Introduction to Deep Learning

Presentation Title

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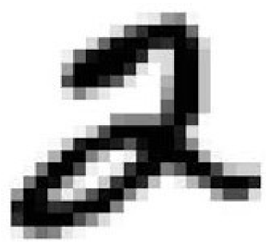
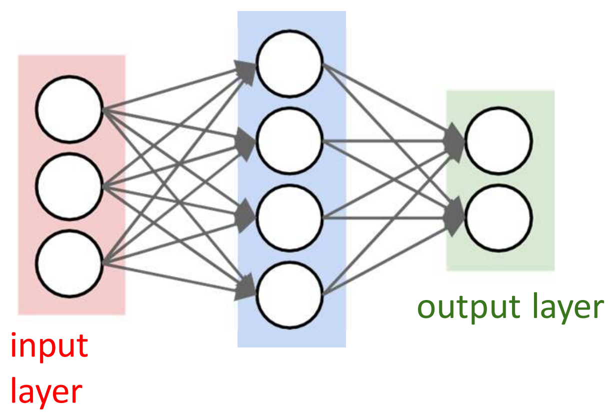
Multi-Layer Perception Issue



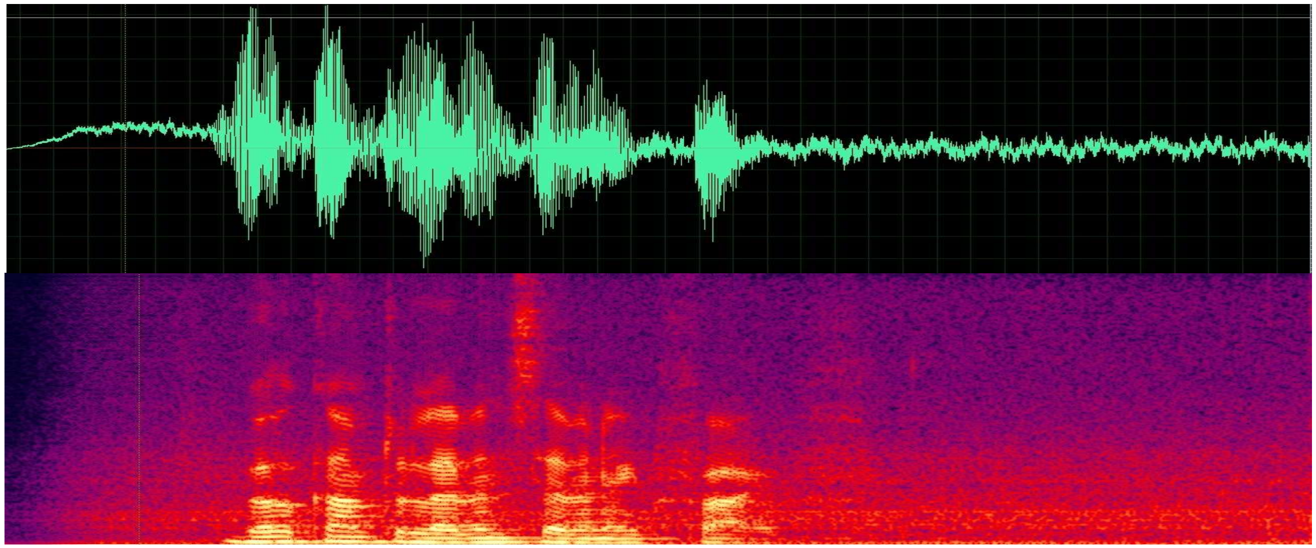
Or, more generally
a vector input



- Can recognize patterns in data
  - E.g. digits
  - Or any other vector data

Slide credit: Bhiksha Raj

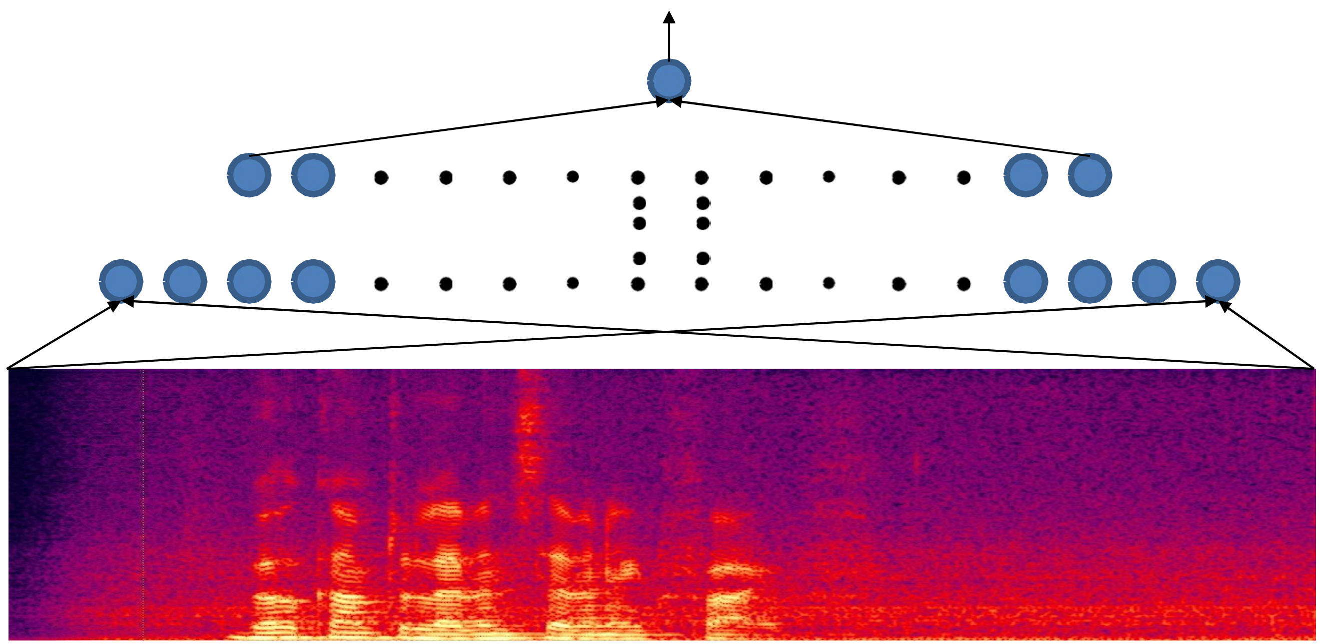
A new problem



- Does this signal contain the word “Welcome”?
- Compose an MLP for this problem.
  - Assuming all recordings are exactly the same length..

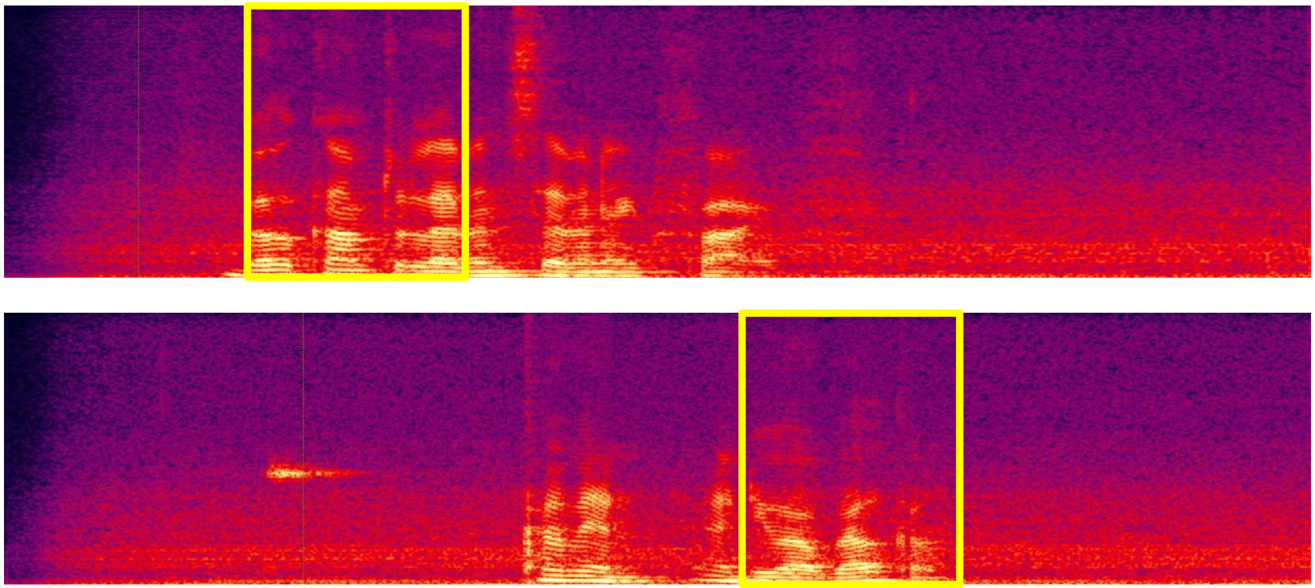
Slide credit: Bhiksha Raj

Finding a Welcome



- Trivial solution: Train an MLP for the entire recording

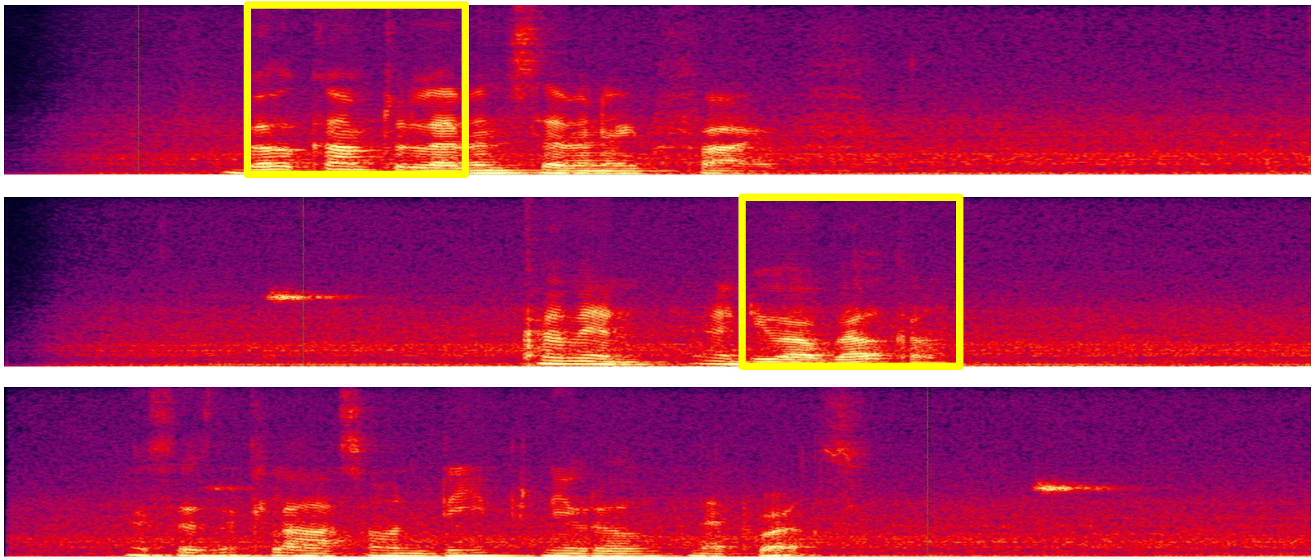
Finding a Welcome



- Problem with trivial solution: Network that finds a "welcome" in the top recording will not find it in the lower one
  - Unless trained with both
  - Will require a very large network and a large amount of training data to cover every case

Slide credit: Bhiksha Raj

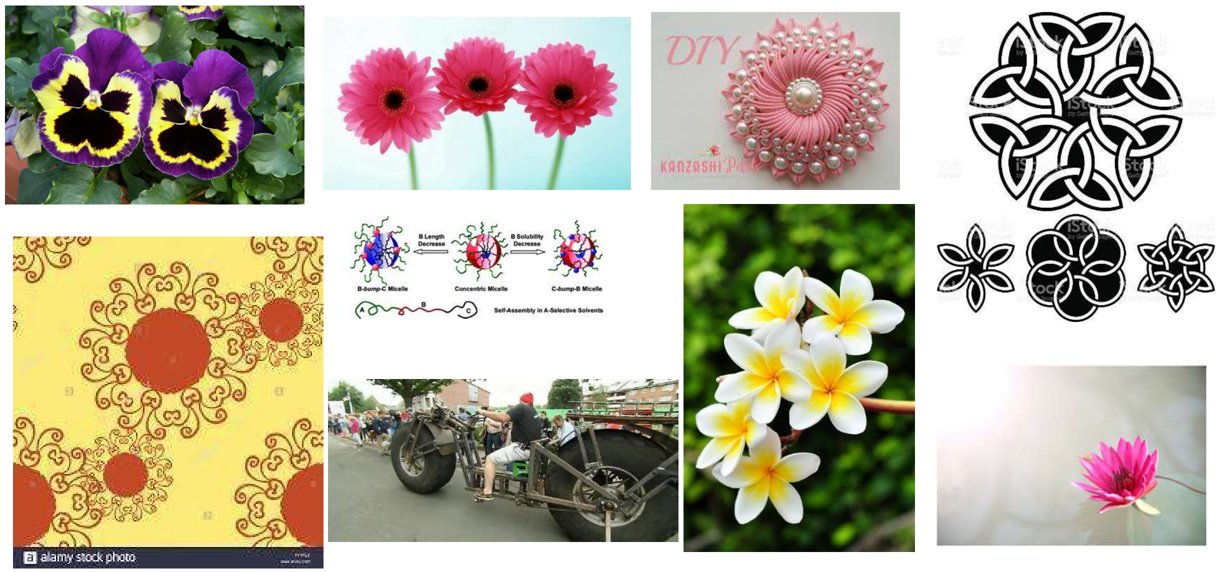
Finding a Welcome



- Need a *simple* network that will fire regardless of the location of "Welcome"
  - and not fire when there is none

Slide credit: Bhiksha Raj

Flowers

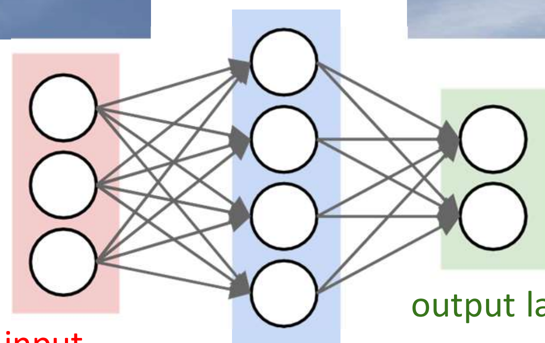


- Is there a flower in any of these images

Boston University School/college name here

Slide credit: Bhiksha Raj

A problem



- Will an MLP that recognizes the left image as a flower also recognize the one on the right as a flower?

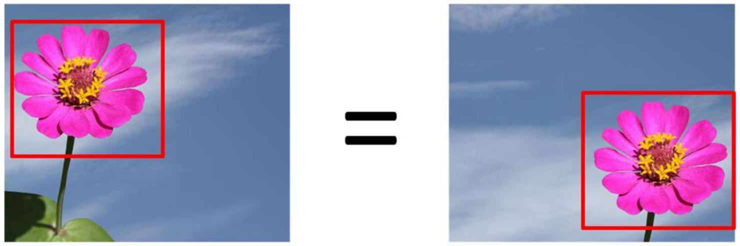
Slide credit: Bhiksha Raj

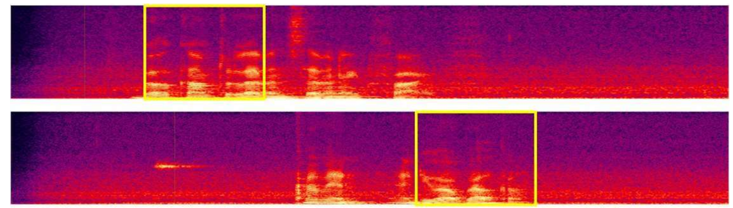
A problem

- Need a network that will “fire” regardless of the precise location of the target object

Slide credit: Bhiksha Raj

The need for *shift invariance*

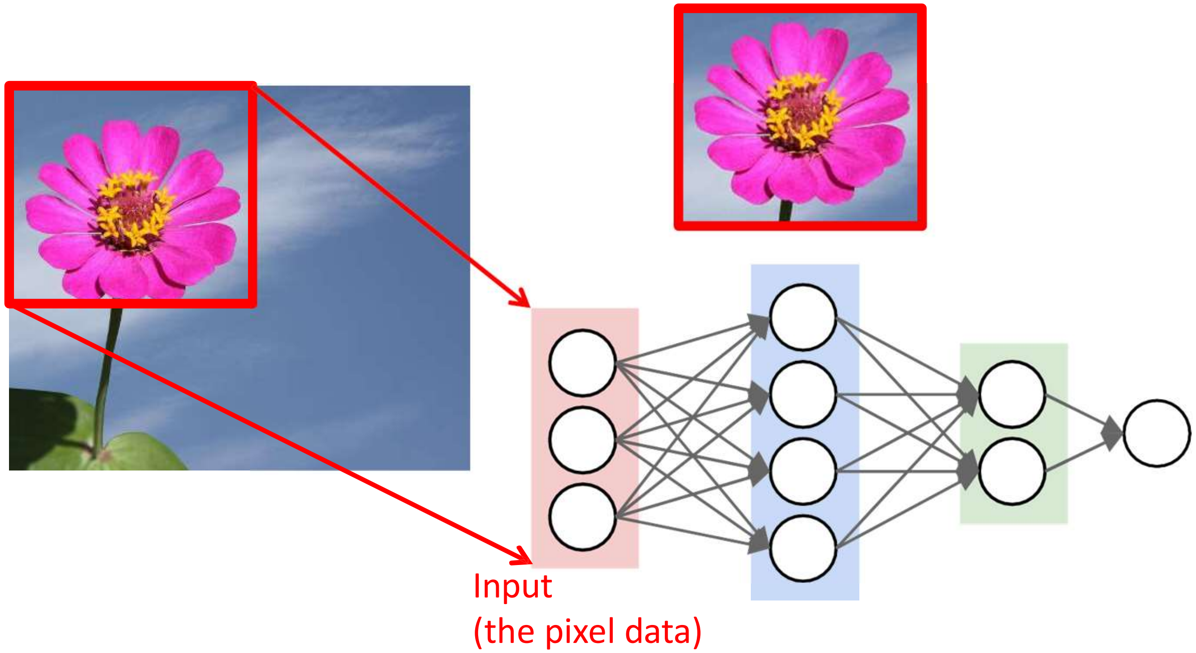




- In many problems the *location* of a pattern is not important
  - Only the presence of the pattern
- Conventional MLPs are sensitive to the location of the pattern
  - Moving it by one component results in an entirely different input that the MLP won't recognize
- Requirement: Network must be *shift invariant*

Slide credit: Bhiksha Raj

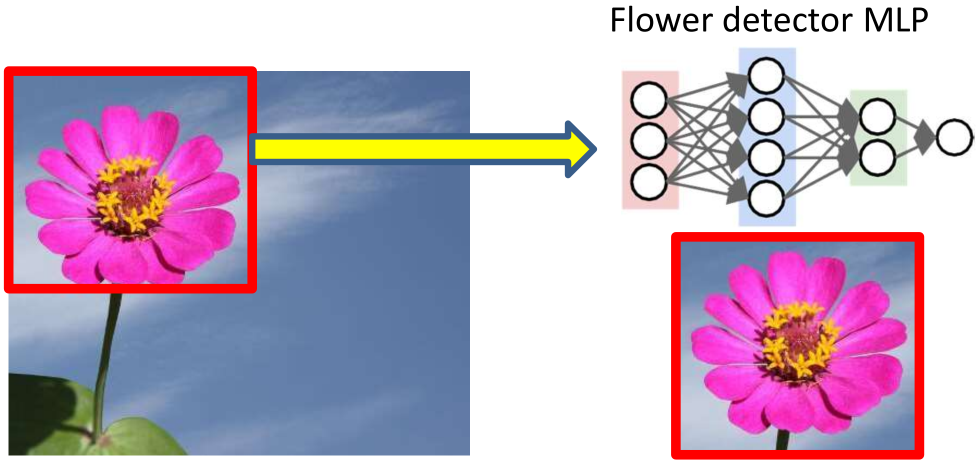
The 2-d analogue: Does this picture **have a flower?**



- *Scan* for the desired object
  - "Look" for the target object at each position

Slide credit: Bhiksha Raj

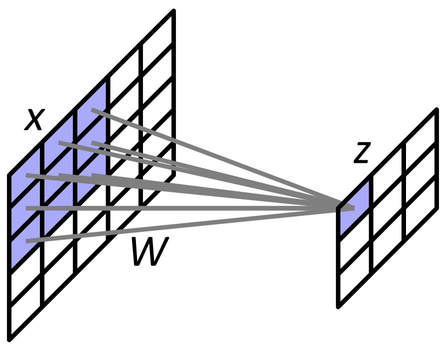
Solution: Scan

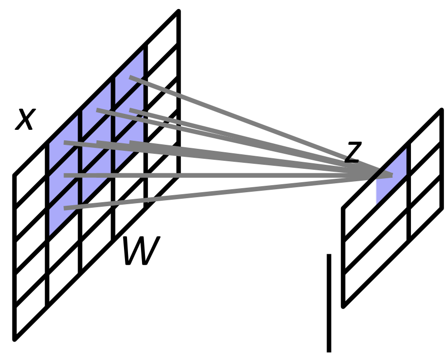


- *Scan* for the desired object
- At each location, the entire region is sent through the MLP

Slide credit: Bhiksha Raj

Advantages of convolutions





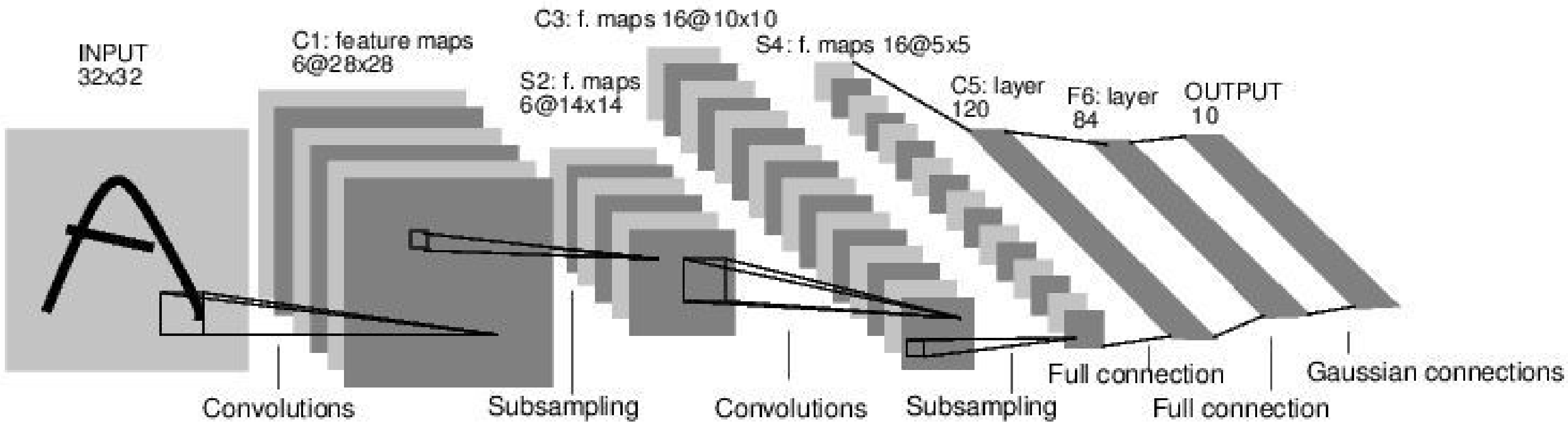
Drastically reduces the parameter count

- 256x256 grayscale image ⟹ 256x256 single-channel hidden layer: 4 *billion parameters* in fully connected network to *9 parameters* in 3x3 convolution

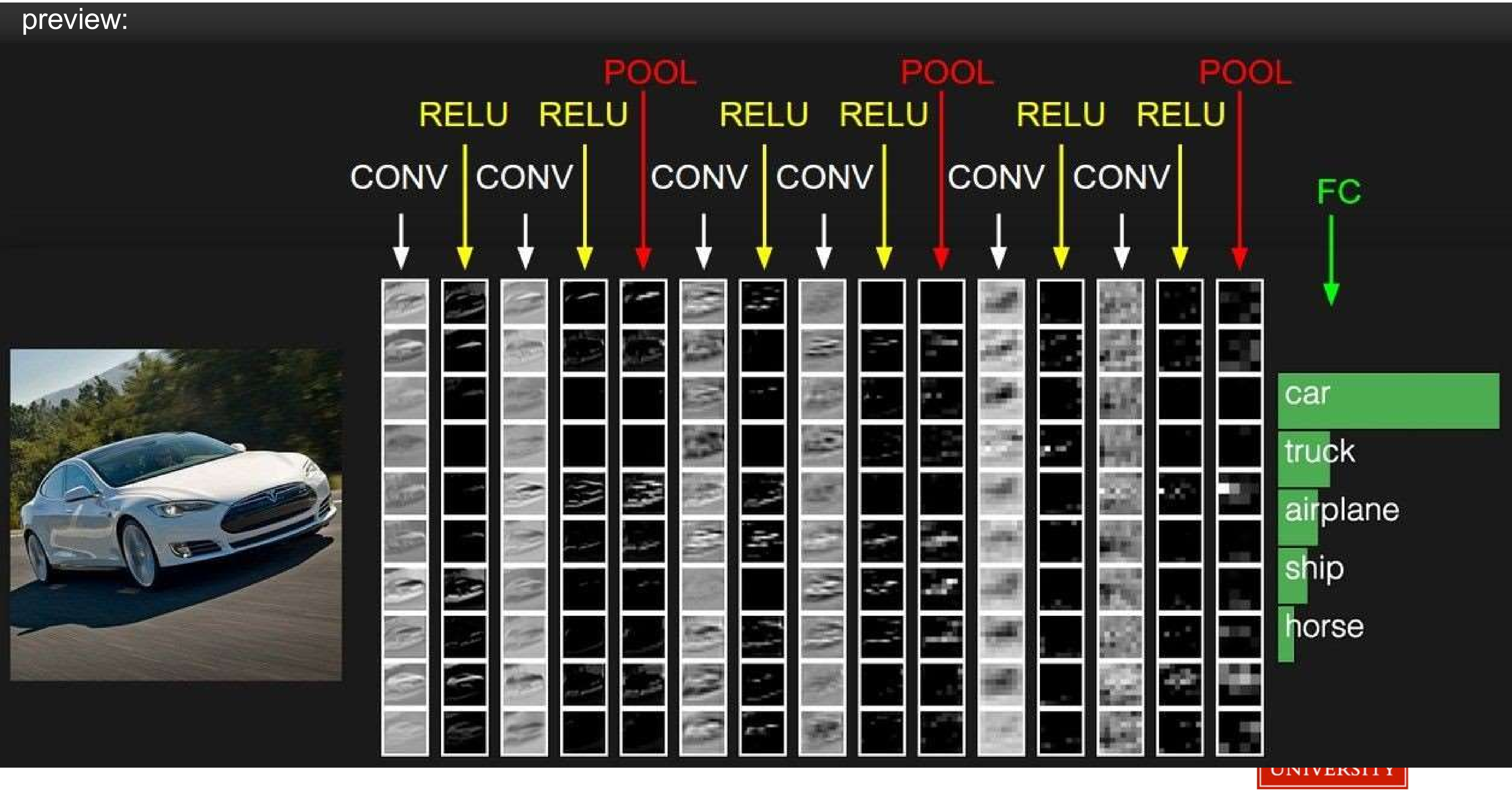
Captures (some) “natural” invariances

- Shifting input image one pixel to the right shifts creates a hidden shifts the hidden unit “image”

Convolutional Neural Networks

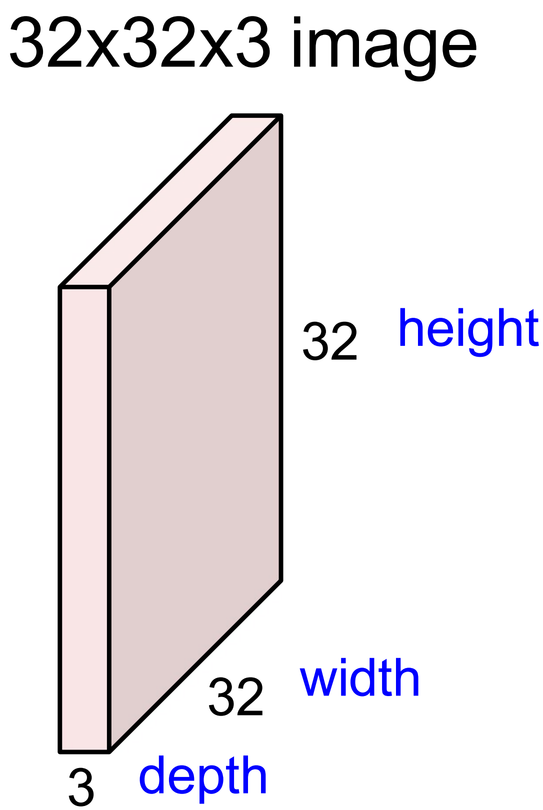


[LeNet-5, LeCun 1980]



Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Convolution Layer



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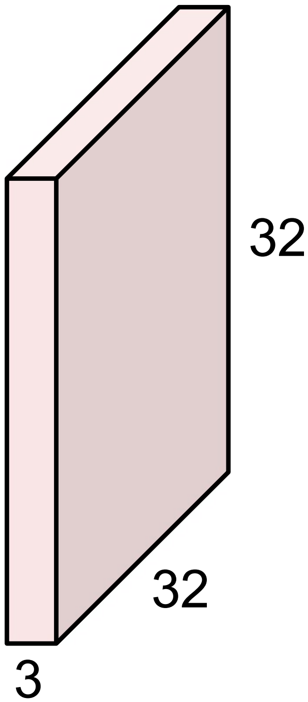
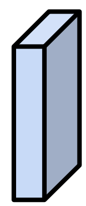
Convolution Layer

32x32x3 image



5x5x3 filter



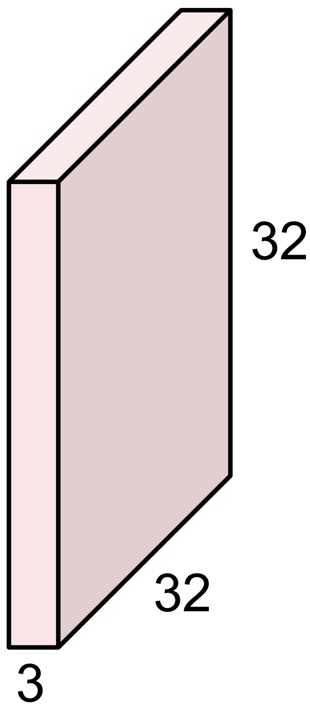
Convolve the filter with the image
i.e. "slide over the image spatially, computing dot products"

Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

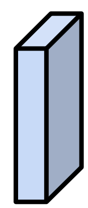
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter



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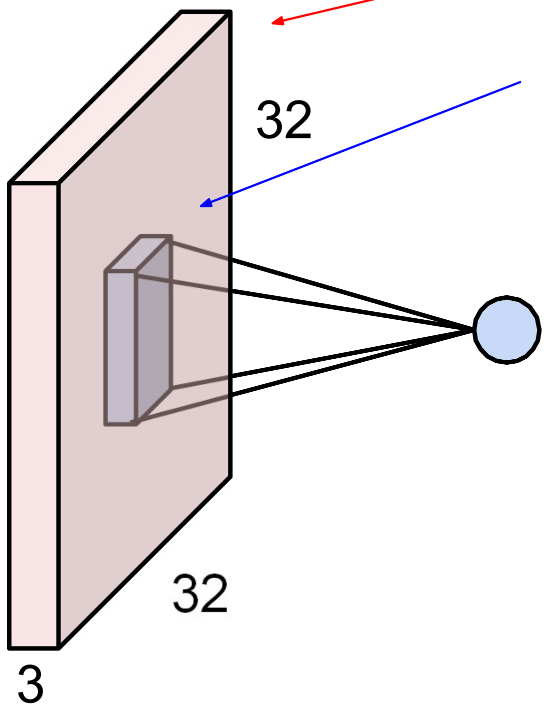
Convolution Layer



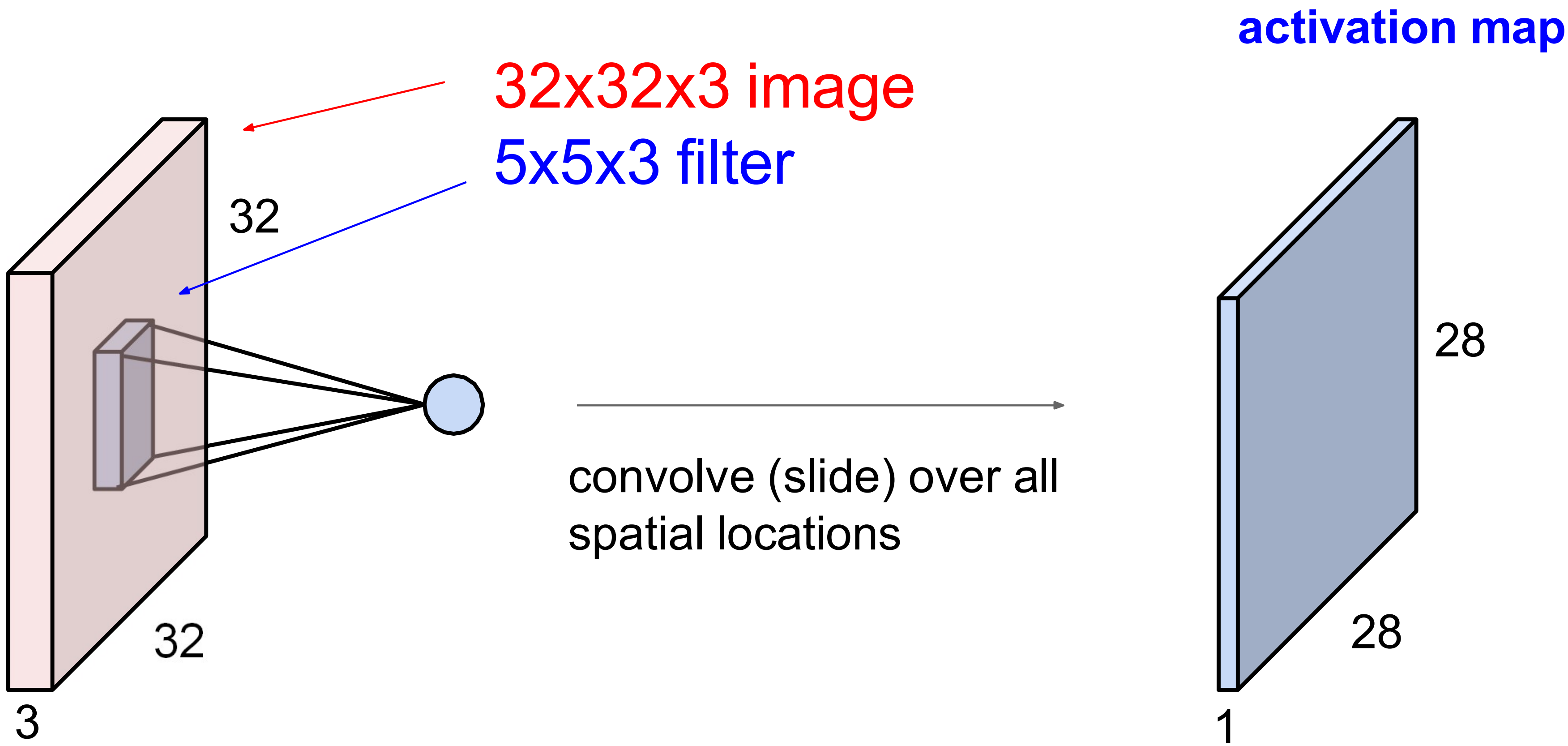
32x32x3 image

5x5x3 filter w

1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image (i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolution Layer



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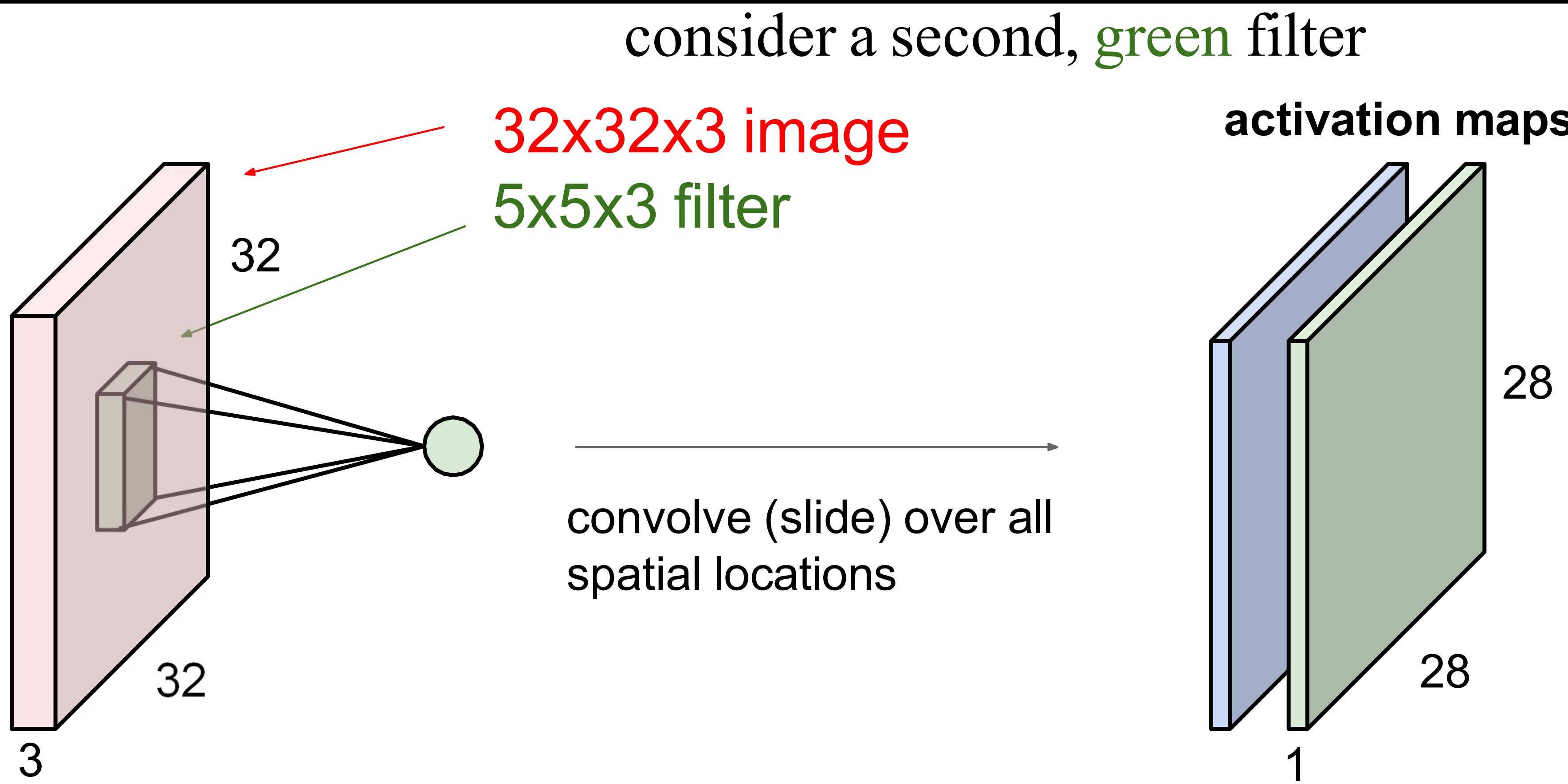
Convolution Layer



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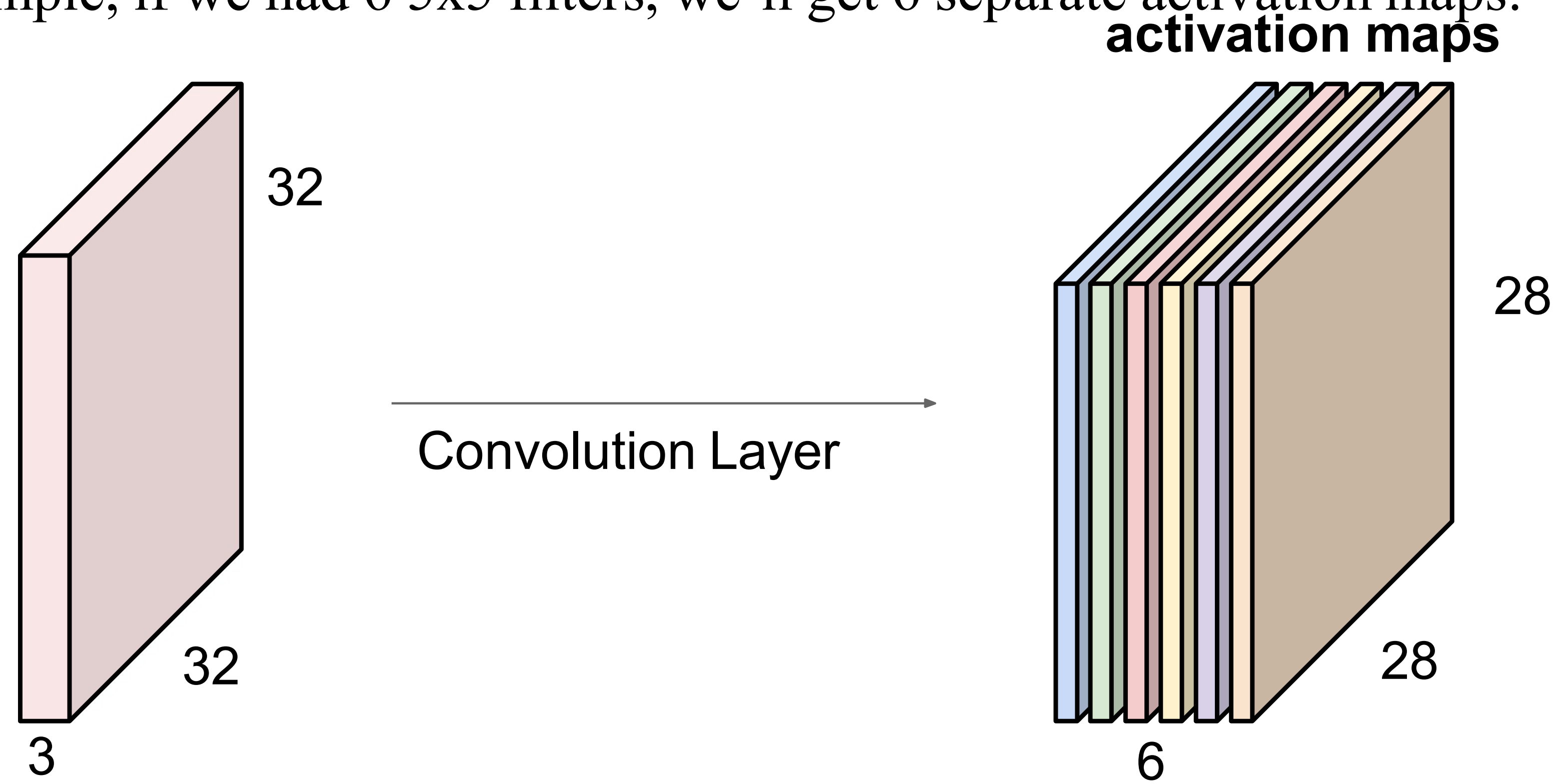
Convolution Layer

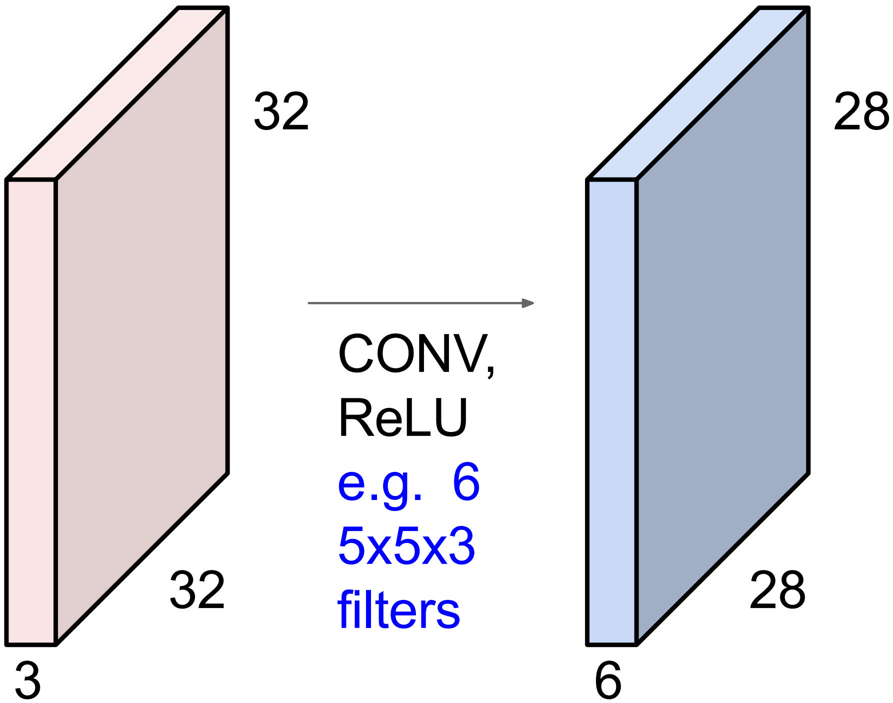
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

Convolution Layer

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



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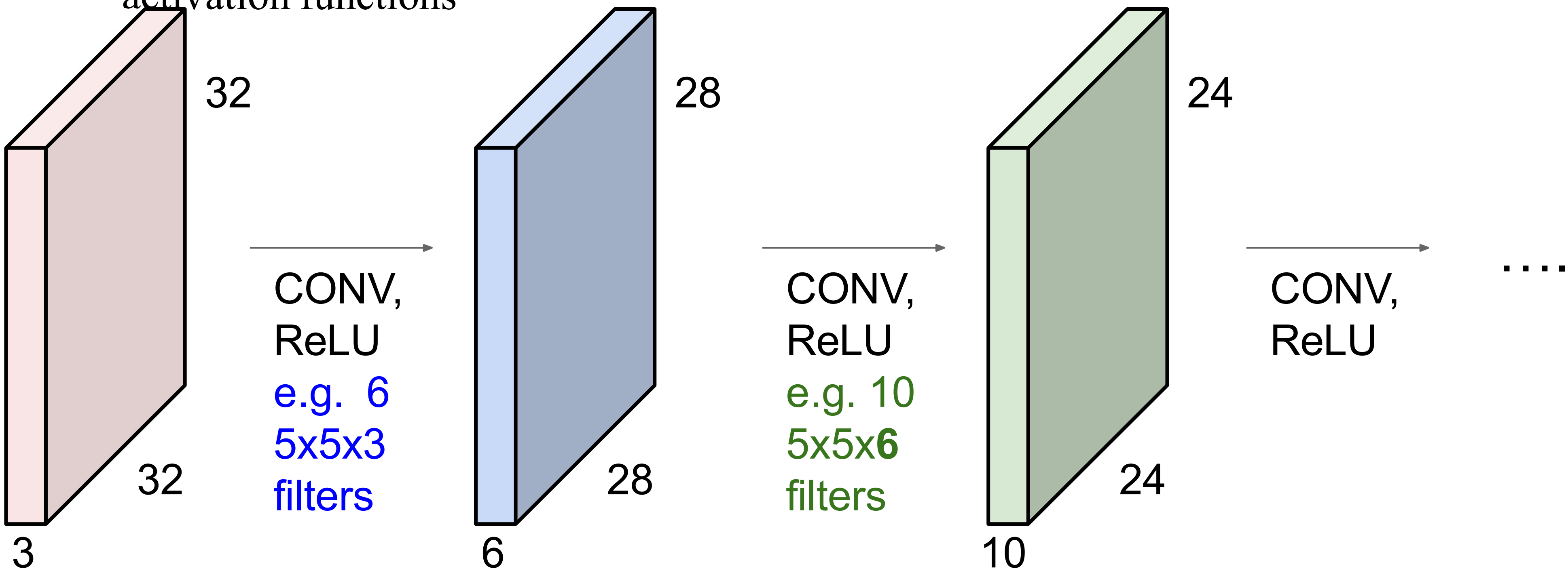
Convolution Layer

Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



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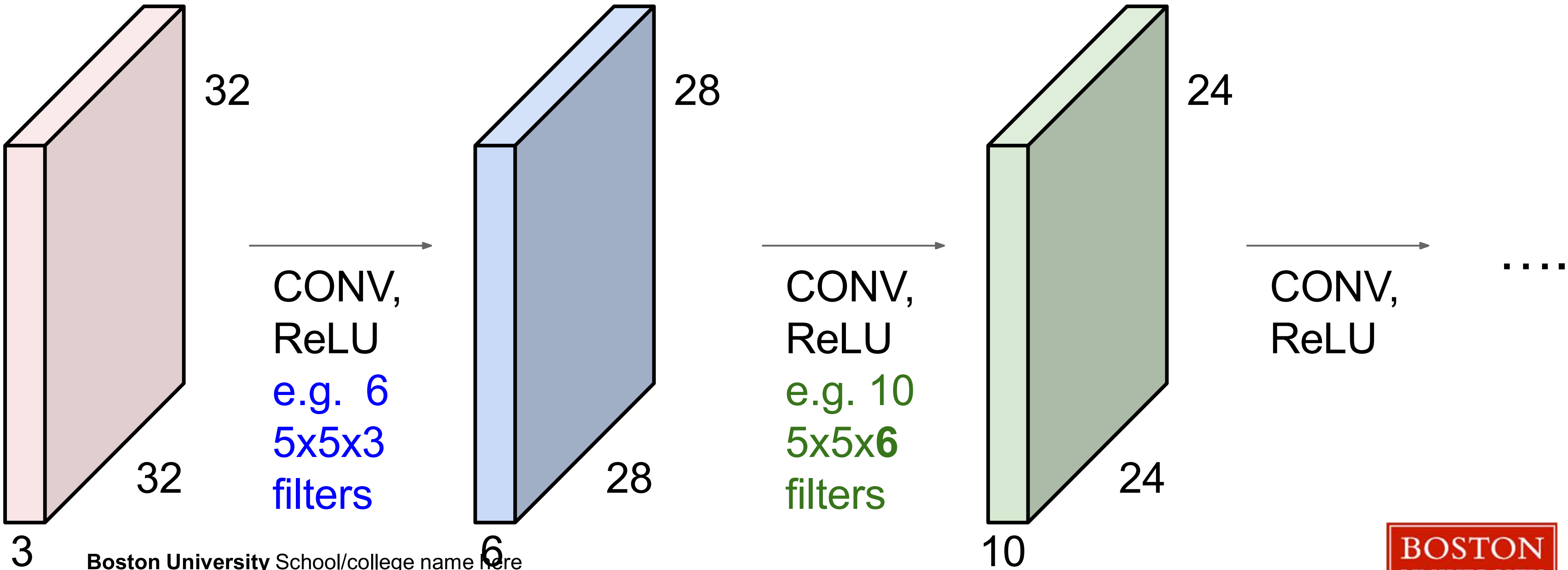
Remember back to…

E.g. 32x32 input convolved repeatedly with 5x5 filters shrinks volumes spatially! (32 -> 28 -> 24 ...). Shrinking too fast is not good, doesn't work well.



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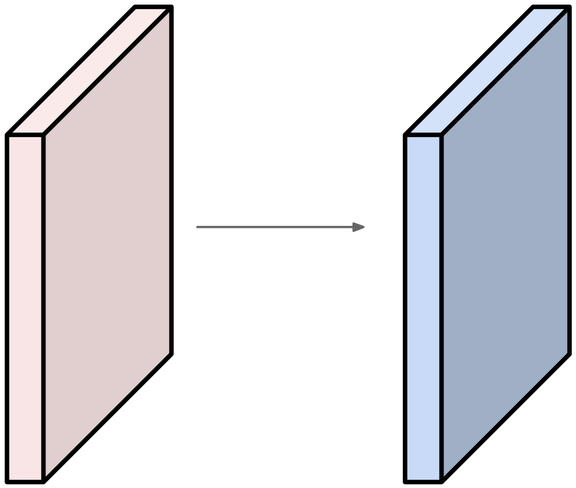
Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2

Output volume size: ?



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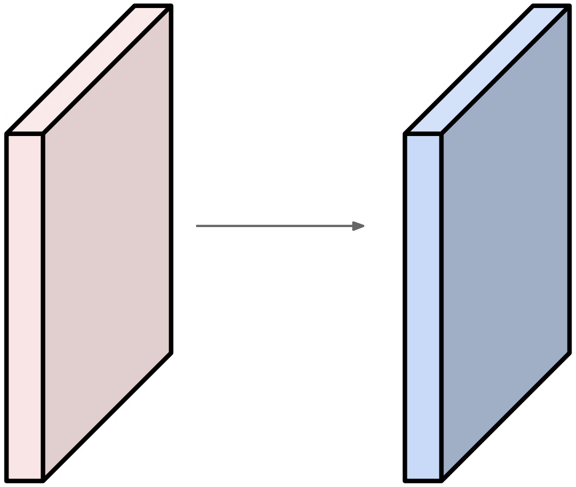


Output volume size:

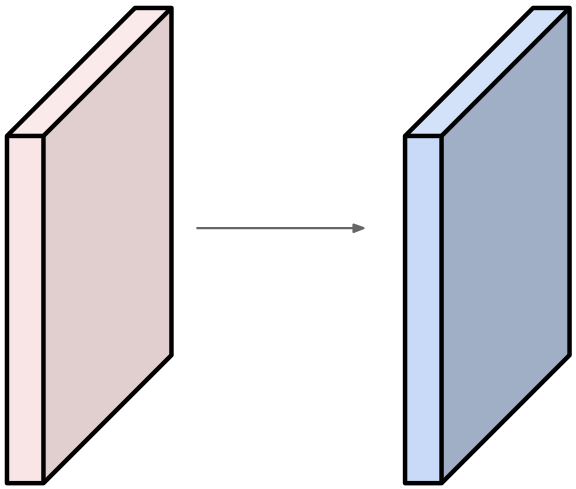
(32+2*2-5)/1+1 = 32 spatially, so

32x32x10

Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Examples time:

Input volume: **32x32x3**
10 5x5 filters with stride 1, pad 2



Number of parameters in this layer?

Examples time:

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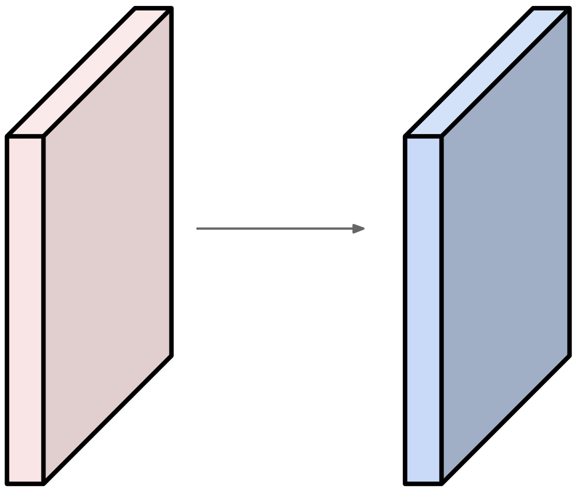


Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Convolutions in image processing

Convolutions (typically with *prespecified* filters) are a common operation in many computer vision applications: convolution networks just move to *learned* filters

Original image x

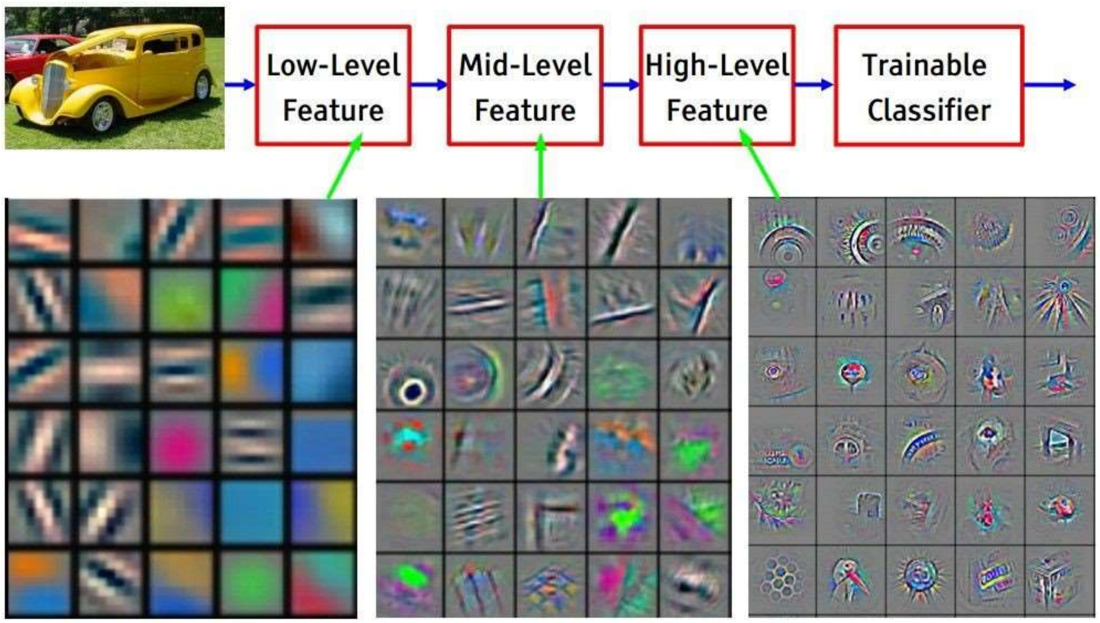
Gaussian blur

Image gradient

$$x * \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 4 & 4 & 1 \end{bmatrix} / 273$$

$$\left(\left(x * \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \right)^2 + \left(x * \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \right)^2 \right)^{\frac{1}{2}}$$

Preview



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

[From recent Yann LeCun slides]

Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Convolutions in detail

- Convolutions are a basic primitive in many computer vision and image processing algorithms

- Idea is to "slide" the weights $h \times h$ weight m (called a filter, with kernel size h) over the image to produce a new image, written $y = x * m$

$$\begin{bmatrix} z_{11} & z_{12} & z_{13} & z_{14} & z_{15} \\ z_{21} & z_{22} & z_{23} & z_{24} & z_{25} \\ z_{31} & z_{32} & z_{33} & z_{34} & z_{35} \\ z_{41} & z_{42} & z_{43} & z_{44} & z_{45} \\ z_{51} & z_{52} & z_{53} & z_{54} & z_{55} \end{bmatrix} * \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ w_{31} & w_{32} & w_{33} \end{bmatrix} = \begin{bmatrix} y_{11} & y_{12} & y_{13} \\ y_{21} & y_{22} & y_{23} \\ y_{31} & y_{32} & y_{33} \end{bmatrix}$$

Slide credit: J. Zico Kolter and Tianqi Chen

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$$y_{11} = z_{11}w_{11} + z_{12}w_{12} + z_{13}w_{13} + z_{21}w_{21} + \ldots$$

Slide credit: J. Zico Kolter and Tianqi Chen

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$$y_{12} = z_{12}w_{11} + z_{13}w_{12} + z_{14}w_{13} + z_{22}w_{21} + \ldots$$

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Slide credit: J. Zico Kolter and Tianqi Chen

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$$y_{13} = z_{13}w_{11} + z_{14}w_{12} + z_{15}w_{13} + z_{23}w_{21} + \ldots$$

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$$
\begin{array}{|c|c|c|c|c|}
\hline
z_{11} & z_{12} & z_{13} & z_{14} & z_{15} \\
\hline
z_{21} & z_{22} & z_{23} & z_{24} & z_{25} \\
\hline
z_{31} & z_{32} & z_{33} & z_{34} & z_{35} \\
\hline
z_{41} & z_{42} & z_{43} & z_{44} & z_{45} \\
\hline
z_{51} & z_{52} & z_{53} & z_{54} & z_{55} \\
\hline
\end{array}
\; * \;
\begin{array}{|c|c|c|}
\hline
w_{11} & w_{12} & w_{13} \\
\hline
w_{21} & w_{22} & w_{23} \\
\hline
w_{31} & w_{32} & w_{33} \\
\hline
\end{array}
\; = \;
\begin{array}{|c|c|c|}
\hline
y_{11} & y_{12} & y_{13} \\
\hline
y_{21} & y_{22} & y_{23} \\
\hline
y_{31} & y_{32} & 33 \\
\hline
\end{array}
$$

$$y_{21} = z_{21}w_{11} + z_{22}w_{12} + z_{23}w_{13} + z_{31}w_{21} + \ldots$$

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$$
\begin{bmatrix}
z_{11} & z_{12} & z_{13} & z_{14} & z_{15} \\
z_{21} & z_{22} & z_{23} & z_{24} & z_{25} \\
z_{31} & z_{32} & z_{33} & z_{34} & z_{35} \\
z_{41} & z_{42} & z_{43} & z_{44} & z_{45} \\
z_{51} & z_{52} & z_{53} & z_{54} & z_{55}
\end{bmatrix}
*
\begin{bmatrix}
w_{11} & w_{12} & w_{13} \\
w_{21} & w_{22} & w_{23} \\
w_{31} & w_{32} & w_{33}
\end{bmatrix}
=
\begin{bmatrix}
y_{11} & y_{12} & y_{13} \\
y_{21} & y_{22} & y_{23} \\
y_{31} & y_{32} & 33
\end{bmatrix}
$$

$$y_{22} = z_{22}w_{11} + z_{23}w_{12} + z_{24}w_{13} + z_{32}w_{21} + \ldots$$

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$$

$$y_{23} = z_{23}w_{11} + z_{24}w_{12} + z_{25}w_{13} + z_{33}w_{21} + \ldots$$

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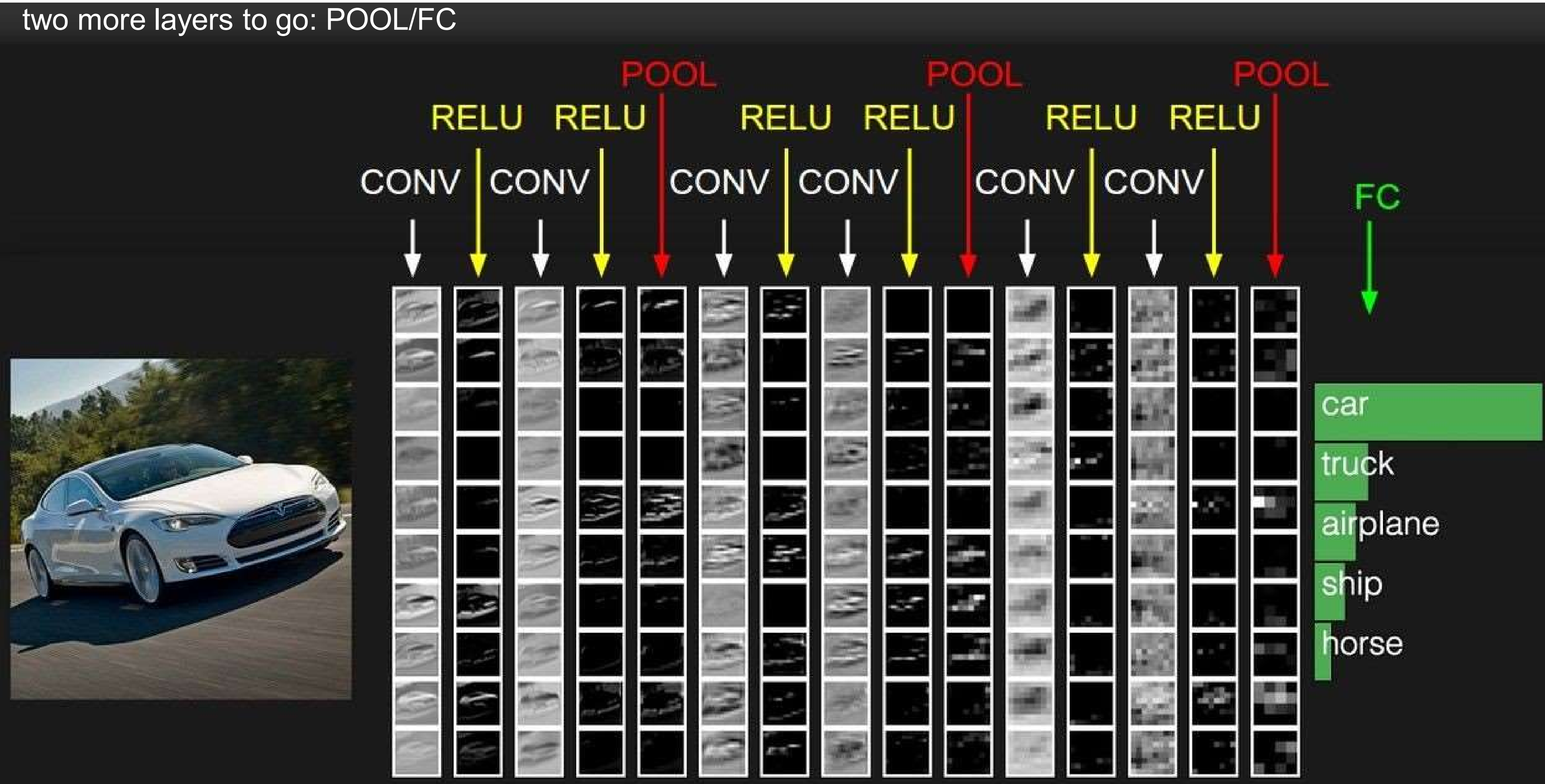

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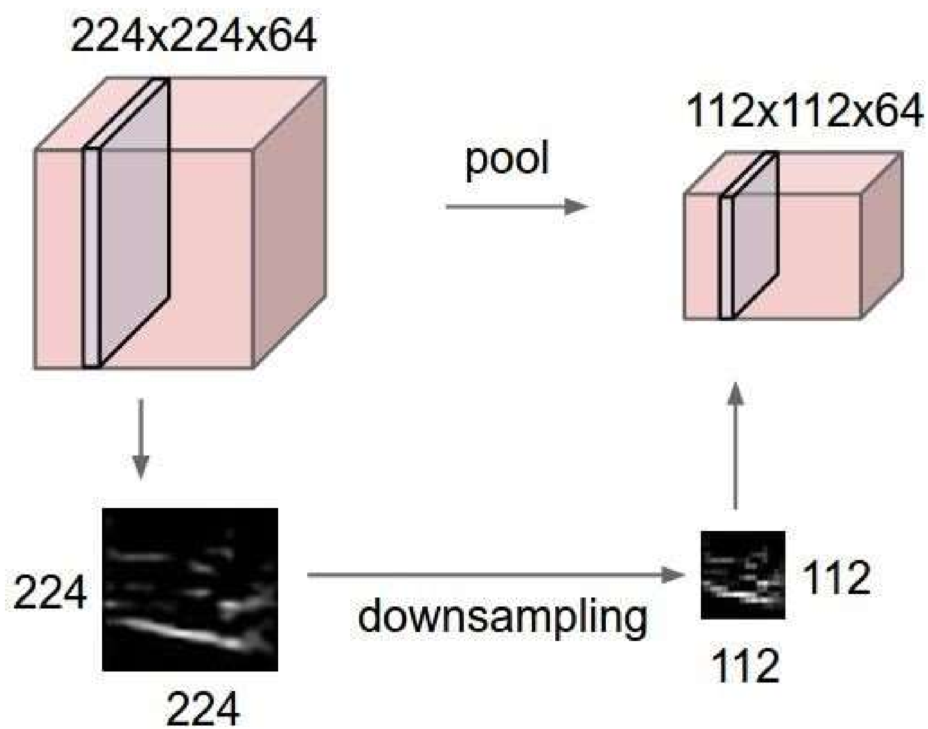
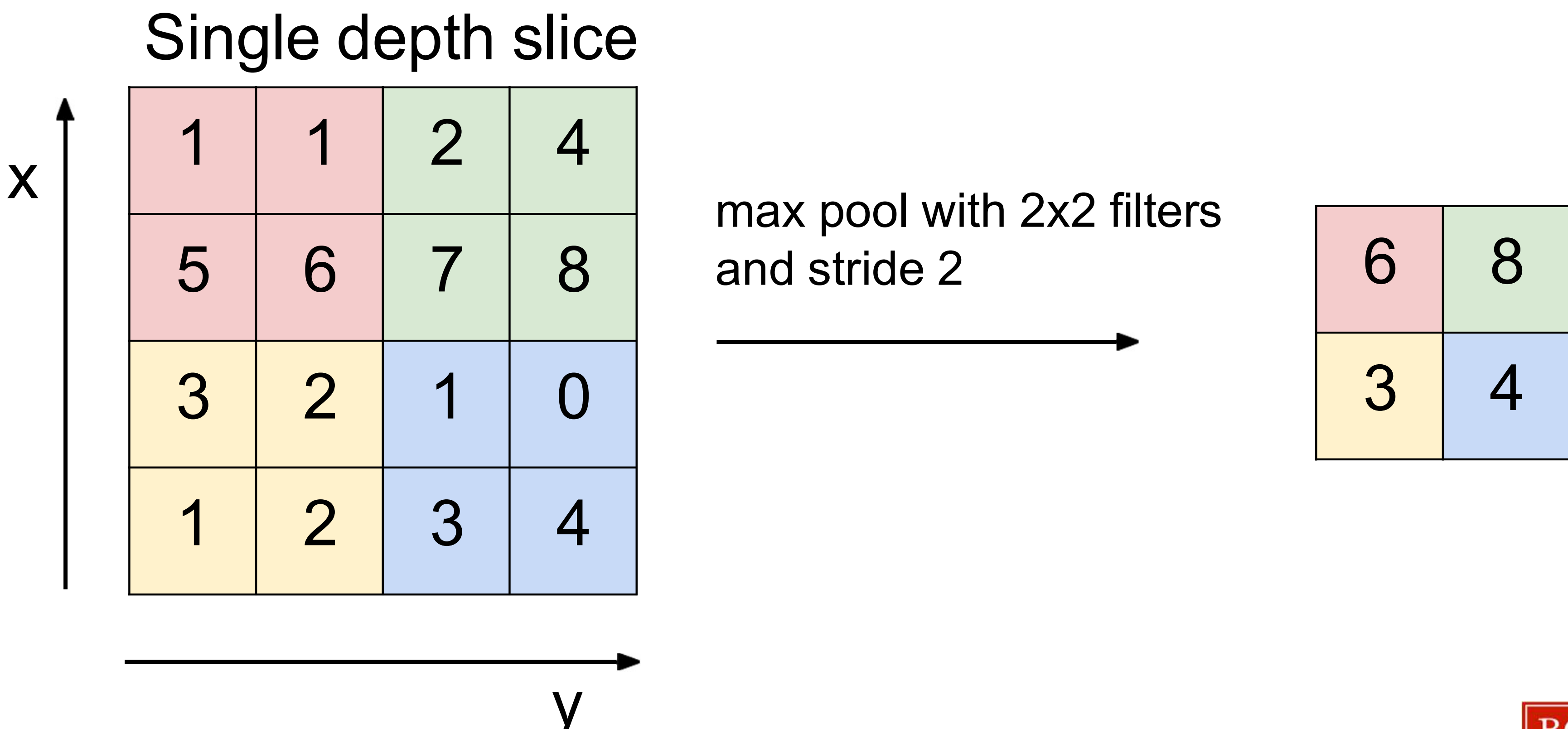
Pooling layer

- makes the representations smaller and more manageable
- operates over each activation map independently:



Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

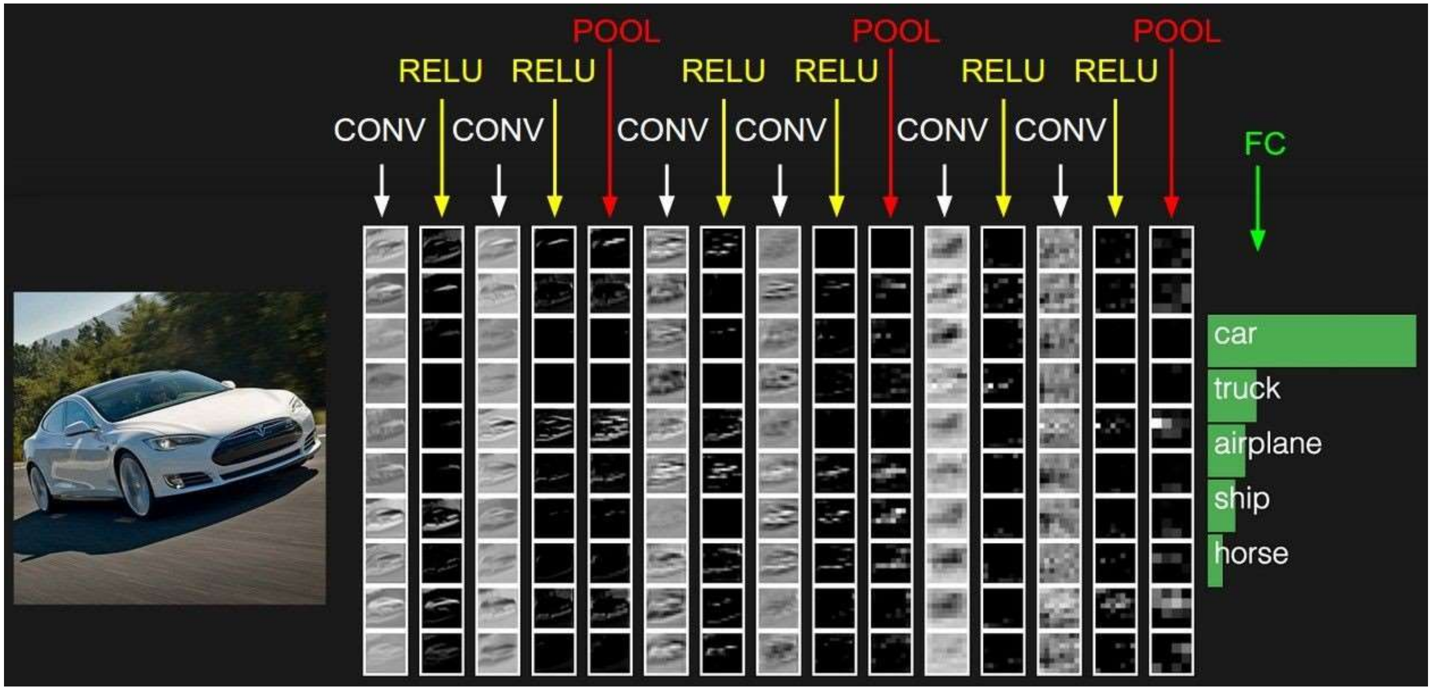
MAX POOLING



Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Fully Connected Layer (FC layer)

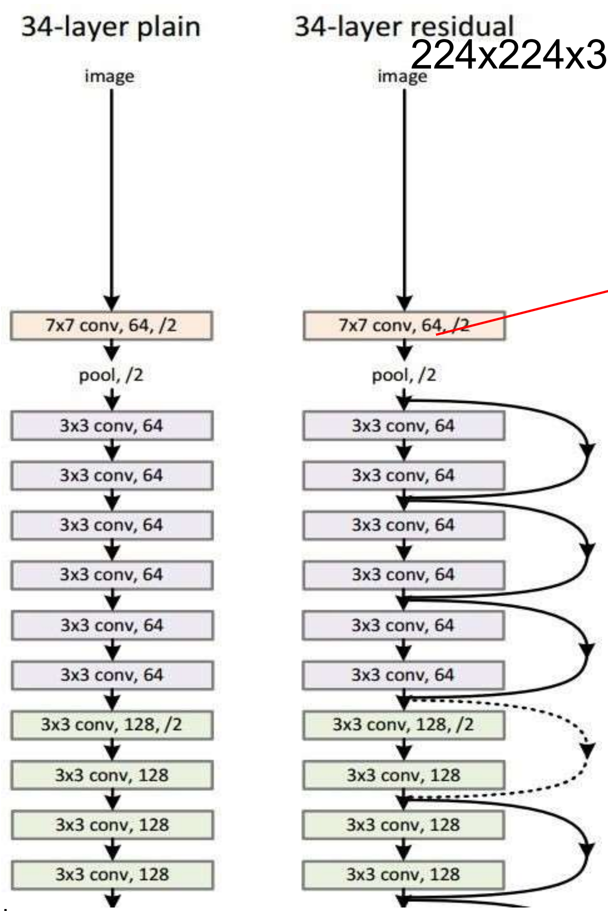
Contains neurons that connect to the entire input volume, as in ordinary Neural Networks



Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

Case Study: ResNet

[He et al., 2015]



spatial dimension
only 56x56!

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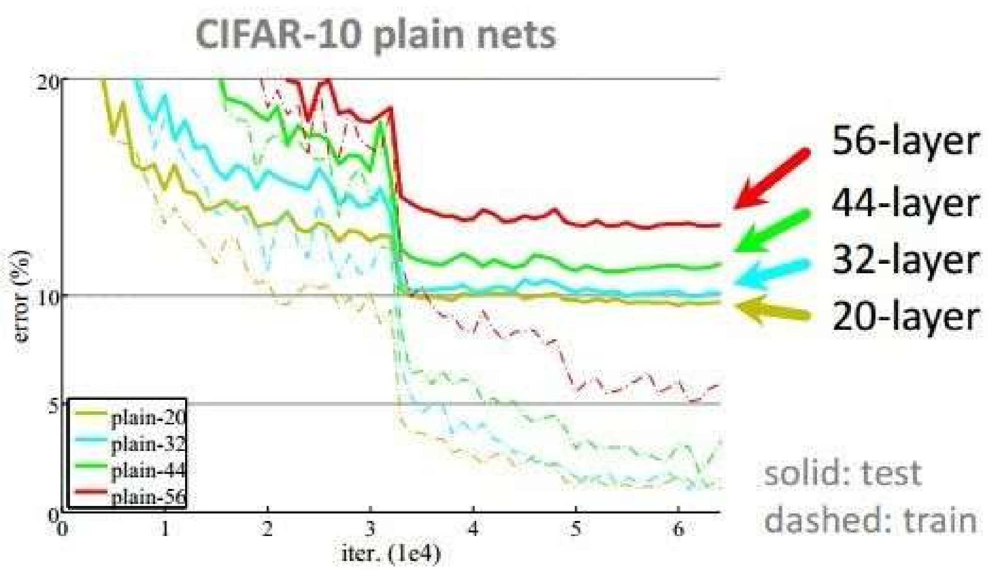
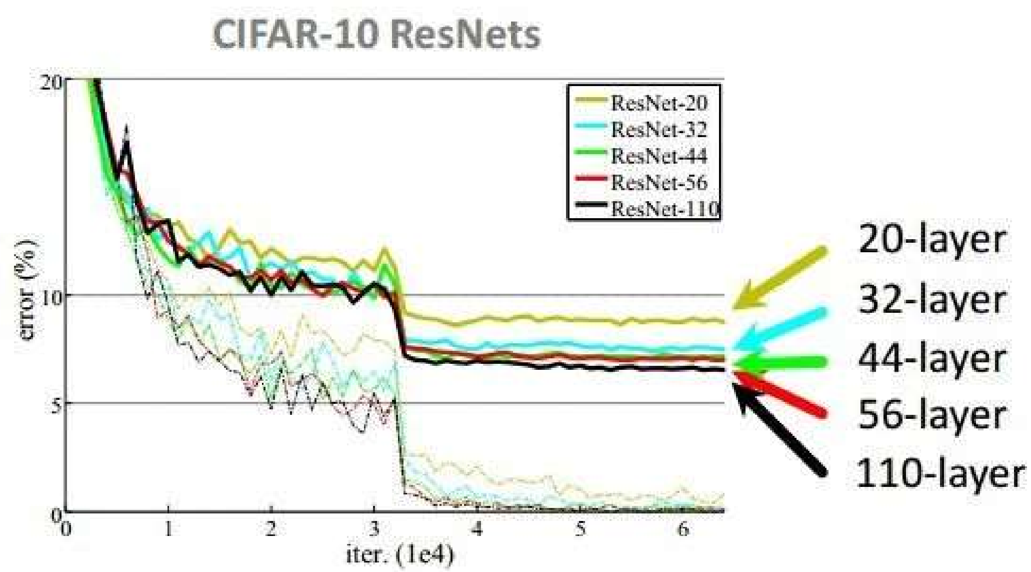
Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

CIFAR-10 experiments





Slide credit: Fei-Fei Li, Andrej Karpathy and Justin Johnson

The End

Thanks for your attention.

I would be glad if you have any question.

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