

Lecture 5: Image Classification with CNNs

Administrative

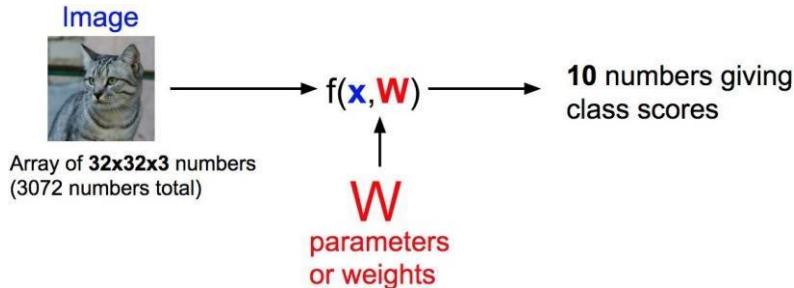
Course project is released at

<https://course.cse.ust.hk/comp4471/project.html>

If you want to find teammates, you can sign up at

<https://docs.google.com/document/d/1lymetG0mv1uALXdfEjOiiwf3UueARKfsSxx6jjp55TE/edit?tab=t.0>

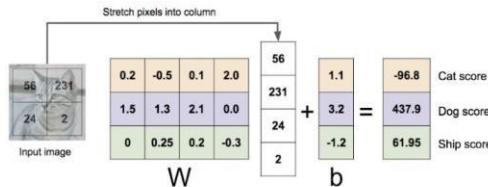
Recap: Image Classification with Linear Classifier



$$f(x, W) = Wx + b$$

Algebraic Viewpoint

$$f(x, W) = Wx$$



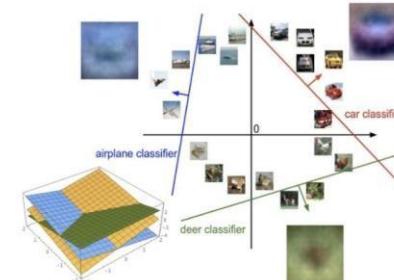
Visual Viewpoint

One template per class



Geometric Viewpoint

Hyperplanes cutting up space



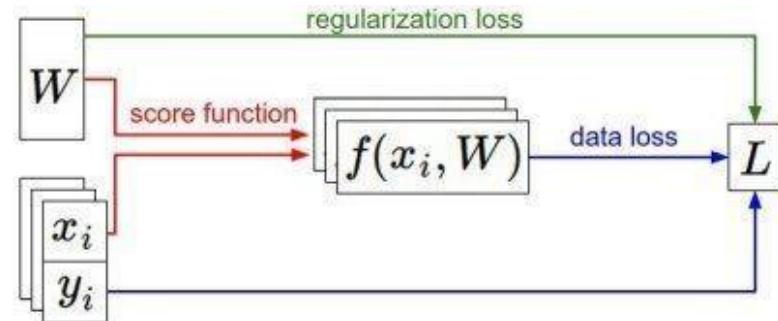
Recap: Loss Function

- We have some dataset of (x, y)
- We have a **score function**: $s = f(x; W) = Wx$
- We have a **loss function**:

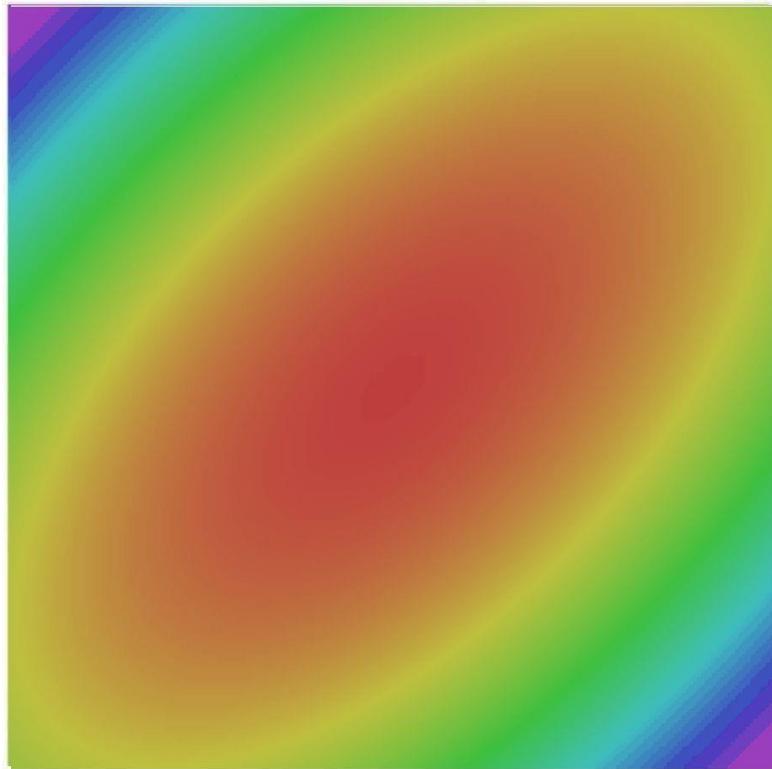
$$L_i = -\log\left(\frac{e^{sy_i}}{\sum_j e^{sj}}\right) \text{ Softmax}$$

$$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1) \text{ SVM}$$

$$L = \frac{1}{N} \sum_{i=1}^N L_i + R(W) \text{ Full loss}$$



Recap: Optimization



- SGD
- SGD+Momentum
- RMSProp
- Adam

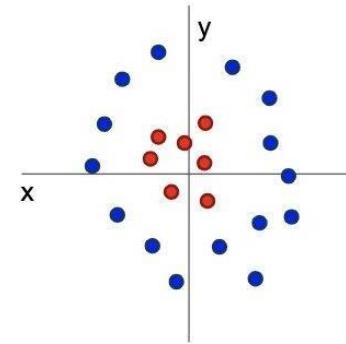
Problem: Linear Classifiers are not very powerful

Visual Viewpoint



Linear classifiers learn
one template per class

Geometric Viewpoint



Linear classifiers
can only draw linear
decision boundaries

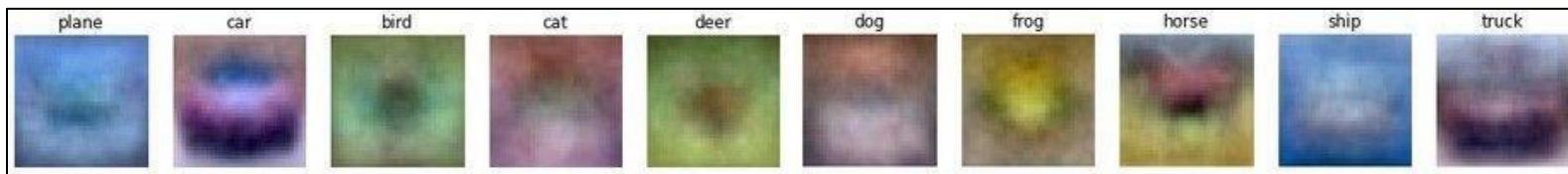
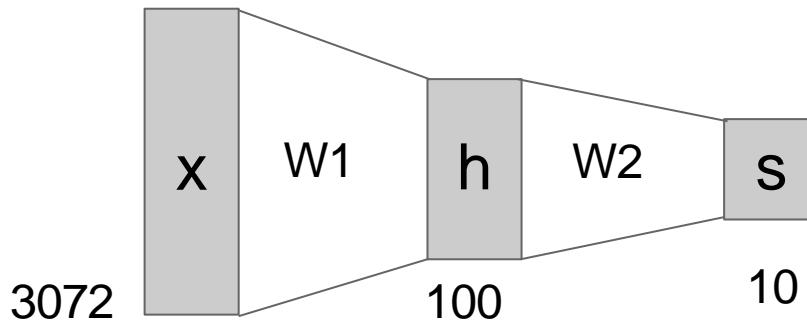
Last time: Neural Networks

Linear score function:

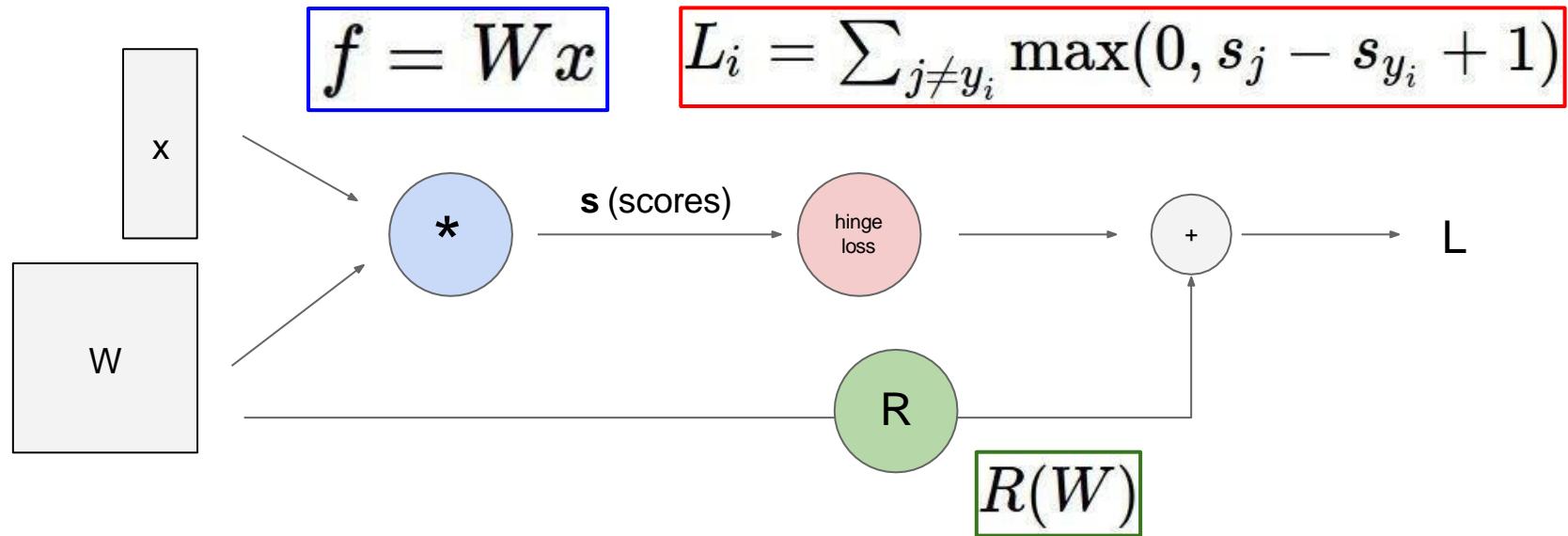
$$f = Wx$$

2-layer Neural Network

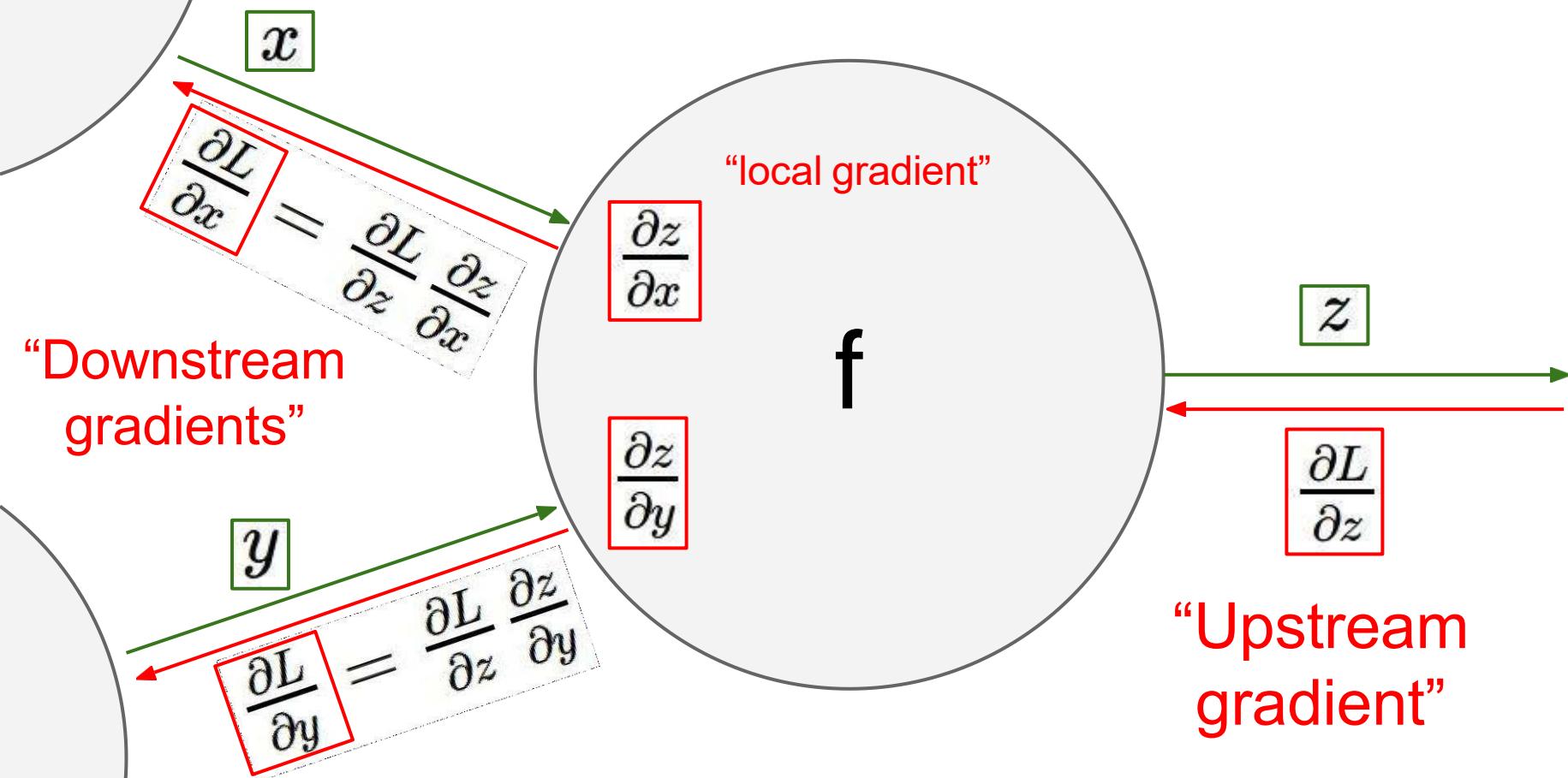
$$f = W_2 \max(0, W_1 x)$$



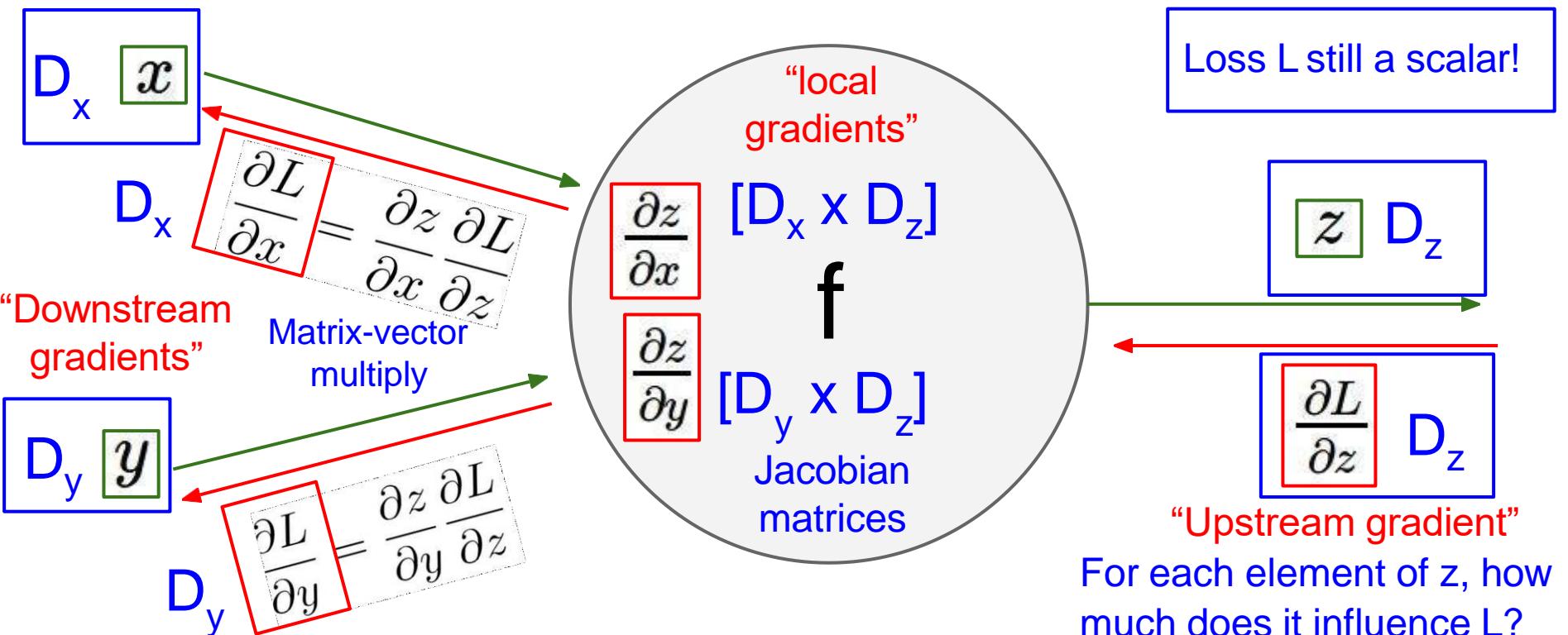
Last time: Computation Graph



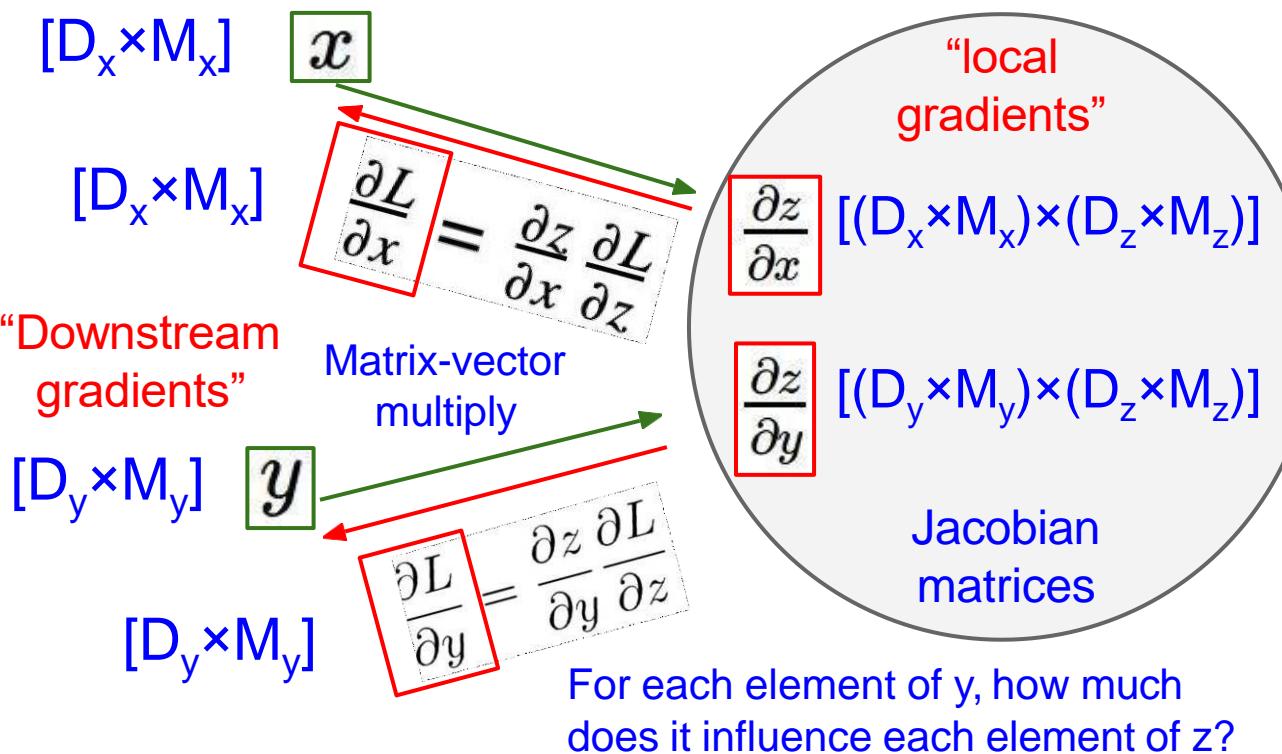
Last time: Backpropagation



Backprop with Vectors

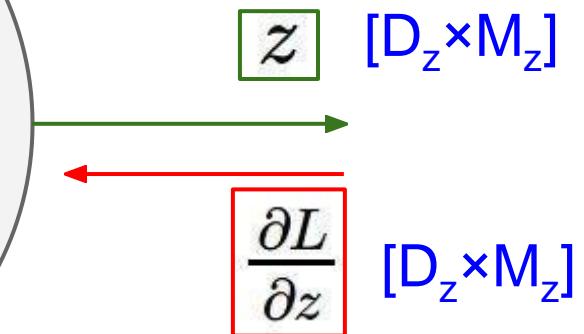


Backprop with Matrices (or Tensors)



Loss L still a scalar!

dL/dx always has the same shape as x !



"Upstream gradient"
For each element of z , how much does it influence L ?

Image Classification: A core task in Computer Vision



(assume given a set of labels)
{dog, cat, truck, plane, ...}



cat
dog
bird
deer
truck

This image by Nikita is
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Pixel space

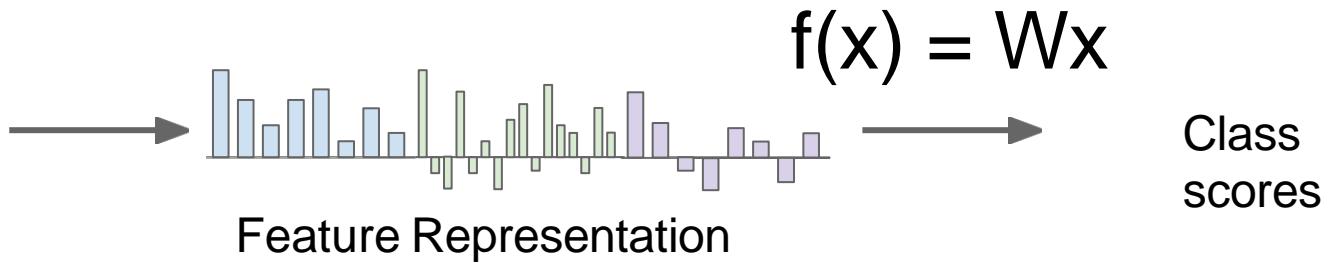


$$f(x) = Wx$$

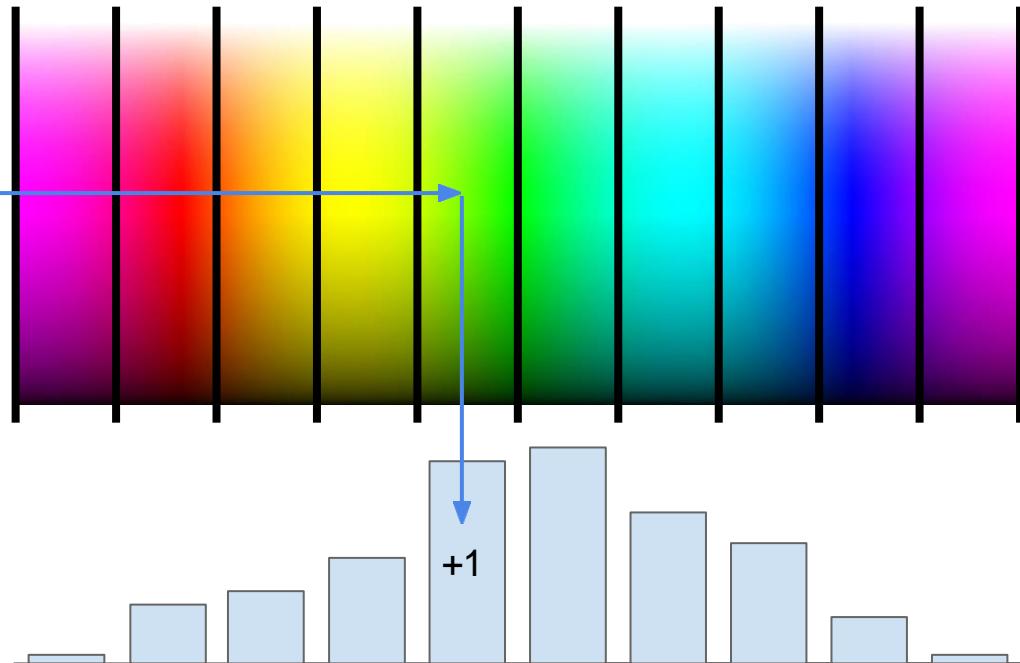
Class scores



Image features



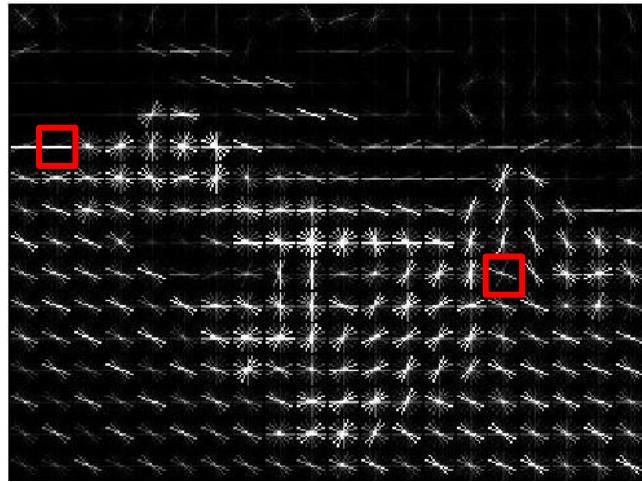
Example: Color Histogram



Example: Histogram of Oriented Gradients (HoG)



Divide image into 8x8 pixel regions
Within each region quantize edge
direction into 9 bins



Example: 320x240 image gets divided
into 40x30 bins; in each bin there are
9 numbers so feature vector has
 $30 \times 40 \times 9 = 10,800$ numbers

Example: Bag of Words

Step 1: Build codebook



Extract random patches



Cluster patches to
form “codebook”
of “visual words”



Step 2: Encode images

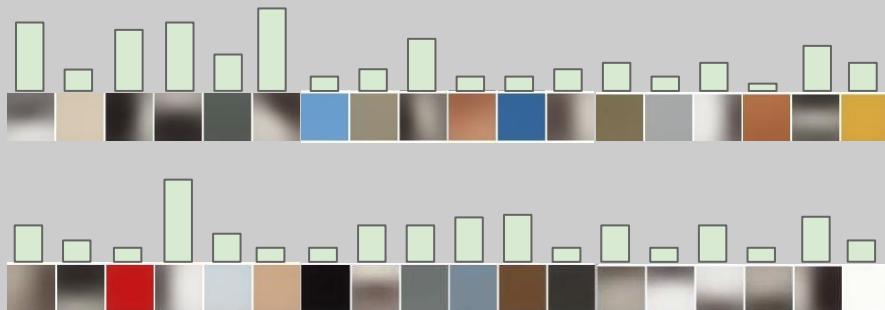


Image Features

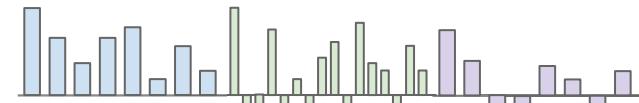
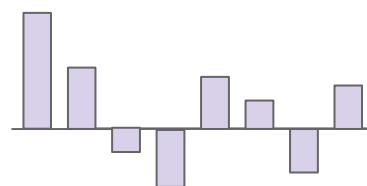
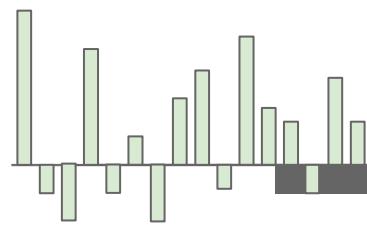
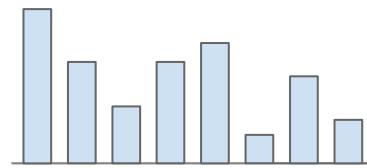


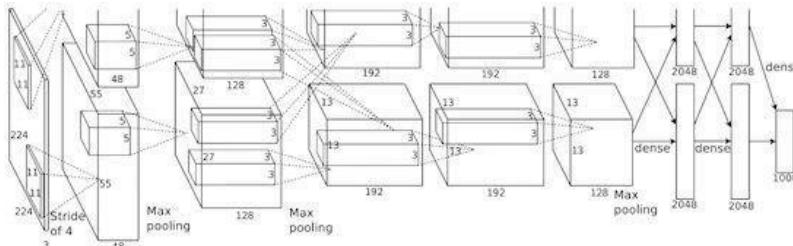
Image features vs. ConvNets



f



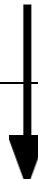
10 numbers giving scores for classes



Krizhevsky, Sutskever, and Hinton, "Imagenet classification with deep convolutional neural networks", NIPS 2012.
Figure copyright Krizhevsky, Sutskever, and Hinton, 2012.
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training

10 numbers giving scores for classes



Last Time: Neural Networks

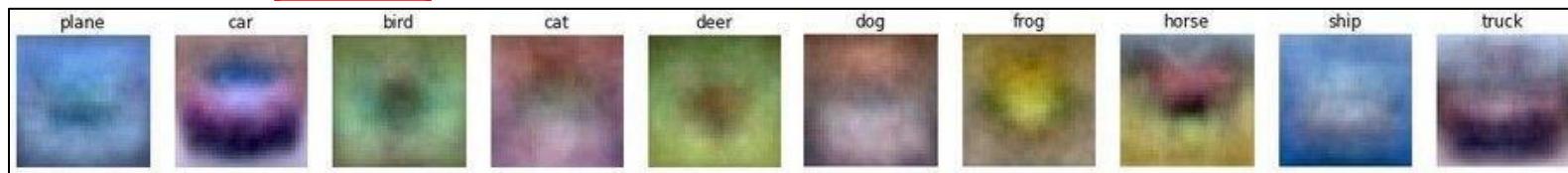
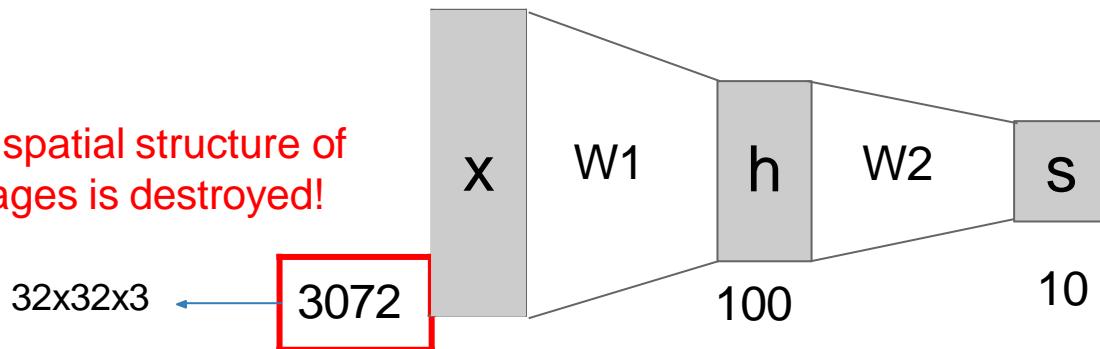
Linear score function:

$$f = Wx$$

2-layer Neural Network

$$f = W_2 \max(0, W_1 x)$$

The spatial structure of images is destroyed!



Next: Convolutional Neural Networks

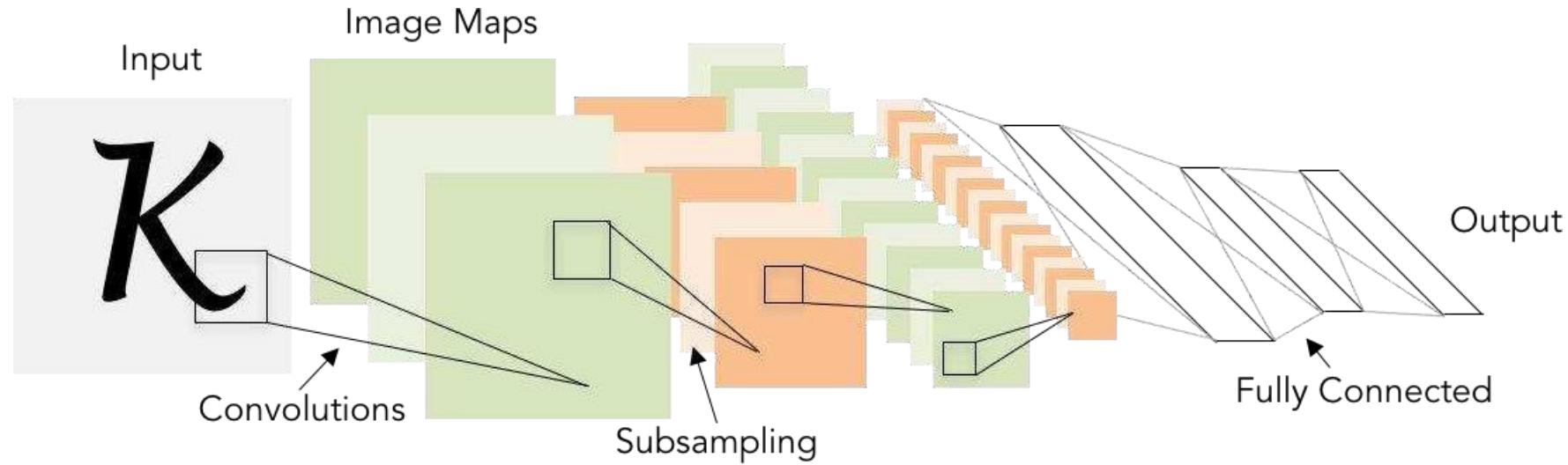


Illustration of LeCun et al. 1998 from CS231n 2017 Lecture 1

A bit of history...

The **Mark I Perceptron** machine was the first implementation of the perceptron algorithm.

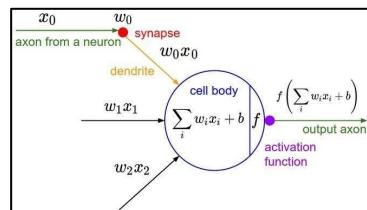
The machine was connected to a camera that used 20×20 cadmium sulfide photocells to produce a 400-pixel image.

recognized
letters of the alphabet

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

update rule:

$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}$$

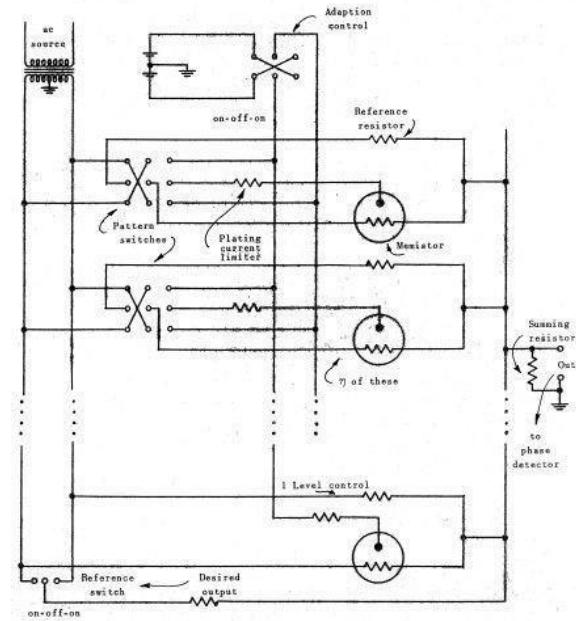
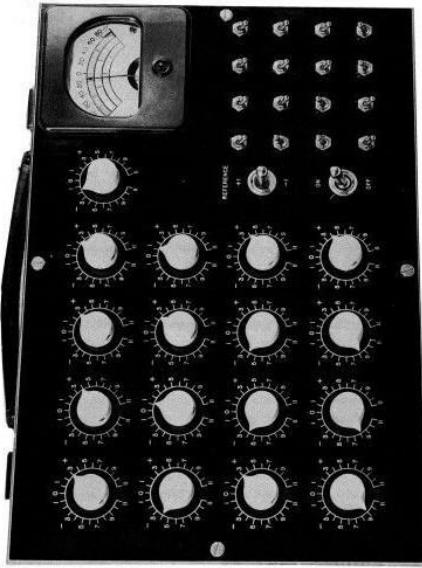
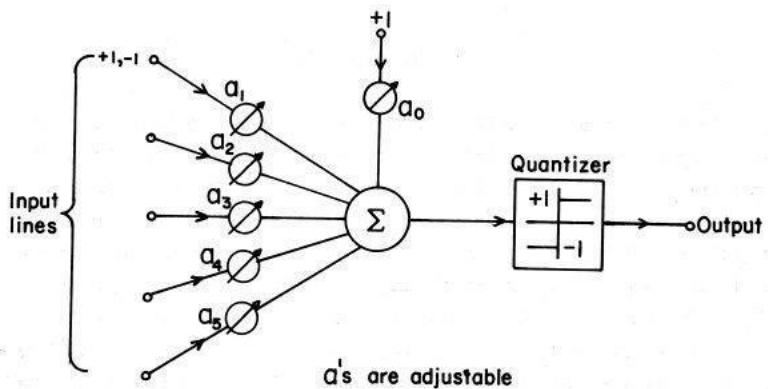


Frank Rosenblatt, ~1957: Perceptron



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A bit of history...

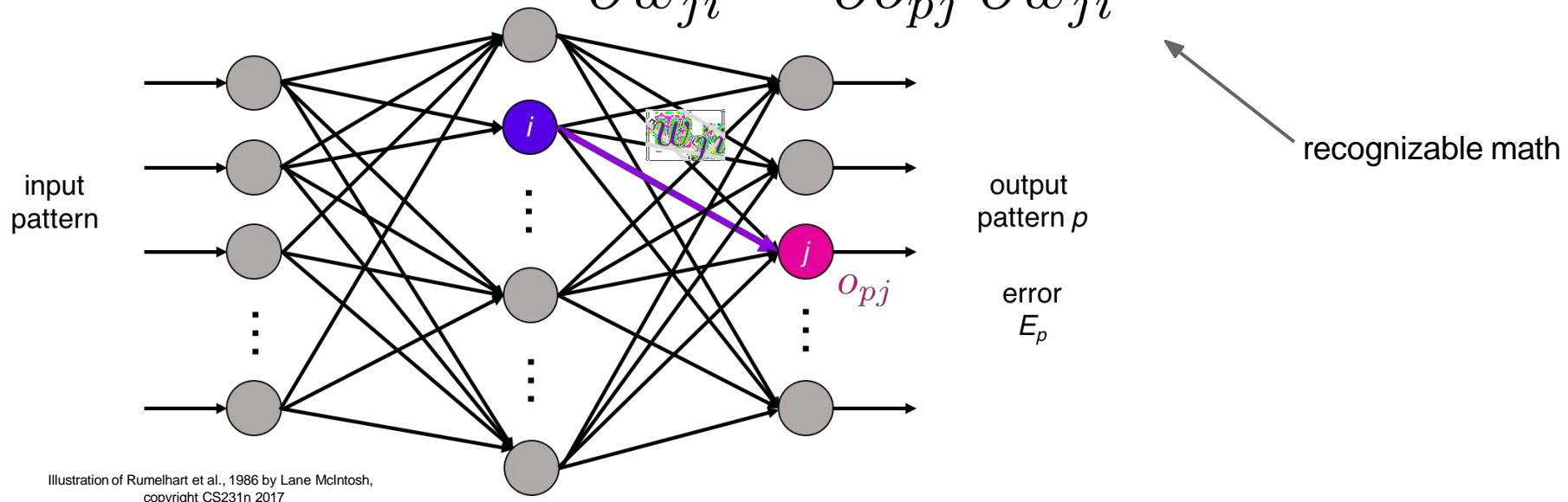


Widrow and Hoff, ~1960: Adaline/Madaline

These figures are reproduced from [Widrow 1960, Stanford Electronics Laboratories Technical Report](#) with permission from [Stanford University Special Collections](#).

A bit of history...

$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$



Rumelhart et al., 1986: First time back-propagation became popular

A bit of history...

[Hinton and Salakhutdinov 2006]

Reinvigorated research in
Deep Learning

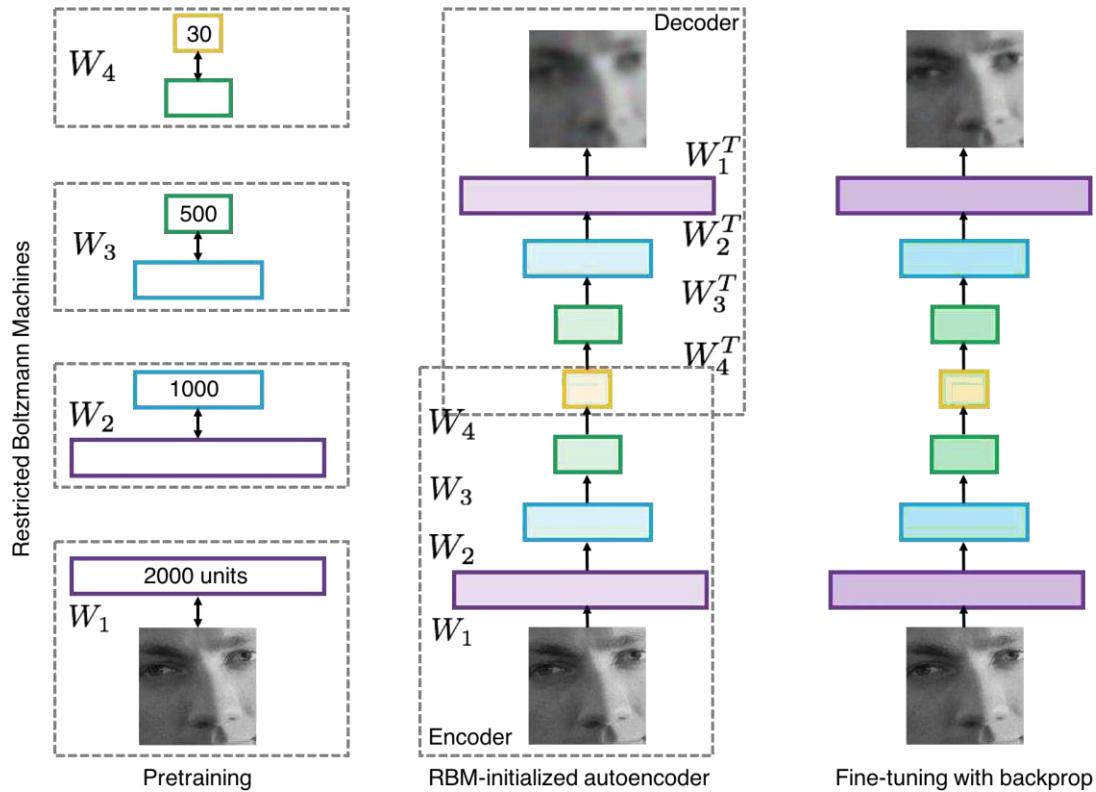


Illustration of Hinton and Salakhutdinov 2006 by Lane McIntosh, copyright CS231n 2017

First strong results

Acoustic Modeling using Deep Belief Networks

Abdel-rahman Mohamed, George Dahl, Geoffrey Hinton, 2010

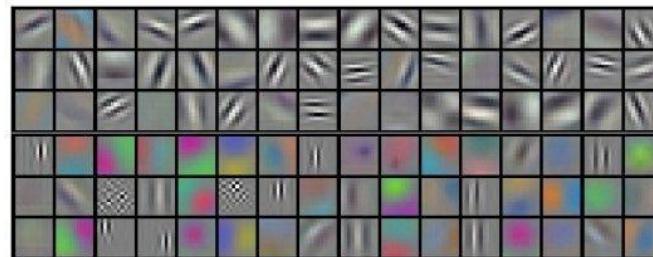
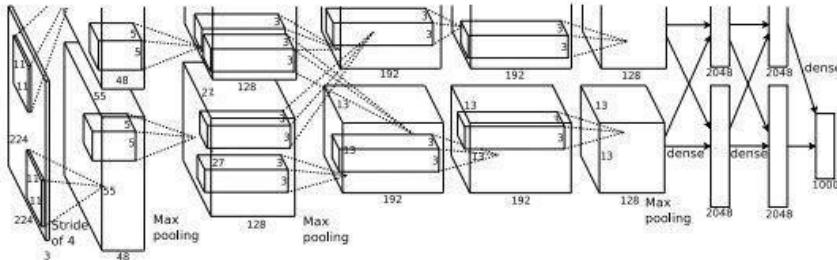
Context-Dependent Pre-trained Deep Neural Networks

for Large Vocabulary Speech Recognition

George Dahl, Dong Yu, Li Deng, Alex Acero, 2012

Imagenet classification with deep convolutional neural networks

Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012



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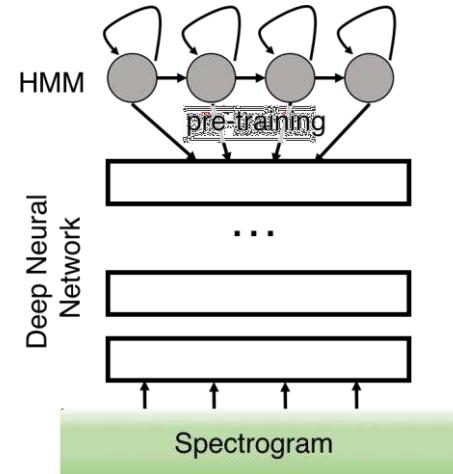


Illustration of Dahl et al. 2012 by Lane McIntosh, copyright CS231n 2017

A bit of history:

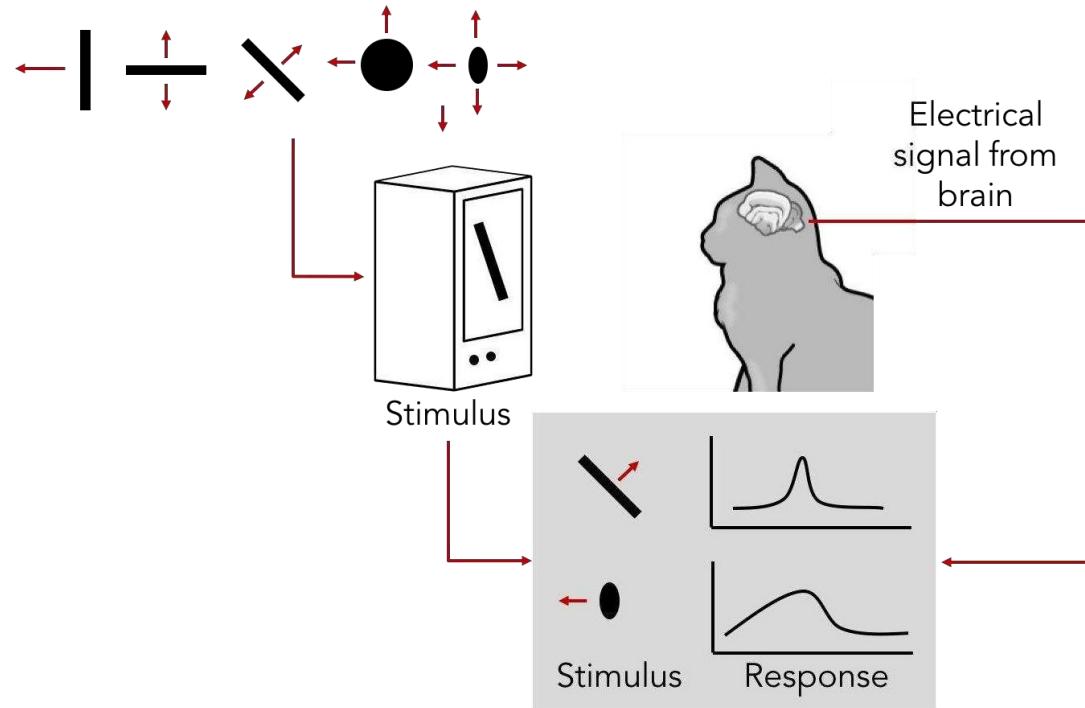
**Hubel & Wiesel,
1959**

RECEPTIVE FIELDS OF SINGLE
NEURONES IN
THE CAT'S STRIATE CORTEX

1962

RECEPTIVE FIELDS, BINOCULAR
INTERACTION
AND FUNCTIONAL ARCHITECTURE IN
THE CAT'S VISUAL CORTEX

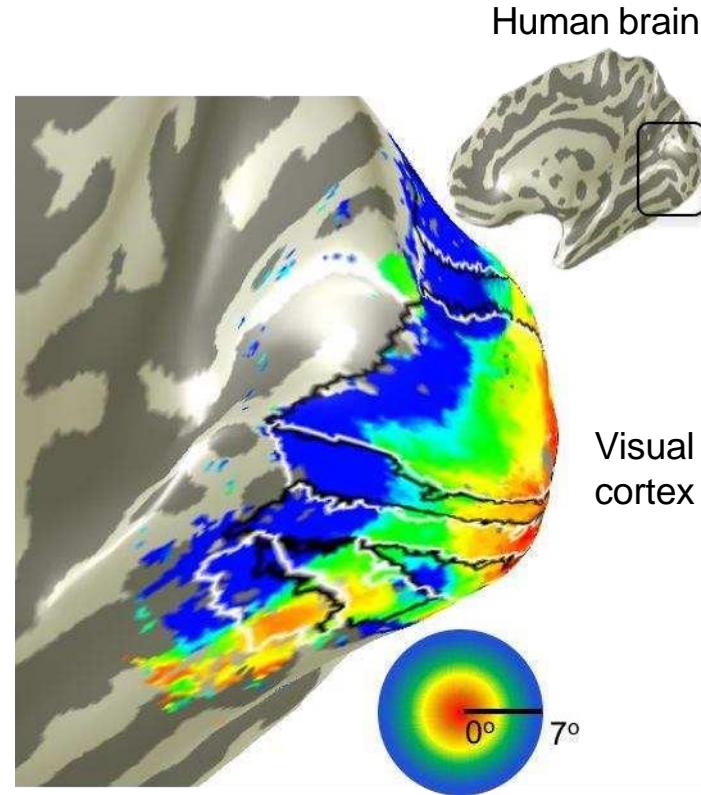
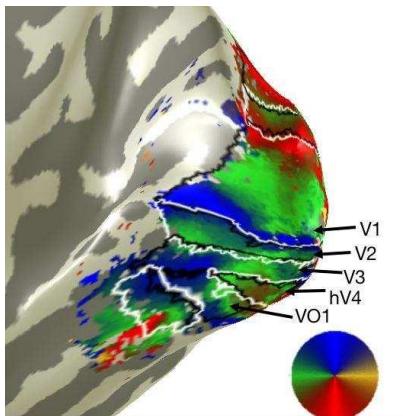
1968...



[Cat image](#) by CNX OpenStax is licensed under CC BY 4.0; changes made

A bit of history

Topographical mapping in the cortex:
nearby cells in cortex represent
nearby regions in the visual field



Retinotopy images courtesy of Jesse Gomez in the Stanford Vision & Perception Neuroscience Lab.

Hierarchical organization

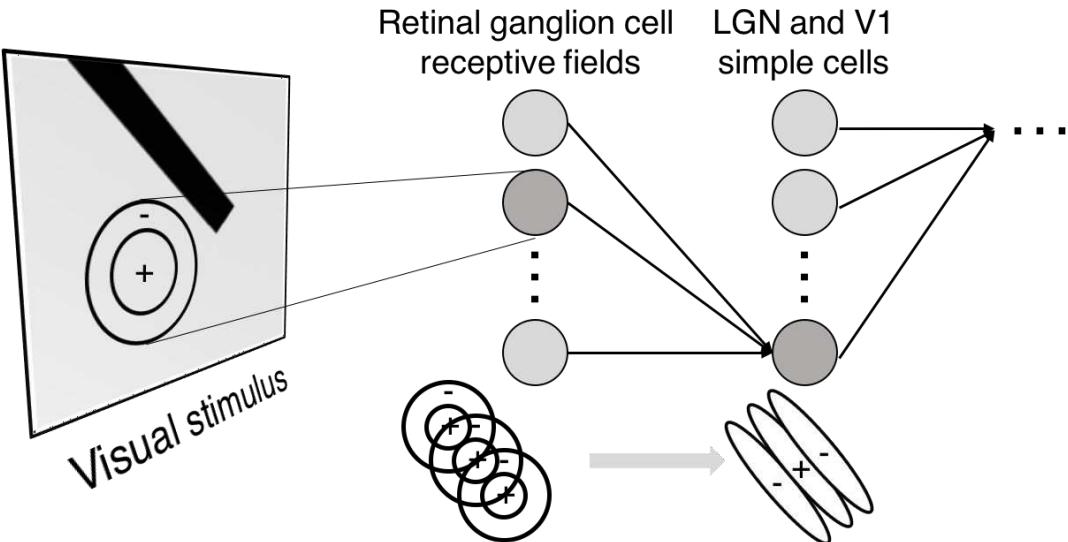
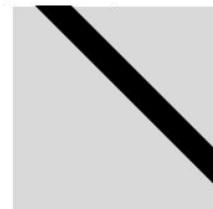


Illustration of hierarchical organization in early visual pathways by Lane McIntosh, copyright CS231n 2017

Simple cells:
Response to light orientation

Complex cells:
Response to light orientation and movement

Hypercomplex cells:
response to movement with an end point



No response

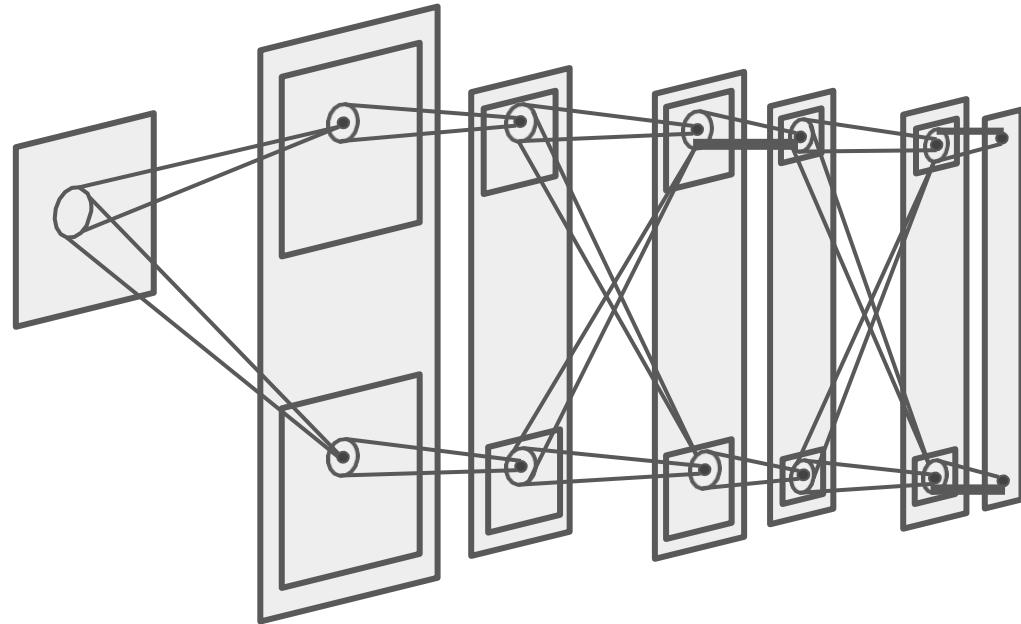


Response
(end point)

A bit of history:

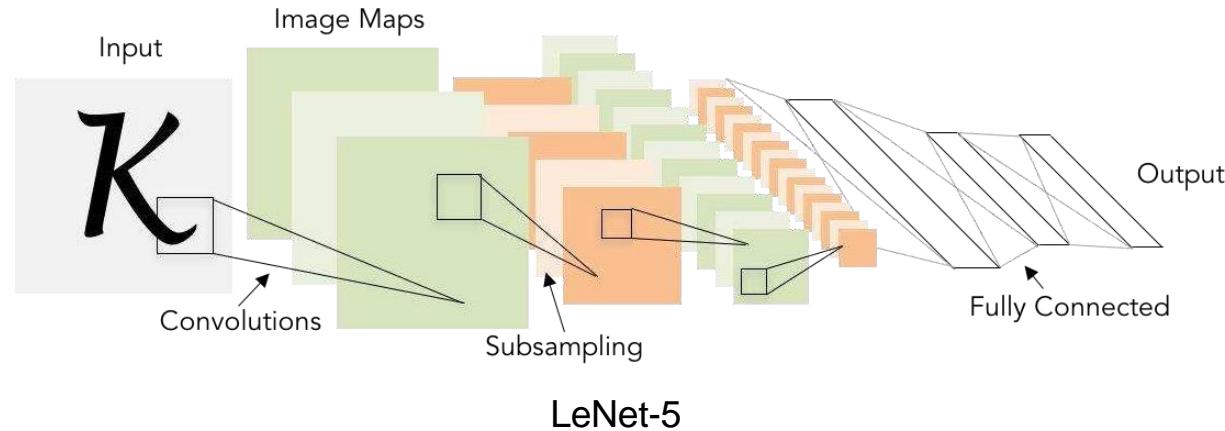
Neocognitron [Fukushima 1980]

“sandwich” architecture (SCSCSC...)
simple cells: modifiable parameters
complex cells: perform pooling



A bit of history: Gradient-based learning applied to document recognition

[LeCun, Bottou, Bengio, Haffner 1998]



A bit of history: ImageNet Classification with Deep Convolutional Neural Networks *[Krizhevsky, Sutskever, Hinton, 2012]*

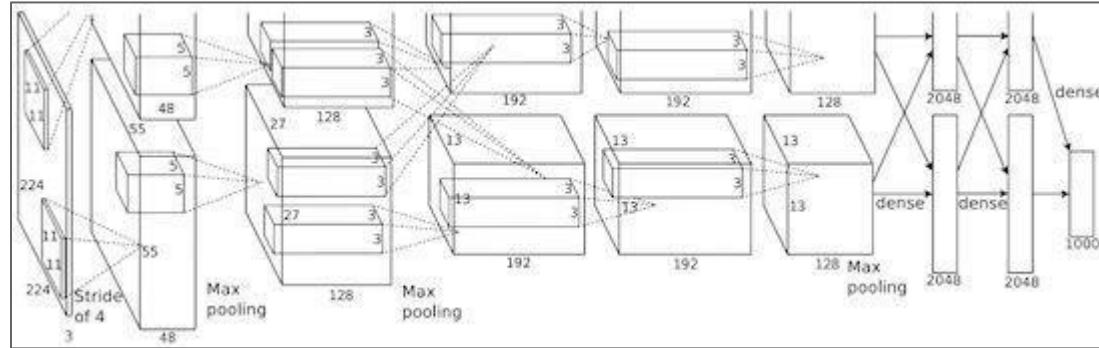


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

“AlexNet”

Fast-forward to today: ConvNets are everywhere

Classification



Retrieval



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Fast-forward to today: ConvNets are everywhere

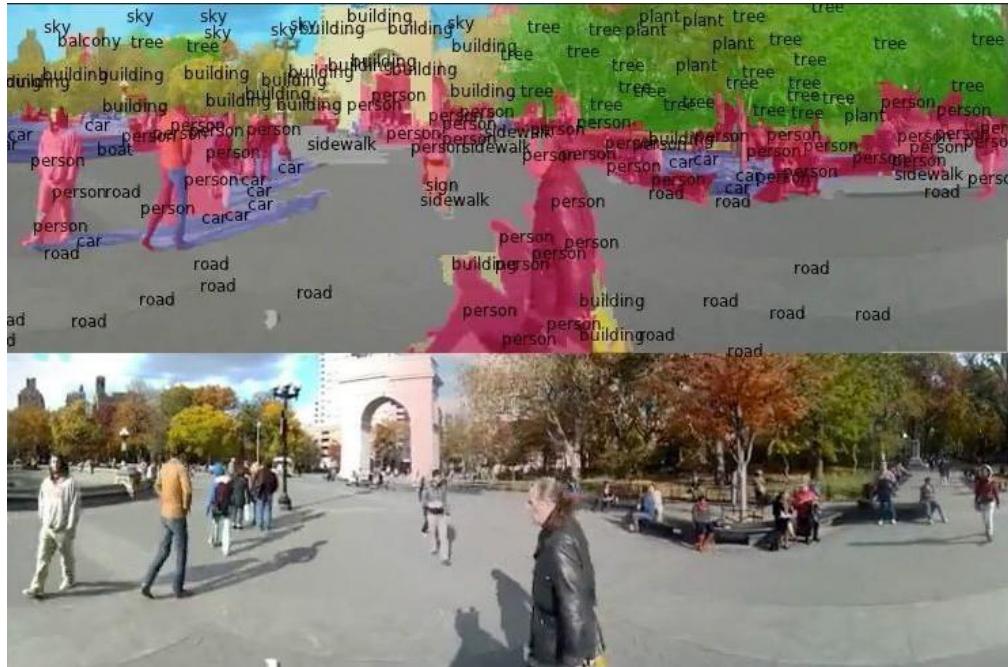
Detection



Figures copyright Shaoqing Ren, Kaiming He, Ross Girshick, Jian Sun, 2015. Reproduced with permission.

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

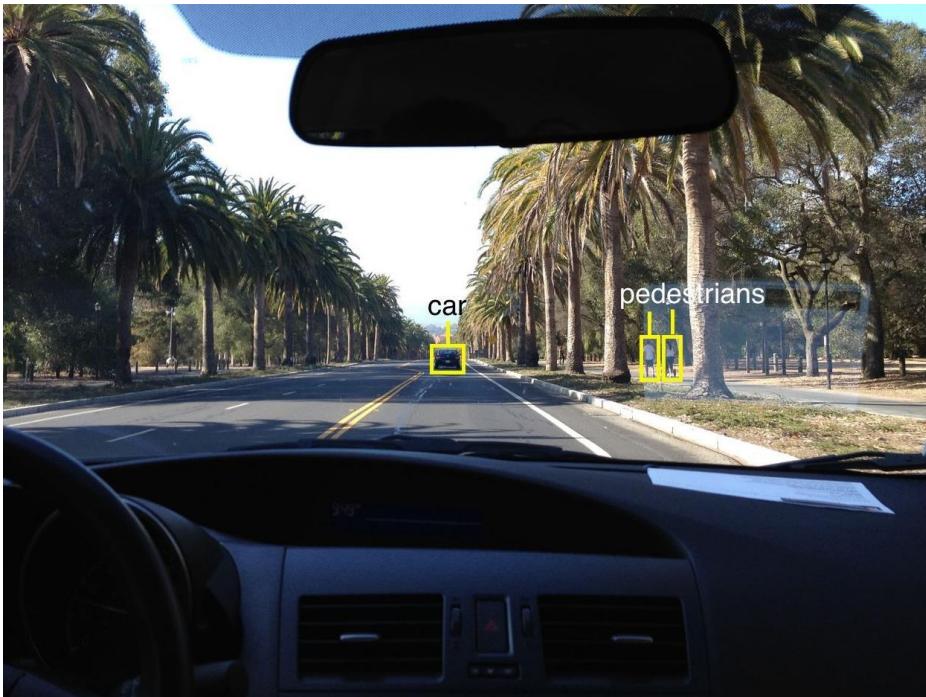
Segmentation



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[Farabet et al., 2012]

Fast-forward to today: ConvNets are everywhere



self-driving cars

Photo by Lane McIntosh. Copyright CS231n 2017.



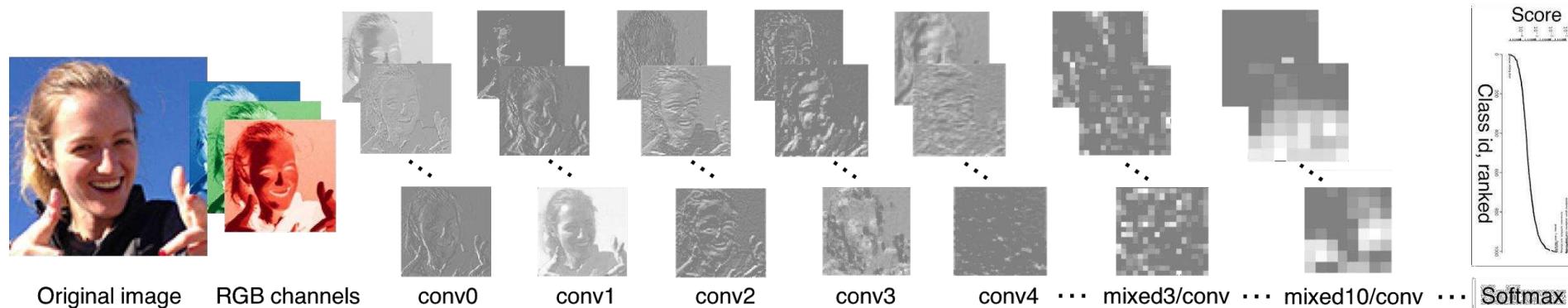
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NVIDIA Tesla line

(these are the GPUs on rye01.stanford.edu)

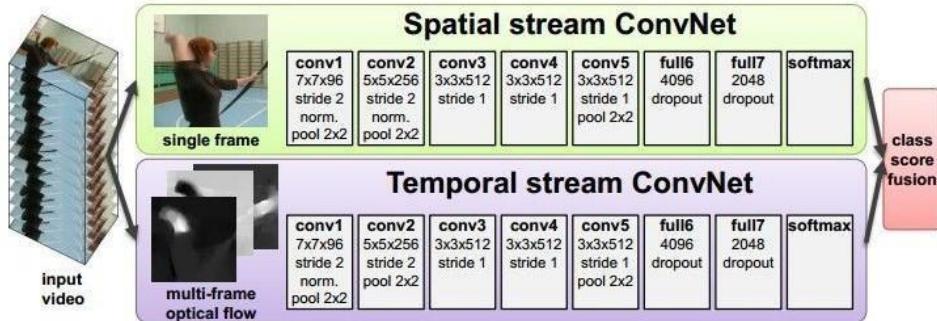
Note that for embedded systems a typical setup would involve NVIDIA Tegras, with integrated GPU and ARM-based CPU cores.

Fast-forward to today: ConvNets are everywhere



[Taigman et al. 2014]

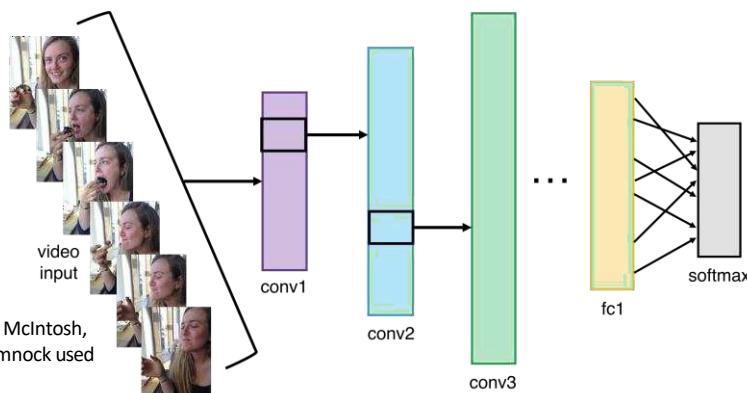
Activations of [inception-v3 architecture](#) [Szegedy et al. 2015] to image of Emma McIntosh, used with permission. Figure and architecture not from Taigman et al. 2014.



[Simonyan et al. 2014]

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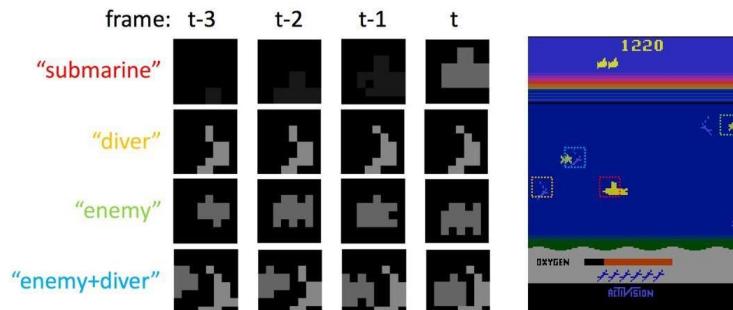


Fast-forward to today: ConvNets are everywhere

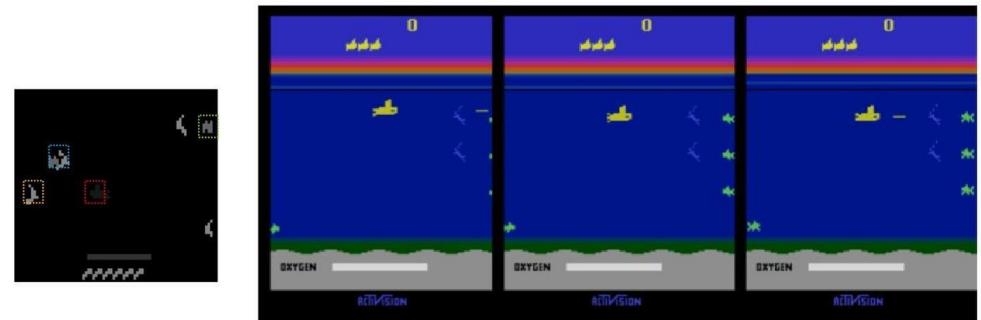


Images are examples of pose estimation, not actually from Toshev & Szegedy 2014. Copyright Lane McIntosh.

[Toshev, Szegedy 2014]

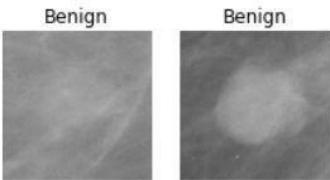


[Guo et al. 2014]



Figures copyright Xiaoxiao Guo, Satinder Singh, Honglak Lee, Richard Lewis, and Xiaoshi Wang, 2014. Reproduced with permission.

Fast-forward to today: ConvNets are everywhere



[Levy et al. 2016]

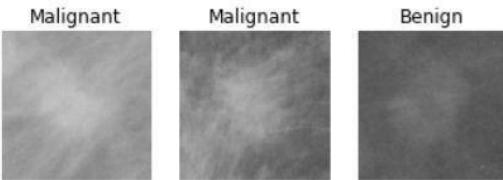


Figure copyright Levy et al. 2016.
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[Dieleman et al. 2014]

From left to right: [public domain by NASA](#), usage [permitted](#) by
ESA/Hubble, [public domain by NASA](#), and [public domain](#).



[Sermanet et al. 2011]
[Ciresan et al.]

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Whale recognition, Kaggle Challenge

Photo and figure by Lane McIntosh; not actual
example from Mnih and Hinton, 2010 paper.



Mnih and Hinton, 2010

No errors



A white teddy bear sitting in the grass



A man riding a wave on top of a surfboard

Minor errors



A man in a baseball uniform throwing a ball



A cat sitting on a suitcase on the floor

Somewhat related



A woman is holding a cat in her hand



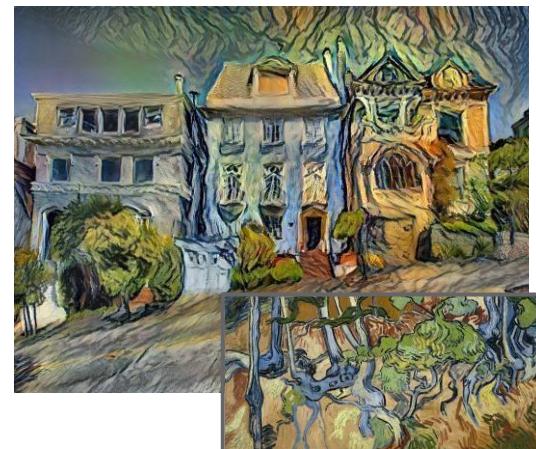
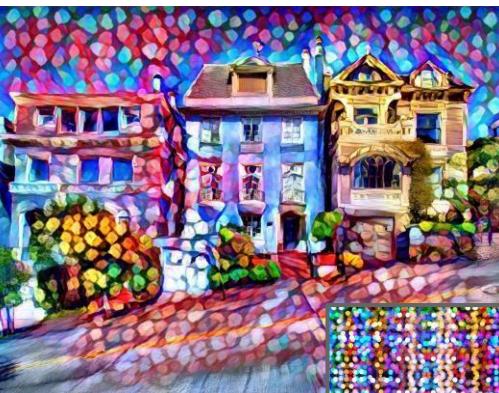
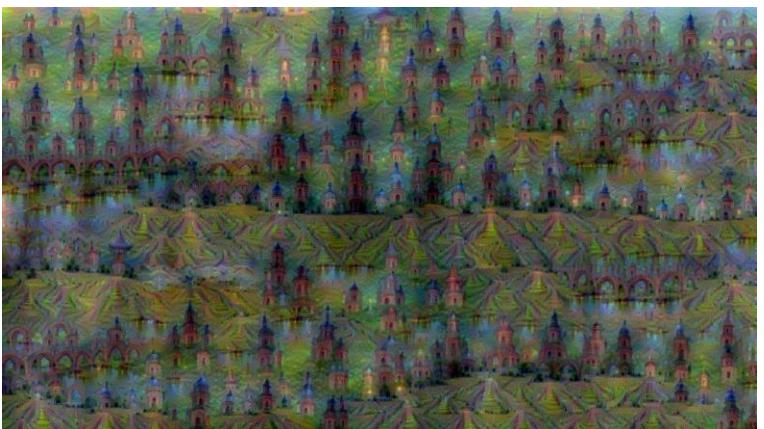
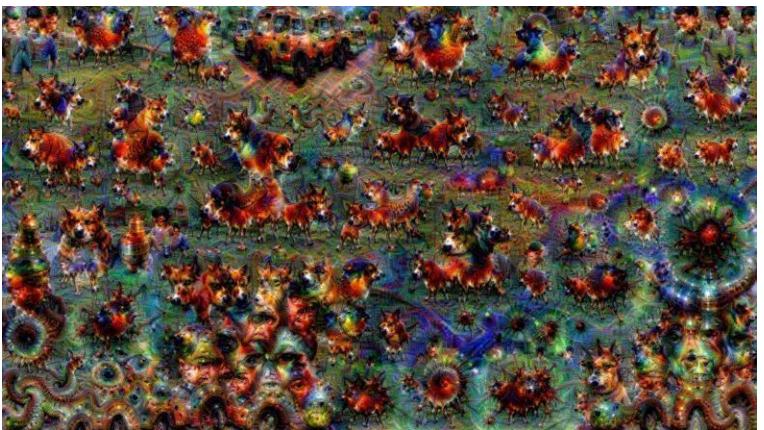
A woman standing on a beach holding a surfboard

Image Captioning

[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

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Captions generated by Justin Johnson using [NeuralTalk2](#)



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Starry Night and Tree Roots by Van Gogh are in the public domain

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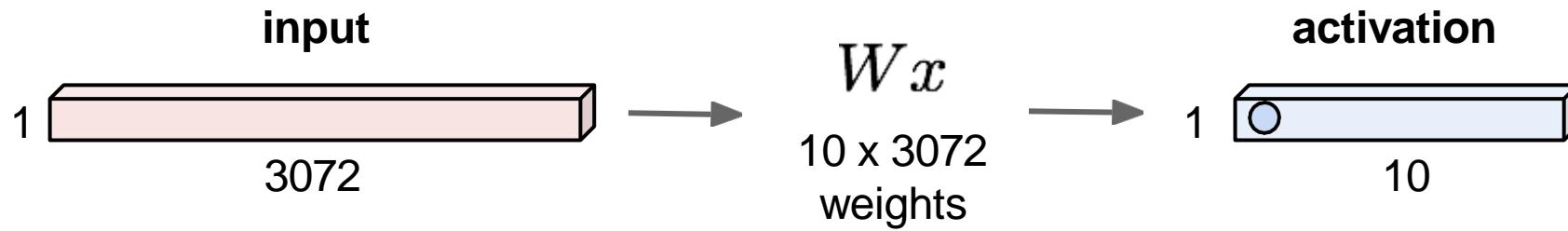
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Gatys et al, "Image Style Transfer using Convolutional Neural Networks", CVPR 2016
Gatys et al, "Controlling Perceptual Factors in Neural Style Transfer", CVPR 2017

Convolutional Neural Networks

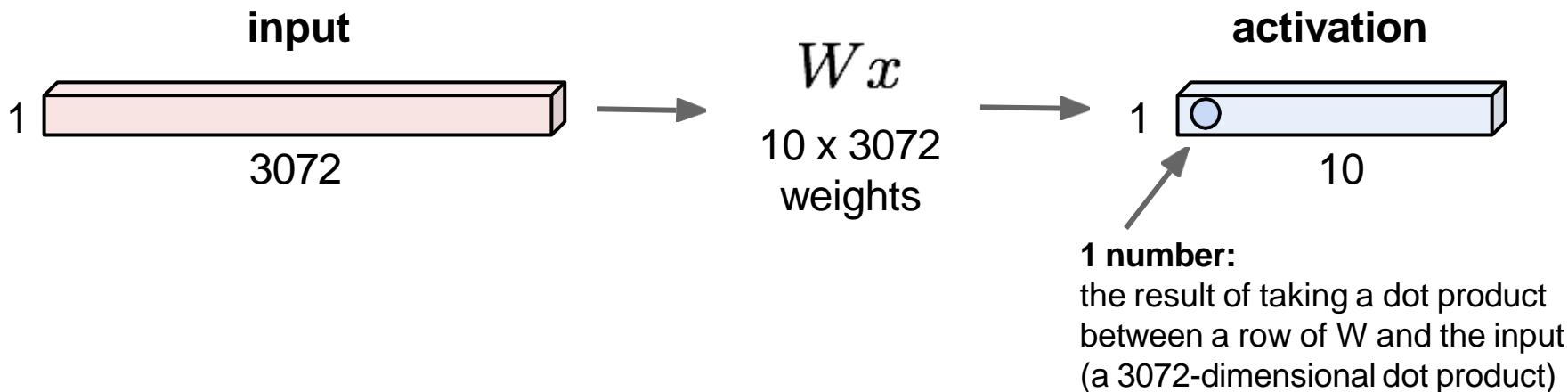
Recap: Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



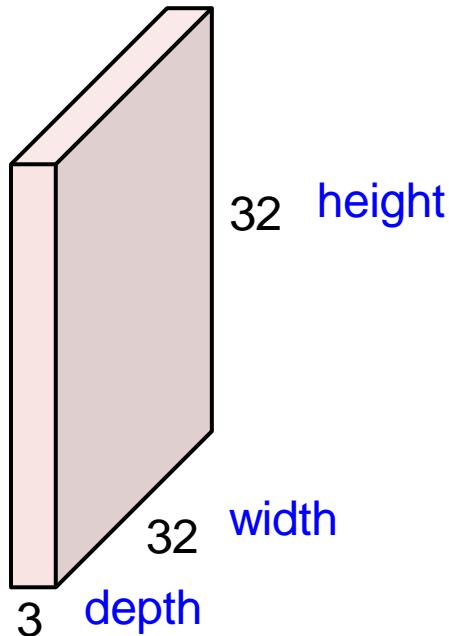
Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1



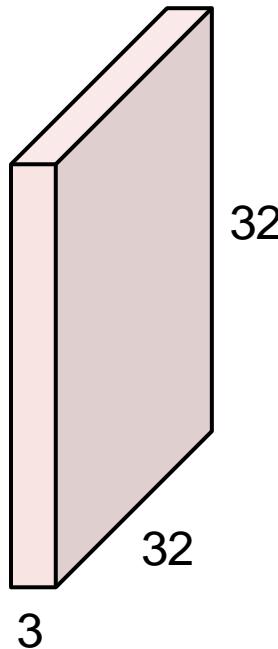
Convolution Layer

32x32x3 image -> preserve spatial structure



Convolution Layer

32x32x3 image



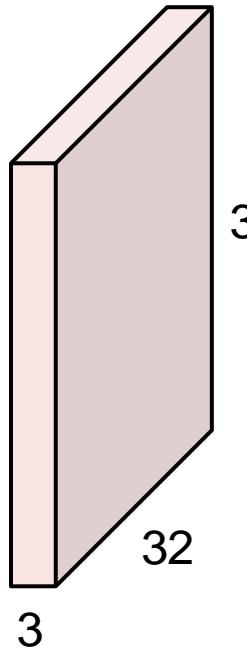
5x5x3 filter



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

Convolution Layer

32x32x3 image



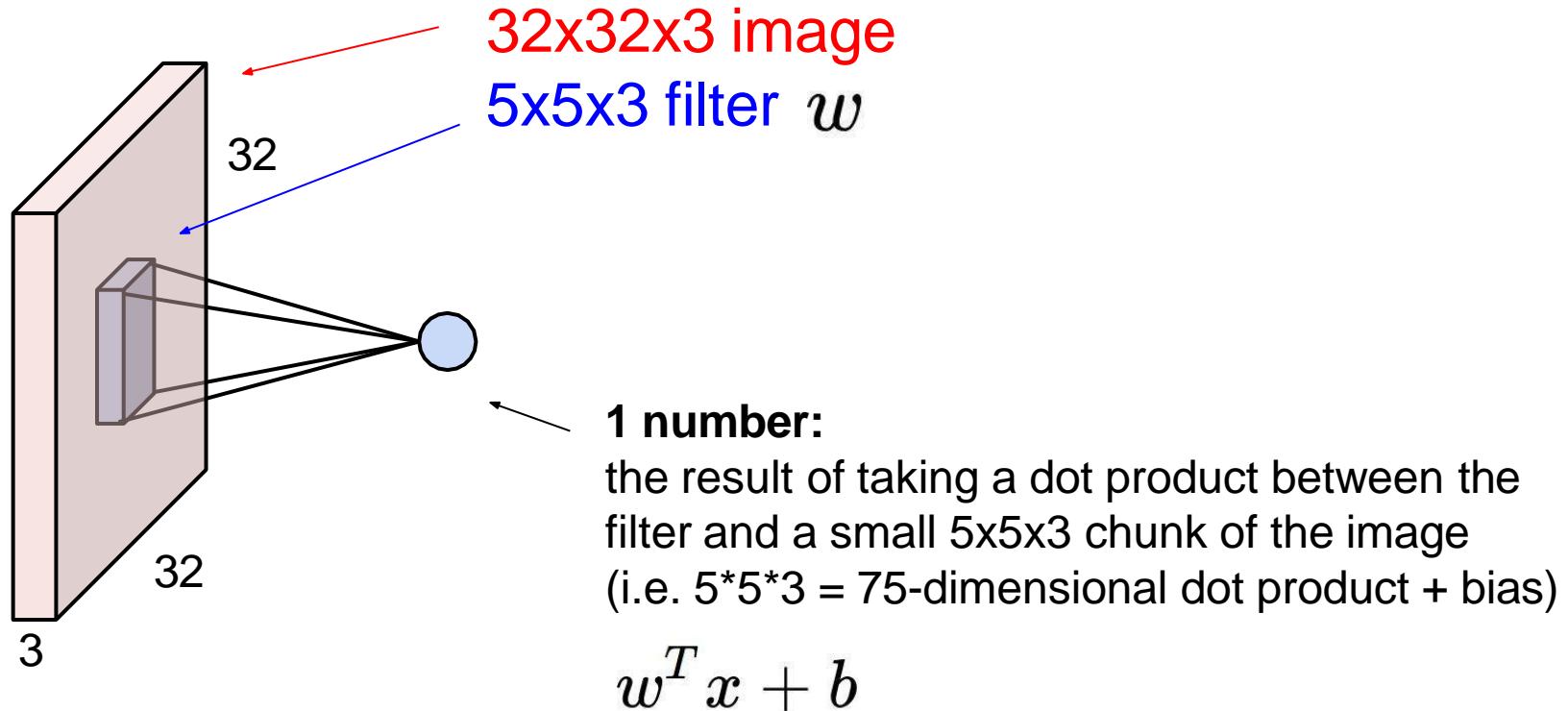
5x5x3 filter



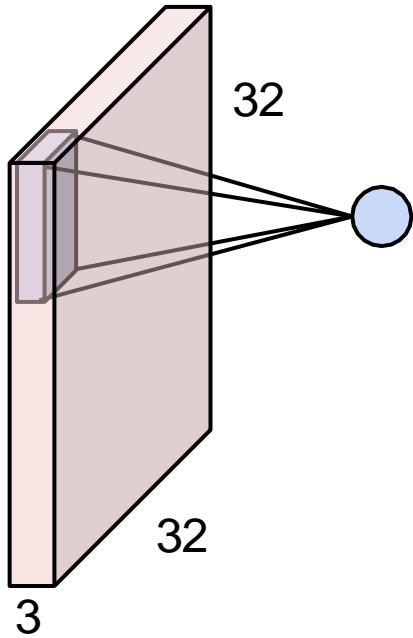
Filters always extend the full depth of the input volume

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

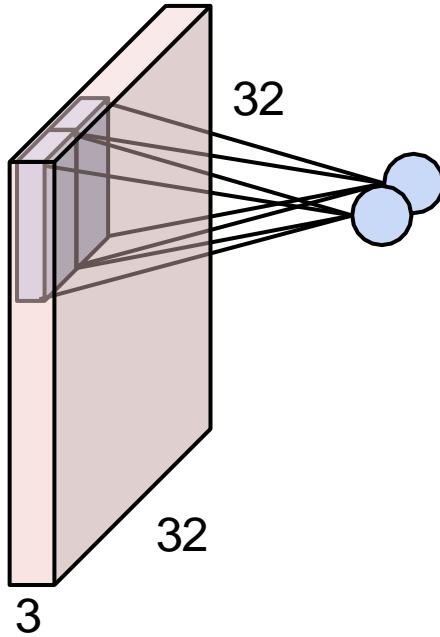
Convolution Layer



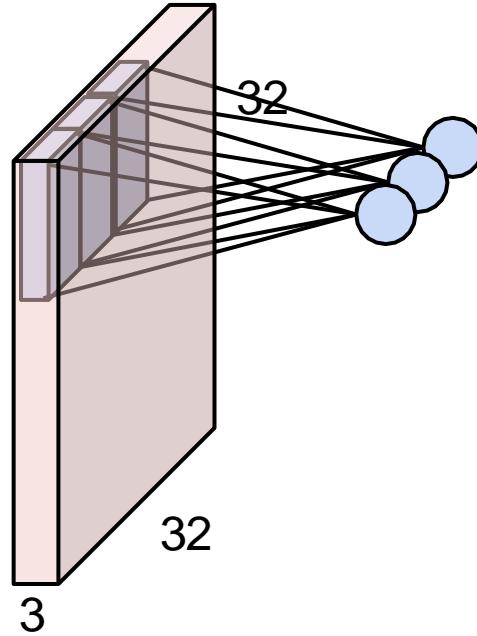
Convolution Layer



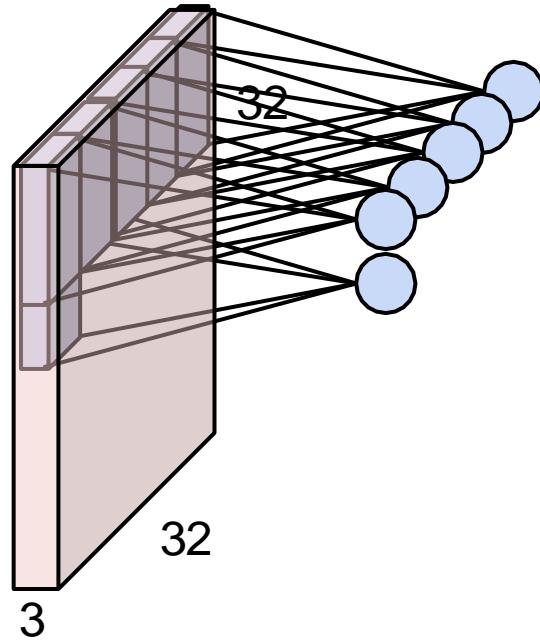
Convolution Layer



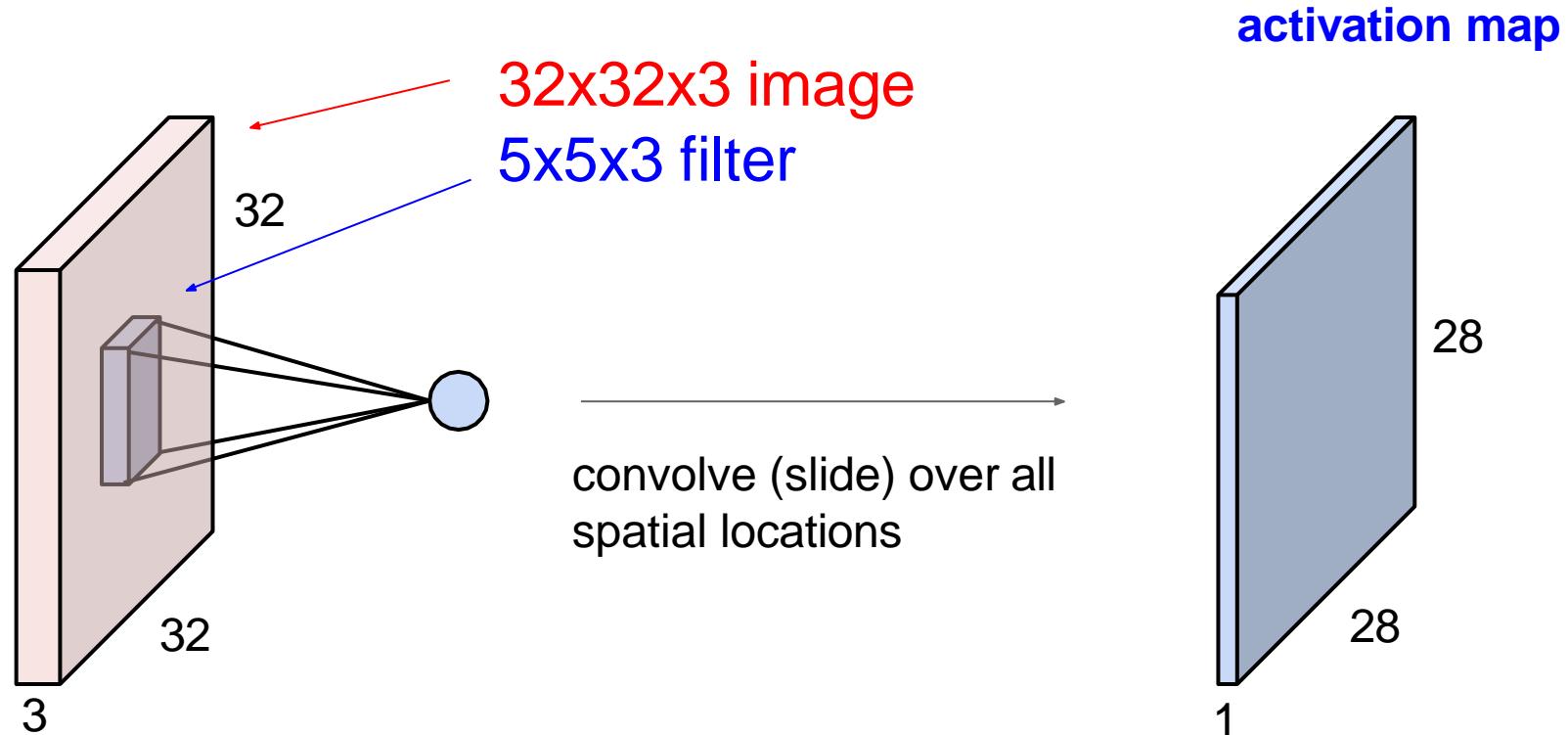
Convolution Layer



Convolution Layer

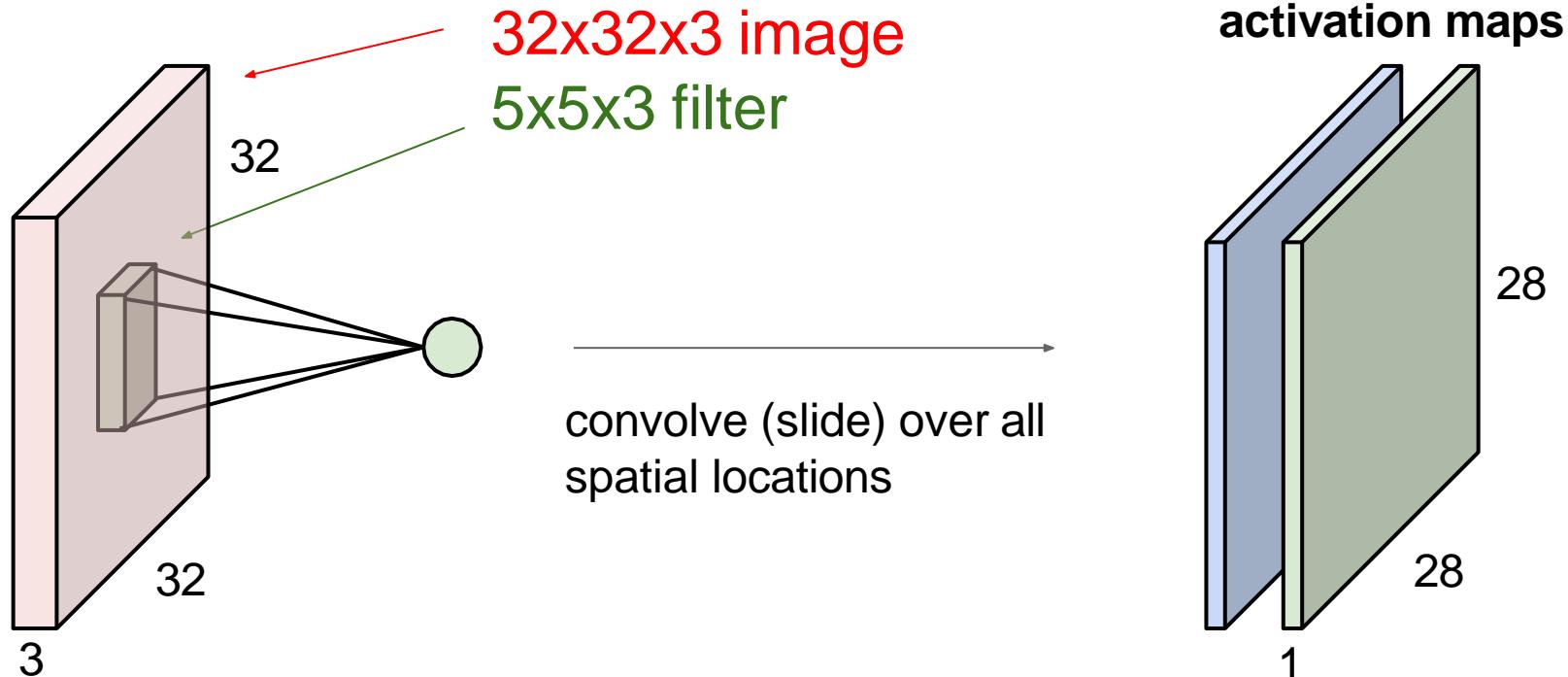


Convolution Layer



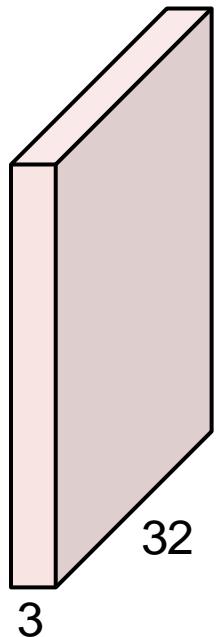
Convolution Layer

consider a second, green filter

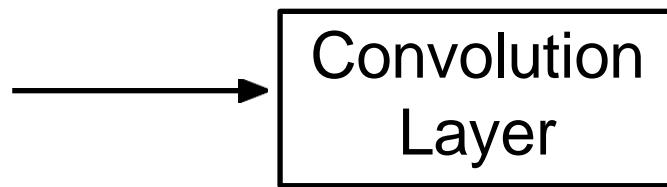


Convolution Layer

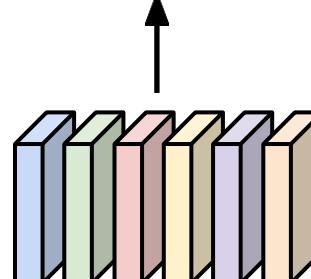
3x32x32 image



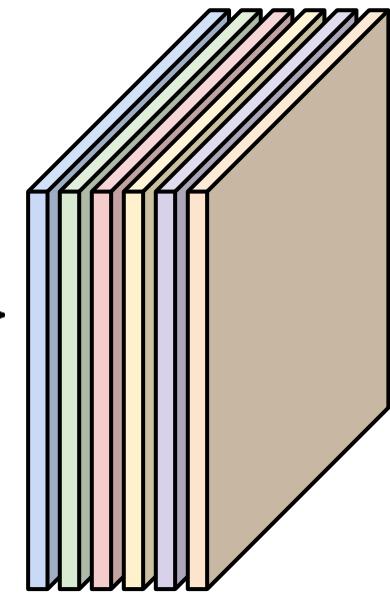
Consider 6 filters,
each 3x5x5



6x3x5x5
filters



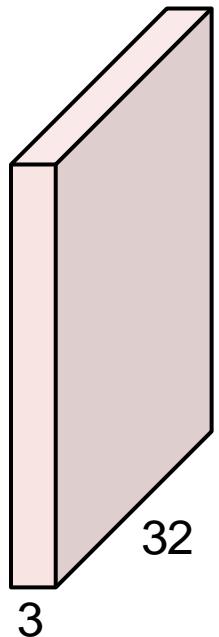
6 activation maps,
each 1x28x28



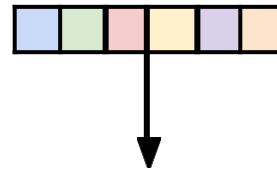
Stack activations to get a
6x28x28 output image!

Convolution Layer

3x32x32 image

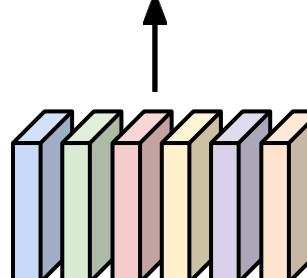


Also 6-dim bias vector:

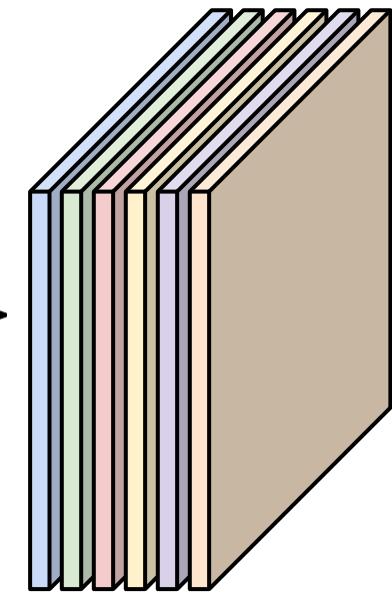


Convolution
Layer

6x3x5x5
filters



6 activation maps,
each 1x28x28

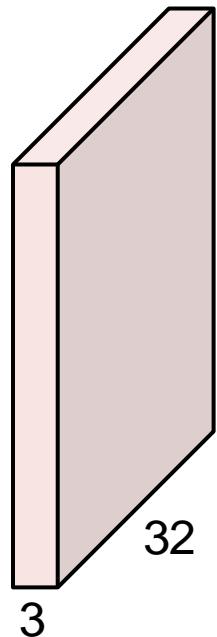


Stack activations to get a
6x28x28 output image!

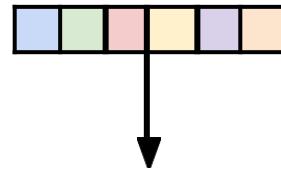
Convolution Layer

28x28 grid, at each point a 6-dim vector

3x32x32 image

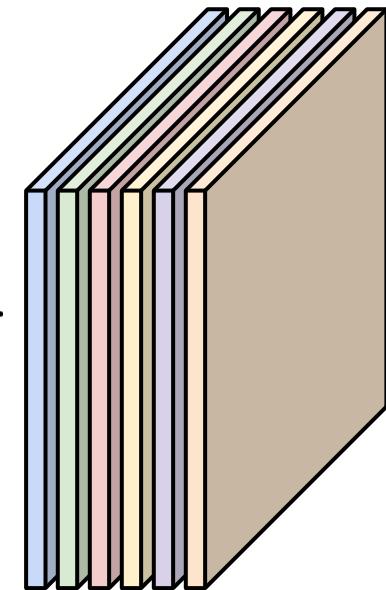
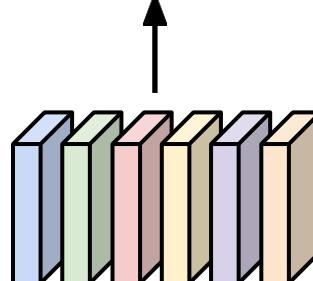


Also 6-dim bias vector:



Convolution
Layer

6x3x5x5
filters

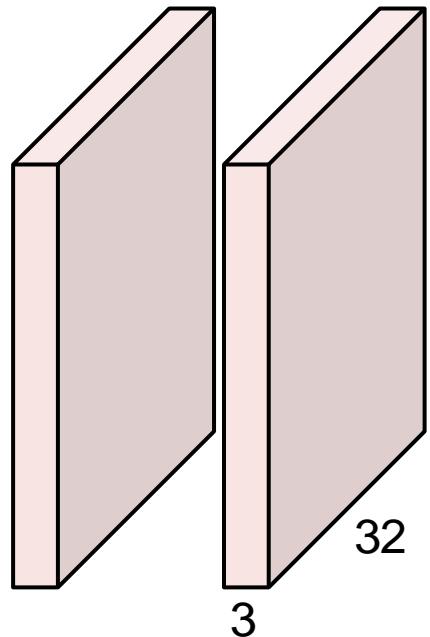


Stack activations to get a 6x28x28 output image!

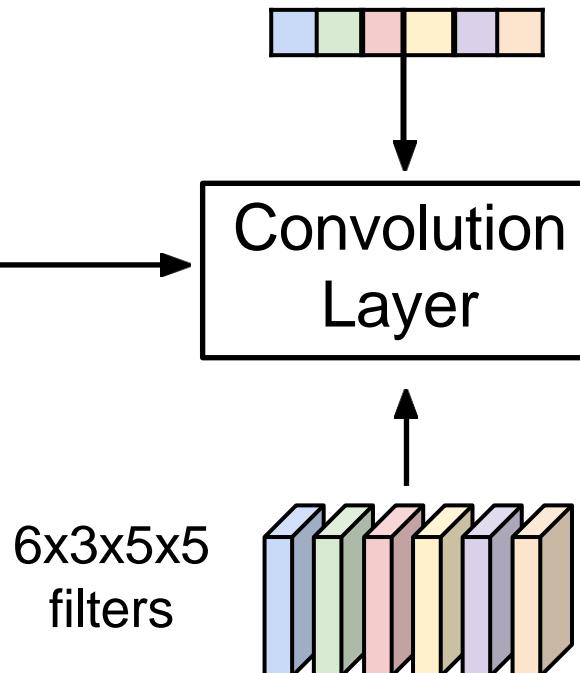
Convolution Layer

2x3x32x32

Batch of images

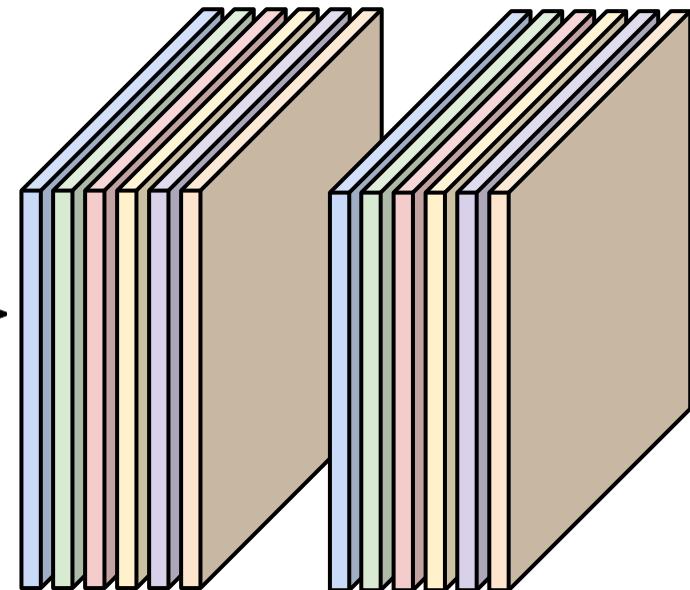


Also 6-dim bias vector:



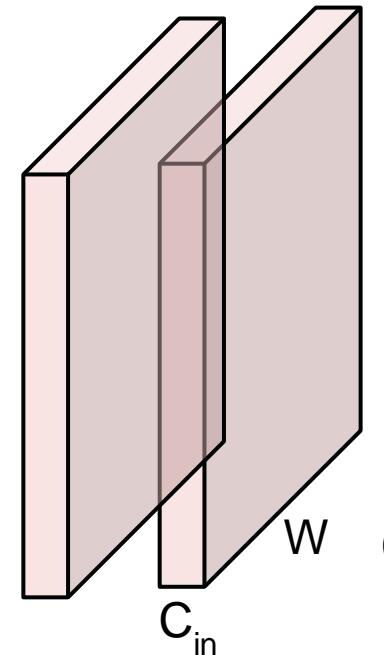
2x6x28x28

Batch of outputs



Convolution Layer

$N \times C_{in} \times H \times W$
Batch of images



Also C_{out} -dim bias vector:

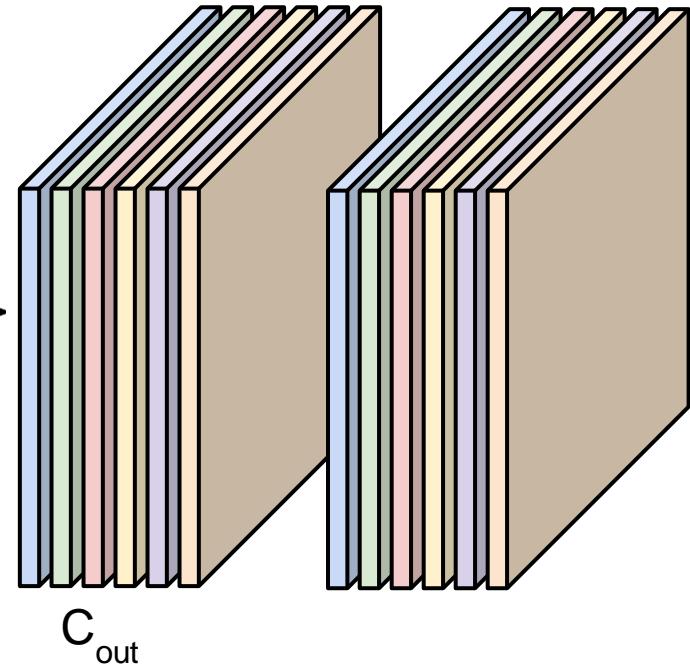


Convolution
Layer

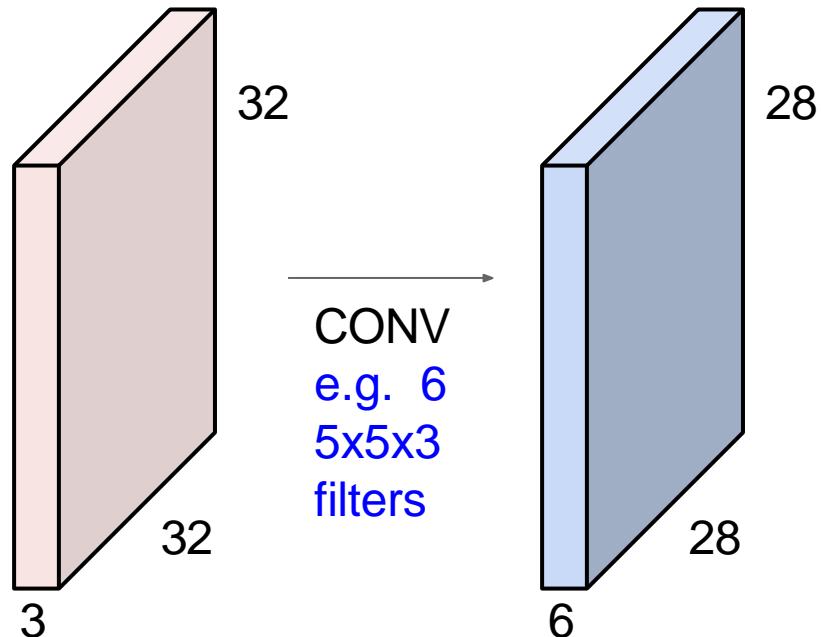


$C_{out} \times C_{in} \times K_w \times K_h$
filters

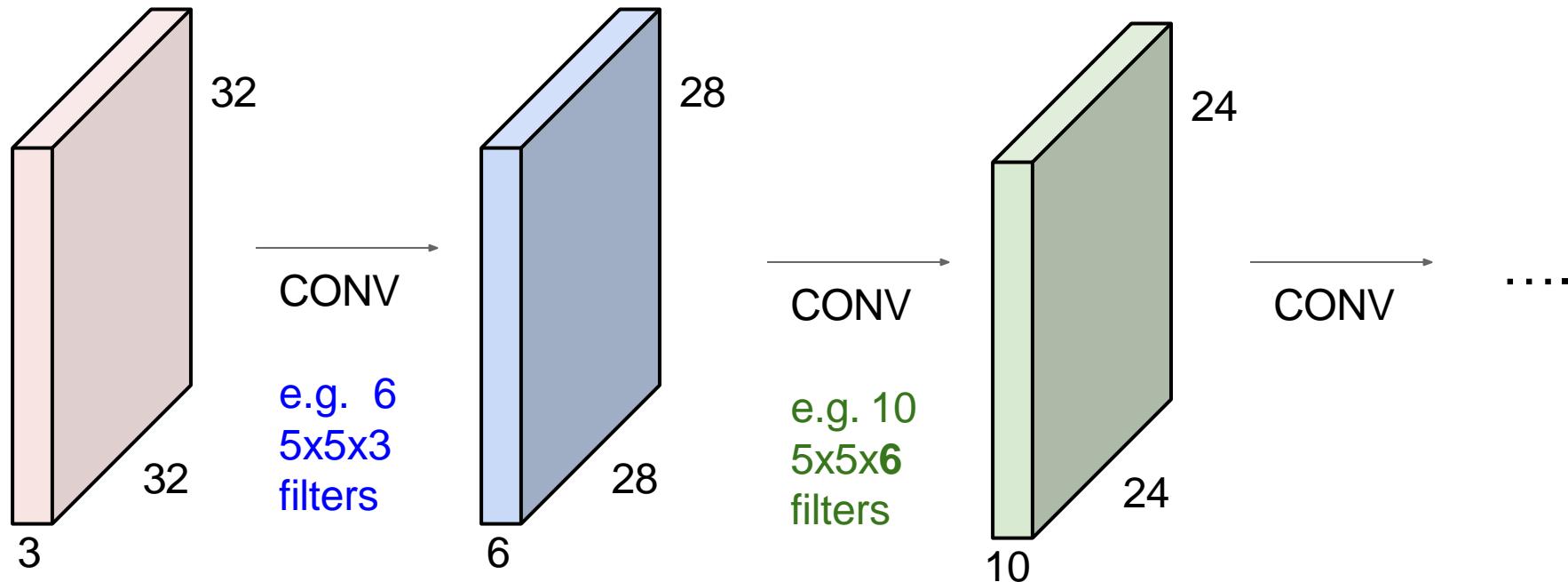
$N \times C_{out} \times H' \times W'$
Batch of outputs



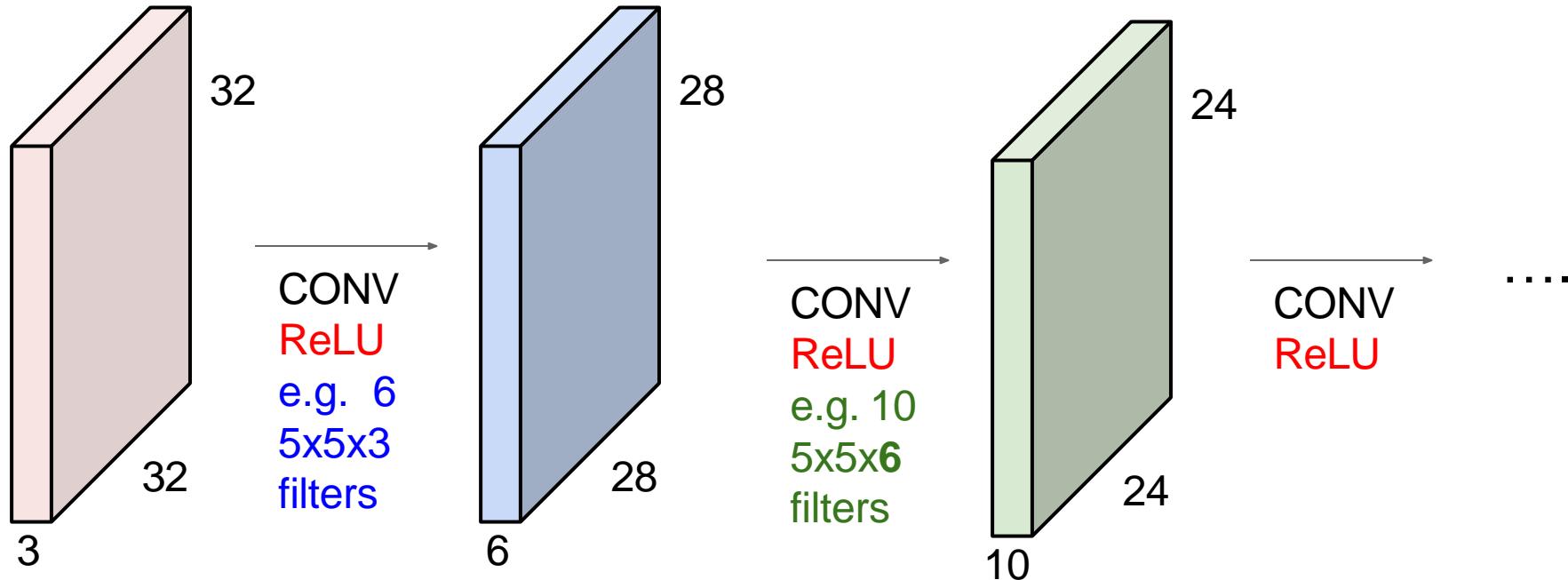
Preview: ConvNet is a sequence of Convolution Layers



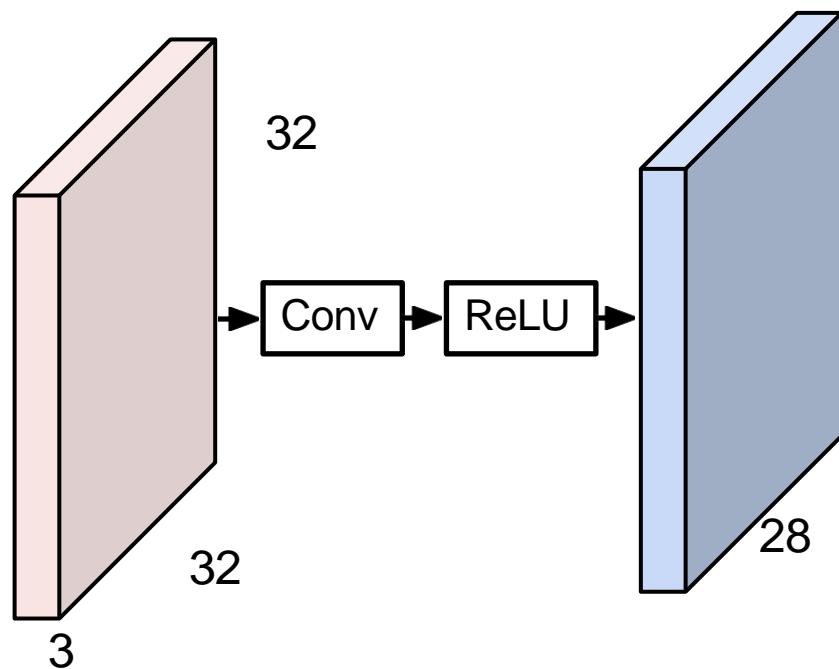
Preview: ConvNet is a sequence of Convolution Layers



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



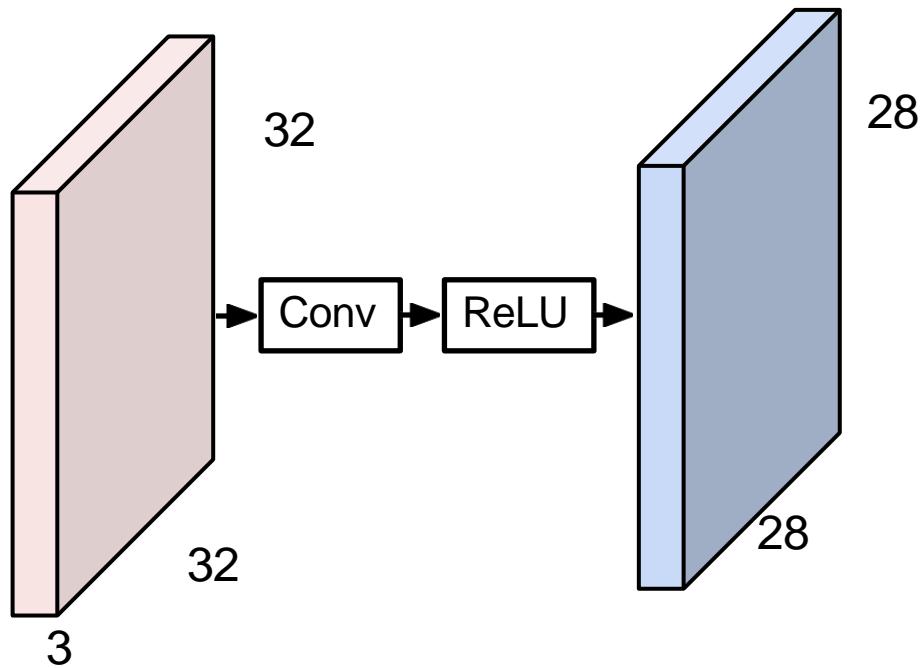
Preview: What do convolutional filters learn?



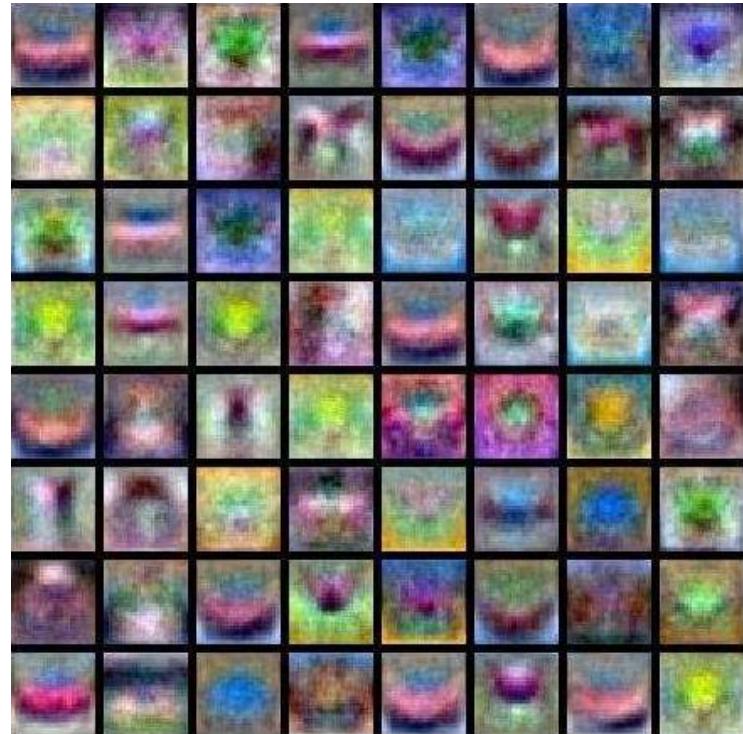
28
Linear classifier: One template per class



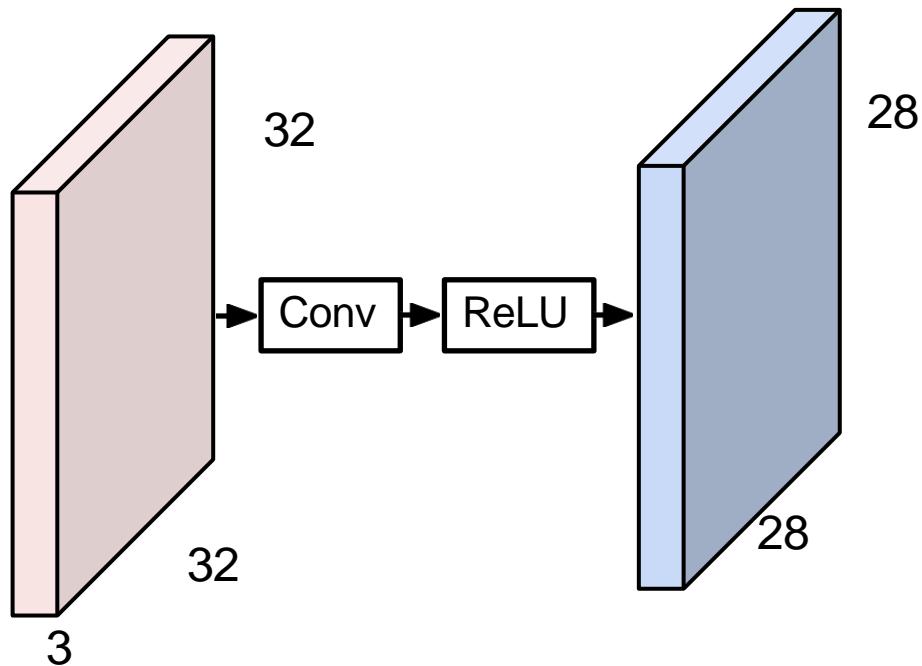
Preview: What do convolutional filters learn?



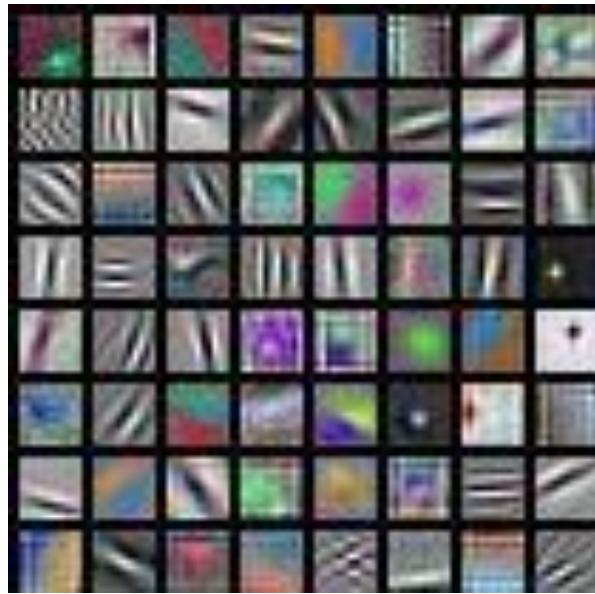
MLP: Bank of whole-image templates



Preview: What do convolutional filters learn?



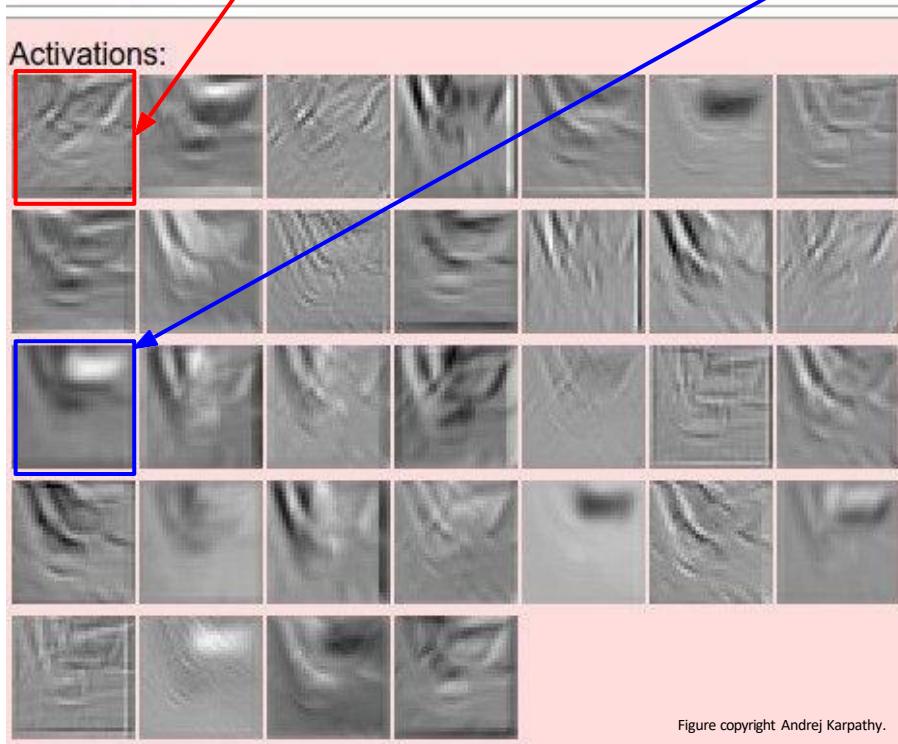
First-layer conv filters: local image templates
(Often learns oriented edges, opposing colors)



AlexNet: 64 filters, each 3x11x11



one filter =>
one activation map



example 5x5 filters
(32 total)

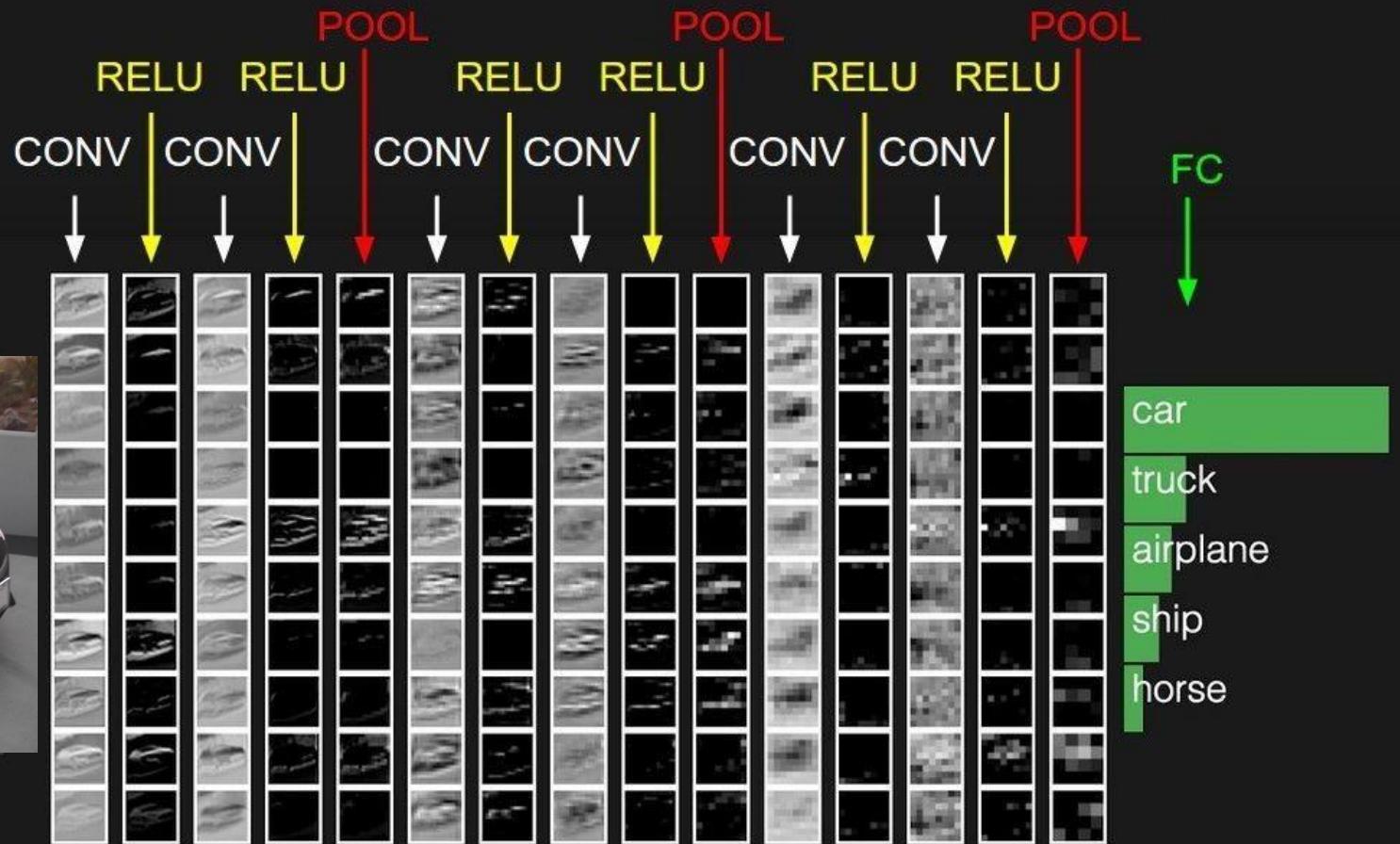
We call the layer convolutional
because it is related to convolution
of two signals:

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1, n_2] \cdot g[x - n_1, y - n_2]$$

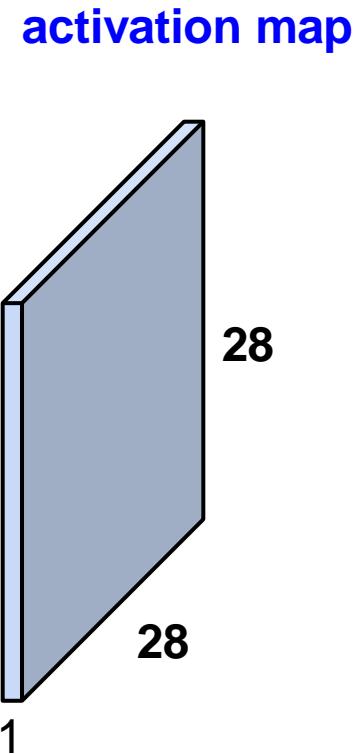
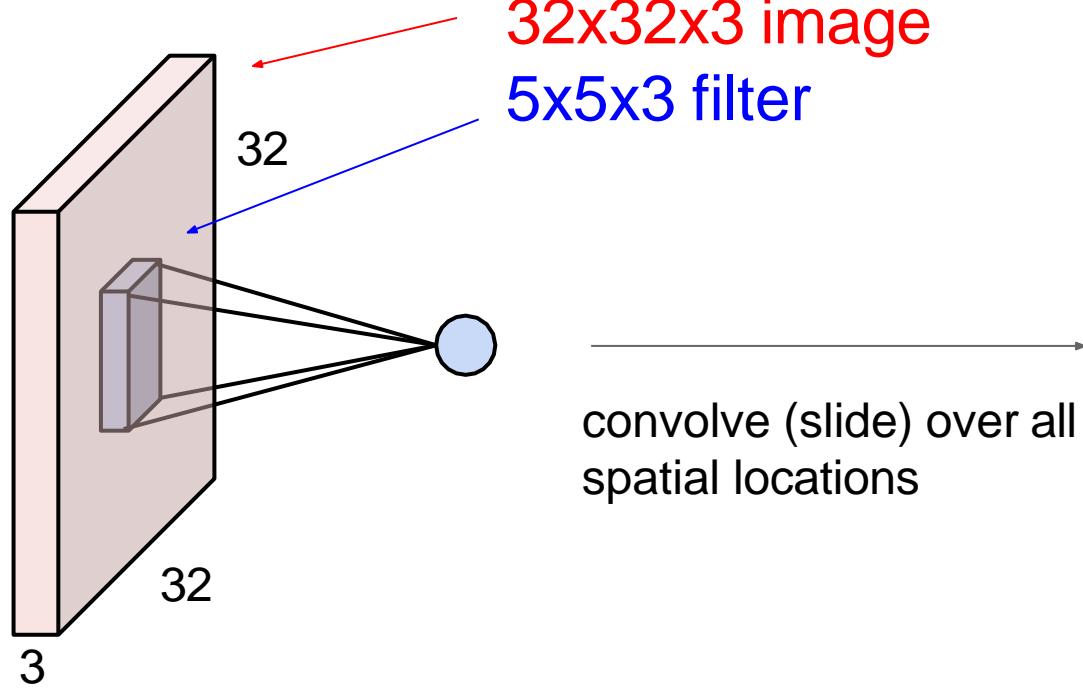


elementwise multiplication and sum of
a filter and the signal (image)

preview:

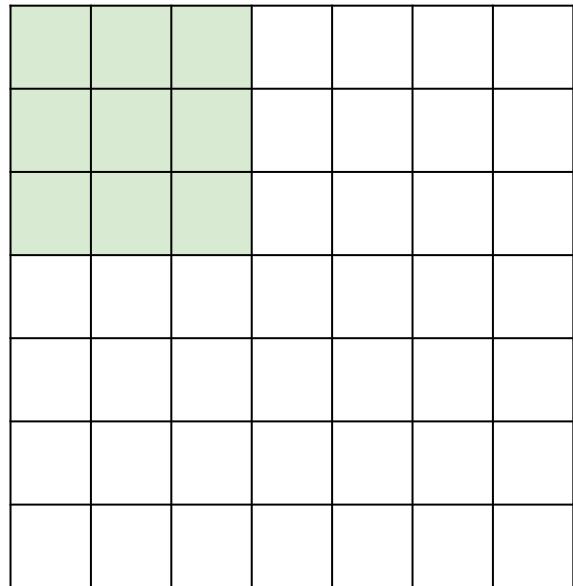


A closer look at spatial dimensions:



A closer look at spatial dimensions:

7

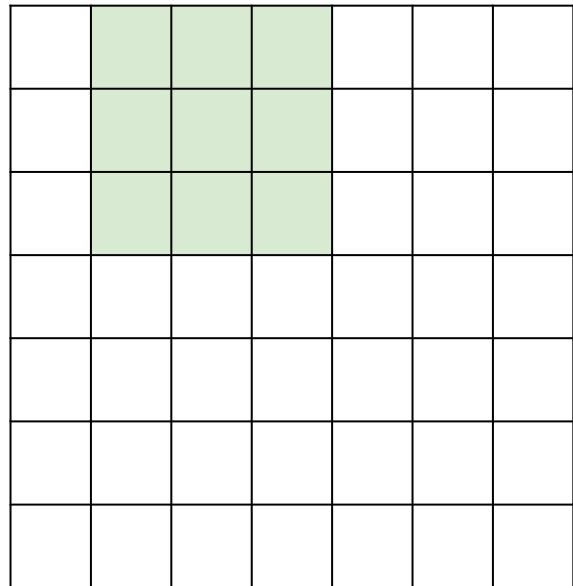


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

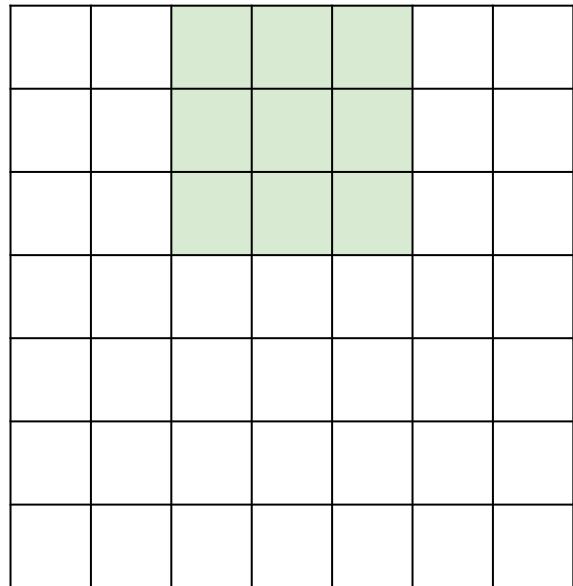


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

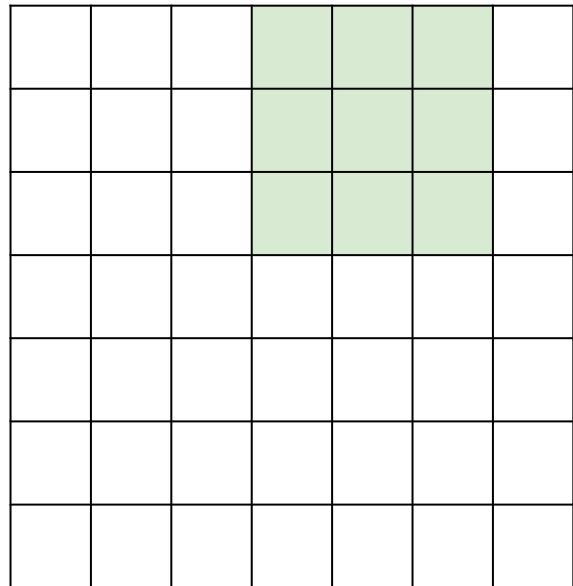


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

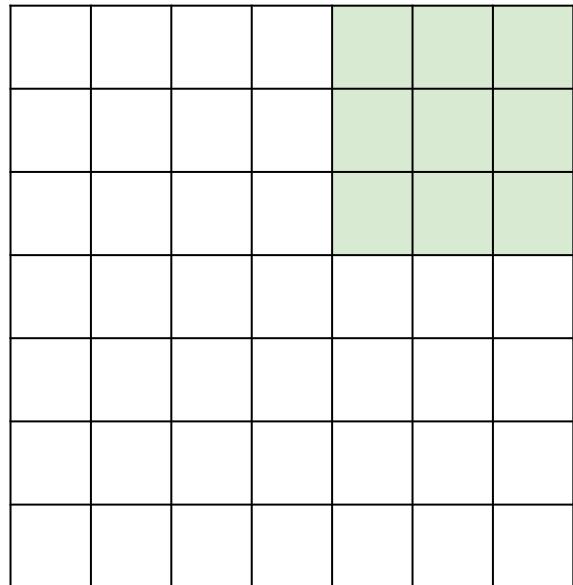


7x7 input (spatially)
assume 3x3 filter

7

A closer look at spatial dimensions:

7

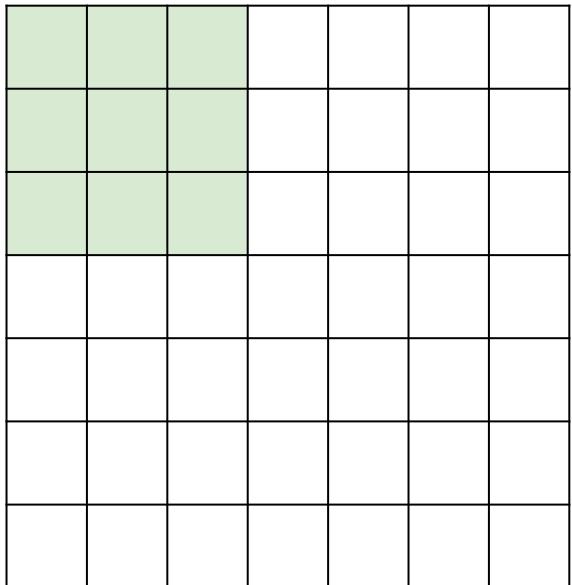


7x7 input (spatially)
assume 3x3 filter

=> 5x5 output

A closer look at spatial dimensions:

7

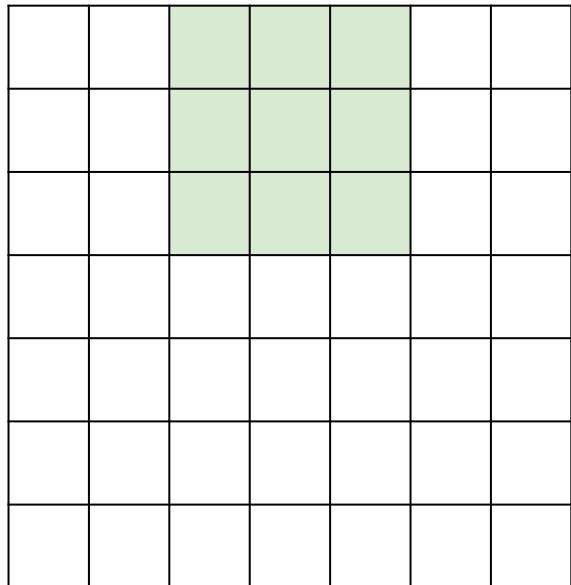


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:

7

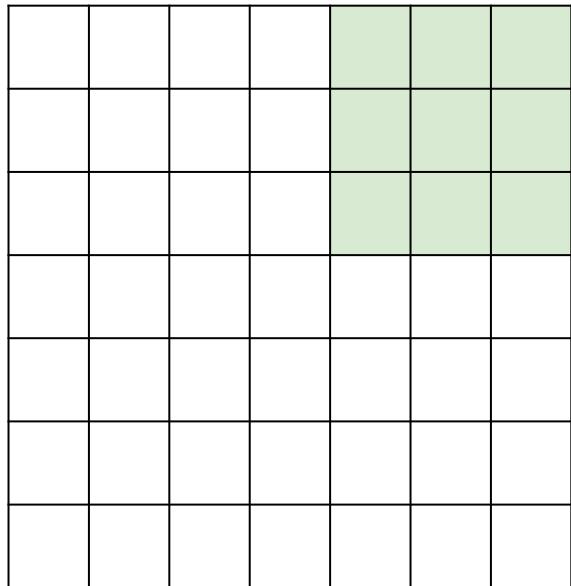


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:

7

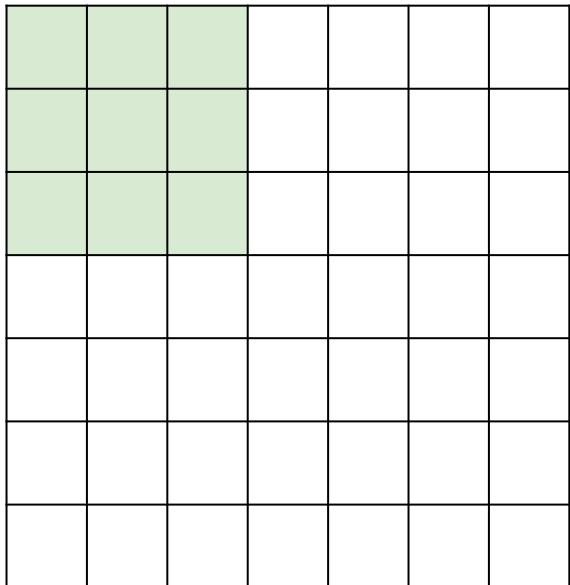


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:

7

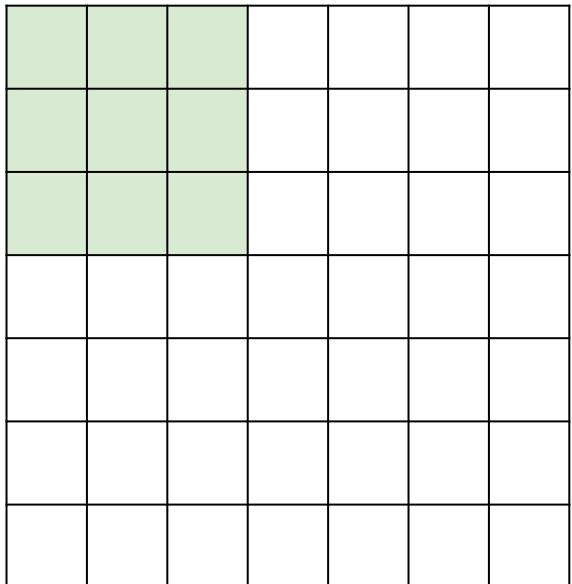


7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:

7



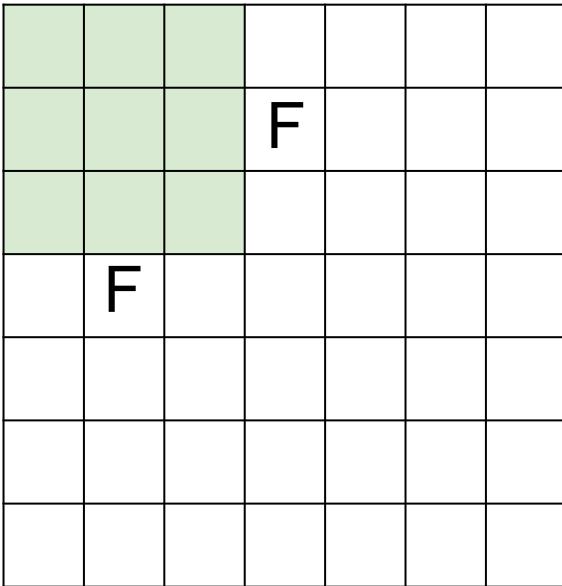
7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

doesn't fit!

cannot apply 3x3 filter on
7x7 input with stride 3.

N



N

Output size:
(N - F) / stride + 1

e.g. N = 7, F = 3:

$$\text{stride 1} \Rightarrow (7 - 3)/1 + 1 = 5$$

$$\text{stride 2} \Rightarrow (7 - 3)/2 + 1 = 3$$

$$\text{stride 3} \Rightarrow (7 - 3)/3 + 1 = 2.33 :\backslash$$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with **stride 1**

pad with 1 pixel border => what is the output?

(recall:)

$$(N - F) / \text{stride} + 1$$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with **stride 1**

pad with 1 pixel border => what is the output?

7x7 output!

(recall:)

$$(N + 2P - F) / \text{stride} + 1$$

In practice: Common to zero pad the border

0	0	0	0	0	0		
0							
0							
0							
0							

e.g. input 7x7

3x3 filter, applied with stride 1

pad with 1 pixel border => what is the output?

7x7 output!

in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with $(F-1)/2$. (will preserve size spatially)

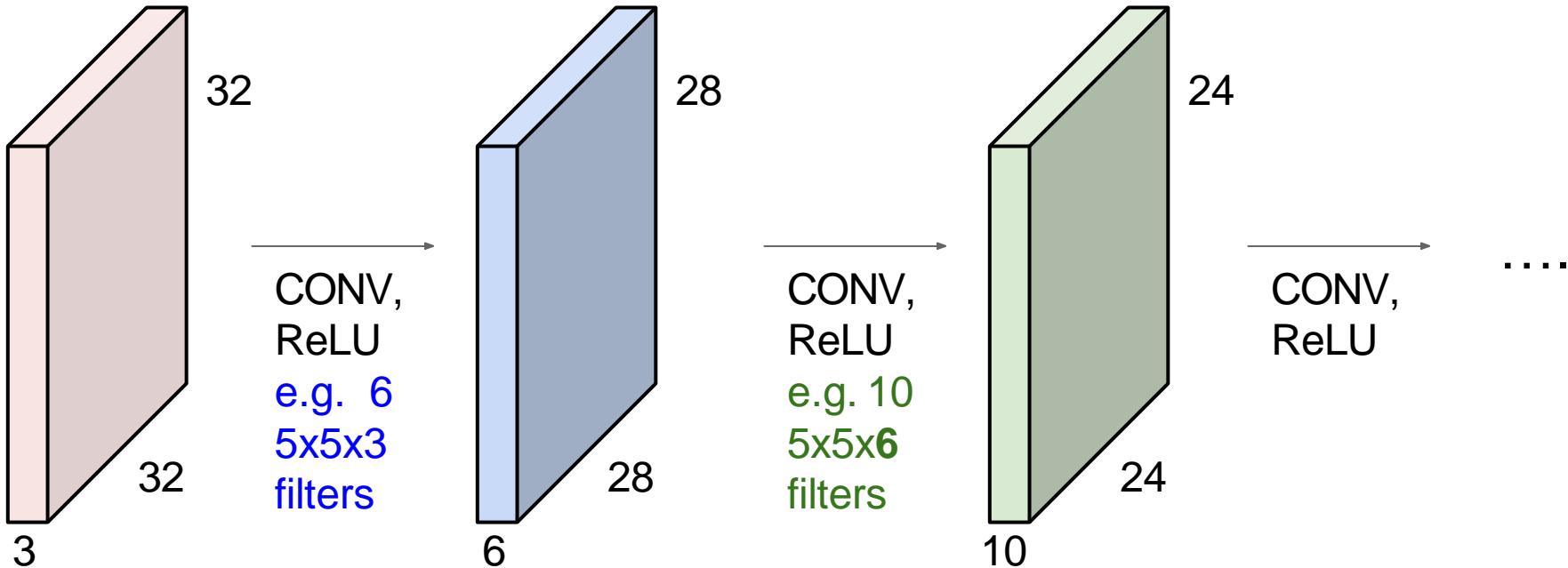
e.g. $F = 3 \Rightarrow$ zero pad with 1

$F = 5 \Rightarrow$ zero pad with 2

$F = 7 \Rightarrow$ zero pad with 3

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.

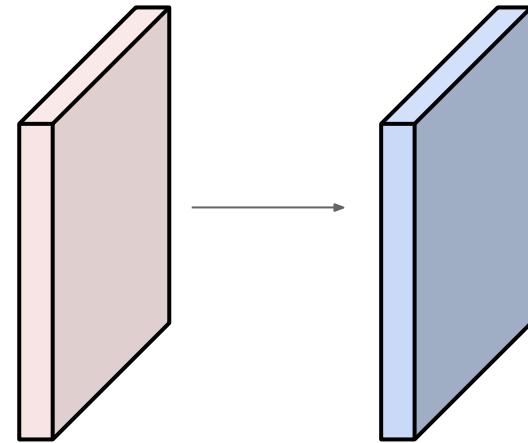


Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

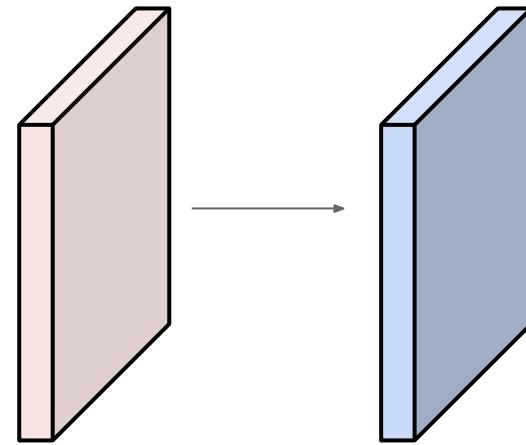
Output volume size: ?



Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad **2**



Output volume size:

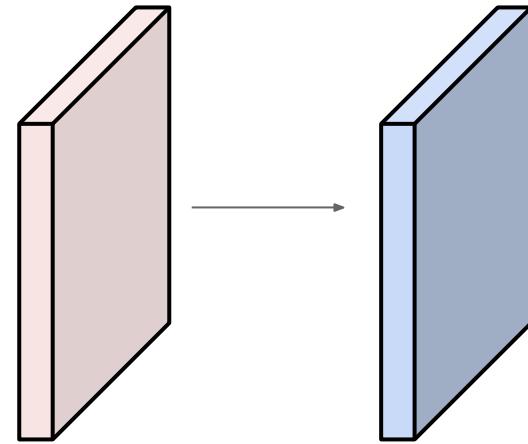
$(32+2*2-5)/1+1 = 32$ spatially, so

32x32x10

Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

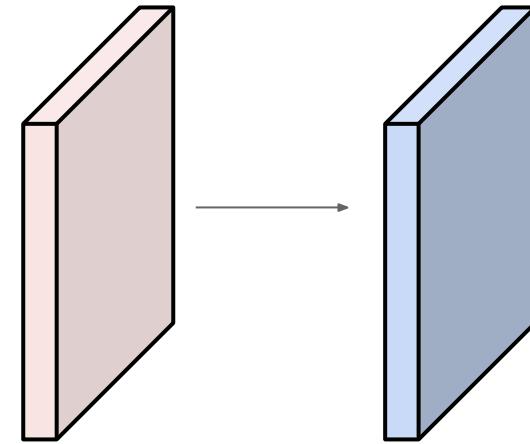


Number of parameters in this layer?

Examples time:

Input volume: **32x32x3**

10 5x5 filters with stride 1, pad 2

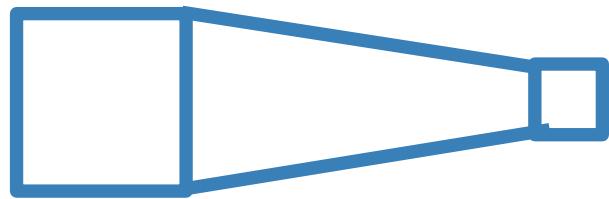


Number of parameters in this layer?

each filter has $5*5*3 + 1 = 76$ params (+1 for bias)
=> $76*10 = 760$

Receptive Fields

For convolution with kernel size K, each element in the output depends on a $K \times K$ **receptive field** in the input

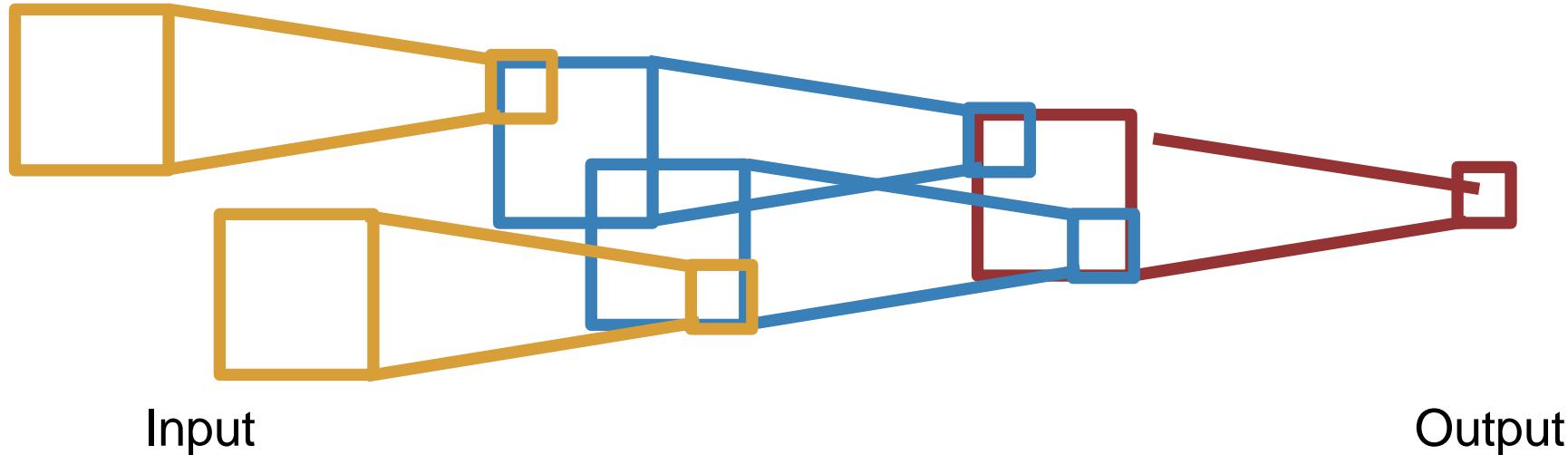


Input

Output

Receptive Fields

Each successive convolution adds $K - 1$ to the receptive field size
With L layers the receptive field size is $1 + L * (K - 1)$



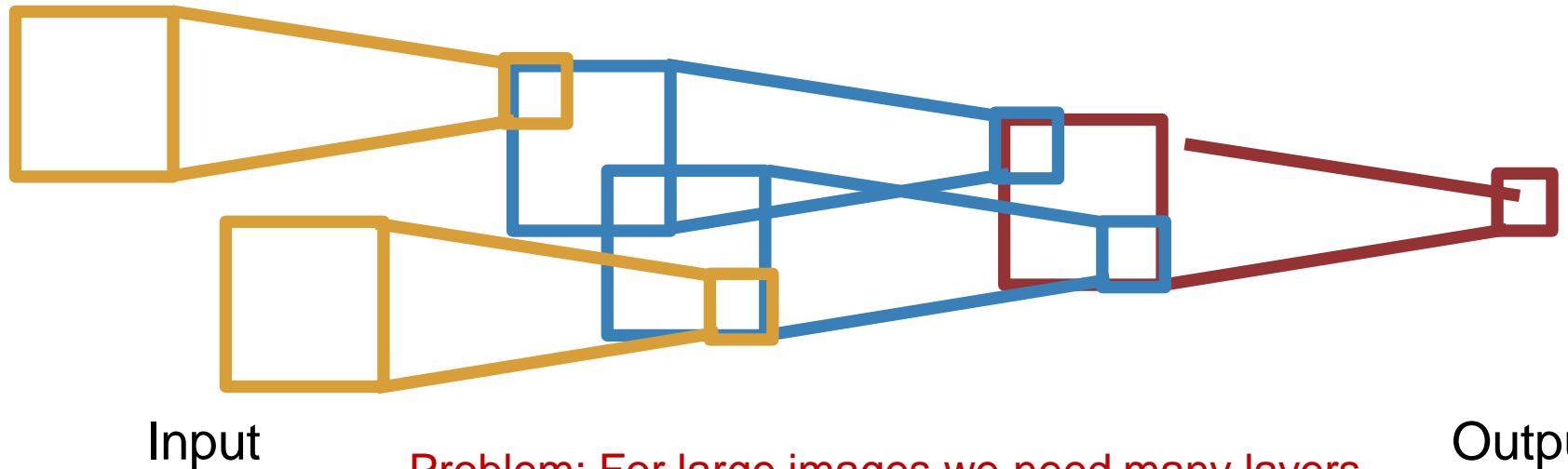
Input

Output

Be careful – “receptive field in the input” vs. “receptive field in the previous layer”

Receptive Fields

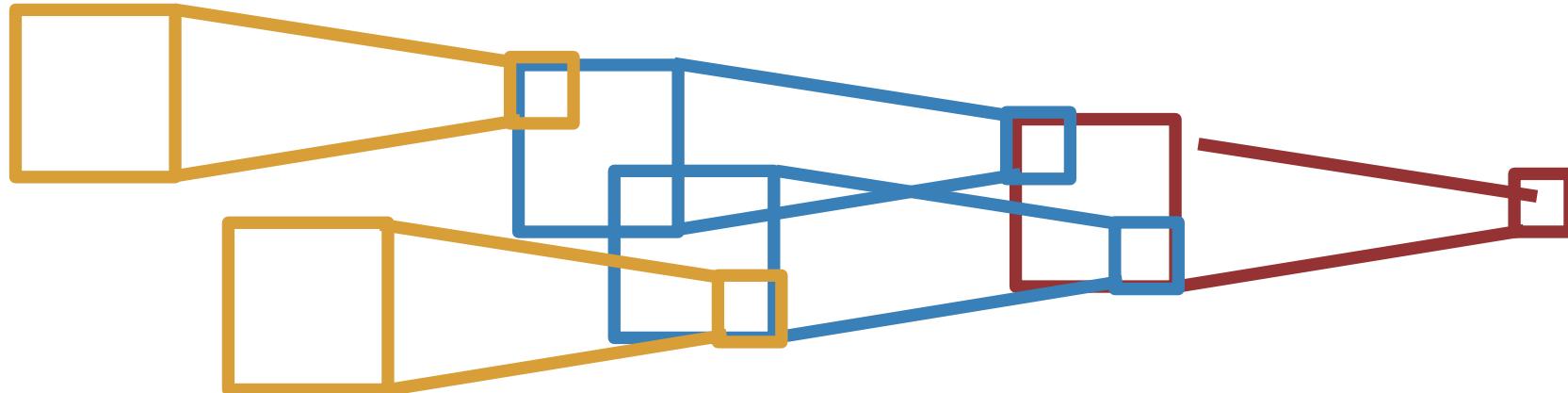
Each successive convolution adds $K - 1$ to the receptive field size
With L layers the receptive field size is $1 + L * (K - 1)$



Problem: For large images we need many layers
for each output to “see” the whole image

Receptive Fields

Each successive convolution adds $K - 1$ to the receptive field size
With L layers the receptive field size is $1 + L * (K - 1)$



Input

Problem: For large images we need many layers
for each output to “see” the whole image

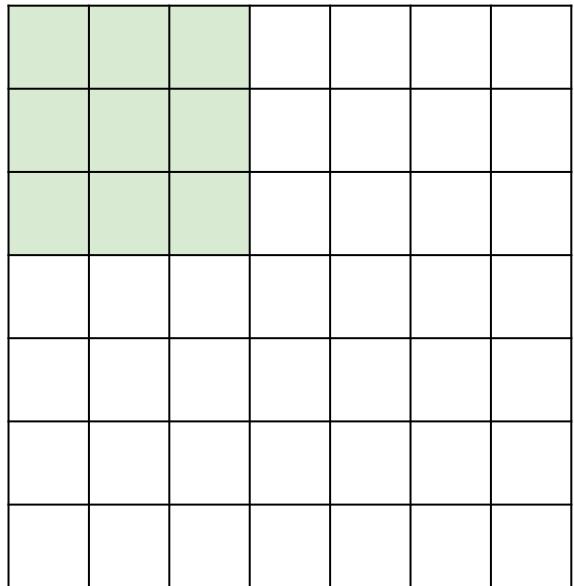
Solution: Downsample inside the network

Output

Slide inspiration: Justin Johnson

Solution: Strided Convolution

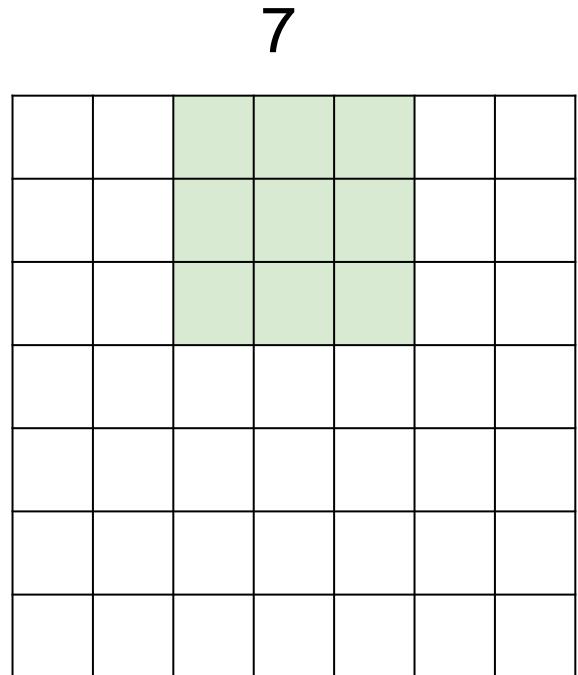
7



7

7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

Solution: Strided Convolution



7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

=> 3x3 output!

Convolution layer: summary

Let's assume input is $W_1 \times H_1 \times C$

Conv layer needs 4 hyperparameters:

- Number of filters **K**
- The filter size **F**
- The stride **S**
- The zero padding **P**

This will produce an output of $W_2 \times H_2 \times K$

where:

- $W_2 = (W_1 - F + 2P)/S + 1$
- $H_2 = (H_1 - F + 2P)/S + 1$

Number of parameters: F^2CK and K biases

Convolution layer: summary

Common settings:

Let's assume input is $W_1 \times H_1 \times C$

Conv layer needs 4 hyperparameters:

- Number of filters **K**
- The filter size **F**
- The stride **S**
- The zero padding **P**

K = (powers of 2, e.g. 32, 64, 128, 512)

- $F = 3, S = 1, P = 1$
- $F = 5, S = 1, P = 2$
- $F = 5, S = 2, P = ?$ (whatever fits)
- $F = 1, S = 1, P = 0$

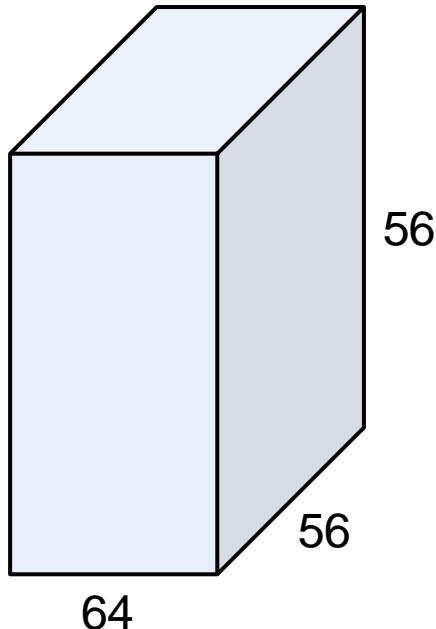
This will produce an output of $W_2 \times H_2 \times K$

where:

- $W_2 = (W_1 - F + 2P)/S + 1$
- $H_2 = (H_1 - F + 2P)/S + 1$

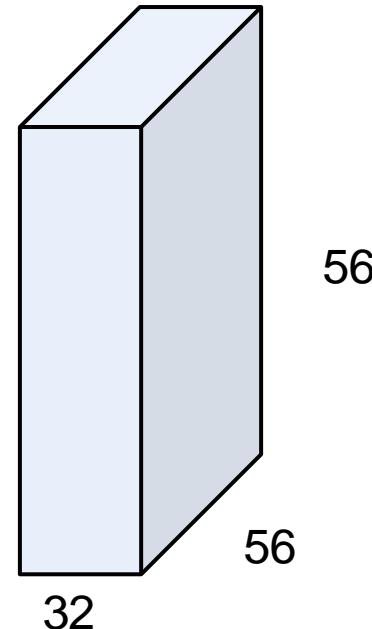
Number of parameters: F^2CK and K biases

(btw, 1x1 convolution layers make perfect sense)

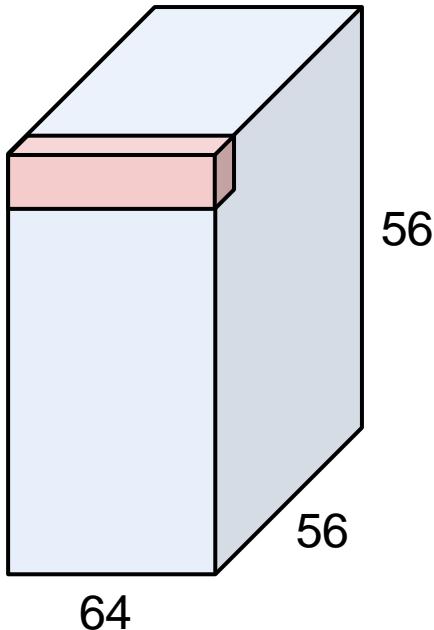


1x1 CONV
with 32 filters

(each filter has size
1x1x64, and performs a
64-dimensional dot
product)

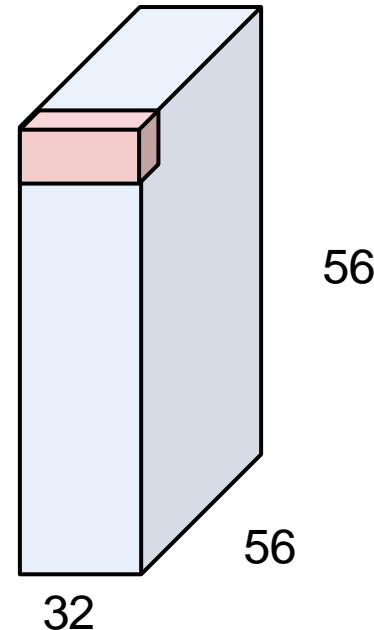


(btw, 1x1 convolution layers make perfect sense)



1x1 CONV
with 32 filters

(each filter has size
 $1 \times 1 \times 64$, and performs a
64-dimensional dot
product)



Example: CONV layer in PyTorch

Conv2d

```
CLASS torch.nn.Conv2d(in_channels, out_channels, kernel_size, stride=1, padding=0,  
dilation=1, groups=1, bias=True)
```

[SOURCE]

Applies a 2D convolution over an input signal composed of several input planes.

In the simplest case, the output value of the layer with input size (N, C_{in}, H, W) and output $(N, C_{\text{out}}, H_{\text{out}}, W_{\text{out}})$ can be precisely described as:

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) * \text{input}(N_i, k)$$

where $*$ is the valid 2D cross-correlation operator, N is a batch size, C denotes a number of channels, H is a height of input planes in pixels, and W is width in pixels.

- `stride` controls the stride for the cross-correlation, a single number or a tuple.
- `padding` controls the amount of implicit zero-paddings on both sides for `padding` number of points for each dimension.
- `dilation` controls the spacing between the kernel points; also known as the à trous algorithm. It is harder to describe, but this [link](#) has a nice visualization of what `dilation` does.
- `groups` controls the connections between inputs and outputs. `in_channels` and `out_channels` must both be divisible by `groups`. For example,
 - At `groups=1`, all inputs are convolved to all outputs.
 - At `groups=2`, the operation becomes equivalent to having two conv layers side by side, each seeing half the input channels, and producing half the output channels, and both subsequently concatenated.
 - At `groups= in_channels`, each input channel is convolved with its own set of filters, of size: $\left\lfloor \frac{C_{\text{out}}}{C_{\text{in}}} \right\rfloor$.

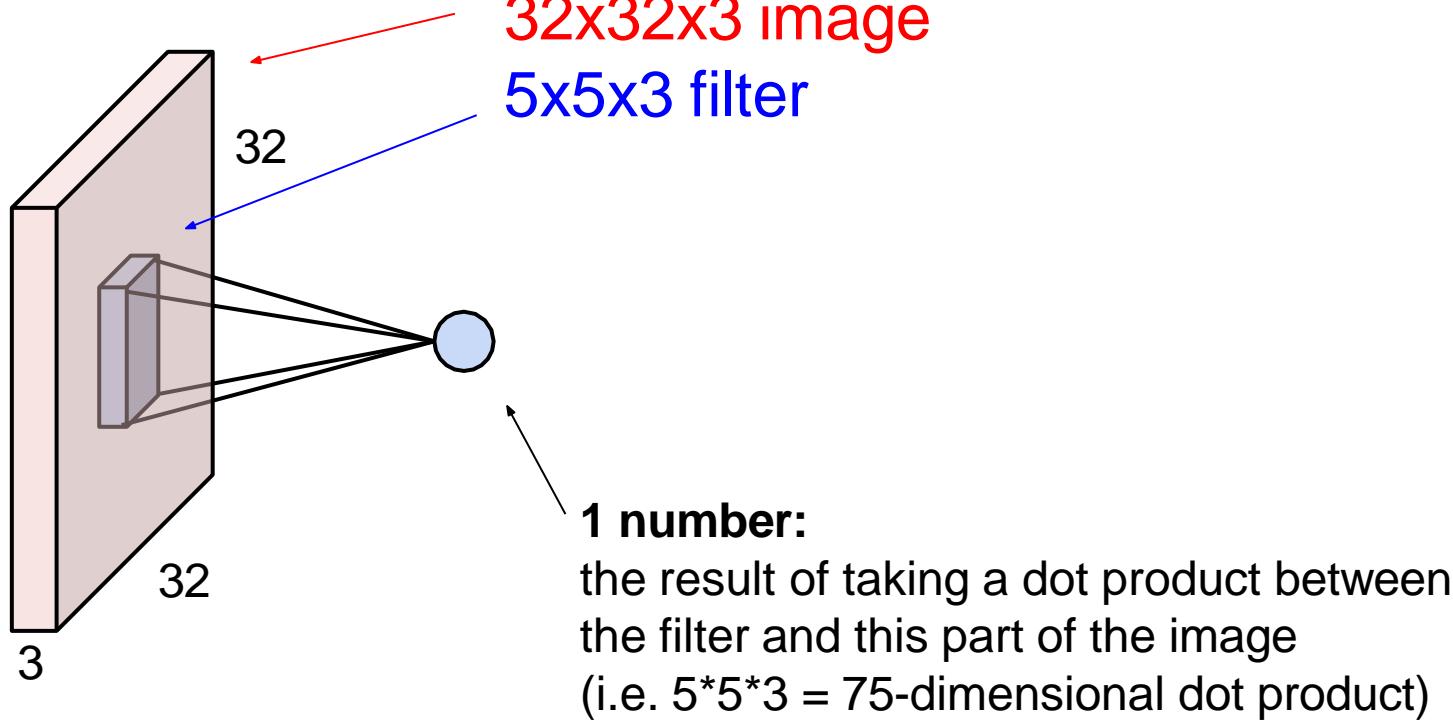
The parameters `kernel_size`, `stride`, `padding`, `dilation` can either be:

- a single `int` – in which case the same value is used for the height and width dimension
- a `tuple` of two `ints` – in which case, the first `int` is used for the height dimension, and the second `int` for the width dimension

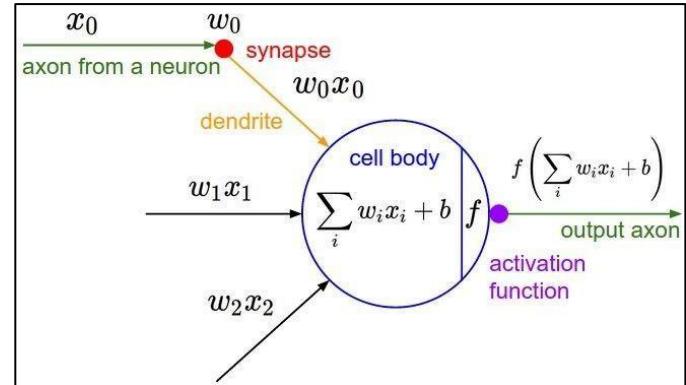
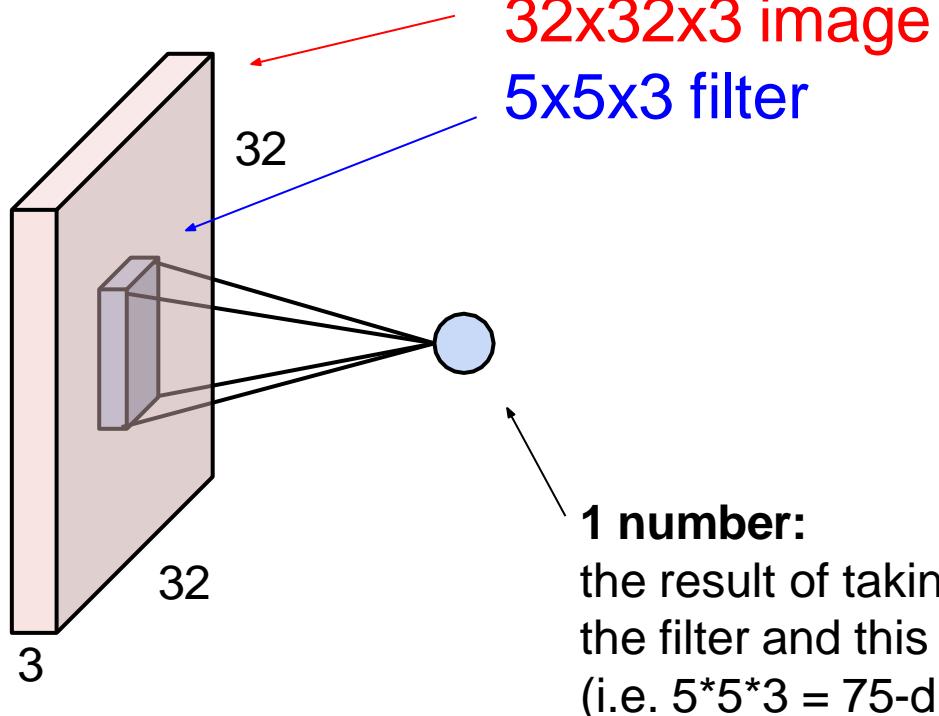
Conv layer needs 4 hyperparameters:

- Number of filters **K**
- The filter size **F**
- The stride **S**
- The zero padding **P**

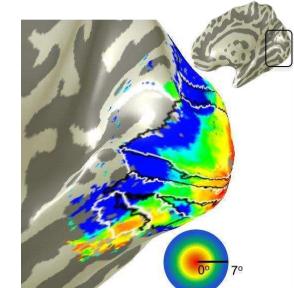
The brain/neuron view of CONV Layer



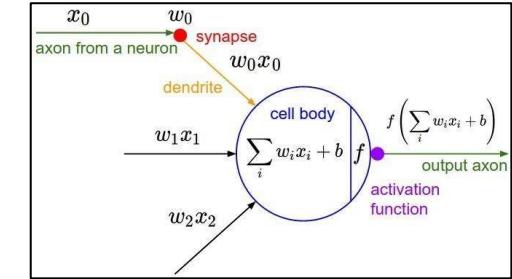
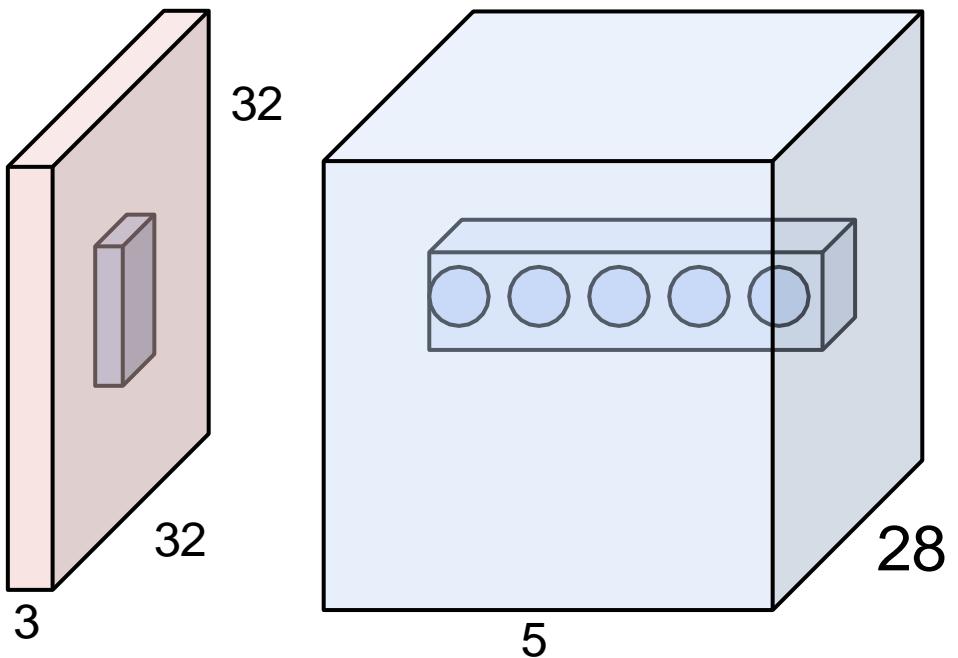
The brain/neuron view of CONV Layer



It's just a neuron with local connectivity...



The brain/neuron view of CONV Layer



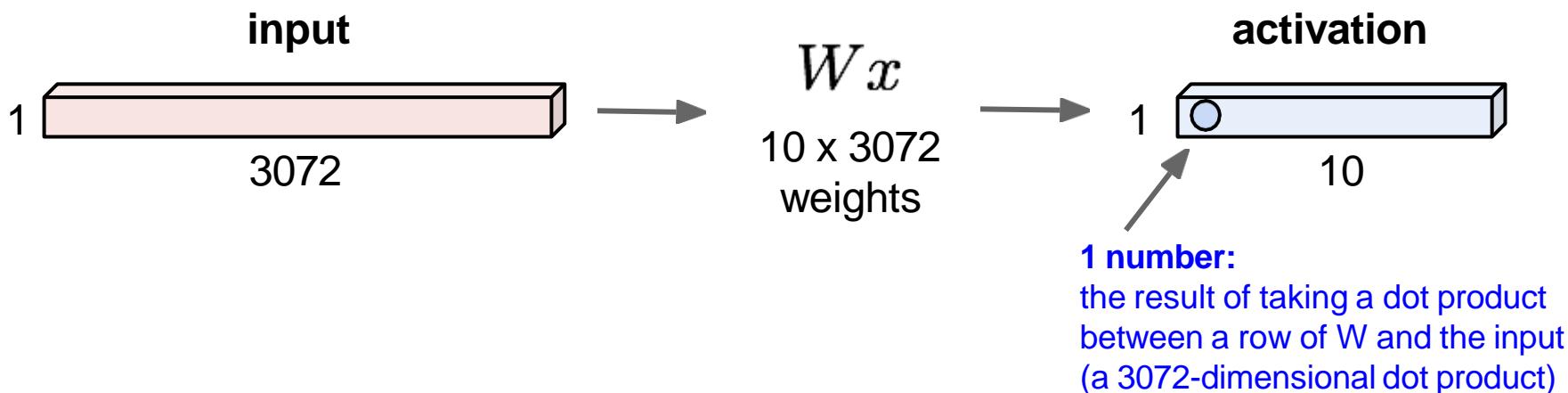
E.g. with 5 filters,
CONV layer consists of
neurons arranged in a 3D grid
($28 \times 28 \times 5$)

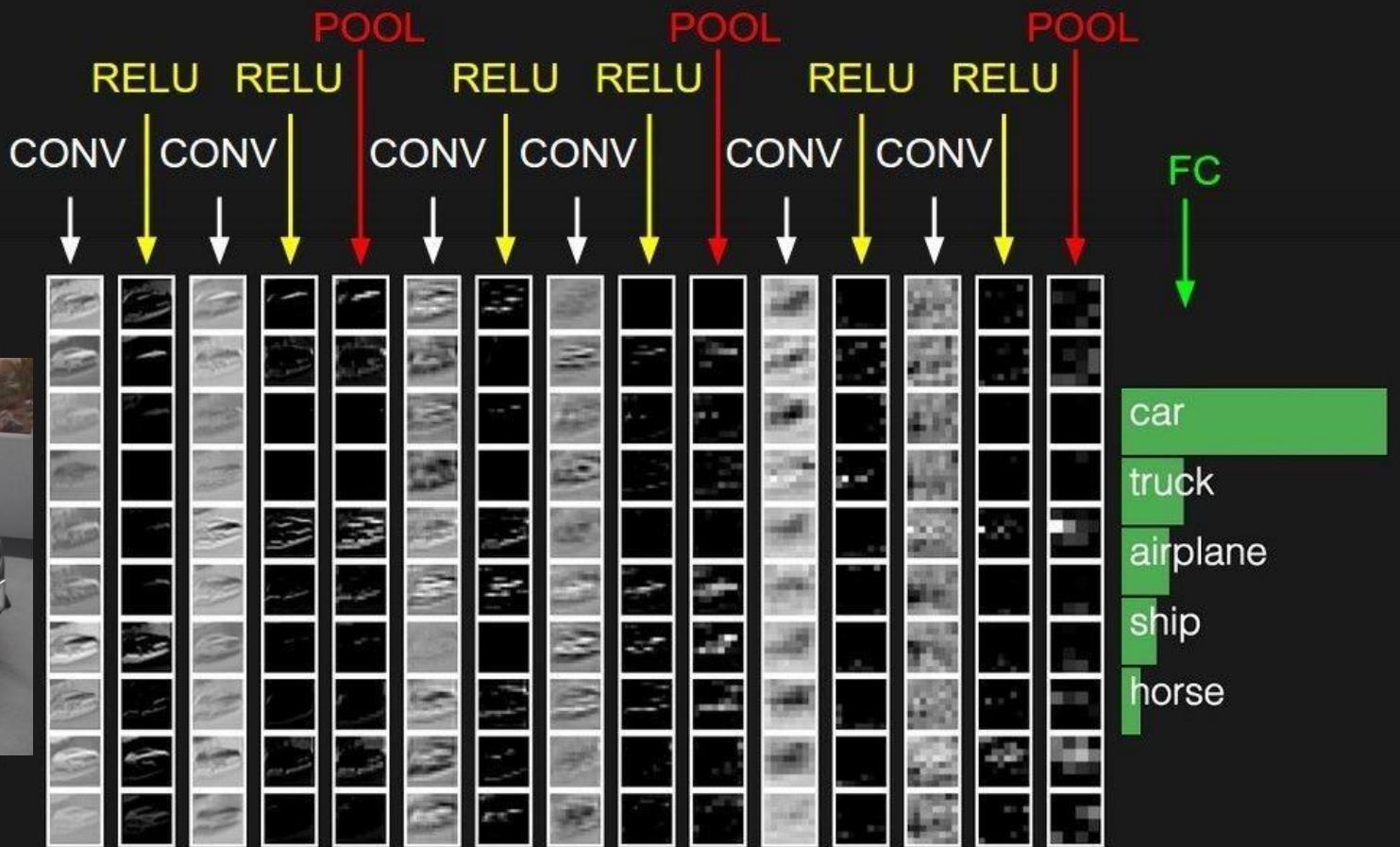
There will be 5 different
neurons all looking at the same
region in the input volume

Reminder: Fully Connected Layer

32x32x3 image -> stretch to 3072 x 1

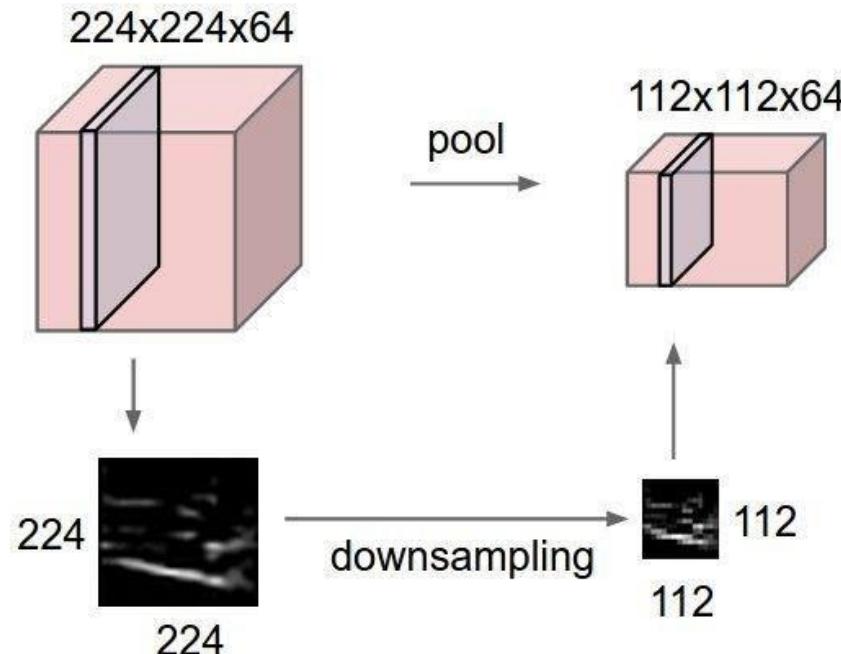
Each neuron looks at the full input volume





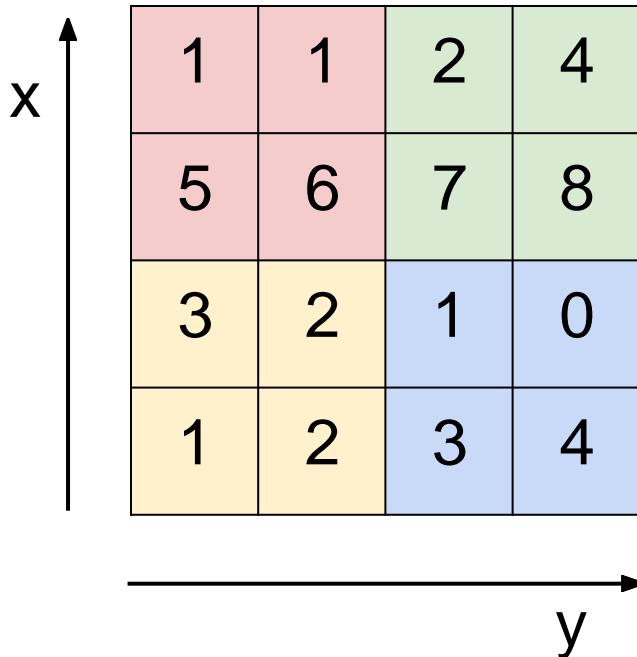
Pooling layer

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



MAX POOLING

Single depth slice



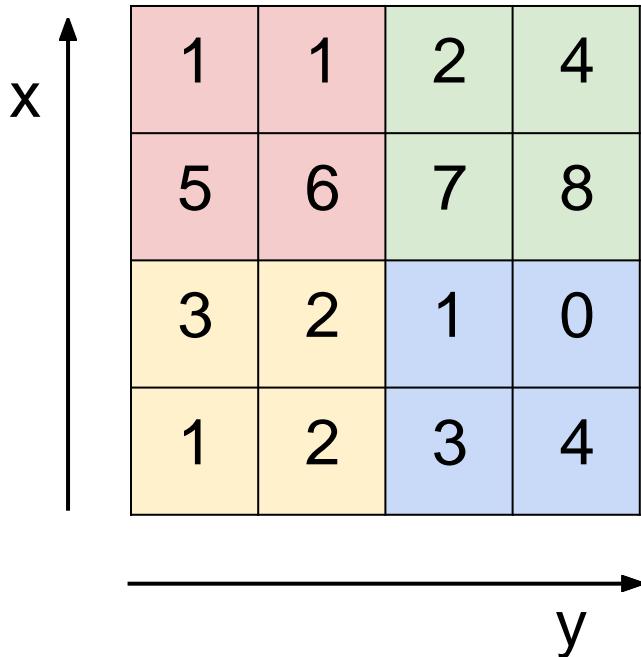
max pool with 2x2 filters
and stride 2

The output tensor after applying a 2x2 max pooling filter with stride 2. It contains four cells, each being the maximum value from a 2x2 receptive field in the input. The top-left cell is 6 (from the 5, 6 row), the top-right is 8 (from the 7, 8 row), the bottom-left is 3 (from the 3, 2 row), and the bottom-right is 4 (from the 1, 0 row).

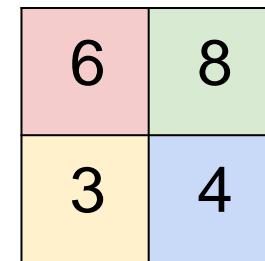
6	8
3	4

MAX POOLING

Single depth slice



max pool with 2x2 filters
and stride 2



- No learnable parameters
- Introduces spatial invariance

Pooling layer: summary

Let's assume input is $W_1 \times H_1 \times C$

Conv layer needs 2 hyperparameters:

- The spatial extent **F**
- The stride **S**

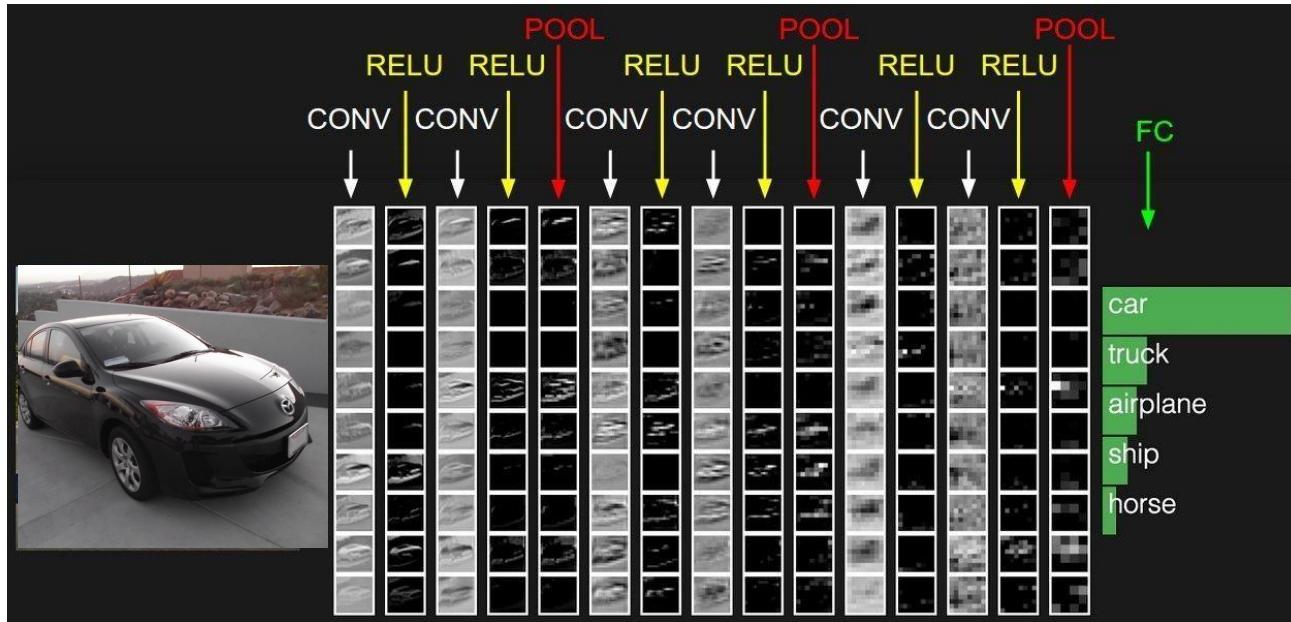
This will produce an output of $W_2 \times H_2 \times C$ where:

- $W_2 = (W_1 - F)/S + 1$
- $H_2 = (H_1 - F)/S + 1$

Number of parameters: 0

Fully Connected Layer (FC layer)

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



[ConvNetJS demo: training on CIFAR-10]

ConvNetJS CIFAR-10 demo

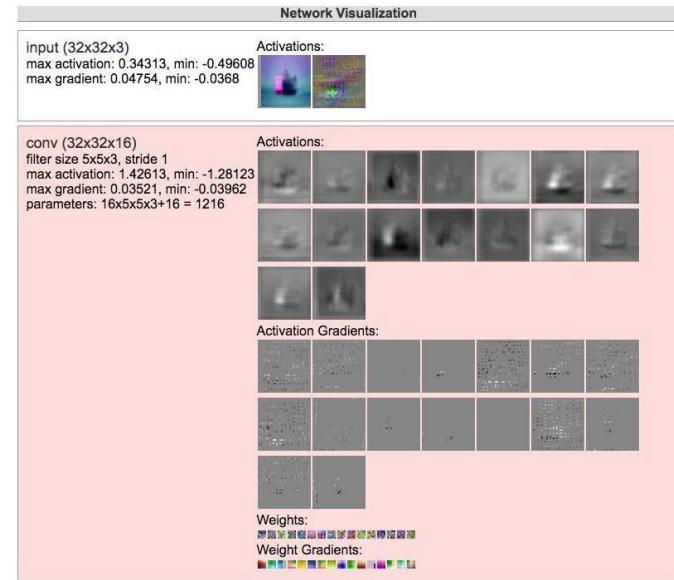
Description

This demo trains a Convolutional Neural Network on the [CIFAR-10 dataset](#) in your browser, with nothing but Javascript. The state of the art on this dataset is about 90% accuracy and human performance is at about 94% (not perfect as the dataset can be a bit ambiguous). I used [this python script](#) to parse the [original files](#) (python version) into batches of images that can be easily loaded into page DOM with img tags.

This dataset is more difficult and it takes longer to train a network. Data augmentation includes random flipping and random image shifts by up to 2px horizontally and vertically.

By default, in this demo we're using Adadelta which is one of per-parameter adaptive step size methods, so we don't have to worry about changing learning rates or momentum over time. However, I still included the text fields for changing these if you'd like to play around with SGD+Momentum trainer.

Report questions/bugs/suggestions to [@karpathy](#).



<http://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html>

Summary

- ConvNets stack CONV,POOL,FC layers
- Trend towards smaller filters and deeper architectures
- Trend towards getting rid of POOL/FC layers (just CONV)
- Historically architectures looked like
 $[(CONV-RELU)^*N-POOL?]^*M-(FC-RELU)^*K, SOFTMAX$
where N is usually up to ~5, M is large, $0 \leq K \leq 2$.
- But recent advances such as ResNet/GoogLeNet have challenged this paradigm

Next time: CNN Architectures

