Lecture 14:
– Deep Convolutional Networks
Last time... Three key ideas

• (Hierarchical) Compositionality
  - Cascade of non-linear transformations
  - Multiple layers of representations

• End-to-End Learning
  - Learning (goal-driven) representations
  - Learning to feature extract

• Distributed Representations
  - No single neuron “encodes” everything
  - Groups of neurons work together
Last time... **Intro. to Deep Learning**

**VISION**

<table>
<thead>
<tr>
<th>Process</th>
<th>Supervised</th>
<th>Unsupervised</th>
<th>Fixed</th>
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<tbody>
<tr>
<td>SIFT/HOG</td>
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<td>K-Means/pooling</td>
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<td>Classifier</td>
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<td>“Learned”</td>
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<td>“car”</td>
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**SPEECH**

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<td>MFCC</td>
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<td>Mixture of Gaussians</td>
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<td>Classifier</td>
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**NLP**

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<tr>
<td>Parse Tree Syntactic</td>
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<td>n-grams</td>
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<td>Classifier</td>
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<td>“+”</td>
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This burrito place is yummy and fun!
Last time... Intro. to Deep Learning

- “Shallow” models

  ![Image of a yellow car](image)

  hand-crafted Feature Extractor
  fixed

  “Simple” Trainable Classifier
  learned

- Deep models

  ![Image of a yellow car](image)

  Trainable Feature-Transform / Classifier

  Trainable Feature-Transform / Classifier

  Trainable Feature-Transform / Classifier

  Learned Internal Representations
Last time... ConvNet is a sequence of Convolutional Layers, interspersed with activation functions

CONV, ReLU  e.g. 6  5x5x3 filters

CONV, ReLU  e.g. 10  5x5x6 filters

...
Last time... The brain/neuron view of CONV Layer

E.g. with 5 filters, CONV layer consists of neurons arranged in a 3D grid (28x28x5)

There will be 5 different neurons all looking at the same region in the input volume
Last time… Convolutional Neural Networks
Case studies
Case Study: LeNet-5 [LeCun et al., 1998]

Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

=>

Q: what is the output volume size? Hint: \((227-11)/4+1 = 55\)
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images

**First layer** (CONV1): 96 11x11 filters applied at stride 4

=>

Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?
**Case Study: AlexNet**

[Krizhevsky et al. 2012]

Input: 227x227x3 images

**First layer (CONV1):** 96 11x11 filters applied at stride 4

=>

Output volume **[55x55x96]**

Parameters: \((11\times11\times3)\times96 = 35K\)
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2

Q: what is the output volume size? Hint: \((55-3)/2+1 = 27\)
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96

Q: what is the number of parameters in this layer?
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images
After CONV1: 55x55x96

Second layer (POOL1): 3x3 filters applied at stride 2
Output volume: 27x27x96
Parameters: 0!
Case Study: AlexNet

[Krizhevsky et al. 2012]

Input: 227x227x3 images
After CONV1: 55x55x96
After POOL1: 27x27x96

...
Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)
Case Study: AlexNet

[Krizhevsky et al. 2012]

Full (simplified) AlexNet architecture:

[227x227x3] INPUT
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[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%
Case Study: ZFNet

[Zeiler and Fergus, 2013]

AlexNet but:
CONV1: change from (11x11 stride 4) to (7x7 stride 2)
CONV3,4,5: instead of 384, 384, 256 filters use 512, 1024, 512

ImageNet top 5 error: 15.4% -> 14.8%
Case Study: VGGNet

[Simonyan and Zisserman, 2014]

Only 3x3 CONV stride 1, pad 1 and 2x2 MAX POOL stride 2

best model

11.2% top 5 error in ILSVRC 2013

->

7.3% top 5 error

<table>
<thead>
<tr>
<th>ConvNet Configuration</th>
<th>A</th>
<th>A-LRN</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>11 weight layers</td>
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<td>13 weight layers</td>
<td>16 weight layers</td>
<td>16 weight layers</td>
<td>19 weight layers</td>
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<table>
<thead>
<tr>
<th>input (224 x 224 RGB image)</th>
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<tbody>
<tr>
<td>conv3-64 conv3-64 LRN conv3-64 conv3-64 conv3-64 conv3-64</td>
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<tr>
<td>conv3-128 conv3-128 conv3-128 conv3-128 conv3-128 conv3-128</td>
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<tr>
<td>maxpool conv3-256 conv3-256 conv3-256 conv3-256 conv3-256 conv3-256</td>
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<tr>
<td>conv3-512 conv3-512 conv3-512 conv3-512 conv3-512 conv3-512</td>
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<tr>
<td>FC-4096</td>
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<td>FC-4096</td>
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<tr>
<td>FC-1000</td>
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<tr>
<td>.soft-max</td>
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</table>

Table 2: Number of parameters (in millions).

<table>
<thead>
<tr>
<th>Network</th>
<th>A, A-LRN</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of parameters</td>
<td>133</td>
<td>133</td>
<td>134</td>
<td>138</td>
<td>144</td>
</tr>
</tbody>
</table>
INPUT: [224x224x3]  memory: 224*224*3=150K  params: 0

CONV3-64: [224x224x64]  memory: 224*224*64=3.2M  params: (3*3)*64 = 1,728

CONV3-64: [224x224x64]  memory: 224*224*64=3.2M  params: (3*3)*64 = 36,864

POOL2: [112x112x64]  memory: 112*112*64=800K  params: 0

CONV3-128: [112x112x128]  memory: 112*112*128=1.6M  params: (3*3)*128 = 73,728

CONV3-128: [112x112x128]  memory: 112*112*128=1.6M  params: (3*3)*128 = 147,456

POOL2: [56x56x128]  memory: 56*56*128=400K  params: 0

CONV3-256: [56x56x256]  memory: 56*56*256=800K  params: (3*3)*256 = 294,912

CONV3-256: [56x56x256]  memory: 56*56*256=800K  params: (3*3)*256 = 589,824

POOL2: [28x28x256]  memory: 28*28*256=200K  params: 0

CONV3-512: [28x28x512]  memory: 28*28*512=400K  params: (3*3)*512 = 1,179,648

CONV3-512: [28x28x512]  memory: 28*28*512=400K  params: (3*3)*512 = 2,359,296

POOL2: [14x14x512]  memory: 14*14*512=100K  params: 0

CONV3-512: [14x14x512]  memory: 14*14*512=100K  params: (3*3)*512 = 2,359,296

CONV3-512: [14x14x512]  memory: 14*14*512=100K  params: (3*3)*512 = 2,359,296

POOL2: [7x7x512]  memory: 7*7*512=25K  params: 0

FC: [1x1x4096]  memory: 4096  params: 7*7*512*4096 = 102,760,448

FC: [1x1x4096]  memory: 4096  params: 4096*4096 = 16,777,216

FC: [1x1x1000]  memory: 1000  params: 4096*1000 = 4,096,000

(not counting biases)
INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
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FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~ 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters
INPUT: [224x224x3] memory: 224*224*3=150K params: 0

CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64) = 1,728

CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864

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FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216

FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

Note:
Most memory is in early CONV
Most params are in late FC
Case Study: GoogLeNet [Szegedy et al., 2014]

Inception module

ILSVRC 2014 winner (6.7% top 5 error)
Case Study: ResNet [He et al., 2015]
ILSVRC 2015 winner
(3.6% top 5 error)

MSRA @ ILSVRC & COCO 2015 Competitions

- 1st places in all five main tracks
  - ImageNet Classification: “Ultra-deep” (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

*improvements are relative numbers

Case Study: ResNet [He et al., 2015]
ILSVRC 2015 winner
(3.6% top 5 error)

Revolution of Depth

2-3 weeks of training on 8 GPU machine
at runtime: faster than a VGGNet! (even though it has 8x more layers)

(slide from Kaiming He’s recent presentation)
Case Study: ResNet [He et al., 2015]

34-layer plain

image

7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128

34-layer residual

image

7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 128, /2
3x3 conv, 128
3x3 conv, 128
3x3 conv, 128

224x224x3

spatial dimension only 56x56!
Case Study Bonus: DeepMind’s AlphaGo
The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a $23 \times 23$ image, then convolves $k$ filters of kernel size $5 \times 5$ with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a $21 \times 21$ image, then convolves $k$ filters of kernel size $3 \times 3$ with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size $1 \times 1$ with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used $k = 192$ filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with $k = 128, 256$ and 384 filters.

**policy network:**

[19x19x48] Input
CONV1: 192 5x5 filters, stride 1, pad 2 => [19x19x192]
CONV2..12: 192 3x3 filters, stride 1, pad 1 => [19x19x192]
CONV: 1 1x1 filter, stride 1, pad 0 => [19x19] *(probability map of promising moves)*
Summary

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Typical architectures look like

  \[(CONV-RELU)^N-POOL?]^M-(FC-RELU)^K,SOFTMAX\]

  where $N$ is usually up to $\sim5$, $M$ is large, $0 \leq K \leq 2$.

  - but recent advances such as ResNet/GoogLeNet challenge this paradigm
Understanding ConvNets
RGB Input Image 224 x 224 x 3

7x7x3 Convolution
3x3 Max Pooling
Down Sample 4x
55 x 55 x 96

5x5x96 Convolution
3x3 Max Pooling
Down Sample 4x
13 x 13 x 256

3x3x256 Convolution
13 x 13 x 354

Logistic Regression
≈ 1000 Classes

Standard 4096 Units

Standard 4096 Units

3x3x354 Convolution
3x3 Max Pooling
Down Sample 2x
6 x 6 x 256

3x3x354 Convolution
13 x 13 x 354

http://www.image-net.org/
Visualizing CNN (Layer 1)

Visualizing CNN (Layer 2)

Part that Triggered Filter

Top Image Patches

Visualizing CNN (Layer 3)

Part that Triggered Filter

Top Image Patches

Visualizing CNN (Layer 4)

Part that Triggered Filter

Top Image Patches

Visualizing CNN (Layer 5)

Part that Triggered Filter

Top Image Patches

Deep Visualization Toolbox

yosinski.com/deepvis

#deepvis

Jason Yosinski  Jeff Clune  Anh Nguyen  Thomas Fuchs  Hod Lipson

Cornell University  University of Wyoming  NASA  Jet Propulsion Laboratory  California Institute of Technology
Tips and Tricks
• Shuffle the training samples

• Use Dropout and Batch Normalization for regularization
Input representation

- Centered (0-mean) RGB values.

“Given a rectangular image, we first rescaled the image such that the shorter side was of length 256, and then cropped out the central 256×256 patch from the resulting image”
Data Augmentation

• The neural net has 60M real-valued parameters and 650,000 neurons

• It overfits a lot. Therefore, they train on 224x224 patches extracted randomly from 256x256 images, and also their horizontal reflections.

“This increases the size of our training set by a factor of 2048, though the resulting training examples are, of course, highly inter-dependent.”

[Krizhevsky et al. 2012]
Data Augmentation

• Alter the intensities of the RGB channels in training images.

“Specifically, we perform PCA on the set of RGB pixel values throughout the ImageNet training set. To each training image, we add multiples of the found principal components, with magnitudes proportional to the corresponding eigenvalues times a random variable drawn from a Gaussian with mean zero and standard deviation 0.1…This scheme approximately captures an important property of natural images, namely, that object identity is invariant to changes in the intensity and color of the illumination. This scheme reduces the top-1 error rate by over 1%.”

[Krizhevsky et al. 2012]
Data Augmentation

Horizontal flips
Data Augmentation

Get creative!

Random mix/combinations of:
- translation
- rotation
- stretching
- shearing,
- lens distortions, ... (go crazy)
Transfer Learning with ConvNets

1. Train on Imagenet
**Transfer Learning with ConvNets**

1. Train on ImageNet

2. Small dataset: **feature extractor**
   - Freeze these
   - Train this
Transfer Learning with ConvNets

1. Train on ImageNet

2. Small dataset: feature extractor
   - Freeze these
   - Train this

3. Medium dataset: finetuning
   - more data = retrain more of the network (or all of it)
   - Freeze these
   - Train this
Transfer Learning with ConvNets

1. Train on Imagenet

2. Small dataset: feature extractor
   - Freez these
   - Train this

3. Medium dataset: finetuning
   - more data = retrain more of the network (or all of it)
   - Freeze these
   - Tip: use only ~1/10th of the original learning rate in finetuning top layer, and ~1/100th on intermediate layers
   - Train this
Today ConvNets are everywhere

[Classification

Retrieval

slide by Fei-Fei Li, Andrej Karpathy & Justin Johnson

[Krizhevsky 2012]
Today ConvNets are everywhere

Detection

Segmentation

[Faster R-CNN: Ren, He, Girshick, Sun 2015]

[Farabet et al., 2012]
Today ConvNets are everywhere

self-driving cars

NVIDIA Tegra X1
Today ConvNets are everywhere

[Simonyan et al. 2014]

[Goodfellow 2014]

[Taigman et al. 2014]
Today ConvNets are everywhere

[Toshev, Szegedy 2014]

[Mnih 2013]
Today ConvNets are everywhere

[Ciresan et al. 2013]

[Sermanet et al. 2011]
[Ciresan et al.]
Today ConvNets are everywhere
Today ConvNets are everywhere

Whale recognition, Kaggle Challenge

Mnih and Hinton, 2010
Today ConvNets are everywhere

- A person riding a motorcycle on a dirt road.
- Two dogs play in the grass.
- A skateboarder does a trick on a ramp.
- A dog is jumping to catch a frisbee.
- A group of young people playing a game of frisbee.
- Two hockey players are fighting over the puck.
- A little girl in a pink hat is blowing bubbles.
- A refrigerator filled with lots of food and drinks.
- A herd of elephants walking across a dry grass field.
- A close up of a cat laying on a couch.
- A red motorcycle parked on the side of the road.
- A yellow school bus parked in a parking lot.

[Vinyals et al., 2015]
Today ConvNets are everywhere

reddit.com/r/deepdream
Frameworks

- Torch [http://torch.ch/](http://torch.ch/) Very efficient. But you must LIKE Lua … Google and Facebook love it
- Theano [http://deeplearning.net/software/theano/](http://deeplearning.net/software/theano/) Compiled from Python. Not as efficient as Torch
- CXXNet [https://github.com/dmlc/cxxnet](https://github.com/dmlc/cxxnet) Simpler than Caffe. More efficient
- Parameter Server bindings to [https://github.com/dmlc/minerva, Caffe, CXXNet, …](https://github.com/dmlc/minerva, Caffe, CXXNet, …)