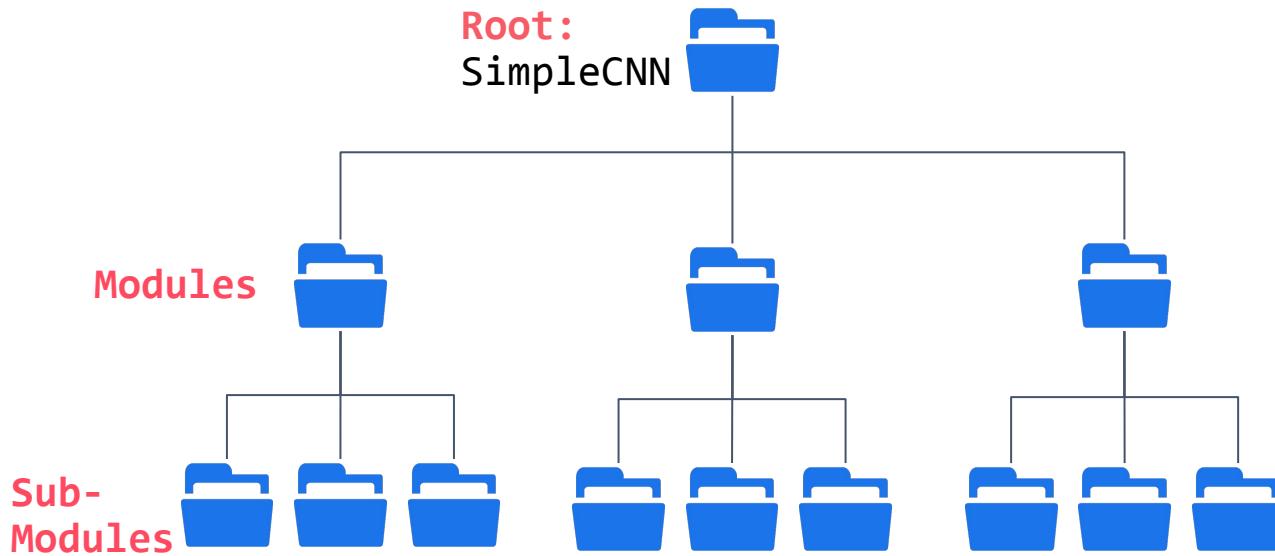
```
for name, module in model.named_modules():
    if name: # Skip the model itself
        print(name)
```

Methods for exploring inside nested blocks:

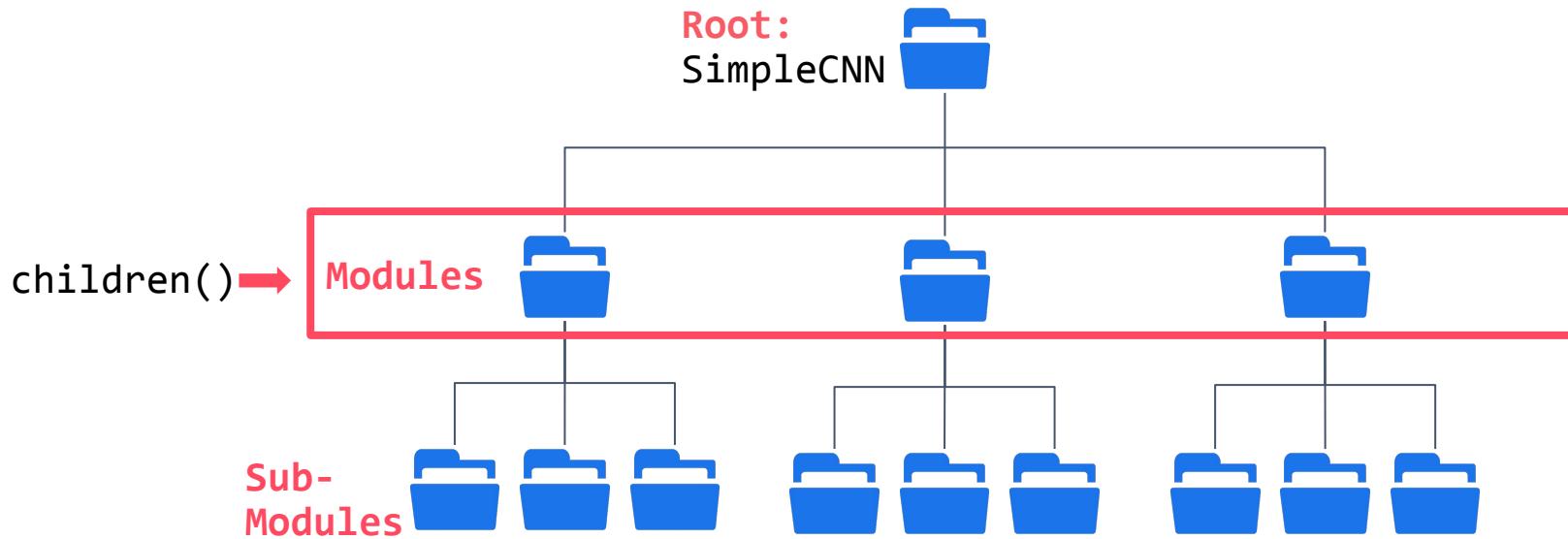
```
for name, module in model.named_children():
    print(name, module)
```

```
for name, module in model.named_modules():
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```

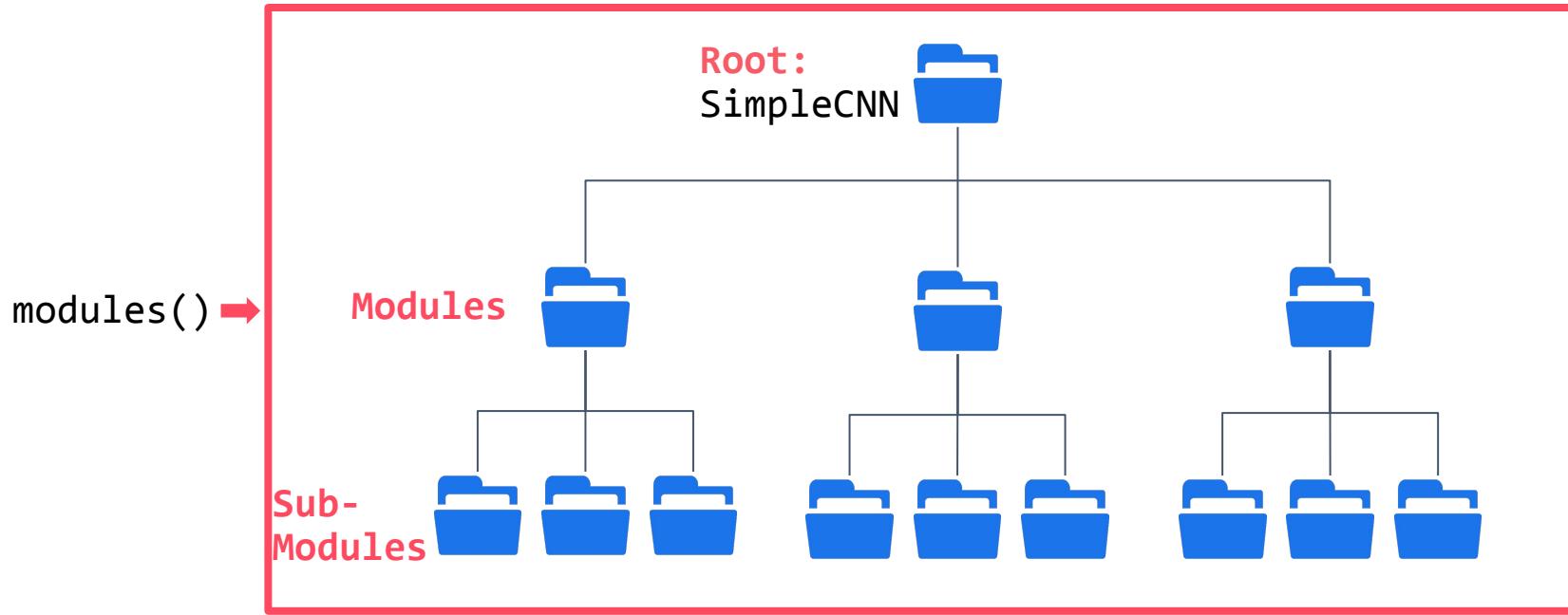
Module Organization



Module Organization



Module Organization



What happens when something goes wrong?

Error:

```
RuntimeError: mat1 and mat2 shapes cannot be multiplied (32x2048 and 1024x512)
```

Print the weight shape:

```
print(model.fc1.weight.shape)  
> fc1.weight.shape: torch.Size([512, 1024])
```

What happens when something goes wrong?

```
for name, param in model.named_parameters():
    if 'fc1.weight' in name:
        print(f"{name}: {param.shape}")
```

```
fc1.weight: torch.Size([512, 1024])
```

```
RuntimeError: mat1 and mat2 shapes cannot be multiplied (32x2048 and 1024x512)
```

Trace the shape through your model:

```
def forward(self, x):
    print(f"Input: {x.shape}")
    x = self.features(x)
    print(f"After features: {x.shape}")
    x = x.flatten(1)
    print(f"Flattened: {x.shape}")
    x = self.classifier(x)
    return x
```

Trace the shape through your model:

```
def forward(self, x):
    print(f"Input: {x.shape}")
    x = self.features(x)
    print(f"After features: {x.shape}")
    x = x.flatten(1)
    print(f"Flattened: {x.shape}")
    x = self.classifier(x)
    return x
```

You've now mastered the basics of PyTorch

- Creating data pipelines
- Building and training models
- Evaluating performance
- Learning to inspect what's under the hood

What's next?

- Using advanced PyTorch tools.
- Working with visual data using Torchvision.
- Explore text models.
- Optimizing hyperparameters
- Building real-world machine learning pipelines.