- Deep Learning:- Deep learning is used to define learning on multilayer structures that gradually (hierarchically) transform the input data representation into a form that allows for the grouping of similar and frequent data patterns (i.e. certain combinations of them) present in the input data for use in classification or regression (e.g. prediction).
- Deep structures consist of many (tens or even hundreds) layers that perform various transformations, selections and non-linear transformations, which distinguishes them from the so-called shallow structures, which usually consist of one, two or three layers of such transformations, and this learning is called shallow learning.
- These structures are often referred to as artificial neural networks, but it is worth noting that they have little in common with biological neural networks and the way data is processed in the brain, although some ideas have been inspired by biological processes.

- The structure of the deep network consists of successive layers that perform various transformations and operations in different order:
- adaptive filtration (in convolution layers - conv),
- selection (e.g. maximum value - maxpooling),
- calculations (e.g. average value - avgpooling),
- regularization (e.g. using dropout),
- normalization (e.g. by balancing the results in the softmax layer).
- As a result, there is a multi-stage process of transforming the input data representation into a form that enables the achievement of the set goals.
- There is no real intelligence here, and the idea is quite simple, but due to the large number of such transformations in different configurations, incredible results can be achieved!

- Convolutional Neural Networks:
- Share parameters - so the same features may be recognized in any part of the image!
- Use sparse connections, so the convolutional layers are not connected in all-to-all manner (densely/fully-connected), which saves a lot of parameters and allows to train the network faster.
- Outputs depend directly only on some selected areas of the input images, so the neurons can specialize in recognizing, but their position in the convolutional layer defines the location where the features have been found.

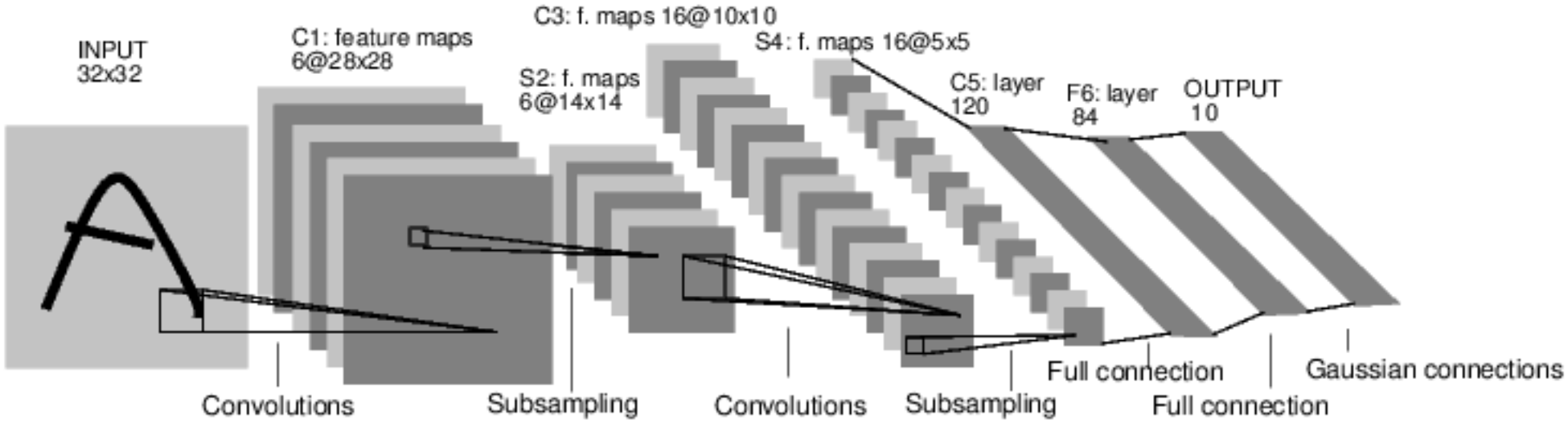
Convolutional Neural Networks

- Networks built specifically for problems with low dimensional (e.g. 2-*d*) grid-like local structure
  - Character recognition – where neighboring pixels will have high correlations and local features (edges, corners, etc.), while distant pixels (features) are un-correlated
  - Natural images have the property of being stationary, meaning that the statistics of one part of the image are the same as any other part
  - Some biological plausibility from visual cortex
  - While standard NN nodes take input from all nodes in the previous layer, CNNs enforce that a node receives only a small set of features which are spatially or temporally close to each other called *receptive fields* from one layer to the next (e.g. 3x3, 5x5), thus enforcing ability to handle local 2-D structure.
    - Can find edges, corners, endpoints, etc.
    - Good for problems with local 2-D structure, but lousy for general learning with abstract features having no prescribed feature ordering or locality

Convolutions

- Typical MLPs have a connection from every node in the previous layer, and the net value for a node is the scalar dot product of the inputs and weights (e.g. matrix multiply). Convolutional nets are somewhat different:
  - Nodes still do a scalar dot product (convolution) from the previous layer, but with only a small portion (receptive field) of the nodes in the previous layer – *Sparse representation*
  - Every node has the exact same weight values from the preceding layer – *Shared parameters*, tied weights, a LOT less unique weight values. Regularization by having same weights looking at more input situations
  - Each node has it's shared weight convolution computed on a receptive field slightly shifted, from that of it's neighbor, in the previous layer – *Translation invariance*.
  - Each node's convolution scalar is then passed through a non-linear activation function (ReLU, tanh, etc.)

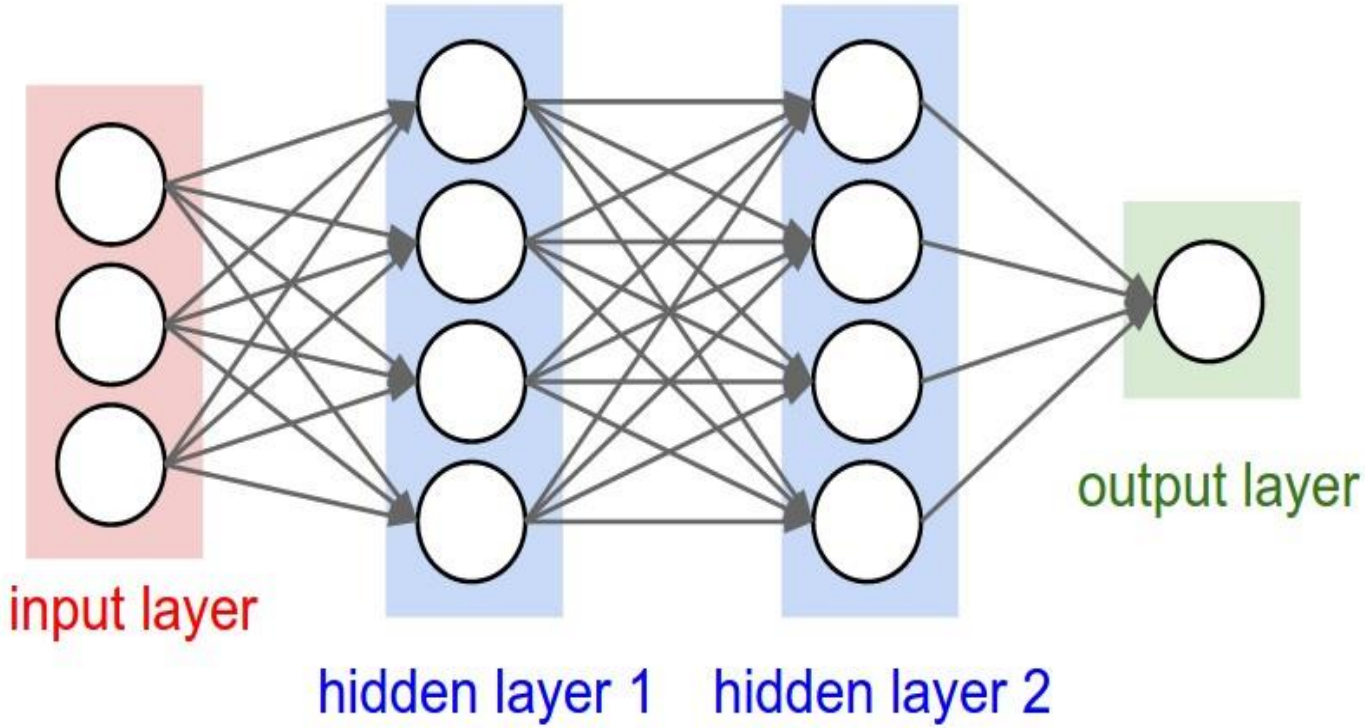
Convolutional Neural Networks (aka ConvNets, CNNs)



[LeNet-5, LeCun 1998]

Slides shamelessly borrowed from Karpathy, Ransato, Seitz, and Palmer

Neural Networks for Visual Data

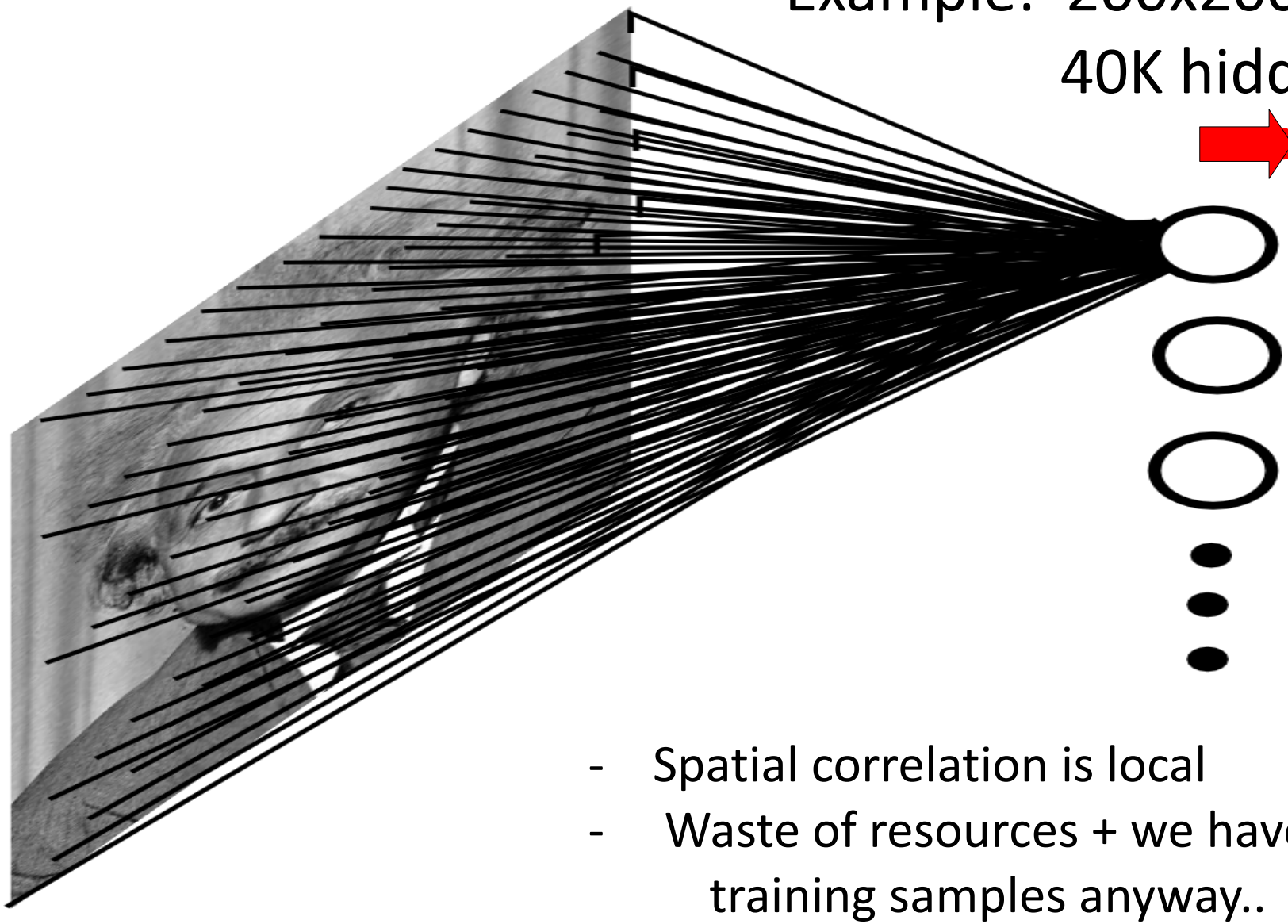


Fully Connected Layer

Example: 200x200 image

40K hidden units

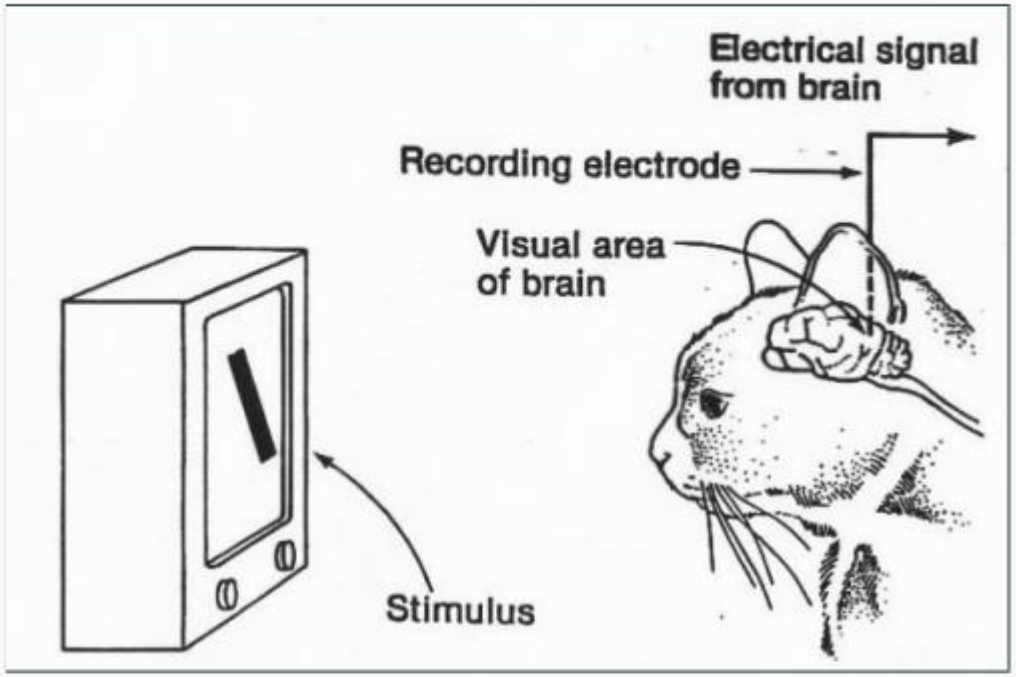
parameters!!!

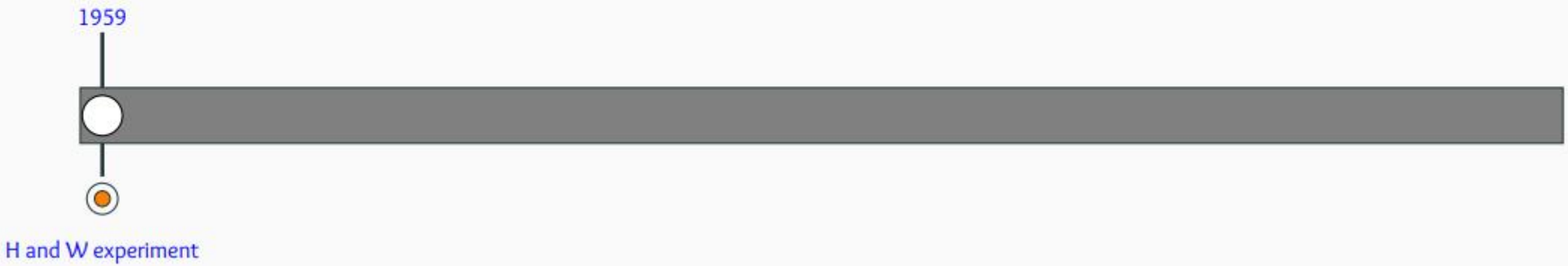


- Spatial correlation is local
- Waste of resources + we have not enough training samples anyway..

Hubel and Wiesel Experiment

Experimentally showed that each neuron has a fixed receptive field - i.e. a neuron will fire only in response to a visual stimuli in a specific region in the visual space [18]





Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify

Viewpoint variation

Scale variation

Deformation

Occlusion

Illumination conditions

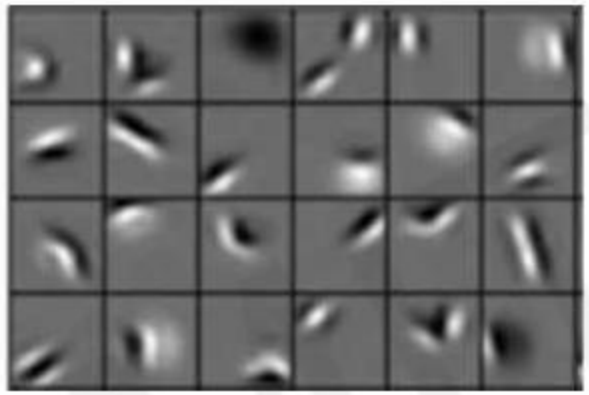
Background clutter

Intra-class variation

Learning Feature Representations

Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

Mid level features

Eyes, ears, nose

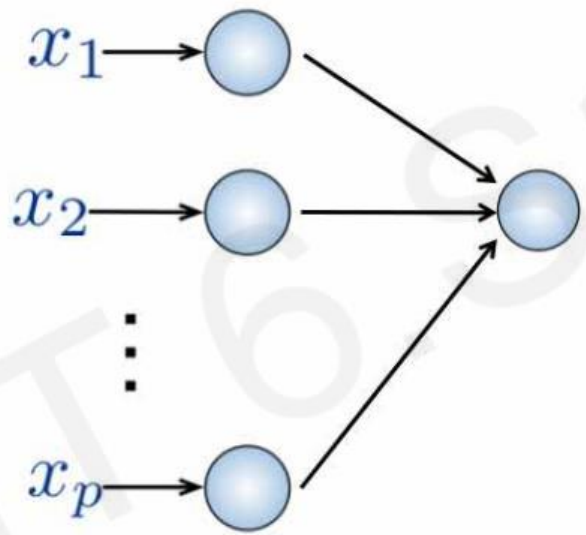
High level features

Facial structure

Fully Connected Neural Network

Input:

- 2D image
- Vector of pixel values



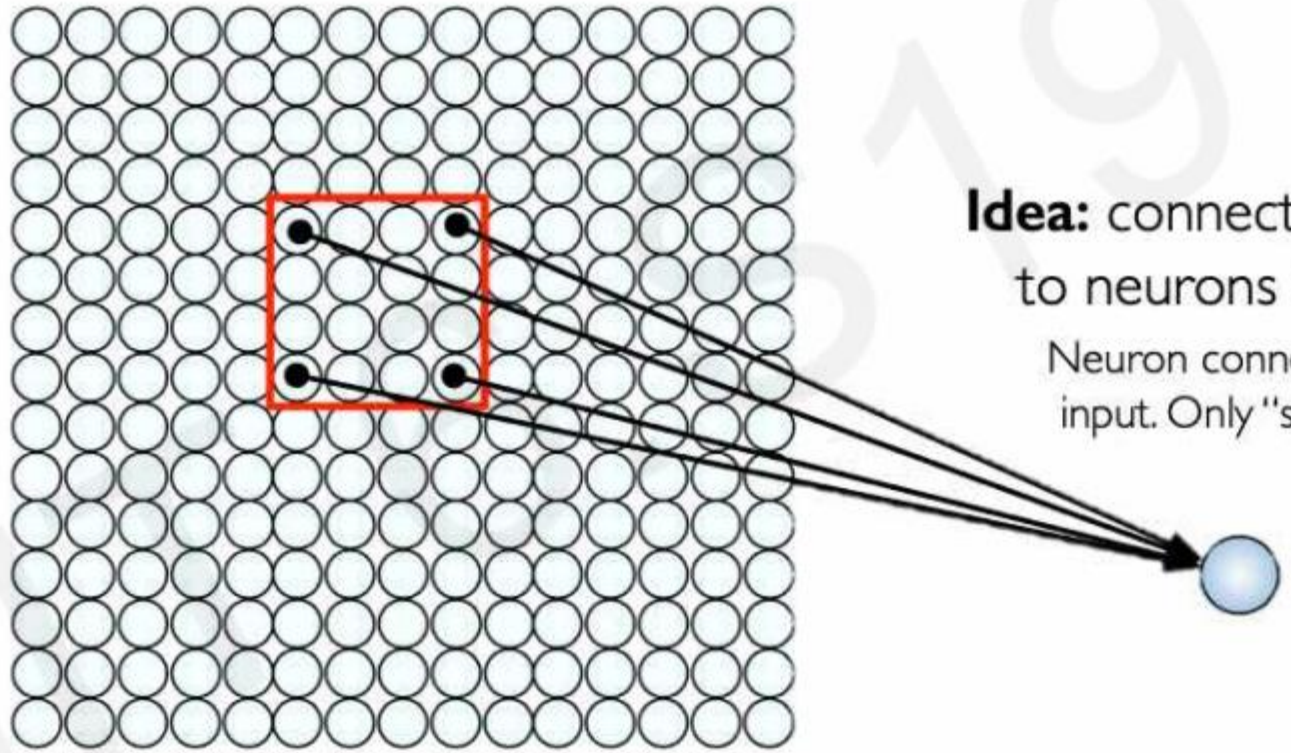
Fully Connected:

- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

How can we use **spatial structure** in the input to inform the architecture of the network?

Using Spatial Structure

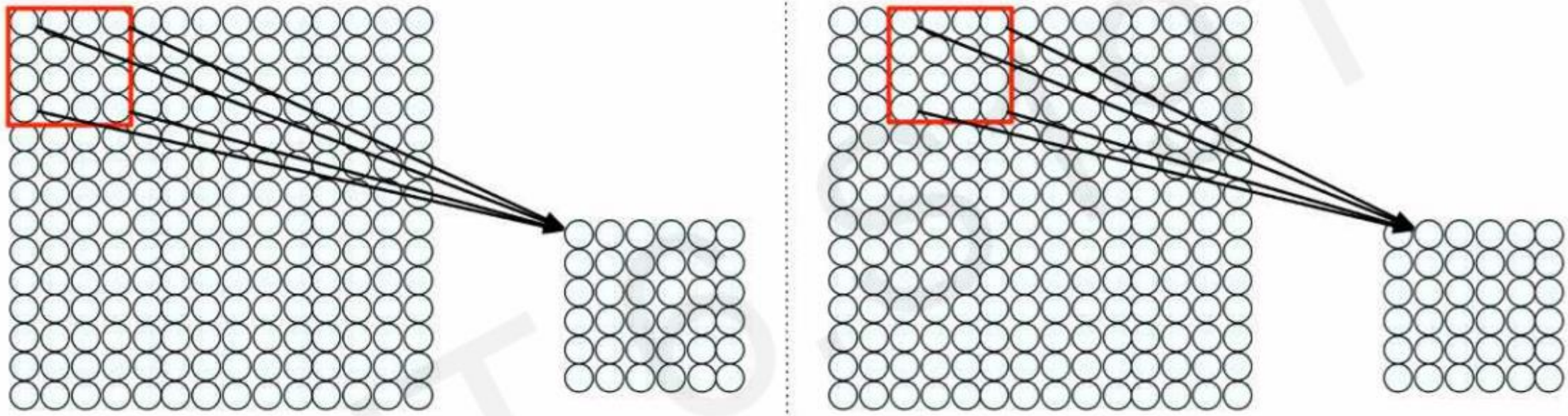
Input: 2D image.
Array of pixel values



Idea: connect patches of input to neurons in hidden layer.

Neuron connected to region of input. Only "sees" these values.

Using Spatial Structure



Connect patch in input layer to a single neuron in subsequent layer.
Use a sliding window to define connections.
How can we **weight** *the patch to detect particular features?*

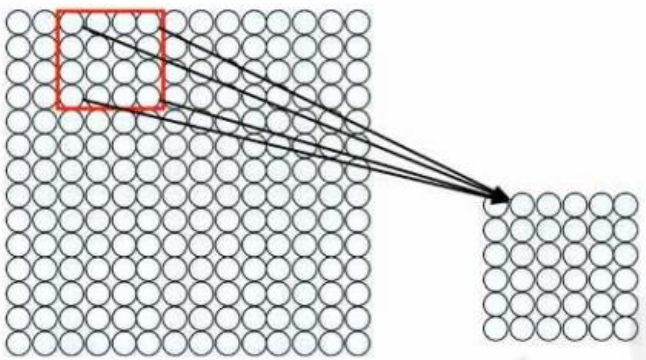
Applying Filters to Extract Features

1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) Spatially **share** parameters of each filter
(features that matter in one part of the input should matter elsewhere)

Feature Extraction with Convolution



- Filter of size 4x4 : 16 different weights
- Apply this same filter to 4x4 patches in input
- Shift by 2 pixels for next patch

This "patchy" operation is **convolution**

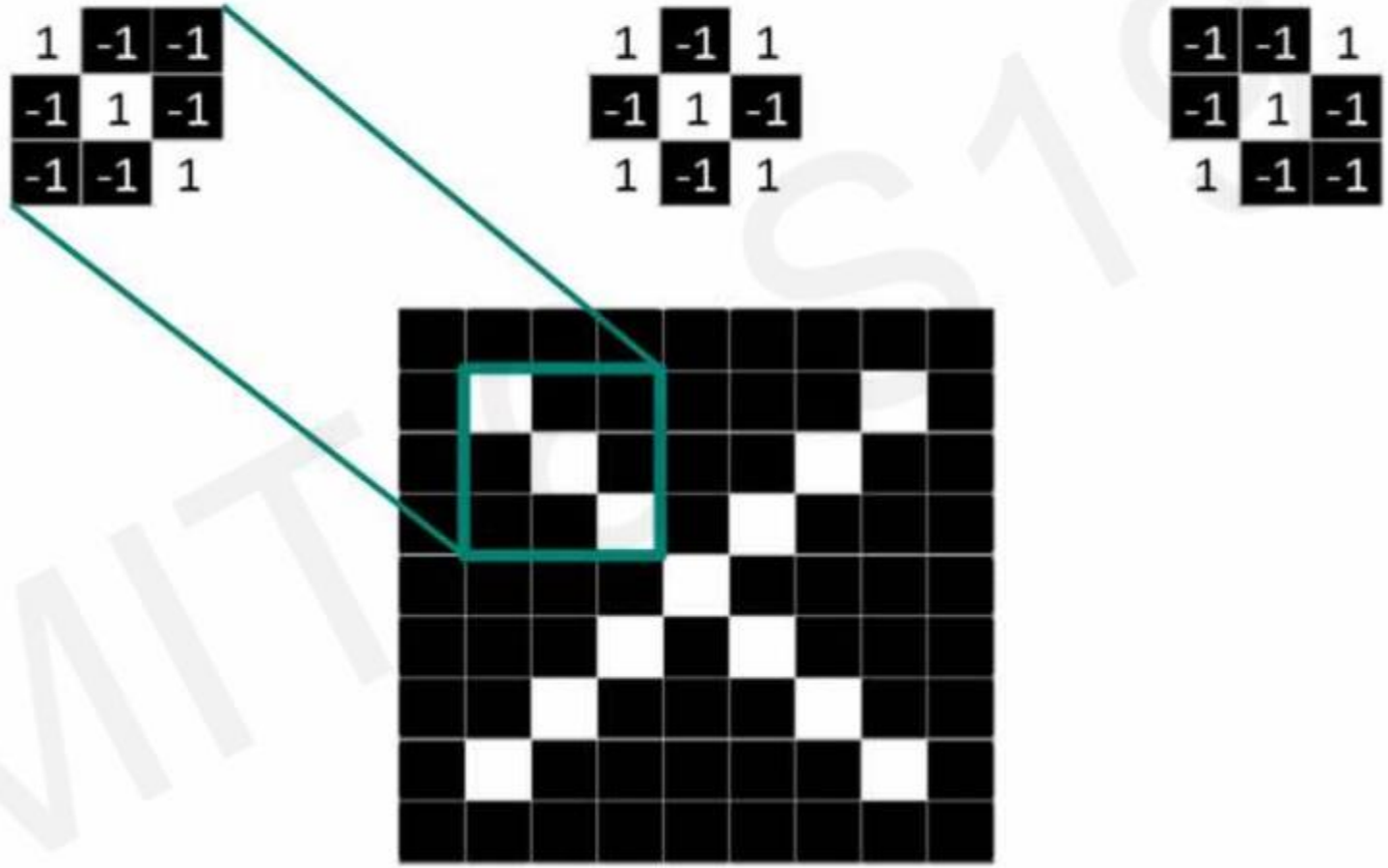
1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) **Spatially share** parameters of each filter

Filters to Detect X Features

filters



Filters and Convolutions

Filters are commonly used in computer graphics, and allow us to find edges and convolve images:

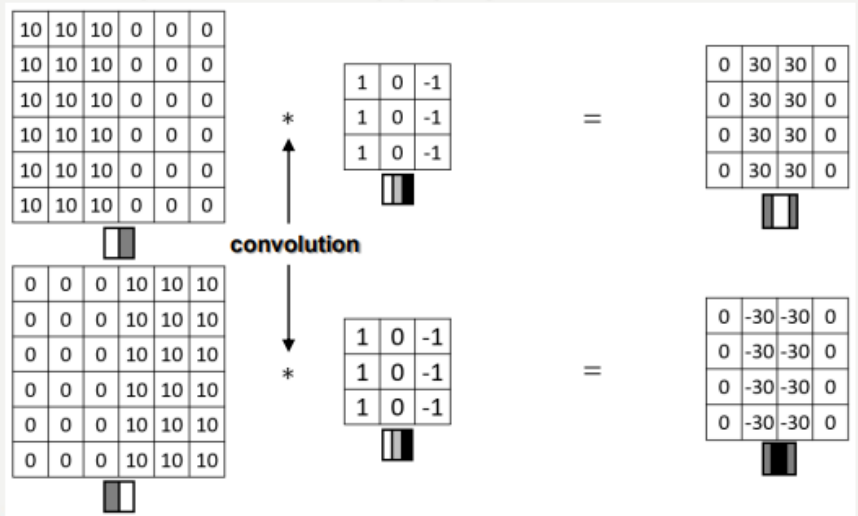
1	0	-1
1	0	-1
1	0	-1

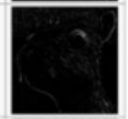
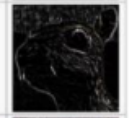
Vertical

1	1	1
0	0	0
-1	-1	-1

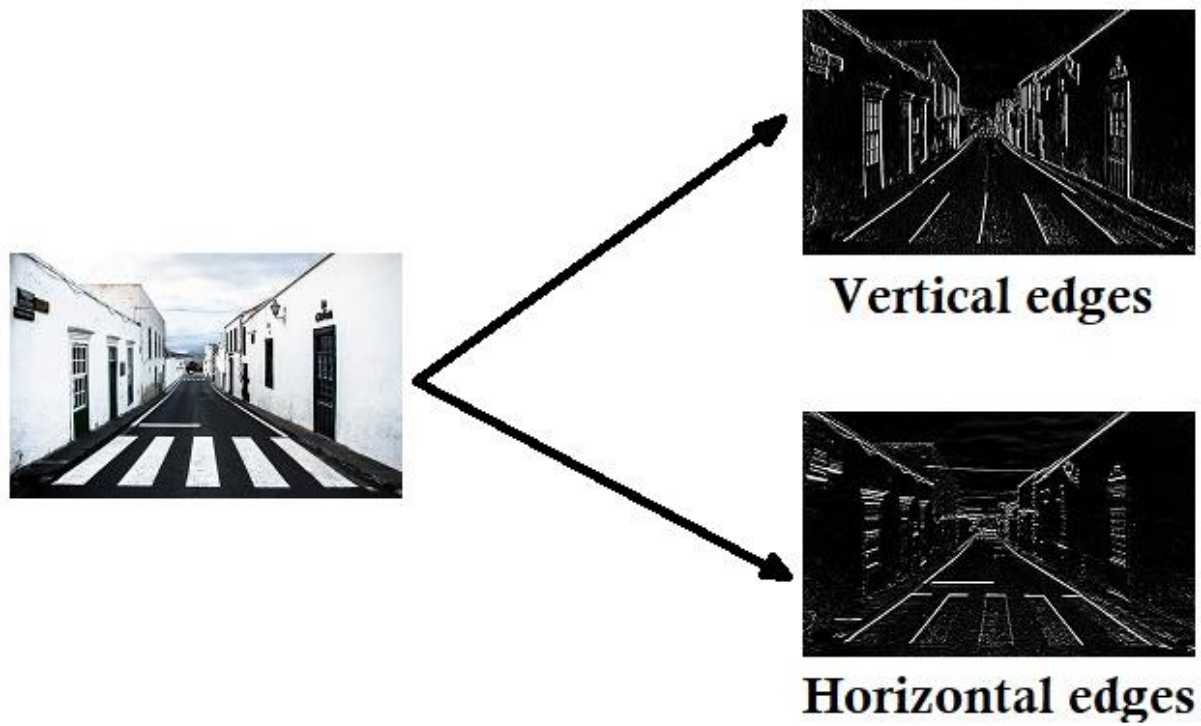
Horizontal

The example result of applying the vertical-line filter:



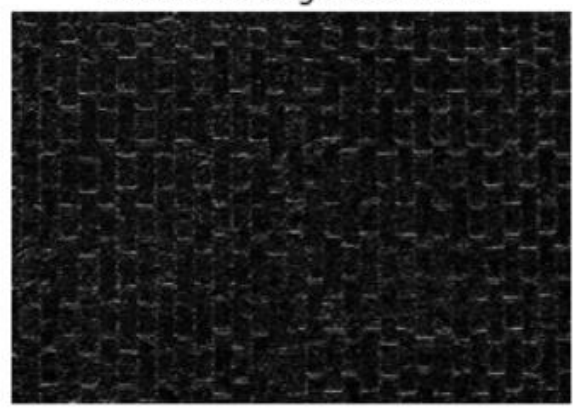
Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

In this post we will see how we can detect the edges in the picture, as the essential task in a computer vision.

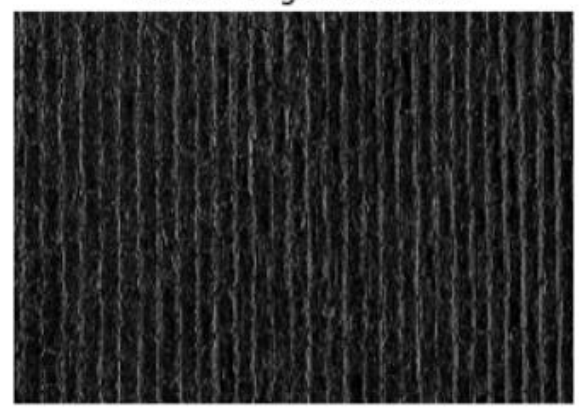


original image

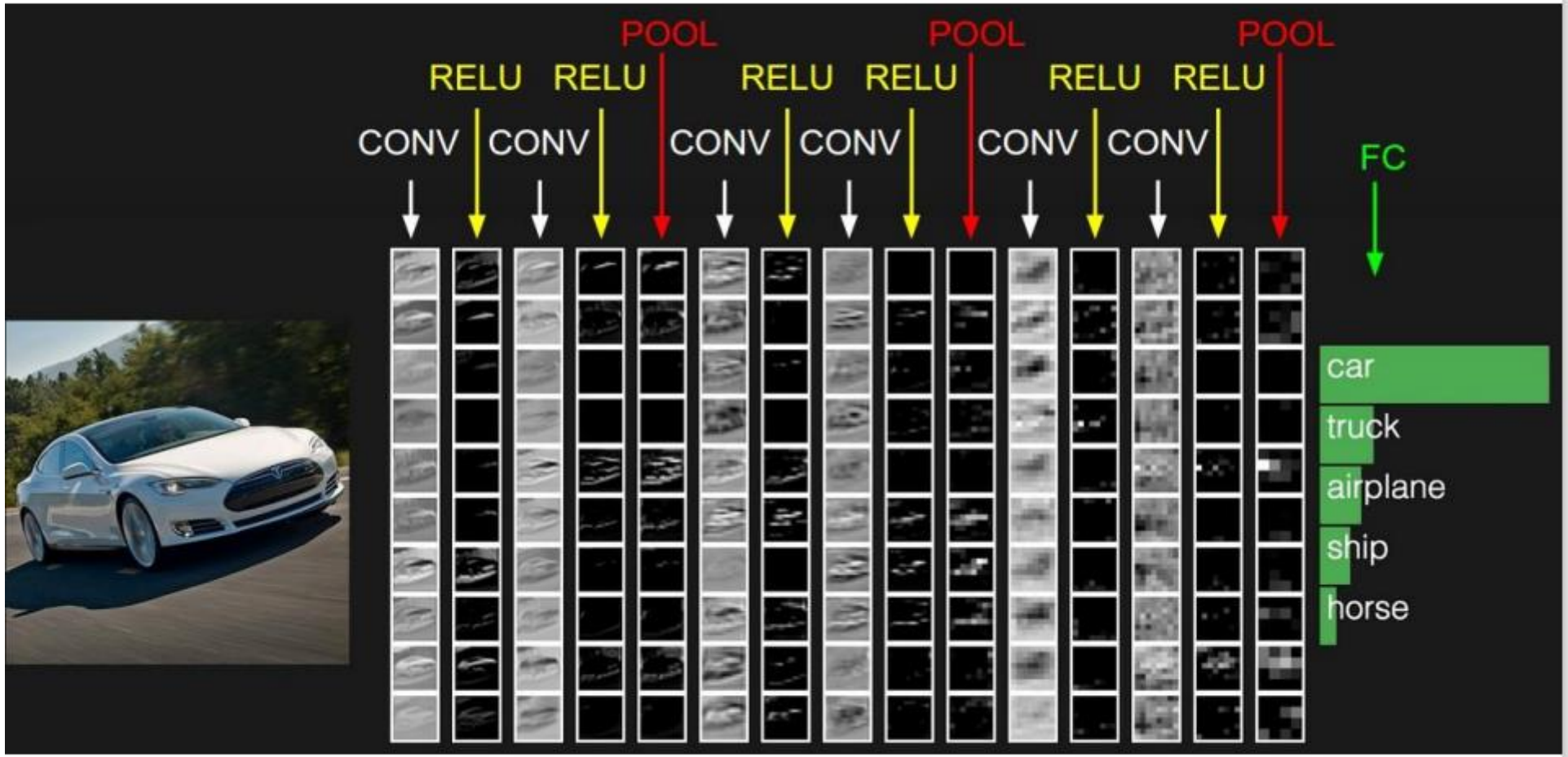
horizontal edge detection



vertical edge detection



Convolutional Neural Networks



Layers used to build ConvNets

Input Layer (Input image)

Convolutional Layer

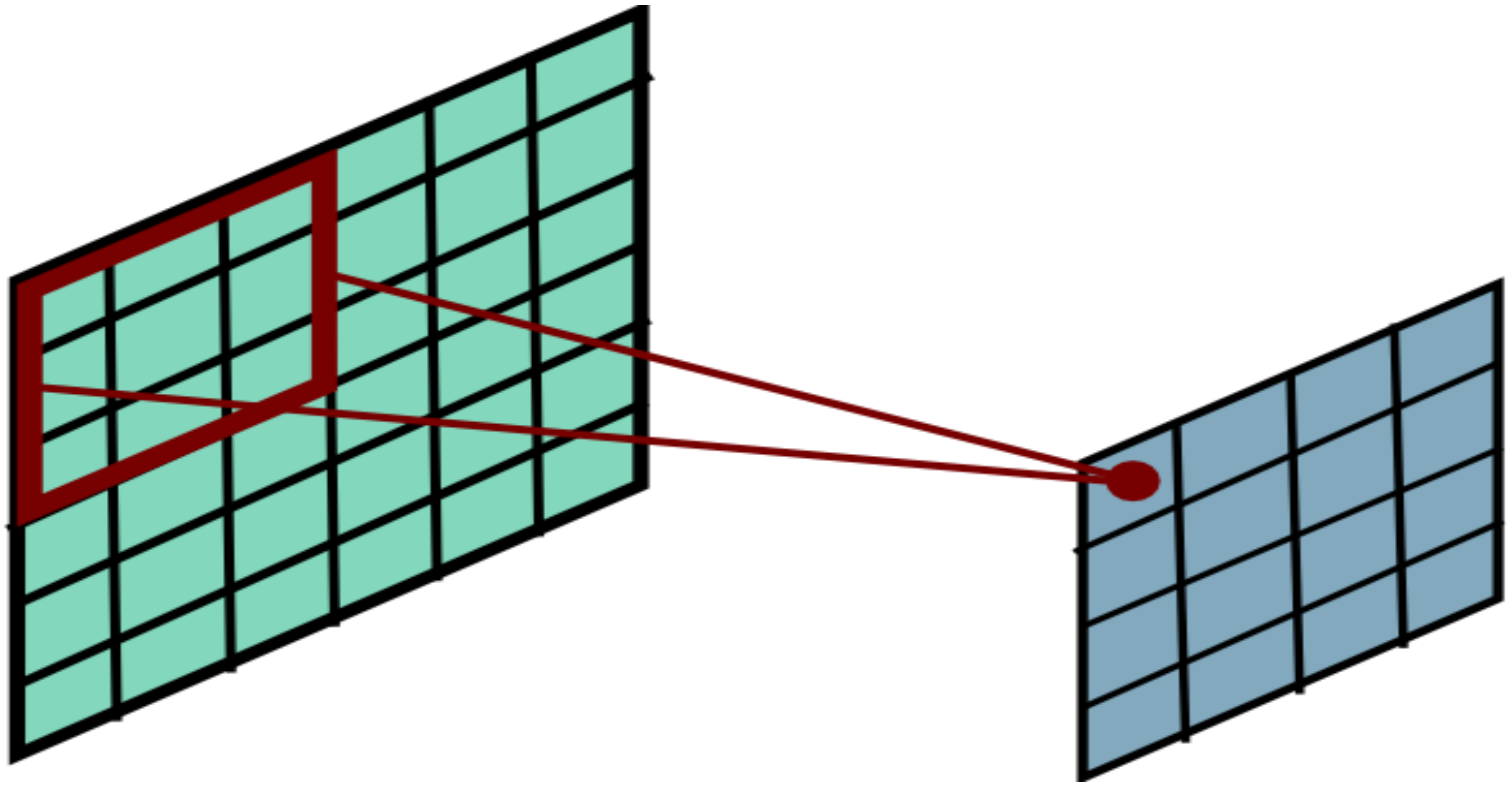
Non-linearity Layer (such as Sigmoid, Tanh, ReLU, PReLU, ELU, Swish, etc.)

Pooling Layer (such as Max Pooling, Average Pooling, etc.)

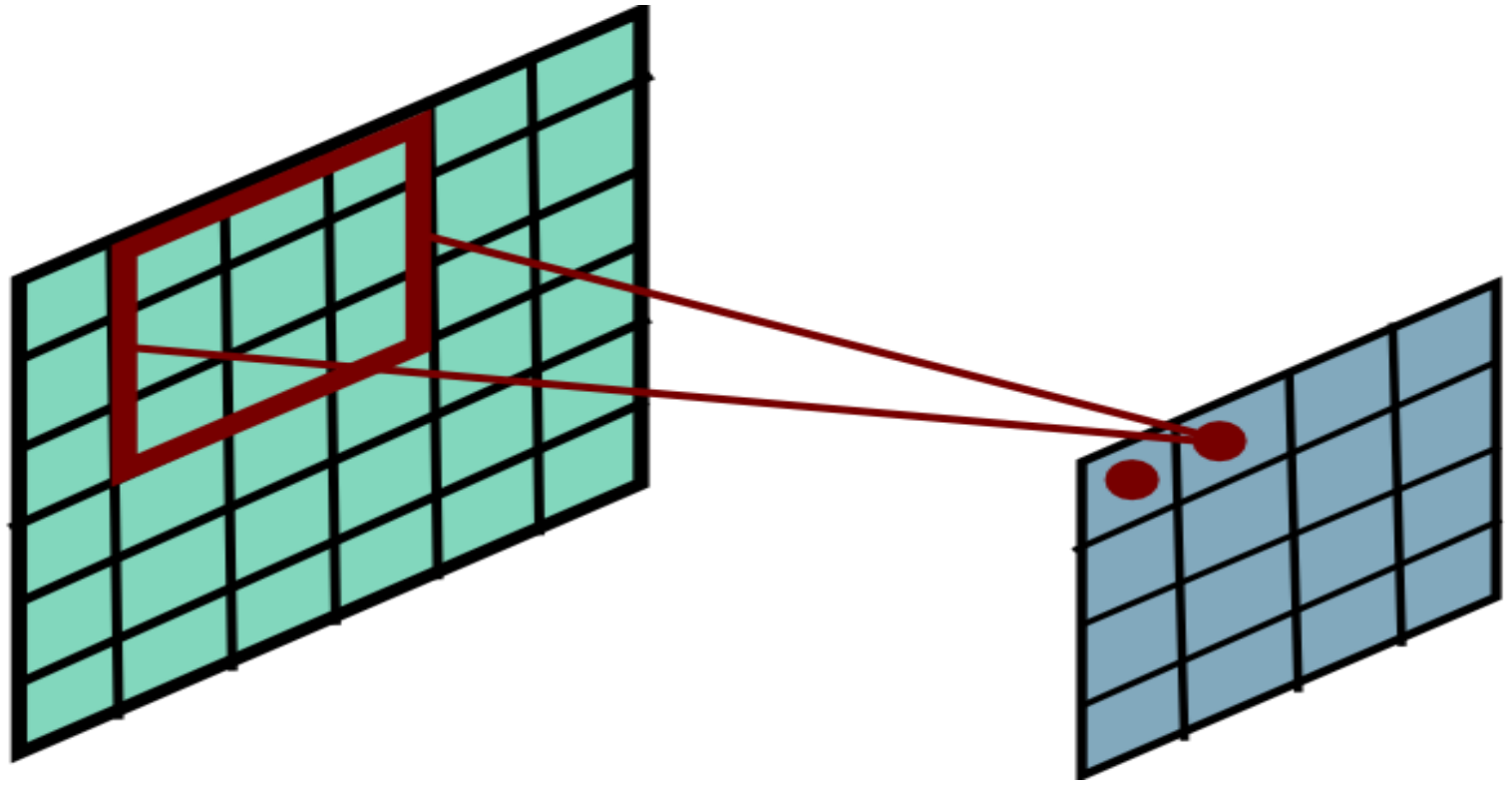
Fully-Connected Layer

Classification Layer (Softmax, etc.)

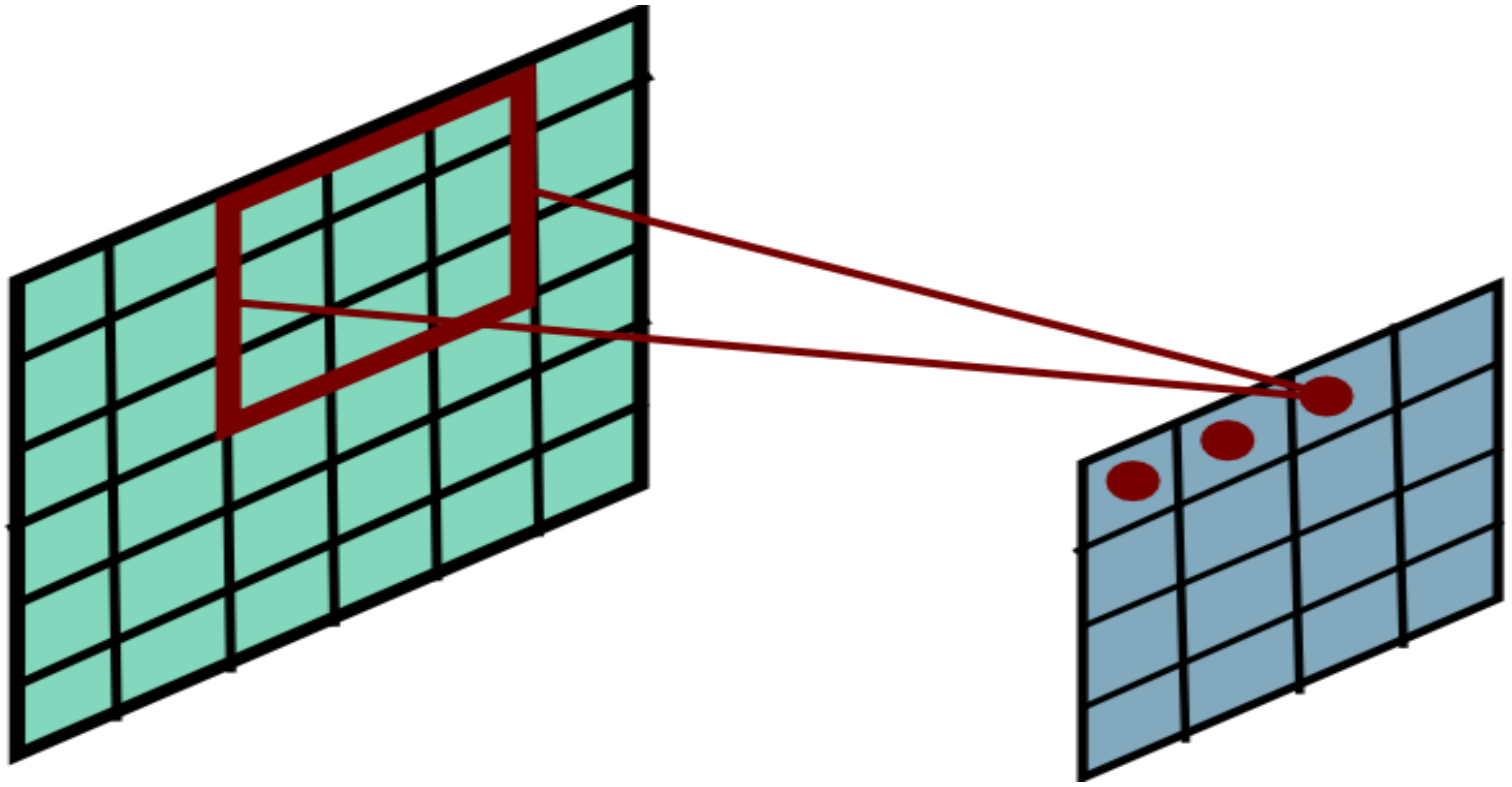
Convolutional Layer



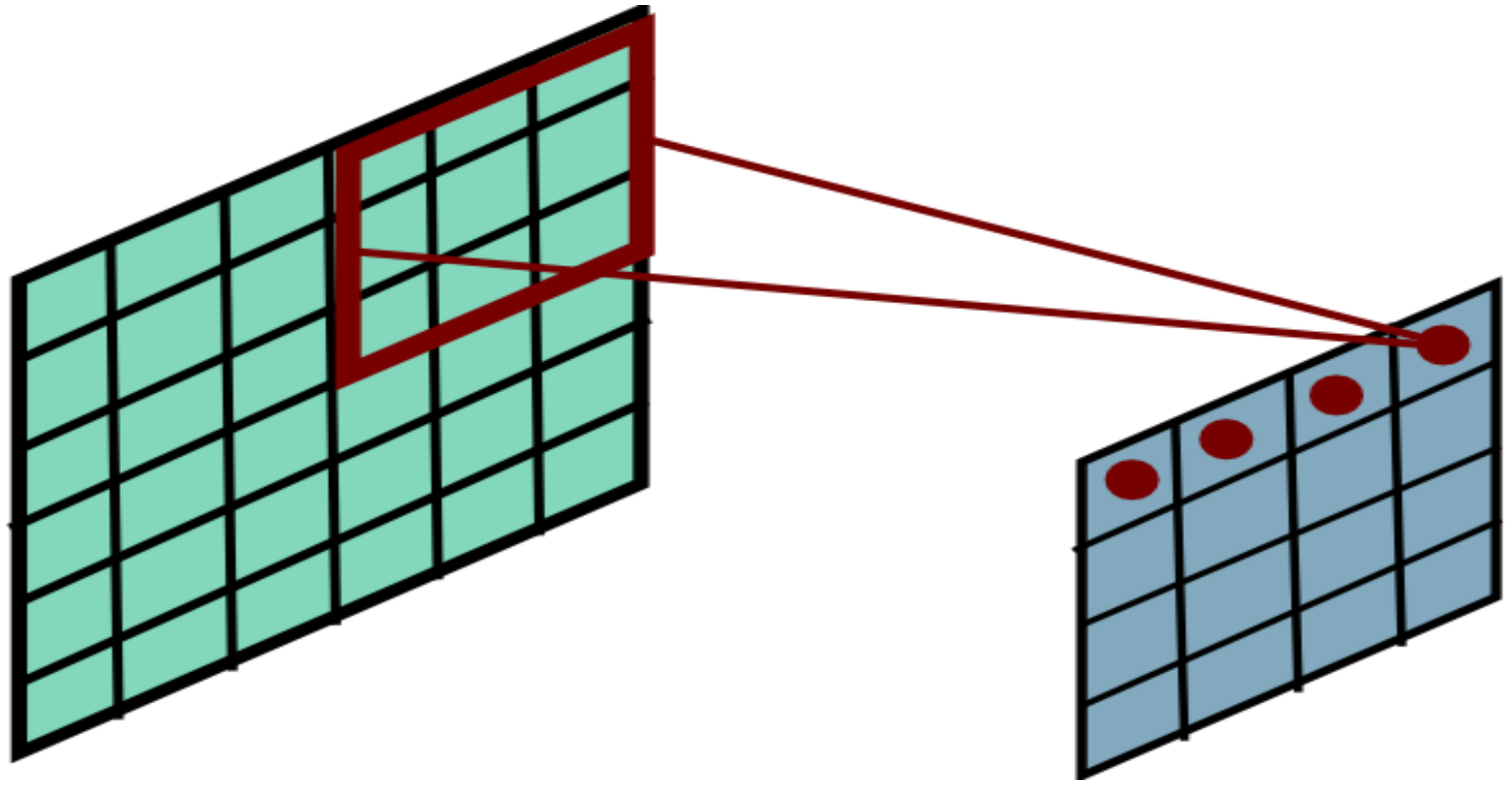
Convolutional Layer



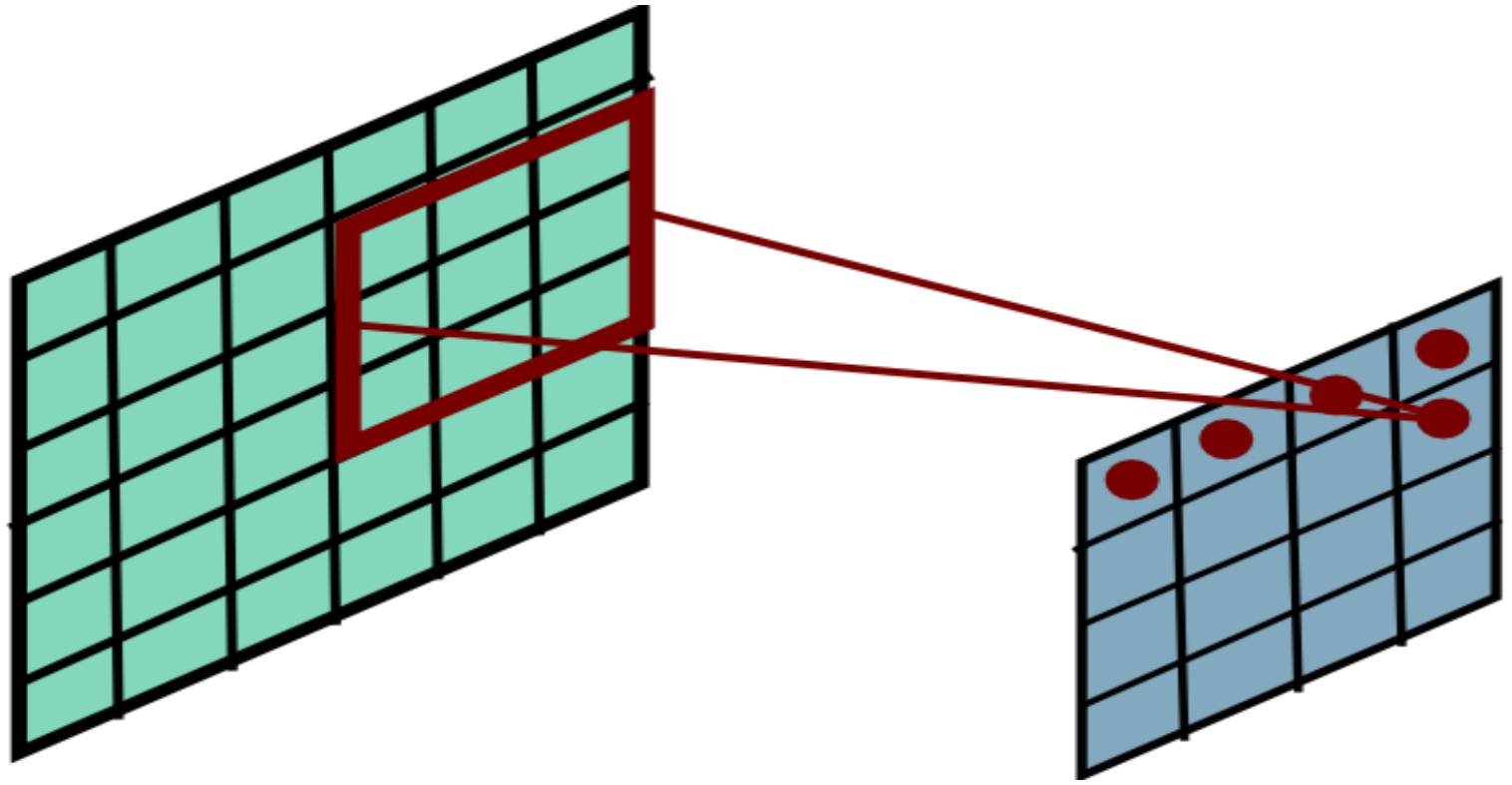
Convolutional Layer



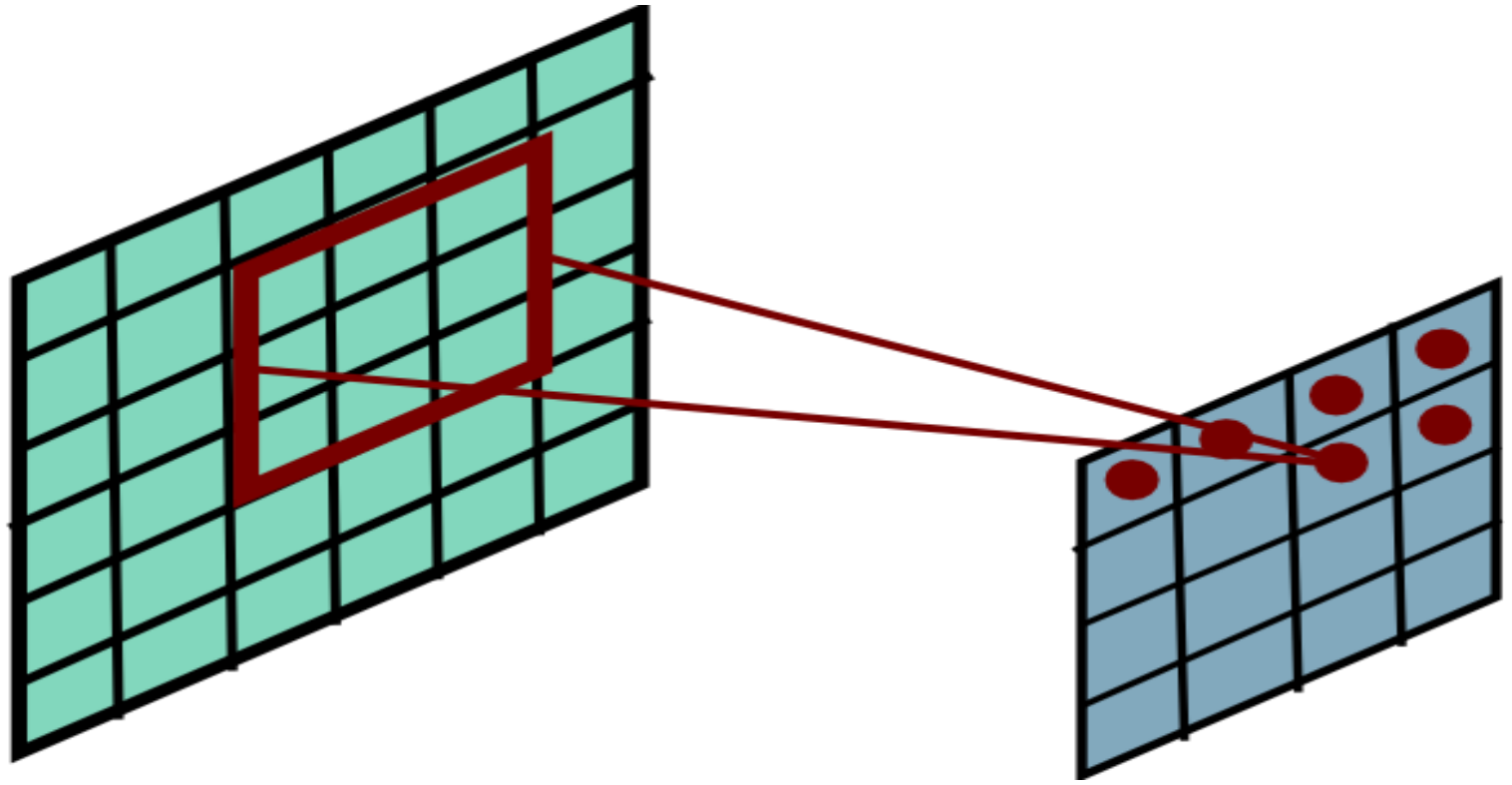
Convolutional Layer



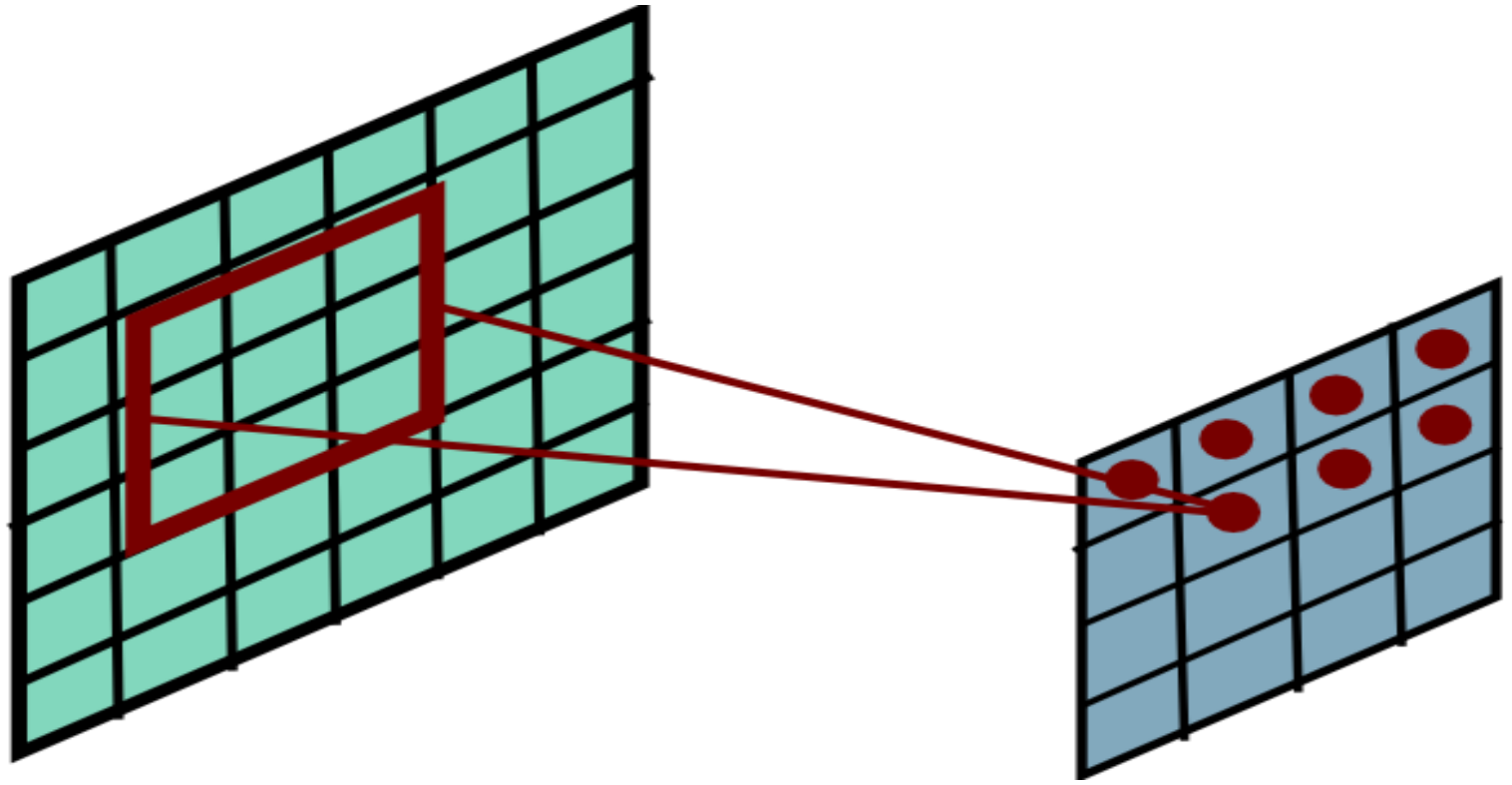
Convolutional Layer



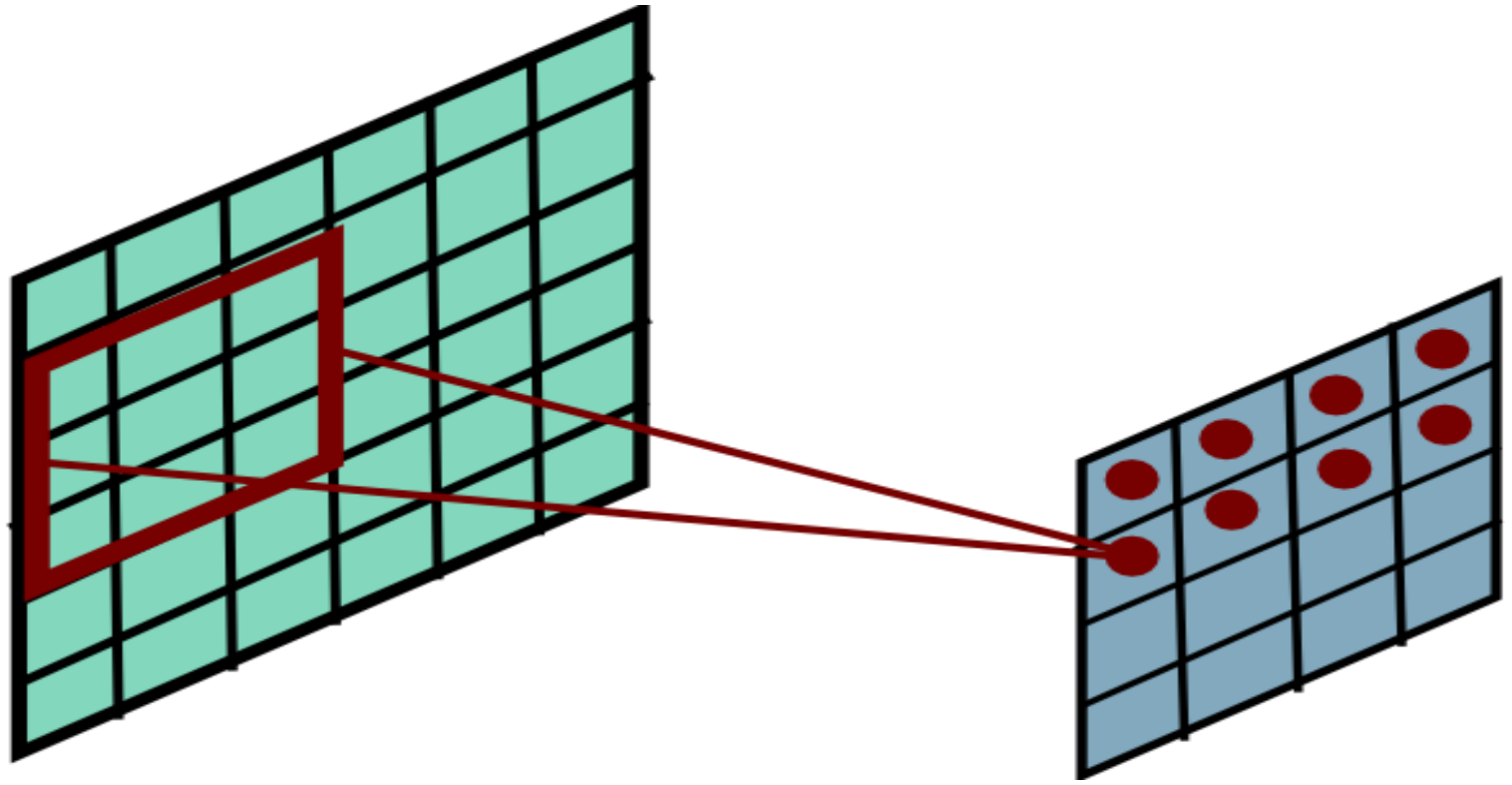
Convolutional Layer



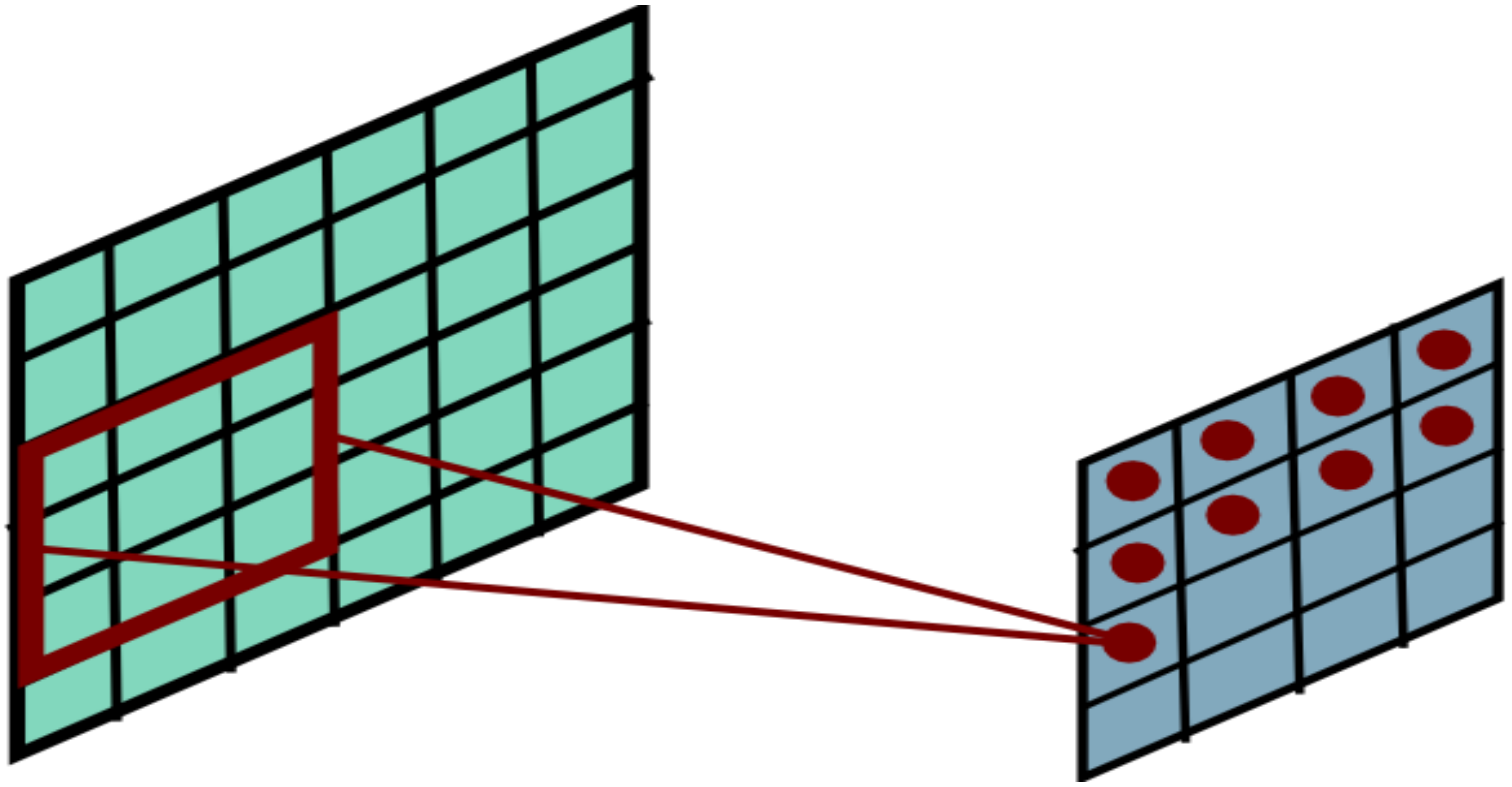
Convolutional Layer



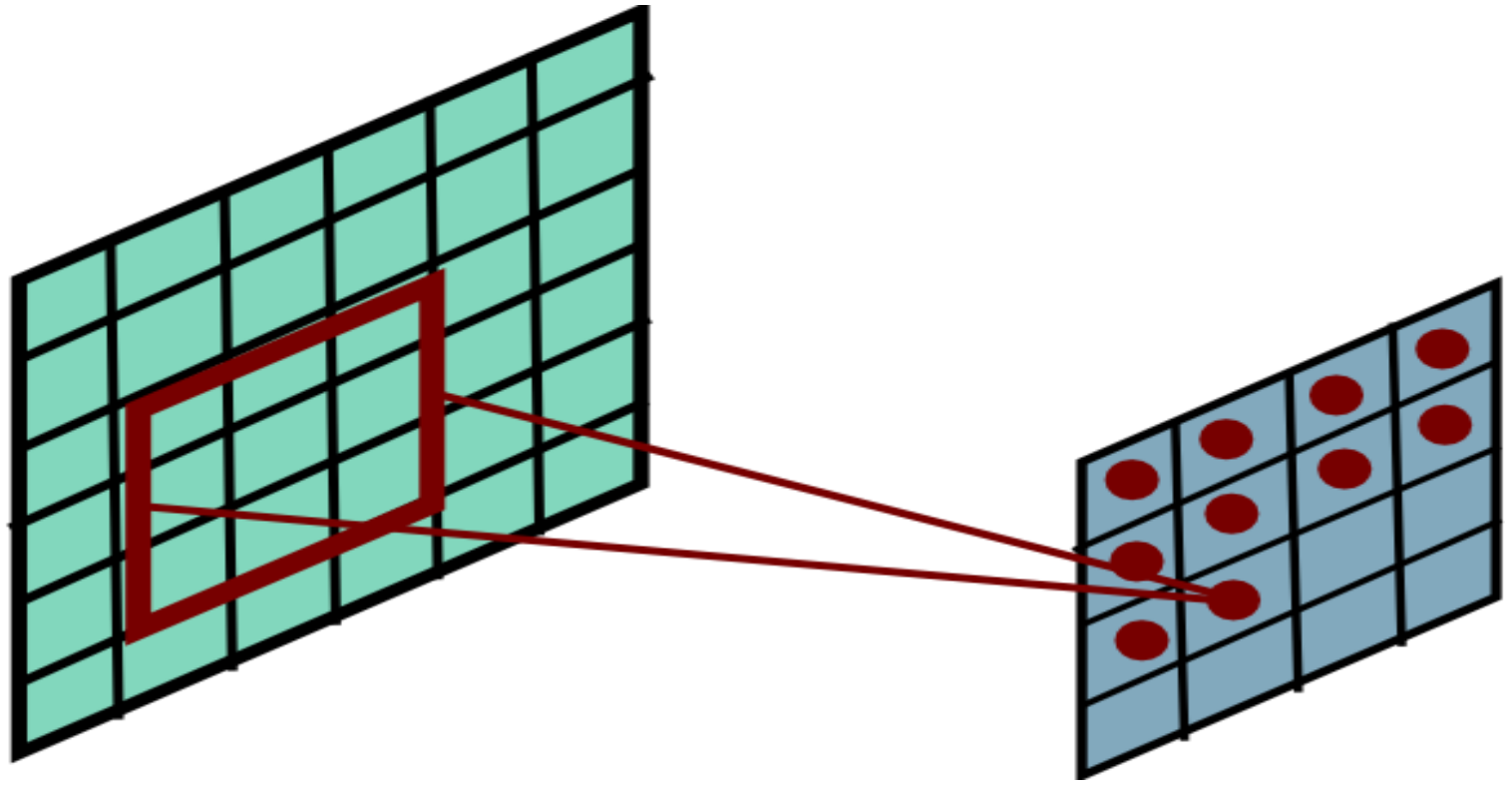
Convolutional Layer



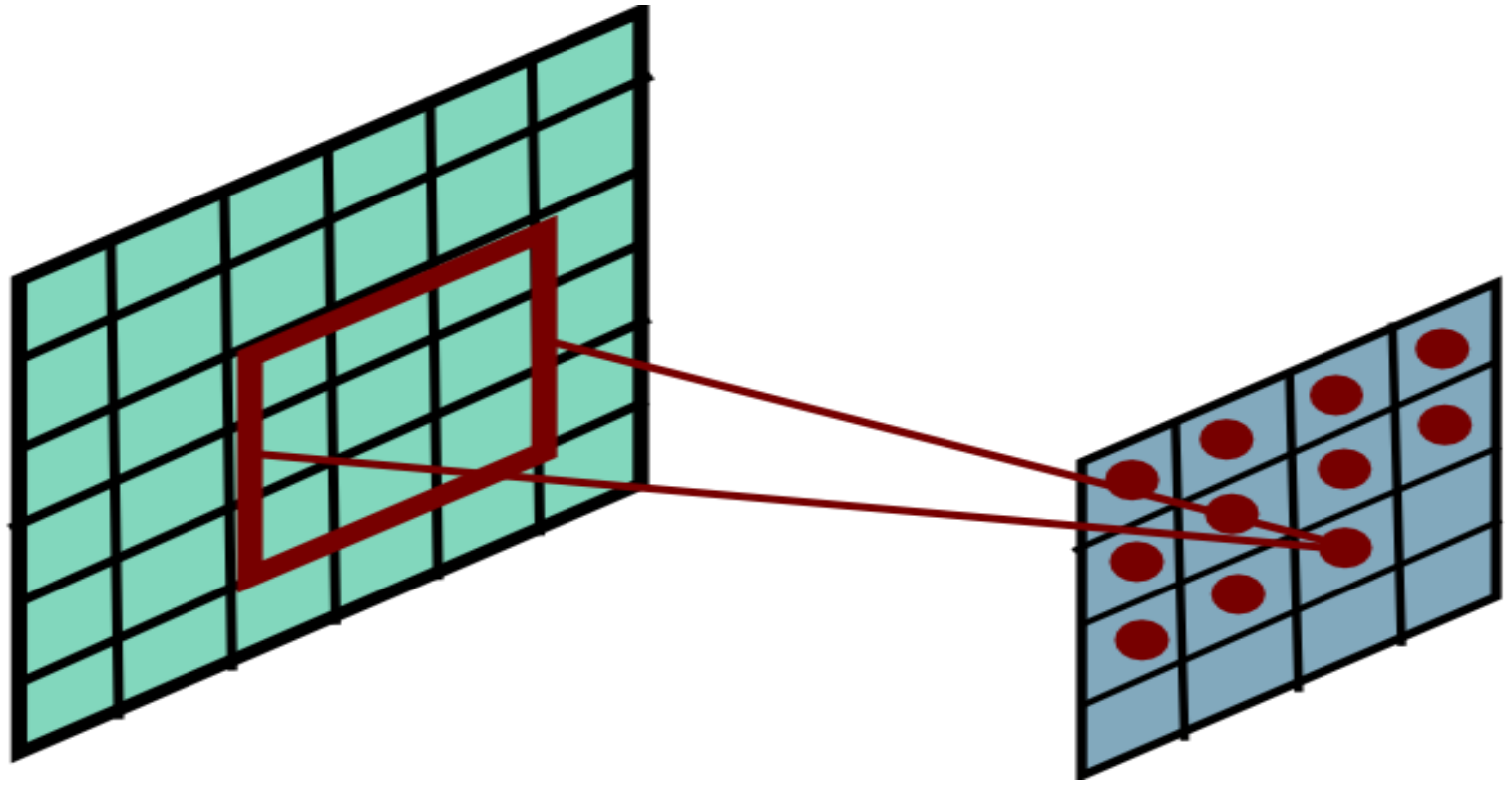
Convolutional Layer



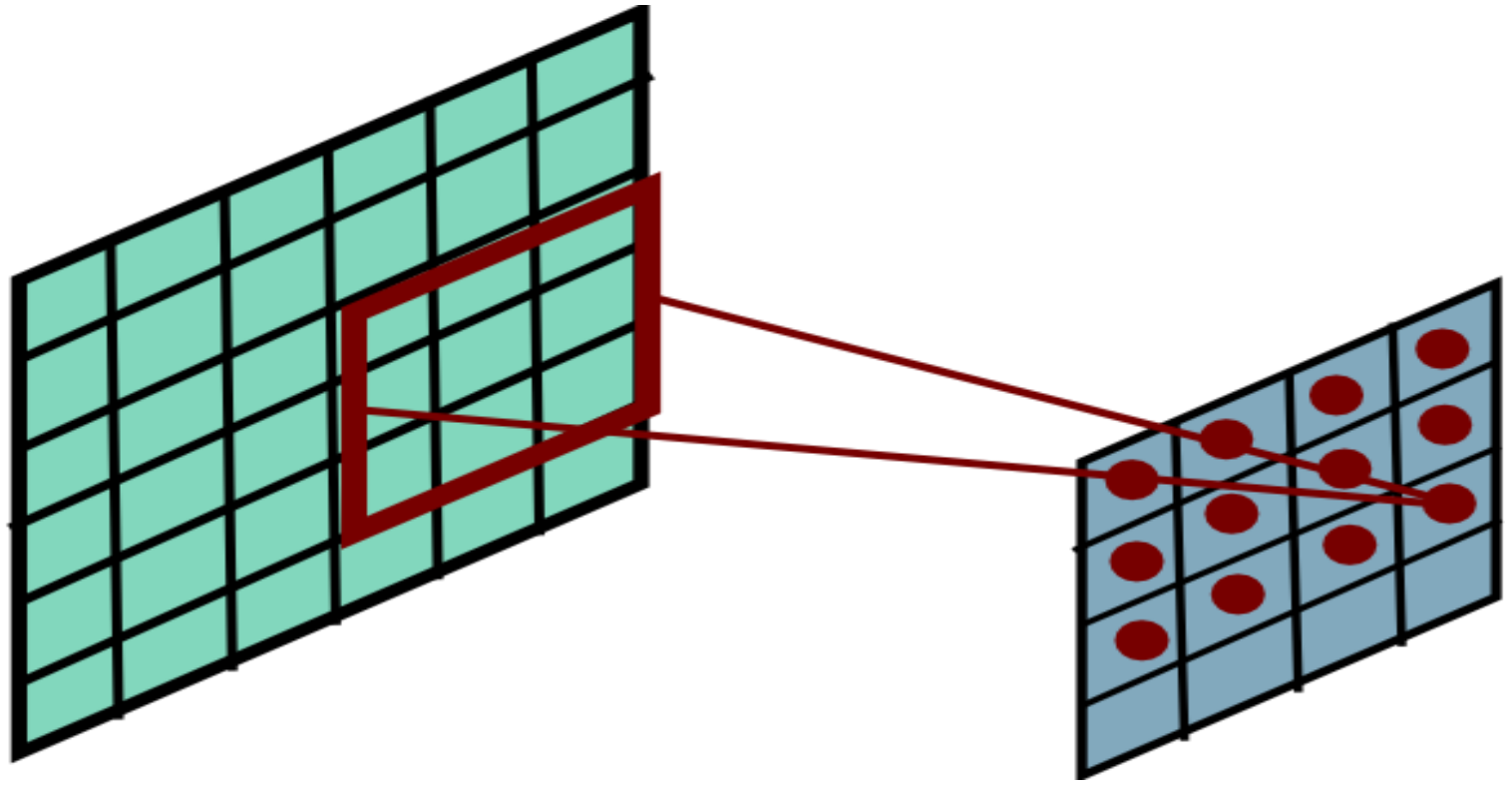
Convolutional Layer



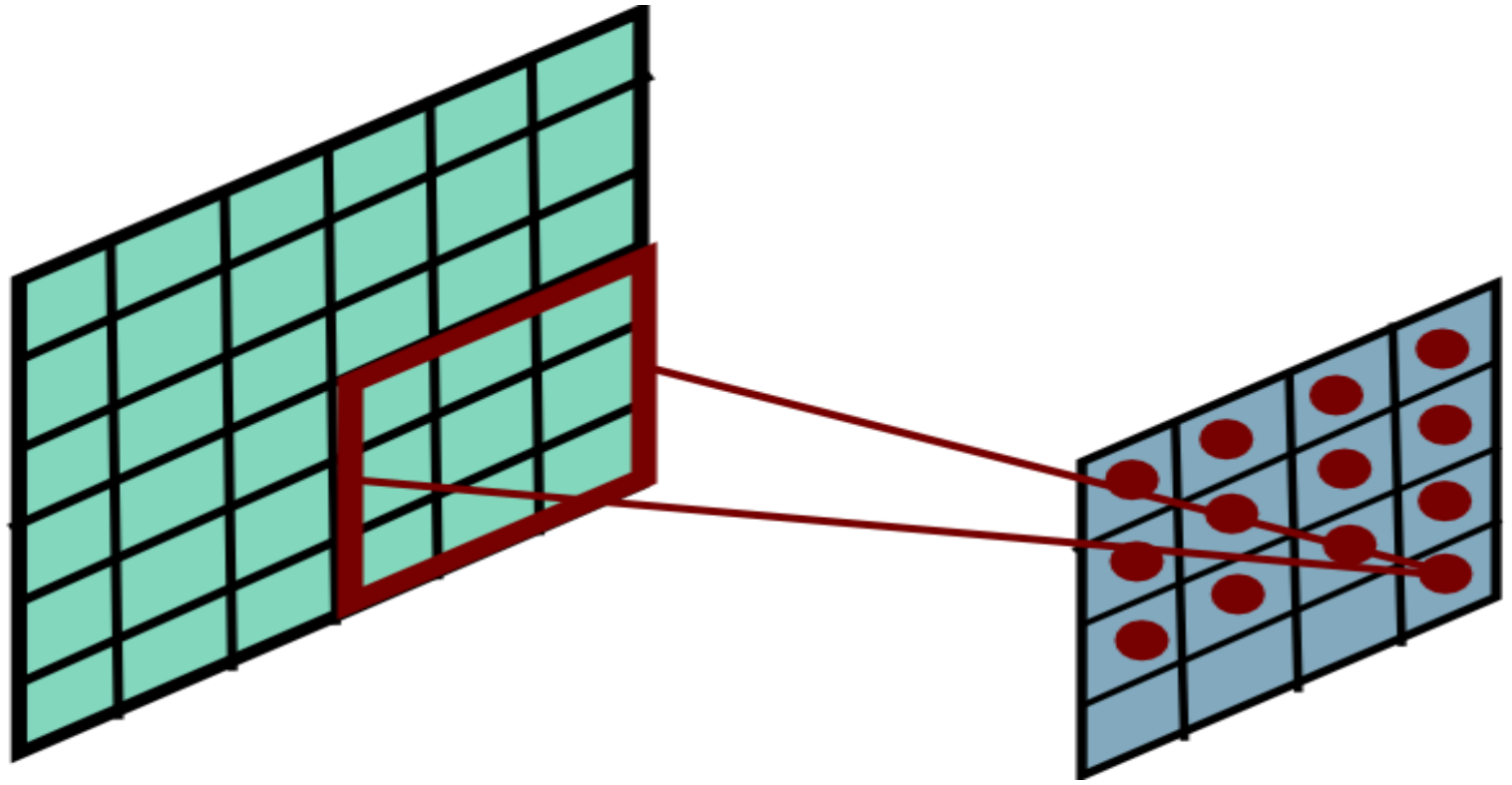
Convolutional Layer



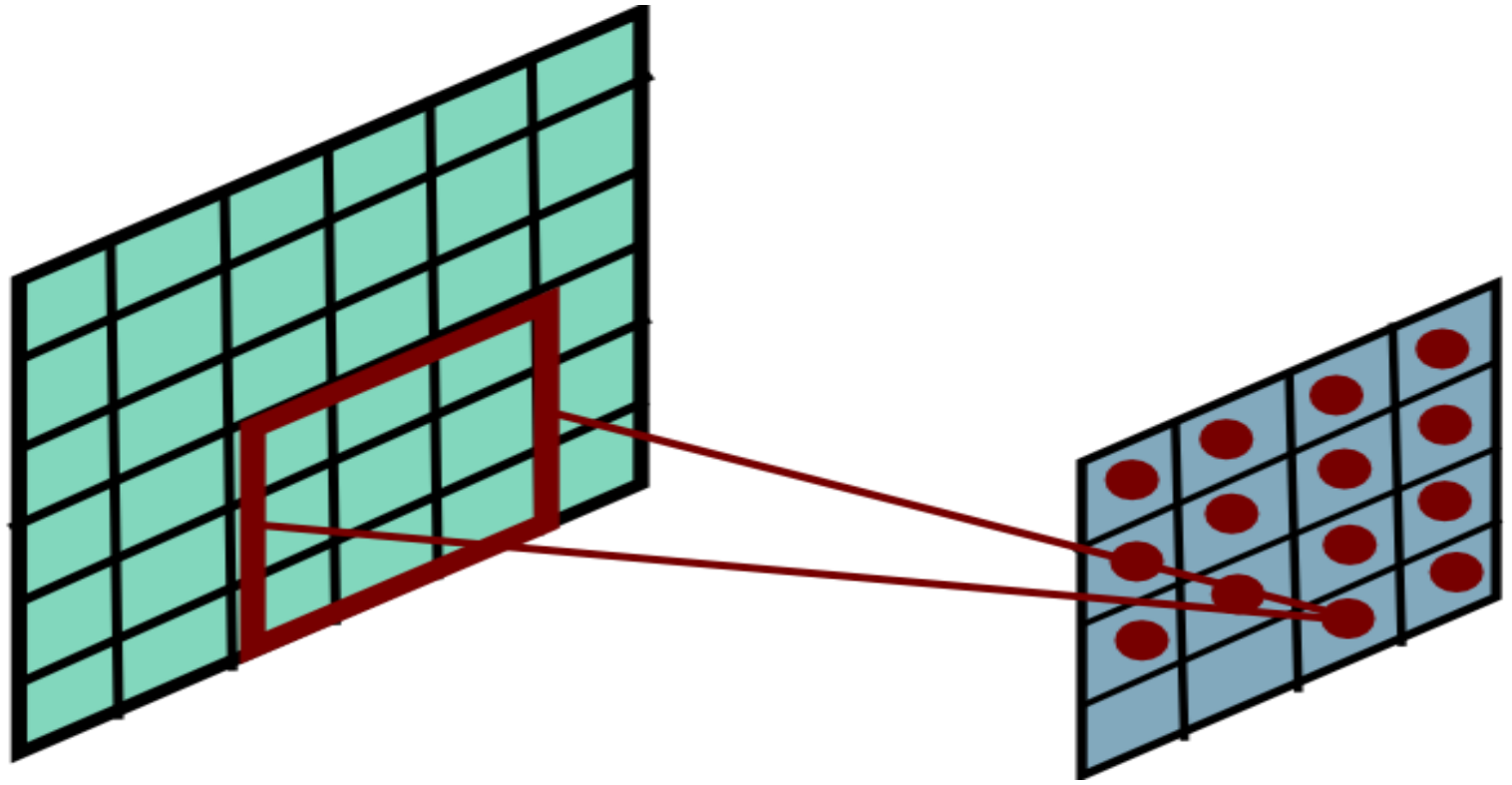
Convolutional Layer



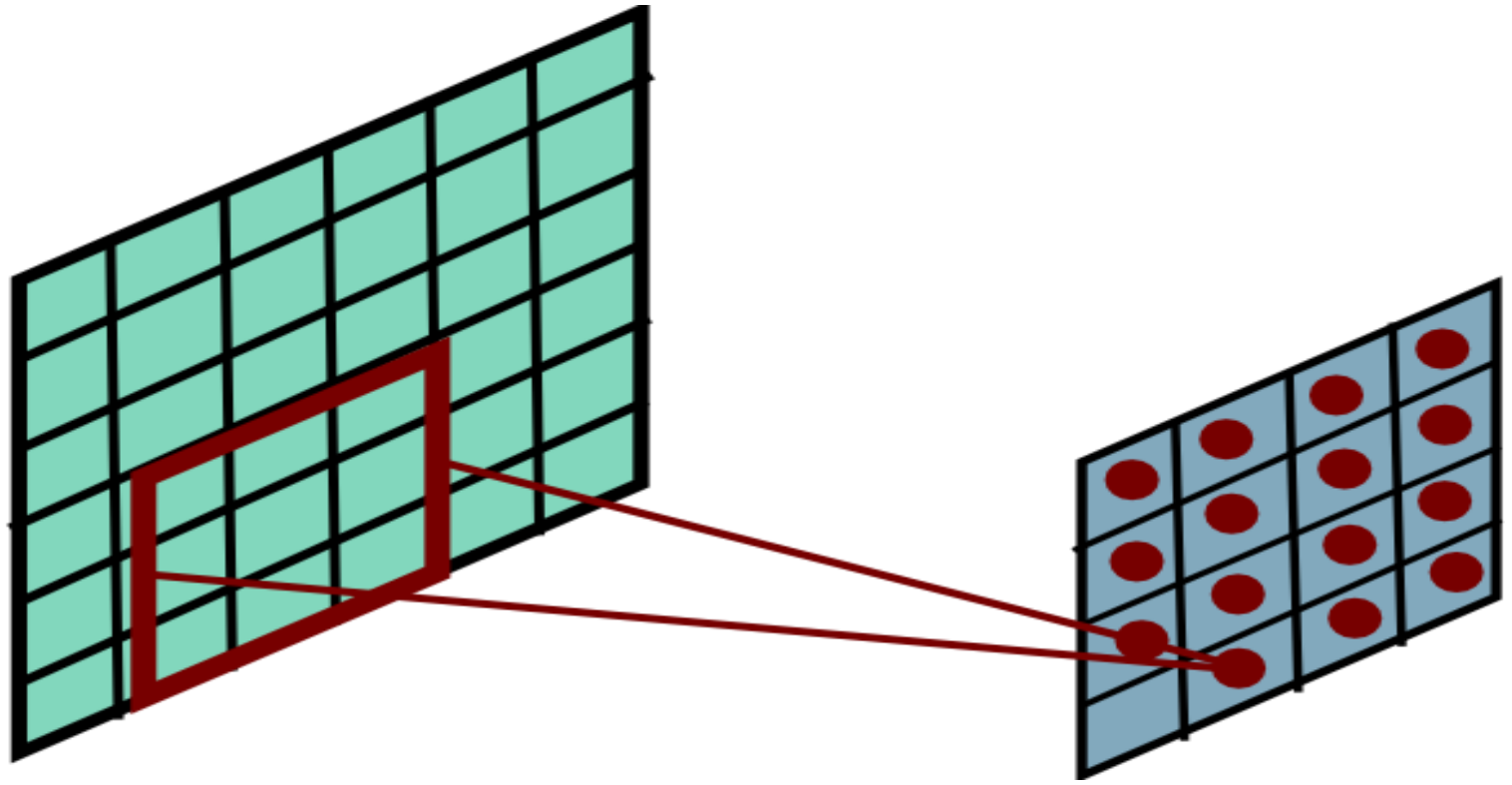
Convolutional Layer



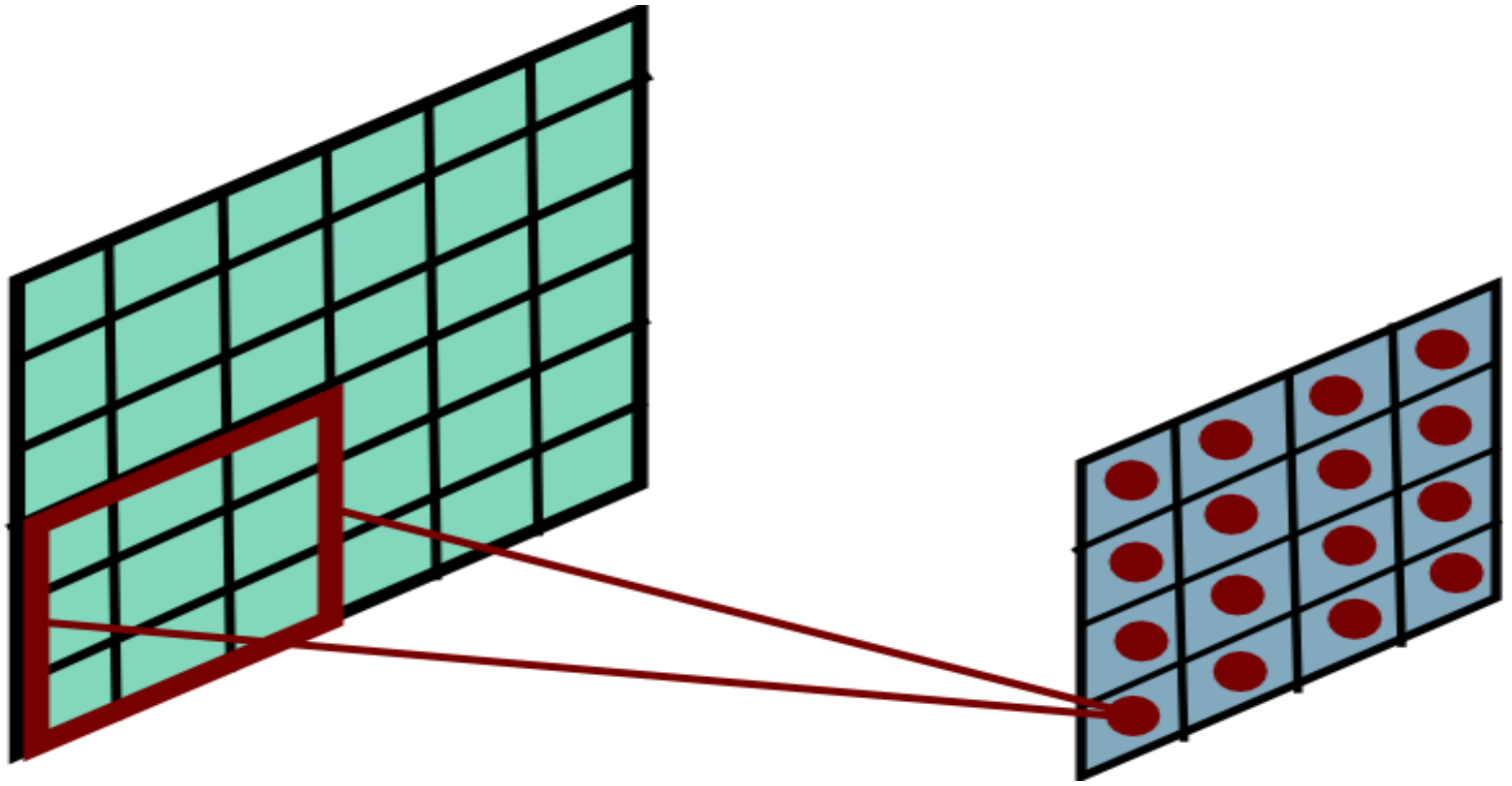
Convolutional Layer



Convolutional Layer

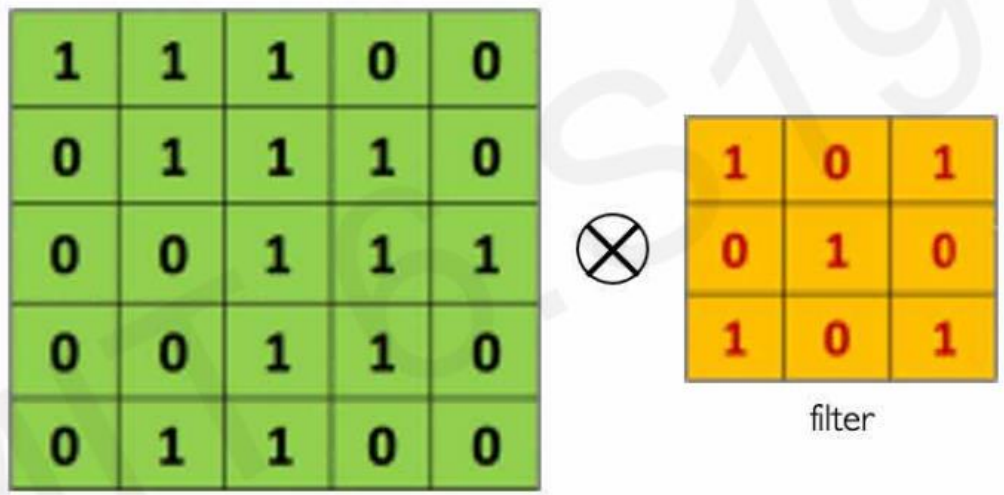


Convolutional Layer



The Convolution Operation

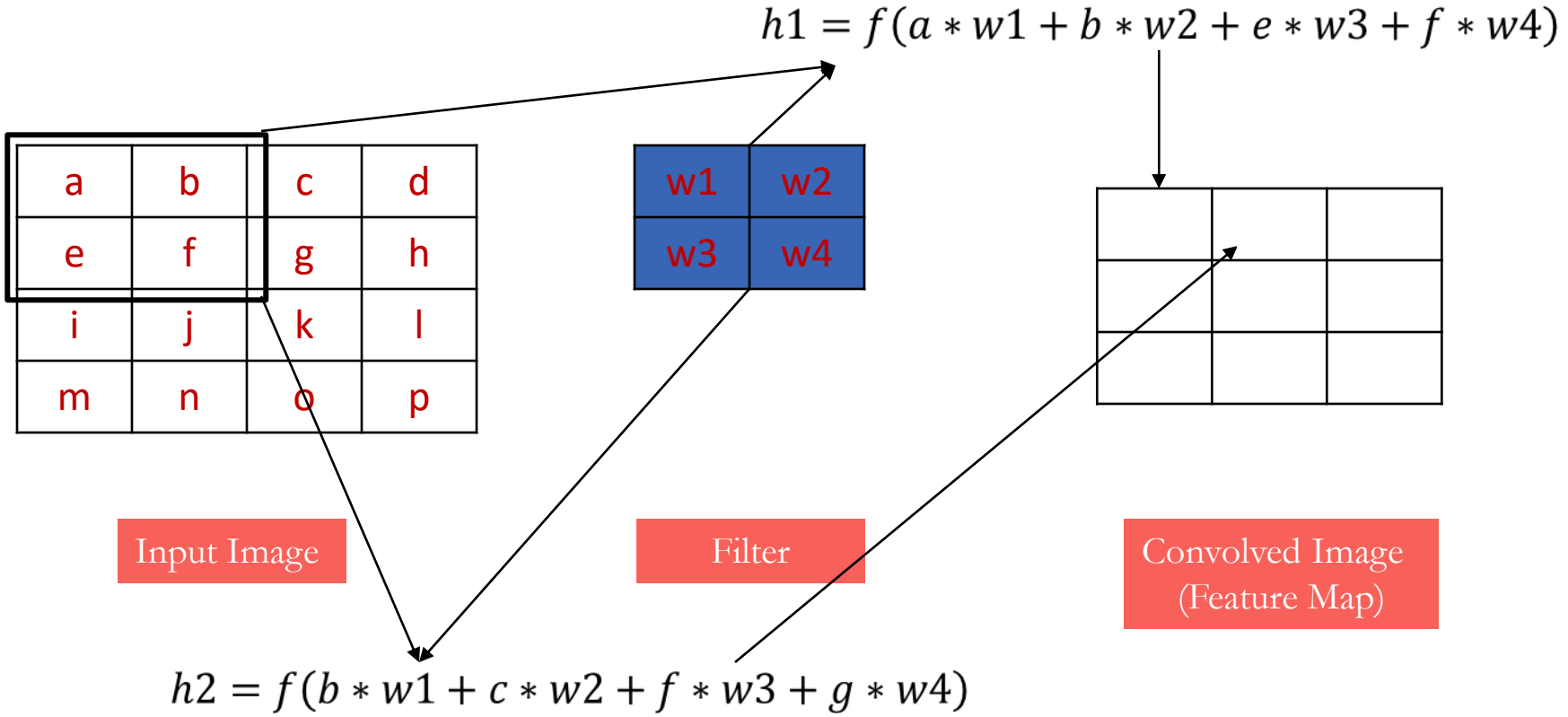
Suppose we want to compute the convolution of a 5x5 image and a 3x3 filter:



We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs…

Convolutional Layers

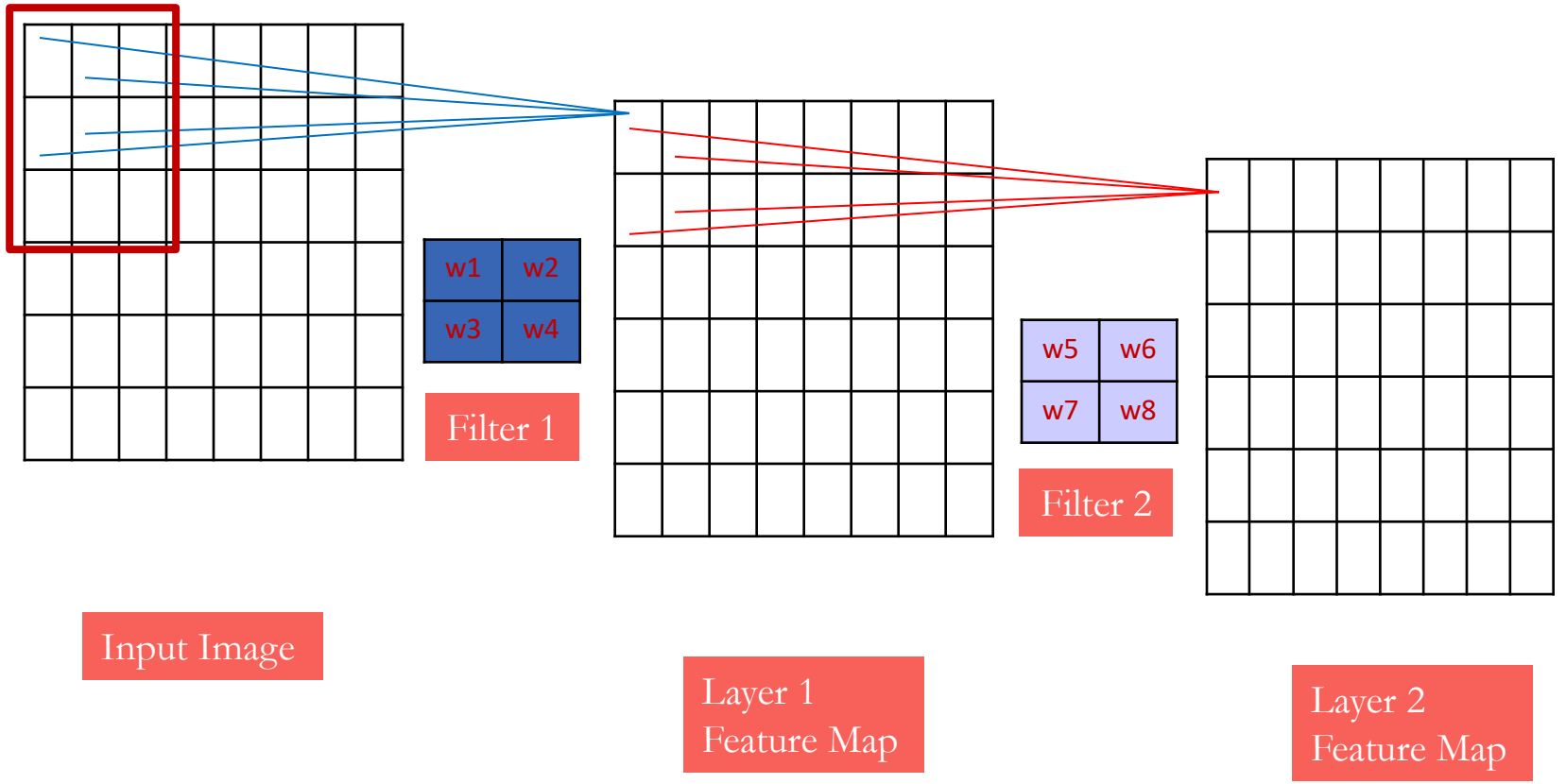
- What is Convolution?



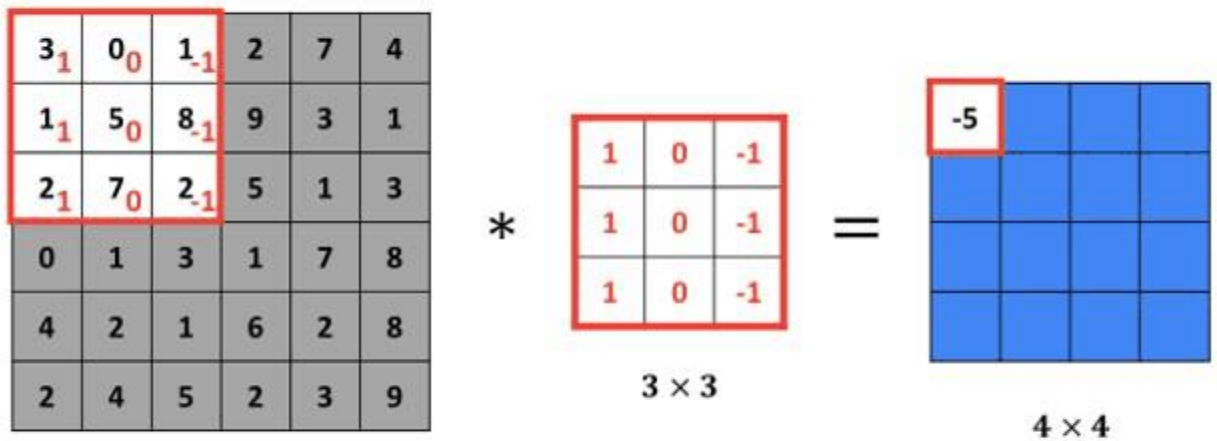
Number of Parameters for one feature map = 4

Number of Parameters for 100 feature map = 4*100

Lower Level to More Complex Features



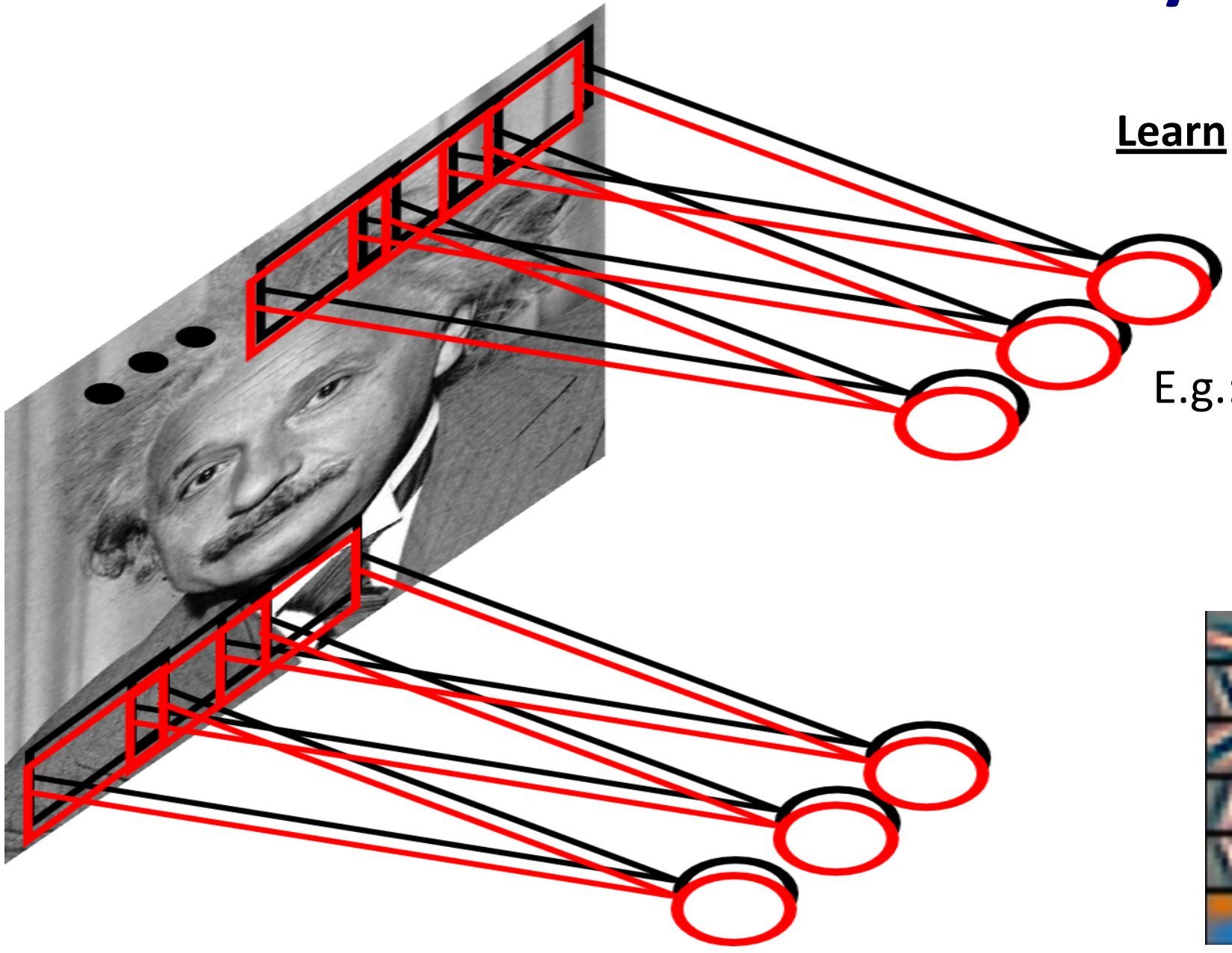
- In Convolutional neural networks, hidden units are only connected to local receptive field.



6×6 $\quad * \quad$ 3×3 $\quad = \quad$ 4×4

$$3 \times 1 + 1 \times 1 + 2 \times 1 + 0 \times 0 + 5 \times 0 + 7 \times 0 + 1 \times -1 + 8 \times -1 + 2 \times -1 = -5$$

Convolutional Layer



Learn multiple filters.

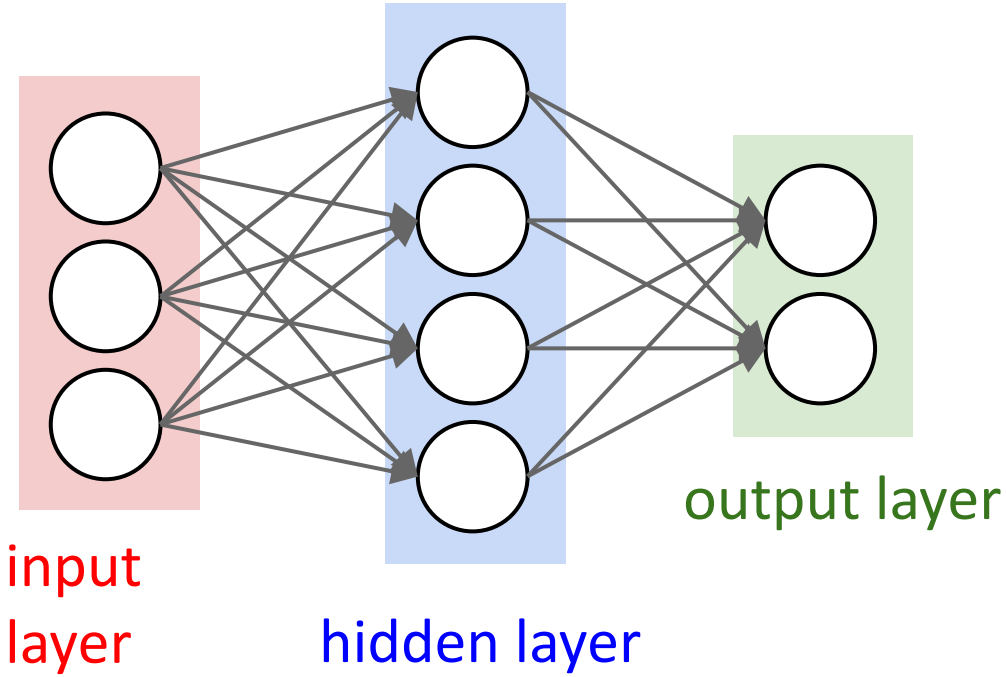
E.g.: 200x200 image

100 Filters

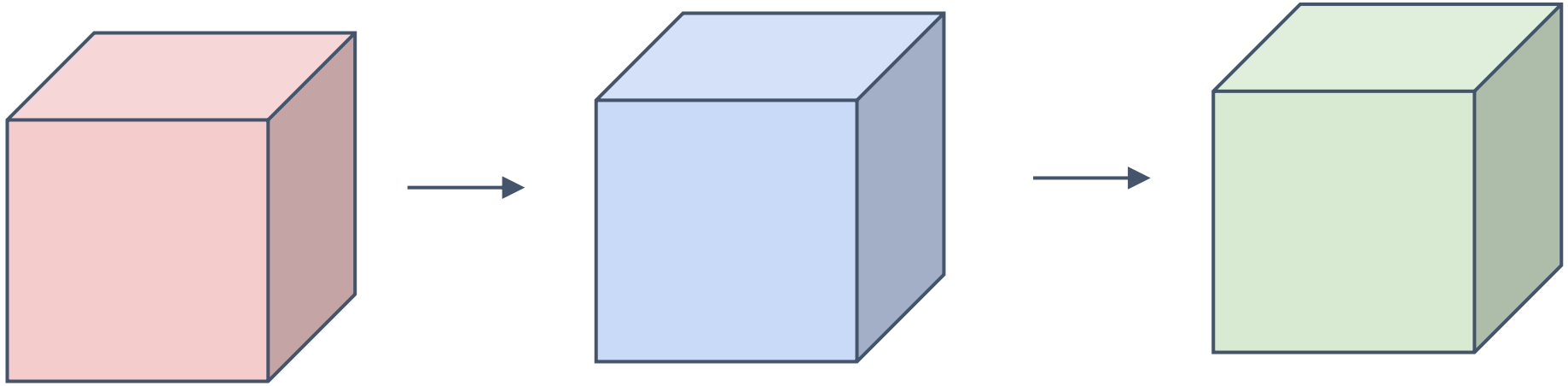
Filter size: 10x10

10K parameters

before:

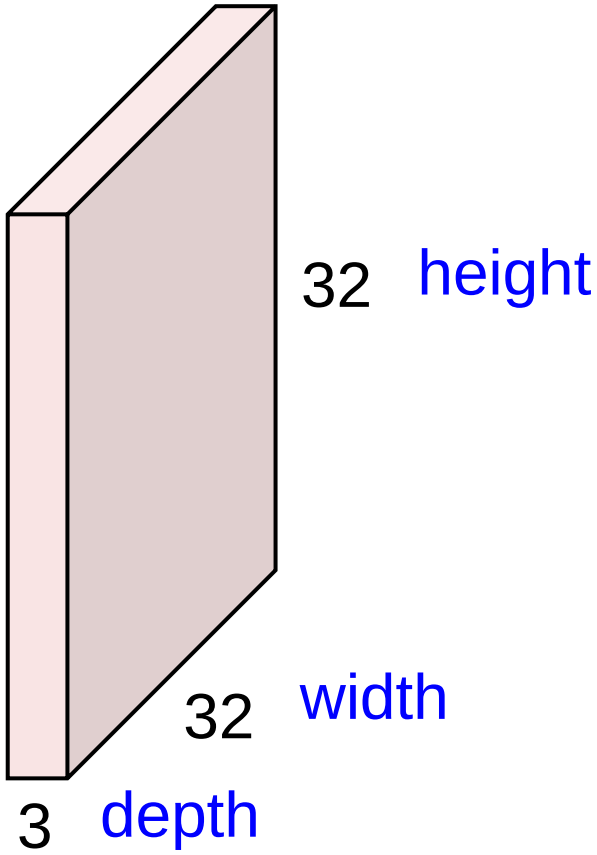


now:



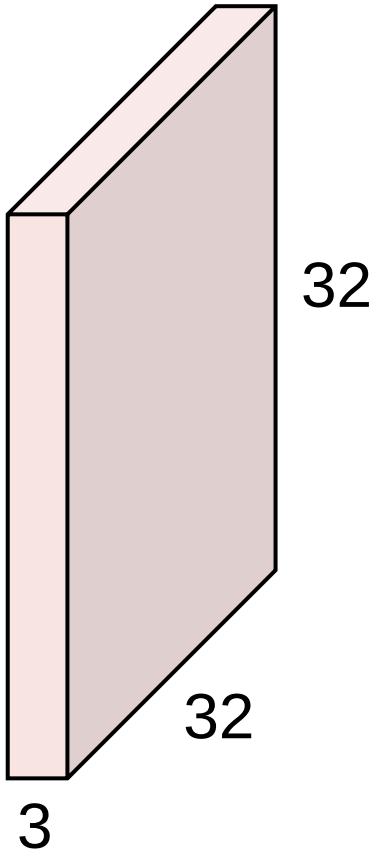
Convolution Layer

32x32x3 image

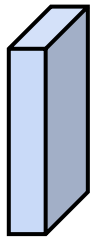


Convolution Layer

32x32x3 image



5x5x3 filter

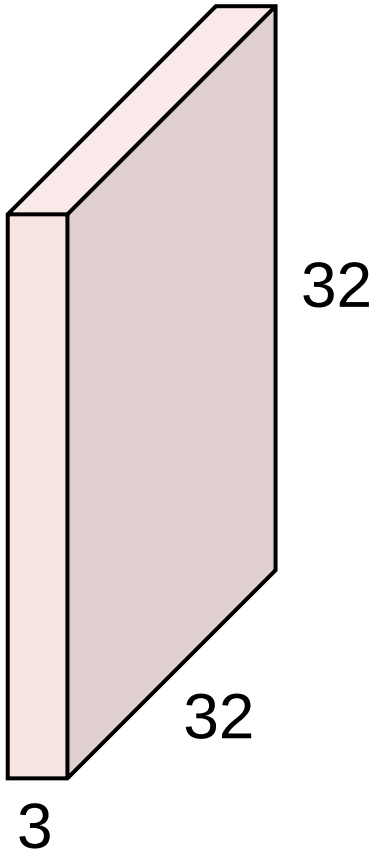


Convolve the filter with the image
i.e. “slide over the image spatially, computing dot products”

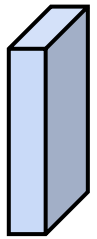
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image

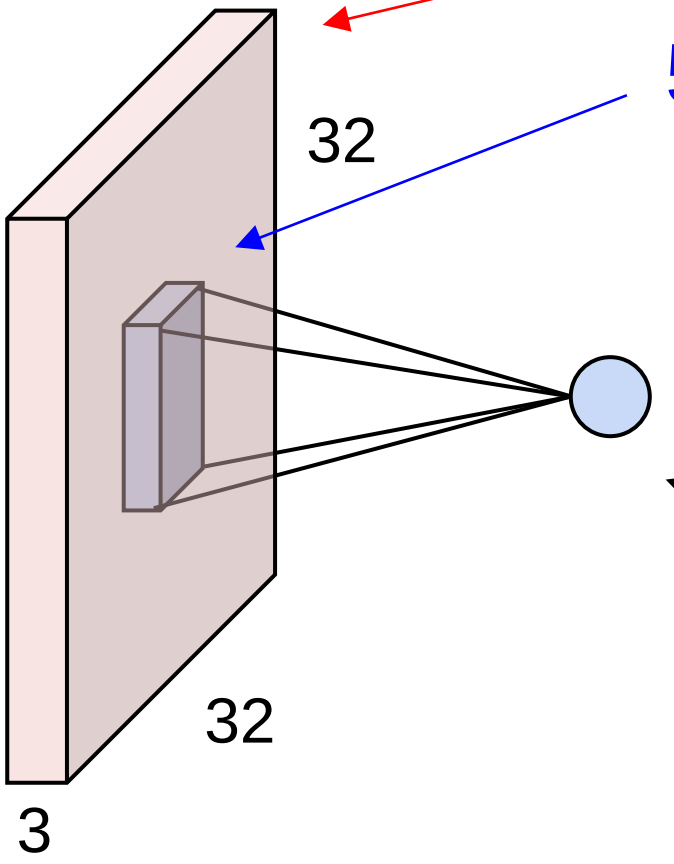


5x5x3 filter



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

Convolution Layer



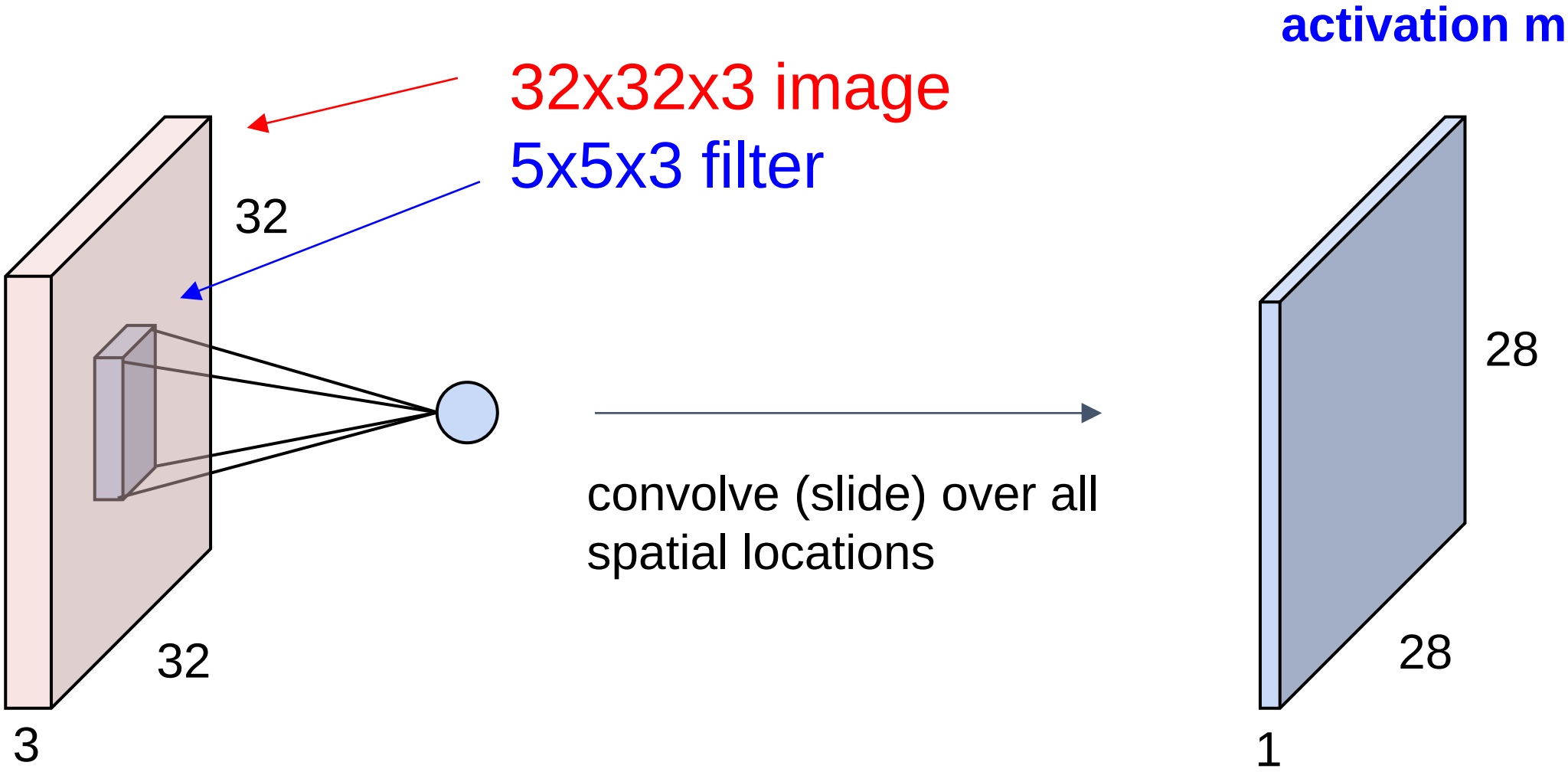
32x32x3 image

5x5x3 filter 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)

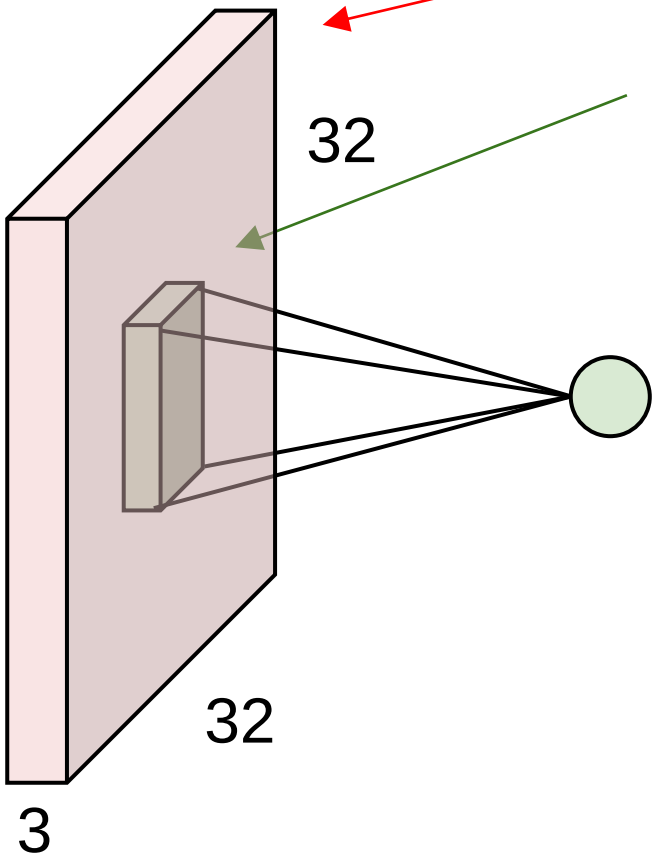
$$w^T x + b$$

Convolution Layer



Convolution Layer

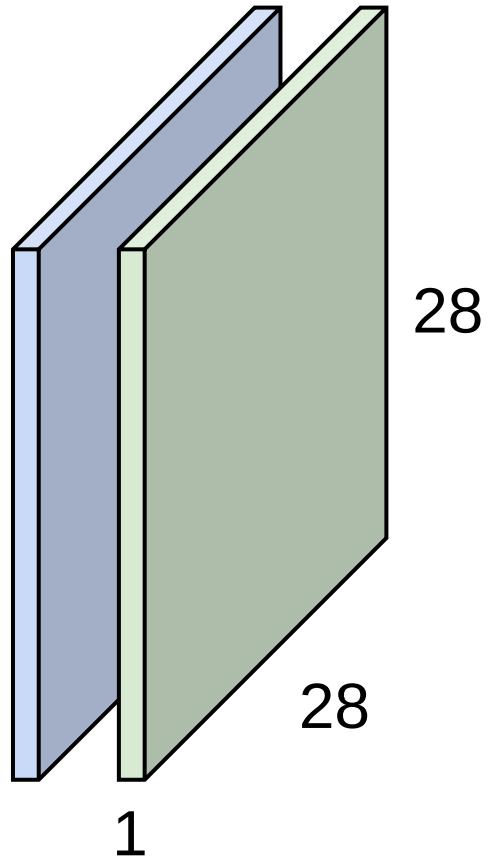
consider a second, green filter



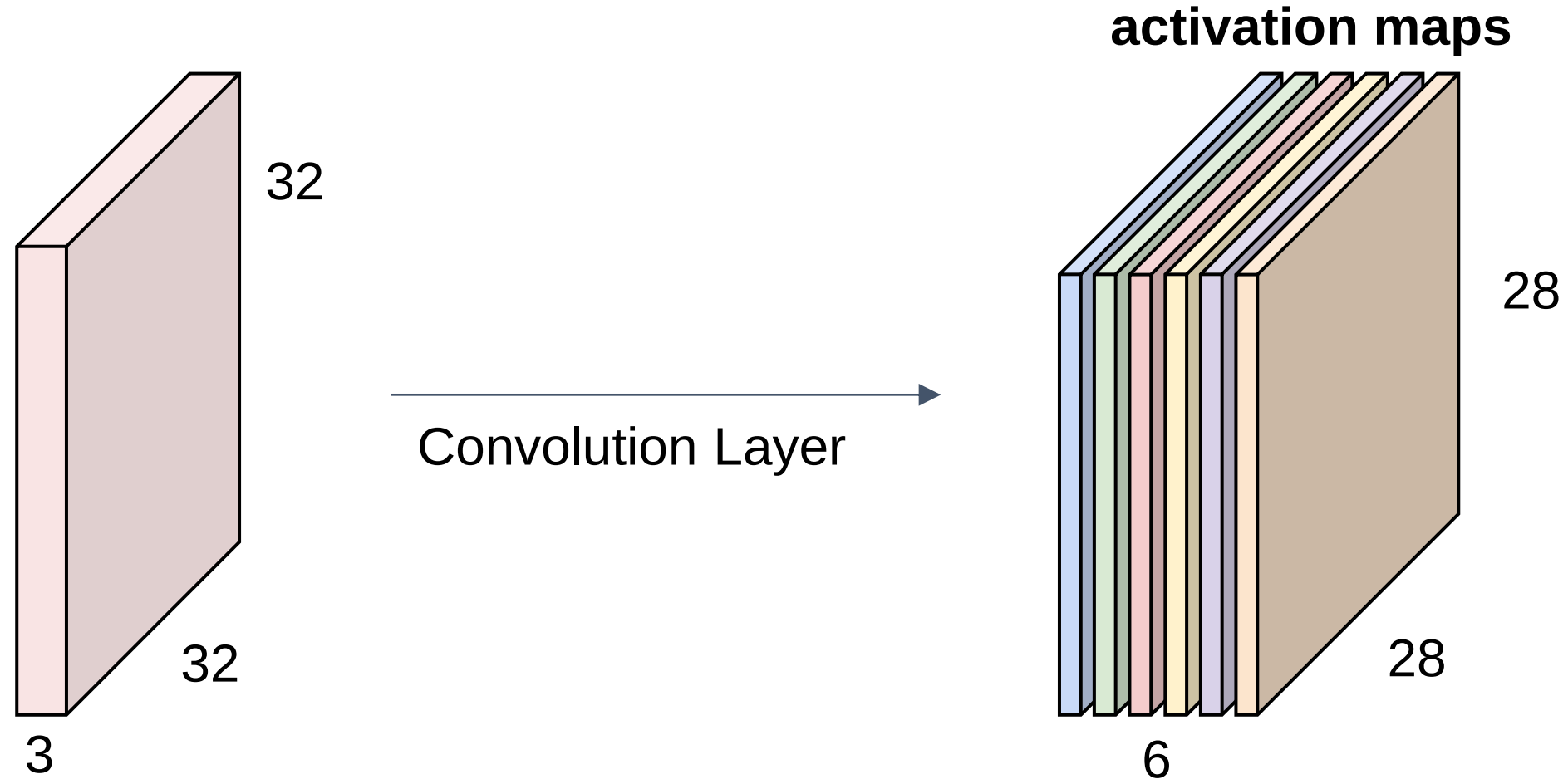
32x32x3 image

5x5x3 filter

convolve (slide) over all spatial locations

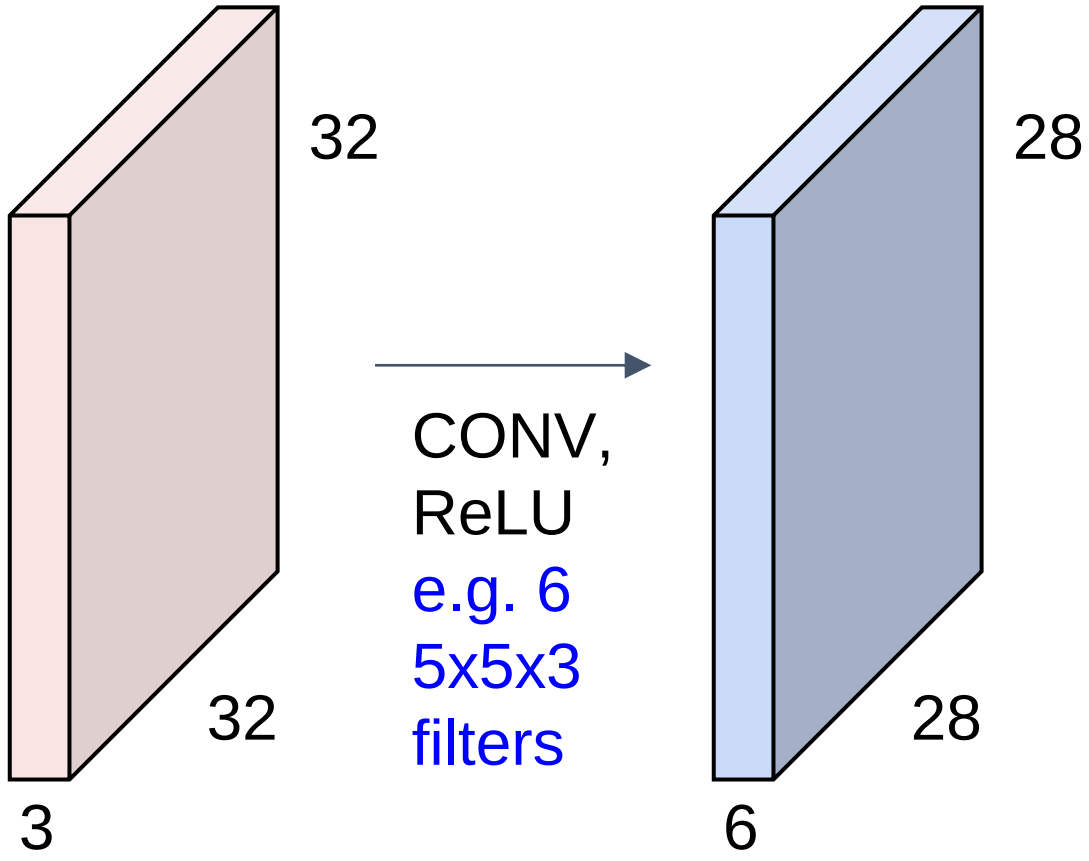


For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:

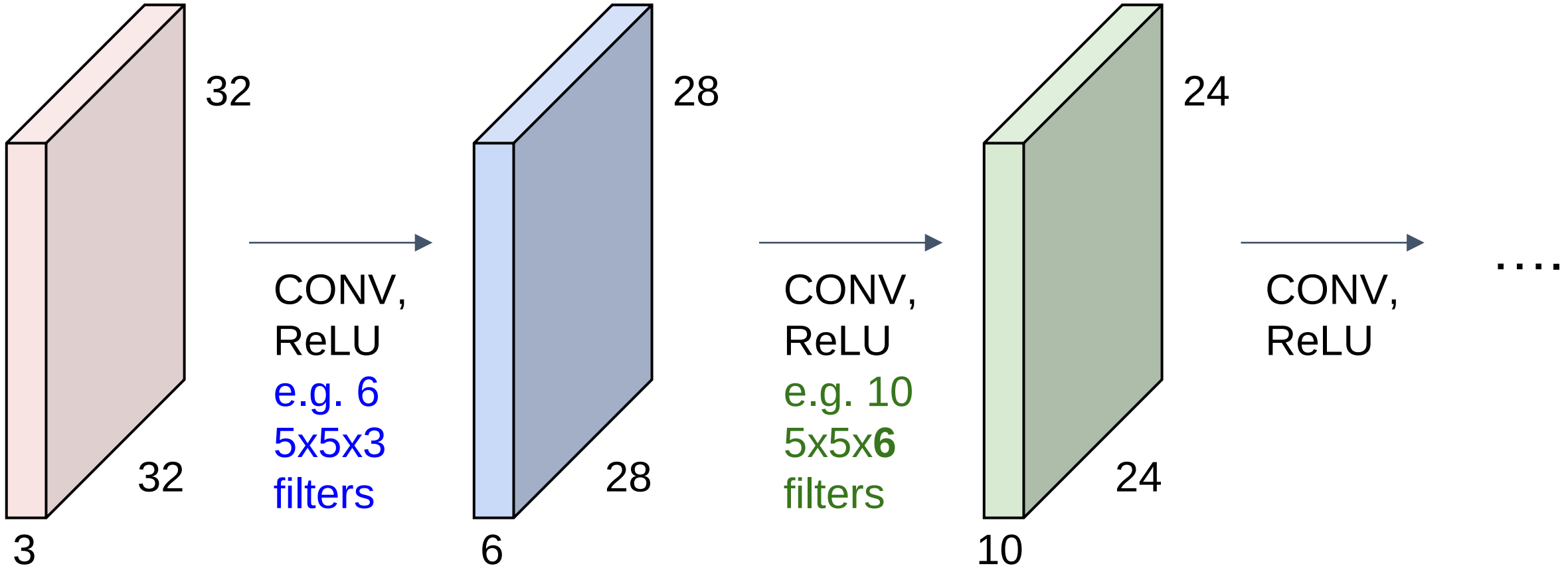


We stack these up to get a "new image" of size 28x28x6!

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

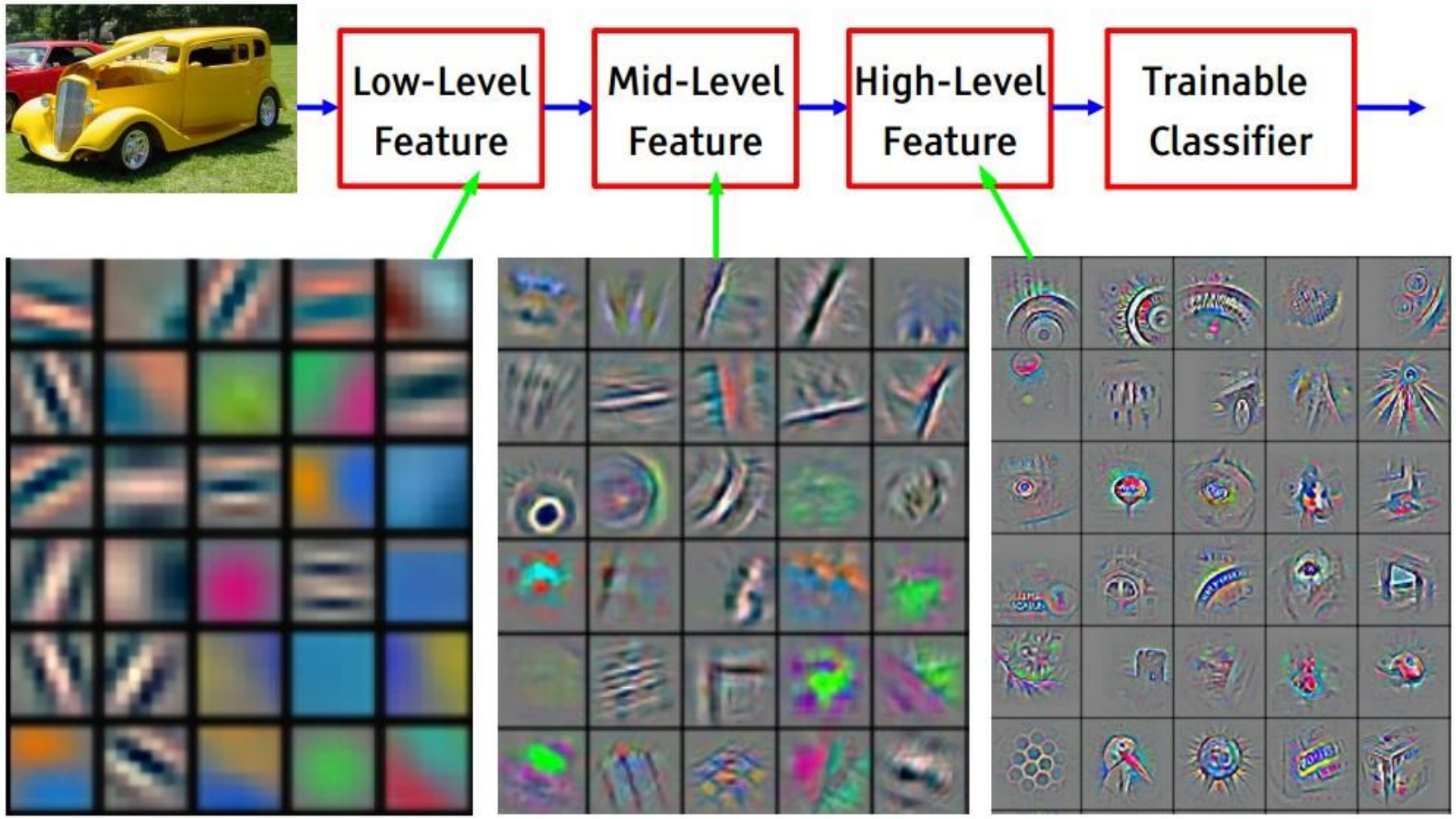


Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions



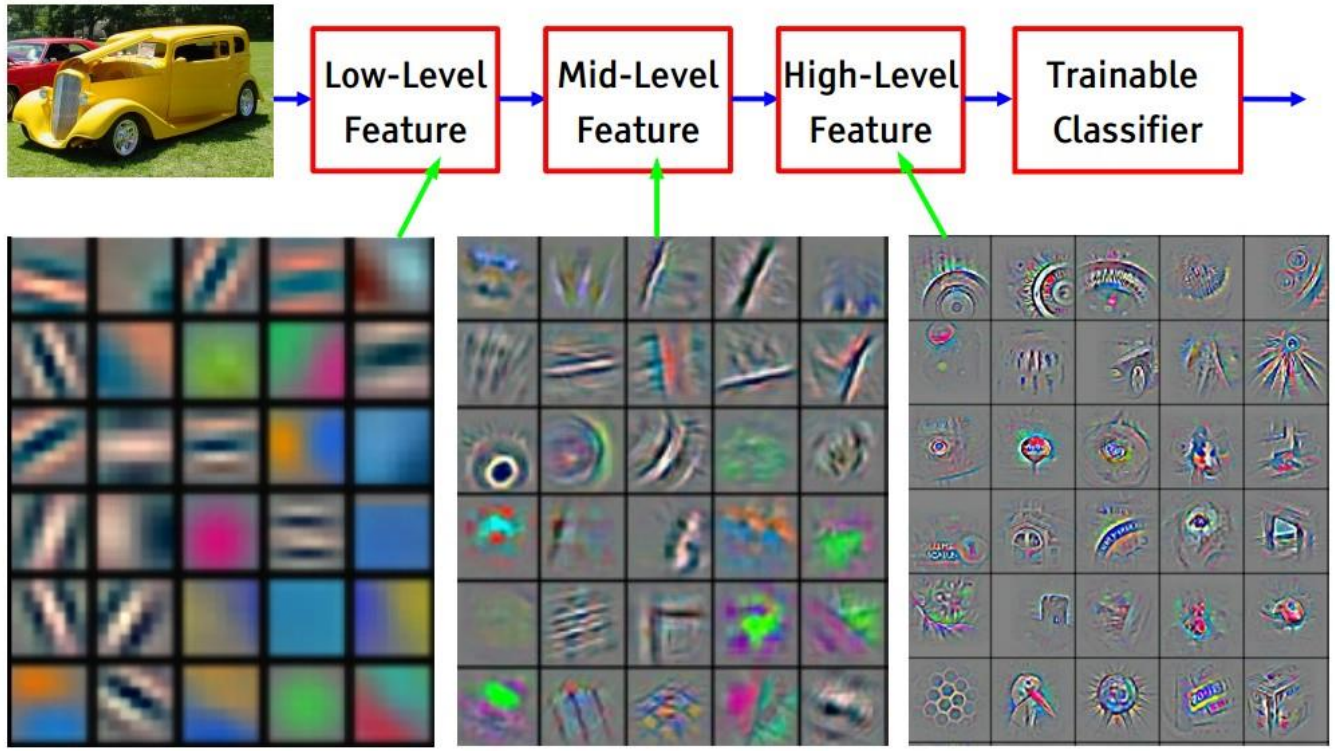
Preview

[From recent Yann LeCun slides]

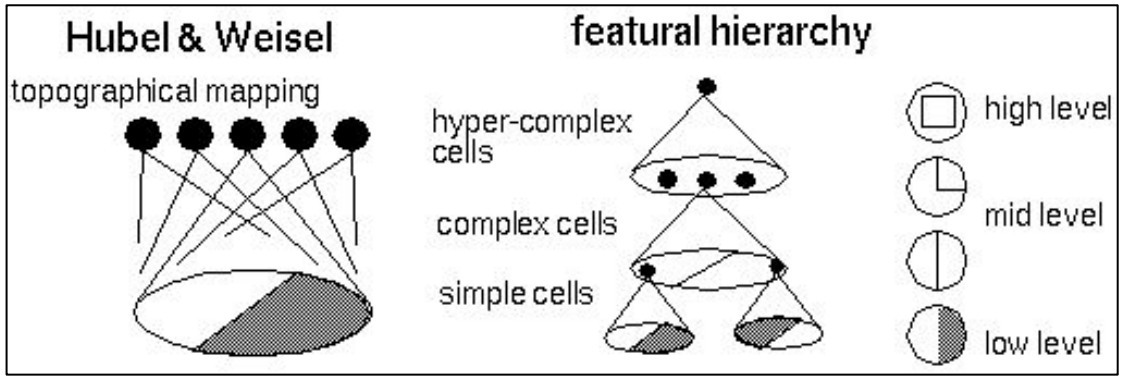


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Preview



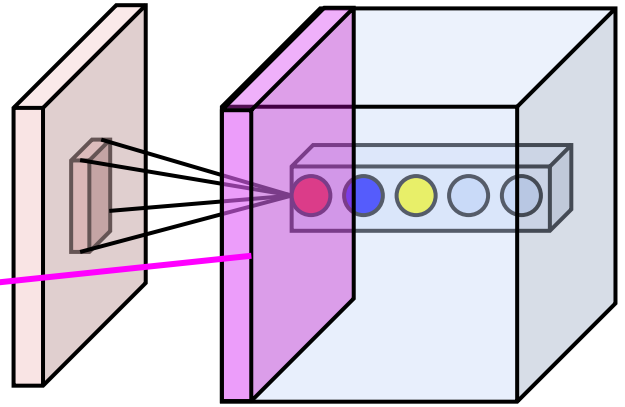
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]



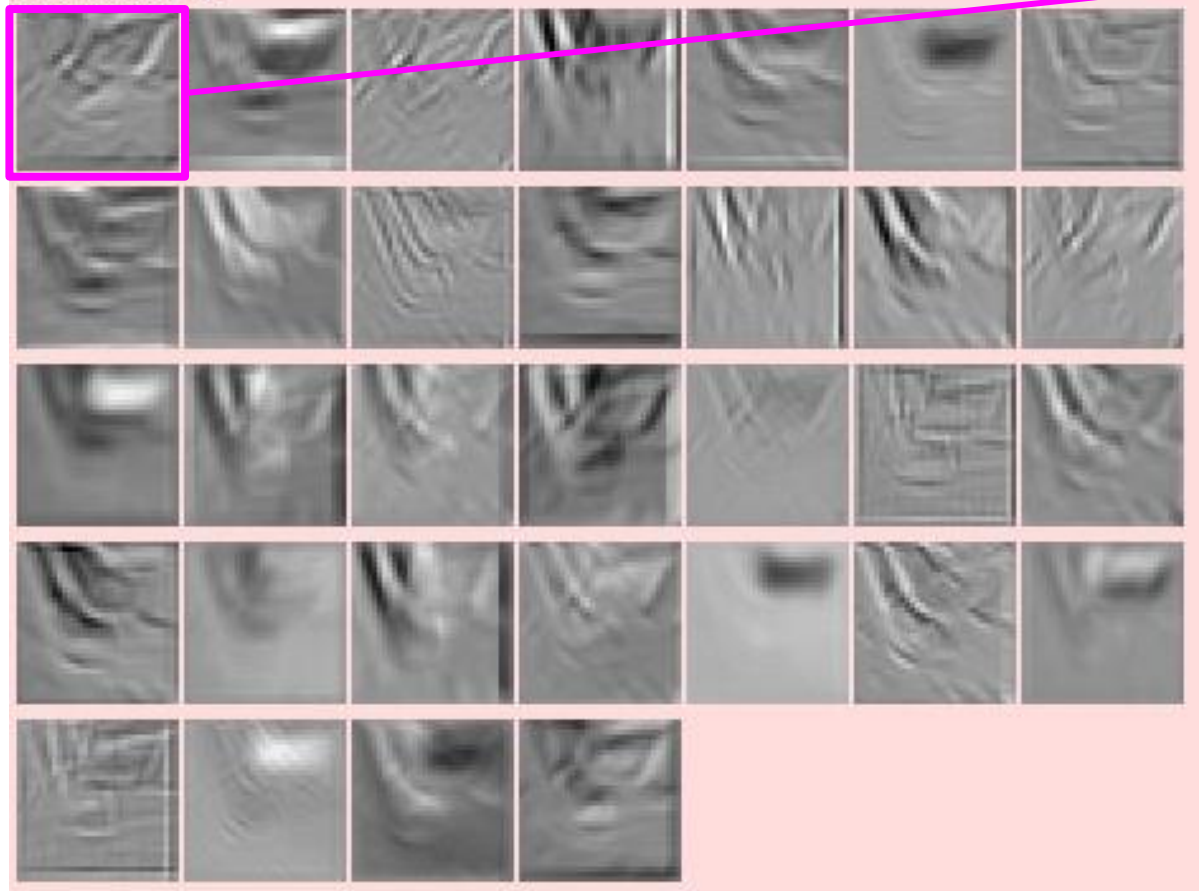
[From recent Yann LeCun slides]

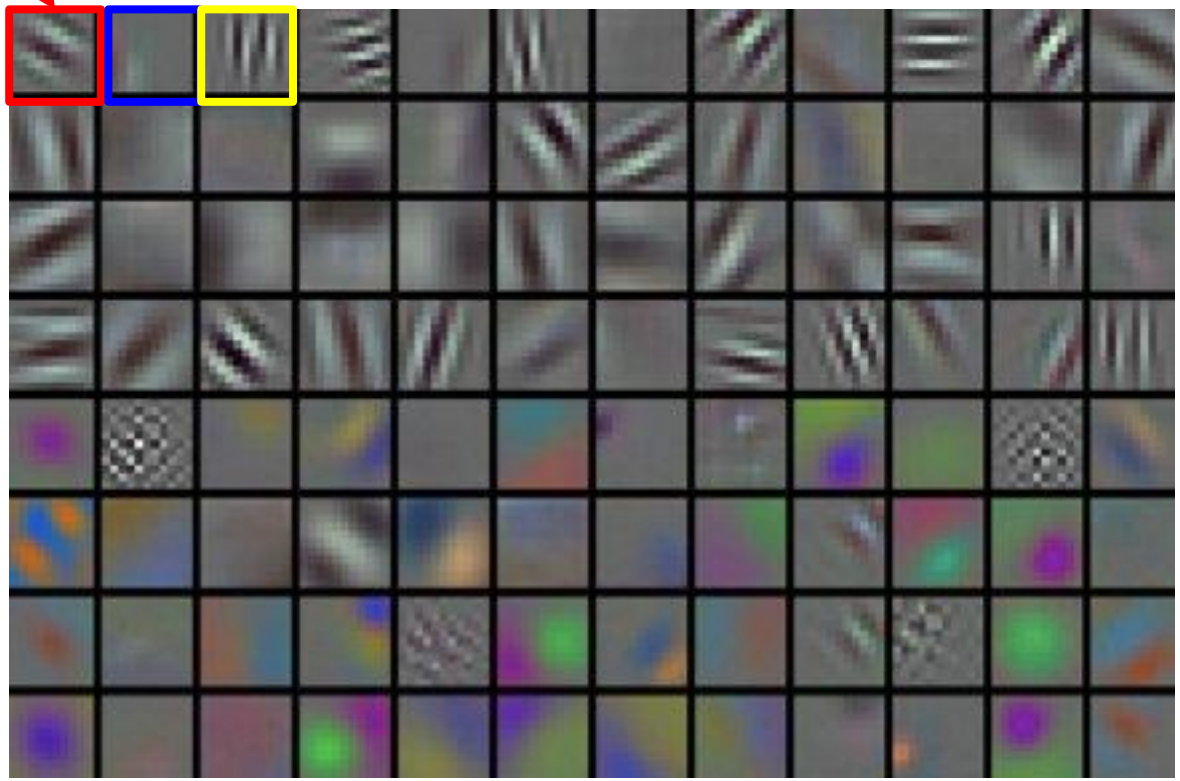
Activations:

convolving the first filter in the input gives the first slice of depth in output volume

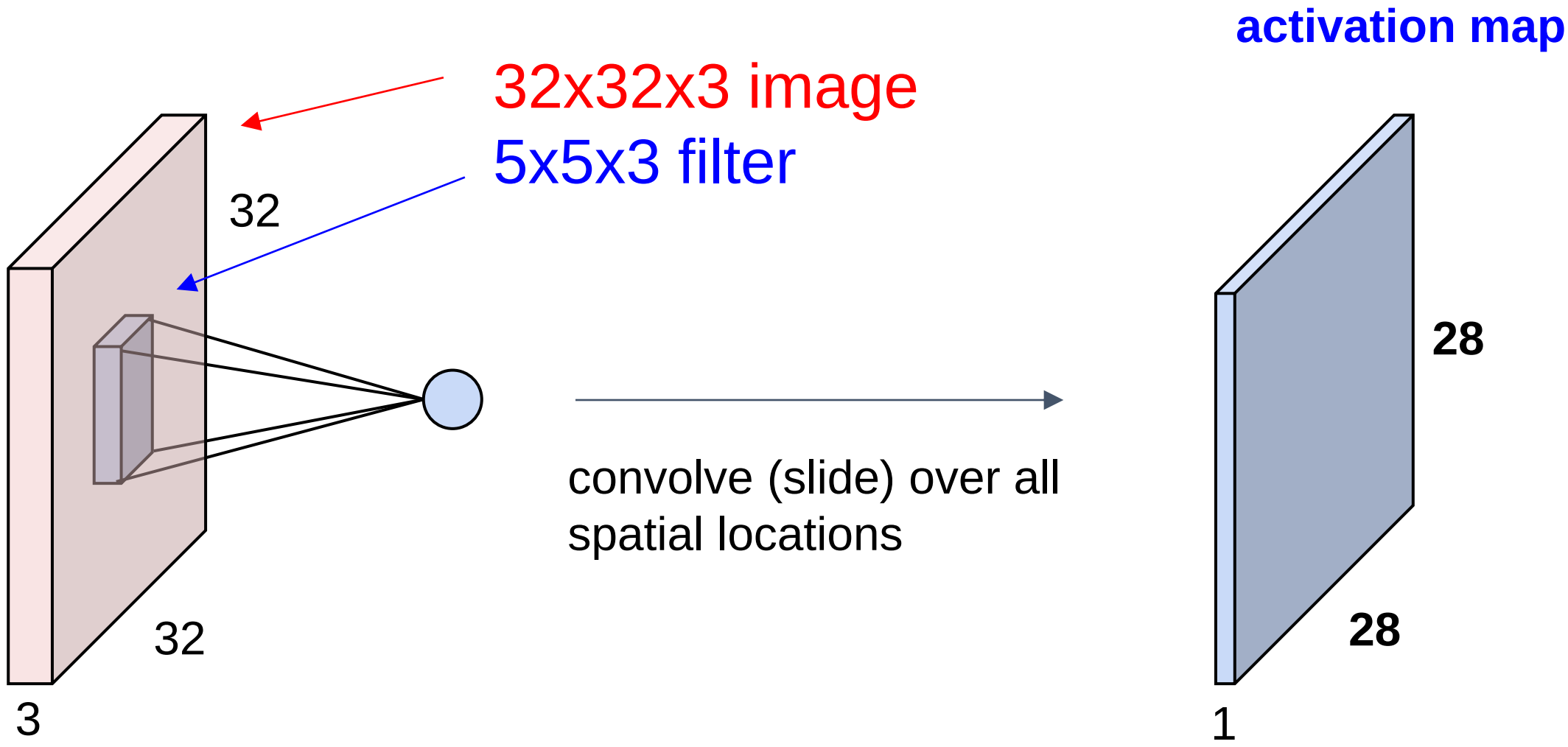


Activations:

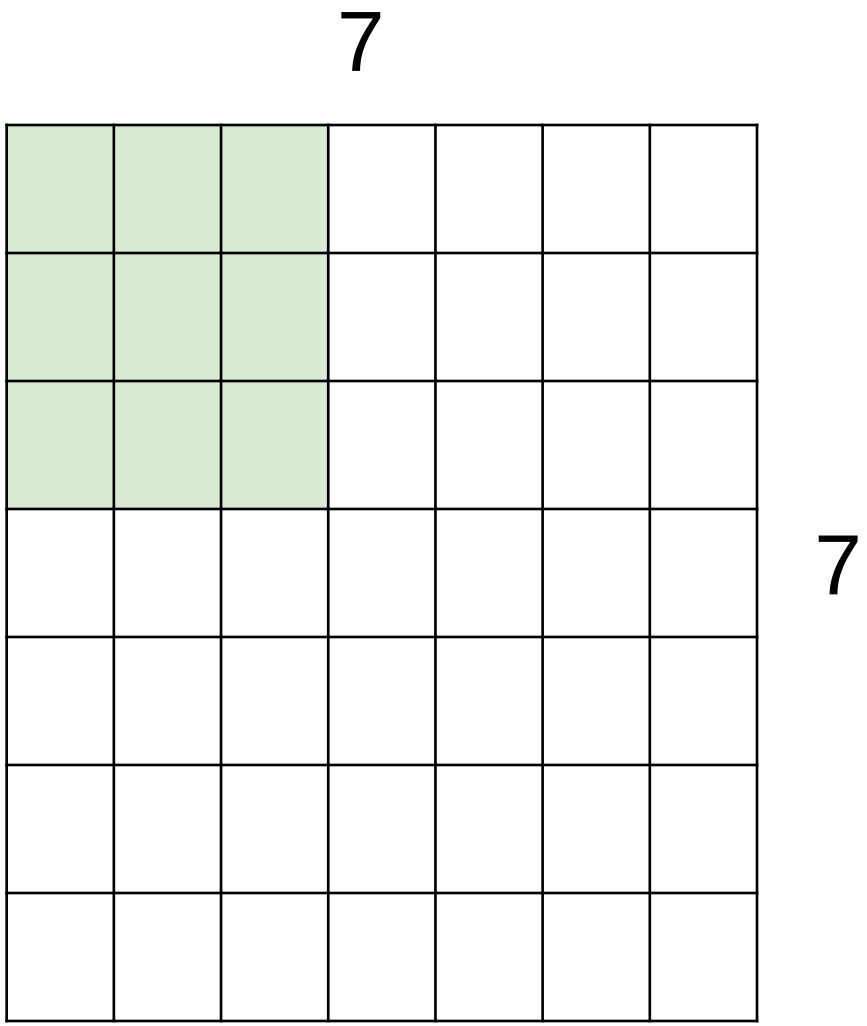




A closer look at spatial dimensions:

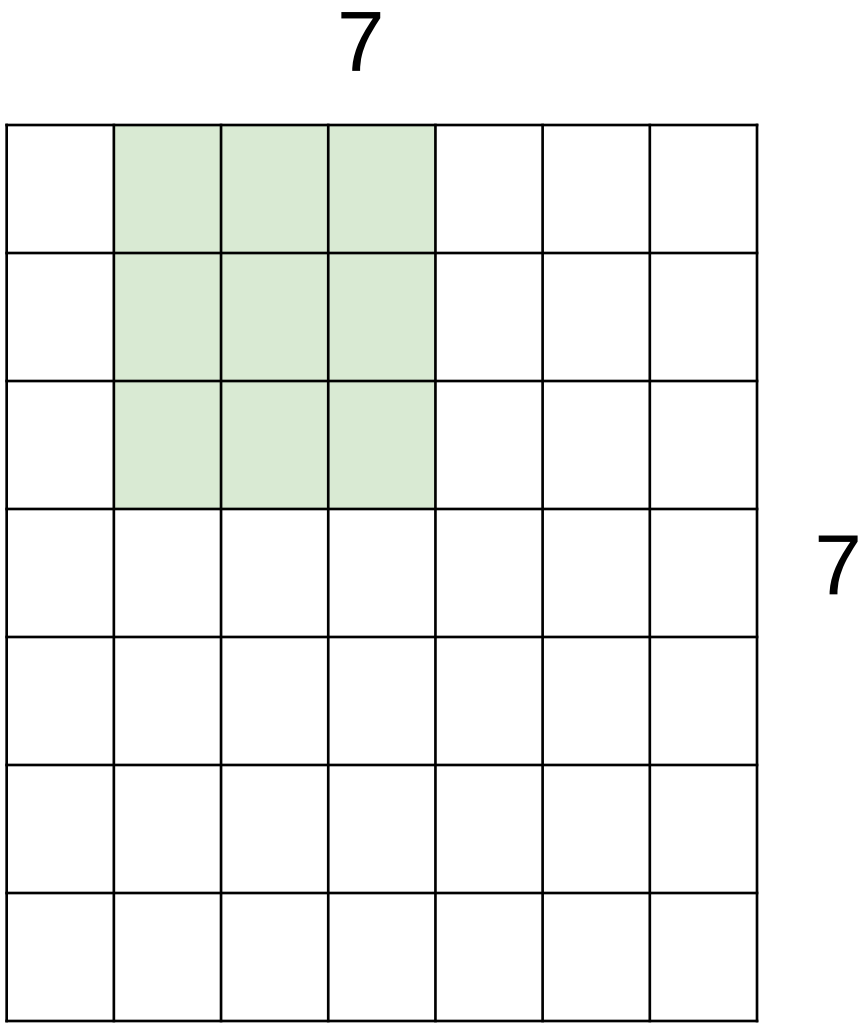


A closer look at spatial dimensions:



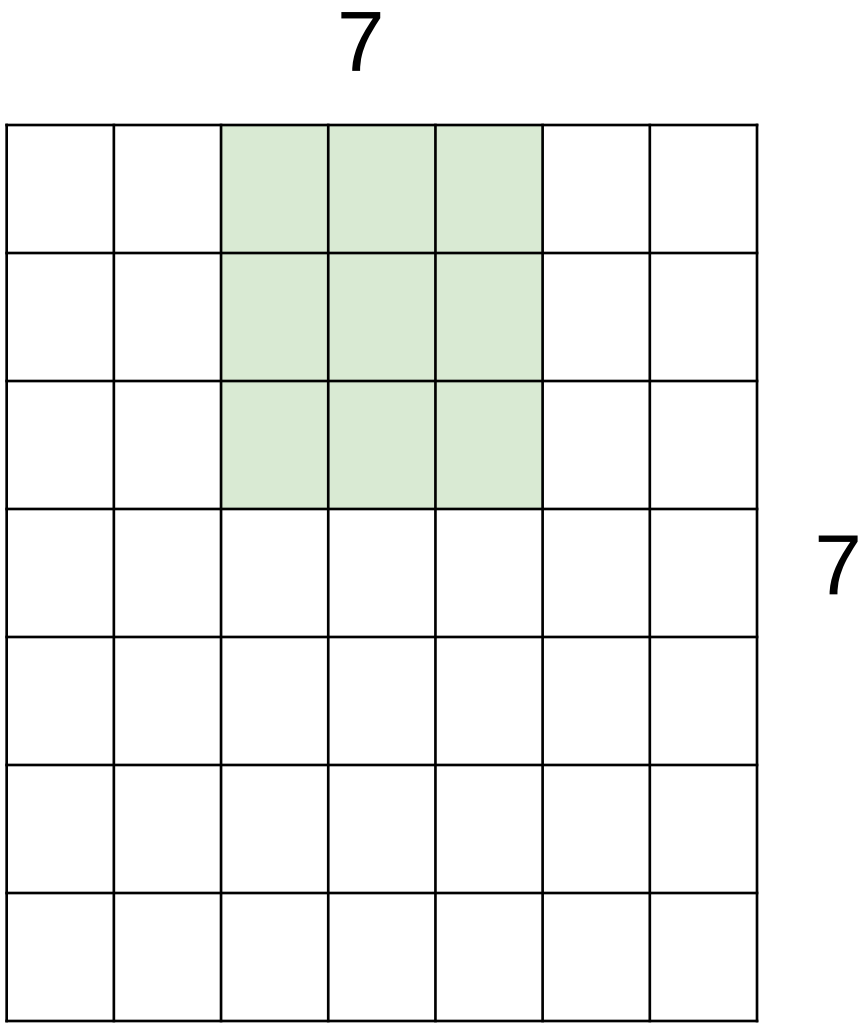
7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

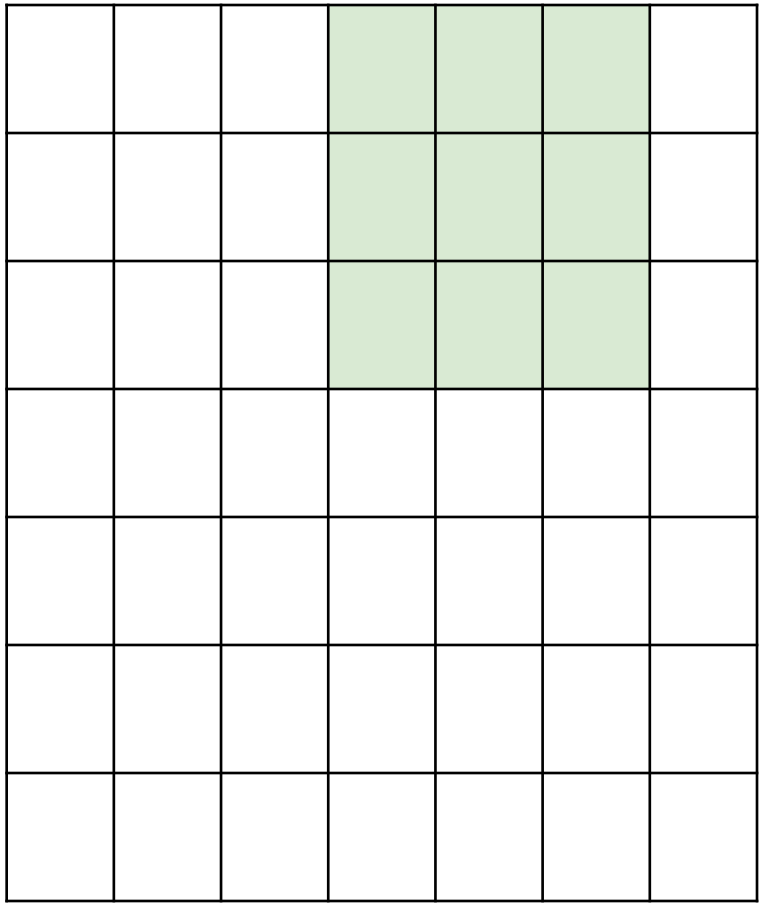
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

A closer look at spatial dimensions:

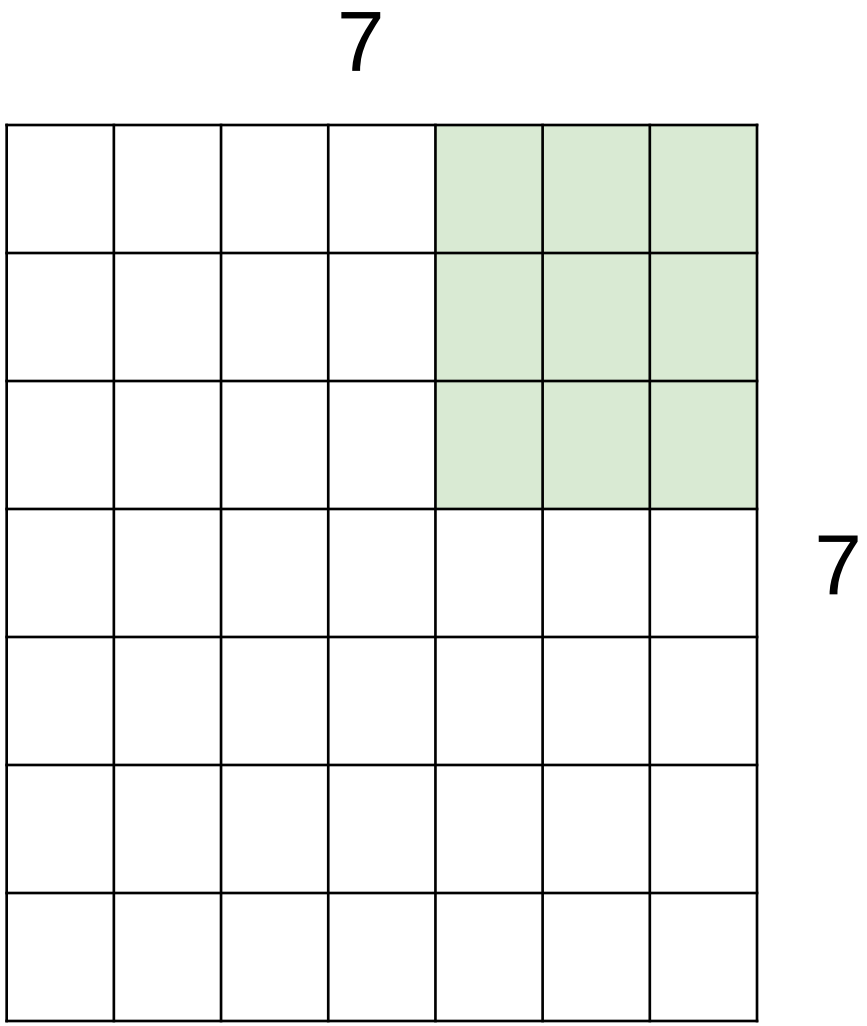
7



7

7x7 input (spatially)
assume 3x3 filter

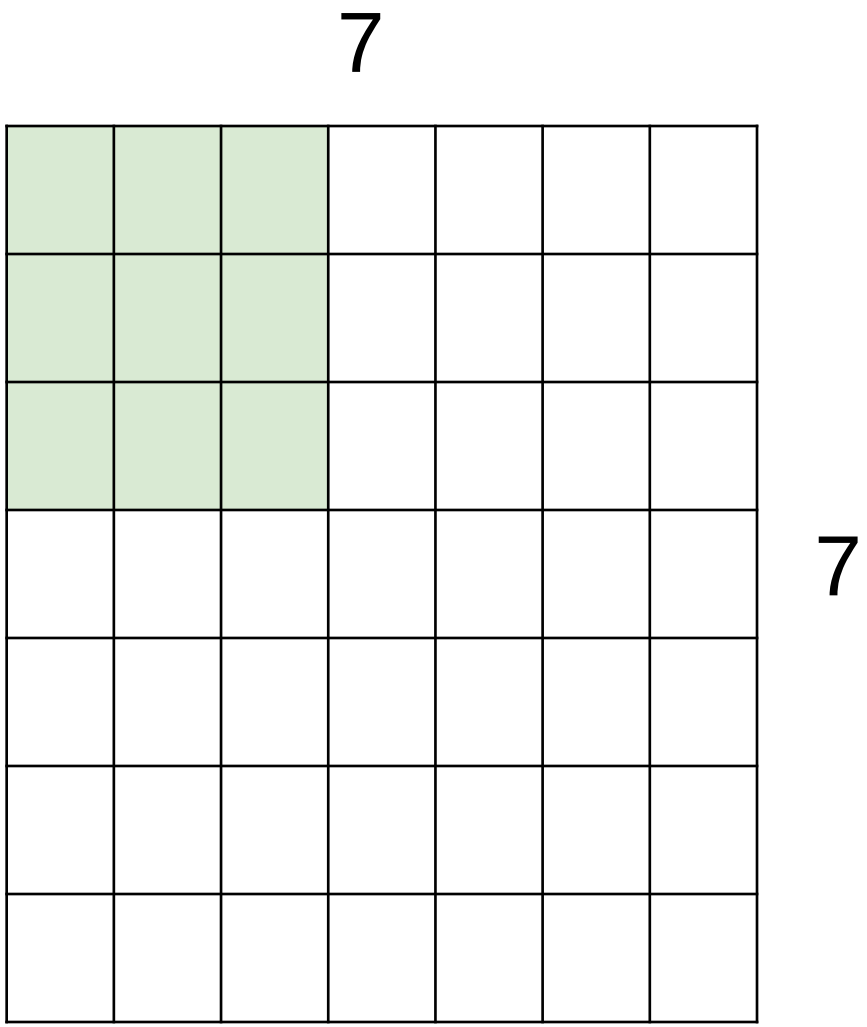
A closer look at spatial dimensions:



7x7 input (spatially)
assume 3x3 filter

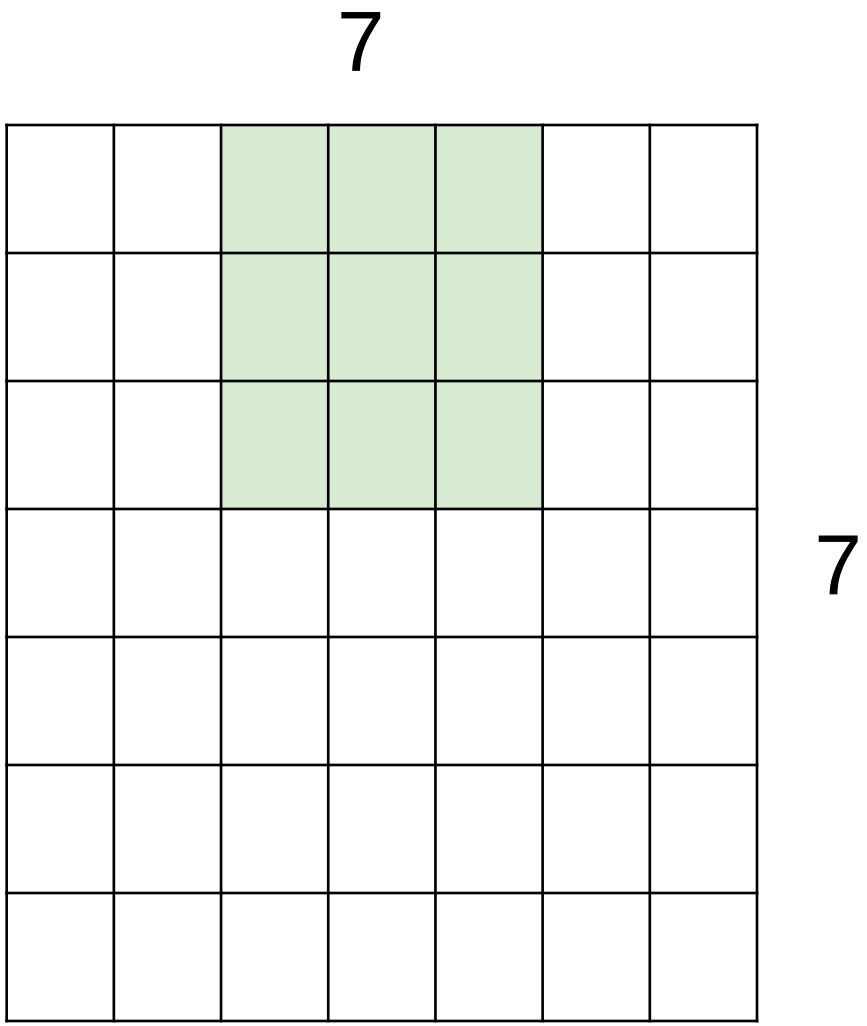
=> 5x5 output

A closer look at spatial dimensions:



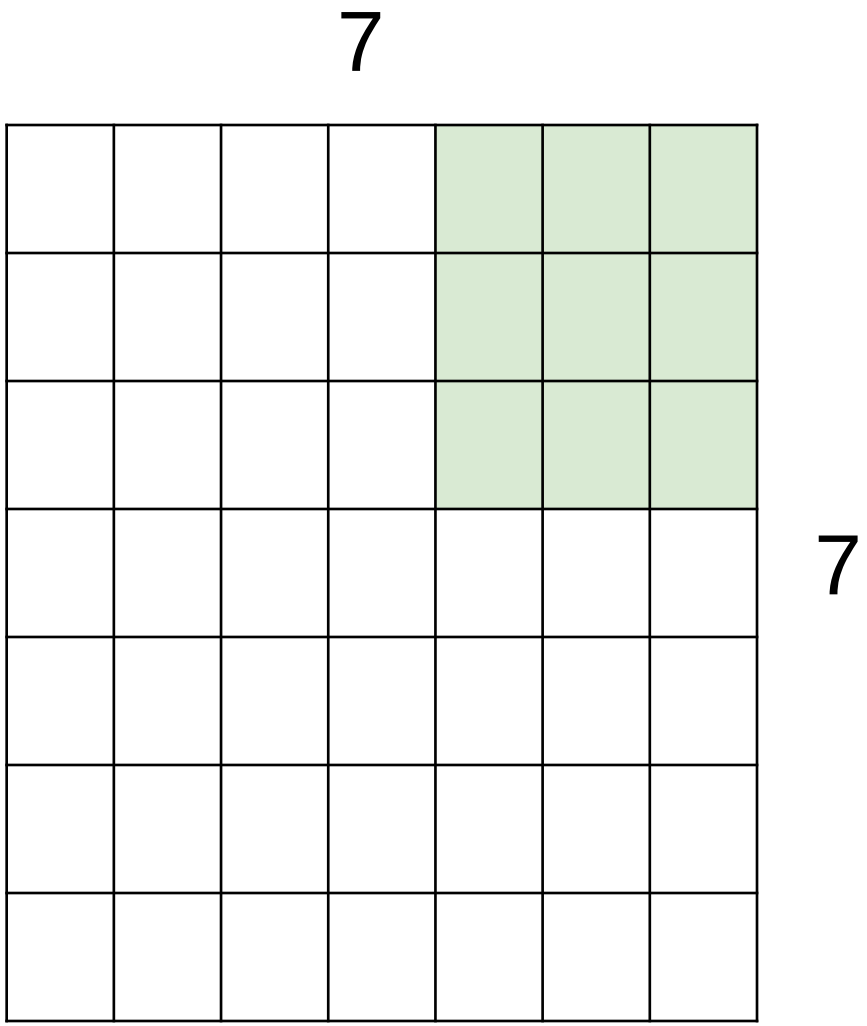
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



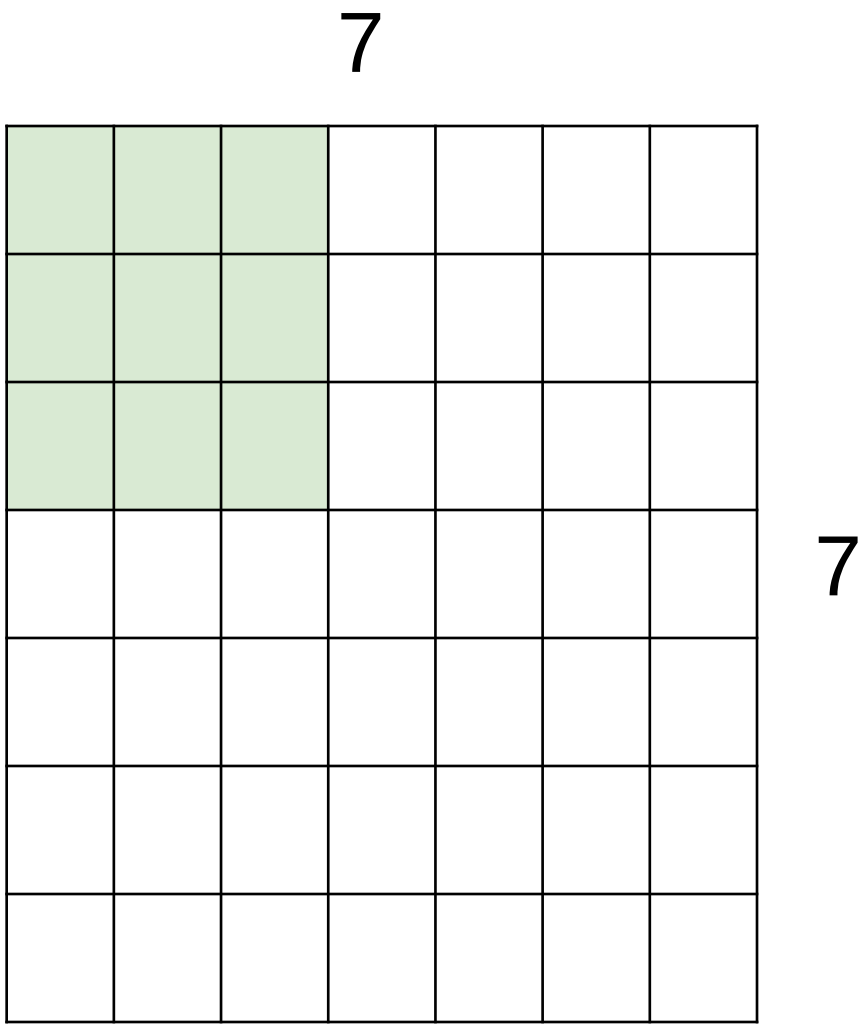
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**

A closer look at spatial dimensions:



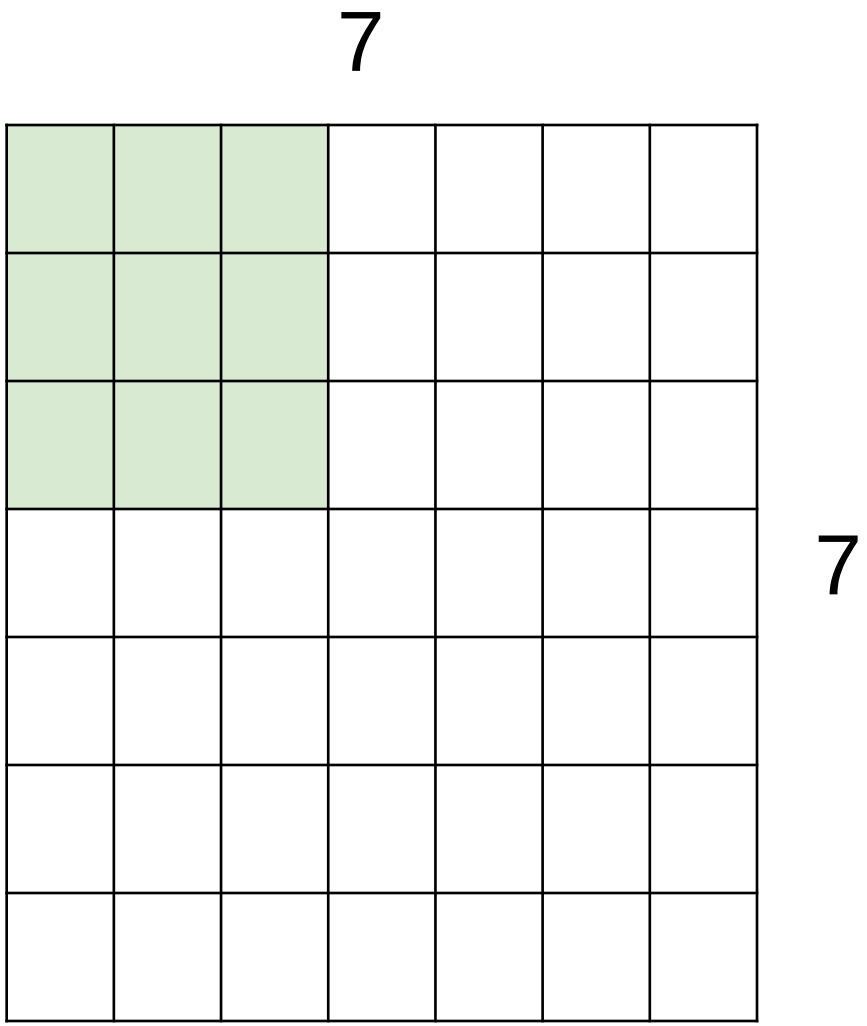
7x7 input (spatially)
assume 3x3 filter
applied **with stride 2**
=> 3x3 output!

A closer look at spatial dimensions:



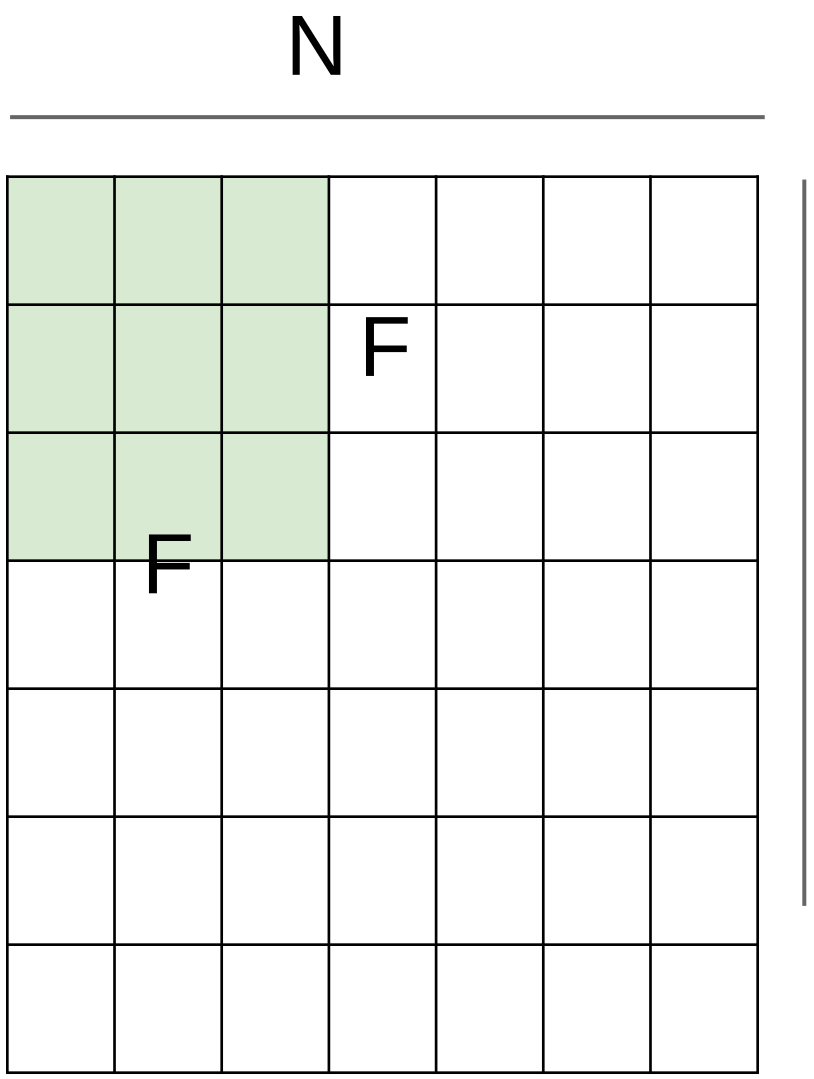
7x7 input (spatially)
assume 3x3 filter
applied **with stride 3?**

A closer look at spatial dimensions:



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

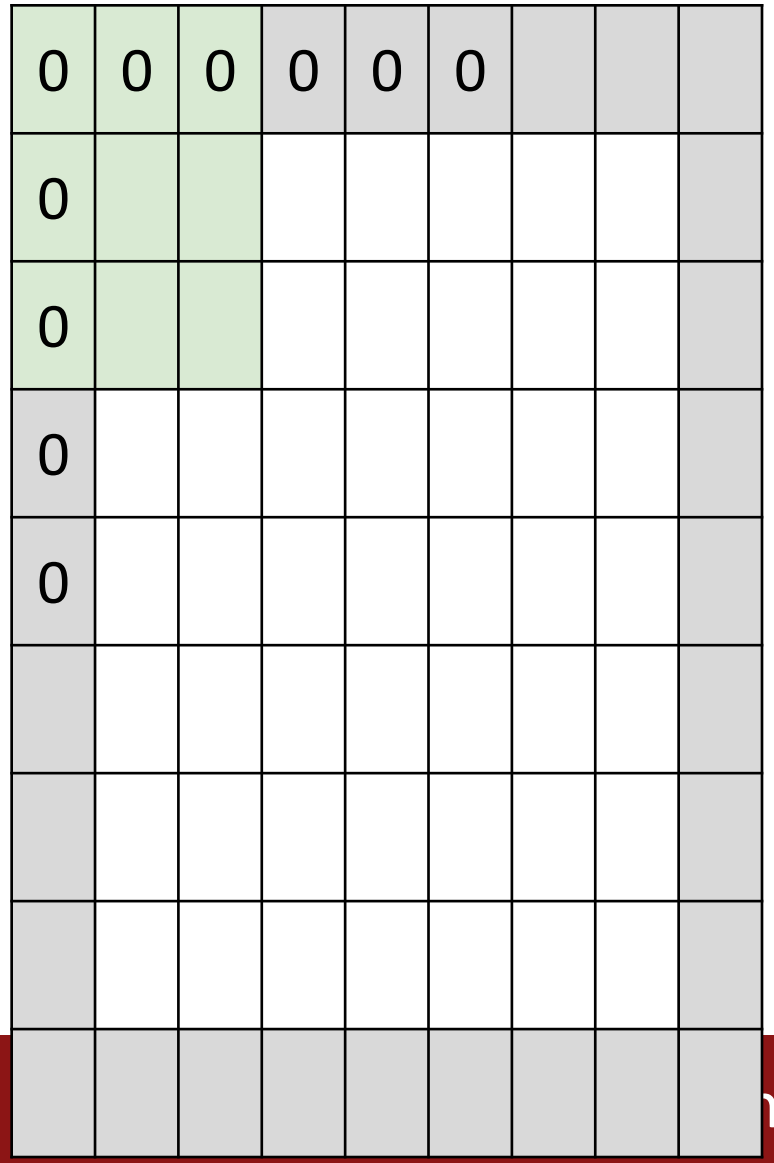
doesn't fit!
cannot apply 3x3 filter on
7x7 input with stride 3.



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

e.g. N = 7, F = 3:
stride 1 => (7 - 3)/1 + 1 = 5
stride 2 => (7 - 3)/2 + 1 = 3
stride 3 => (7 - 3)/3 + 1 = 2.33 :\

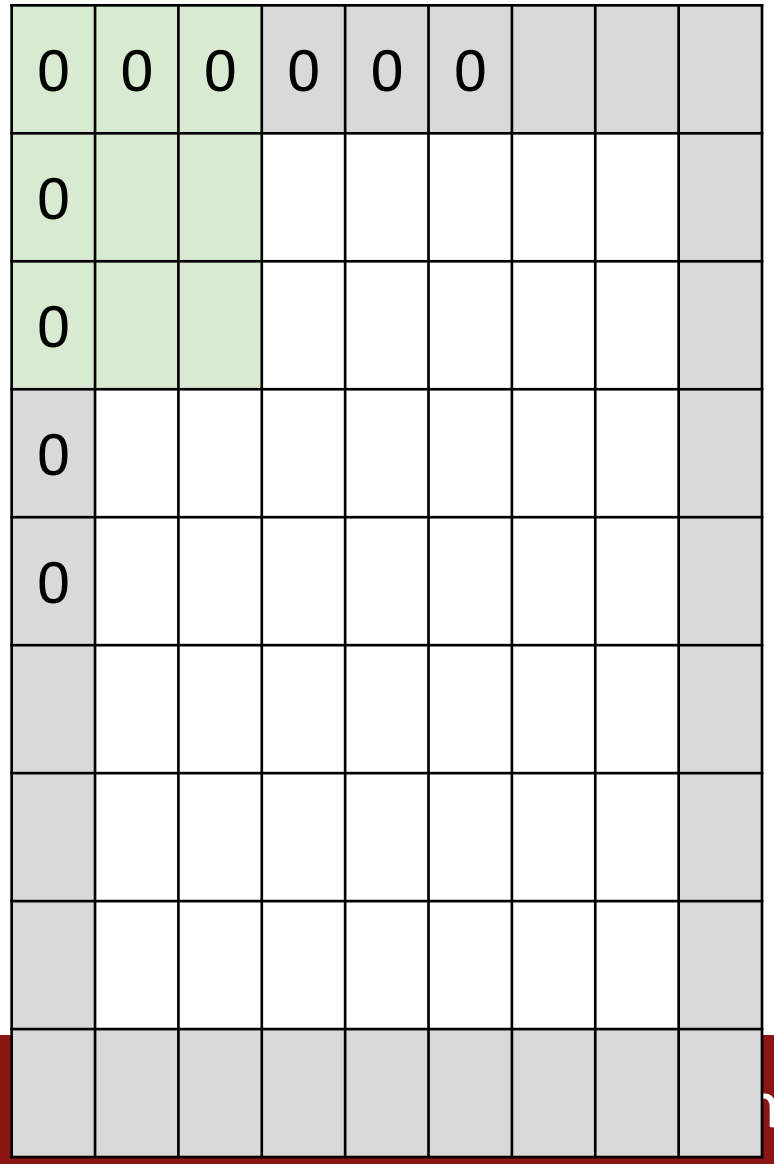
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

(recall:)
(N - F) / stride + 1

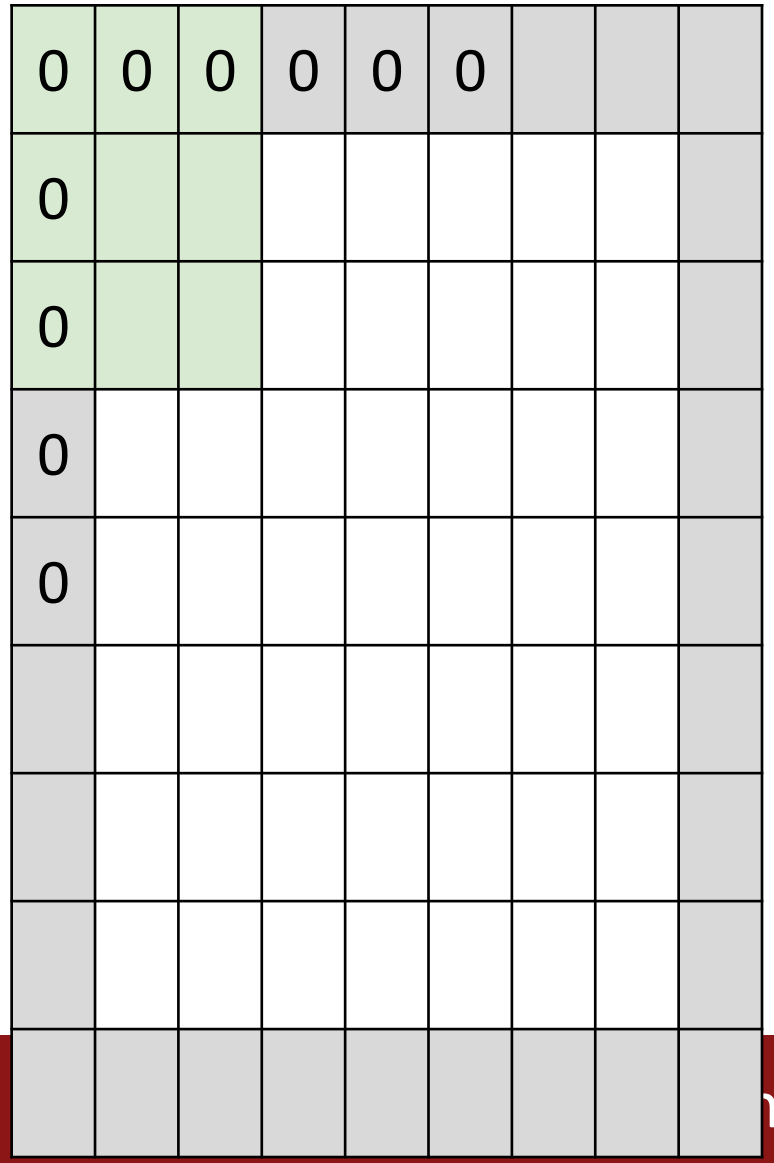
In practice: Common to zero pad the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!

In practice: Common to zero pad the border

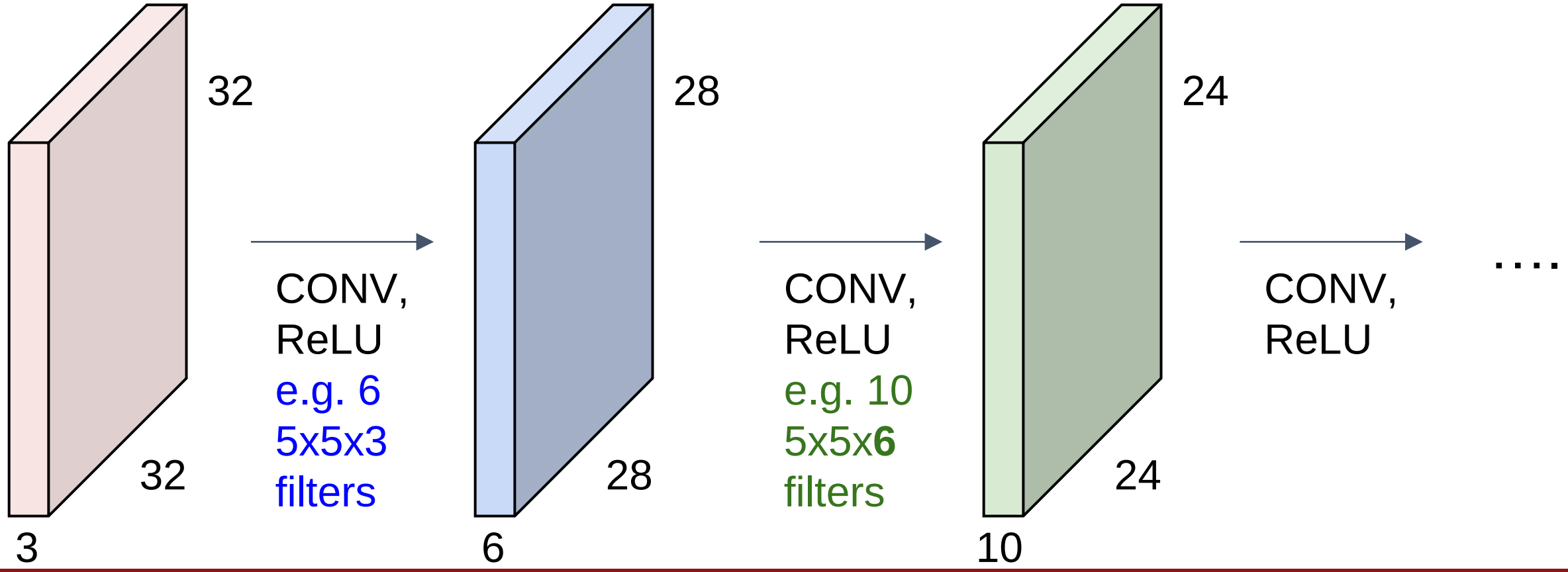


e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

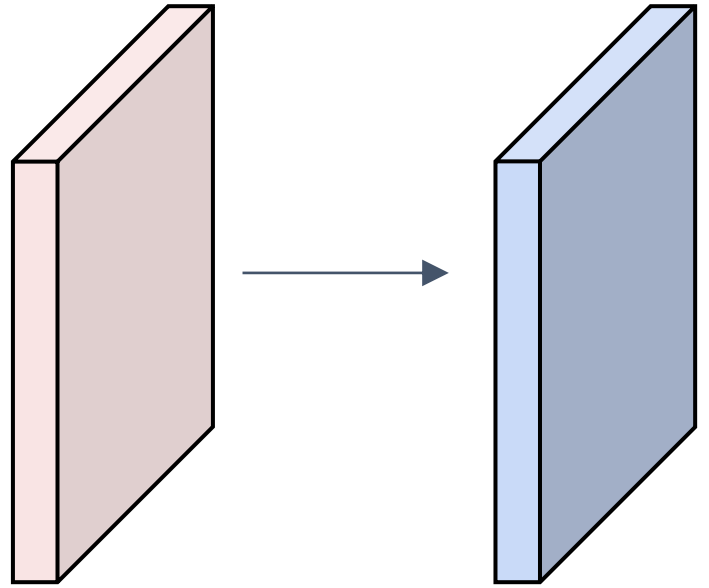
7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

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.



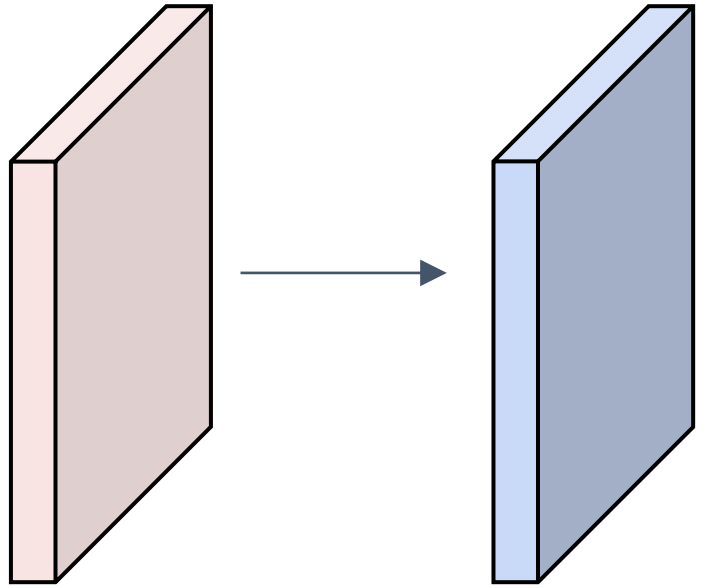
Examples time:



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

Output volume size: ?

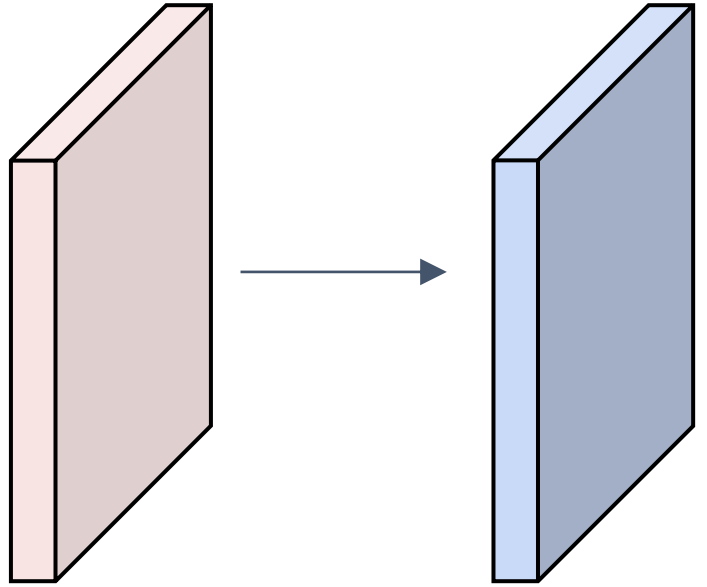
Examples time:



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

Output volume size:
(32+2*2-5)/1+1 = 32 spatially, so
32x32x10

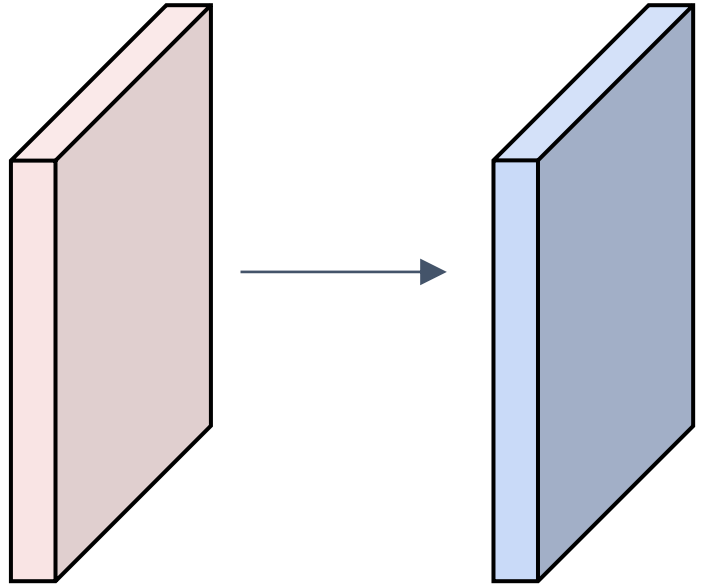
Examples time:



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**

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Summary. To summarize, the Conv Layer:

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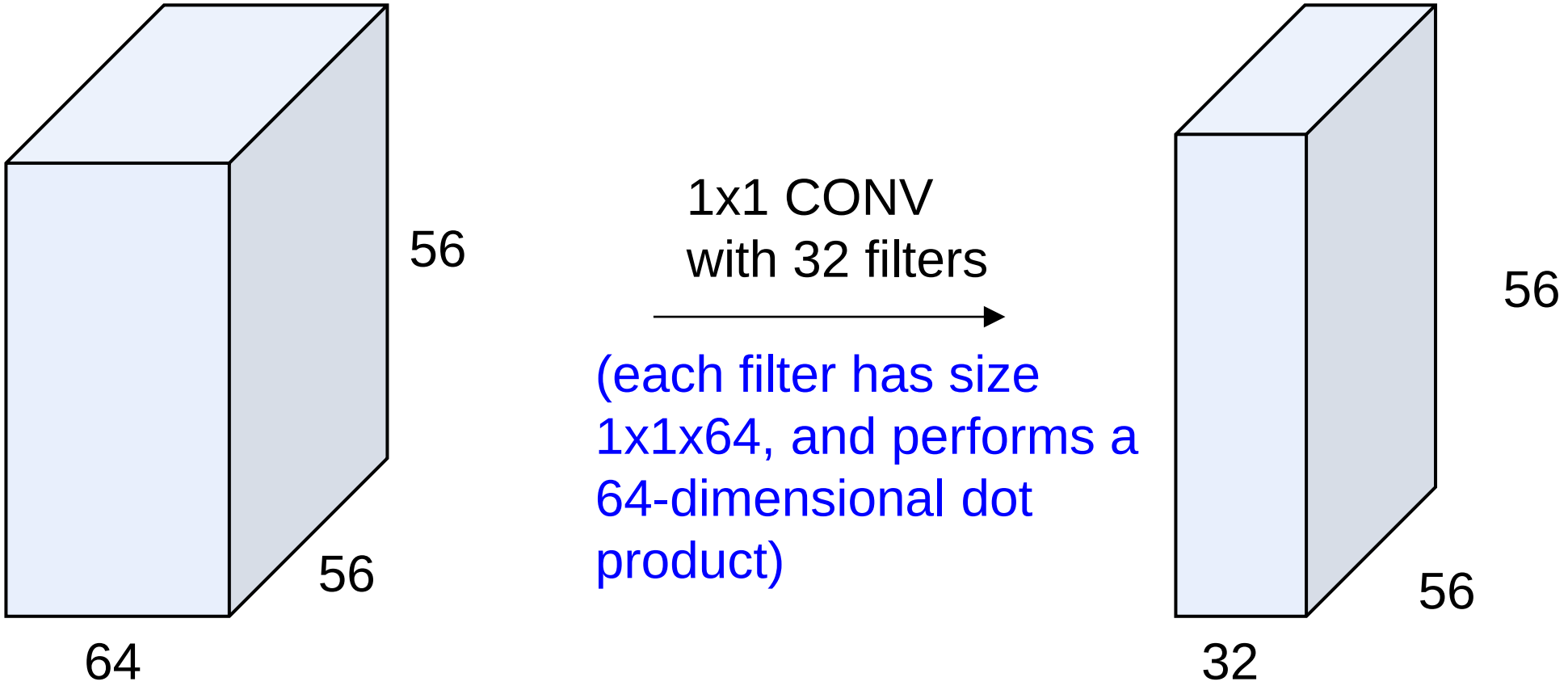
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Common settings:

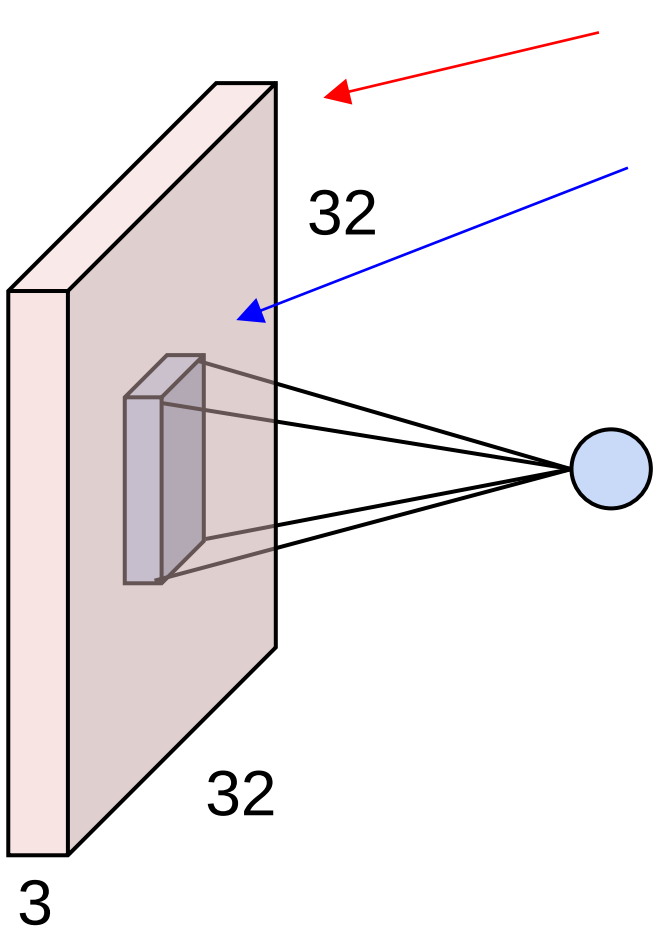
K = (powers of 2, e.g. 32, 64, 128, 512)

- 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

(btw, 1x1 convolution layers make perfect sense)



The brain/neuron view of CONV Layer

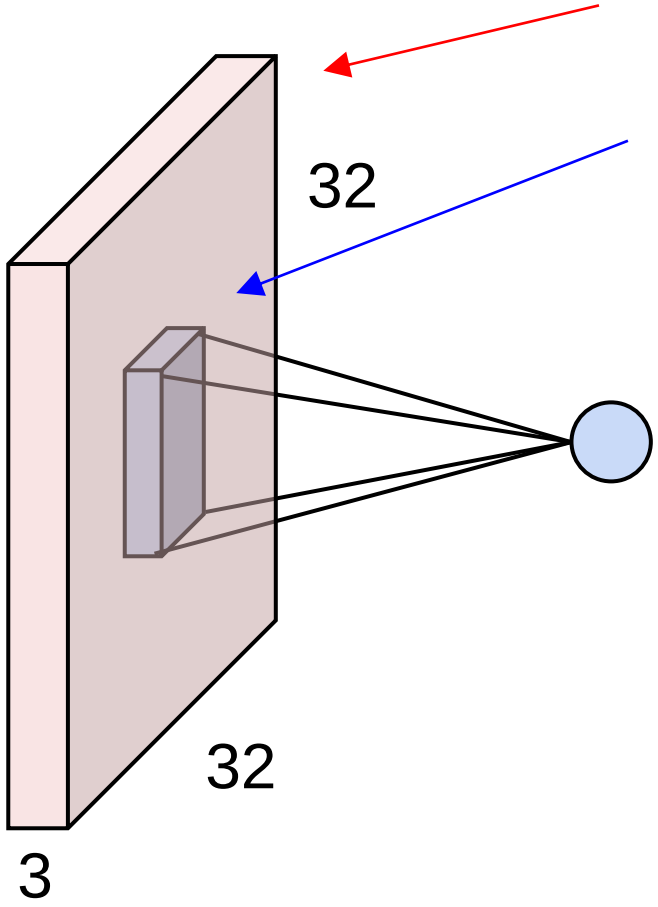


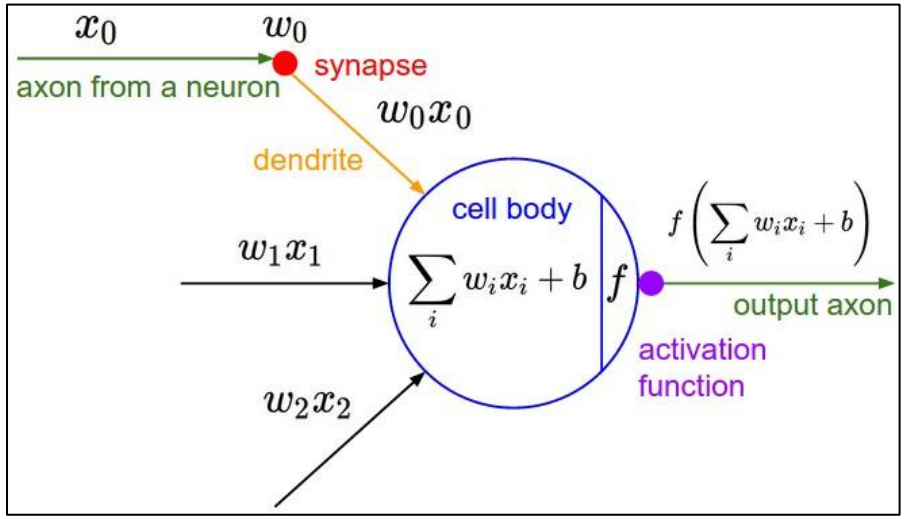
32x32x3 image

5x5x3 filter

1 number:
the result of taking a dot product between the filter and this part of the image
(i.e. 5*5*3 = 75-dimensional dot product)

The brain/neuron view of CONV Layer

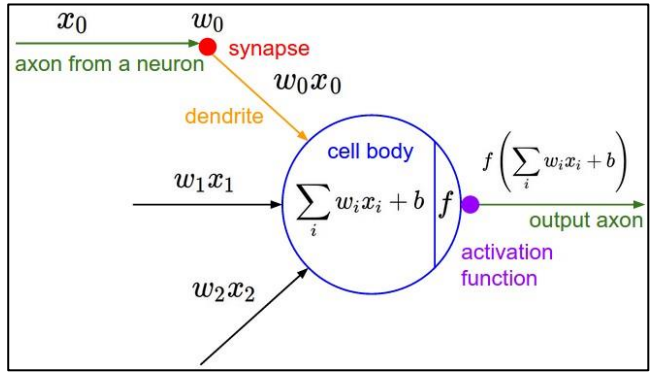


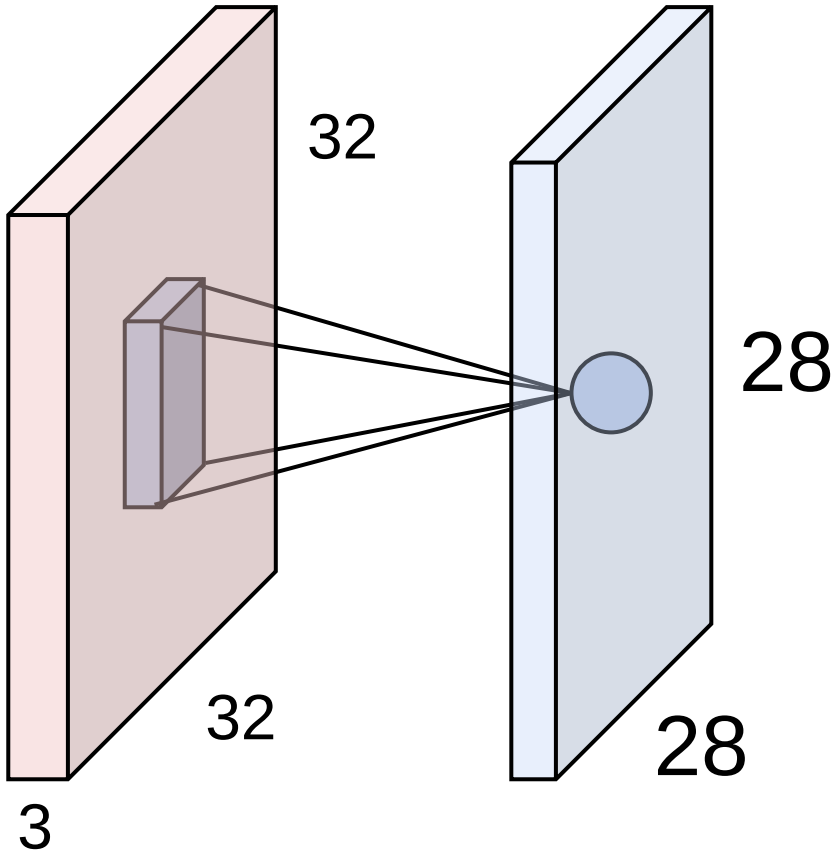


It's just a neuron with local connectivity...

1 number:
the result of taking a dot product between the filter and this part of the image
(i.e. 5*5*3 = 75-dimensional dot product)

The brain/neuron view of CONV Layer



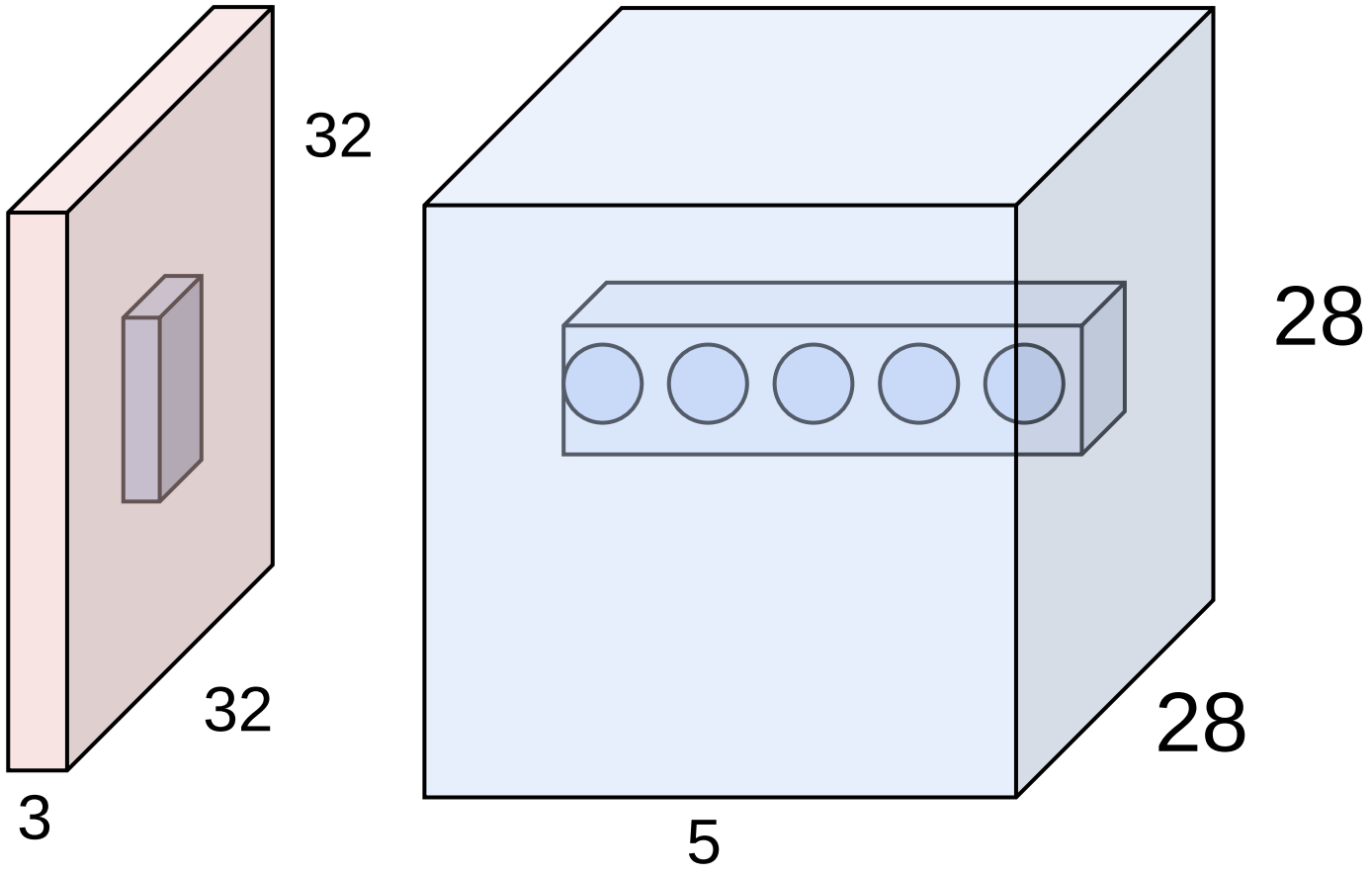


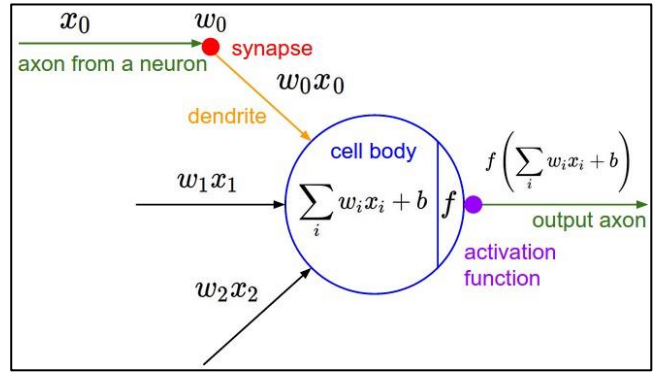
An activation map is a 28x28 sheet of neuron outputs:

1. Each is connected to a small region in the input
2. All of them share parameters

"5x5 filter" -> "5x5 receptive field for each neuron"

The brain/neuron view of CONV Layer

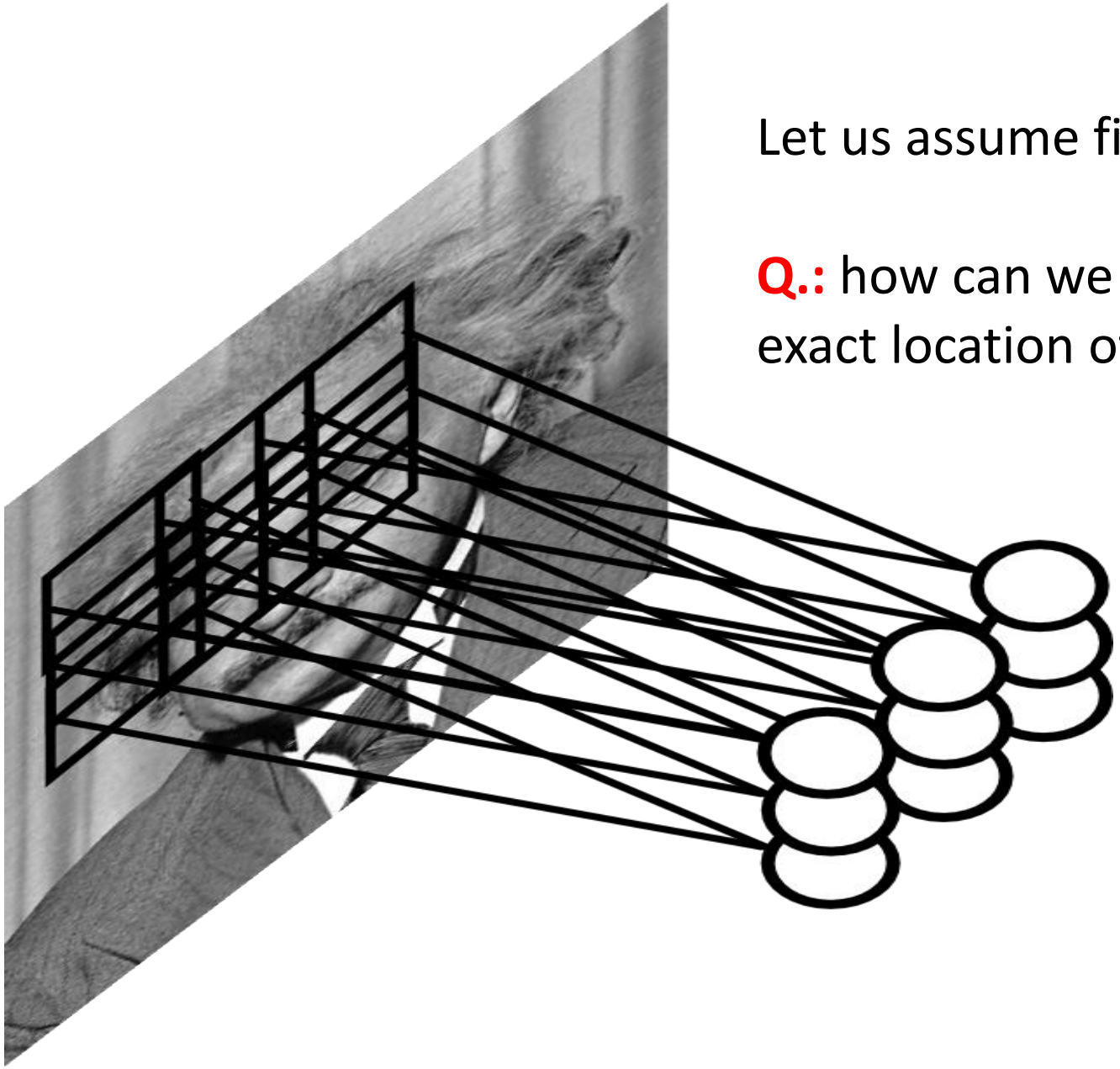




E.g. with 5 filters,
CONV layer consists of neurons arranged in a 3D grid (28x28x5)

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

Pooling Layer

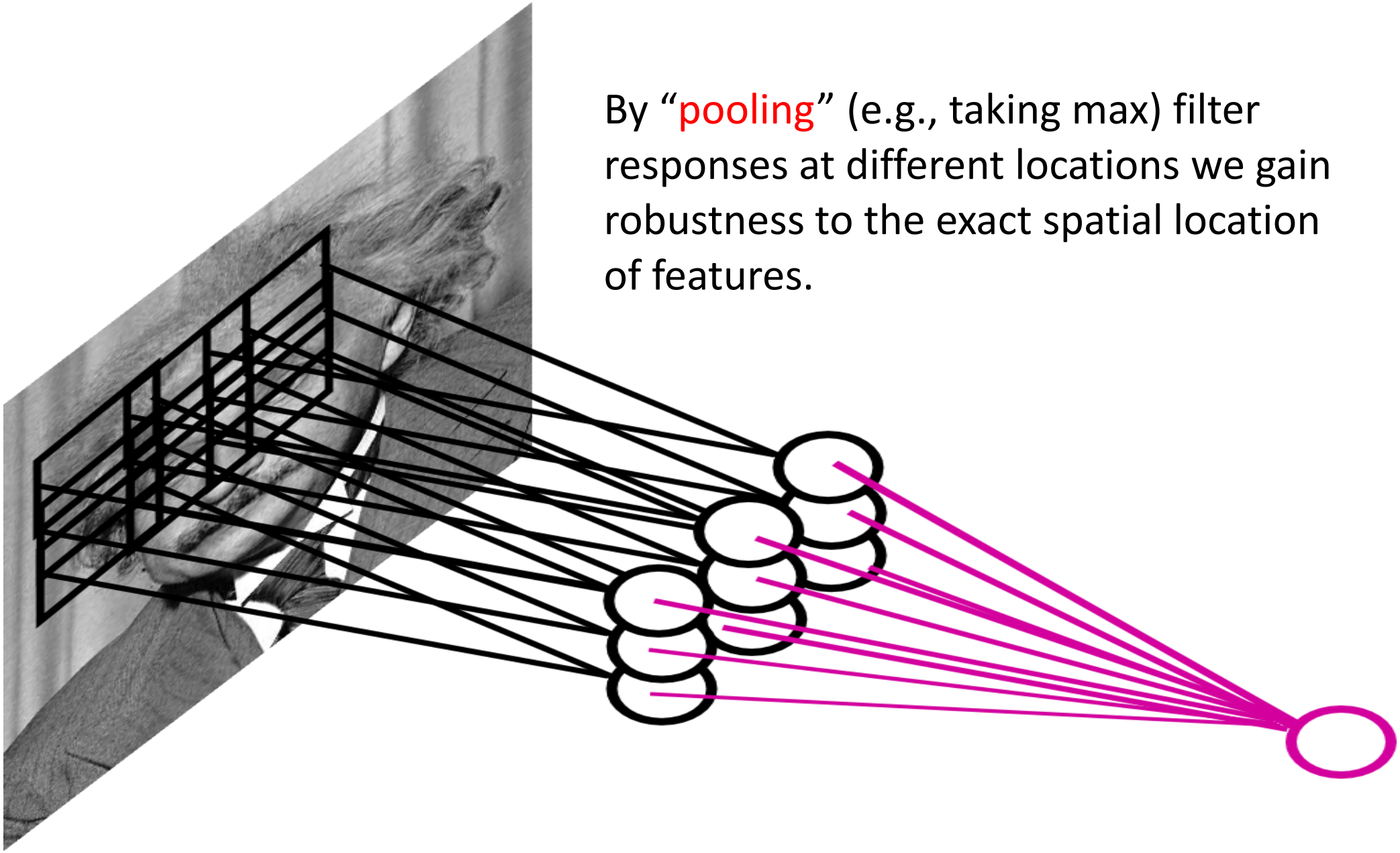


Let us assume filter is an “eye” detector.

Q.: how can we make the detection robust to the exact location of the eye?

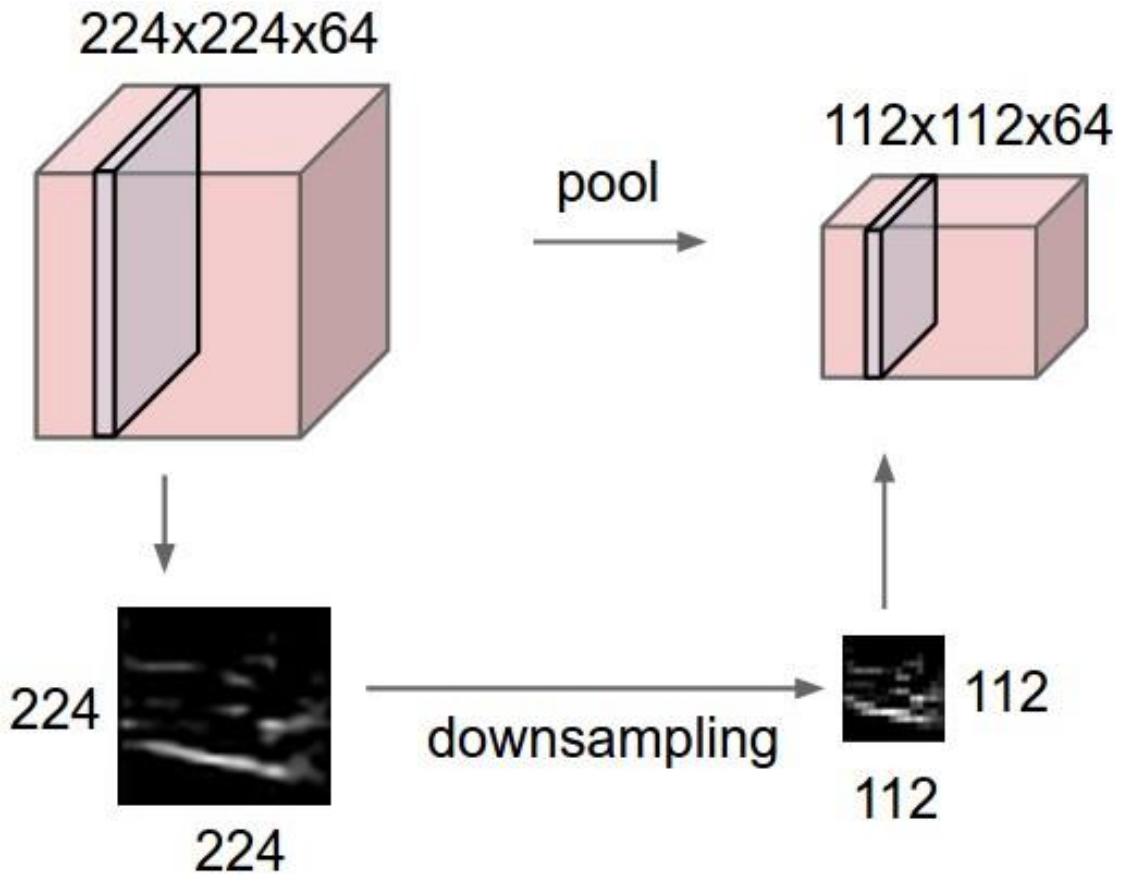
Pooling Layer

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

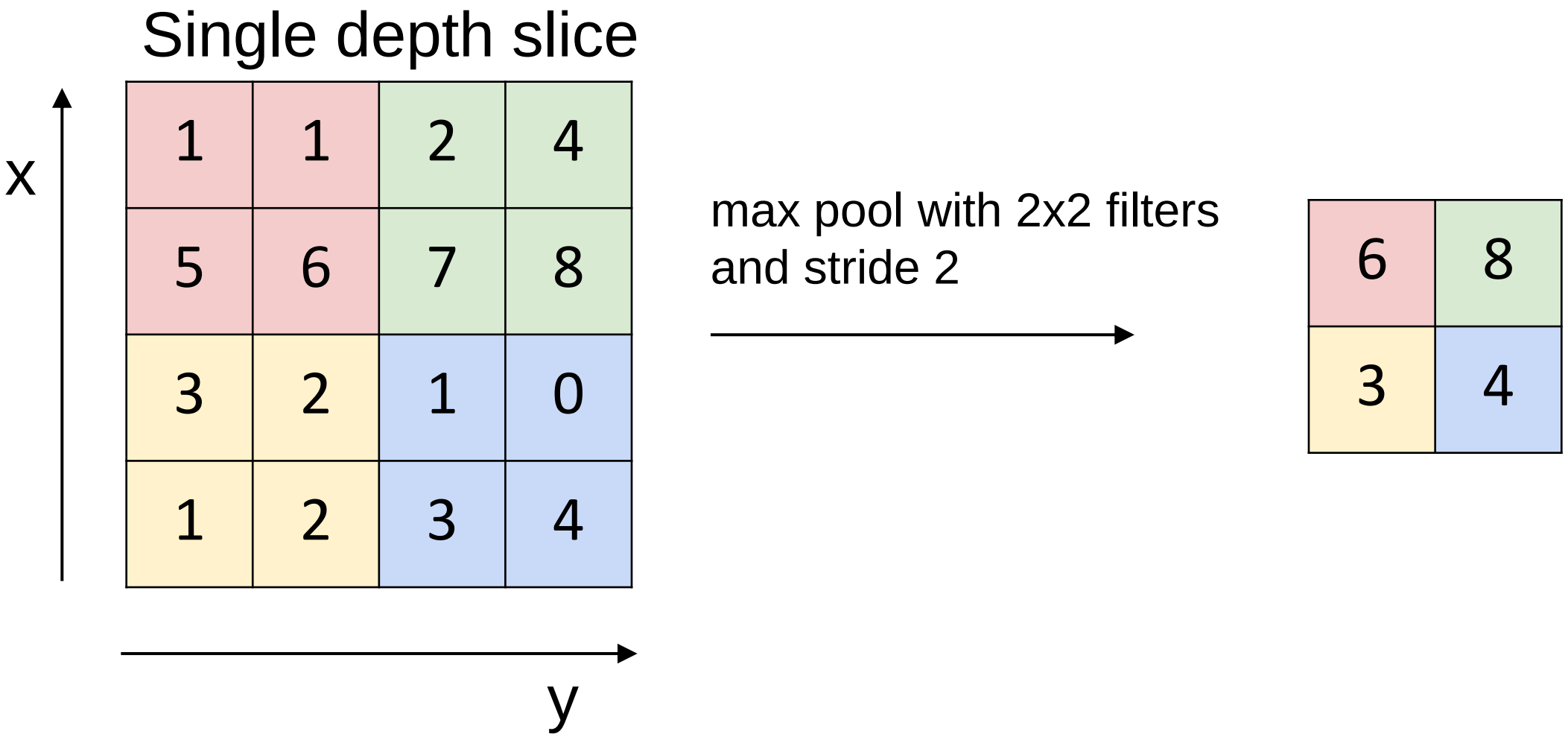


Pooling layer

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



MAX POOLING


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

Pooling

3x3 max-pooling on
5x5 input with
1x1 stride

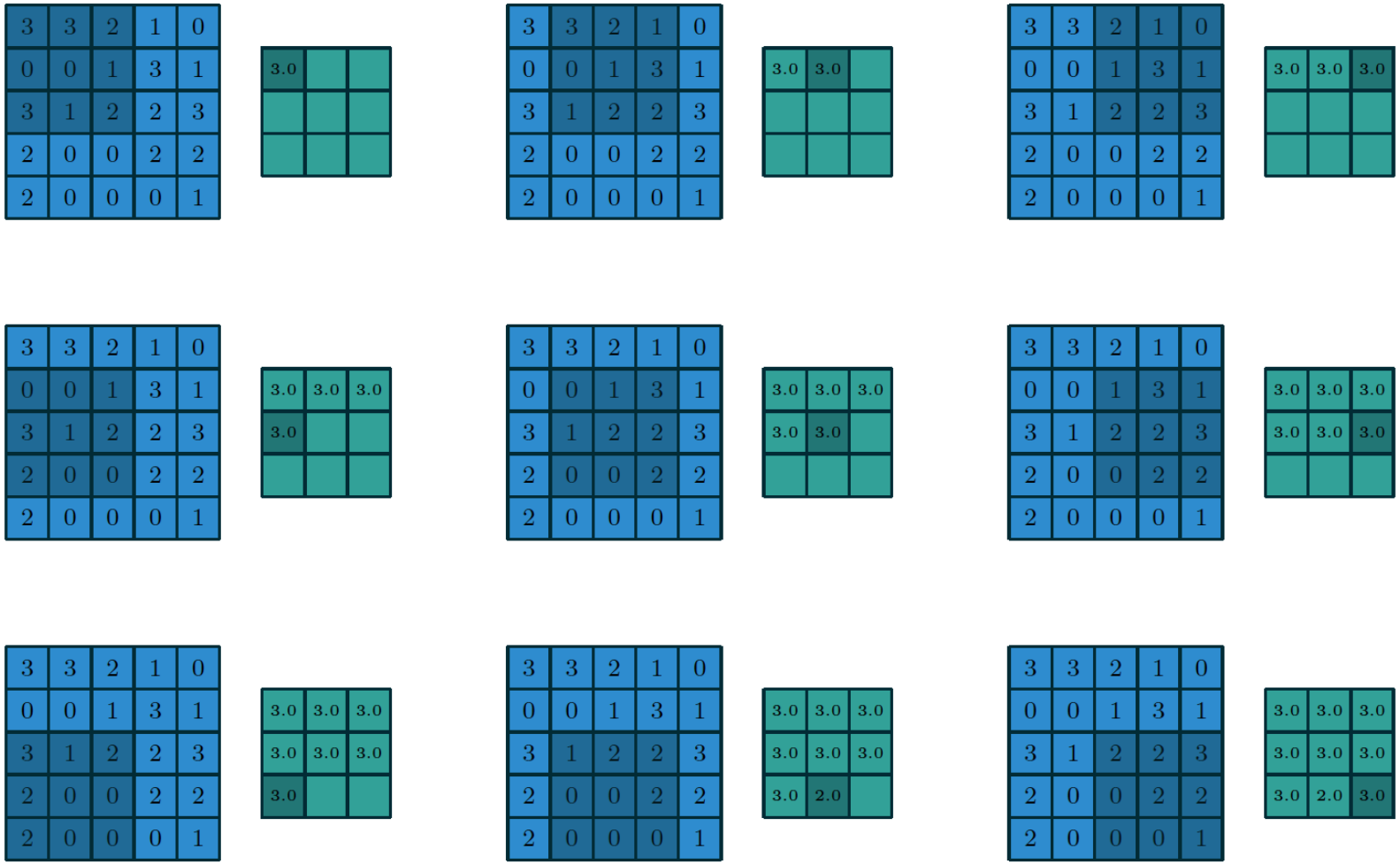


Image courtesy:Vincent Dumoulin

Pooling Arithmetic

(For simplicity we are assuming square input and max pooling kernel)

Input width = Input height = w

Filter width = Filter height = k

Stride = s

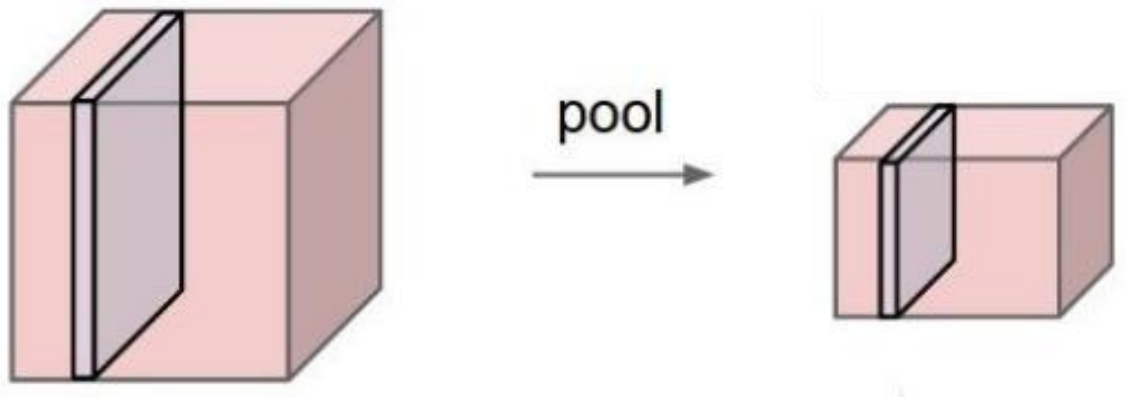
Output size = $\left\lfloor \frac{w-k}{s} \right\rfloor + 1$

Input volume: 32x32x3 [w, h, c].

Max-pooling kernel of size 2x2 [k, k] with stride 2 [s]

What is the output feature map size?

$\left\lfloor \frac{32-2}{2} \right\rfloor + 1 = 16$ So, $16 \times 16 \times 3$ [w, h, c]



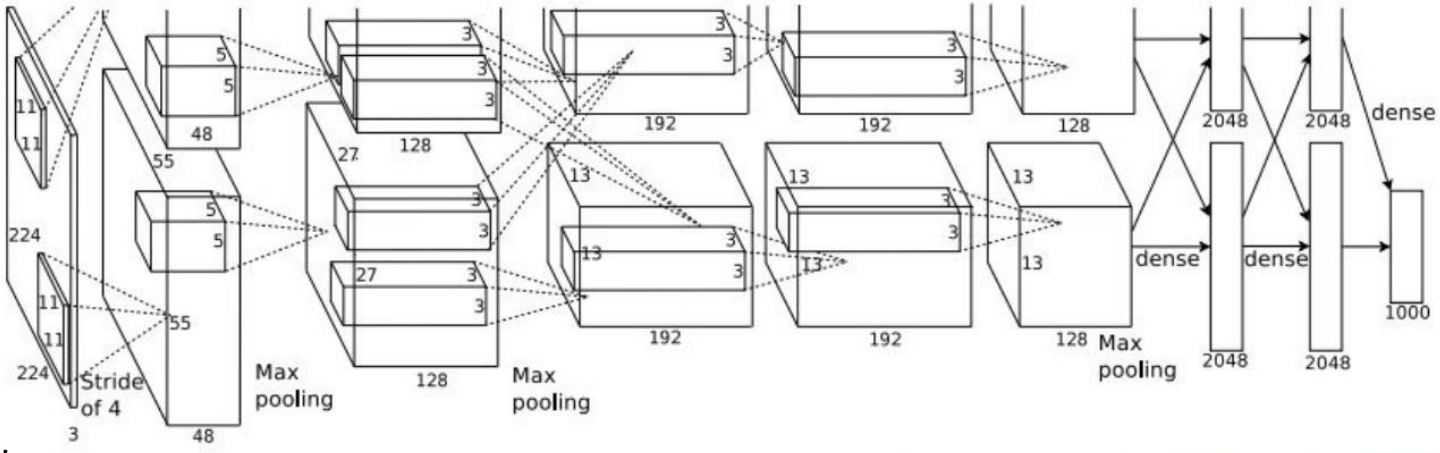
And What is the number of parameters in this pooling layer?

0

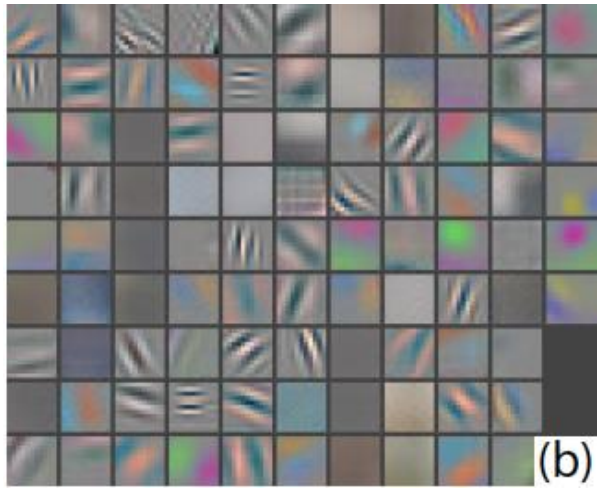
Image courtesy: Andrej Karpathy

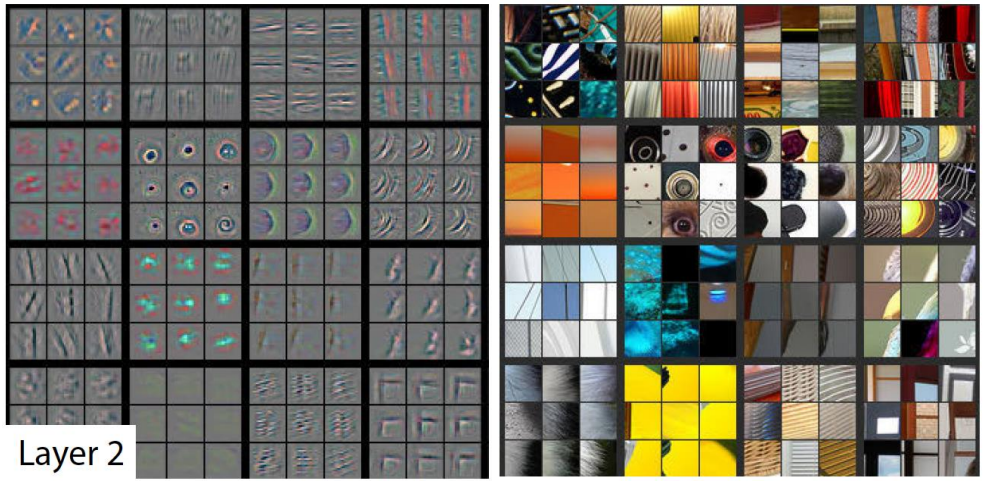
Visualizations

AlexNet (2012)



First layer (CONV1): 96 11x11 filters

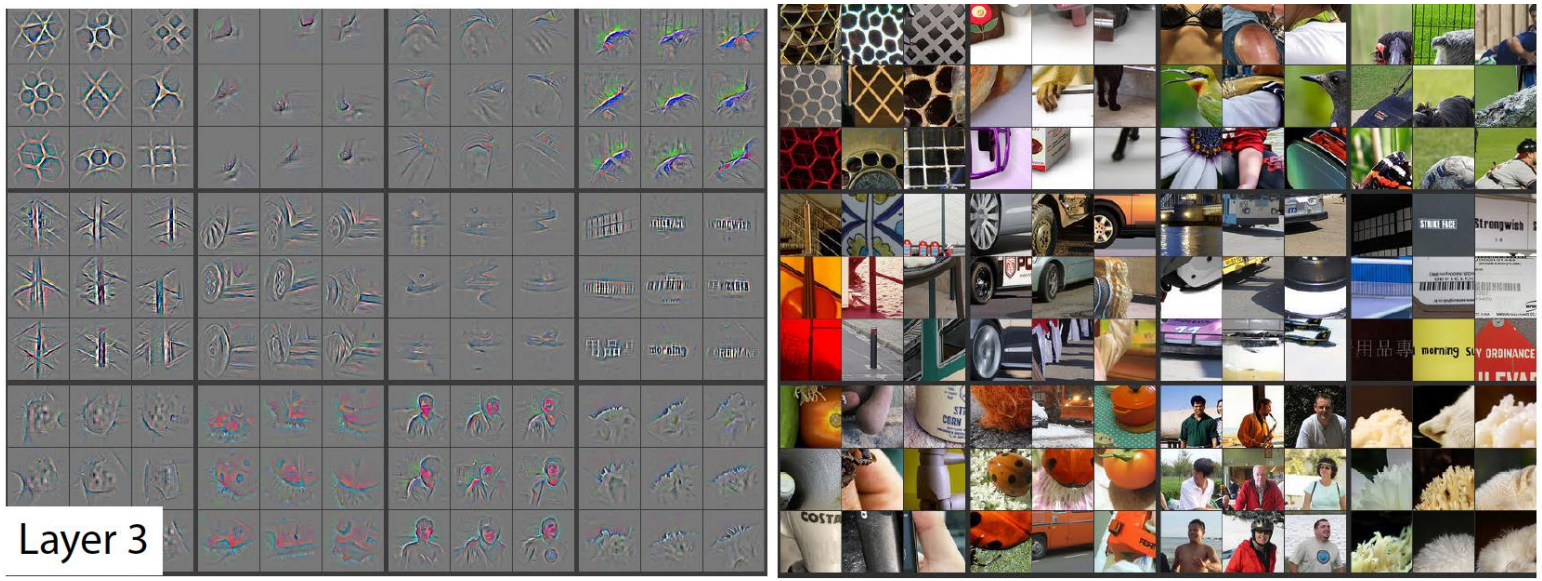




Layer 2

Image courtesy: Zeiler, Fergus, 2013

Visualizations



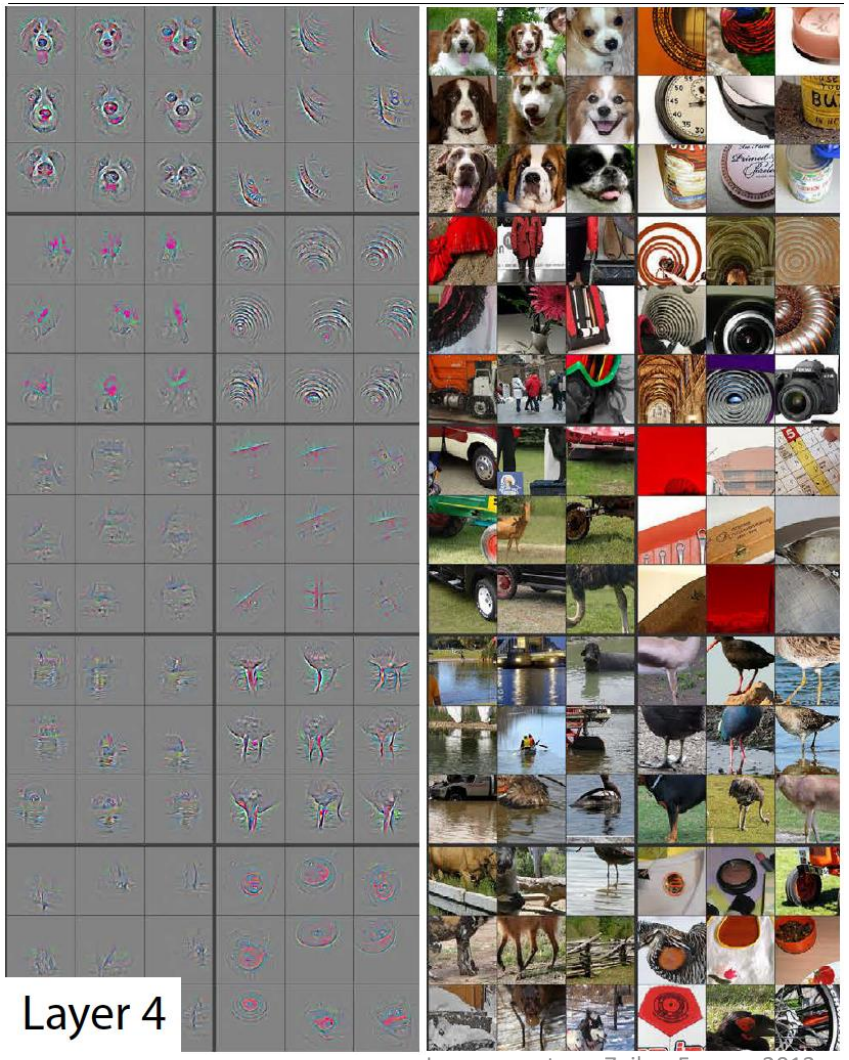
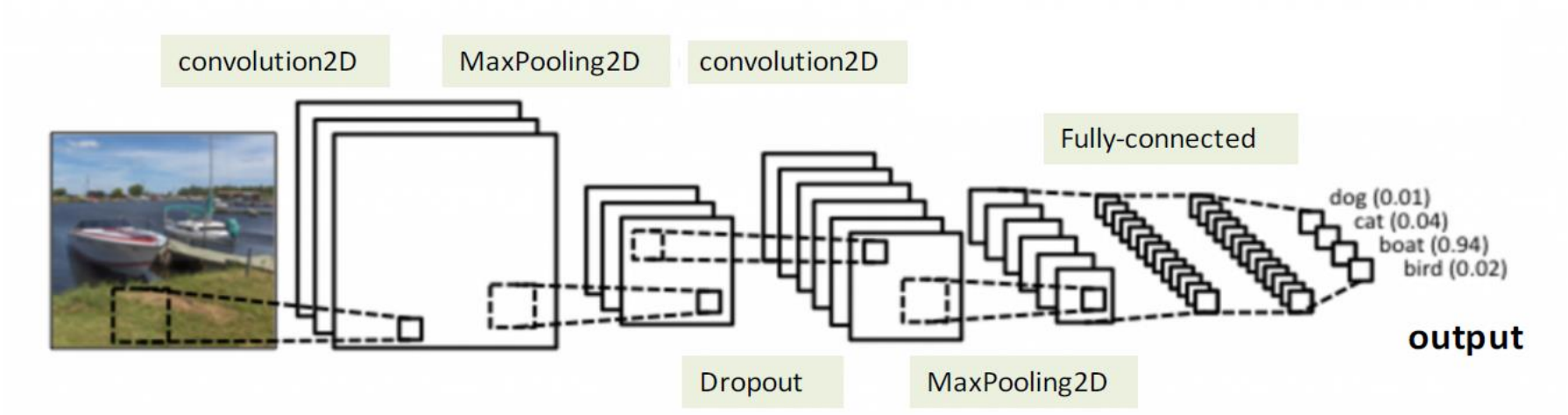
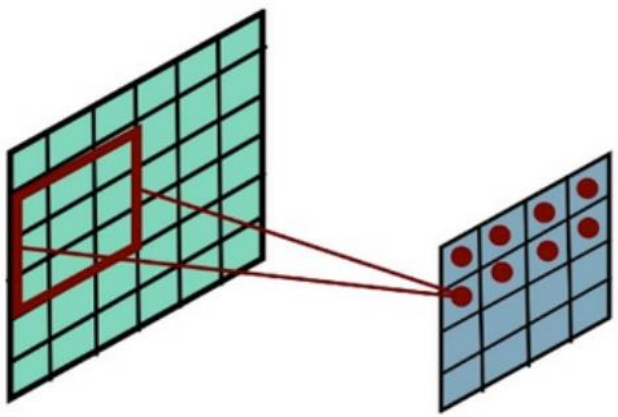


Image courtesy: Zeiler, Fergus, 2013

Deep Convolutional Neural Networks on CIFAR10

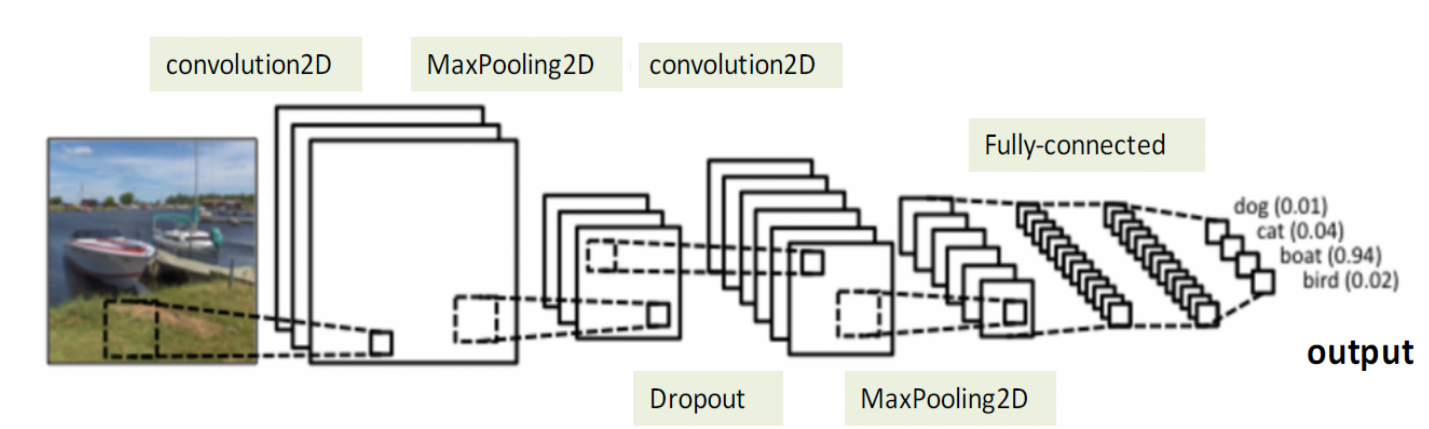




nput image Convolutional output

Convolutional Layer: filters work on every part of the image, therefore, they are searching for the same feature everywhere in the image.

Deep Convolutional Neural Networks on CIFAR10



Convolutional output

1	0	2	3
4	6	6	8
3	1	1	0
1	2	2	4

(2,2) →

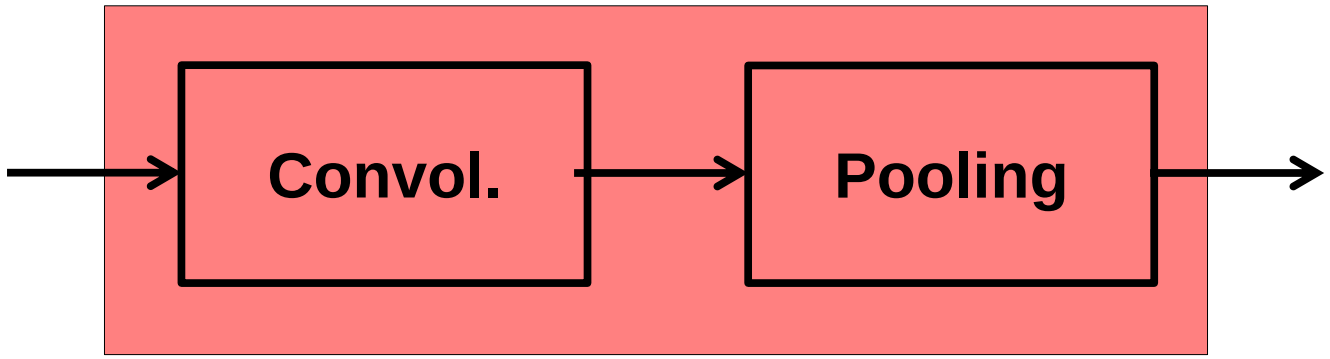
MaxPooling

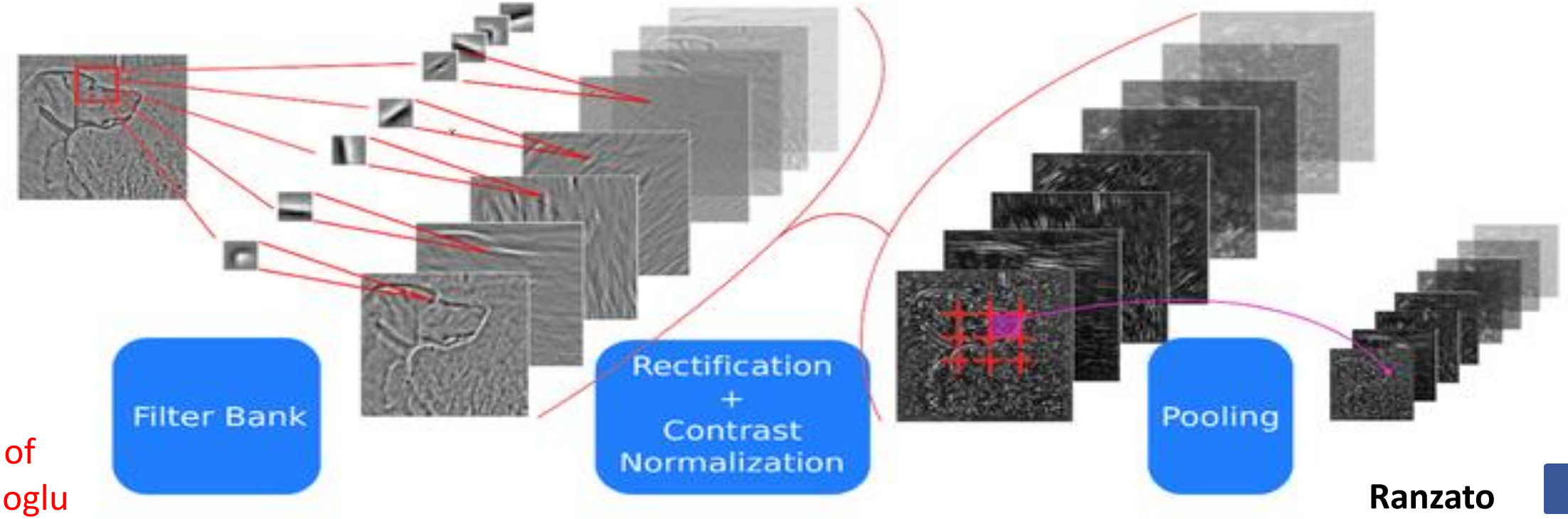
6	8
3	4

MaxPooling: usually present after the convolutional layer. It provides a down-sampling of the convolutional output

ConvNets: Typical Stage

One stage (zoom)





courtesy of
K. Kavukcuoglu

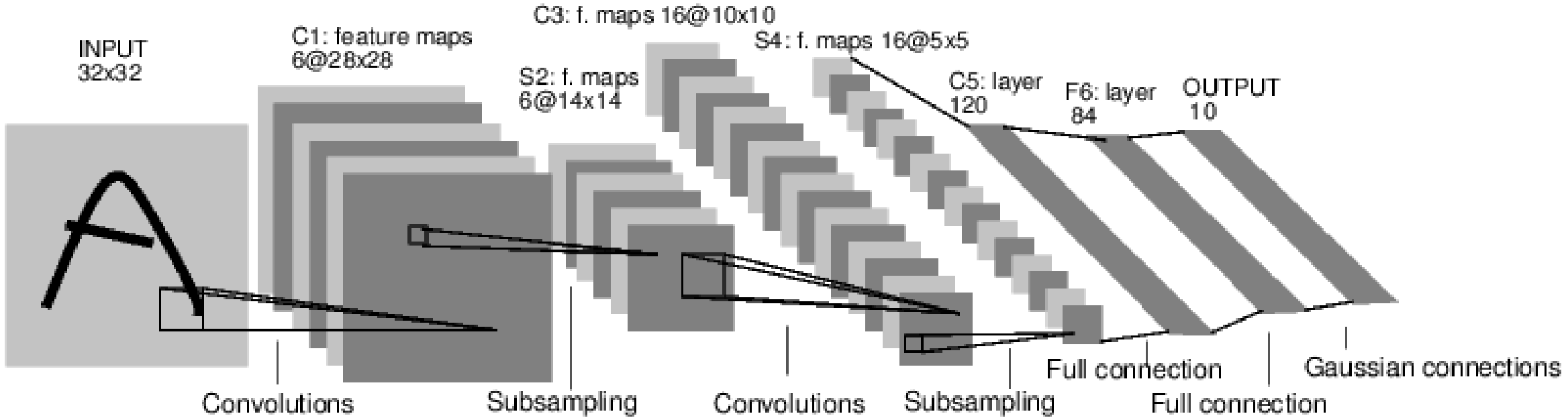
Ranzato

[ConvNetJS demo: training on CIFAR-10]

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

Case Study: LeNet-5

[LeCun et al., 1998]



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-CONV-FC]

LeNet-5

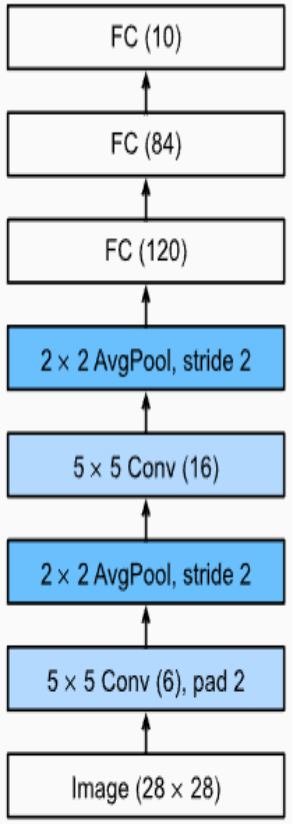
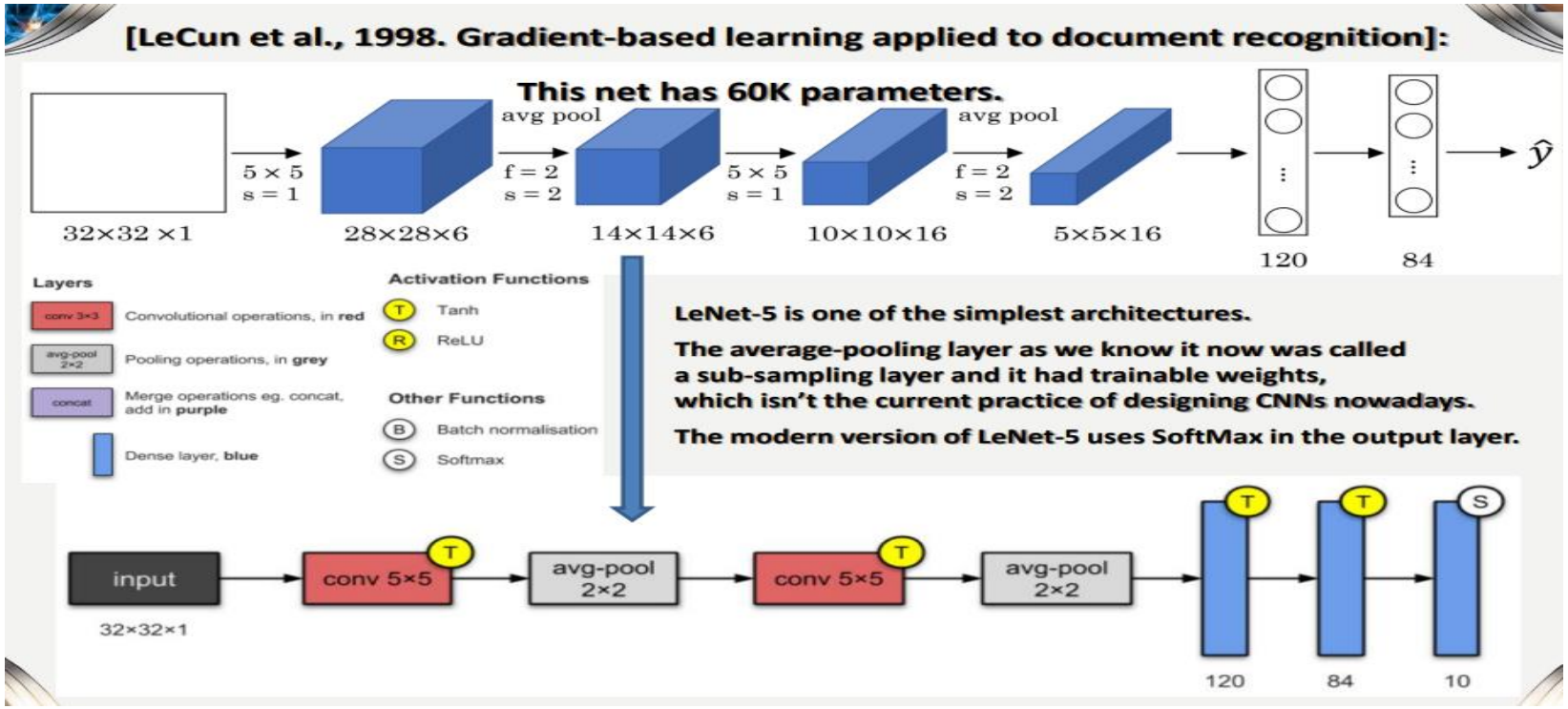
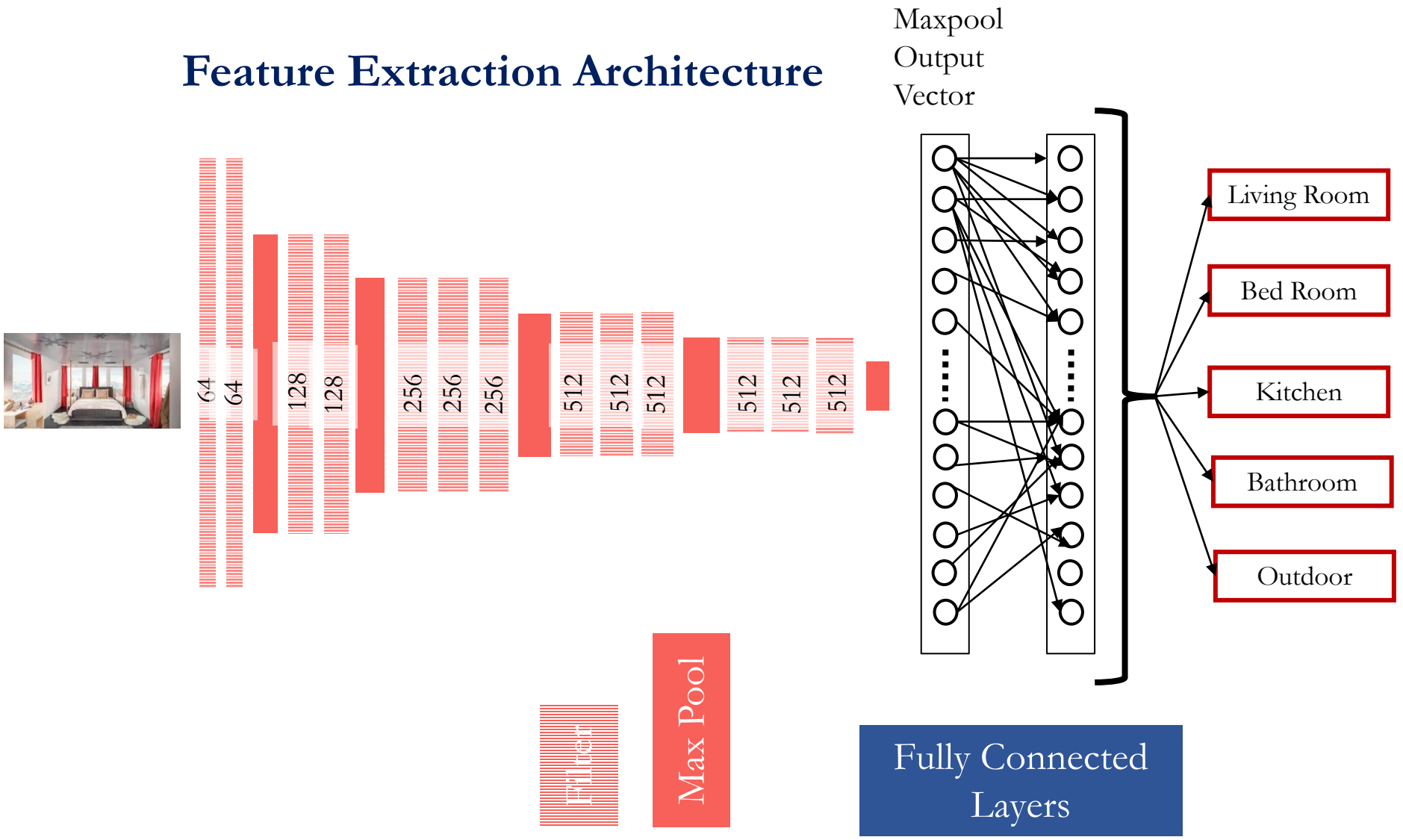


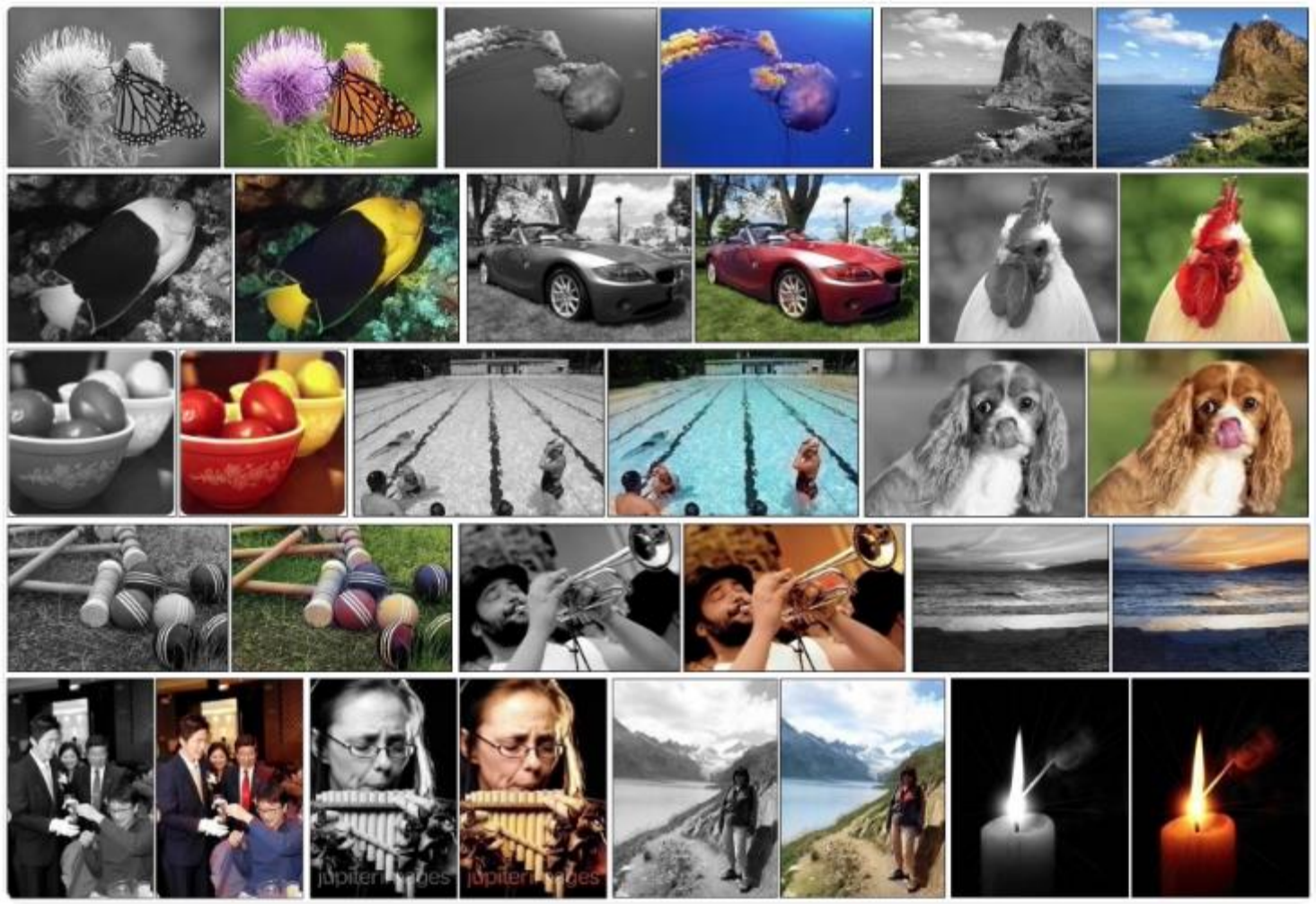
Fig. 7.6.2 Compressed notation for LeNet-5.



Convolutional Neural Network

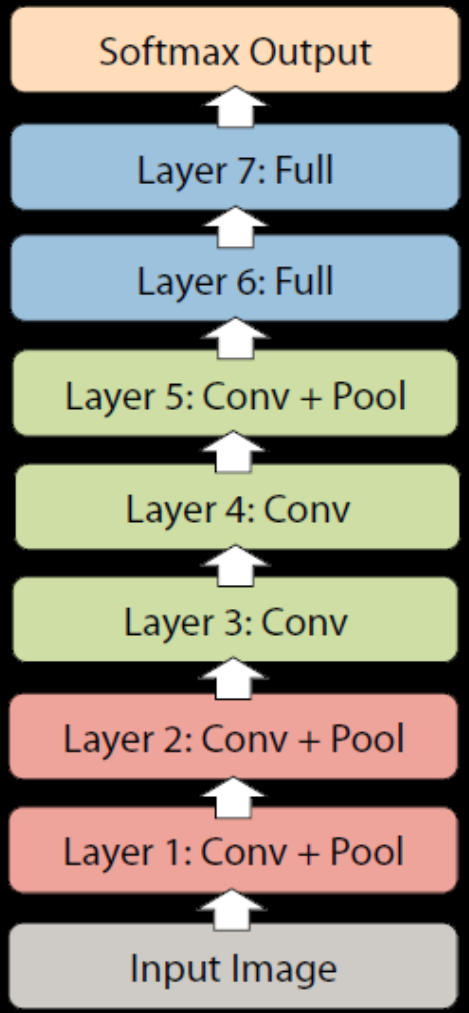


Automatic Colorization of Black and White Images



Why ConvNet should be Deep?

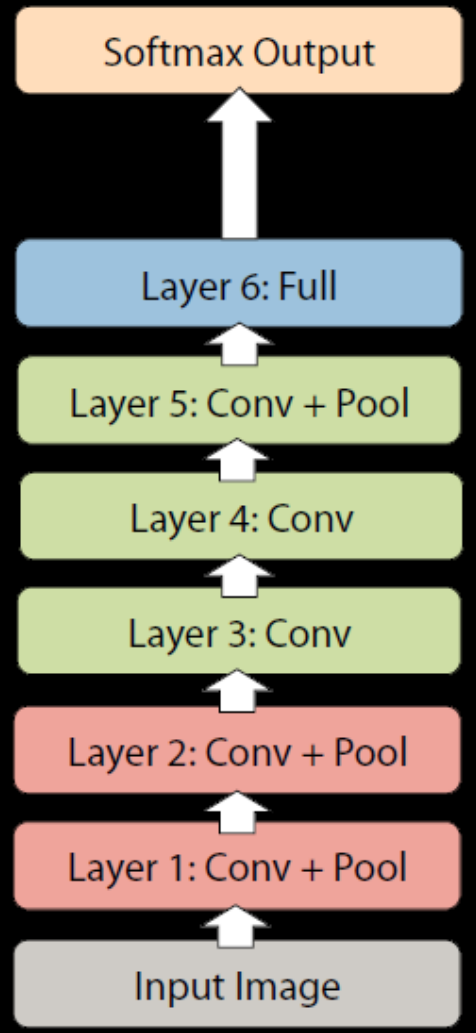
- 8 layers total
- Trained on Imagenet dataset [Deng et al. CVPR'09]
- 18.2% top-5 error
- Our reimplementation:
  18.1% top-5 error



Rob Fergus, NIPS 2013

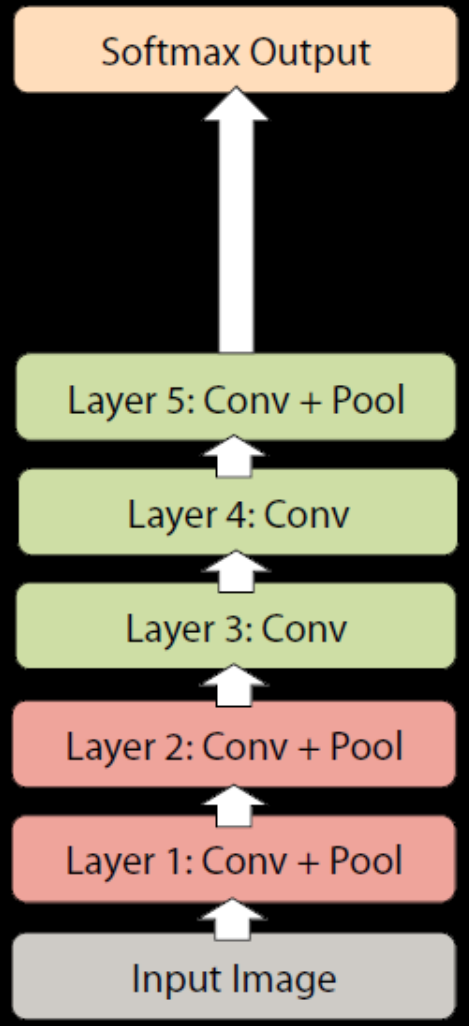
Why ConvNet should be Deep?

- Remove top fully connected layer
  - Layer 7
- Drop 16 million parameters
- Only 1.1% drop in performance!



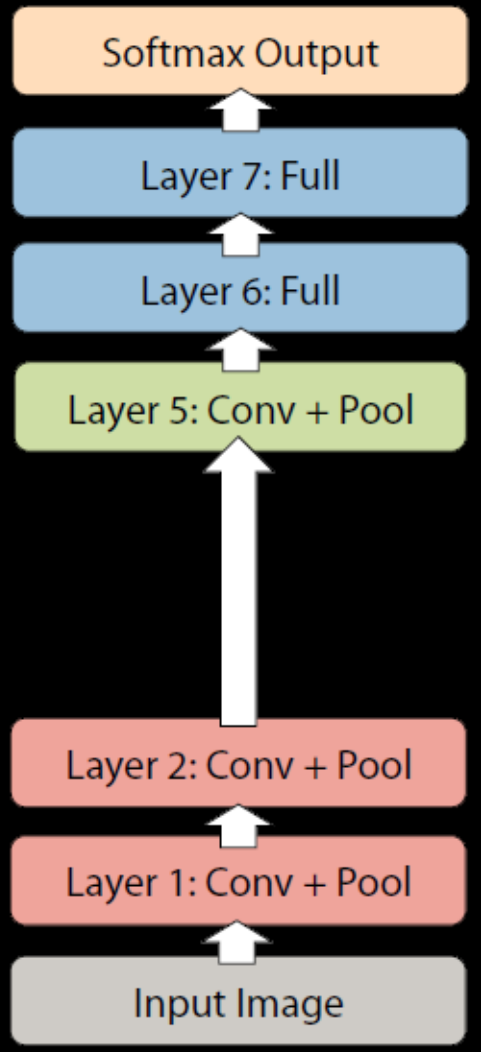
Why ConvNet should be Deep?

- Remove both fully connected layers
  - Layer 6 & 7
- Drop ~50 million parameters
- 5.7% drop in performance



Why ConvNet should be Deep?

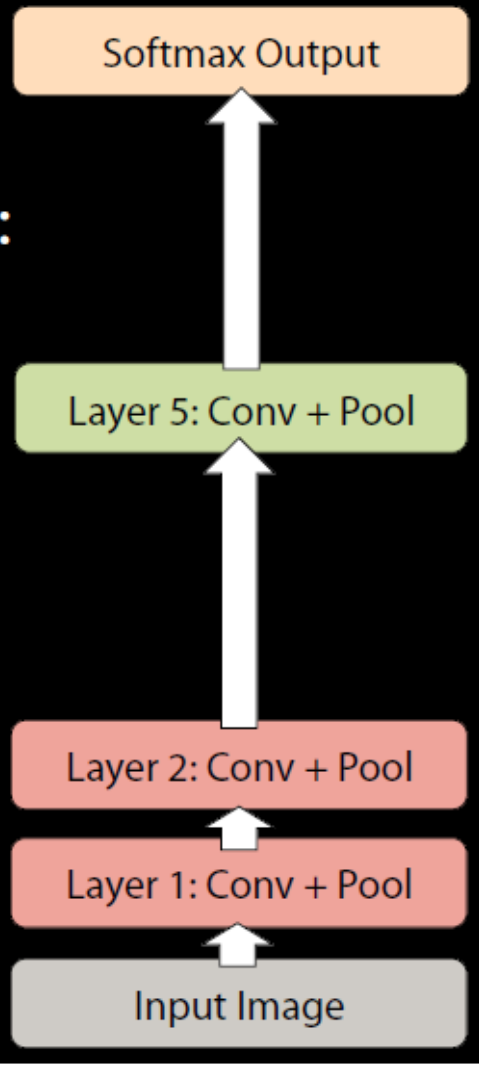
- Now try removing upper feature extractor layers:
  - Layers 3 & 4
- Drop ~1 million parameters
- 3.0% drop in performance



Why ConvNet should be Deep?

- Now try removing upper feature extractor layers & fully connected:
  - Layers 3, 4, 6 ,7
- Now only 4 layers
- 33.5% drop in performance

→Depth of network is key



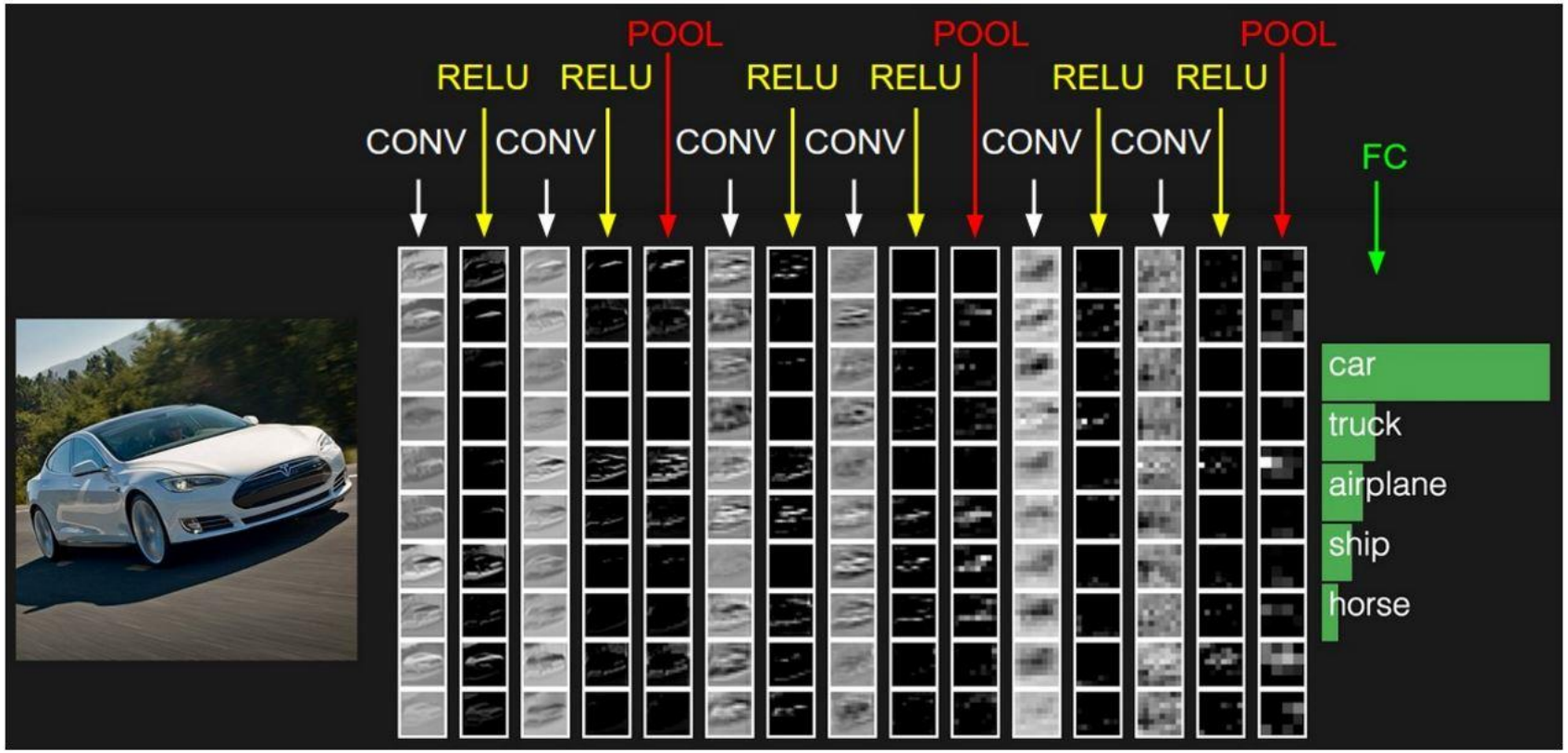
CIFAR-10 dataset

- CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

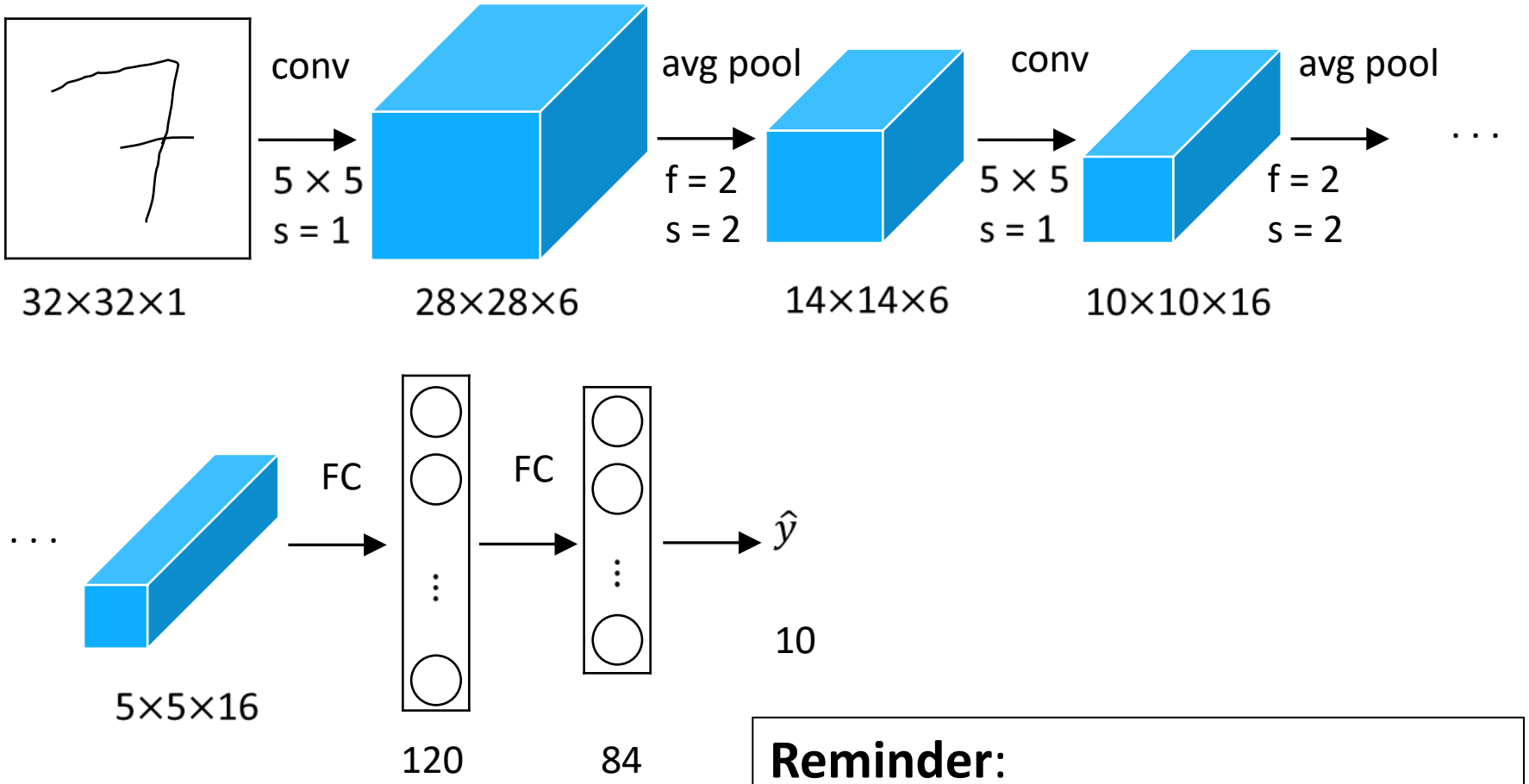
Example (CIFA-10 images)

- input 32x32x3   32x32 pixel with 3 color R G B
- conv   32x32x12   12 filter
- relu   max(0,x)   same size 32x32x12
- pool   down sampling 16x16x12
- fc   compute class score (10 classes for CIFA-10)

Example of CNN layer



LeNet-5



Reminder:
Output size = (N+2P-F)/stride + 1

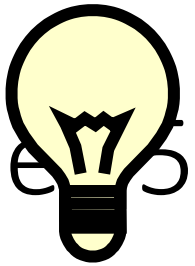
This slide is taken from Andrew Ng

[**LeCun et al.**, **1998**]

The Architecture of Lenet-5

Layer	# filters / neurons	Filter size	Stride	Size of feature map	Activation function
Input	-	-	-	32 X 32 X 1	
Conv 1	6	5 * 5	1	28 X 28 X 6	tanh
Avg. pooling 1		2 * 2	2	14 X 14 X 6	
Conv 2	16	5 * 5	1	10 X 10 X 16	tanh
Avg. pooling 2		2 * 2	2	5 X 5 X 16	
Conv 3	120	5 * 5	1	120	tanh
Fully Connected 1	-	-	-	84	tanh
Fully Connected 2	-	-	-	10	Softmax

LeNet-5



- Only 60K parameters
- As we go deeper in the network: $N_H \downarrow,\ N_W \downarrow,\ N_C \uparrow$
- General structure:
  conv->pool->conv->pool->FC->FC->output

- Different filters look at different channels
- Sigmoid and Tanh nonlinearity

[**LeCun et al.**, **1998**]

exNet

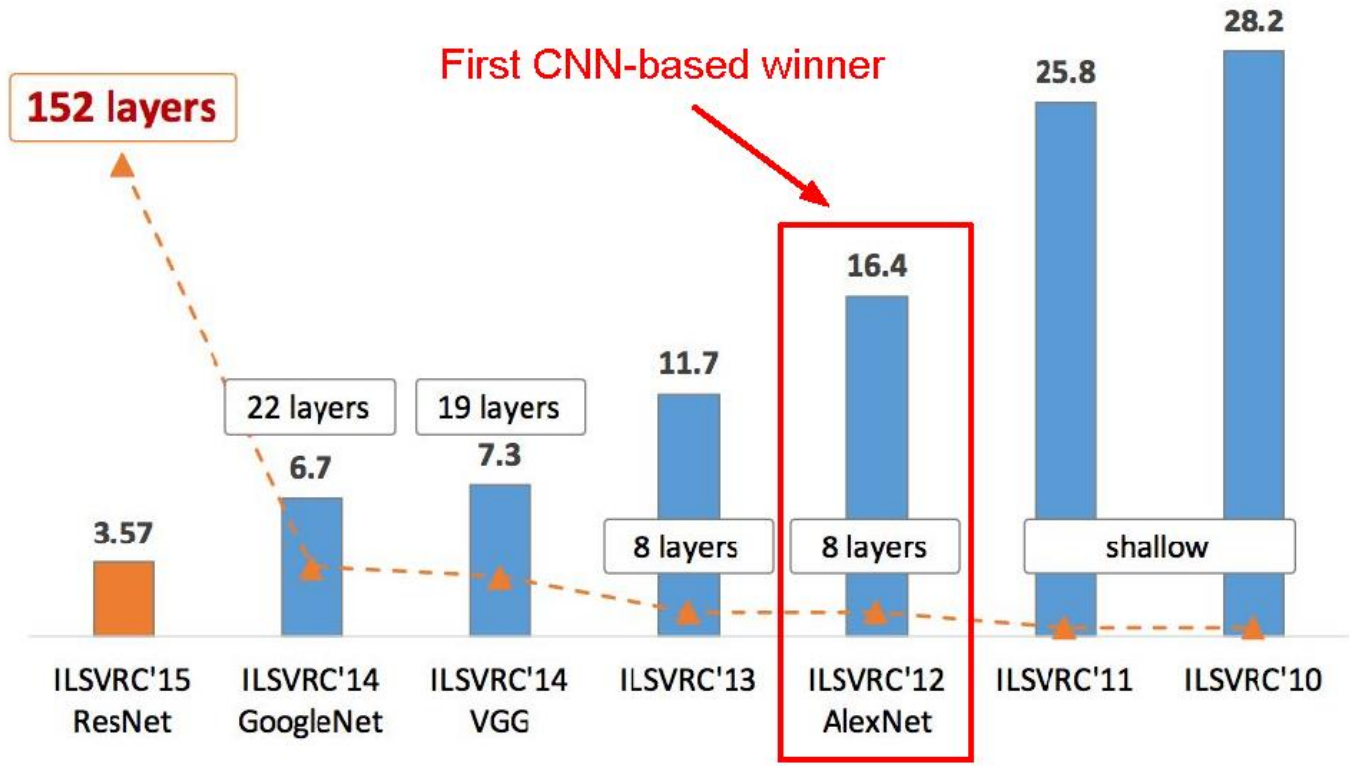
- *ImageNet Classification with Deep Convolutional Neural Networks - Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton; 2012*
- Facilitated by GPUs, highly optimized convolution implementation and large datasets (ImageNet)
- One of the largest CNNs to date
- Has 60 Million parameter compared to 60k parameter of LeNet-5

[**Krizhevsky et al.**, **2012**]

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners

- The annual “Olympics” of computer vision.
- Teams from across the world compete to see who has the best computer vision model for tasks such as classification, localization, detection, and more.
- **2012** marked **the first year where a CNN was used** to achieve a top 5 test error rate of 15.3%.
- The next best entry achieved an error of 26.2%.

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



AlexNet

Architecture

CONV1

MAX POOL1

CONV2

MAX POOL2

CONV3

CONV4

CONV5

Max POOL3

FC6

FC7

FC8

- Input: 227x227x3 images (224x224 before padding)
- First layer: 96 11x11 filters applied at stride 4

- **Output volume size?**

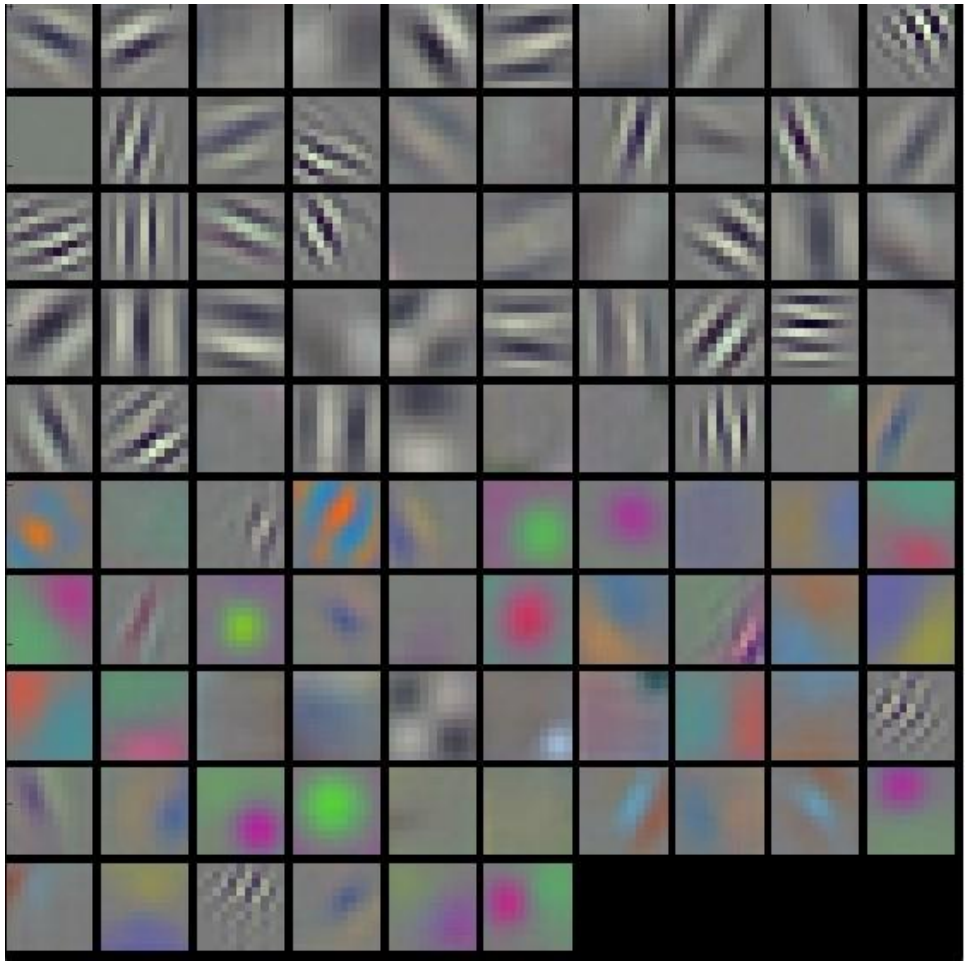
  (N-F)/s+1 = (227-11)/4+1 = 55 -> [55x55x96]

- **Number of parameters in this layer?**

  (11*11*3)*96 = 35K

[Krizhevsky et al., 2012]

AlexNet



[**Krizhevsky et al.**, **2012**]

AlexNet

Architecture

CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

- Input: 227x227x3 images (224x224 before padding)
- After CONV1: 55x55x96
- Second layer: 3x3 filters applied at stride 2

- **Output volume size?**

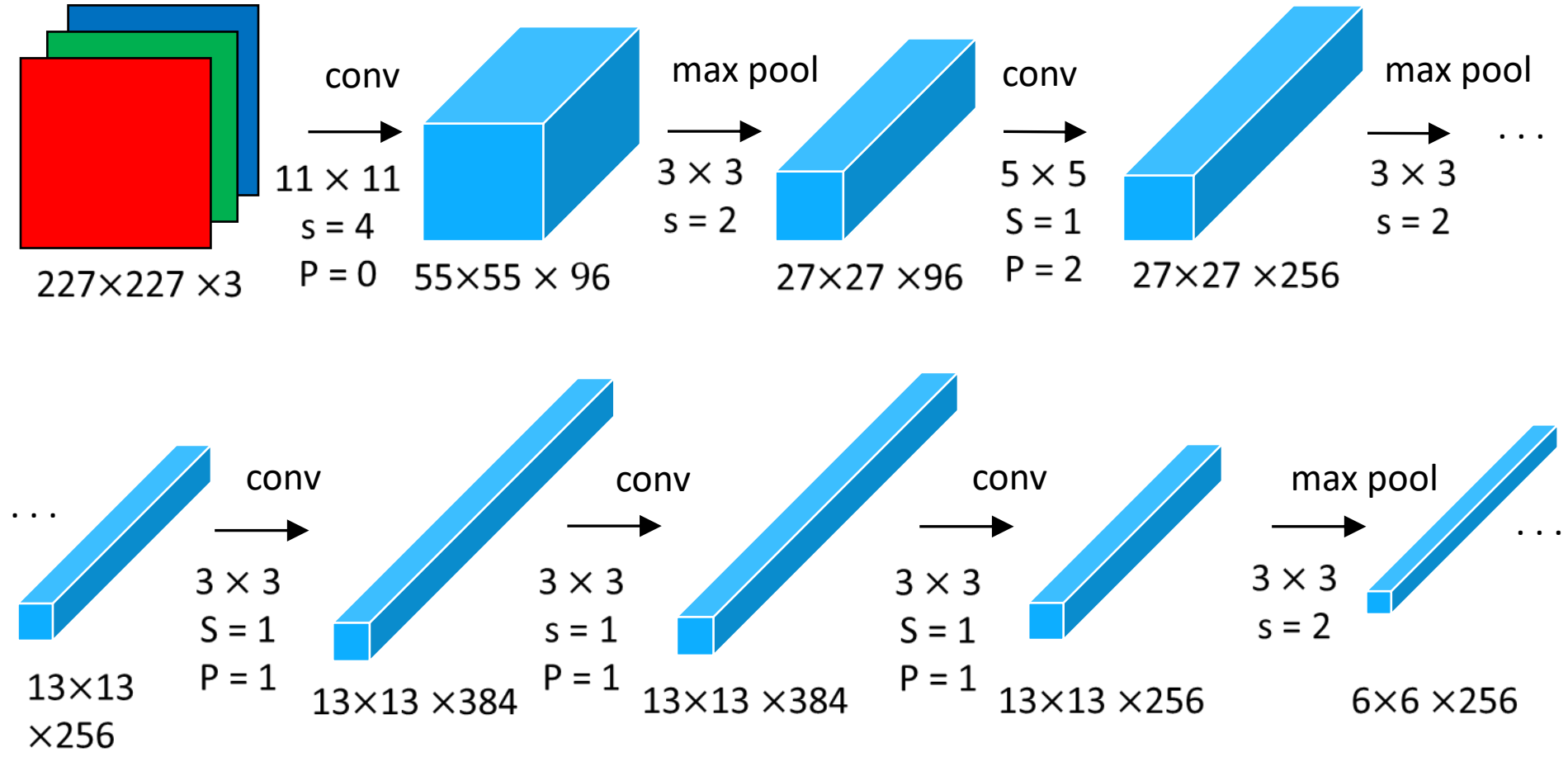
  (N-F)/s+1 = (55-3)/2+1 = 27 -> [27x27x96]

- **Number of parameters in this layer?**

  0!

[Krizhevsky et al., 2012]

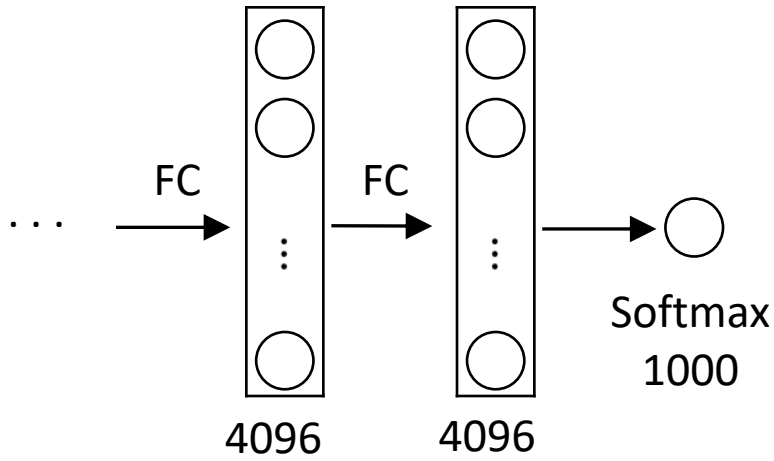
AlexNet



This slide is taken from Andrew Ng

[Krizhevsky et al., 2012]

AlexNet



This slide is taken from Andrew Ng

[**Krizhevsky et al.**, **2012**]

AlexNet

- Trained on GTX 580 GPU with only 3 GB of memory.
- Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.
- CONV1, CONV2, CONV4, CONV5:
  Connections only with feature maps on same GPU.
- CONV3, FC6, FC7, FC8:
  Connections with all feature maps in preceding layer, communication across GPUs.

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[**Krizhevsky et al.**, **2012**]

AlexNet was the coming out party for CNNs in the computer vision community. This was **the first time a model performed so well on a historically difficult ImageNet dataset**. This paper illustrated the benefits of CNNs and backed them up with record breaking performance in the competition.

[**Krizhevsky et al.**, **2012**]

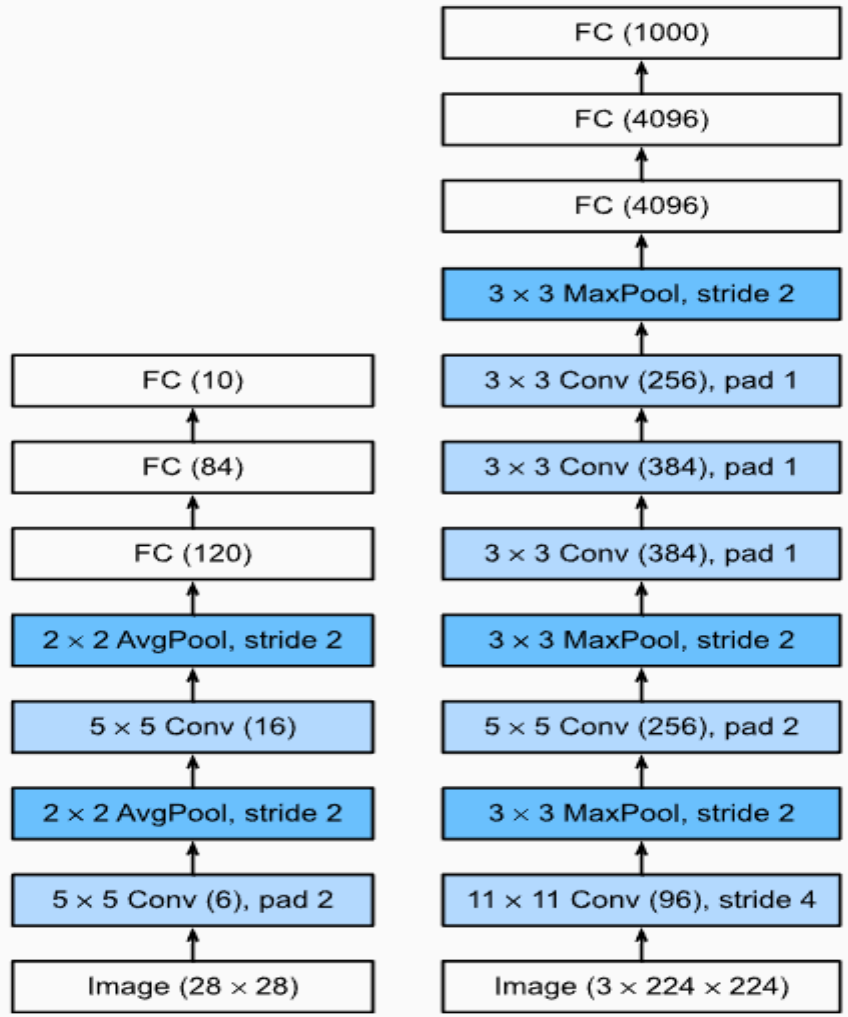
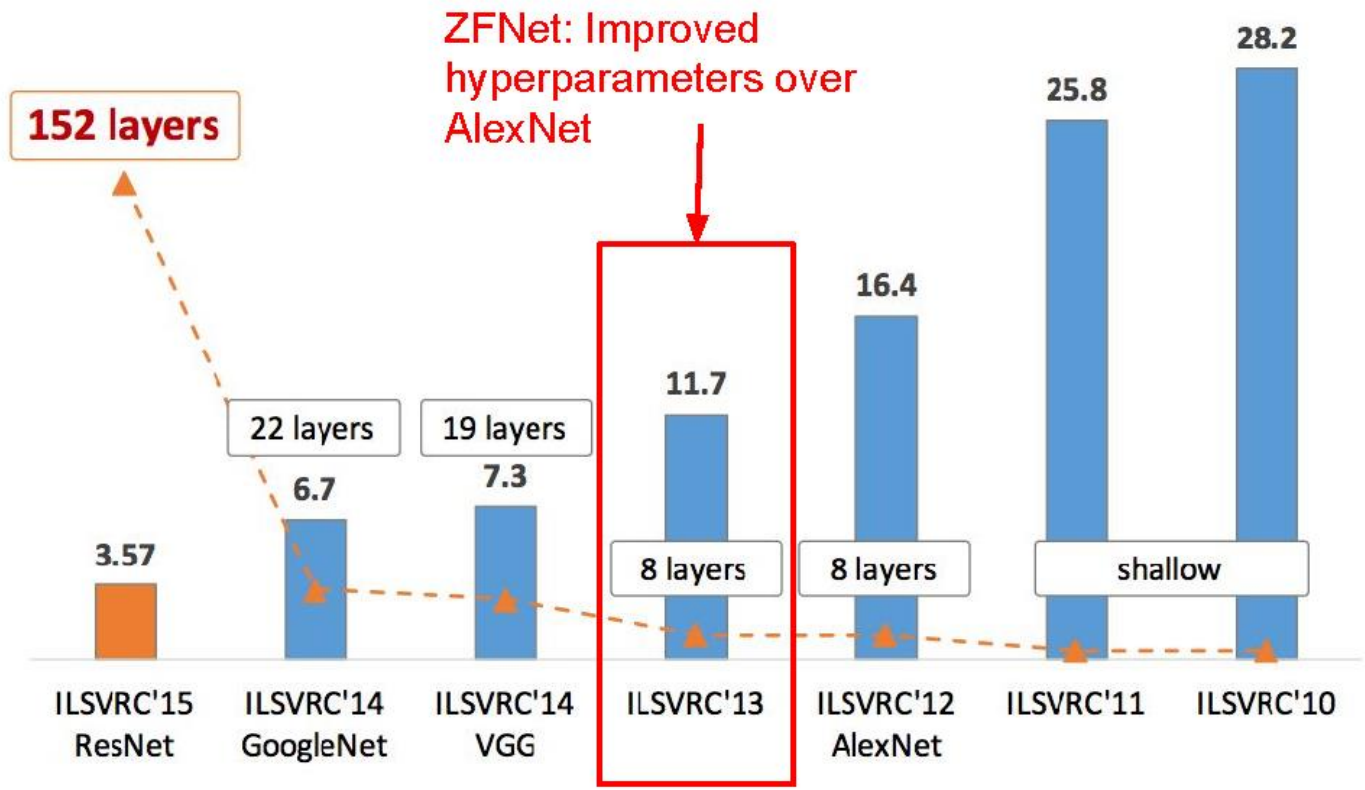
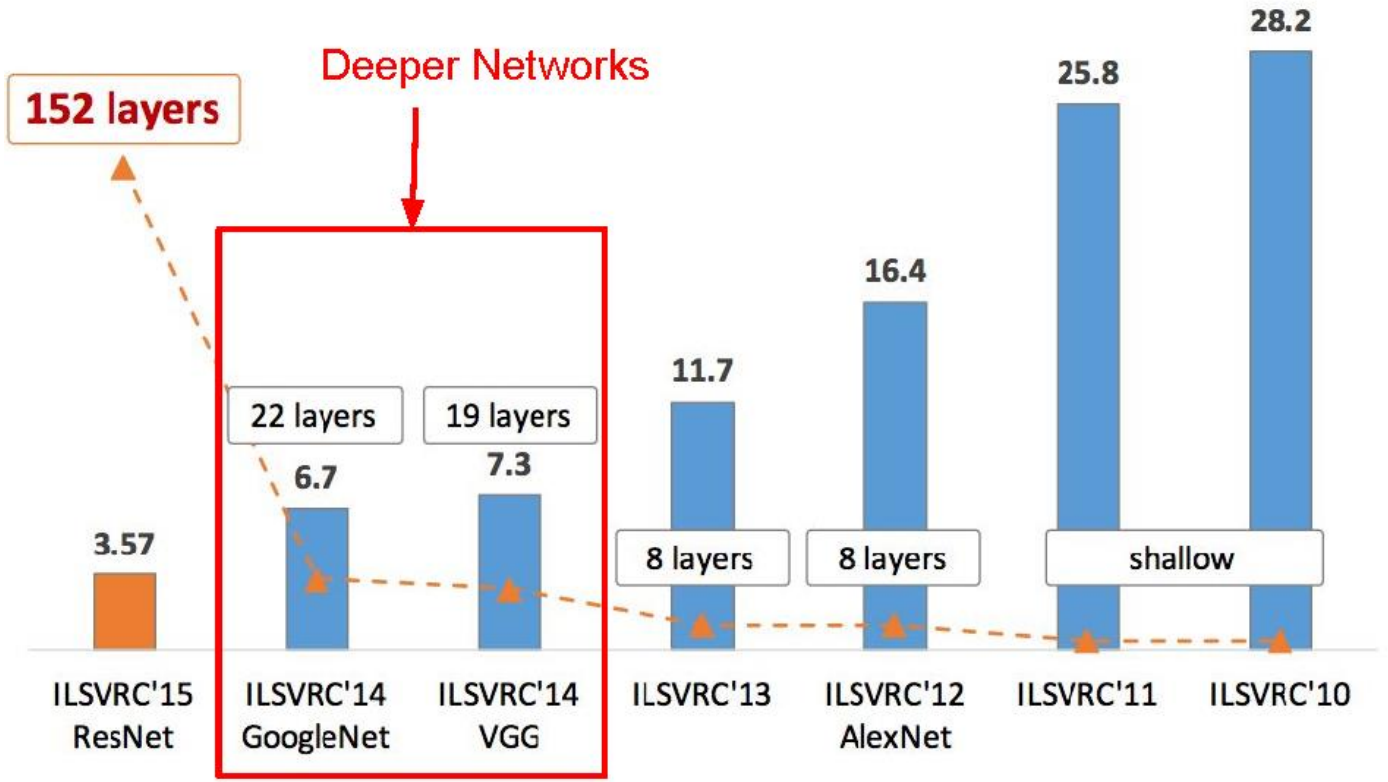


Fig. 8.1.2 From LeNet (left) to AlexNet (right).

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



VGGNet

- *Very Deep Convolutional Networks For Large Scale Image Recognition - Karen Simonyan and Andrew Zisserman; 2015*
- The runner-up at the ILSVRC 2014 competition
- Significantly deeper than AlexNet
- 140 million parameters

[Simonyan and Zisserman, 2014]

VGGNet

Input
3x3 conv, 64
3x3 conv, 64
Pool 1/2
3x3 conv, 128
3x3 conv, 128
Pool 1/2
3x3 conv, 256
3x3 conv, 256
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool 1/2
FC 4096
FC 4096
FC 1000
Softmax

- **Smaller filters**
  Only 3x3 CONV filters, stride 1, pad 1
  and 2x2 MAX POOL , stride 2

- **Deeper network**
  AlexNet: 8 layers
  VGGNet: 16 - 19 layers

- ZFNet: 11.7% top 5 error in ILSVRC'13
- VGGNet: 7.3% top 5 error in ILSVRC'14

[Simonyan and Zisserman, 2014]

VGGNet

- **Why use smaller filters? (3x3 conv)**

Stack of three 3x3 conv (stride 1) layers has the same effective receptive field as one 7x7 conv layer.

- **What is the effective receptive field of three 3x3 conv (stride 1) layers?**

7x7

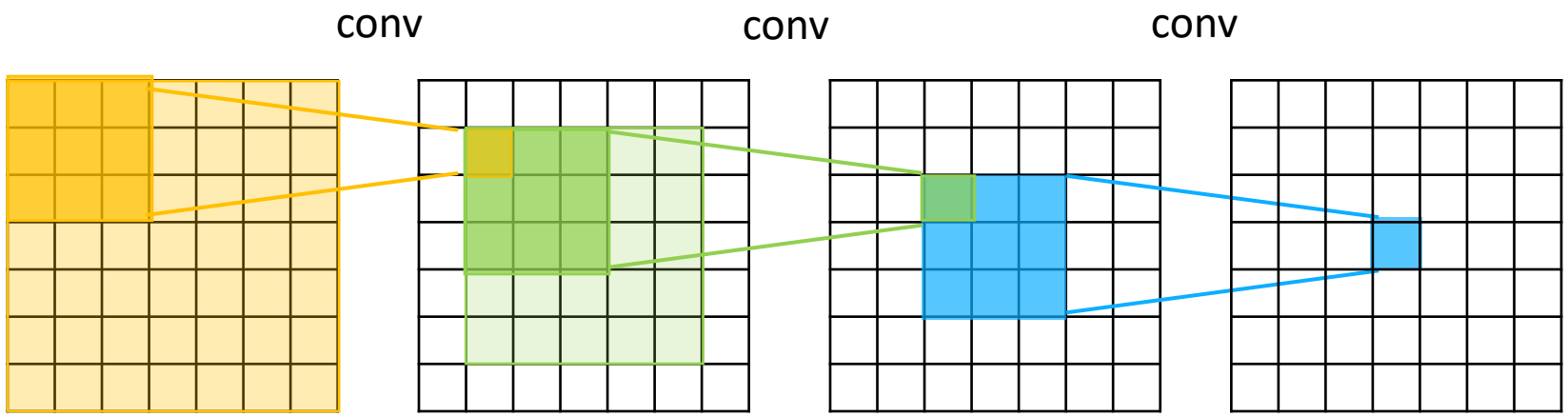
But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer

Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

[Simonyan and Zisserman, 2014]

Reminder: Receptive Field



Input	memory: 224*224*3=150K	params: 0
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*3)*64 = 1,728
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*64)*64 = 36,864
Pool	memory: 112*112*64=800K	params: 0
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*64)*128 = 73,728
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*128)*128 = 147,456
Pool	memory: 56*56*128=400K	params: 0
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*128)*256 = 294,912
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
Pool	memory: 28*28*256=200K	params: 0
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*256)*512 = 1,179,648
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 14*14*512=100K	params: 0
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 7*7*512=25K	params: 0
FC 4096	memory: 4096	params: 7*7*512*4096 = 102,760,448
FC 4096	memory: 4096	params: 4096*4096 = 16,777,216
FC 1000	memory: 1000	params: 4096*1000 = 4,096,000

[Simonyan and Zisserman, 2014]

VGGNet

Input
3x3 conv, 64
3x3 conv, 64
Pool
3x3 conv, 128
3x3 conv, 128
Pool
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
Pool
FC 4096
FC 4096
FC 1000
Softmax

VGG16:

TOTAL memory: 24M * 4 bytes ~= 96MB / image

TOTAL params: 138M parameters

[Simonyan and Zisserman, 2014]

Input	memory: 224*224*3=150K	params: 0
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*3)*64 = 1,728
3x3 conv, 64	memory: 224*224*64=3.2M	params: (3*3*64)*64 = 36,864
Pool	memory: 112*112*64=800K	params: 0
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*64)*128 = 73,728
3x3 conv, 128	memory: 112*112*128=1.6M	params: (3*3*128)*128 = 147,456
Pool	memory: 56*56*128=400K	params: 0
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*128)*256 = 294,912
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
3x3 conv, 256	memory: 56*56*256=800K	params: (3*3*256)*256 = 589,824
Pool	memory: 28*28*256=200K	params: 0
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*256)*512 = 1,179,648
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 28*28*512=400K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 14*14*512=100K	params: 0
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
3x3 conv, 512	memory: 14*14*512=100K	params: (3*3*512)*512 = 2,359,296
Pool	memory: 7*7*512=25K	params: 0
FC 4096	memory: 4096	params: 7*7*512*4096 = 102,760,448
FC 4096	memory: 4096	params: 4096*4096 = 16,777,216
FC 1000	memory: 1000	params: 4096*1000 = 4,096,000

[Simonyan and Zisserman, 2014]

VGGNet

Details/Retrospectives :

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as AlexNet
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks
- Trained on 4 Nvidia Titan Black GPUs for **two to three weeks**.

[Simonyan and Zisserman, 2014]

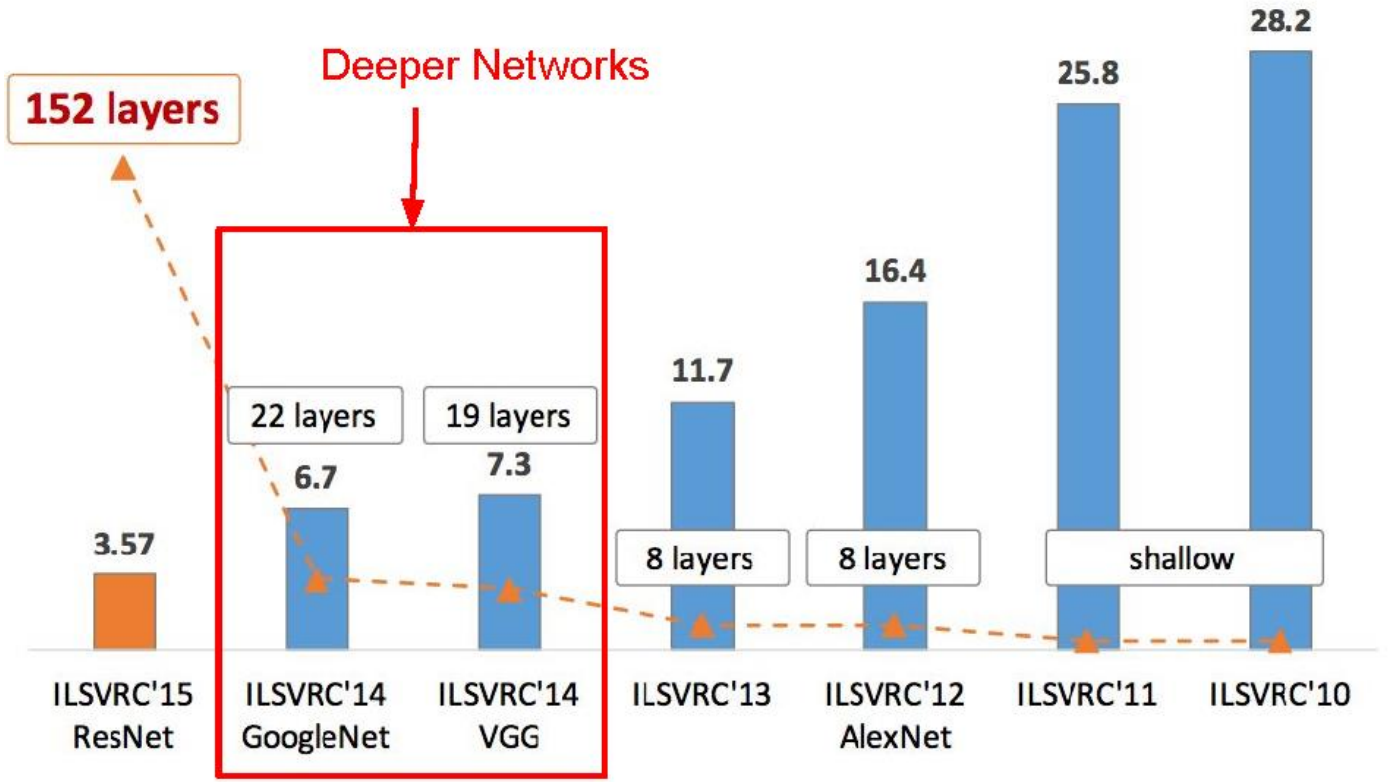
VGG Net reinforced the notion that **convolutional neural networks have to have a deep network of layers in order for this hierarchical representation of visual data to work**.

Keep it deep.

Keep it simple.

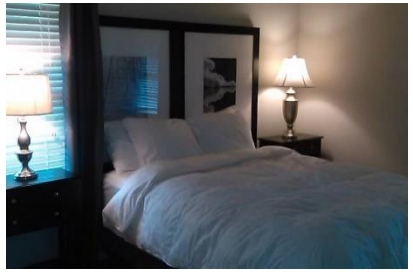
[Simonyan and Zisserman, 2014]

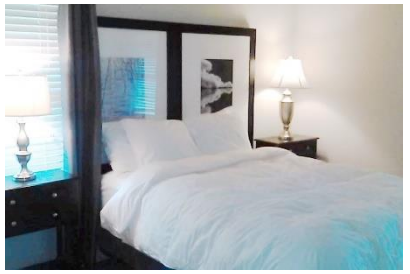
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Slide taken from Fei-Fei & Justin Johnson & Serena Yeung. Lecture 9.

Optimizing Images





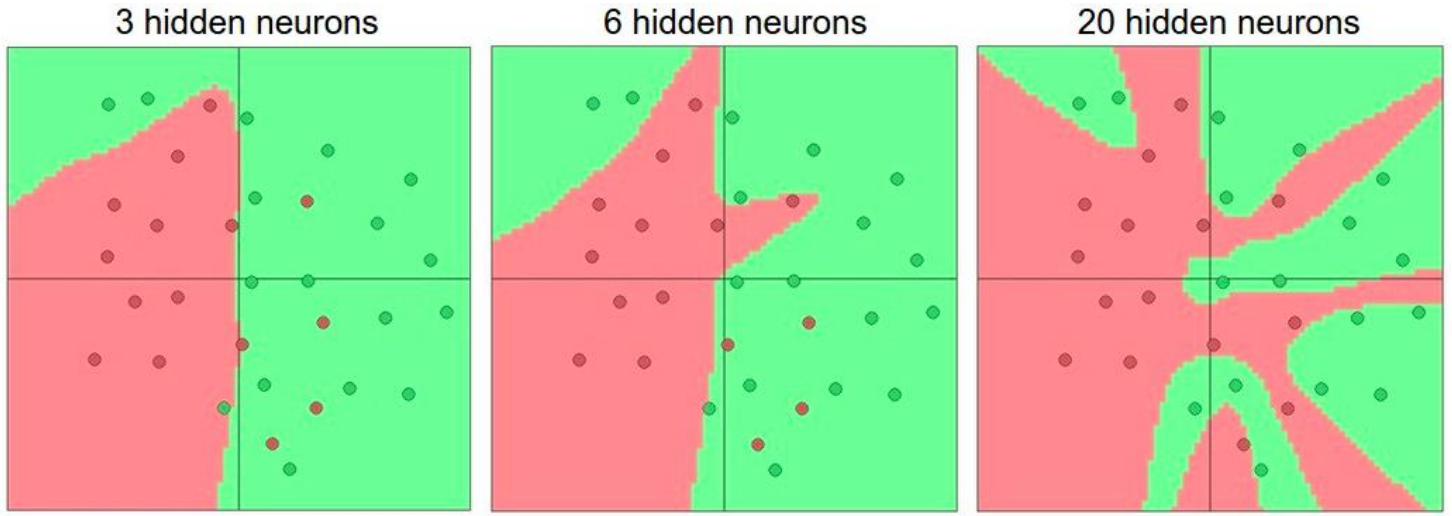
Post Processing Feature Optimization
(Color Curves and Details)

Post Processing Feature Optimization
(Illumination)

Post Processing Feature Optimization
(Color Tone: Warmness)

Activation functions

Non-linearities needed to learn complex (non-linear) representations of data, otherwise the NN would be just a linear function $W_1 W_2 x = Wx$

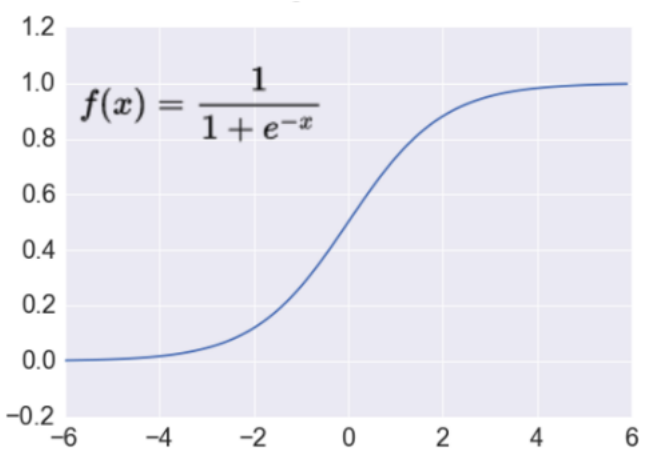


http://cs231n.github.io/assets/nn1/layer_sizes.jpeg

More layers and neurons can approximate more complex functions

Full list: https://en.wikipedia.org/wiki/Activation_function

Activation: Sigmoid



http://adilmoujahid.com/images/activation.png

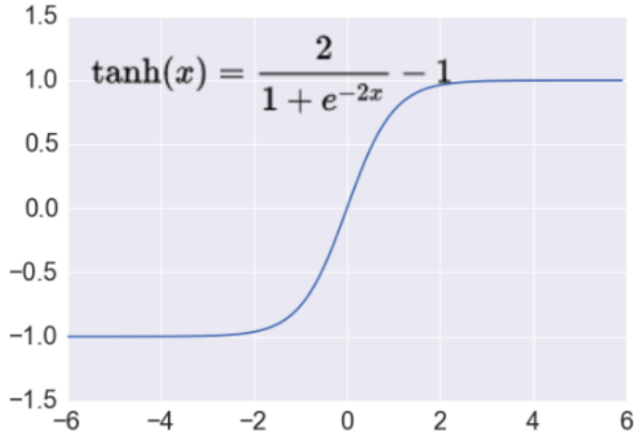
Takes a real-valued number and "squashes" it into range between 0 and 1.

$$R^n \rightarrow [0,1]$$

\+ Nice interpretation as the **firing rate** of a neuron
- 0 = not firing at all
- 1 = fully firing

\- Sigmoid neurons **saturate** and **kill gradients**, thus NN will barely learn
- when the neuron's activation are 0 or 1 (saturate)
  - ☹ gradient at these regions almost zero
  - ☹ almost no signal will flow to its weights
  - ☹ if initial weights are too large then most neurons would saturate

Activation: Tanh



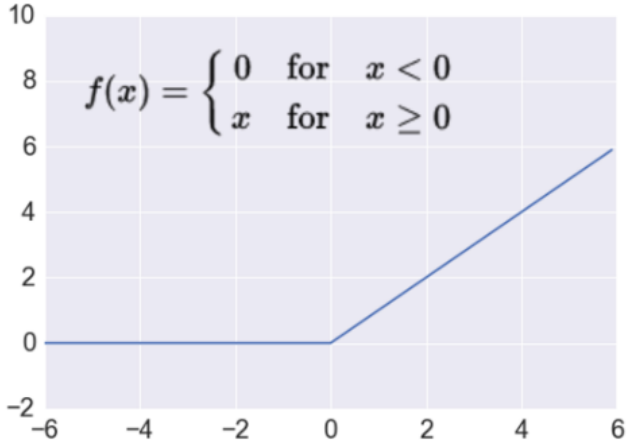
http://adilmoujahid.com/images/activation.png

Takes a real-valued number and "squashes" it into range between -1 and 1.

$$R^n \rightarrow [-1,1]$$

- Like sigmoid, tanh neurons **saturate**
- Unlike sigmoid, output is **zero-centered**
- Tanh is a **scaled sigmoid**: $\tanh(x) = 2sigm(2x) - 1$

Activation: ReLU



http://adilmoujahid.com/images/activation.png

Takes a real-valued number and thresholds it at zero $f(x) = \max(0, x)$

$$R^n \rightarrow R^n_+$$

Most Deep Networks use ReLU nowadays

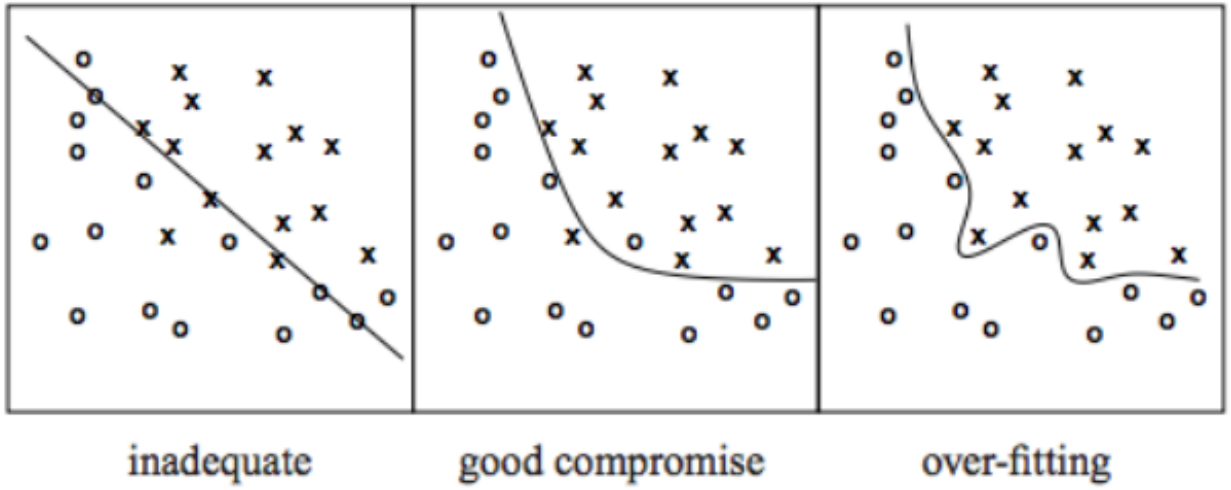
☺ Trains much **faster**
- accelerates the convergence of SGD
- due to linear, non-saturating form

☺ Less expensive operations
- compared to sigmoid/tanh (exponentials etc.)
- implemented by simply thresholding a matrix at zero

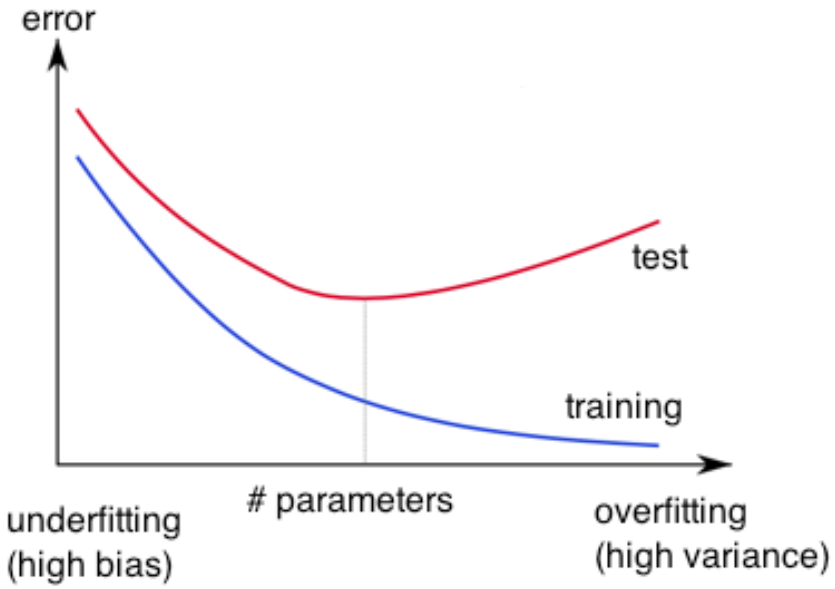
☺ More **expressive**

☺ Prevents the **gradient vanishing problem**

Overfitting



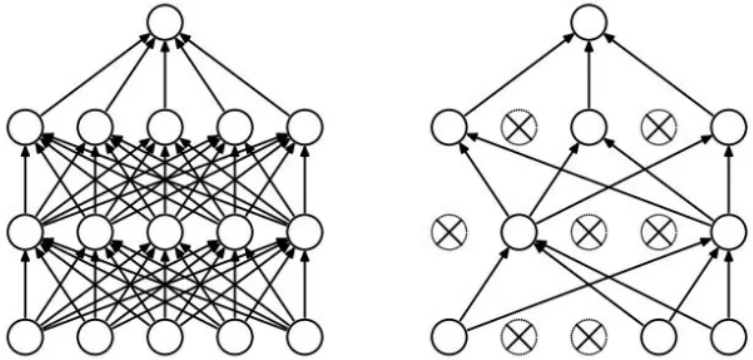
http://wiki.bethanycrane.com/overfitting-of-data



https://www.neuraldesigner.com/images/learning/selection_error.svg

Learned hypothesis may **fit** the training data very well, even outliers (**noise**) but fail to **generalize** to new examples (test data)

Regularization



Dropout

- Randomly drop units (along with their connections) during training
- Each unit retained with fixed probability p, independent of other units
- Hyper-parameter p to be chosen (tuned)

Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." Journal of machine learning research (2014)

L2 = weight decay

- Regularization term that penalizes big weights, added to the objective
- Weight decay value determines how dominant regularization is during gradient computation
- Big weight decay coefficient → big penalty for big weights

Early-stopping

- Use validation error to decide when to stop training
- Stop when monitored quantity has not improved after n subsequent epochs
- n is called patience

```
import numpy as np
from keras.models import Sequential
from keras.layers import Activation, Dense, Dropout
from keras.layers import Conv2D, MaxPooling2D, Flatten
from keras.utils import to_categorical, plot_model
from keras.datasets import mnist

# load mnist dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# compute the number of labels
num_labels = len(np.unique(y_train))

# convert to one-hot vector
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)

# input image dimensions
image_size = x_train.shape[1]
# resize and normalize
x_train = np.reshape(x_train,[-1, image_size, image_size, 1])
x_test = np.reshape(x_test,[-1, image_size, image_size, 1])
x_train = x_train.astype('float32') / 255
x_test = x_test.astype('float32') / 255

# network parameters
```

```
# image is processed as is (square grayscale)
input_shape = (image_size, image_size, 1)
batch_size = 128
kernel_size = 3
pool_size = 2
filters = 64
dropout = 0.2

# model is a stack of CNN-ReLU-MaxPooling
model = Sequential()
model.add(Conv2D(filters=filters,
                 kernel_size=kernel_size,
                 activation='relu',
                 input_shape=input_shape))
model.add(MaxPooling2D(pool_size))
model.add(Conv2D(filters=filters,
                 kernel_size=kernel_size,
                 activation='relu'))
model.add(MaxPooling2D(pool_size))
model.add(Conv2D(filters=filters,
                 kernel_size=kernel_size,
                 activation='relu'))
model.add(Flatten())
# dropout added as regularizer
model.add(Dropout(dropout))
# output layer is 10-dim one-hot vector
model.add(Dense(num_labels))
model.add(Activation('softmax'))
model.summary()
plot_model(model, to_file='cnn-mnist.png', show_shapes=True)

# loss function for one-hot vector
# use of adam optimizer
# accuracy is good metric for classification tasks
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
# train the network
model.fit(x_train, y_train, epochs=10, batch_size=batch_size)

loss, acc = model.evaluate(x_test, y_test, batch_size=batch_size)
print("\nTest accuracy: %.1f%%" % (100.0 * acc))
```