CSC2515 Lecture 6: Convolutional Networks

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Midterm Test

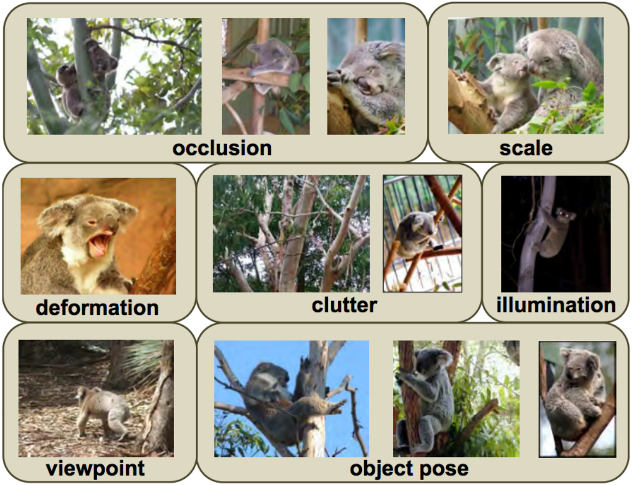
- Wednesday, Oct. 30, from 4:10-5:40pm
- Health Sciences building, room 610
- Covers all lectures up through Lecture 6 (i.e. this one)
- You're only responsible for things covered in lecture, but we might ask harder questions about things you got to practice in homeworks and tutorials.
- Practice tests will be posted on the course web site.

Neural Nets for Visual Object Recognition

- People are very good at recognizing shapes
    - Intrinsically difficult, computers are bad at it
- Why is it difficult?

Why is it a Problem?

- Difficult scene conditions



[From: Grauman & Leibe]

Why is it a Problem?

- Huge within-class variations. Recognition is mainly about modeling variation.

[Pic from: S. Lazebnik]

Why is it a Problem?

- Tons of classes

[Biederman]

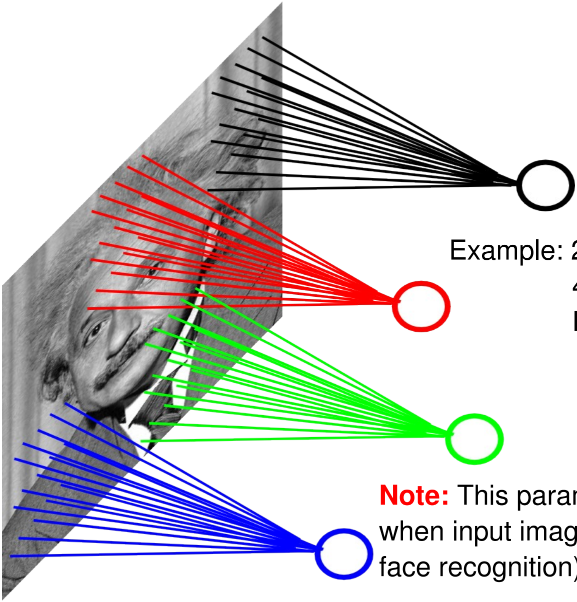
Neural Nets for Object Recognition

- People are very good at recognizing object
  - Intrinsically difficult, computers are bad at it
- Some reasons why it is difficult:
  - Segmentation: Real scenes are cluttered
  - Invariances: We are very good at ignoring all sorts of variations that do not affect class
  - Deformations: Natural object classes allow variations (faces, letters, chairs)
  - A huge amount of computation is required

How to Deal with Large Input Spaces

- How can we apply neural nets to images?
- Images can have millions of pixels, i.e., $\mathbf{x}$ is very high dimensional
- How many parameters do I have?
- Prohibitive to have fully-connected layers
- What can we do?
- We can use a locally connected layer

Locally Connected Layer



Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

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When Will this Work?

- This is good when the input is (roughly) registered

General Images

- The object can be anywhere

[Slide: Y. Zhu]

General Images

- The object can be anywhere

[Slide: Y. Zhu]

General Images

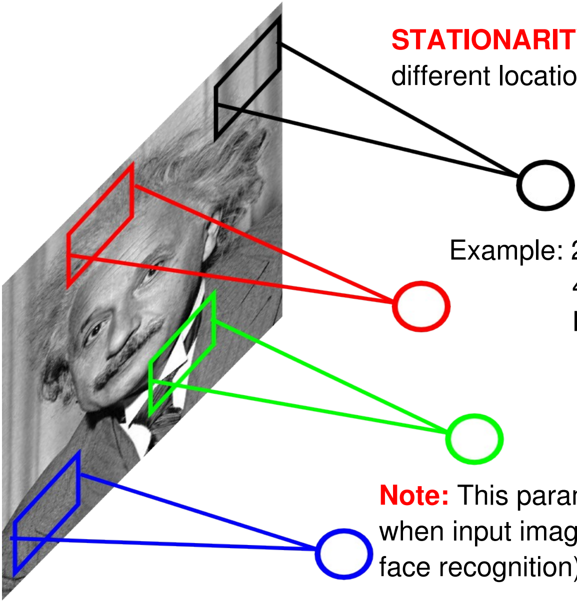
- The object can be anywhere

[Slide: Y. Zhu]

The Invariance Problem

- Our perceptual systems are very good at dealing with invariances
  - translation, rotation, scaling
  - deformation, contrast, lighting
- We are so good at this that it's hard to appreciate how difficult it is
  - It's one of the main difficulties in making computers perceive
  - We still don't have generally accepted solutions

Locally Connected Layer



STATIONARITY? Statistics is similar at different locations

Example: 200x200 image
40K hidden units
Filter size: 10x10
4M parameters

Note: This parameterization is good when input image is registered (e.g., face recognition).

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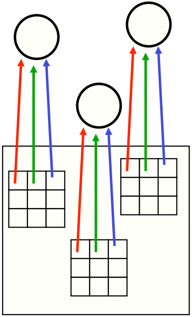
The replicated feature approach

The red connections all have the same weight.



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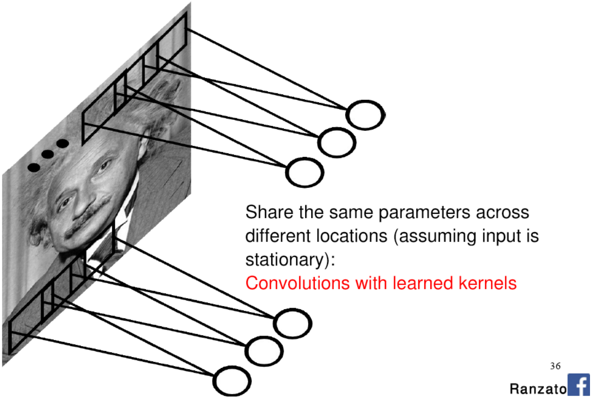
- Adopt approach apparently used in monkey visual systems
- Use many different copies of the same feature detector.
  - Copies have slightly different positions.
  - Could also replicate across scale and orientation.
    - Tricky and expensive
  - Replication **reduces the number of free parameters** to be learned.
- Use several **different feature types**, each with its own replicated pool of detectors.
  - Allows each patch of image to be represented in several ways.

Convolutional Neural Net

- Idea: statistics are similar at different locations (Lecun 1998)
- Connect each hidden unit to a small input patch and share the weight across space
- This is called a convolution layer and the network is a convolutional network



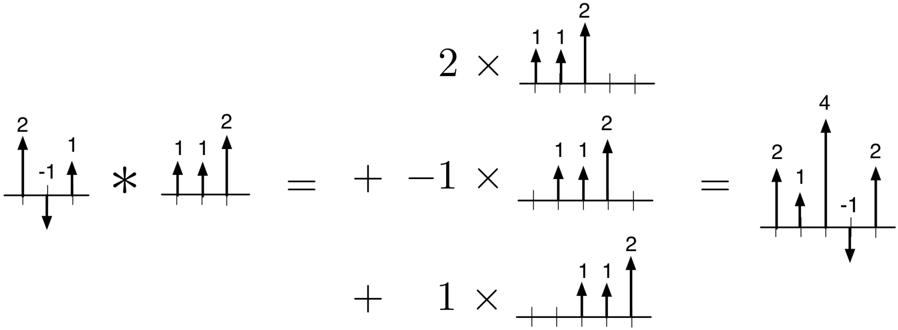
Convolution

- Convolution layers are named after the convolution operation.
- If a and b are two arrays,

$$(a * b)_t = \sum_{\tau} a_\tau b_{t-\tau}.$$

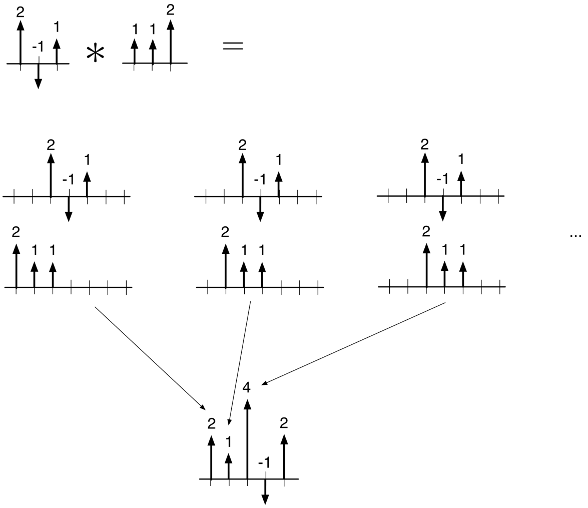
Convolution

Method 1: translate-and-scale



Convolution

Method 2: flip-and-filter



Convolution

Convolution can also be viewed as matrix multiplication:

$$(2, -1, 1) * (1, 1, 2) = \begin{pmatrix} 1 & & \\ 1 & 1 & \\ 2 & 1 & 1 \\ & 2 & 1 \\ & & 2 \end{pmatrix} \begin{pmatrix} 2 \\ -1 \\ 1 \end{pmatrix}$$

Aside: This is how convolution is typically implemented. (More efficient than the fast Fourier transform (FFT) for modern conv nets on GPUs!)

Convolution

Some properties of convolution:

- Commutativity

$$a * b = b * a$$

- Linearity

$$a * (\lambda_1 b + \lambda_2 c) = \lambda_1 a * b + \lambda_2 a * c$$

2-D Convolution

2-D convolution is defined analogously to 1-D convolution.

If A and B are two 2-D arrays, then:

$$(A * B)_{ij} = \sum_s \sum_t A_{st} B_{i-s,j-t}.$$

2-D Convolution

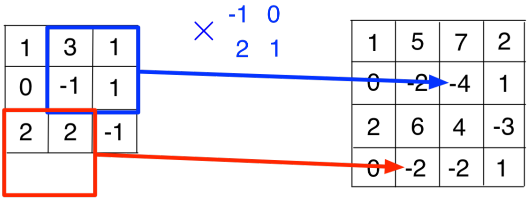
Method 1: Translate-and-Scale

$$
\begin{array}{|c|c|c|}\hline 1 & 3 & 1 \\ \hline 0 & -1 & 1 \\ \hline 2 & 2 & -1 \\ \hline \end{array}
\ast
\begin{array}{|c|c|}\hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array}
=
1 \times \begin{array}{|c|c|c|c|}\hline 1 & 3 & 1 & \\ \hline 0 & -1 & 1 & \\ \hline 2 & 2 & -1 & \\ \hline & & & \\ \hline \end{array}
+ 2 \times \begin{array}{|c|c|c|c|}\hline & 1 & 3 & 1 \\ \hline & 0 & -1 & 1 \\ \hline & 2 & 2 & -1 \\ \hline & & & \\ \hline \end{array}
+ -1 \times \begin{array}{|c|c|c|c|}\hline & & & \\ \hline & 1 & 3 & 1 \\ \hline & 0 & -1 & 1 \\ \hline & 2 & 2 & -1 \\ \hline \end{array}
=
\begin{array}{|c|c|c|c|}\hline 1 & 5 & 7 & 2 \\ \hline 0 & -2 & -4 & 1 \\ \hline 2 & 6 & 4 & -3 \\ \hline 0 & -2 & -2 & 1 \\ \hline \end{array}
$$

2-D Convolution

Method 2: Flip-and-Filter

$$\begin{array}{|c|c|c|} \hline 1 & 3 & 1 \\ \hline 0 & -1 & 1 \\ \hline 2 & 2 & -1 \\ \hline \end{array} \ast \begin{array}{|c|c|} \hline 1 & 2 \\ \hline 0 & -1 \\ \hline \end{array}$$



2-D Convolution

The thing we convolve by is called a kernel, or filter.

What does this filter do?

$*$

0	1	0
1	4	1
0	1	0

What does this filter do?

$$* \begin{bmatrix} 0 & -1 & 0 \\ -1 & 8 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

2-D Convolution

What does this filter do?

$*$

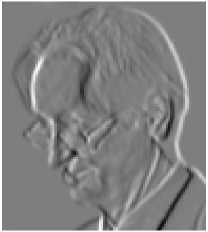
0	-1	0
-1	4	-1
0	-1	0

2-D Convolution

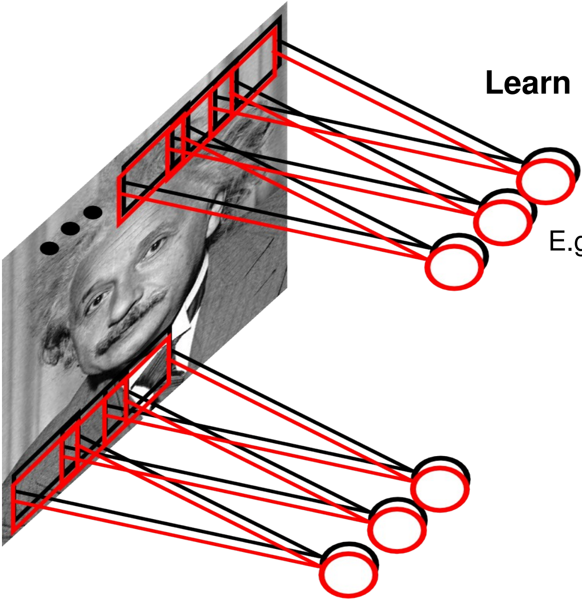
What does this filter do?

$*$

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



Convolutional Layer



Learn multiple filters.

E.g.: 200x200 image
100 Filters
Filter size: 10x10
10K parameters

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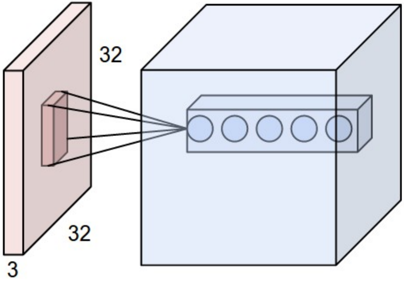
Convolutional Layer



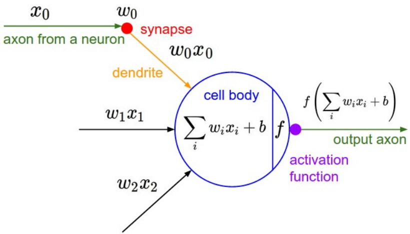


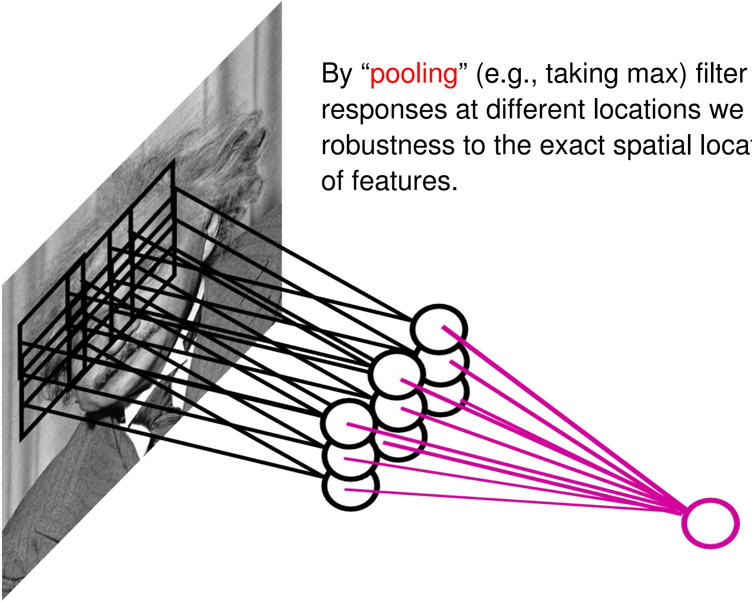
Figure: **Left:** CNN, **right:** Each neuron computes a linear and activation function

Hyperparameters of a convolutional layer:

- The number of filters (controls the **depth** of the output volume)
- The **stride**: how many units apart do we apply a filter spatially (this controls the spatial size of the output volume)
- The size $w \times h$ of the filters

[http://cs231n.github.io/convolutional-networks/]

Pooling Layer



By "pooling" (e.g., taking max) filter responses at different locations we gain robustness to the exact spatial location of features.

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Pooling Options

- Max Pooling: return the maximal argument
- Average Pooling: return the average of the arguments
- Other types of pooling exist.

Pooling

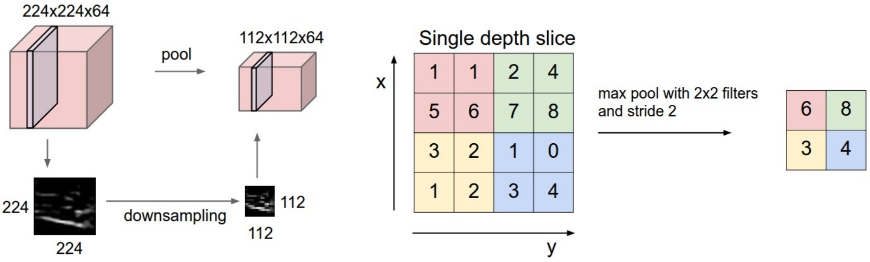


Figure: **Left:** Pooling, **right:** max pooling example

Hyperparameters of a pooling layer:

- The spatial extent F
- The stride

[http://cs231n.github.io/convolutional-networks/]

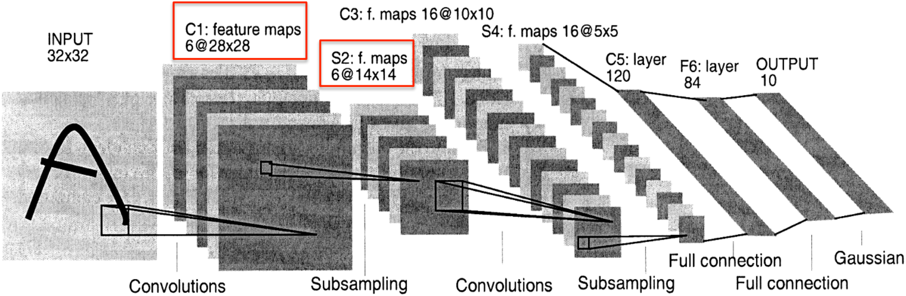
Backpropagation with Weight Constraints

- The backprop procedure from last lecture can be applied directly to conv nets.
- This is covered in csc2516.
- As a user, you don't need to worry about the details, since they're handled by automatic differentiation packages.

MNIST Dataset

- MNIST dataset of handwritten digits
  - **Categories:** 10 digit classes
  - **Source:** Scans of handwritten zip codes from envelopes
  - **Size:** 60,000 training images and 10,000 test images, grayscale, of size 28×28
  - **Normalization:** centered within in the image, scaled to a consistent size
    - The assumption is that the digit recognizer would be part of a larger pipeline that segments and normalizes images.
- In 1998, Yann LeCun and colleagues built a conv net called LeNet which was able to classify digits with 98.9% test accuracy.
  - It was good enough to be used in a system for automatically reading numbers on checks.

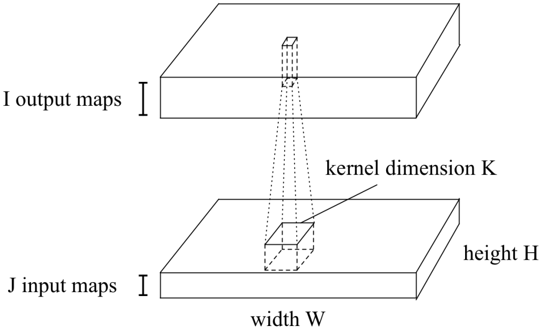
Here's the LeNet architecture, which was applied to handwritten digit recognition on MNIST in 1998:



Size of a Conv Net

- Ways to measure the size of a network:
  - **Number of units.** This is important because the activations need to be stored in memory during training (i.e. backprop).
  - **Number of weights.** This is important because the weights need to be stored in memory, and because the number of parameters determines the amount of overfitting.
  - **Number of connections.** This is important because there are approximately 3 add-multiply operations per connection (1 for the forward pass, 2 for the backward pass).
- We saw that a fully connected layer with M input units and N output units has MN connections and MN weights.
- The story for conv nets is more complicated.

Size of a Conv Net



	fully connected layer	convolution layer
# output units	WHI	WHI
# weights	W^2H^2IJ	K^2IJ
# connections	W^2H^2IJ	WHK^2IJ

Size of a Conv Net

Sizes of layers in LeNet:

Layer	Type	# units	# connections	# weights
C1	convolution	4704	117,600	150
S2	pooling	1176	4704	0
C3	convolution	1600	240,000	2400
S4	pooling	400	1600	0
F5	fully connected	120	48,000	48,000
F6	fully connected	84	10,080	10,080
output	fully connected	10	840	840

Conclusions?

Size of a Conv Net

- Rules of thumb:
  - Most of the units and connections are in the convolution layers.
  - Most of the weights are in the fully connected layers.
- If you try to make layers larger, you'll run up against various resource limitations (i.e. computation time, memory)
- You'll repeat this exercise for AlexNet for homework.
  - Conv nets have gotten a LOT larger since 1998!

ImageNet

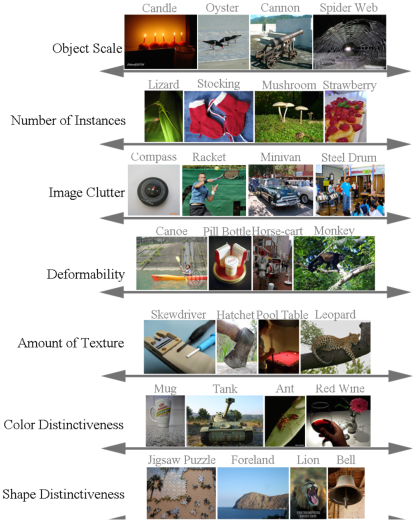
ImageNet is the modern object recognition benchmark dataset. It was introduced in 2009, and has led to amazing progress in object recognition since then.

ImageNet

- Used for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), an annual benchmark competition for object recognition algorithms
- Design decisions
  - **Categories:** Taken from a lexical database called WordNet
    - WordNet consists of "synsets", or sets of synonymous words
    - They tried to use as many of these as possible; almost 22,000 as of 2010
    - Of these, they chose the 1000 most common for the ILSVRC
    - The categories are really specific, e.g. hundreds of kinds of dogs
  - **Size:** 1.2 million full-sized images for the ILSVRC
  - **Source:** Results from image search engines, hand-labeled by Mechanical Turkers
    - Labeling such specific categories was challenging; annotators had to be given the WordNet hierarchy, Wikipedia, etc.
  - **Normalization:** none, although the contestants are free to do preprocessing

ImageNet

Images and object categories vary on a lot of dimensions



Russakovsky et al.

ImageNet

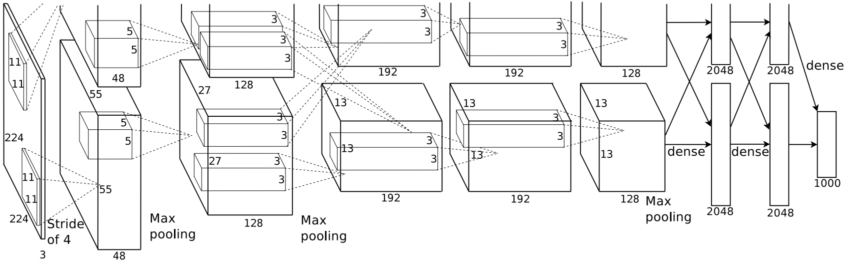
Size on disk:

MNIST
60 MB

ImageNet
50 GB

AlexNet

- AlexNet, 2012. 8 weight layers. 16.4% top-5 error (i.e. the network gets 5 tries to guess the right category).



(Krizhevsky et al., 2012)

- The two processing pathways correspond to 2 GPUs. (At the time, the network couldn't fit on one GPU.)
- AlexNet's stunning performance on the ILSVRC is what set off the deep learning boom of the last 6 years.

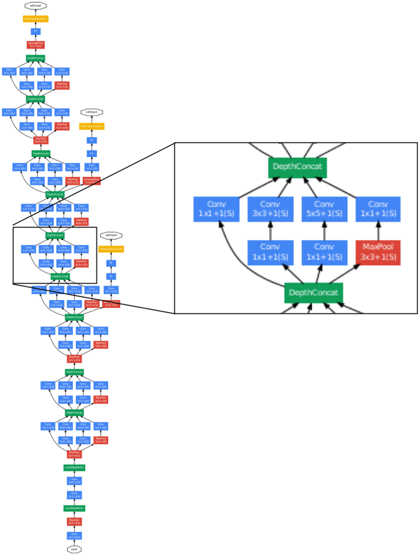
Inception, 2014. ("We need to go deeper!")

22 weight layers

Fully convolutional (no fully connected layers)

Convolutions are broken down into a bunch of smaller convolutions

6.6% test error on ImageNet



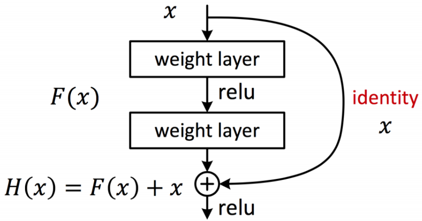
(Szegedy et al., 2014)

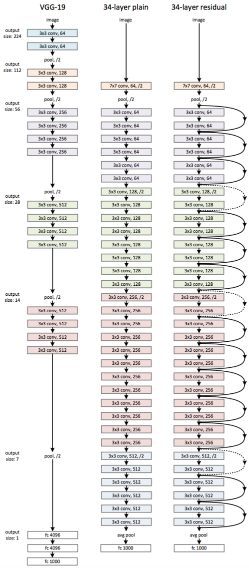
Inception

- They were really aggressive about cutting the number of parameters.
  - Motivation: train the network on a large cluster, run it on a cell phone
    - Memory at test time is the big constraint.
    - Having lots of units is OK, since the activations only need to be stored at training time (for backpropagation).
    - Parameters need to be stored both at training and test time, so these are the memory bottleneck.
  - How they did it
    - No fully connected layers (remember, these have most of the weights)
    - Break down convolutions into multiple smaller convolutions (since this requires fewer parameters total)
  - Inception has "only" 2 million parameters, compared with 60 million for AlexNet
  - This turned out to improve generalization as well. (Overfitting can still be a problem, even with over a million images!)

150 Layers!

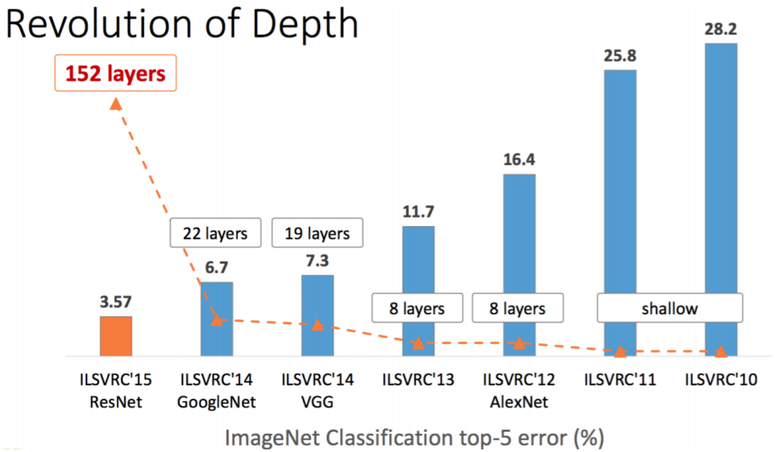
- Networks are now at 150 layers
- They use a skip connections with special form
- In fact, they don't fit on this screen
- Amazing performance!
- A lot of "mistakes" are due to wrong ground-truth



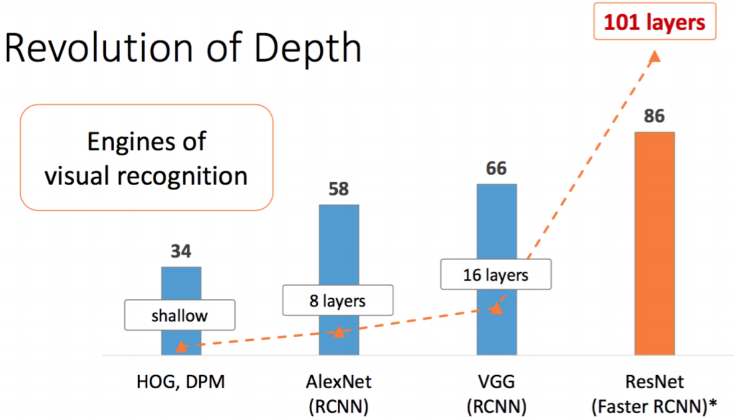


[He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]

Results: Object Classification



Slide: R. Liao, Paper: [He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]



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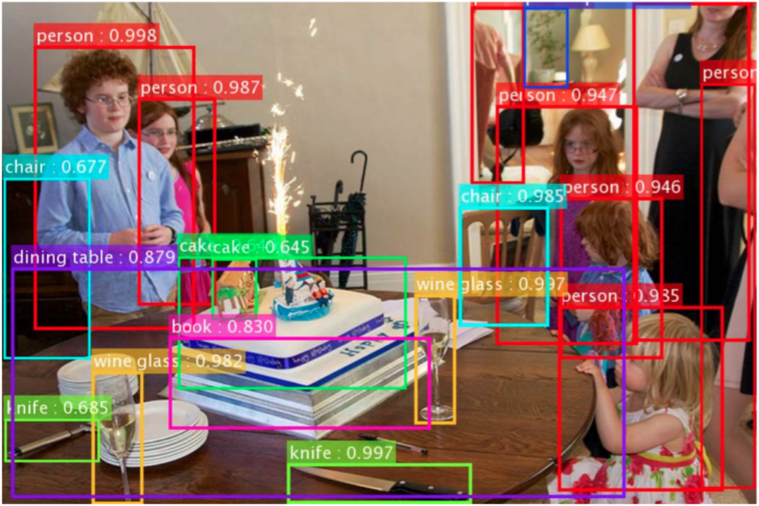
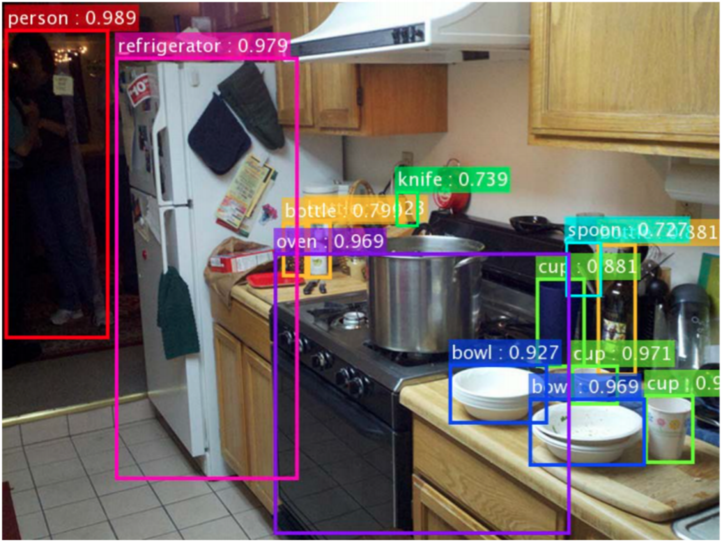
Results: Object Detection



Slide: R. Liao, Paper: [He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]

Results: Object Detection



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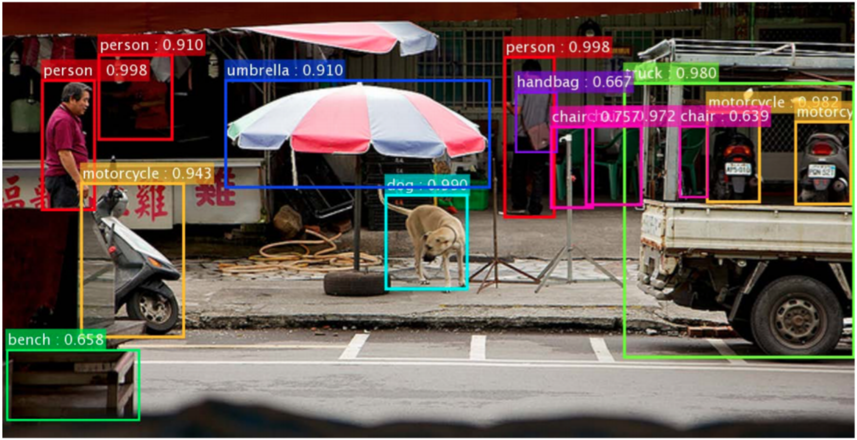
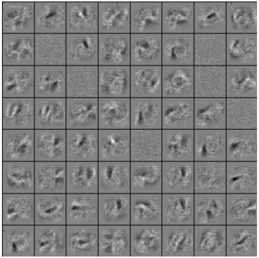


Slide: R. Liao, Paper: [He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]

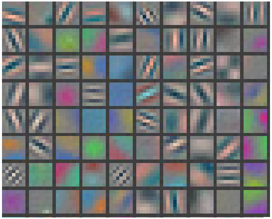
What Do Networks Learn?

- Recall: we can understand what first-layer features are doing by visualizing the weight matrices.

Fully connected (MNIST)



Convolutional (ImageNet)



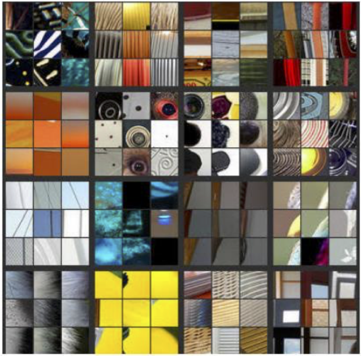
- Higher-level weight matrices are hard to interpret.
- The better the input matches these weights, the more the feature activates.
  - Obvious generalization: visualize higher-level features by seeing what inputs activate them.

What Do Networks Learn?

- One way to formalize: pick the images in the training set which activate a unit most strongly.
- Here's the visualization for layer 1:

What Do Networks Learn?

- Layer 3:



What Do Networks Learn?

- Layer 4:

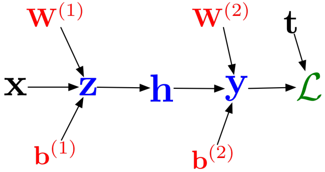
- Layer 5:

What Do Networks Learn?

- Higher layers seem to pick up more abstract, high-level information.
- Problems?
  - Can't tell what the unit is actually responding to in the image.
  - We may read too much into the results, e.g. a unit may detect red, and the images that maximize its activation will all be stop signs.
- Can use input gradients to diagnose what the unit is responding to.
  - Optimize an image from scratch to increase a unit's activation

Optimizing the Image

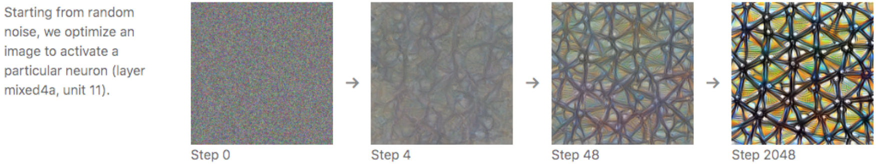
- Recall the computation graph:



- From this graph, you could compute $\partial \mathcal{L} / \partial \mathbf{x}$, but we never made use of this.

Optimizing the Image

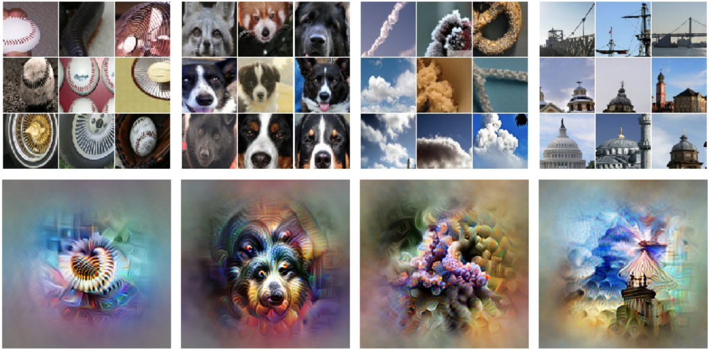
- Can do gradient ascent on an image to maximize the activation of a given neuron.
- Requires a few tricks to make this work; see `https://distill.pub/2017/feature-visualization/`



Optimizing the Image

Dataset Examples show us what neurons respond to in practice

Optimization isolates the causes of behavior from mere correlations. A neuron may not be detecting what you initially thought.



Baseball—or stripes? *mixed4a, Unit 6*

Animal faces—or snouts? *mixed4a, Unit 240*

Clouds—or fluffiness? *mixed4a, Unit 453*

Buildings—or sky? *mixed4a, Unit 492*

Optimizing the Image

- Higher layers in the network often learn higher-level, more interpretable representations

Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a)

https://distill.pub/2017/feature-visualization/

Optimizing the Image

- Higher layers in the network often learn higher-level, more interpretable representations

Parts (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

https://distill.pub/2017/feature-visualization/