Outline

• Brief review of convolutional computations

• Convolutional Neural Networks
  • LeNet (first conv nets)
  • AlexNet

VGG
Review: 2-D Convolution

\[
\begin{bmatrix}
0 & 1 & 2 \\
3 & 4 & 5 \\
6 & 7 & 8
\end{bmatrix} \ast \begin{bmatrix}
0 & 1 \\
2 & 3
\end{bmatrix} = \begin{bmatrix}
19 & 25 \\
37 & 43
\end{bmatrix}
\]

\[
0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3 = 19,
1 \times 0 + 2 \times 1 + 4 \times 2 + 5 \times 3 = 25,
3 \times 0 + 4 \times 1 + 6 \times 2 + 7 \times 3 = 37,
4 \times 0 + 5 \times 1 + 7 \times 2 + 8 \times 3 = 43.
\]
Review: Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels

\[(1 \times 1 + 2 \times 2 + 4 \times 3 + 5 \times 4) + (0 \times 0 + 1 \times 1 + 3 \times 2 + 4 \times 3) = 56\]
Review: Multiple Input Channels

- Input and kernel can be 3D, e.g., an RGB image have 3 channels
- Have a kernel for each channel, and then sum results over channels
Review: Multiple Input Channels

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Review: Multiple Input Channels

• Input and kernel can be 3D, e.g., an RGB image have 3 channels

• Have a kernel for each channel, and then sum results over channels
Output shape

\[
\frac{[ \left( n_h - k_h + p_h + s_h \right) / s_h \right]}{s_h} \times \left[ \frac{\left( n_w - k_w + p_w + s_w \right) / s_w}{s_w} \right]
\]
Consider a convolution layer with 16 filters. Each filter has a size of 11x11x3, a stride of 2x2. Given an input image of size 22x22x3, if we don’t allow a filter to fall outside of the input, what is the output size?

- 11x11x16
- 6x6x16
- 7x7x16
- 5x5x16
Consider a convolution layer with 16 filters. Each filter has a size of 11x11x3, a stride of 2x2. Given an input image of size 22x22x3, if we don’t allow a filter to fall outside of the input, what is the output size?

- 11x11x16
- 6x6x16
- 7x7x16
- 5x5x16

\[
\left\lfloor \frac{n_h - k_h + p_h + s_h}{s_h} \right\rfloor \times \left\lfloor \frac{n_w - k_w + p_w + s_w}{s_w} \right\rfloor = 0
\]
2-D Max Pooling

- Returns the maximal value in the sliding window

\[
\max(0, 1, 3, 4) = 4
\]
Average Pooling

- Max pooling: the strongest pattern signal in a window
- Average pooling: replace max with mean in max pooling
  - The average signal strength in a window
How to train a convolutional neural network?

\[ p_i(x) = \frac{\exp(f_i(x))}{\sum_{j=1}^{N} \exp(f_j(x))}, \quad \text{softmax} \]
**Recall Softmax**

Turns outputs $f$ into probabilities (sum up to 1 across $k$ classes)
Recall Softmax

Turns outputs $f$ into probabilities (sum up to 1 across $k$ classes)

$\text{logits} = \text{pre-softmax}$
How to train a neural network?

Loss function: 
\[ \frac{1}{|D|} \sum_i \ell(x_i, y_i) \]

Per-sample loss:
\[ \ell(x, y) = \sum_{j=1}^{K} - y_j \log p_j \]

Also known as cross-entropy loss or softmax loss
Cross-Entropy Loss

\[ L_{CE} = \sum_i -Y_i \log(p_i) \]

\[ = -Y_3 \log(p_3) \]

\[ = - \log(0.8) \]

**Goal:** push \( p \) and \( Y \) to be identical
Convolutional Neural Networks
Examples
Evolution of neural net architectures

- **1989**: Yann LeCun
  - LeNet

- **2012**:
  - AlexNet

- **2014**:
  - Inception Net
  - VGG

- **2015**:
  - GoogleLeNet

- **2016**:
  - ResNet
  - DenseNet

*Note: The diagrams illustrate the architecture evolution of neural networks from 1989 to 2016, highlighting key milestones and developments.*
LeNet Architecture
(first conv nets)

\[ \sigma(-) = \begin{cases} 
\text{Sigmoid} & \text{(original)} \\
\text{ReLU} & \text{(recent)} 
\end{cases} \]

Gradient-based learning applied to document recognition, by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner
Handwritten Digit Recognition
MNIST

- Centered and scaled
- 50,000 training data
- 10,000 test data
- 28 x 28 images
- 10 classes
Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998
Gradient-based learning applied to document recognition
LeNet Architecture

32x32 image

convolution

6@28x28
C1 feature map

6@14x14
S2 feature map

convolution

pooling

6@14x14
C1 feature map

pooling

16@10x10
S4 feature map

16@5x5
C3 feature map

full

120 - F5 full

84 - F6 full

10 - Out

Gradient-based learning applied to document recognition, by Y. LeCun, L. Bottou, Y. Bengio and P. Haffner
def __init__(self):
    super(LeNet5, self).__init__()
    # Convolution (In LeNet-5, 32x32 images are given as input. Hence padding of 2 is done below)
    self.conv1 = torch.nn.Conv2d(in_channels=1, out_channels=6, kernel_size=5, stride=1, padding=2, bias=True)
    # Max-pooling
    self.max_pool_1 = torch.nn.MaxPool2d(kernel_size=2)
    # Convolution
    self.conv2 = torch.nn.Conv2d(in_channels=6, out_channels=16, kernel_size=5, stride=1, padding=0, bias=True)
    # Max-pooling
    self.max_pool_2 = torch.nn.MaxPool2d(kernel_size=2)
    # Fully connected layer
    self.fc1 = torch.nn.Linear(16*5*5, 120)  # convert matrix with 16*5*5 (= 400) features to a matrix of 120 features (columns)
    self.fc2 = torch.nn.Linear(120, 84)  # convert matrix with 120 features to a matrix of 84 features (columns)
    self.fc3 = torch.nn.Linear(84, 10)  # convert matrix with 84 features to a matrix of 10 features (columns)

https://github.com/bollakarthikeya/LeNet-5-PyTorch/blob/master/lenet5_gpu.py
```python
def forward(self, x):
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv1(x))
    # max-pooling with 2x2 grid
    x = self.max_pool_1(x)
    # convolve, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.conv2(x))
    # max-pooling with 2x2 grid
    x = self.max_pool_2(x)
    # first flatten 'max_pool_2_out' to contain 16*5*5 columns
    # read through https://stackoverflow.com/a/42482819/7551231
    x = x.view(-1, 16*5*5)
    # FC-1, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.fc1(x))
    # FC-2, then perform ReLU non-linearity
    x = torch.nn.functional.relu(self.fc2(x))
    # FC-3
    x = self.fc3(x)

    return x
```

LeNet in Pytorch
Let’s walk through an example using PyTorch

https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html
Deng et al. 2009
AlexNet

- AlexNet won ImageNet competition in 2012
- Deeper and bigger LeNet
- Paradigm shift for computer vision
ImageNet Top-5 Classification Accuracy (%)
AlexNet Architecture

Larger pool size

Larger kernel size, stride because of the increased image size, and more output channels.

AlexNet

3x3 MaxPool, stride 2

11x11 Conv (96), stride 4

image (3x224x224)

LeNet

2x2 AvgPool, stride 2

5x5 Conv (6), pad 2

image (32x32)
AlexNet Architecture

3 additional convolutional layers

More output channels.

AlexNet

LeNet

3x3 MaxPool, stride 2

3x3 Conv (384), pad 1

3x3 Conv (384), pad 1

3x3 Conv (384), pad 1

3x3 MaxPooling, stride 2

5x5 Conv (256), pad 2

2x2 AvgPool, stride 2

5x5 Conv (16)

previous slide
AlexNet Architecture

**AlexNet**
- Dense (4096)
- Dense (4096)
- Dense (1000)

**LeNet**
- Dense (120)
- Dense (84)
- Dense (10)

1000 classes output

Increase hidden size from 120 to 4096
More Differences…

• Change activation function from sigmoid to ReLu (no more vanishing gradient)
More Differences…

- Change activation function from sigmoid to ReLu (no more vanishing gradient)
- Data augmentation

* Drop out
# Complexity

<table>
<thead>
<tr>
<th></th>
<th>AlexNet</th>
<th>LeNet</th>
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<tbody>
<tr>
<td>Conv1</td>
<td>35K</td>
<td>150</td>
</tr>
<tr>
<td>Conv2</td>
<td>614K</td>
<td>2.4K</td>
</tr>
<tr>
<td>Conv3-5</td>
<td>3M</td>
<td></td>
</tr>
<tr>
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<td>0.048M</td>
</tr>
<tr>
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<td>0.01M</td>
</tr>
<tr>
<td>Total</td>
<td>46M</td>
<td>0.06M</td>
</tr>
<tr>
<td>Increase</td>
<td>11x</td>
<td>1x</td>
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</tbody>
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Increase: 11x for AlexNet compared to LeNet
## Complexity

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$11 \times 11 \times 3 \times 96 = 35k$
Which of the following are true about AlexNet? Select all that apply.

A. AlexNet contains 8 layers. The first five are convolutional layers.
B. The last three layers are fully connected layers.
C. Some of the convolutional layers are followed by max-pooling (layers).
D. AlexNet achieved excellent performance in the 2012 ImageNet challenge.

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D. AlexNet achieved excellent performance in the 2012 ImageNet challenge.

All options are true!

ImageNet Top-5 Classification Accuracy (%)
VGG
Progress

- LeNet (1995)
  - 2 convolution + pooling layers
  - 2 hidden dense layers
- AlexNet
  - Bigger and deeper LeNet
  - ReLu, preprocessing
- VGG
  - Bigger and deeper AlexNet (repeated VGG blocks)
Which of the following statement is True for the success of deep models?

- Better design of the neural networks
- Large scale training dataset
- Available computing power
- All of the above
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What we’ve learned today

• Brief review of convolutional computations
• Convolutional Neural Networks
  • LeNet (first conv nets)
    • AlexNet
• PyTorch demo
Acknowledgement

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