CSC 411 Lecture 11: Neural Networks II

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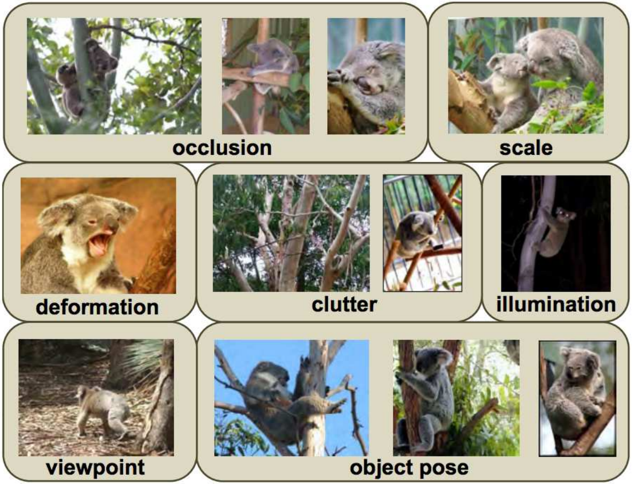
Neural Nets for Visual Object Recognition

- 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]

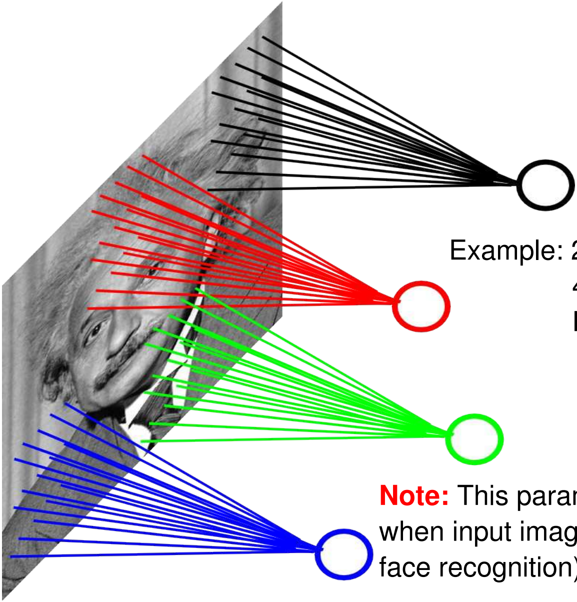
Neural Nets for Object Recognition

- 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?

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

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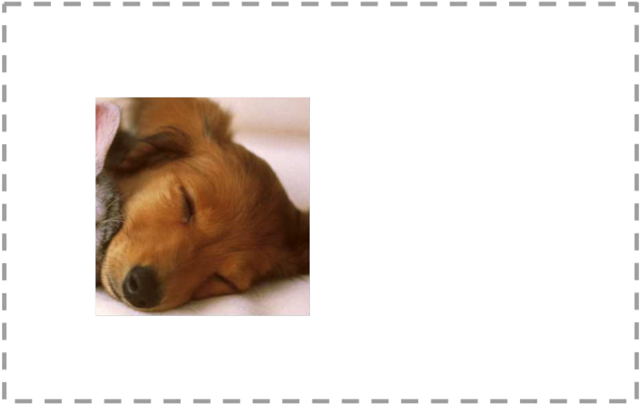
[Slide: Y. Zhu]

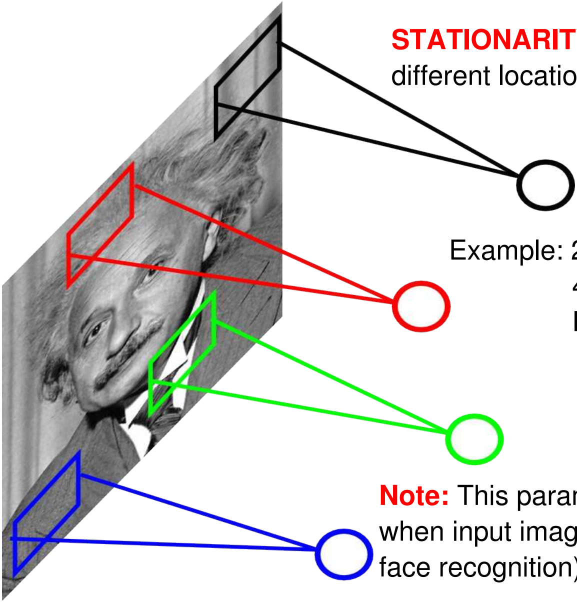
General Images

- The object can be anywhere



[Slide: Y. Zhu]

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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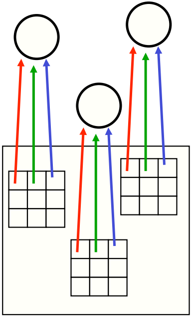
The replicated feature approach

The red connections all have the same weight.



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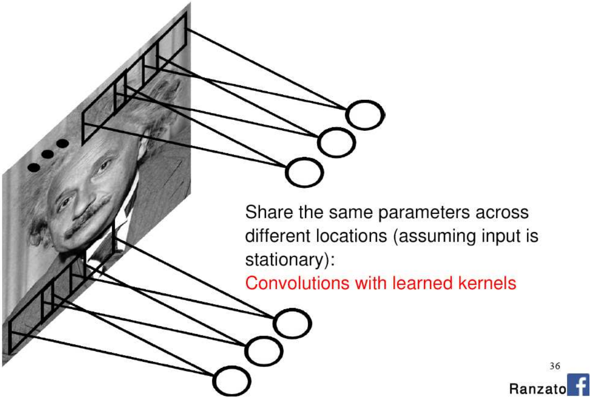
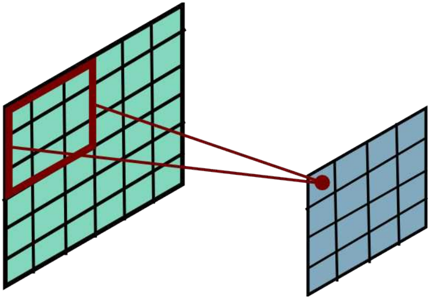
- Adopt approach apparently used in monkey visual systems
- Use many different copies of the same feature detector.
  - Copies have slightly different positions.
  - Could also replicate across scale and orientation.
    - Tricky and expensive
  - Replication reduces number of free parameters to be learned.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



Convolutional Layer



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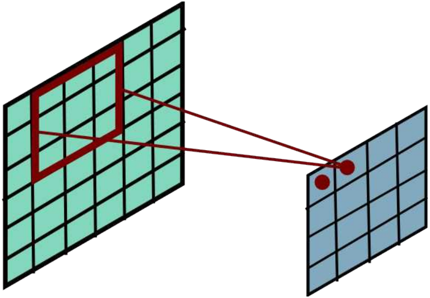
$$h_j^n = \max(0, \sum_{k=1}^{K} h_k^{n-1} * w_{jk}^n)$$

Convolutional Layer



Ranzato

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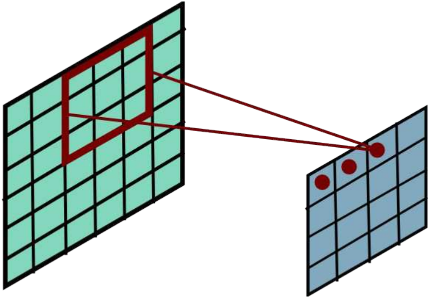

Ranzato

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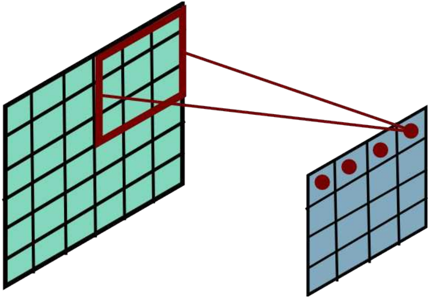
Convolutional Layer



Ranzato

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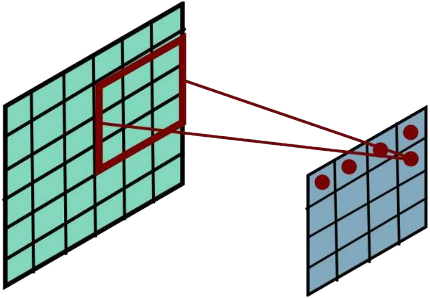
Convolutional Layer



Ranzato

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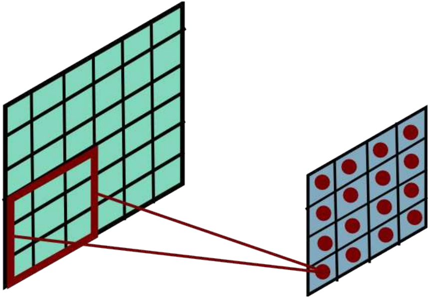
Convolutional Layer



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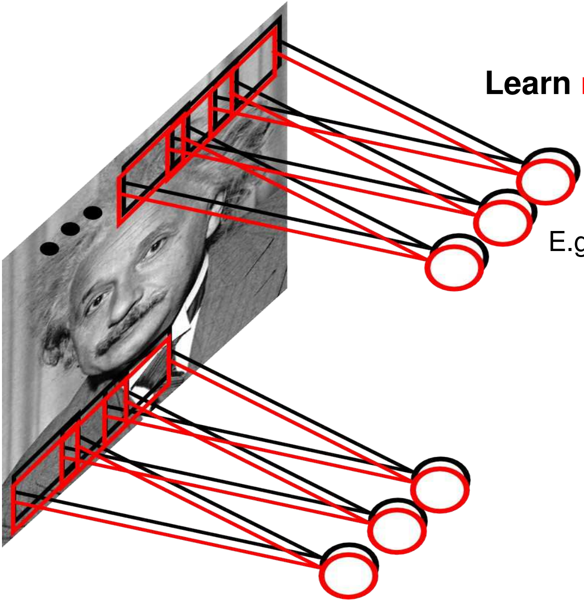
Convolutional Layer



Learn multiple filters.

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

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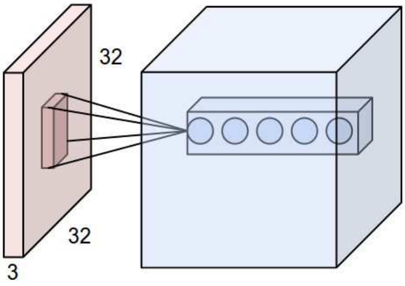
Convolutional Layer



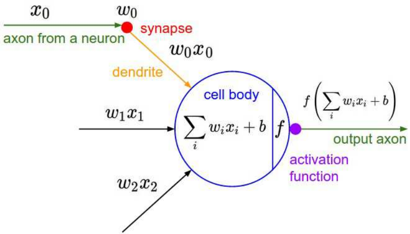


Figure: **Left:** CNN, **right:** Each neuron computes a linear and activation function

Hyperparameters of a convolutional layer:

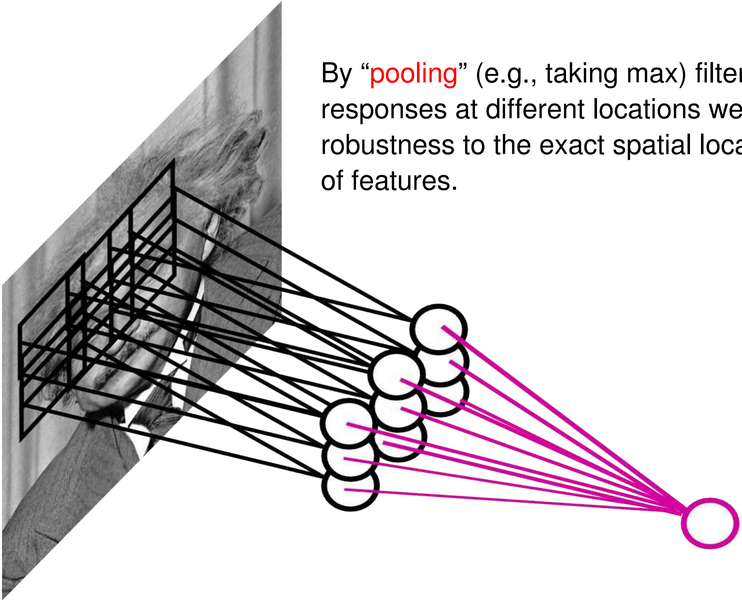
- The number of filters (controls the **depth** of the output volume)
- The **stride**: how many units apart do we apply a filter spatially (this controls the spatial size of the output volume)
- The size $w \times h$ of the filters

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

Output size

- If the input is $HxWxC_{in}$ and the kernel size is $k_1xk_2xC_{out}$ what is the output size?
  - $(H - k_1 + 1) \times (W - k_2 + 1) \times C_{out}$
- Input is $HxWxC_{in}$ and the kernel size is $k_1xk_2xC_{out}$ with stride s?
  - $H_{out} = \lfloor (H - k_1)/s + 1 \rfloor$
- Input is $HxWxC_{in}$ and the kernel size is $k_1xk_2xC_{out}$ with stride s with padding p?
  - $H_{out} = \lfloor (H + 2p - k_1)/s + 1 \rfloor$
- Without padding we can't have a very deep network (the size shrinks every convolution)

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

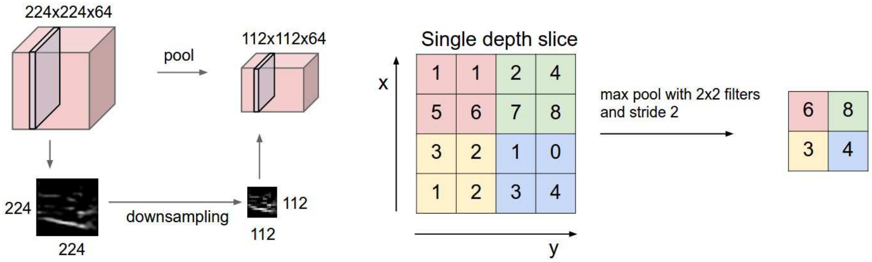


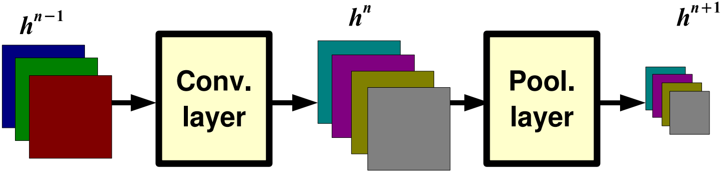
Figure: **Left:** Pooling, **right:** max pooling example

Hyperparameters of a pooling layer:

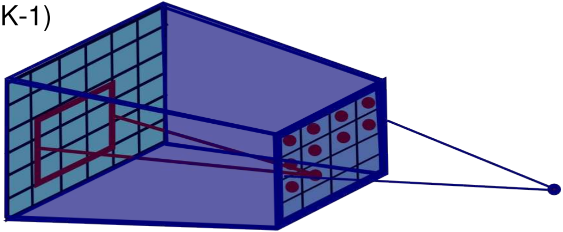
- The spatial extent F
- The stride

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

Pooling Layer: Receptive Field Size



If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: (P+K-1)x(P+K-1)



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Backpropagation with Weight Constraints

- It is easy to modify the backpropagation algorithm to incorporate linear constraints between the weights

$$\begin{aligned} \text{To constrain:} \quad w_1 &= w_2 \\ \text{we need:} \quad \Delta w_1 &= \Delta w_2 \end{aligned}$$

- We compute the gradients as usual, and then modify the gradients so that they satisfy the constraints.

$$\begin{aligned} \text{compute:} \quad & \frac{\partial E}{\partial w_1} \text{ and } \frac{\partial E}{\partial w_2} \\ \text{use:} \quad & \frac{\partial E}{\partial w_1} + \frac{\partial E}{\partial w_2} \text{ for } w_1 \text{ and } w_2 \end{aligned}$$

- So if the weights started off satisfying the constraints, they will continue to satisfy them.
- This is an intuition behind the backprop. In practice, write down the equations and compute derivatives (it's a nice exercise, do it at home)

Now let's make this very deep to get a real state-of-the-art object recognition system

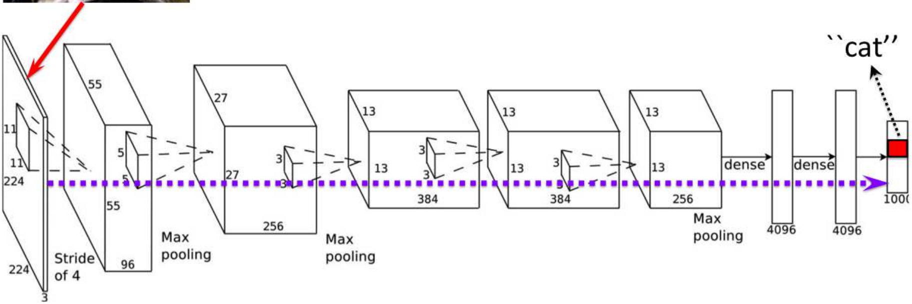
Convolutional Neural Networks (CNN)

- Basic filtering idea from computer vision/image processing
- If our filter is $[-1, 1]$, you get a vertical edge detector
- Now imagine we want to have many filters (e.g., vertical, horizontal, corners, one for dots). We will use a filterbank.
- So applying a filterbank to an image yields a cube-like output, a 3D matrix in which each slice is an output of convolution with one filter. We apply an activation function on each hidden unit (typically a ReLU).
- Do some additional tricks. A popular one is called max pooling. Any idea why you would do this?
- Do some additional tricks. A popular one is called max pooling. Any idea why you would do this? To get invariance to small shifts in position.
- Now add another "layer" of filters. For each filter again do convolution, but this time with the output cube of the previous layer.

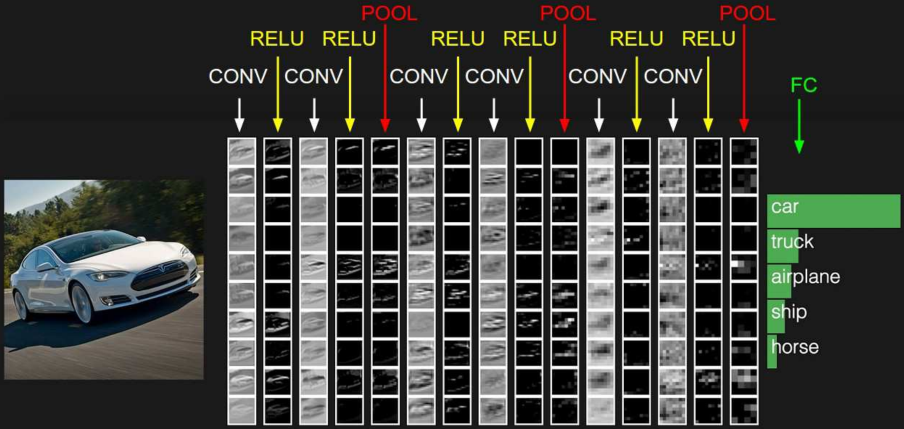
Classification

- Once trained we feed in an image or a crop, run through the network, and read out the class with the highest probability in the last (classif) layer.

What's the class of this object?

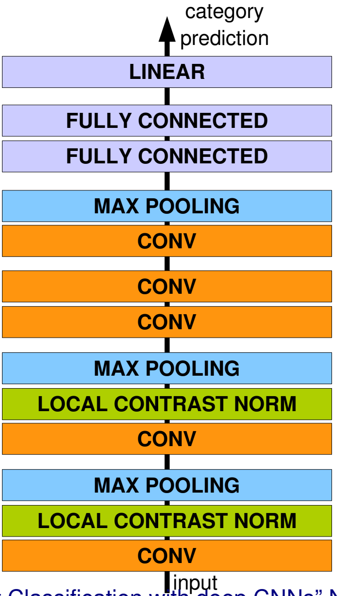


Example



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

Architecture for Classification



Krizhevsky et al. "ImageNet Classification with deep CNNs" NIPS 2012

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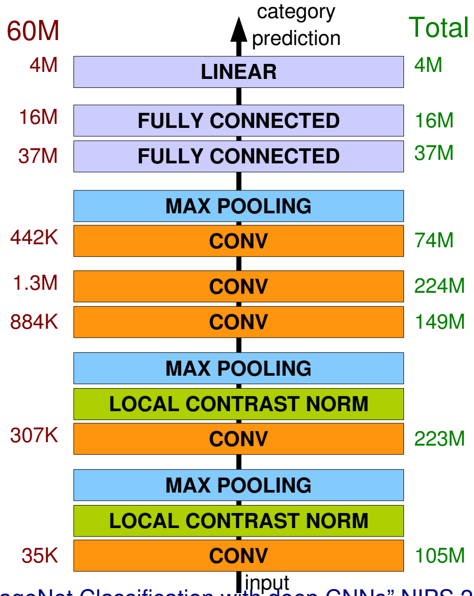
Architecture for Classification

Total nr. params: 60M

Total nr. flops: 832M



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Krizhevsky et al. “ImageNet Classification with deep CNNs” NIPS 2012

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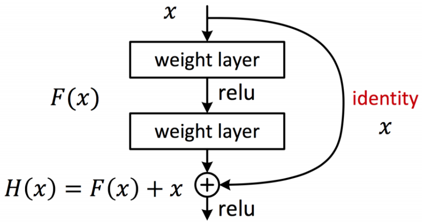
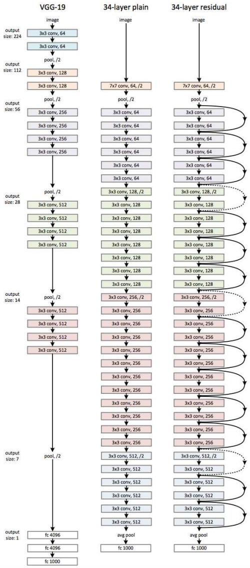
ImageNet

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

150 Layers!

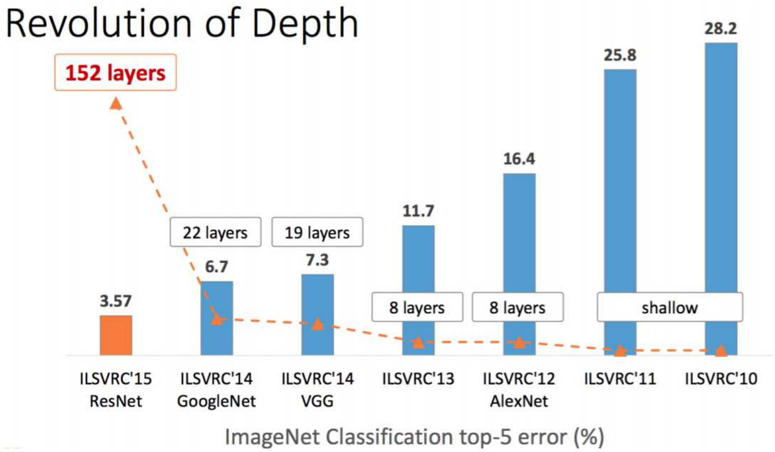
- Networks are now at 150 layers
- They use a skip connections with special form
- In fact, they don't fit on this screen
- Amazing performance!
- A lot of "mistakes" are due to wrong ground-truth





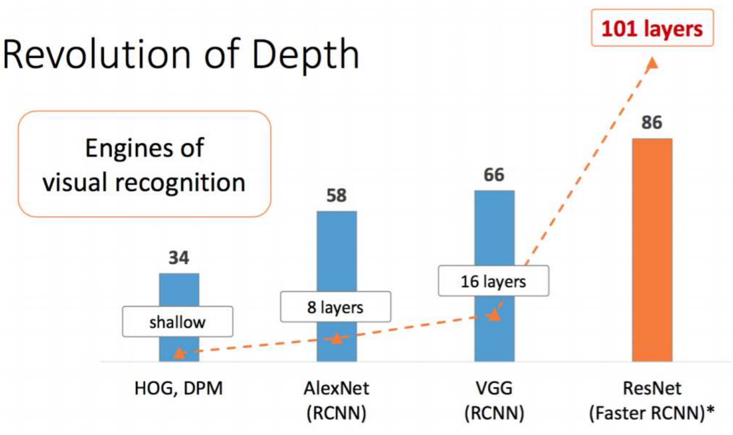
[He, K., Zhang, X., Ren, S. and Sun, J., 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385, 2016]

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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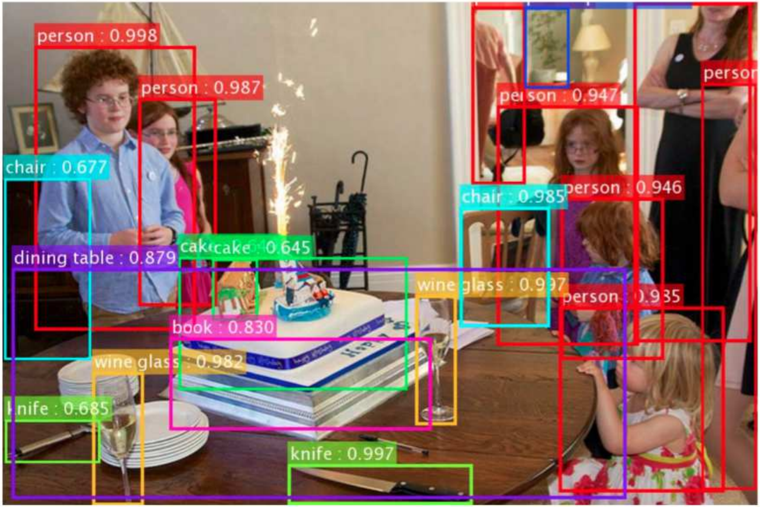

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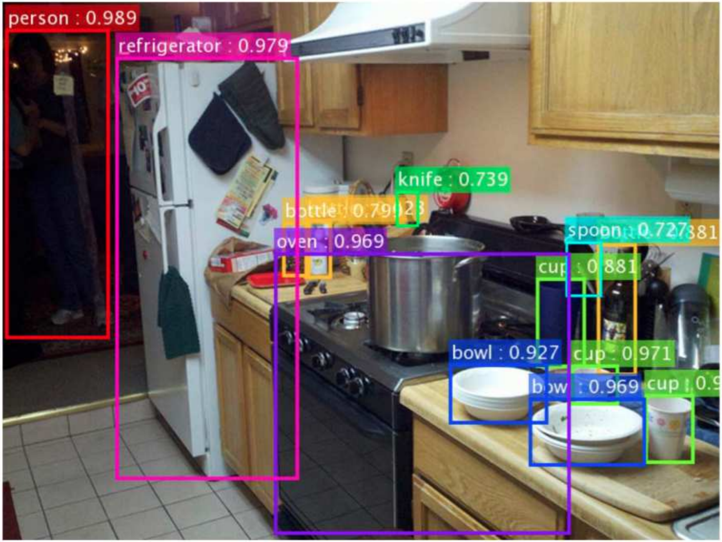

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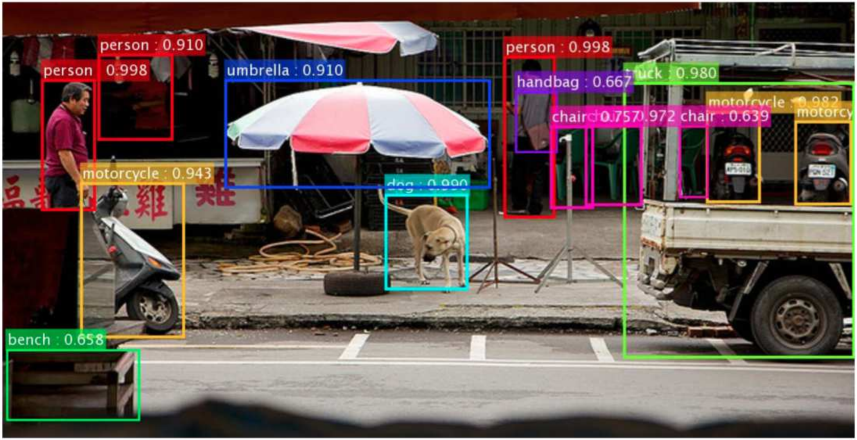

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What do CNNs Learn?

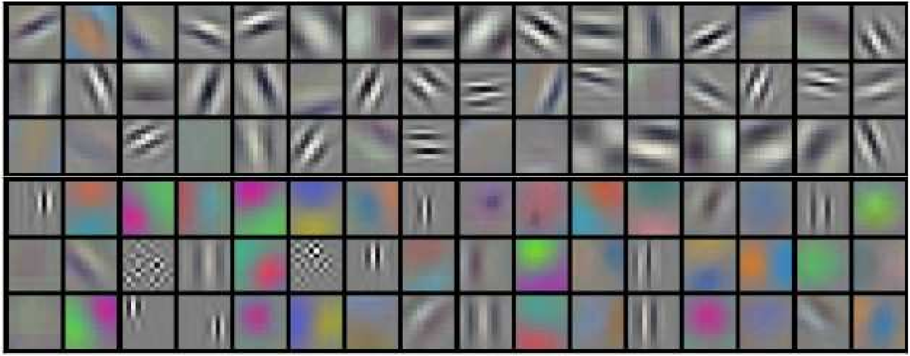


Figure: Filters in the first convolutional layer of Krizhevsky et al

What do CNNs Learn?

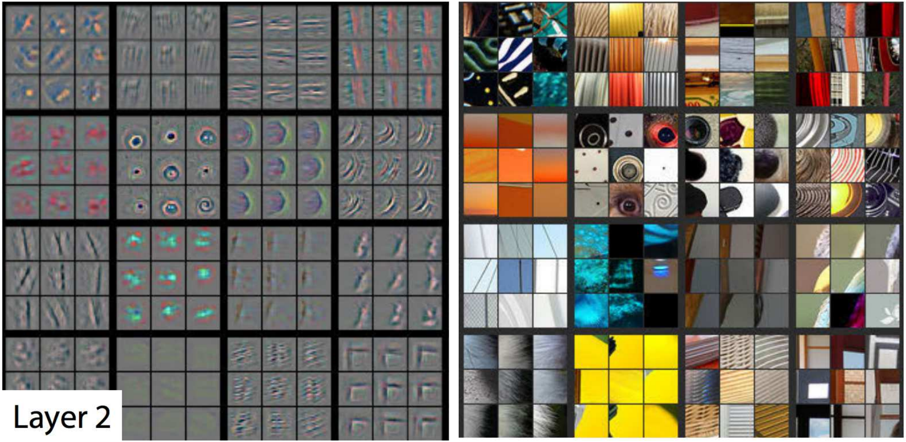


Figure: Filters in the second layer

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

What do CNNs Learn?

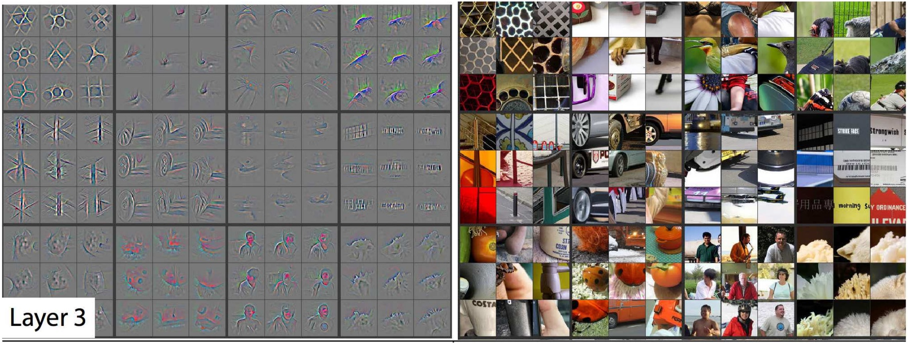
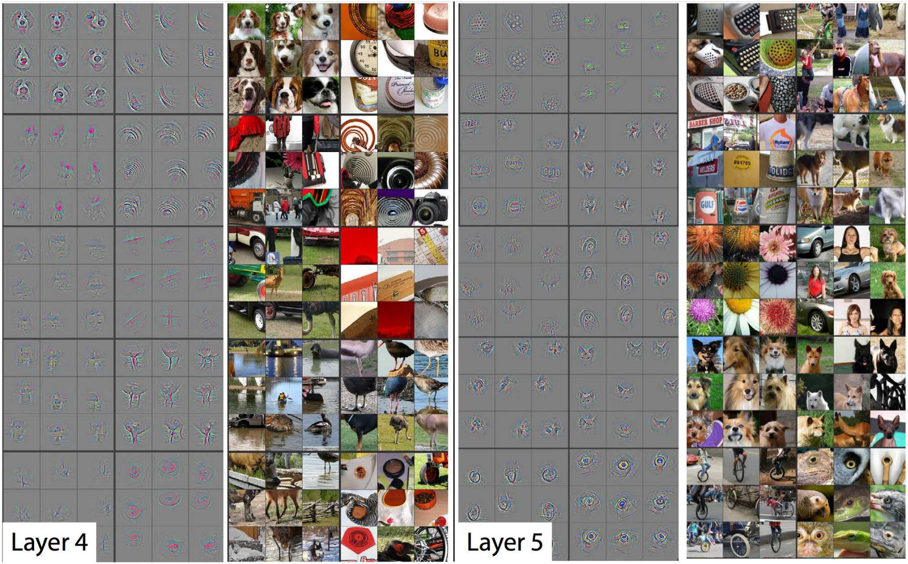


Figure: Filters in the third layer

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

What do CNNs Learn?



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

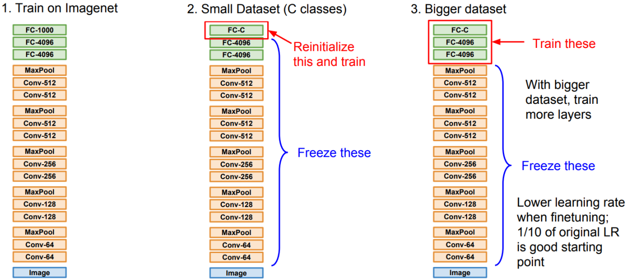
How to Train Good CNNs

- Normalize your data (standard trick: subtract mean, divide by standard deviation)
- Augment your data (add image flips, rotations, etc)
- Keep training data balanced
- Shuffle data before batching
- In training: Random initialization of weights with proper variance
- Monitor your loss function, and accuracy (performance) on validation
- If your labeled image dataset is small: pre-train your CNN on a large dataset (eg Imagenet), and fine-tune on your dataset

[Slide: Y. Zhu, check tutorial slides and code:
http://www.cs.utoronto.ca/~fidler/teaching/2015/CSC2523.html]

Transfer learning

- Main reason DL helps on (almost) any vision task, even when you don't have a huge dataset!



[From: http://cs231n.github.io/]

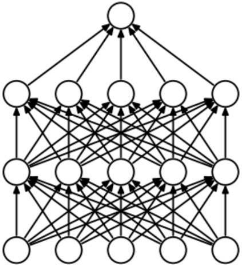
Overfitting

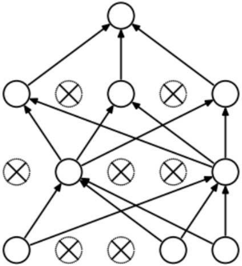
How to control overfitting?

- Early stopping
  - You don't have to take the last iteration!
  - Check validation during training (every few iterations/epoch) and take the best one.
- Weight decay
  - L_2 regularization, usually around $1e-4$
- Adding random noise
  - Dropout
  - Other ideas like Gaussian noise, batch normalization

Dropout

- At each iteration "kill" each neuron with probability p (usually 0.5).


(a) Standard Neural Net


(b) After applying dropout.

- The expected value decreased by p, fix by multiplying by $1/p$.
- At test time just use trained weights.

Links

- Great course dedicated to NN: http://cs231n.stanford.edu
- Over 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