CSC 411 Lecture 11: Neural Networks II

Mengye Ren and Matthew MacKay

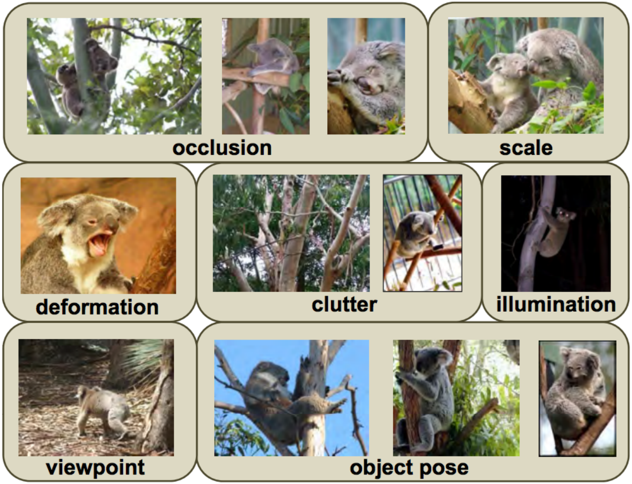
University of Toronto

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]

- Tons of classes

[Biederman]

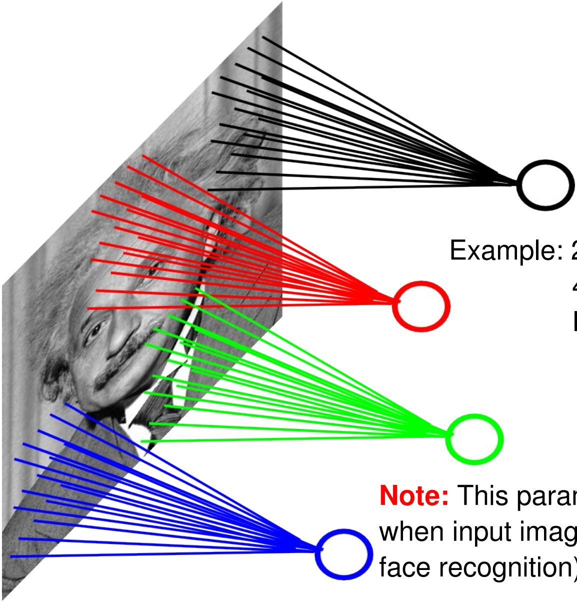
Neural Nets for Object Recognition

- 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

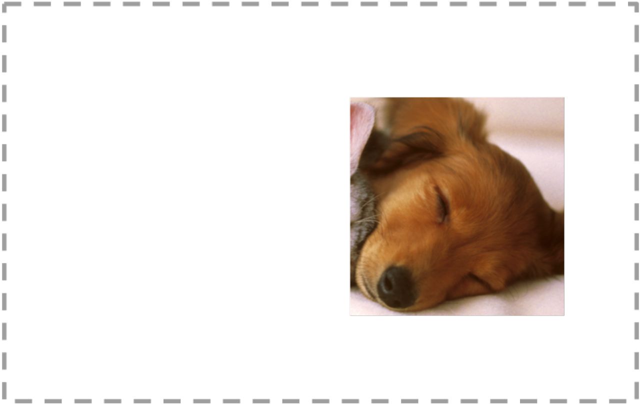
General Images

- The object can be anywhere

[Slide: Y. Zhu]

General Images

- The object can be anywhere



[Slide: Y. Zhu]

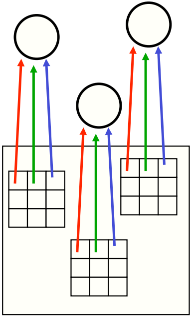
General Images

- The object can be anywhere

[Slide: Y. Zhu]

The replicated feature approach

The red connections all have the same weight.



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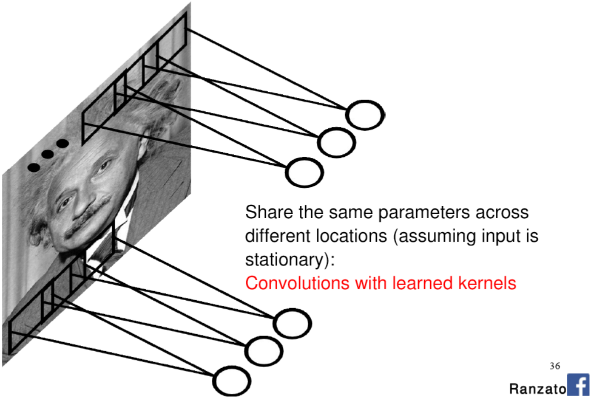
- Adopt approach apparently used in monkey visual systems
- Use many different copies of the same feature detector.
  - Copies have slightly different positions.
  - Could also replicate across scale and orientation.
    - Tricky and expensive
  - Replication **reduces the number of free parameters** 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

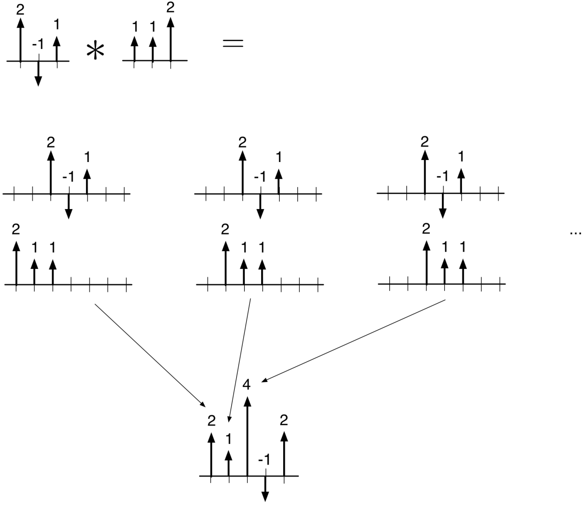


Convolution

- Convolution layers are named after the convolution operation.
- If a and b are two (possibly infinite) 1-D arrays, $a * b$ is another 1-D array:
$$(a * b)_t = \sum_{\tau} a_\tau b_{t-\tau}.$$
- Can think of a as a signal living on a one dimensional line
- Normally a finite so $a_t = 0$ for $t \notin \{1, \ldots, d\}$

Convolution

"Flip and Filter" interpretation:

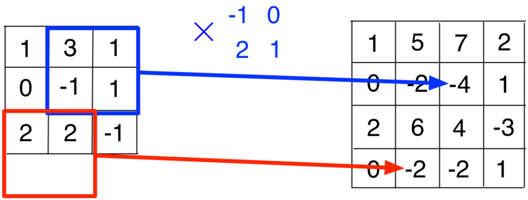


2-D Convolution

2-D convolution is analogous:

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

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



2-D Convolution

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

What does this convolution kernel do?

$*$

0	1	0
1	4	1
0	1	0

2-D Convolution

What does this convolution kernel do?

$$*\begin{array}{|c|c|c|}\hline 0 & -1 & 0 \\ \hline -1 & 8 & -1 \\ \hline 0 & -1 & 0 \\ \hline \end{array}$$

2-D Convolution

What does this convolution kernel do?

$*$

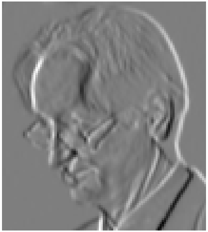
0	-1	0
-1	4	-1
0	-1	0

2-D Convolution

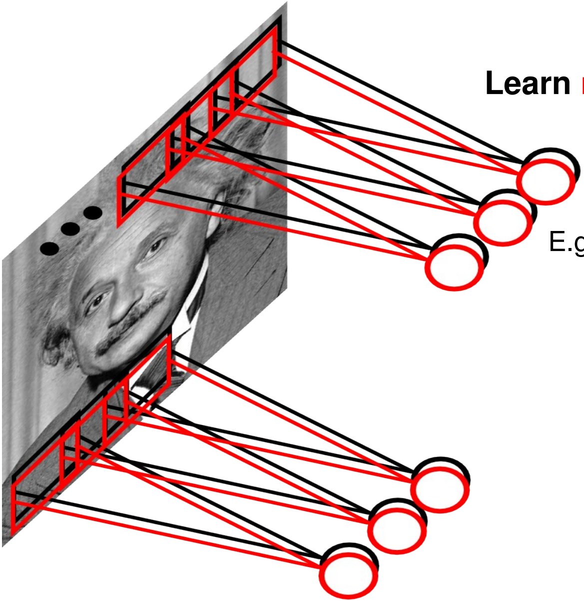
What does this convolution kernel do?

$*$

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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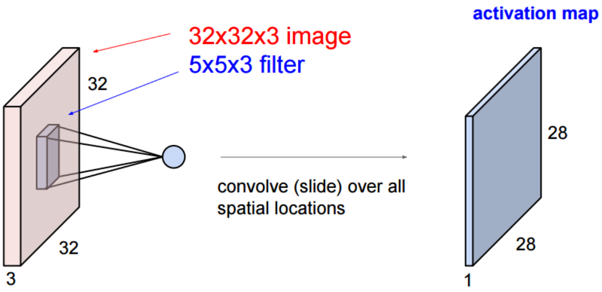
Convolutional Filter

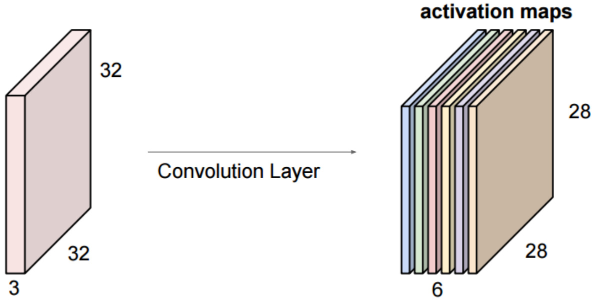


Convolving one filter F with an image I of size $C \times H \times W$ yields an activation map A of size $H' \times W'$

$$I * F = A$$

- H' and W' depend on:
  - the stride: how many units apart do we apply a filter spatially
  - the size of the filter
  - These are hyperparameters!

Convolutional Layer



- We convolve with many filters and stack the resulting activation maps depthwise
  - This will be the "image" we convolve over in the next layer
- This operation is called a convolutional layer
- The number of filters in a layer is a hyperparameter!

Pooling

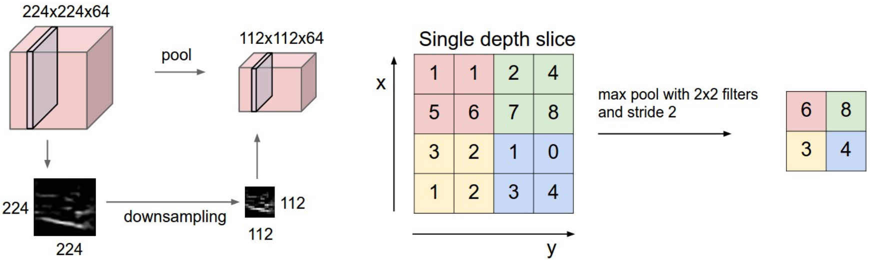


Figure: **Left:** Pooling, **right:** max pooling example

By pooling filter responses at different locations we gain robustness to the exact spatial location of our features

Hyperparameters of a pooling layer:

- The spatial extent F
- The stride

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

Pooling Options

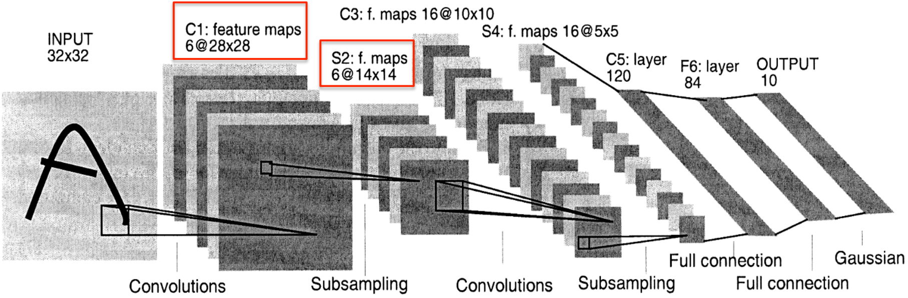
- Max Pooling: return the maximal argument
- Average Pooling: return the average of the arguments
- Other types of pooling exist.

Backpropagation with Weight Constraints

- The backprop procedure from last lecture can be applied directly to conv nets.
- This is covered in csc421.
- As a user, you don't need to worry about the details, since they're handled by automatic differentiation packages.

LeNet

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

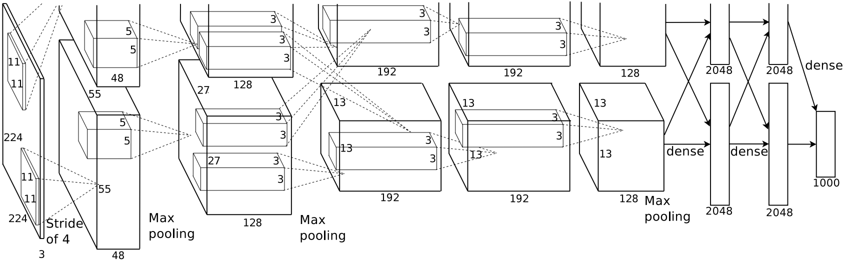


ImageNet

- Imagenet, biggest dataset for object classification: `http://image-net.org/`
- 1000 classes, 1.2M training images, 150K for test

AlexNet

- AlexNet, 2012. 8 weight layers. 16.4% top-5 error (i.e. the network gets 5 tries to guess the right category).
- Closest competitor: 26.1%

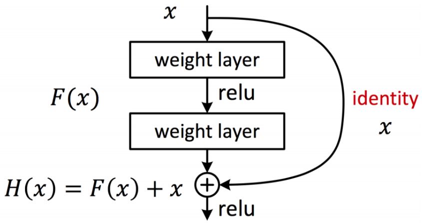


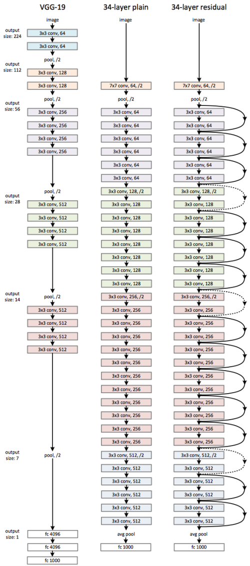
(Krizhevsky et al., 2012)

- 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.

150 Layers!

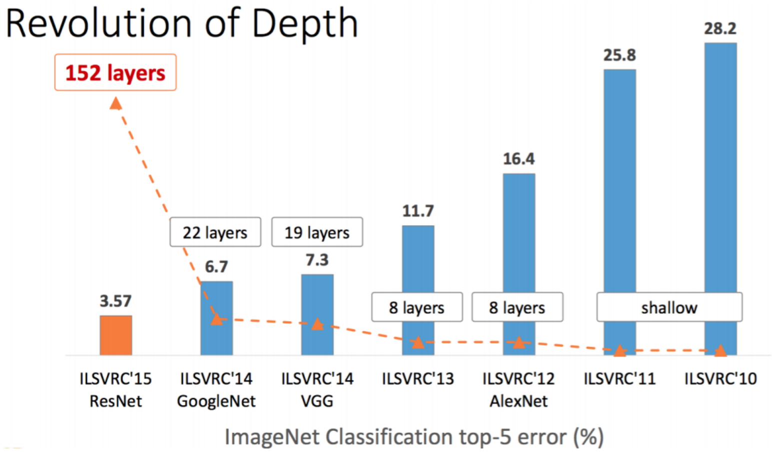
- Networks are now at 150 layers
- They use a skip connections with special form
- In fact, they don't fit on this screen
- Amazing performance!
- A lot of "mistakes" are due to wrong ground-truth





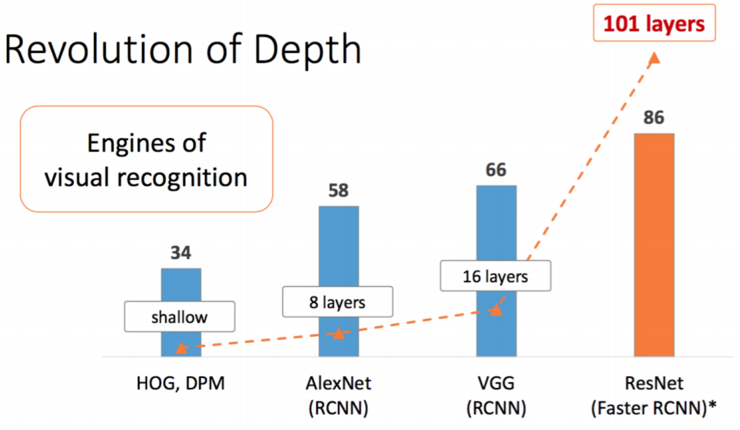
[He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]

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]

Results: Object Detection



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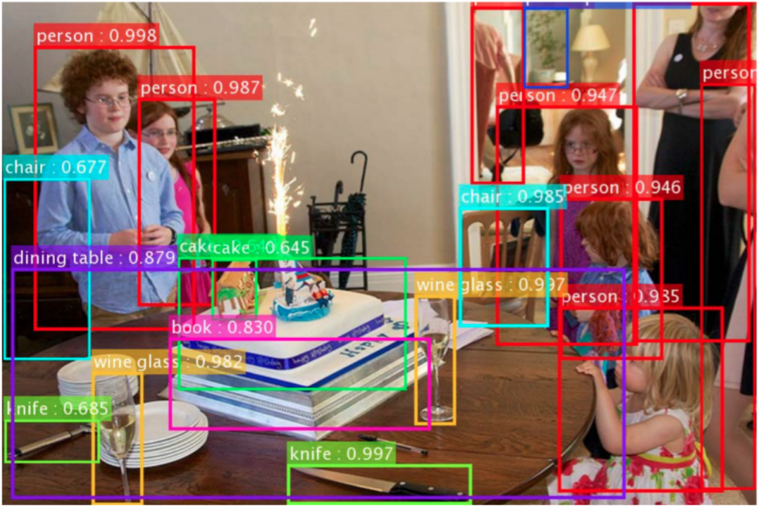

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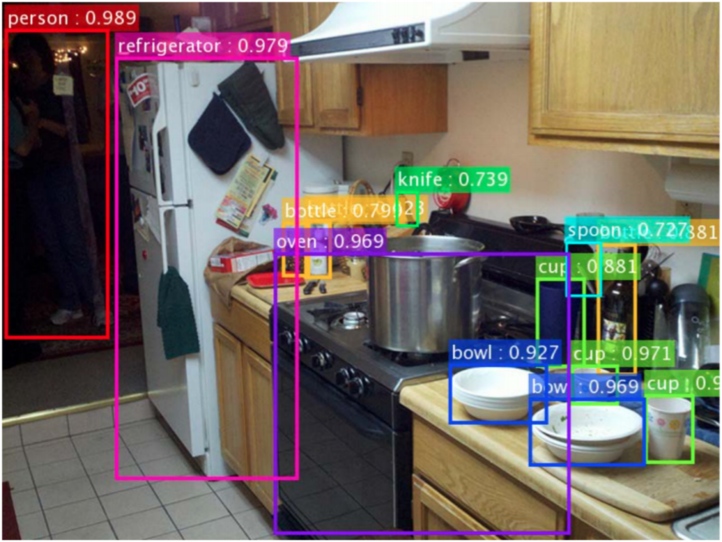

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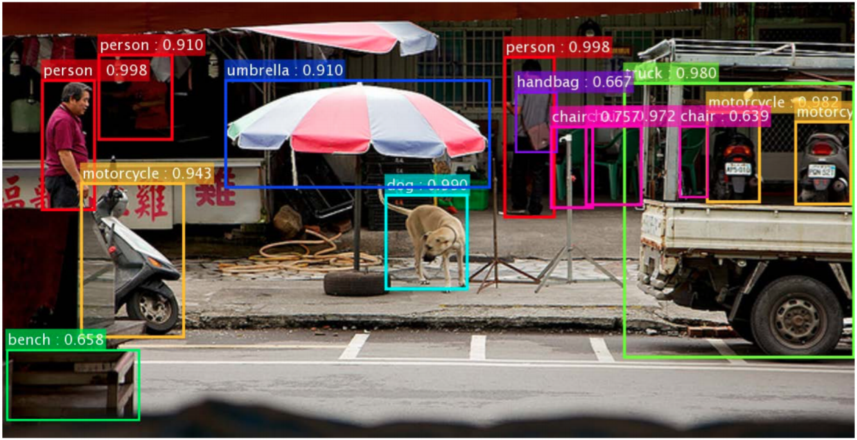

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What do CNNs Learn?

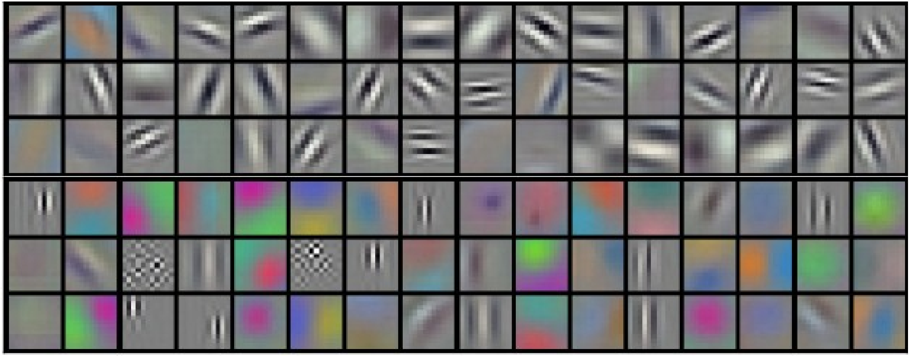


Figure: Filters in the first convolutional layer of Krizhevsky et al

What do CNNs Learn?

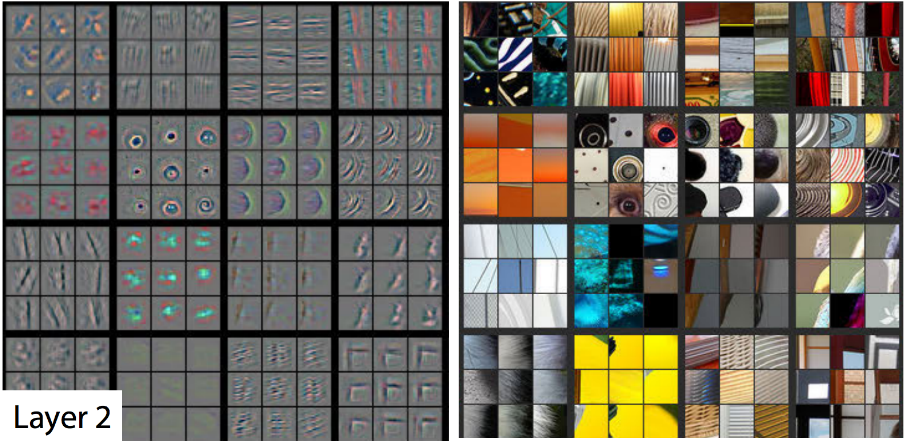


Figure: Filters in the second layer

[http://arxiv.org/pdf/1311.2901v3.pdf]

What do CNNs Learn?

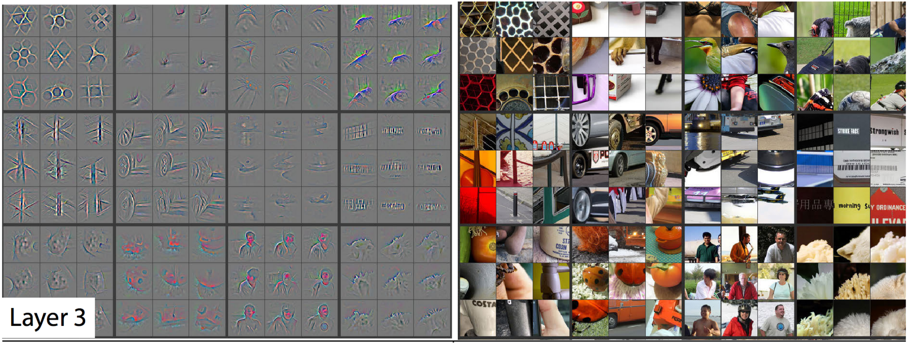
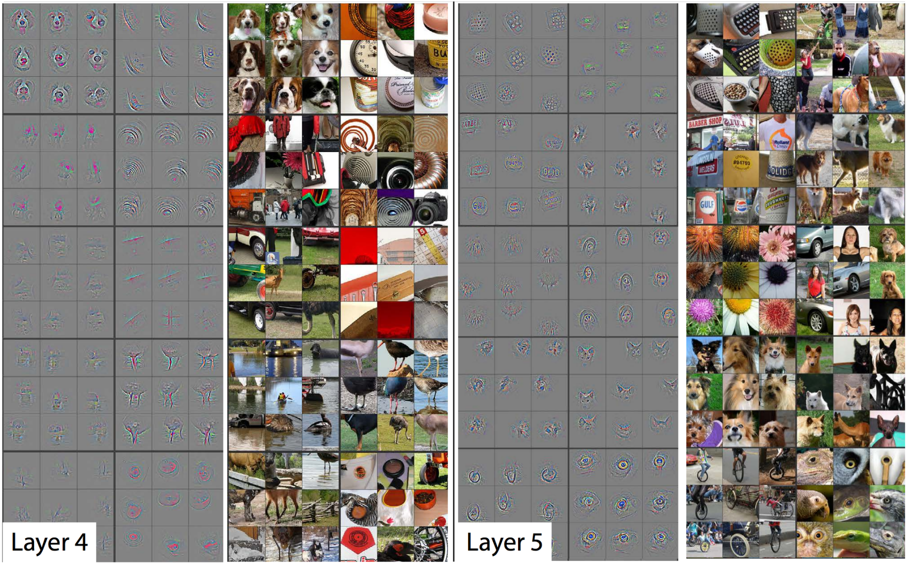


Figure: Filters in the third layer

[http://arxiv.org/pdf/1311.2901v3.pdf]

What do CNNs Learn?



[http://arxiv.org/pdf/1311.2901v3.pdf]

Links

- Great course dedicated to NN: http://cs231n.stanford.edu
- Open source frameworks:
  - Pytorch http://pytorch.org/
  - Tensorflow https://www.tensorflow.org/
  - Caffe http://caffe.berkeleyvision.org/
- Most cited NN papers: https://github.com/terryum/awesome-deep-learning-papers