Deep learning for image processing

STAT 4710

November 22, 2022

Where we are

- ✓ **Unit 1:** R for data mining
- ✓ **Unit 2:** Prediction fundamentals
- ✓ **Unit 3:** Regression-based methods
- ✓ **Unit 4:** Tree-based methods
- **Unit 5:** Deep learning

Lecture 1: Deep learning preliminaries

Lecture 2: Neural networks

Lecture 3: Deep learning for images

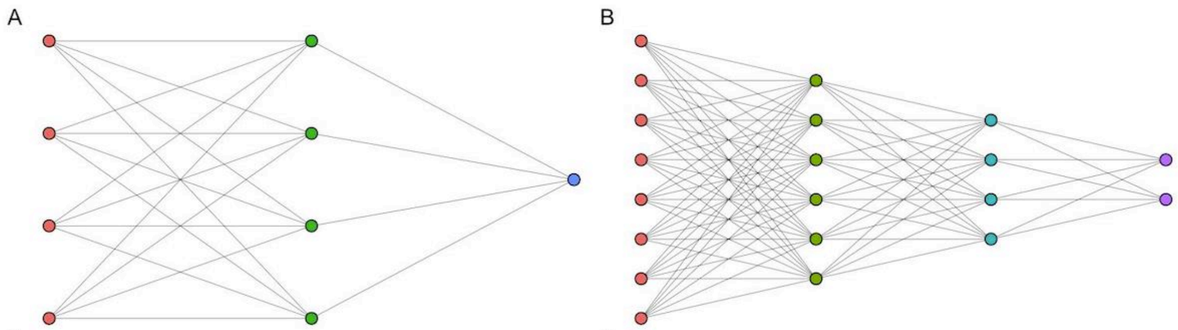
Lecture 4: Deep learning for text

Lecture 5: Unit review and quiz in class

Network architectures

Network architectures

Fully connected architectures



https://community.rstudio.com/t/visualising-neural-network-architectures/41723

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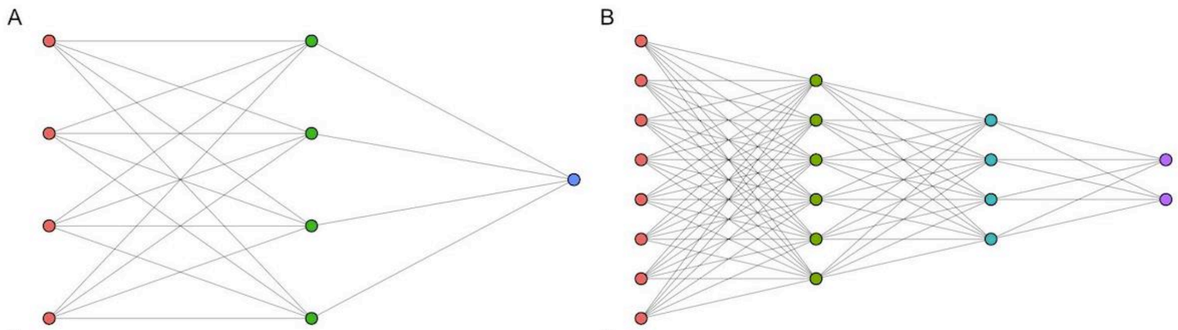

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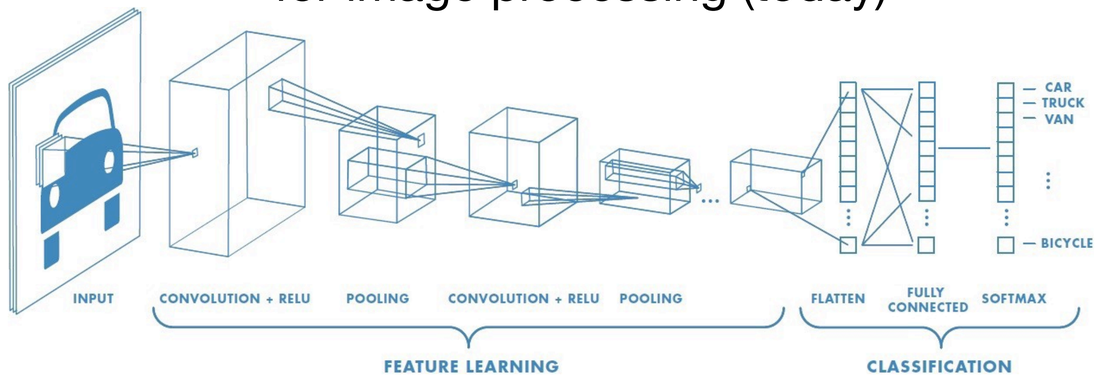
Convolutional neural network (CNN) architectures for image processing (today)



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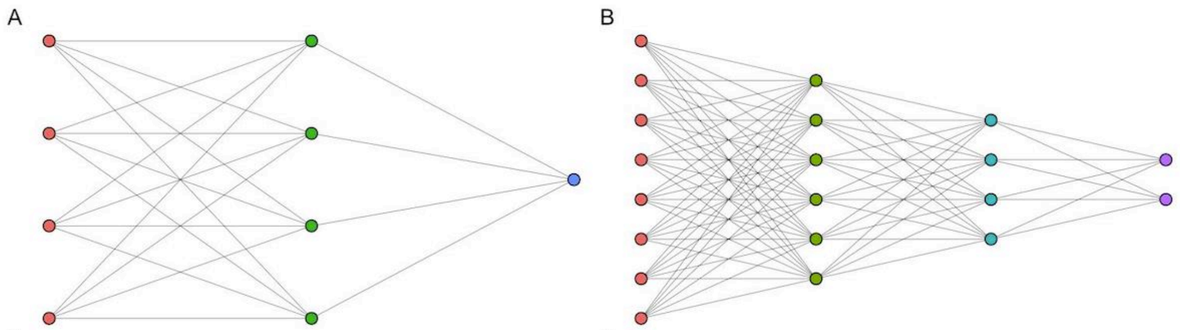

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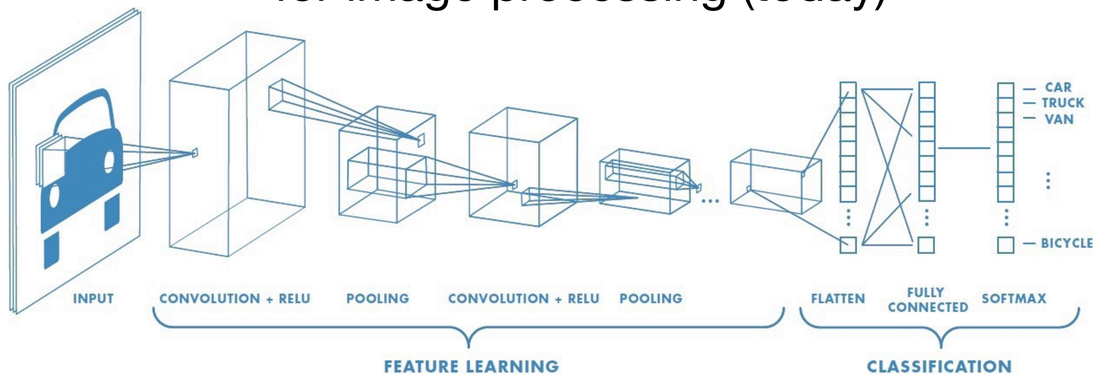

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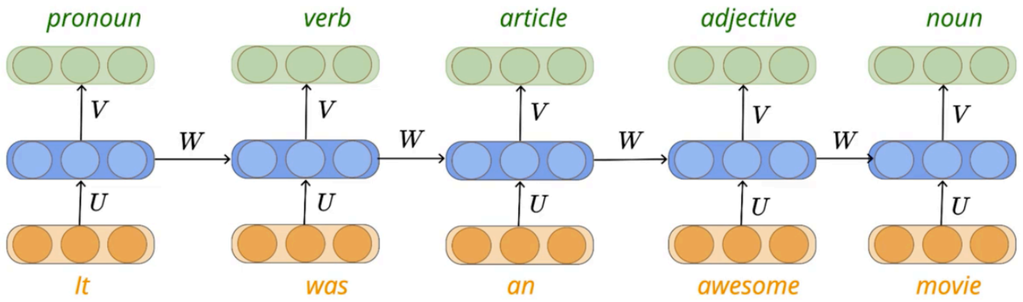
Recurrent neural network architectures for language processing (Thursday)



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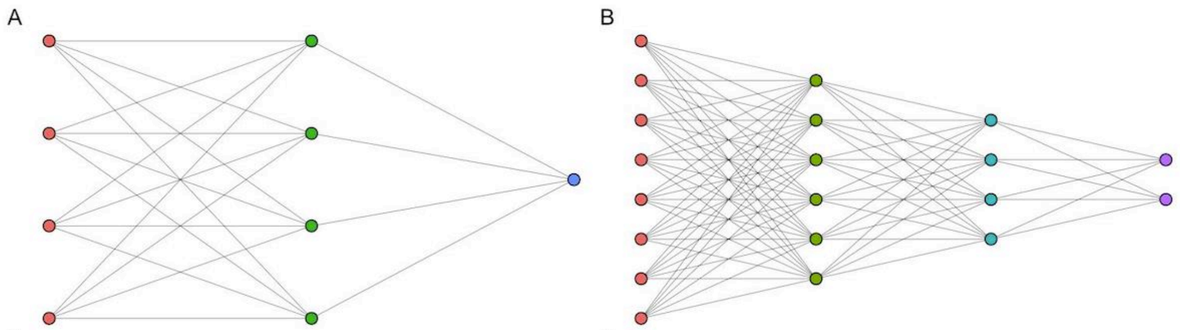

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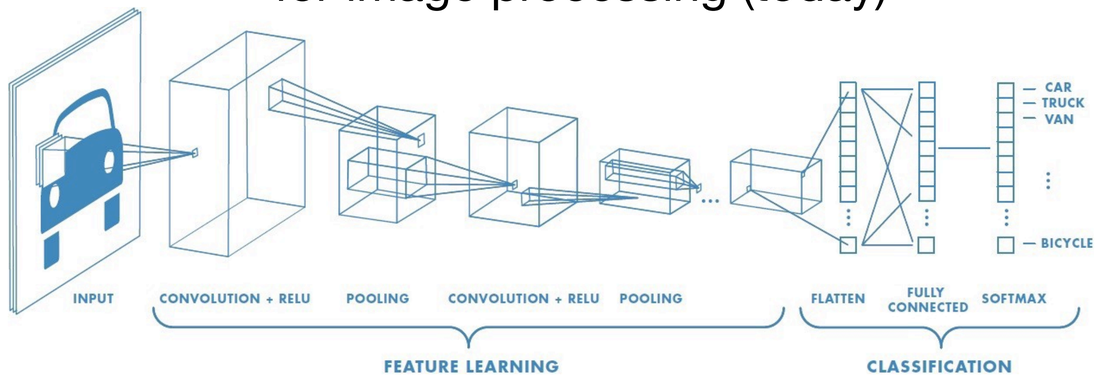

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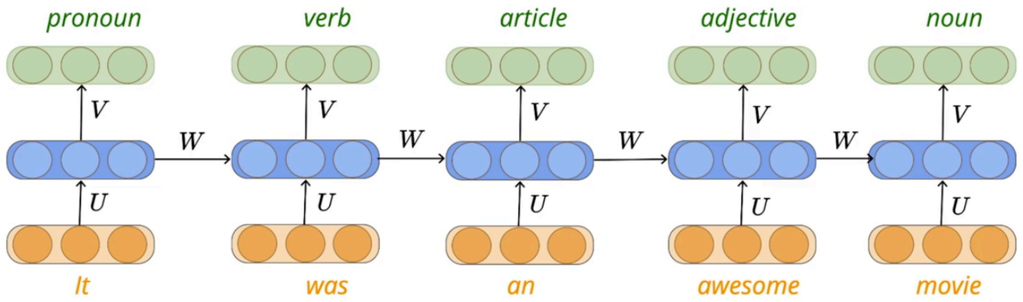

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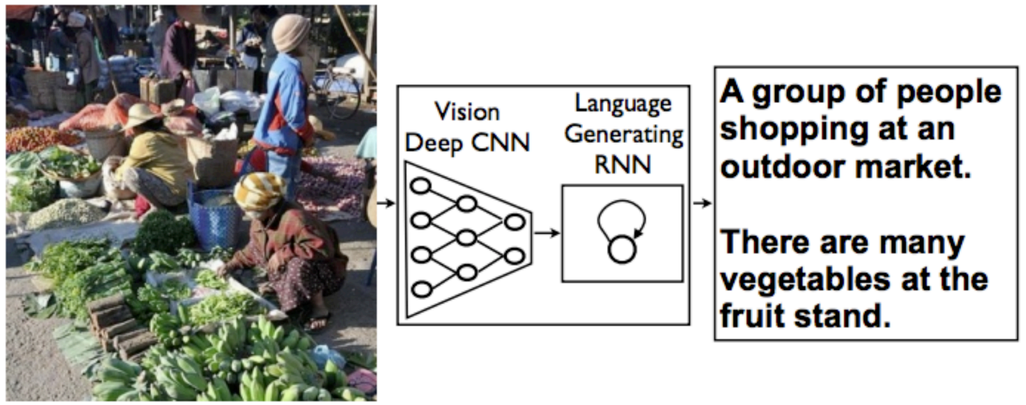
Architecture components are modular and can be composed, e.g. image captioning



https://subscription.packtpub.com/book/big_data_and_business_intelligence/9781788398060/3/ch03lvl1sec22/what-is-caption-generation

Case study: Image classification

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Prototypical computer vision task:

Given an image, classify according to what object it depicts.

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- Intraclass variation

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A large dataset for image classification

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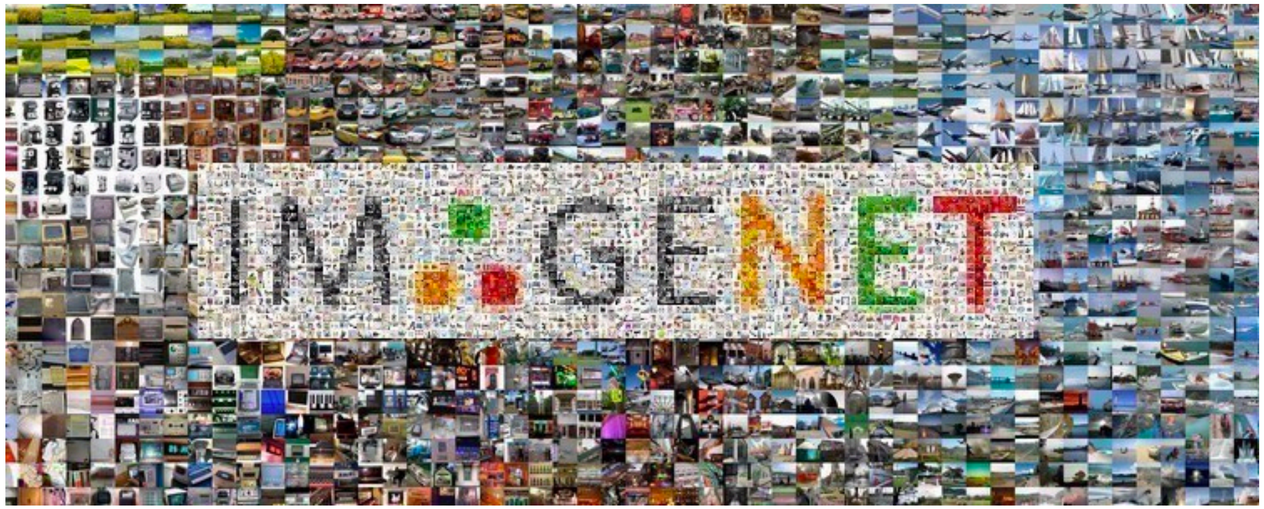
Assembled in 2009 by downloading lots of images from the web and crowdsourcing their labels.



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- Test set: 100,000 images
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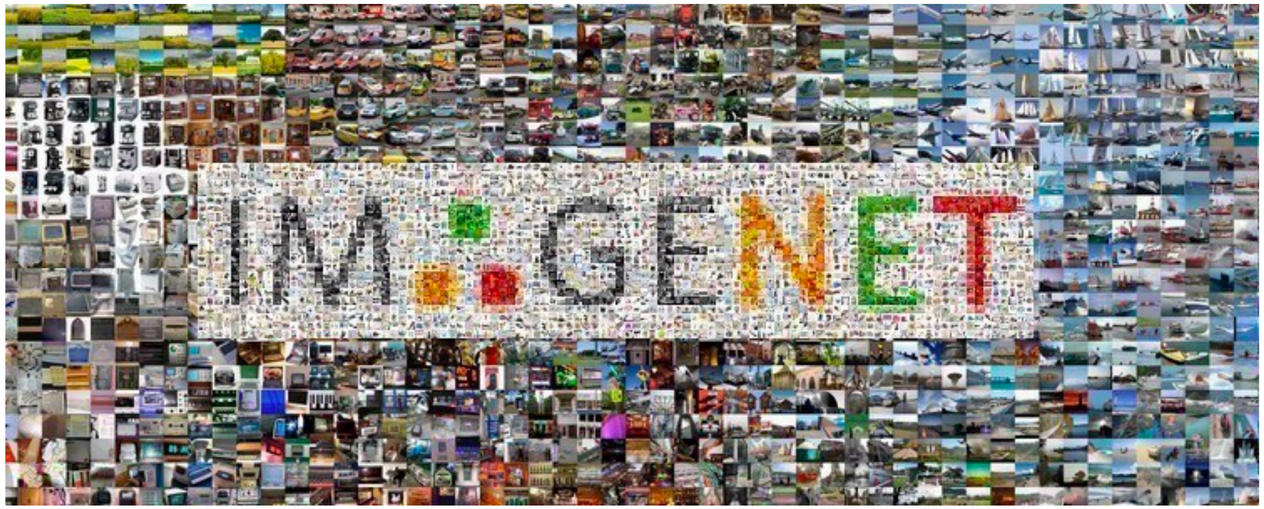

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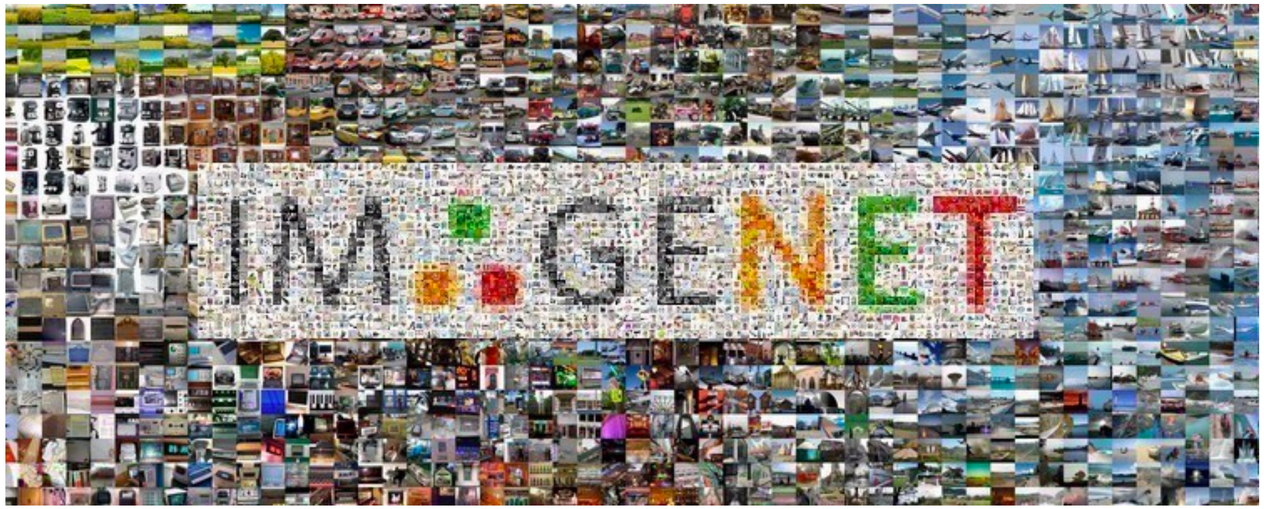
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) held annually between 2010-2017.



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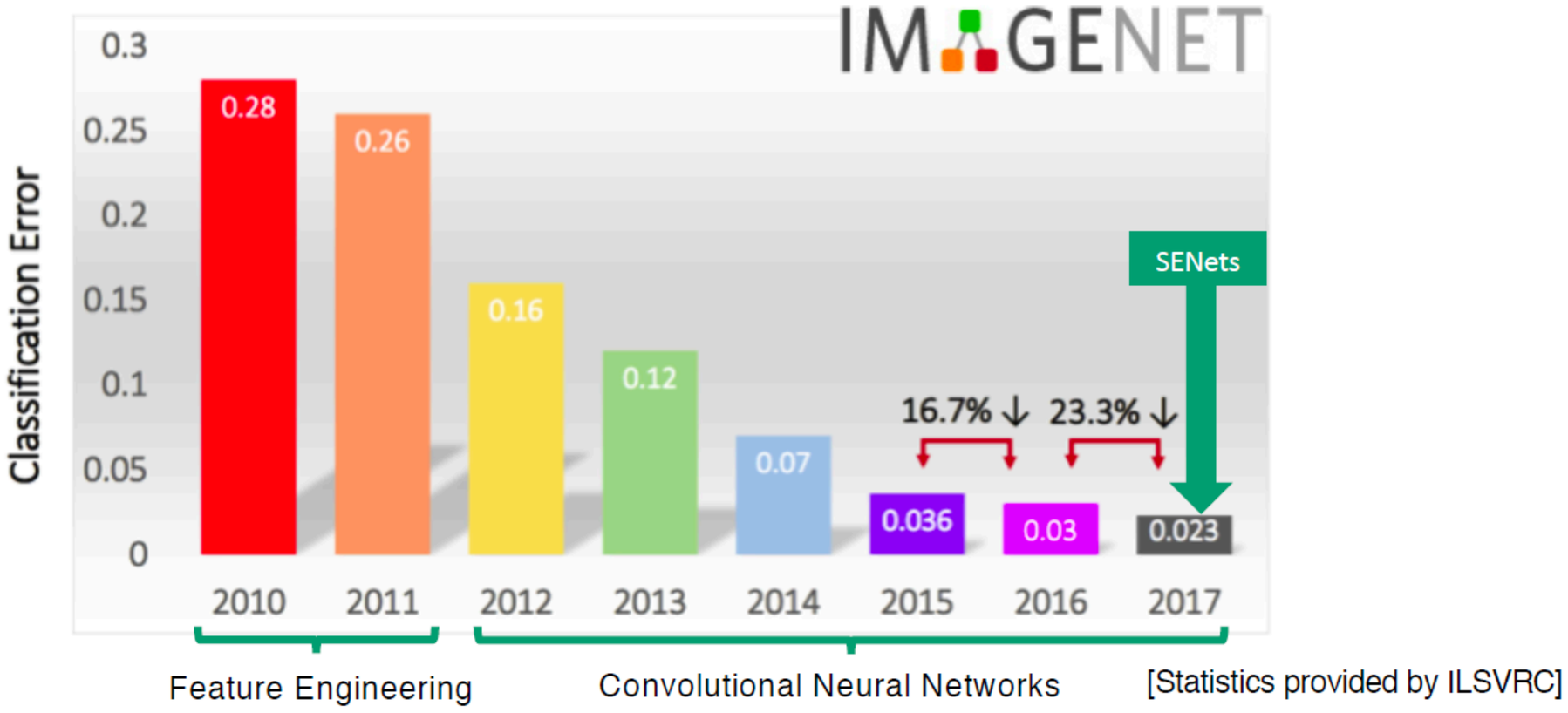
ILSVRC results over the years



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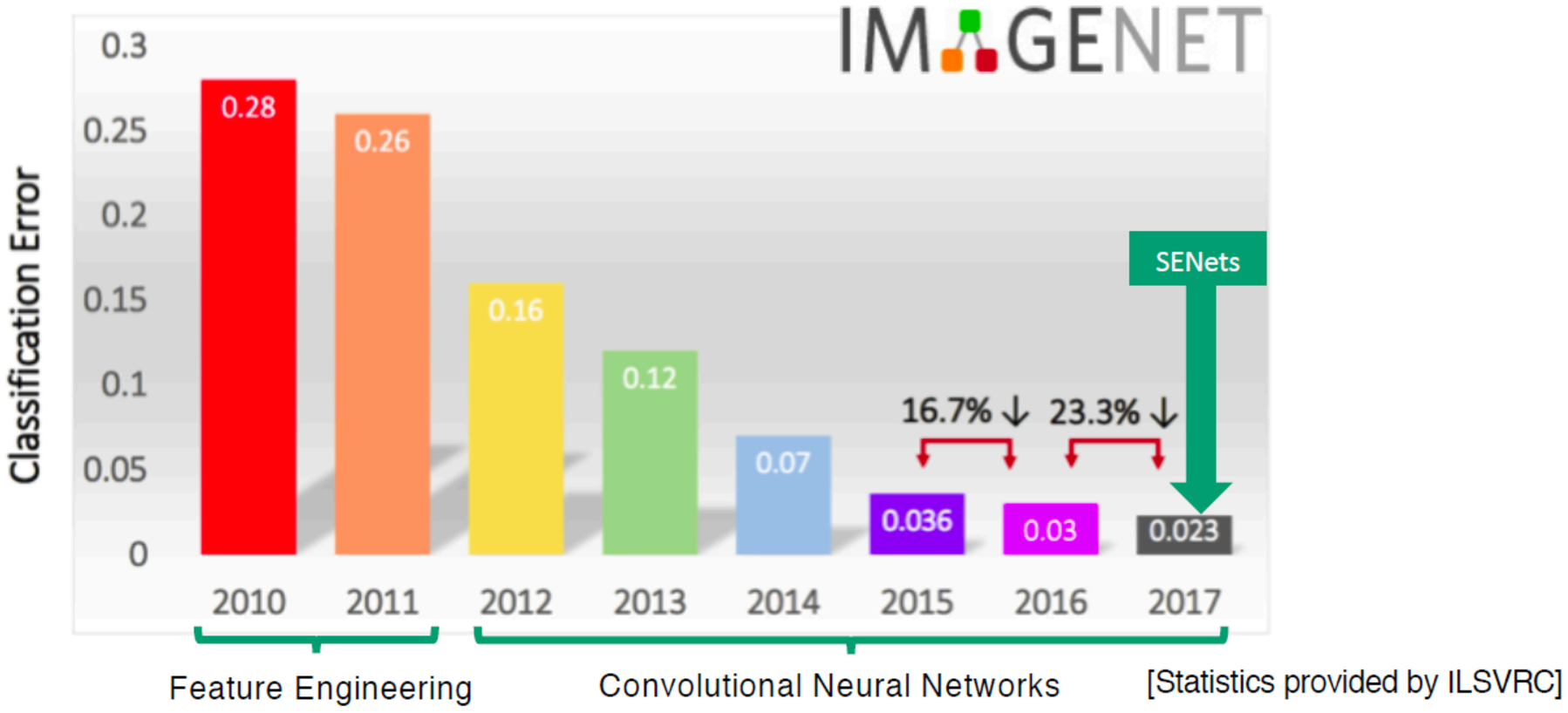

Convolutional neural networks (CNNs) have dominated since 2012.

CNNs are built on image-specific properties

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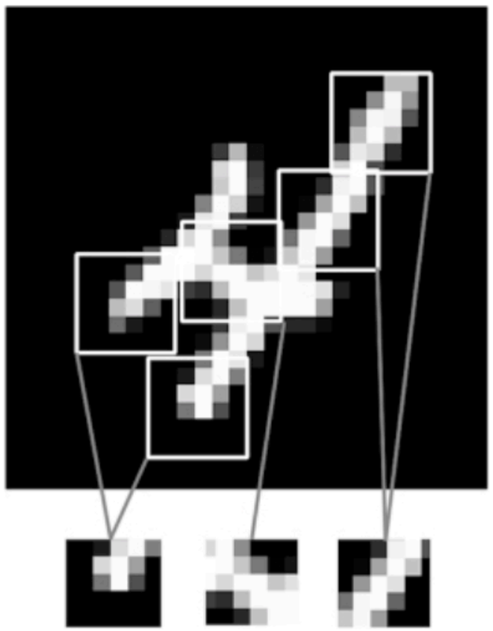
Figure 5.1. Images can be broken into local patterns such as edges, textures, and so on.



Images from *Deep Learning with R* (Chapter 5)

CNNs are built on image-specific properties

Figure 5.1. Images can be broken into local patterns such as edges, textures, and so on.

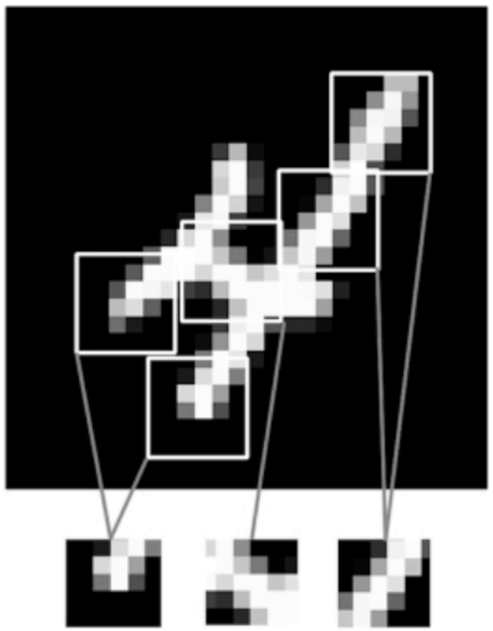
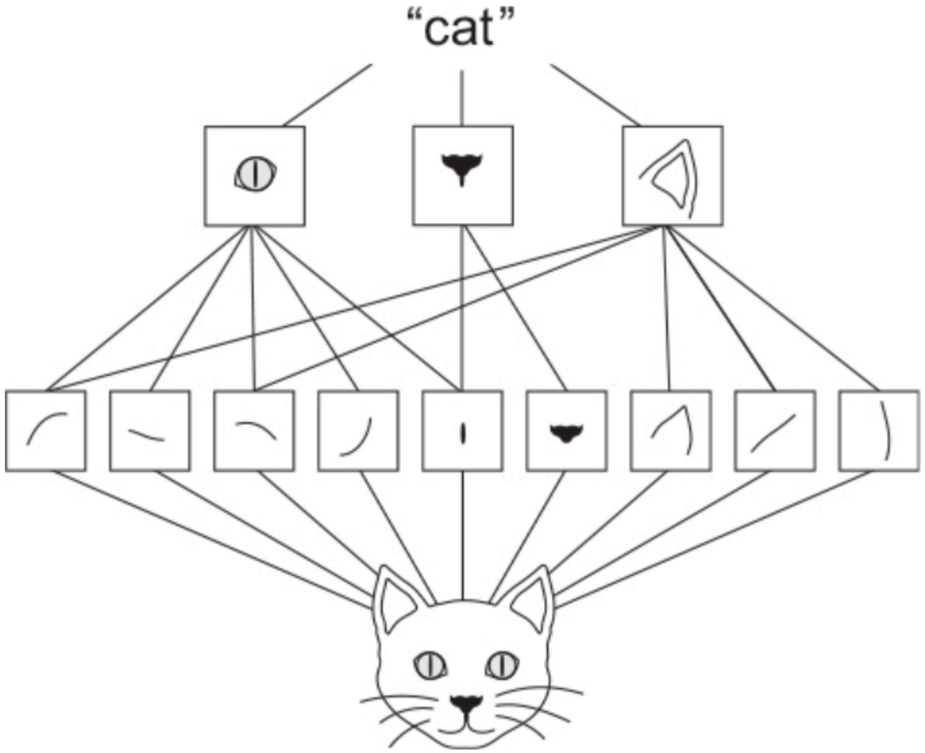


Figure 5.2. The visual world forms a spatial hierarchy of visual modules: hyperlocal edges combine into local objects such as eyes or ears, which combine into high-level concepts such as "cat."



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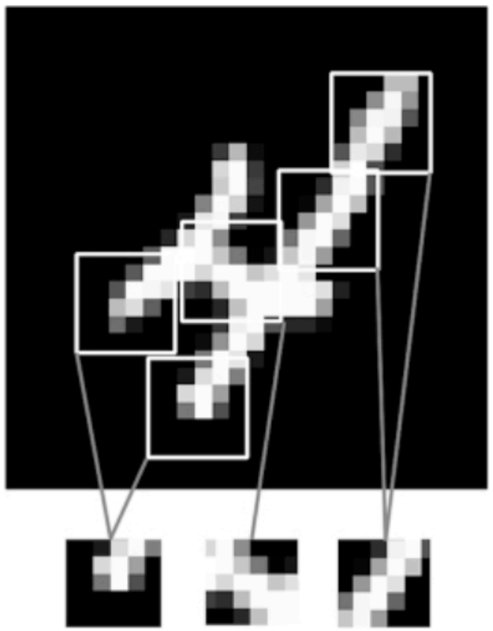

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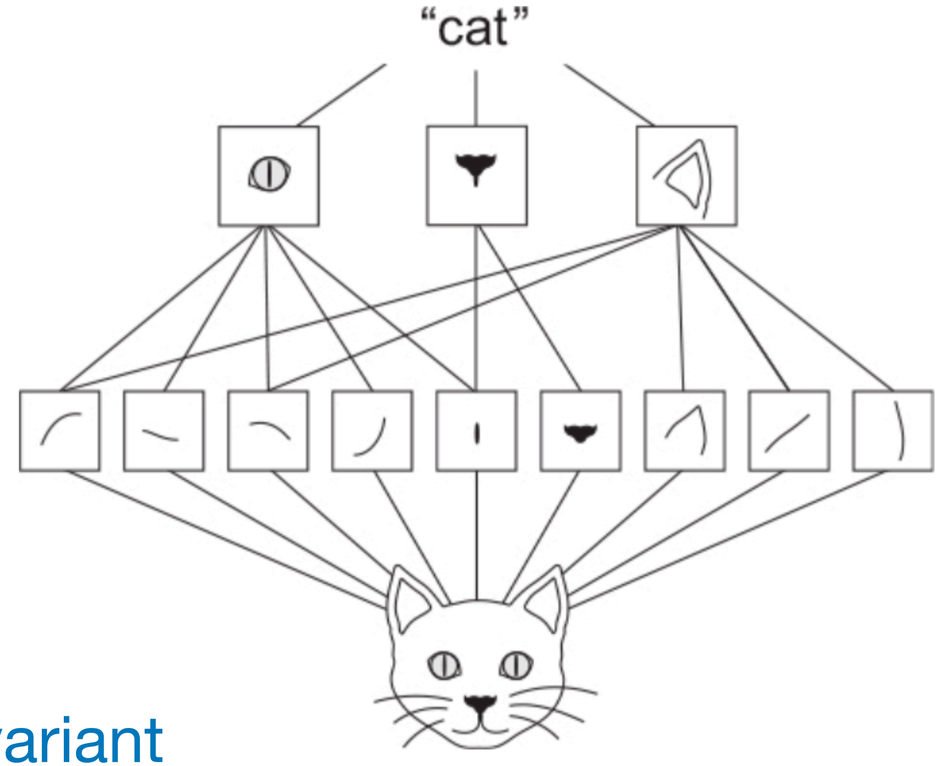


Patterns are

- Local
- Translation-invariant
- Hierarchical

Images from *Deep Learning with R* (Chapter 5)

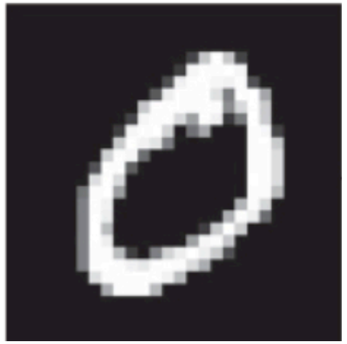
Convolution: Searching for patterns

Filter (3x3)

(pattern)

0	1	2
2	2	0
0	1	2

Input image



3_0	3_1	2_2	1	0
0_2	0_2	1_0	3	1
3_0	1_1	2_2	2	3
2	0	0	2	2
2	0	0	0	1

Activation map

(presence of pattern)

12.0	12.0	17.0
10.0	17.0	19.0
9.0	6.0	14.0

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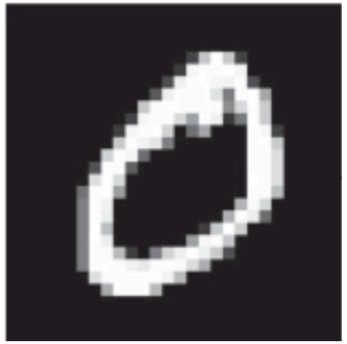

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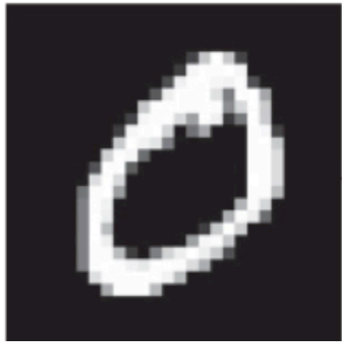

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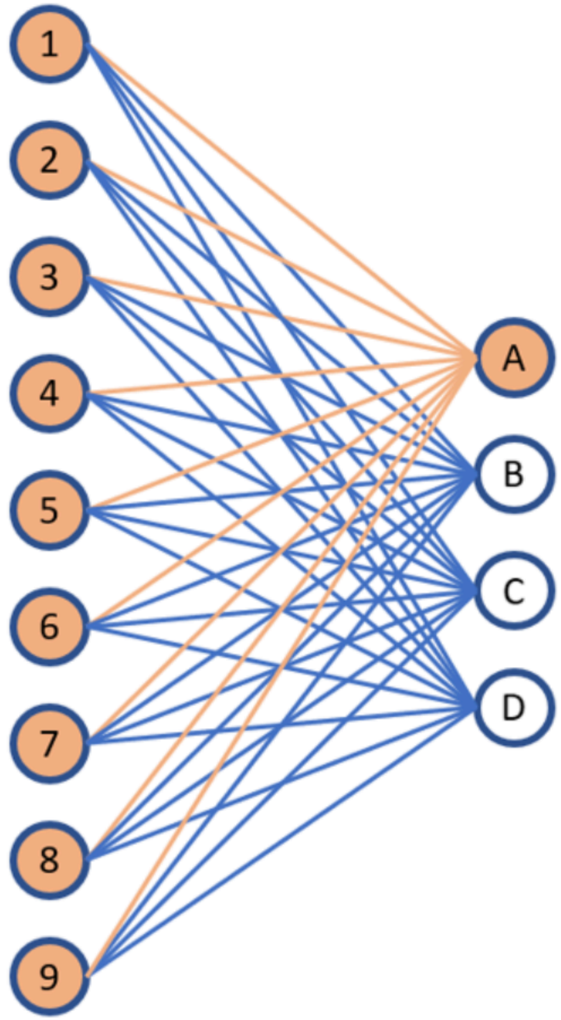
We want to use many filters, each sensitive to a different kind of pattern.

Convolutional layer versus fully-connected layer

A convolutional layer can be visualized similarly to a fully-connected layer.



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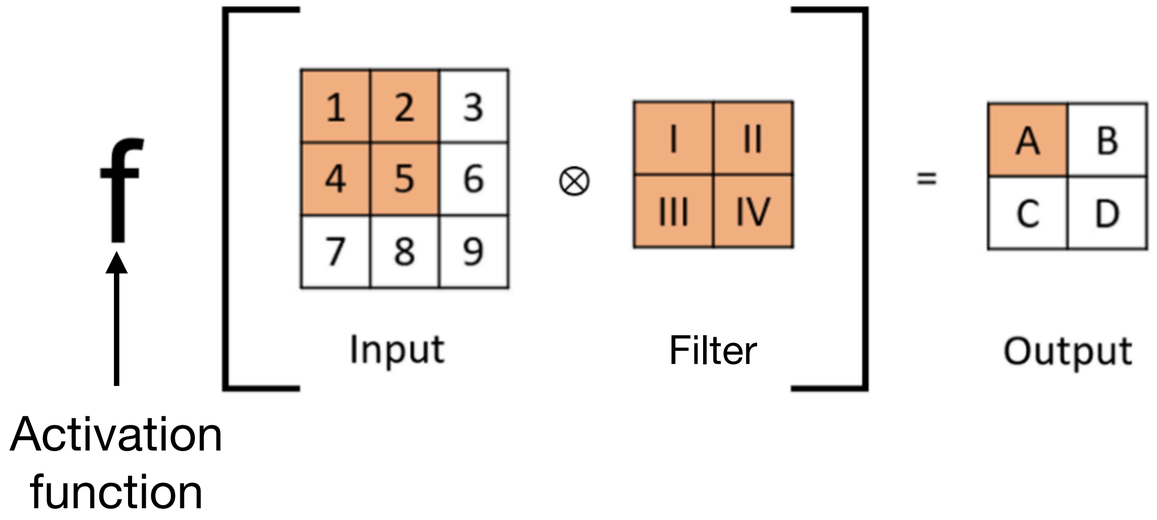

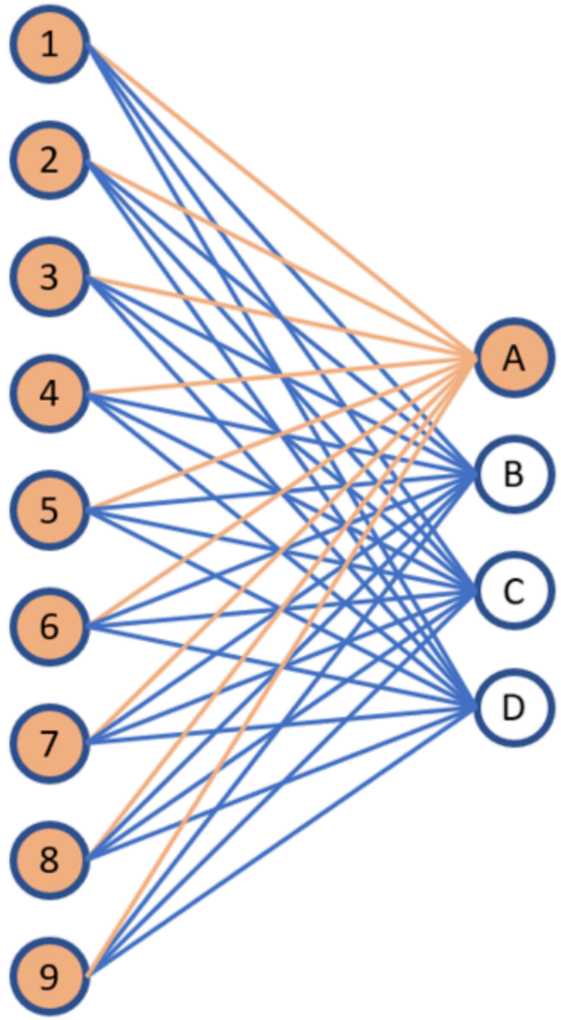

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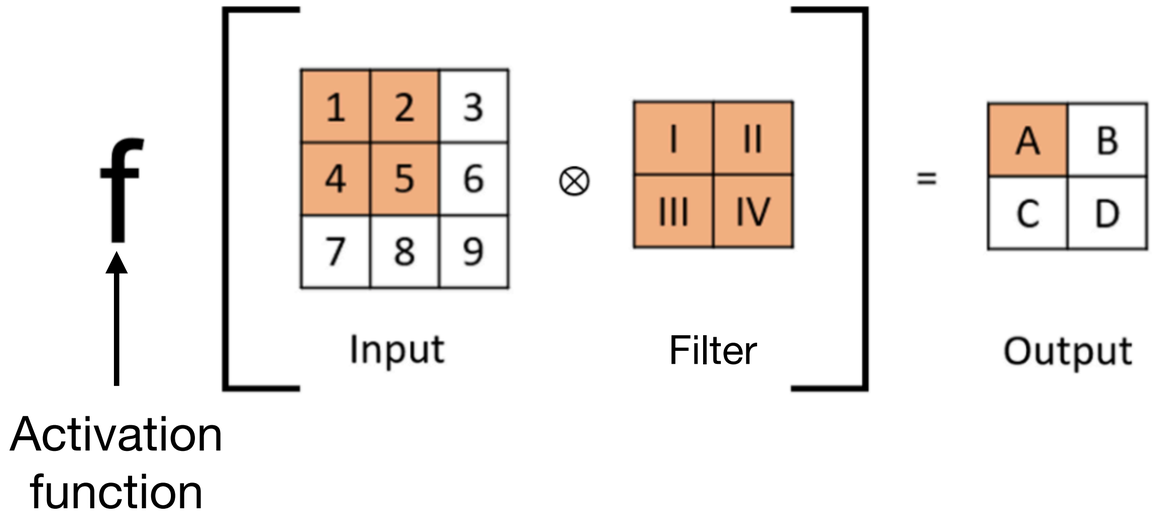

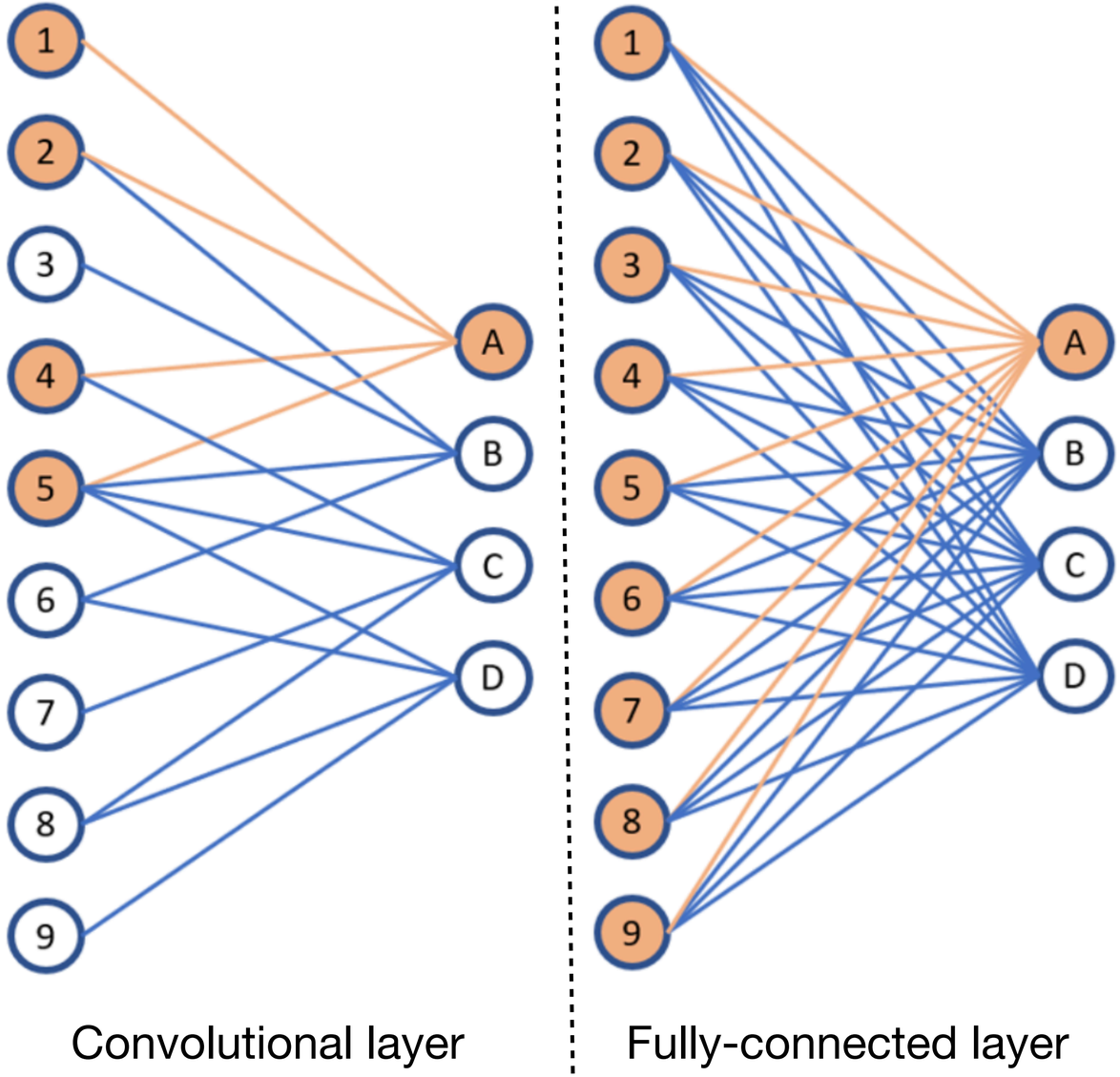

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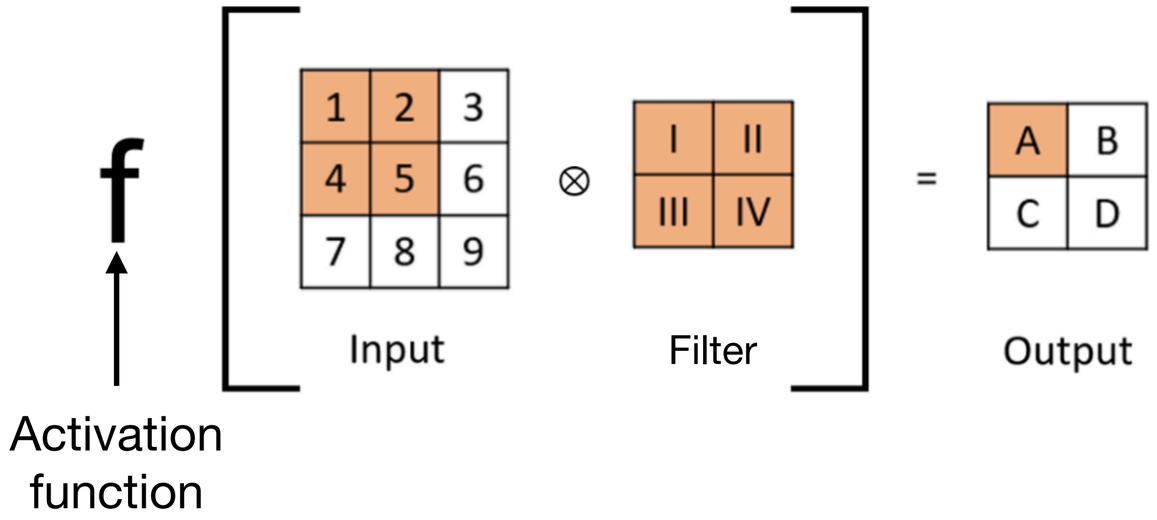

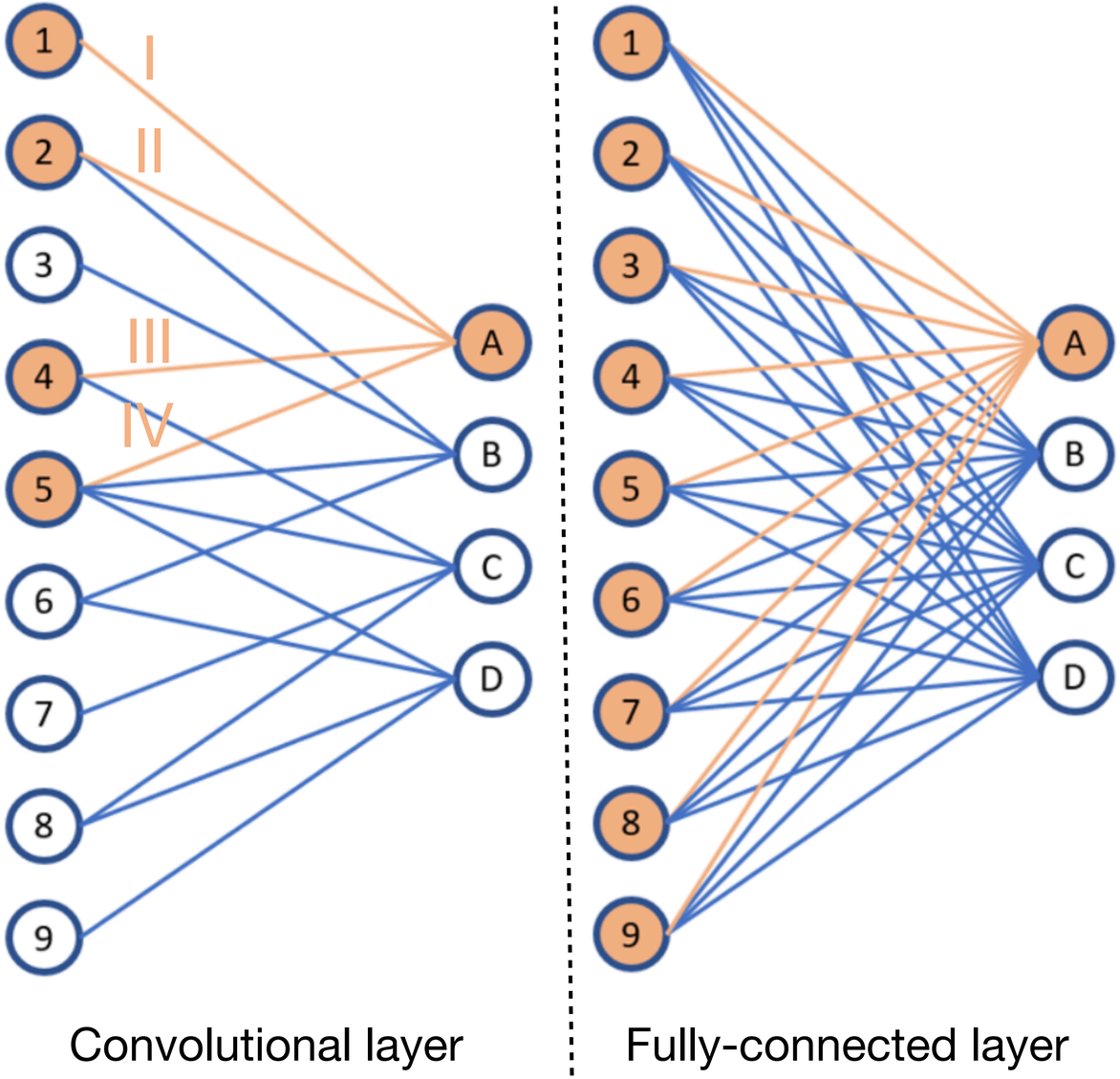

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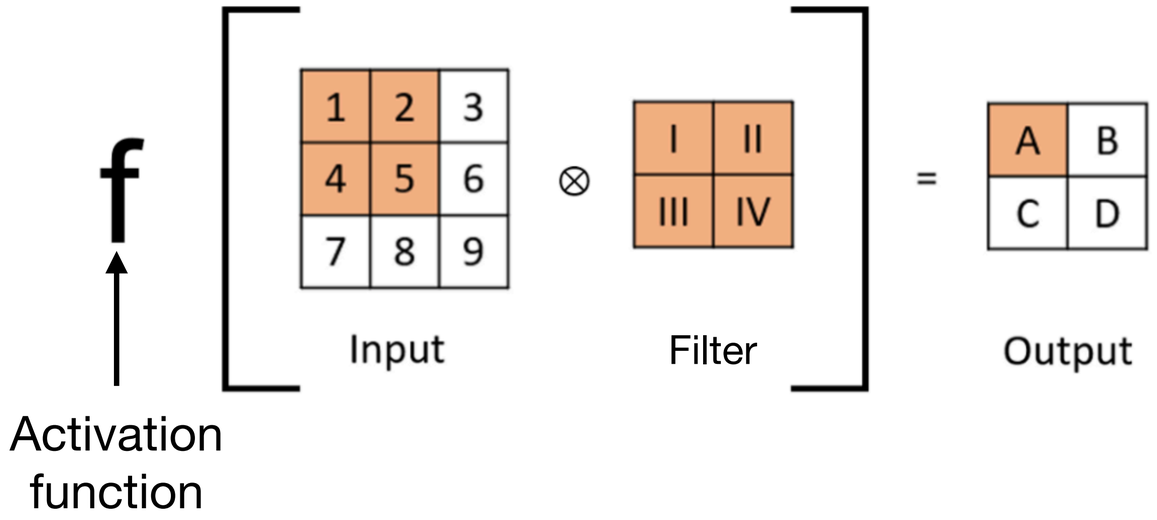

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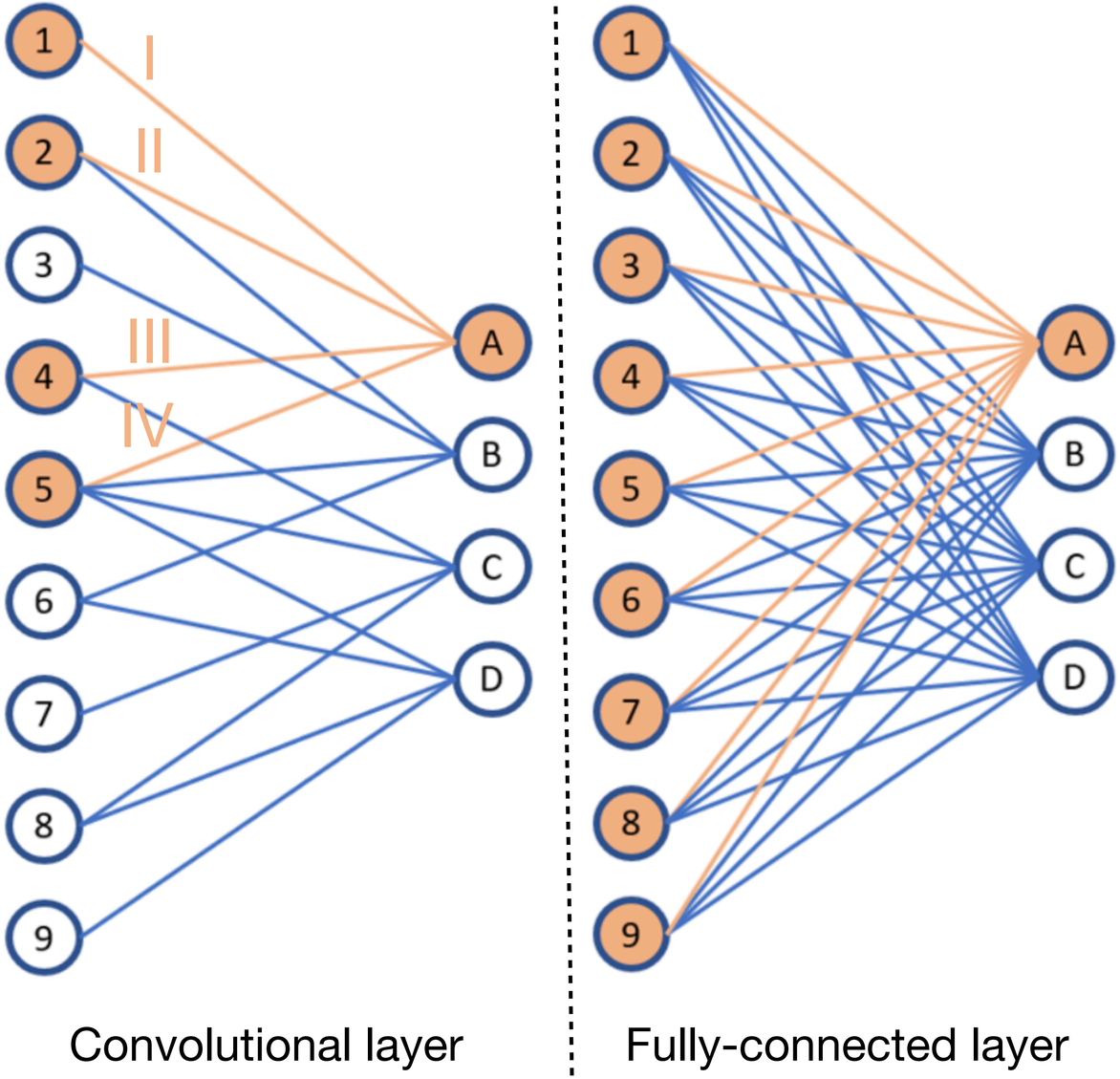

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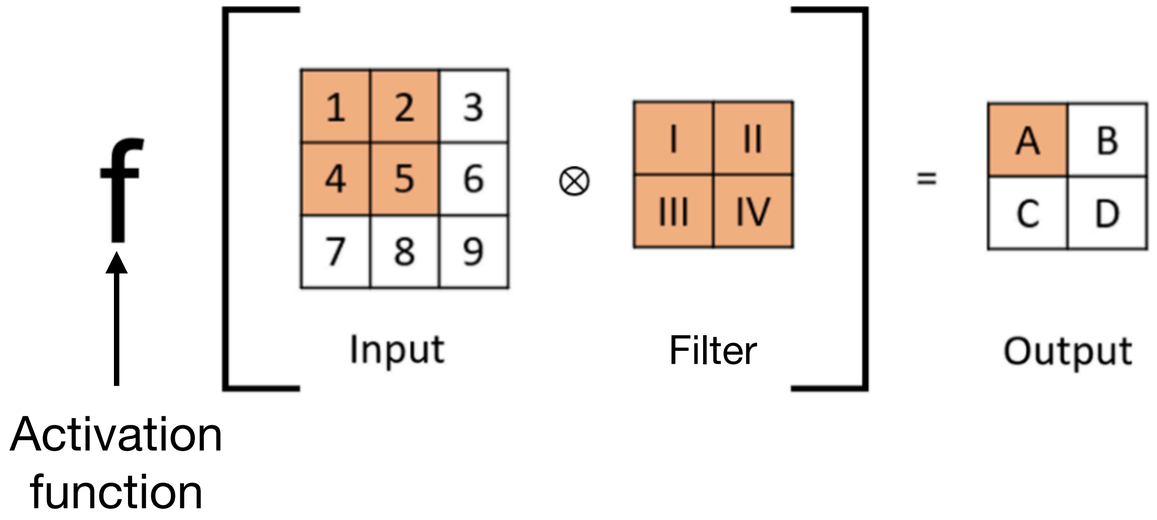

In a convolutional layer:

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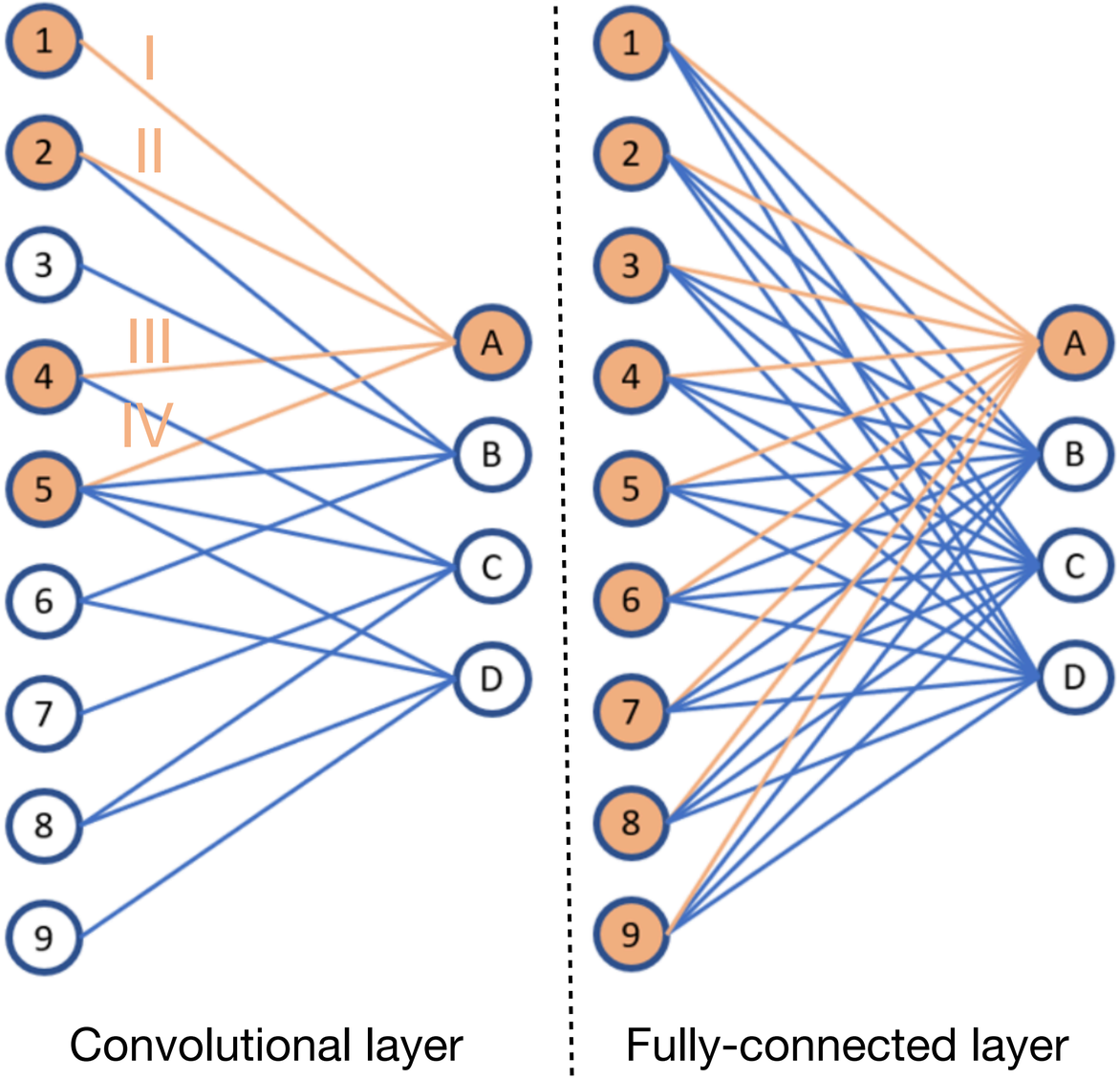

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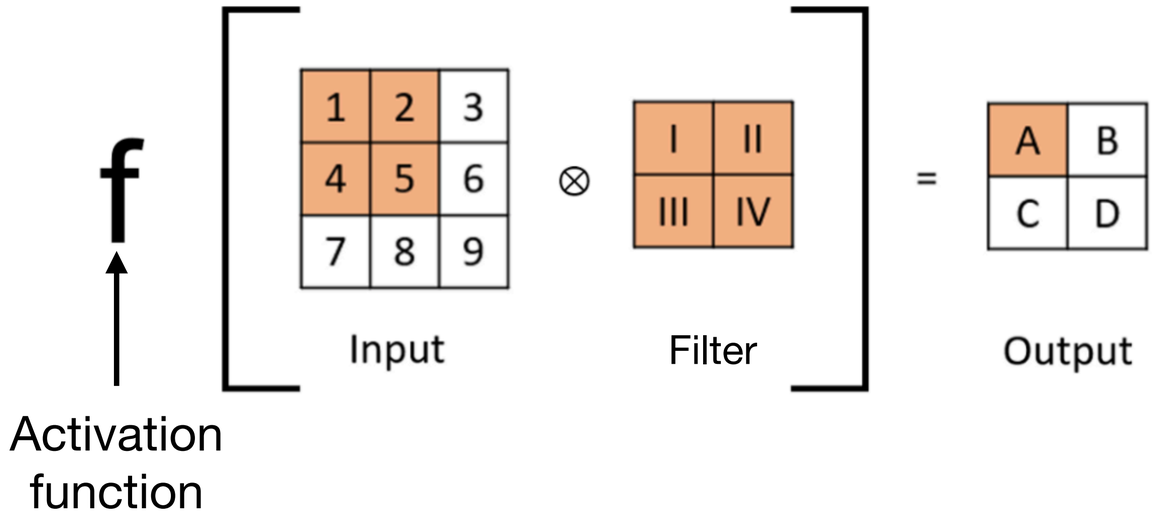
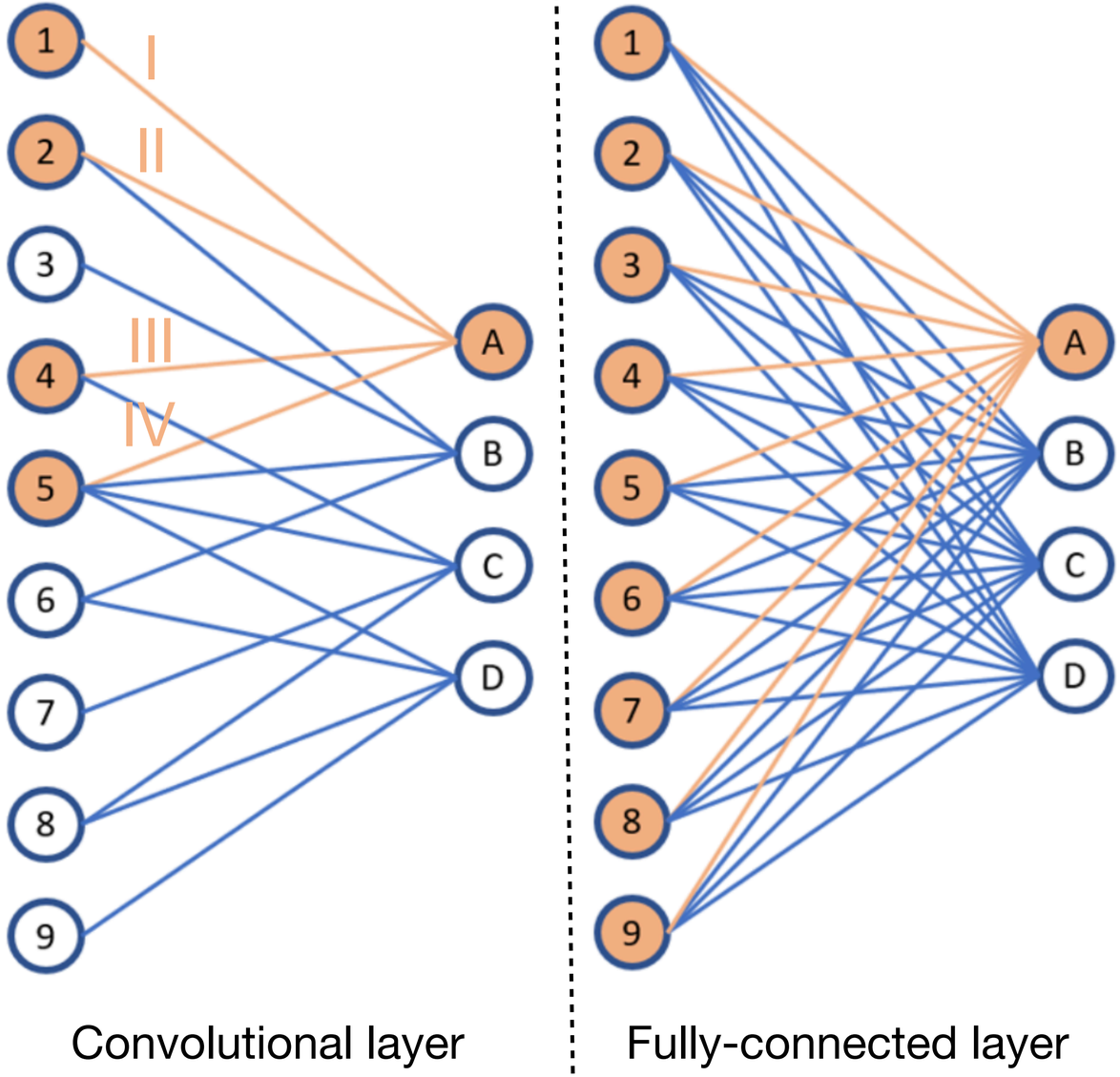


In a convolutional layer:

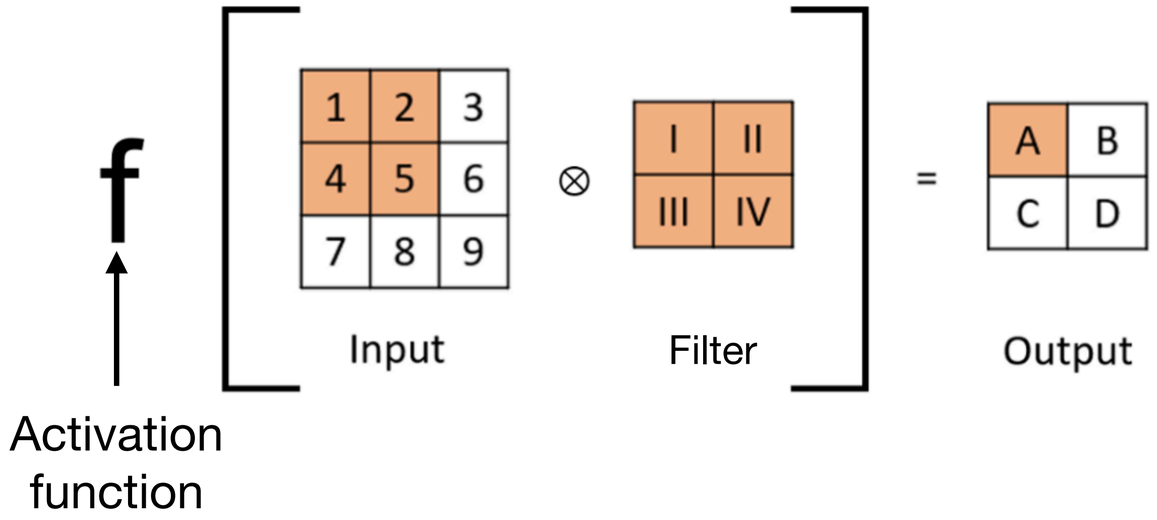
- Not all node pairs are connected with edges
- Weights (from filter) reused across edges



Images from: https://towardsdatascience.com/convolutional-layers-vs-fully-connected-layers-364f05ab460b

Convolutional layer versus fully-connected layer

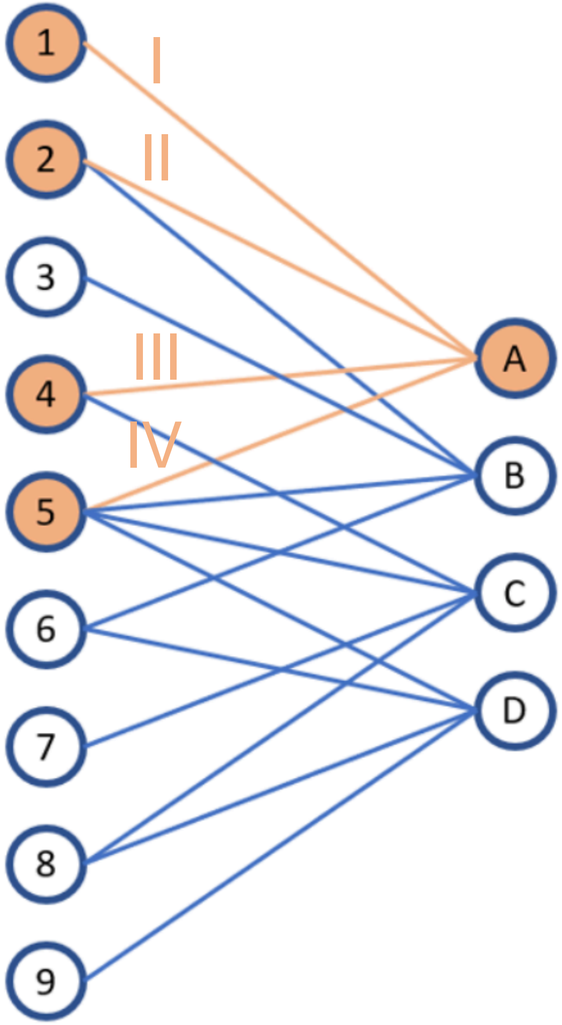
A convolutional layer can be visualized similarly to a fully-connected layer.



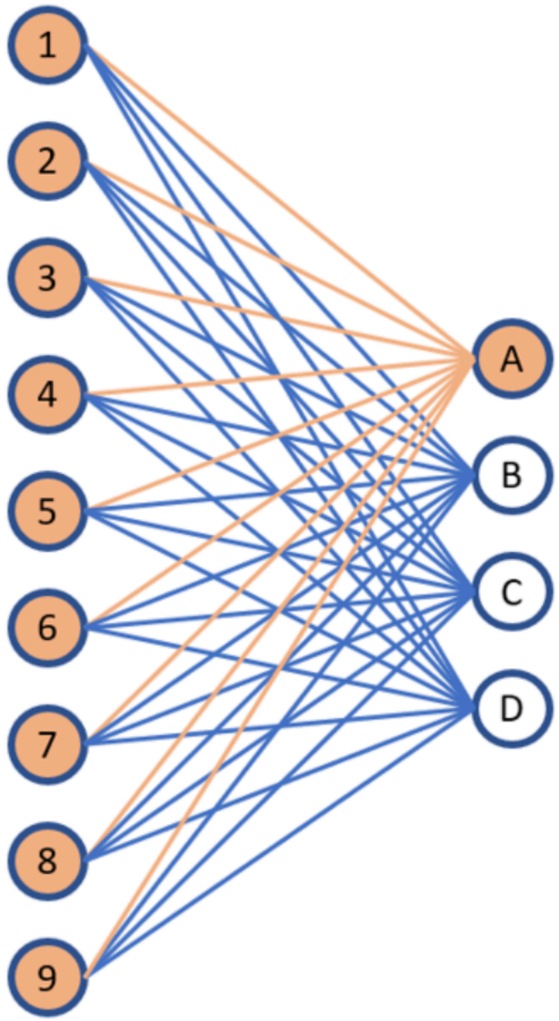
In a convolutional layer:

- Not all node pairs are connected with edges
- Weights (from filter) reused across edges

Consequence: Conv layers have fewer parameters!



Convolutional layer



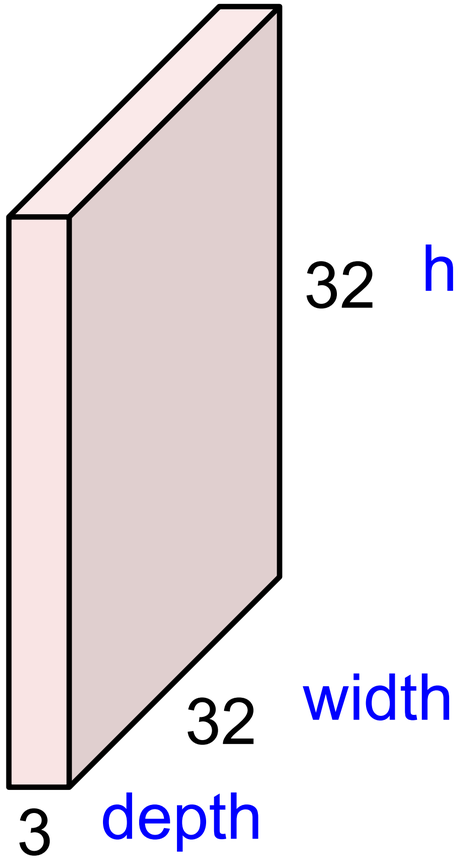
Fully-connected layer

Images from: https://towardsdatascience.com/convolutional-layers-vs-fully-connected-layers-364f05ab460b

Convolution Layer

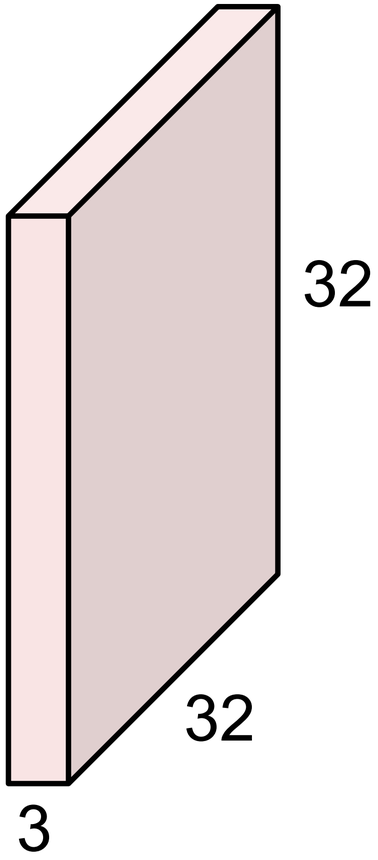
Note: This slide and several following ones are borrowed from Stanford's CS231n.

32x32x3 image (images typically have red, green, and blue channels.)

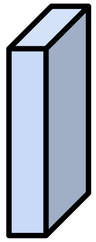


Convolution Layer

32x32x3 image



5x5x3 filter

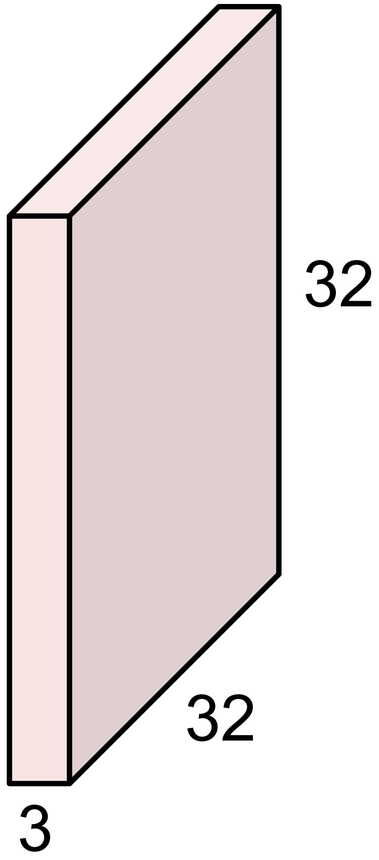


Convolve the filter with the image
i.e. “slide over the image spatially, computing dot products”

Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



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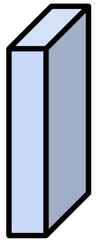

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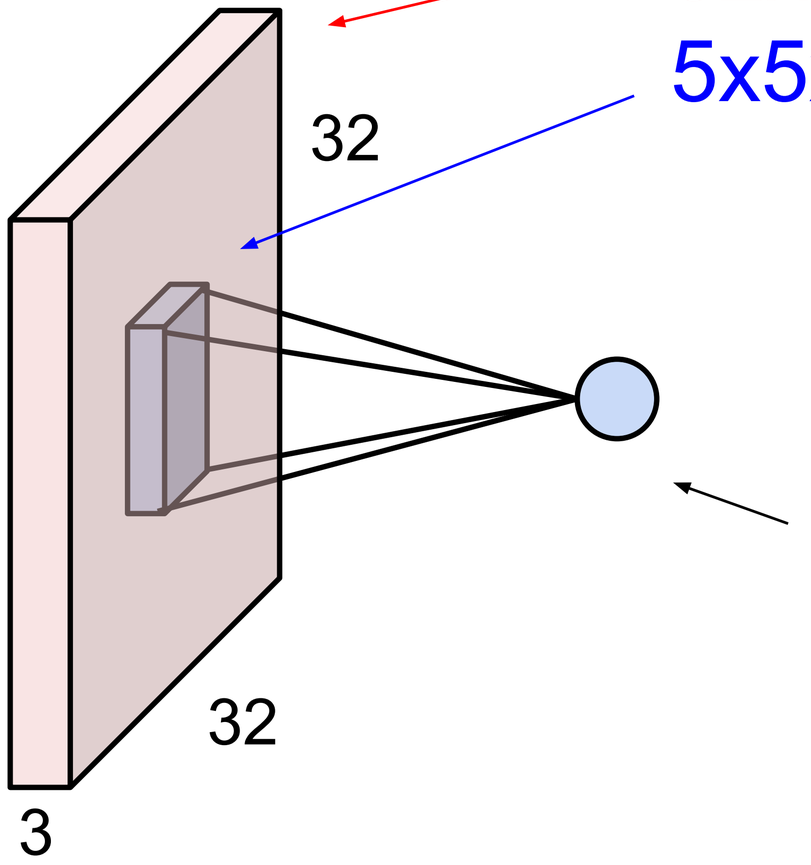
Convolution Layer



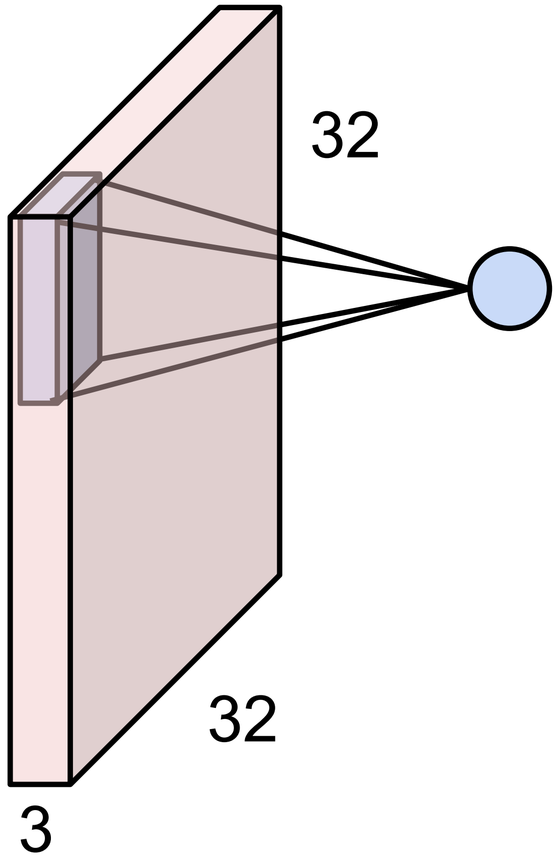
32x32x3 image

5x5x3 filter w

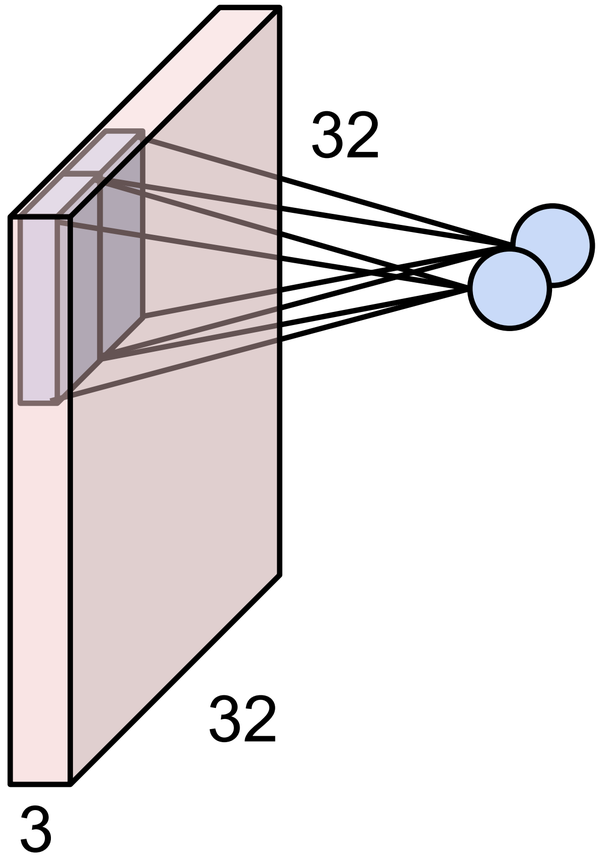
1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolution Layer



Convolution Layer



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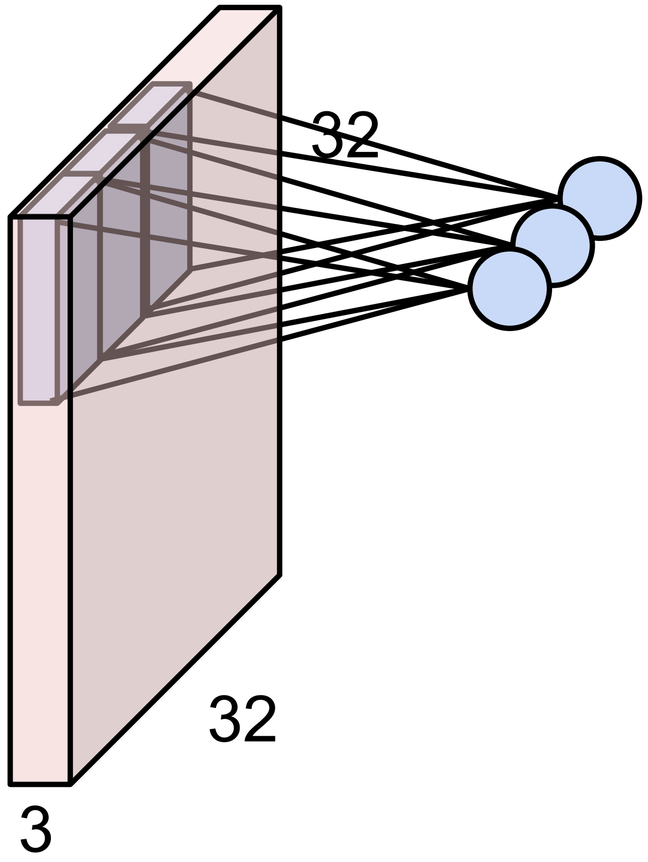
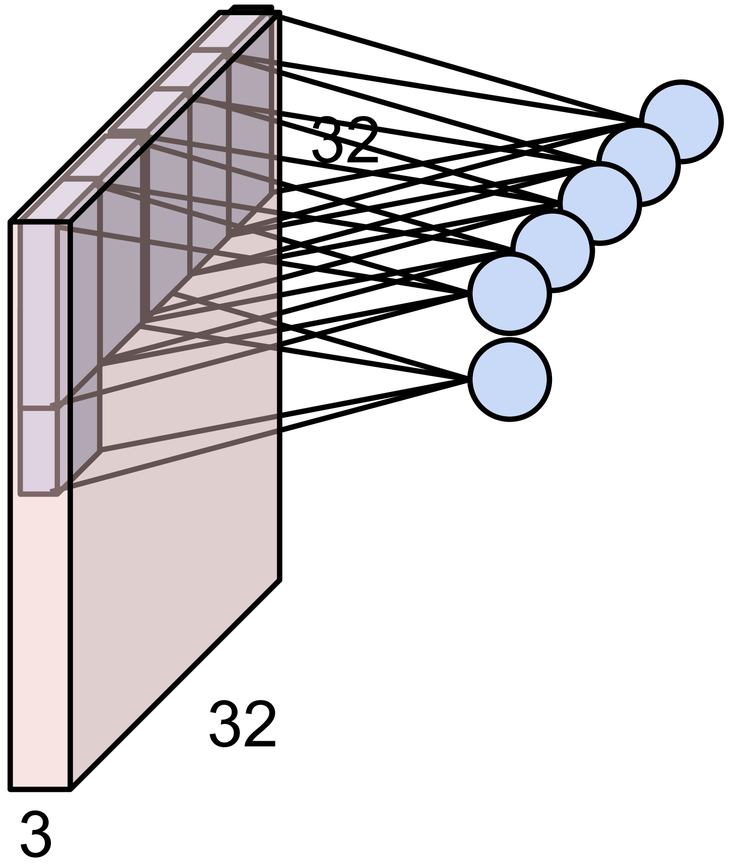
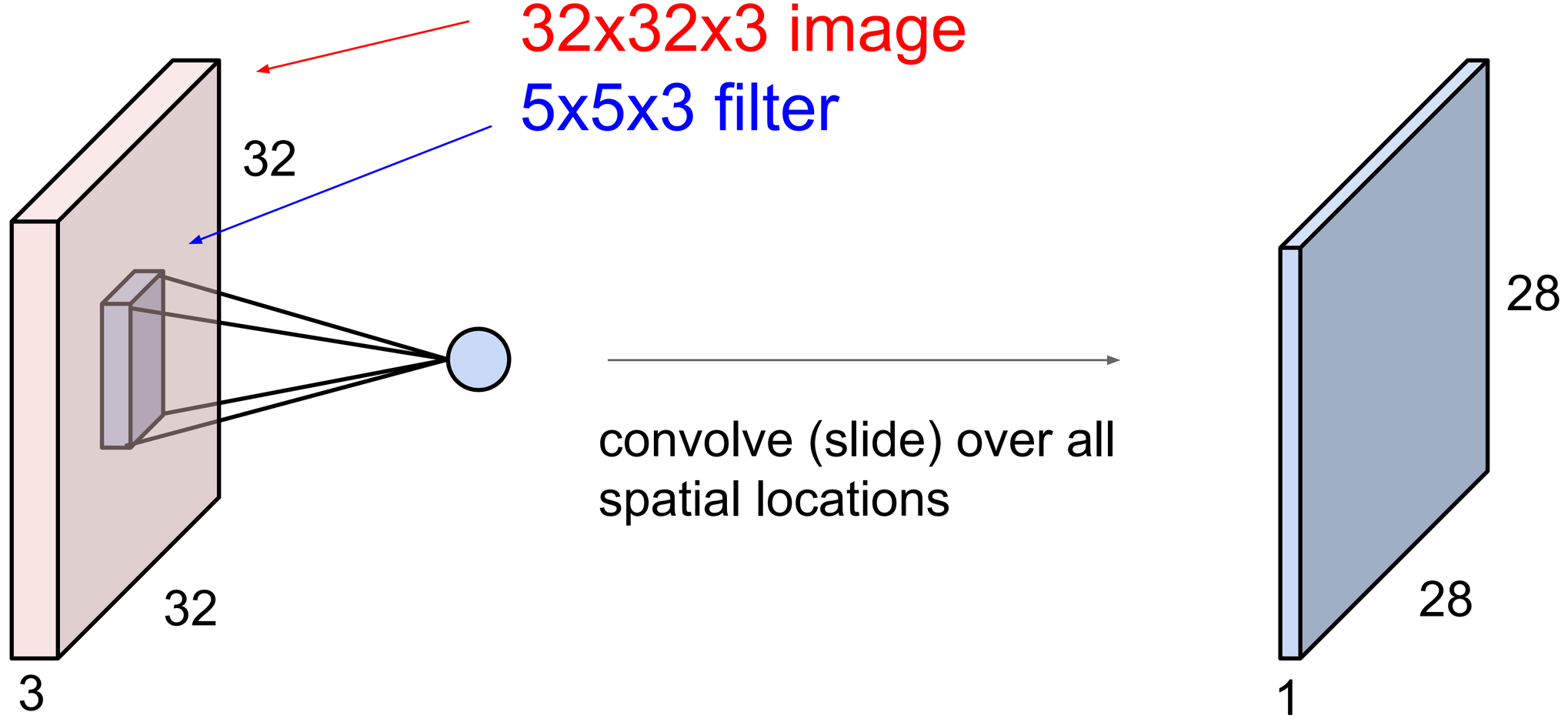


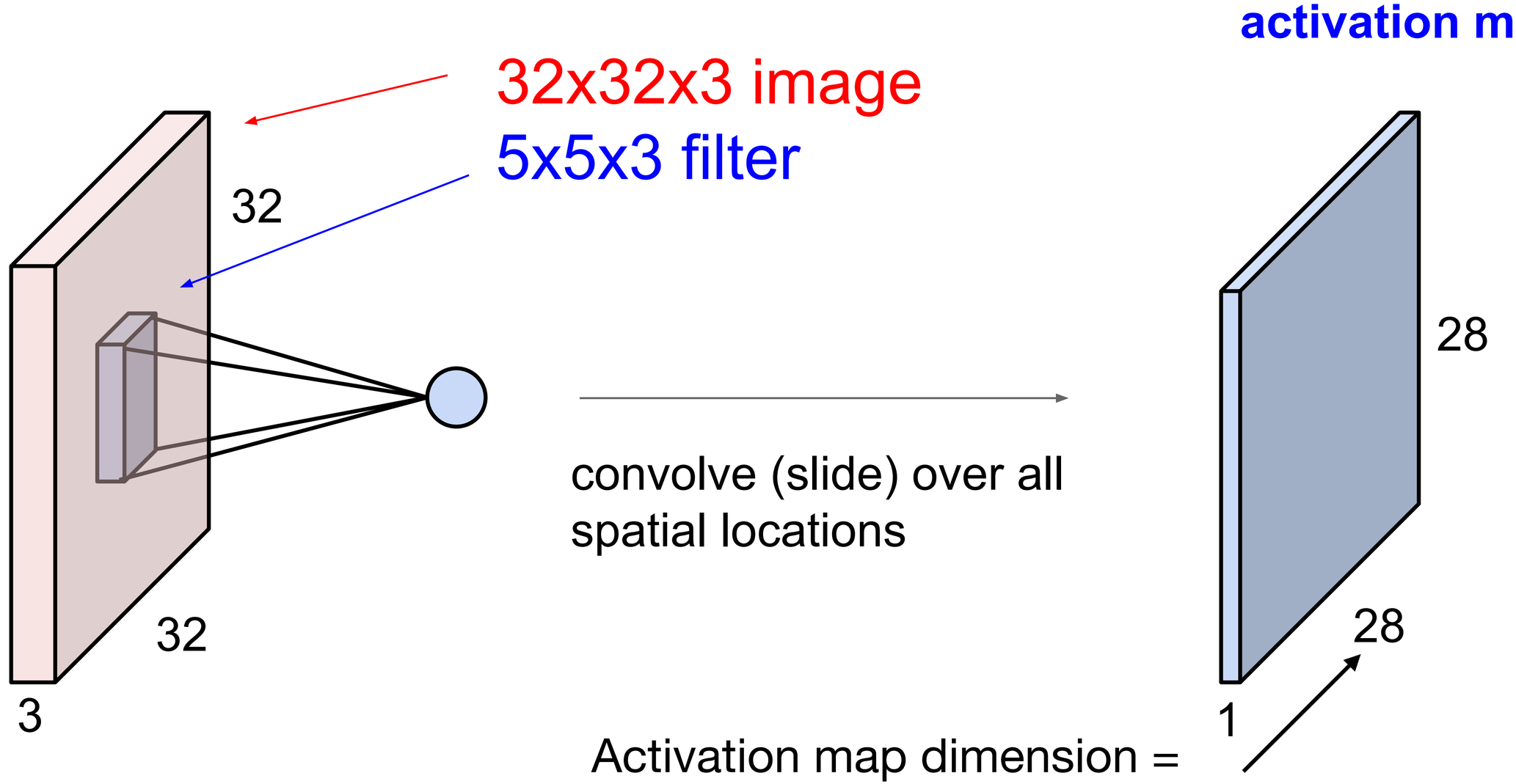
Convolution Layer



Convolution Layer

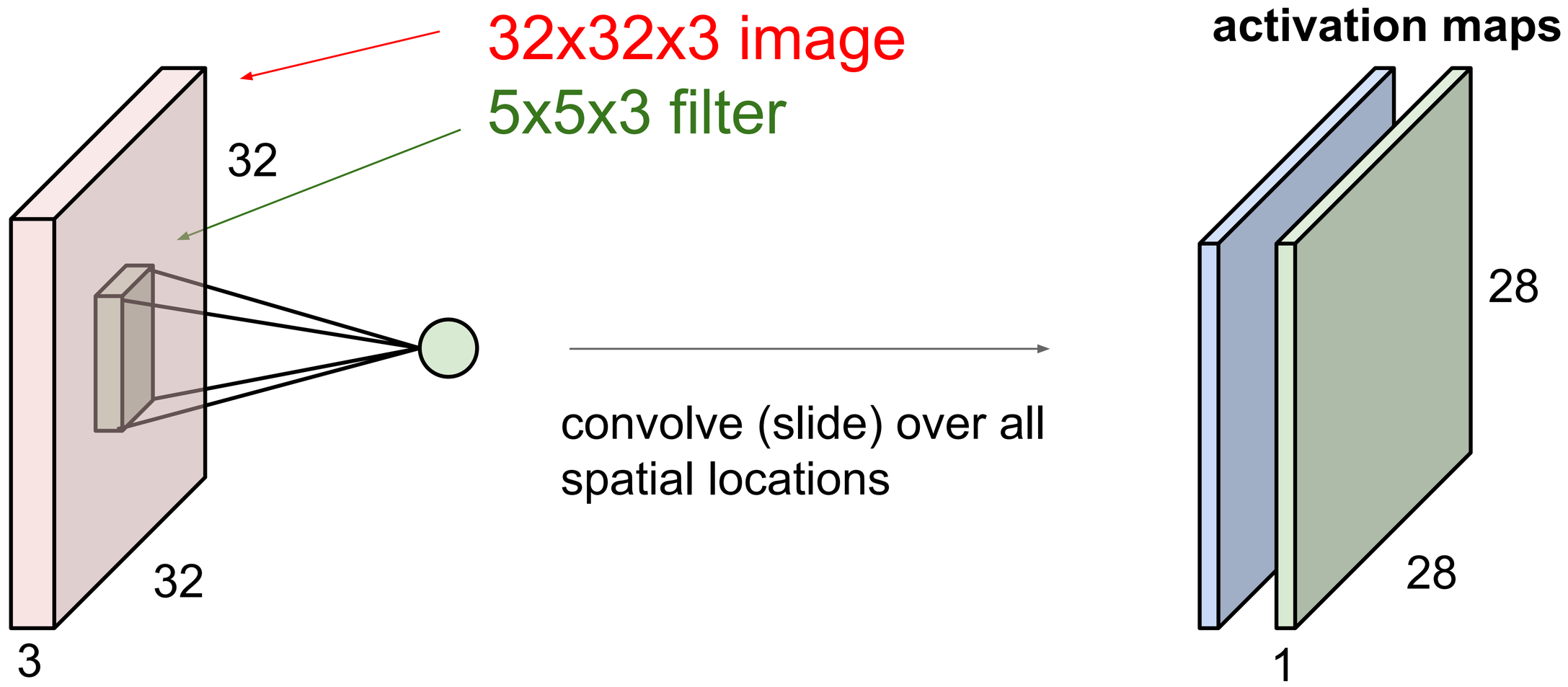


Convolution Layer

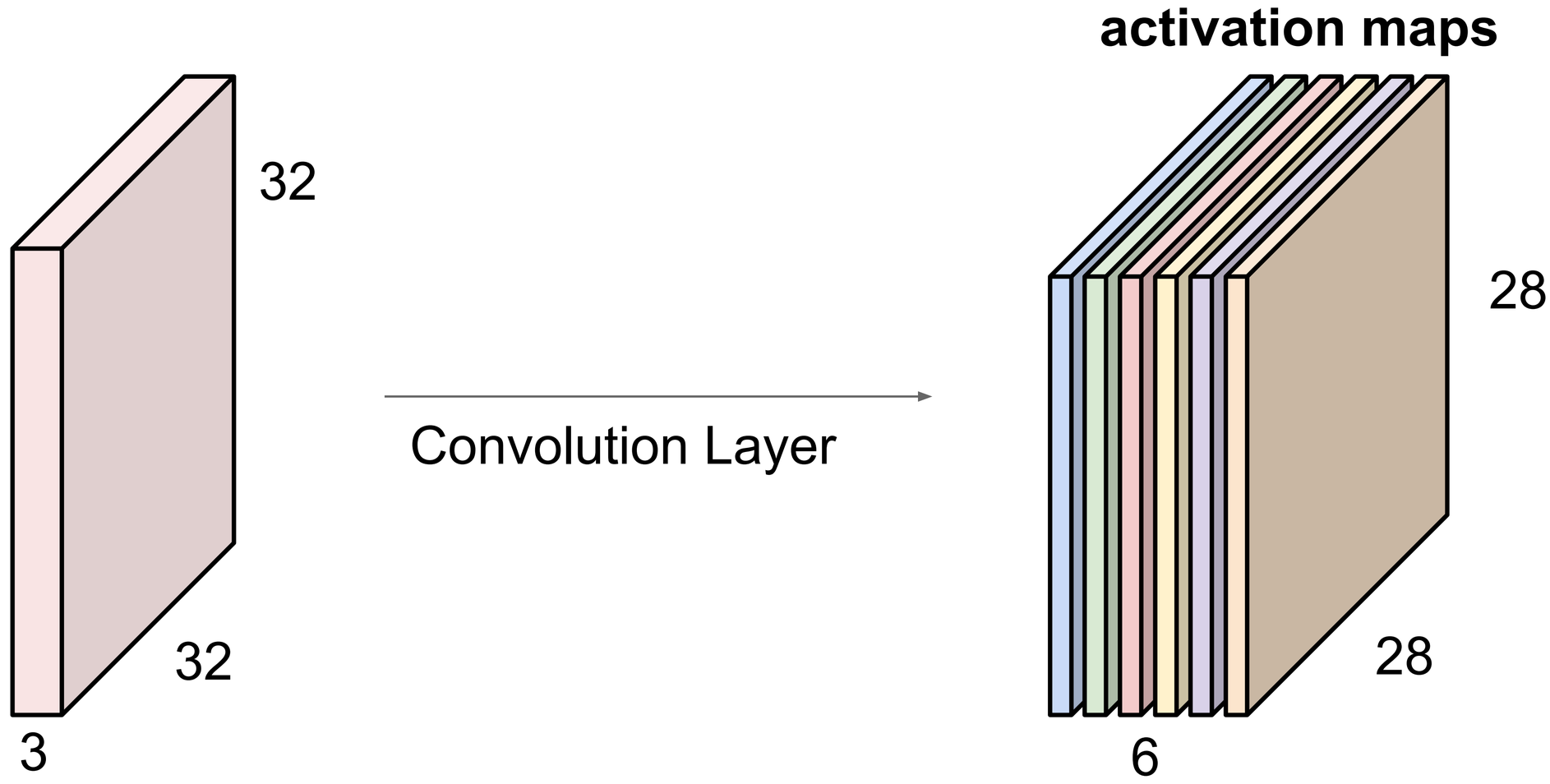


Convolution Layer

consider a second, green filter



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!

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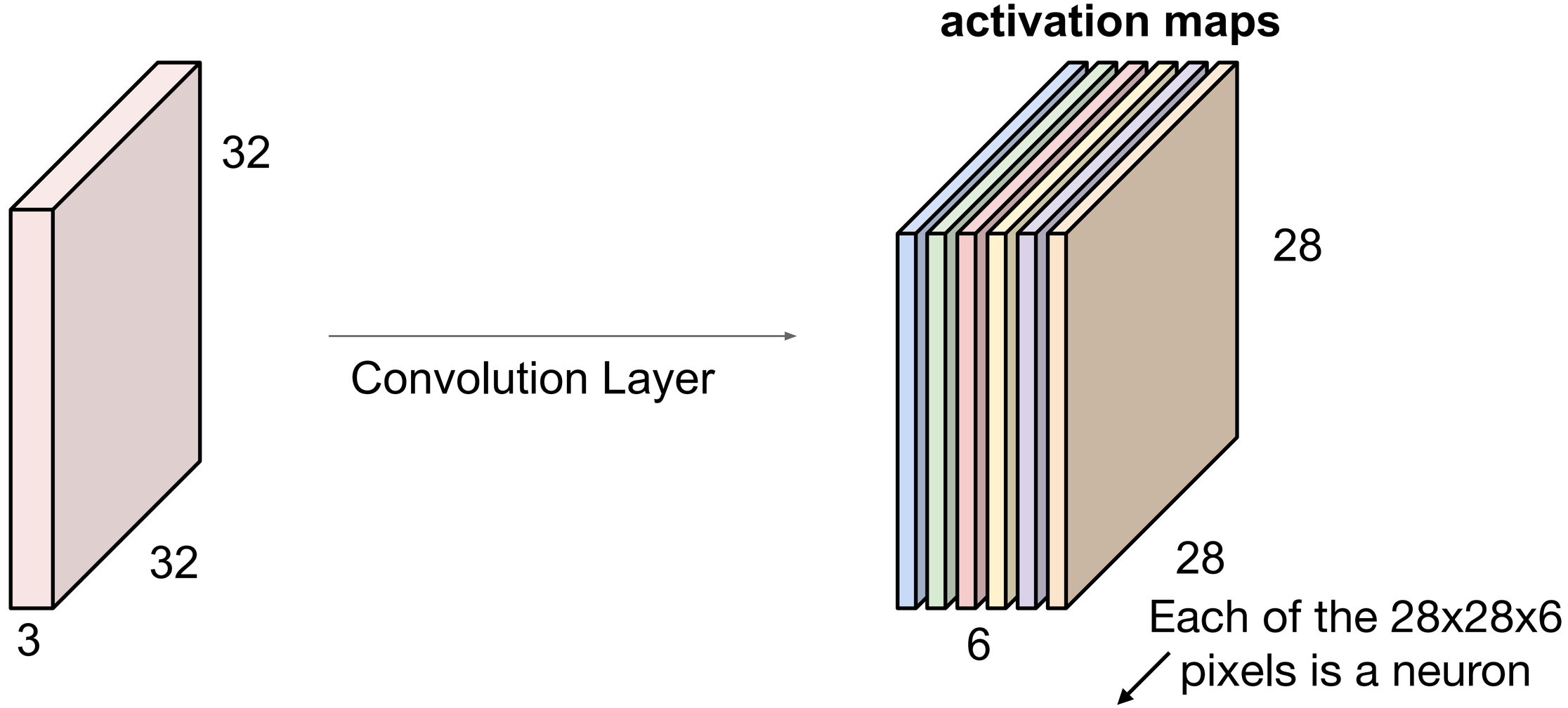

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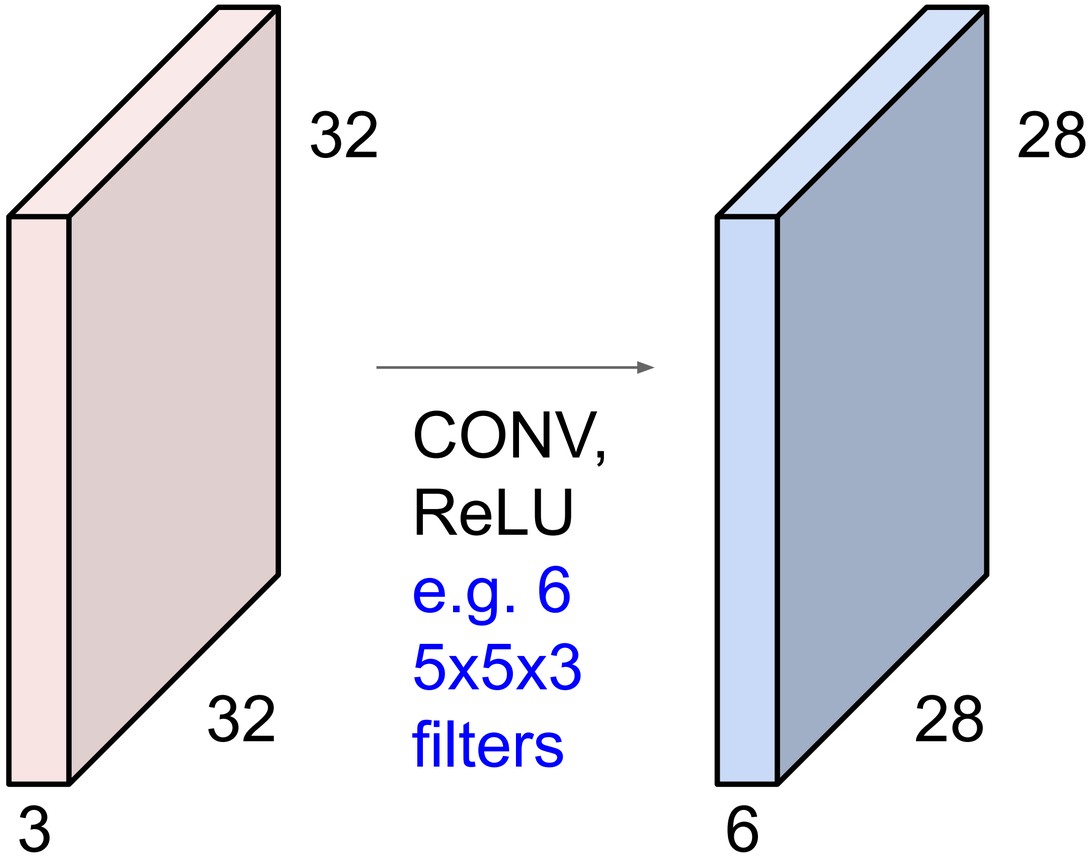
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



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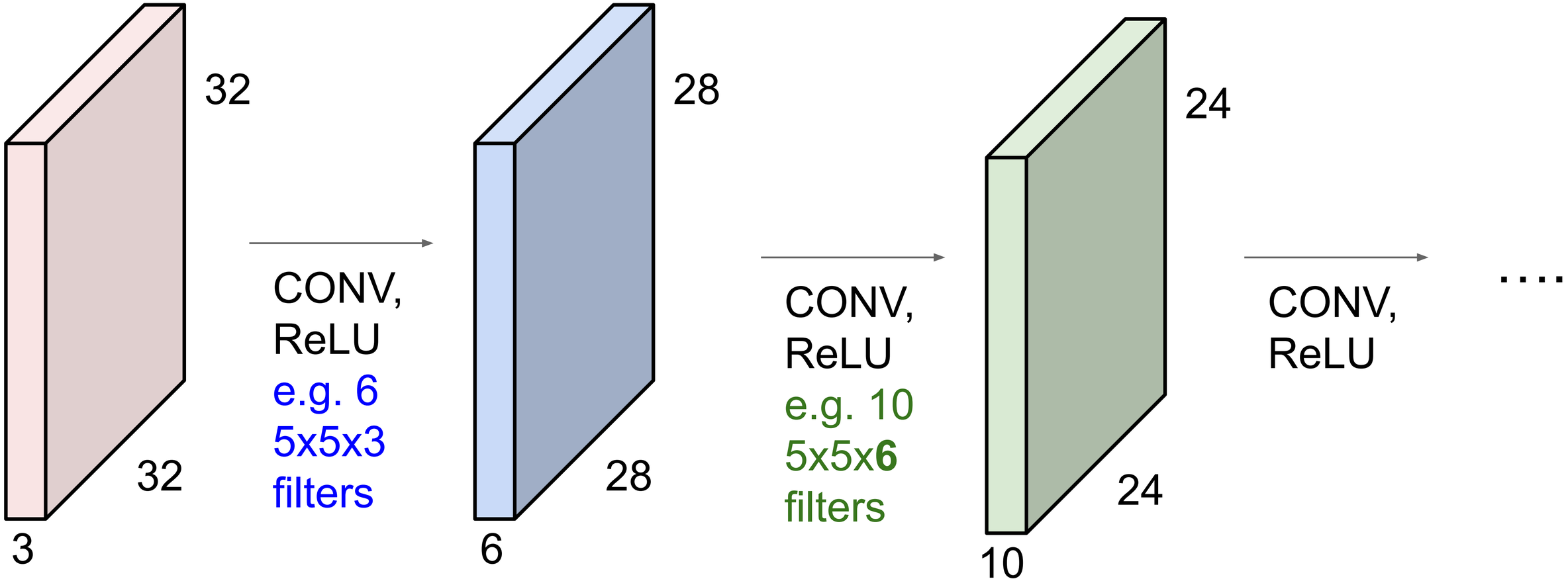

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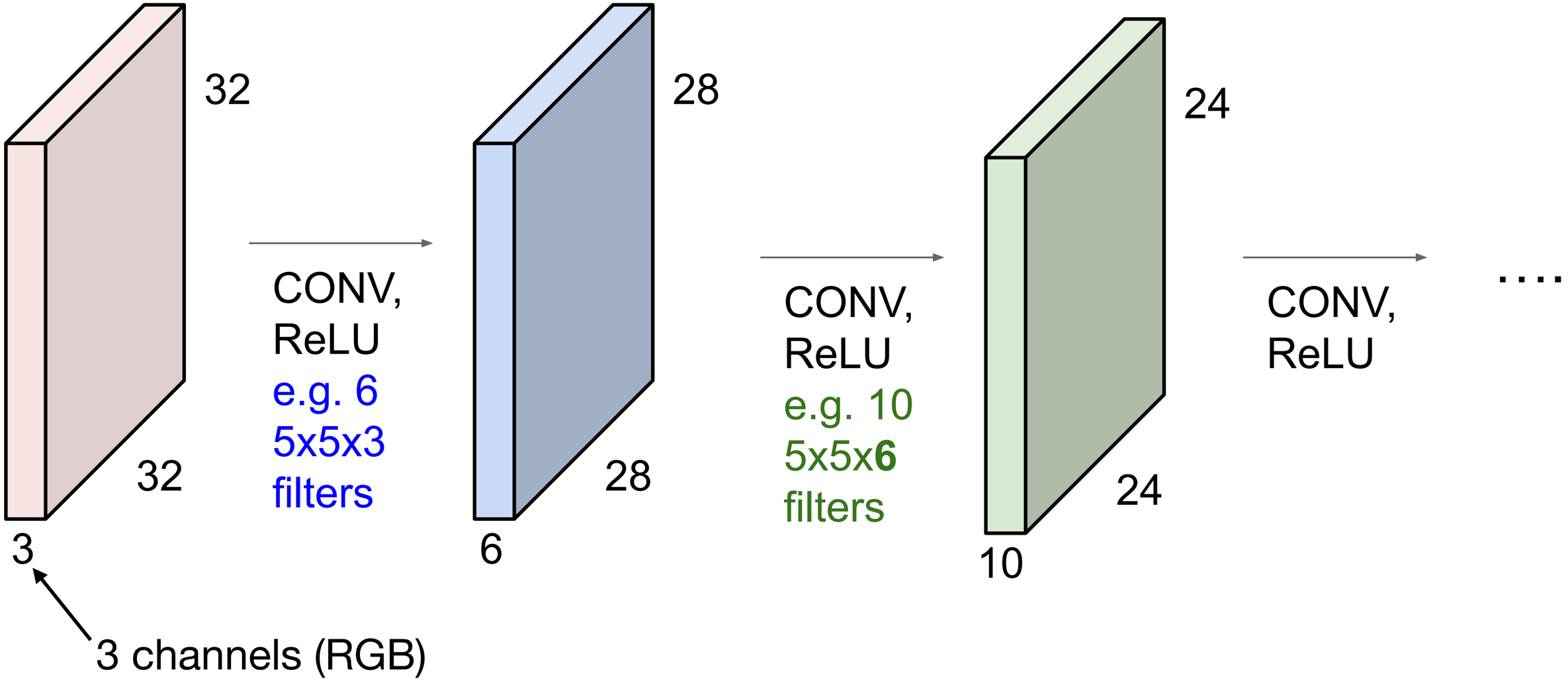

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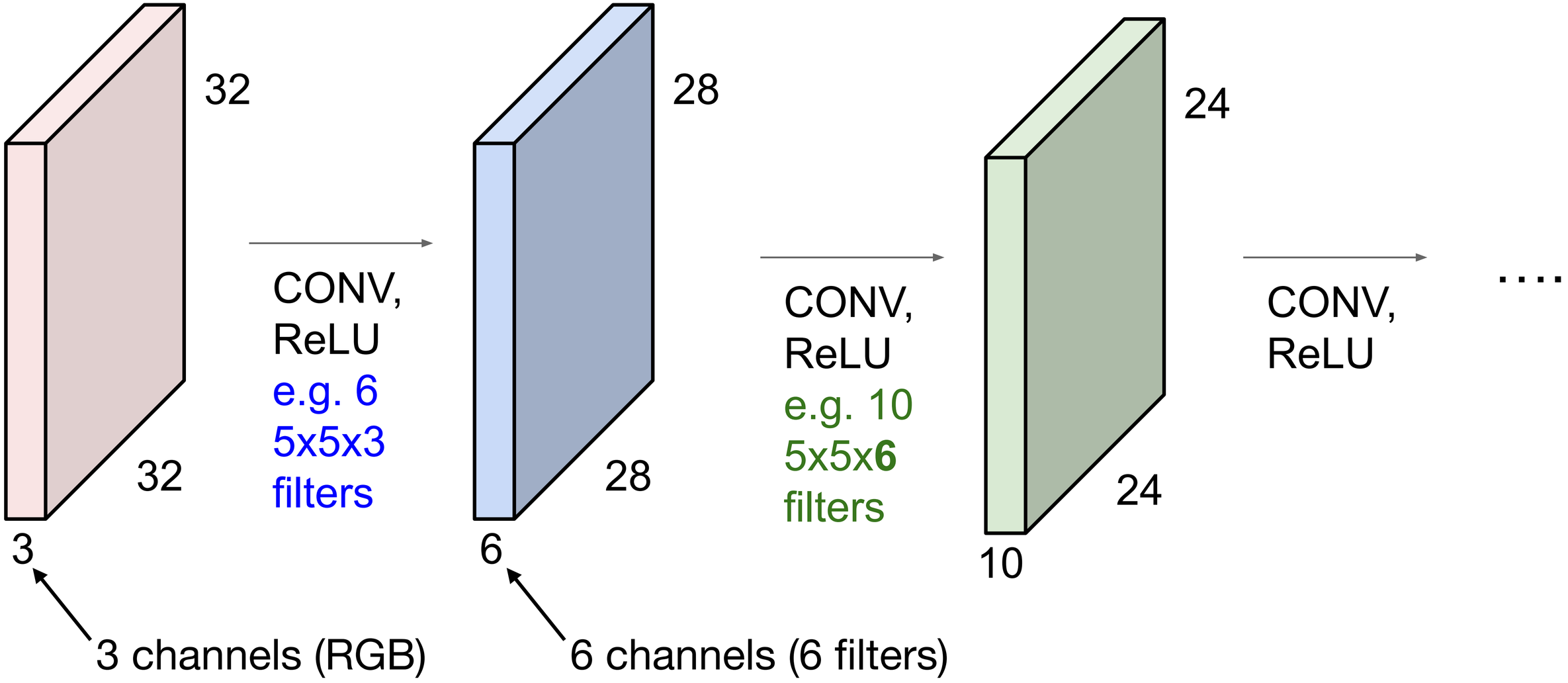

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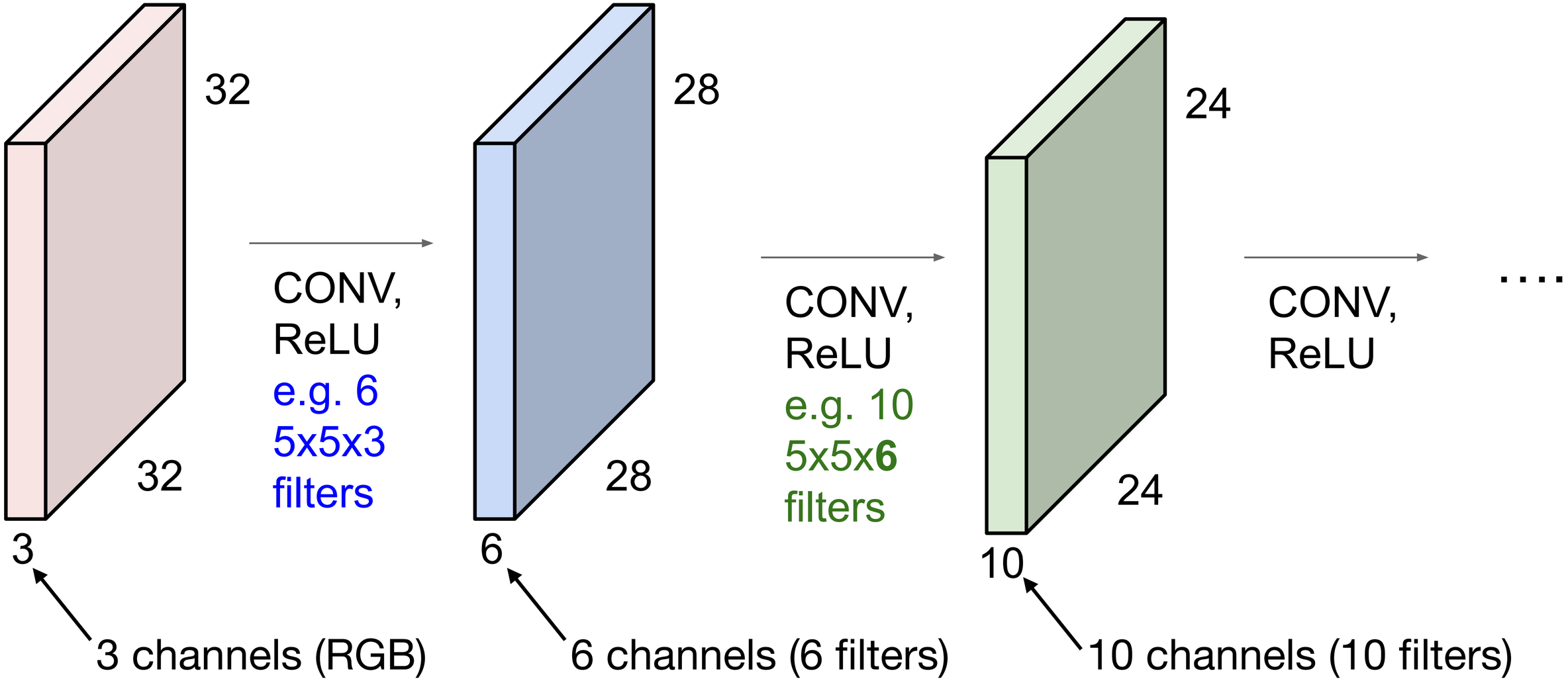
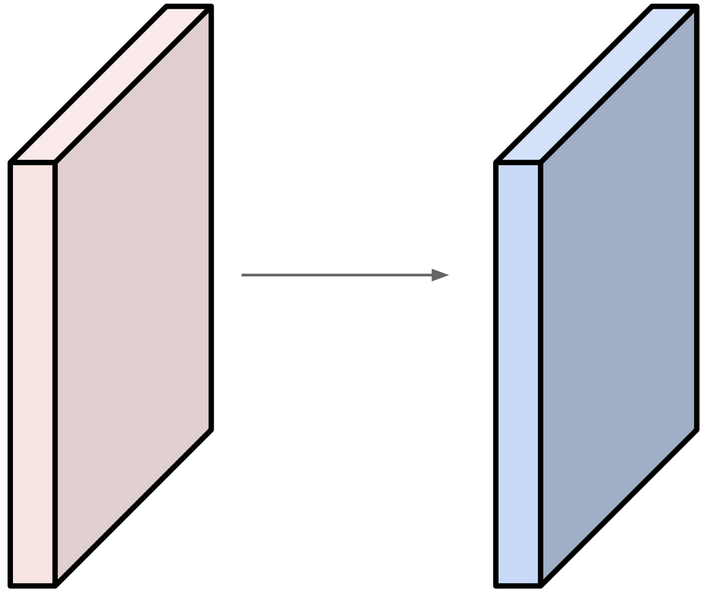


Input volume: **32x32x3**
10 5x5 filters



Number of parameters in this layer?

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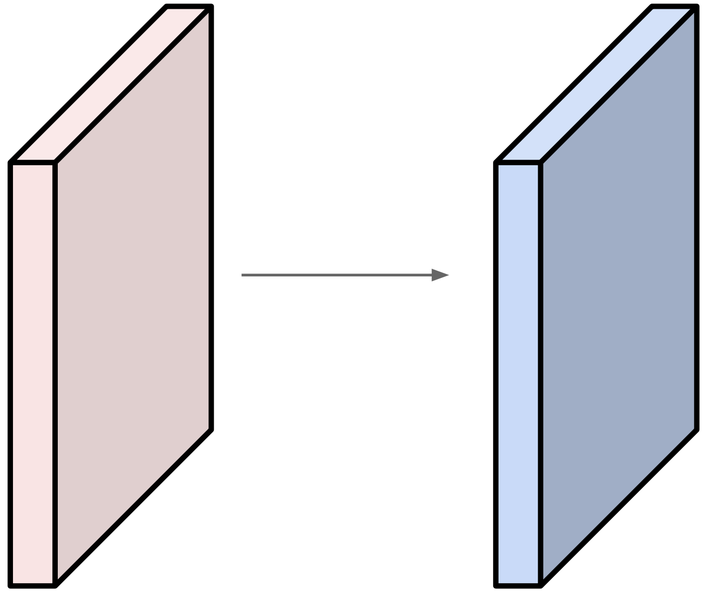

Number of parameters in this layer?
each filter has 5*5*3 + 1 = 76 params (+1 for bias)
=> 76*10 = **760**

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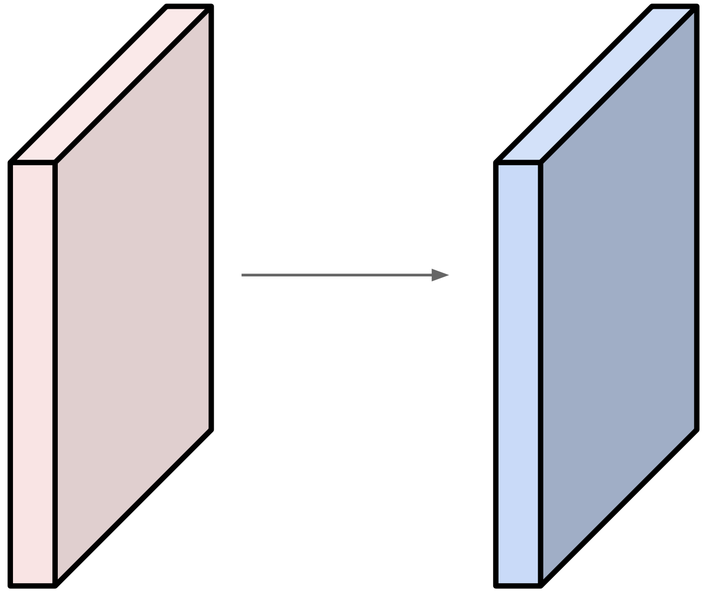
10 5x5 filters



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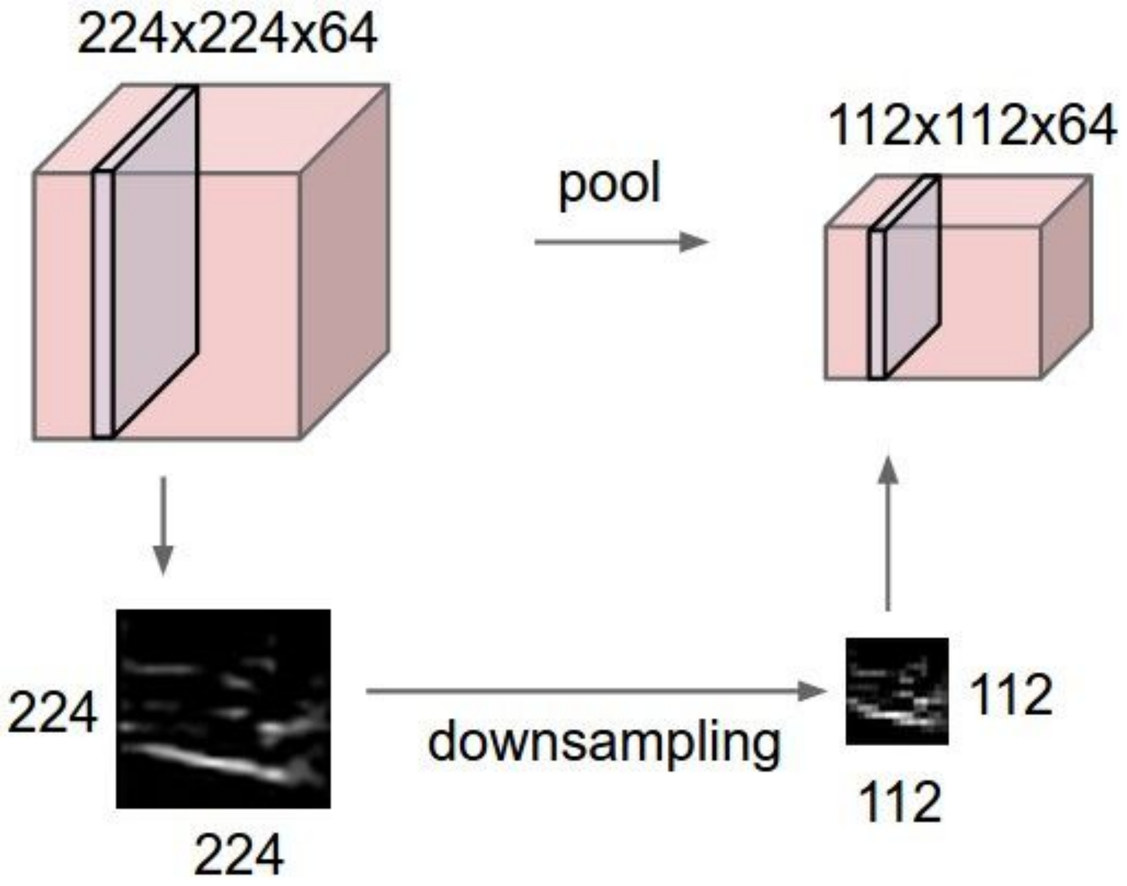
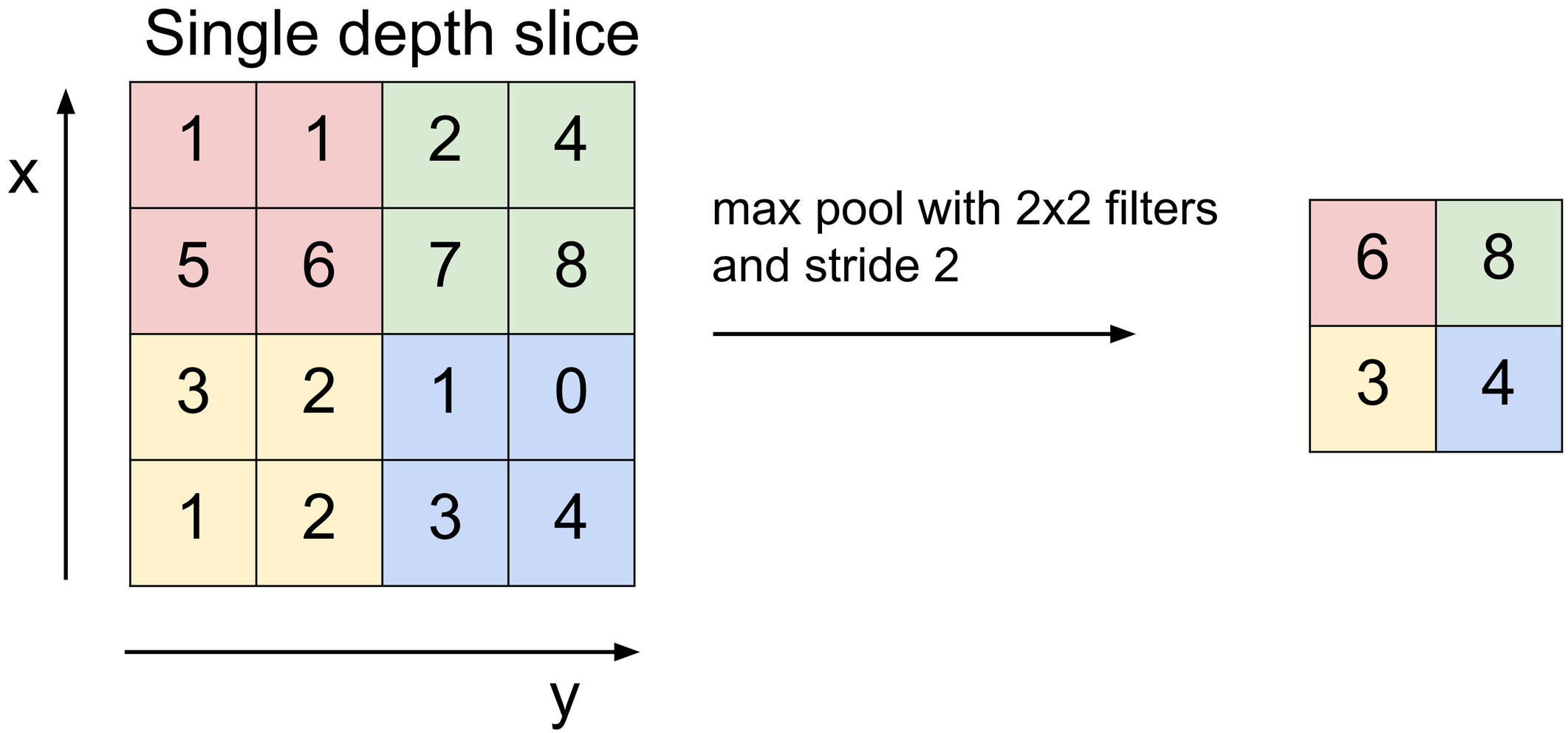
In general, parameters in conv layer =
(filter width x filter height x input channels + 1) x number of filters.

Pooling layer

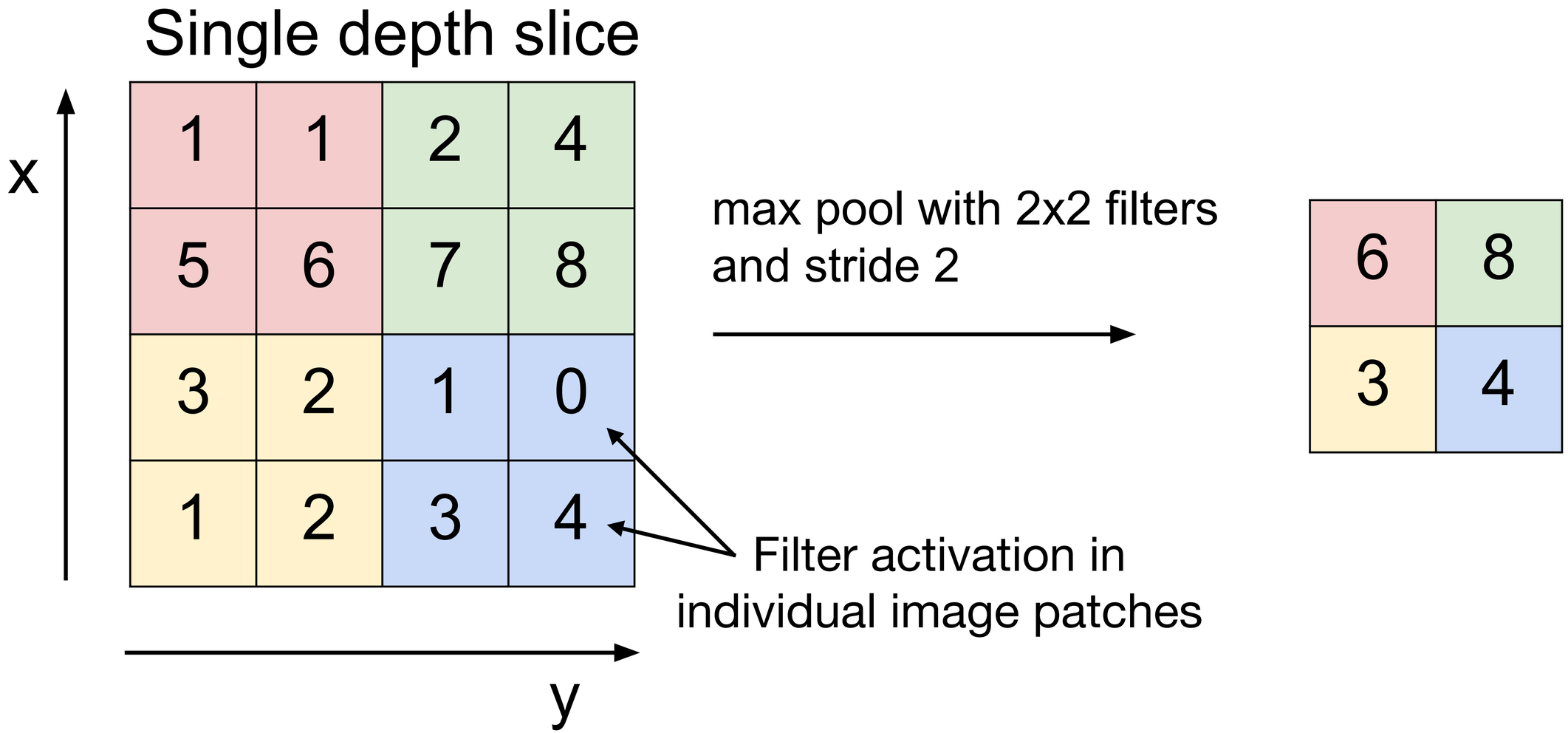
- makes the representations smaller and more manageable
- operates over each activation map independently:



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

MAX POOLING


Single depth slice
x
y
1 1 2 4
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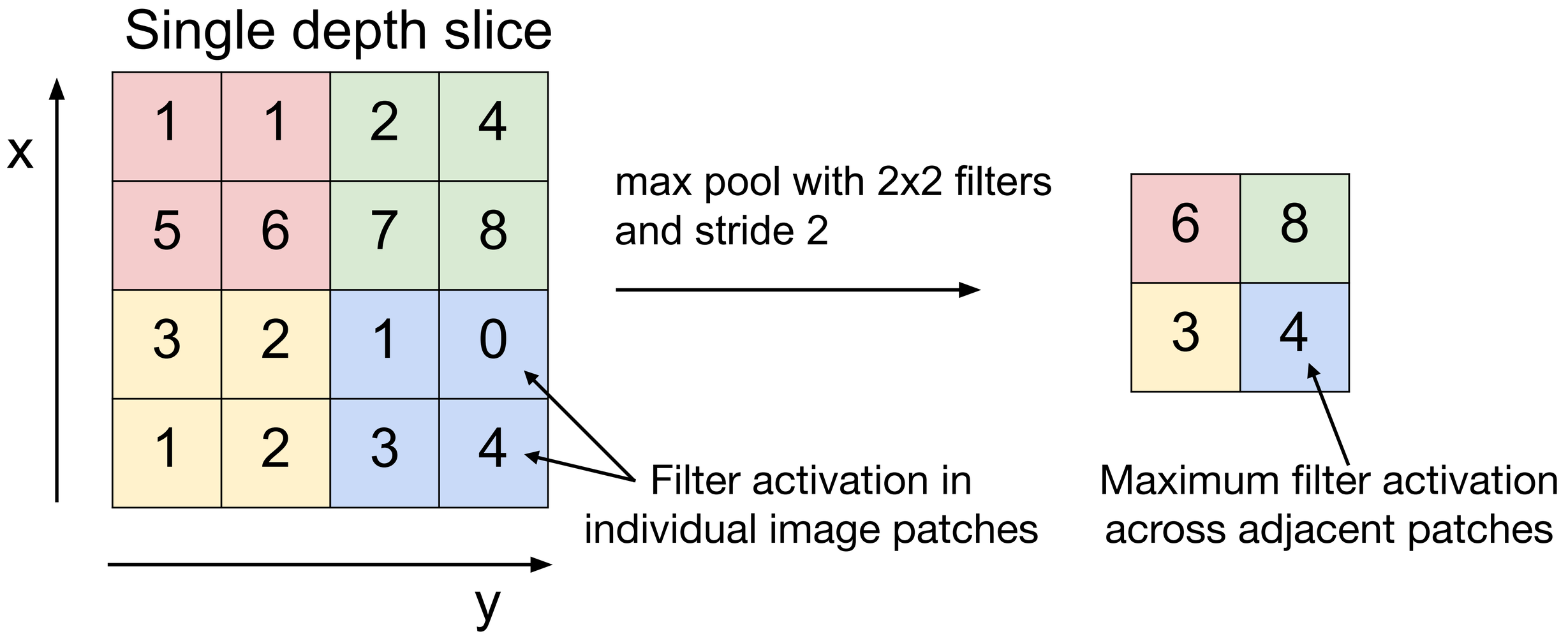
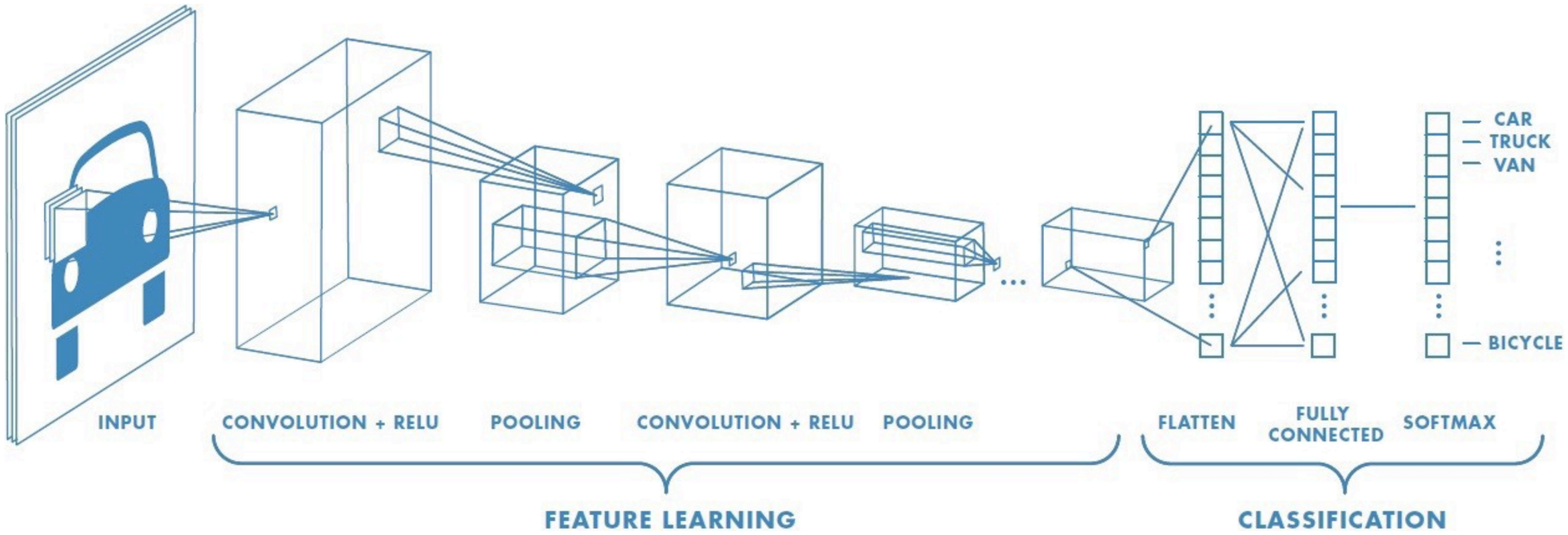
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4
Filter activation in
individual image patches

MAX POOLING

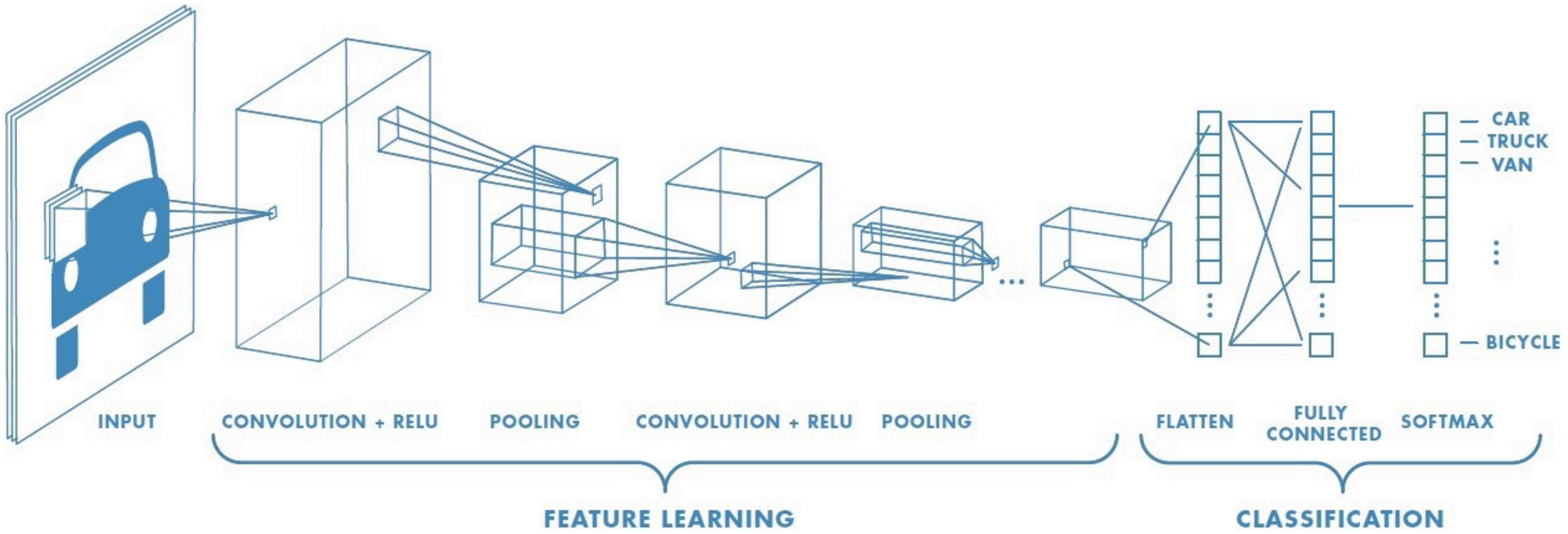

Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4
Filter activation in
individual image patches
Maximum filter activation
across adjacent patches

Convolutional neural networks



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

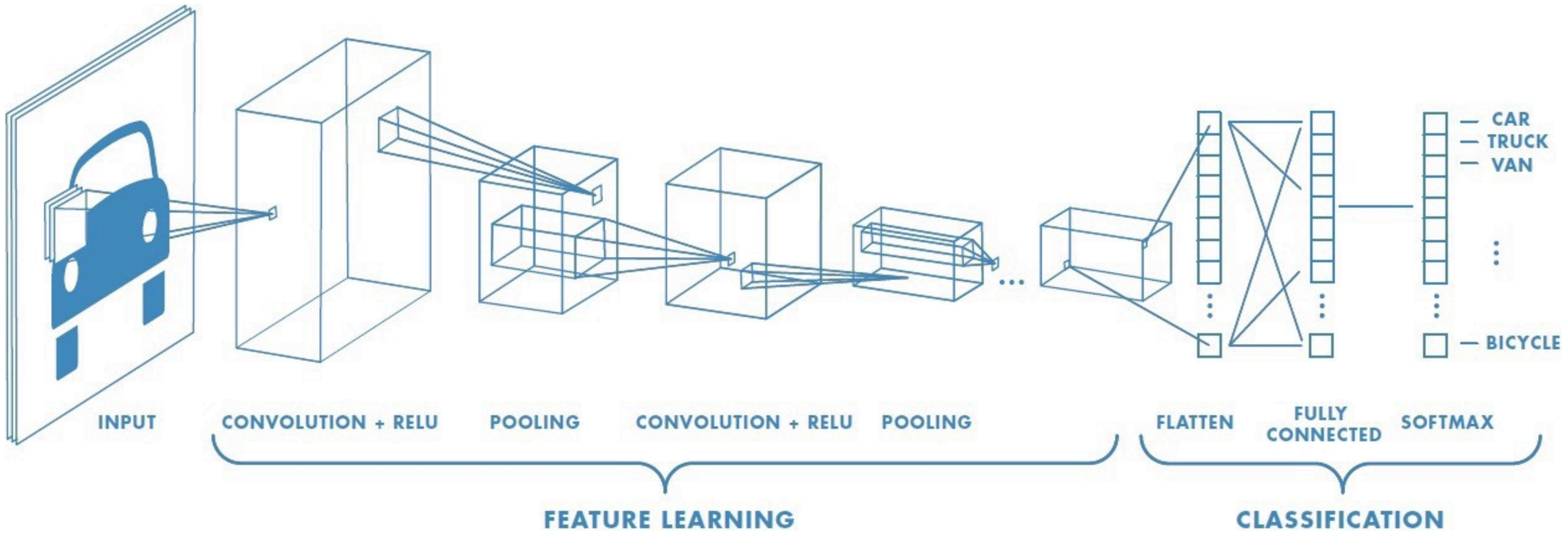
Convolutional neural networks



https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

A CNN stacks together several alternating convolution and pooling layers, followed by a fully connected layer and a softmax output.

Convolutional neural networks



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A CNN stacks together several alternating convolution and pooling layers, followed by a fully connected layer and a softmax output.

Filters, weights in fully connected layer, and biases learned by optimizing cross-entropy loss via stochastic gradient descent.

Interpreting the filters learned by a CNN

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Use neural network for binary classification, e.g. faces versus not faces, cars versus not cars, etc.

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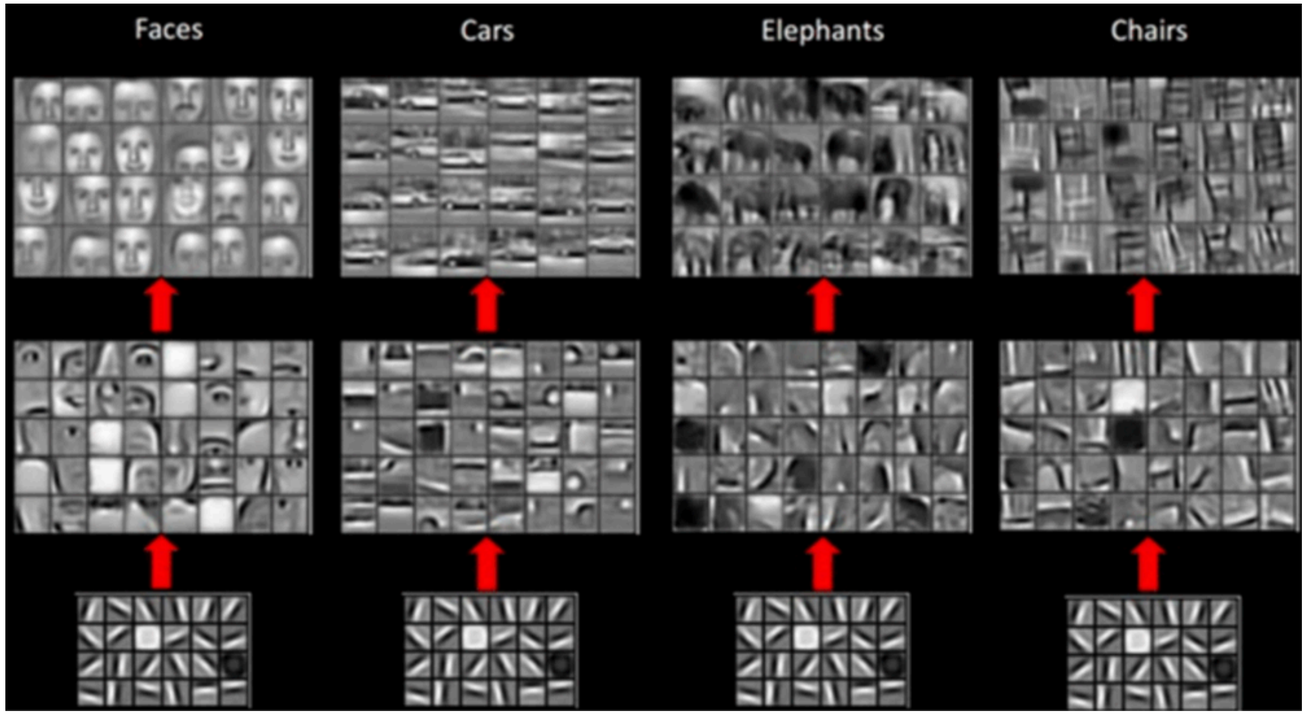
Last layer

Intermediate layer

Initial layer



The original CNN architecture

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LeNet architecture for hand-written digit recognition (1989).

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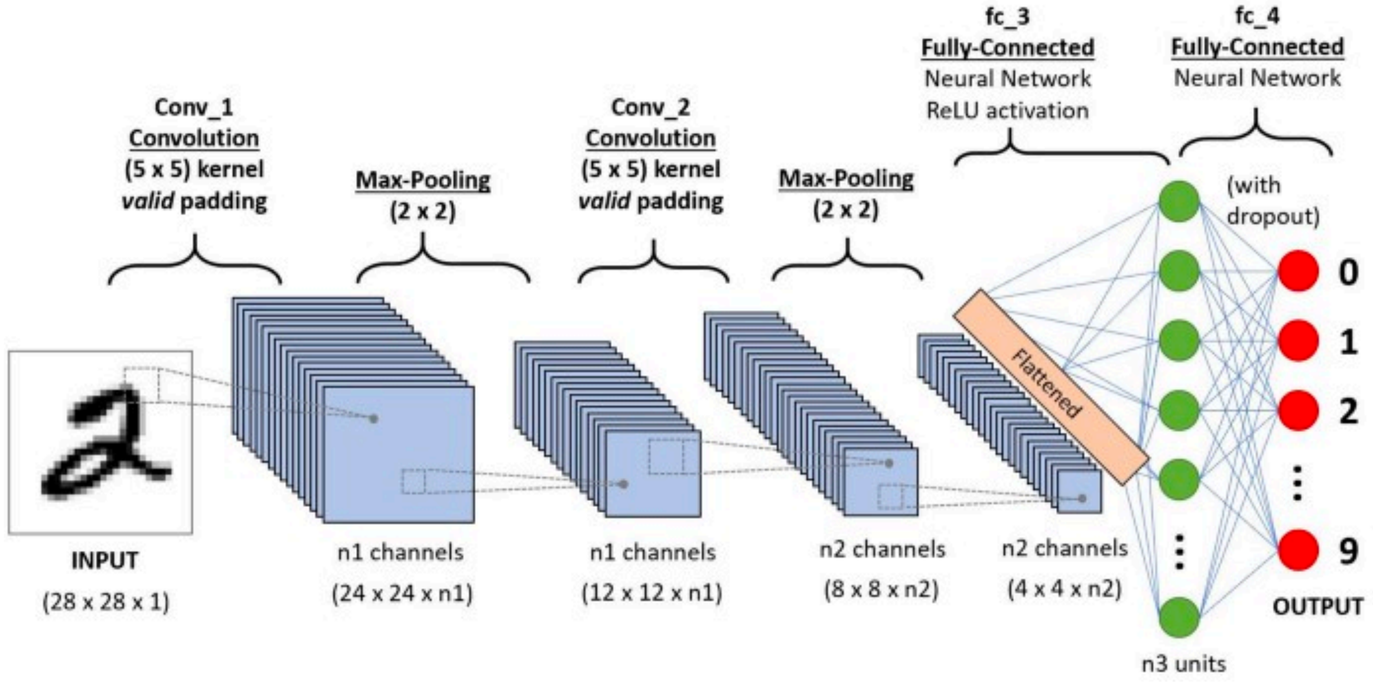

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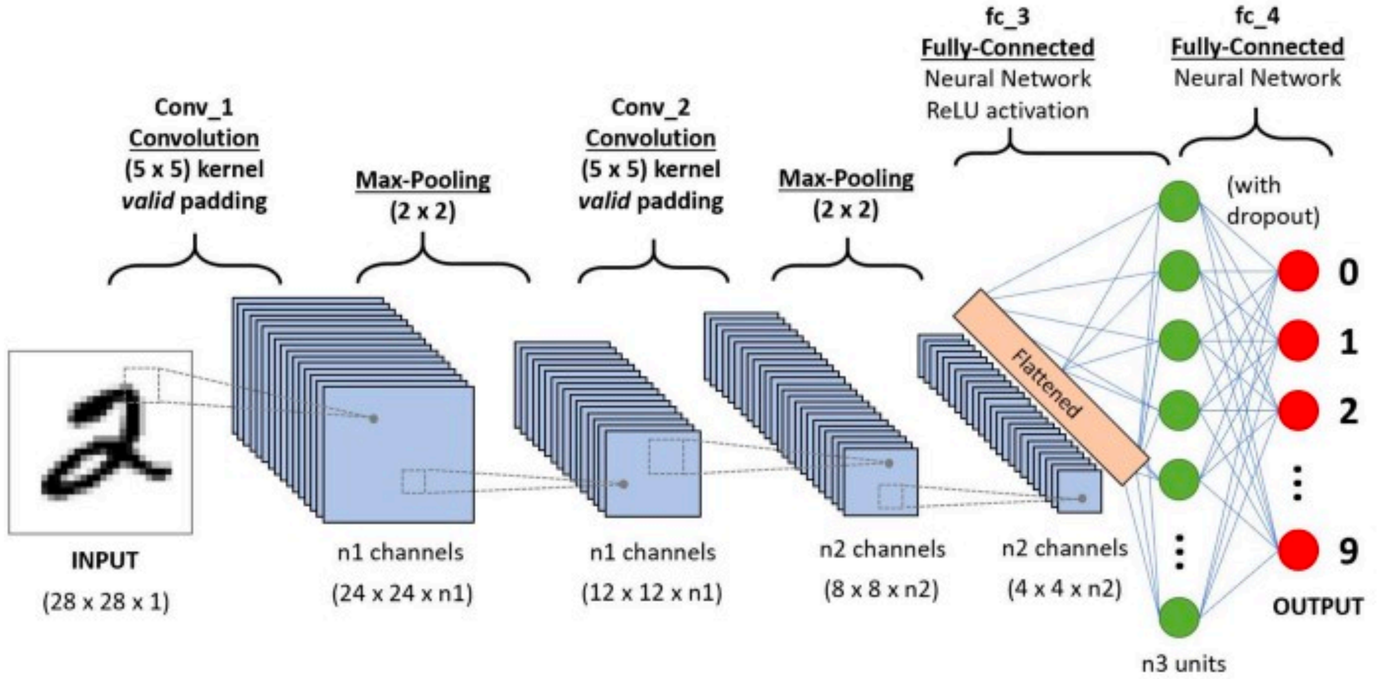
Yann LeCun

The original CNN architecture

LeNet architecture for hand-written digit recognition (1989).

Idea existed decades ago but data and computing power only became available in 2010s.



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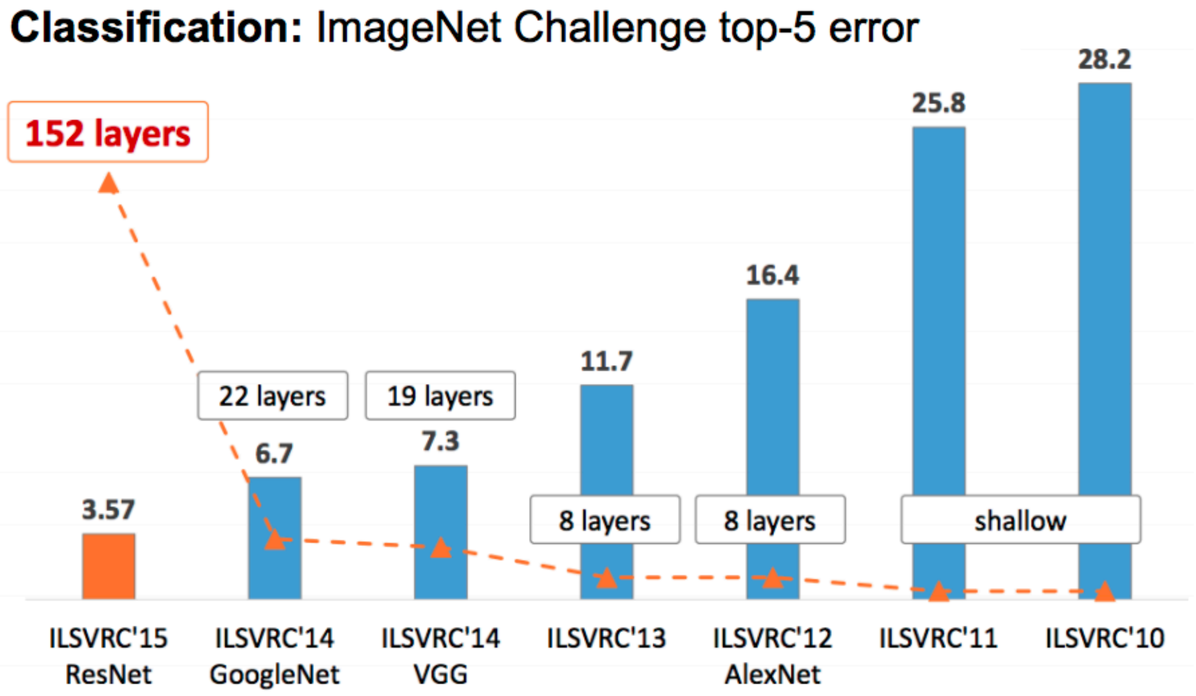
Yann LeCun

Modern CNN architectures

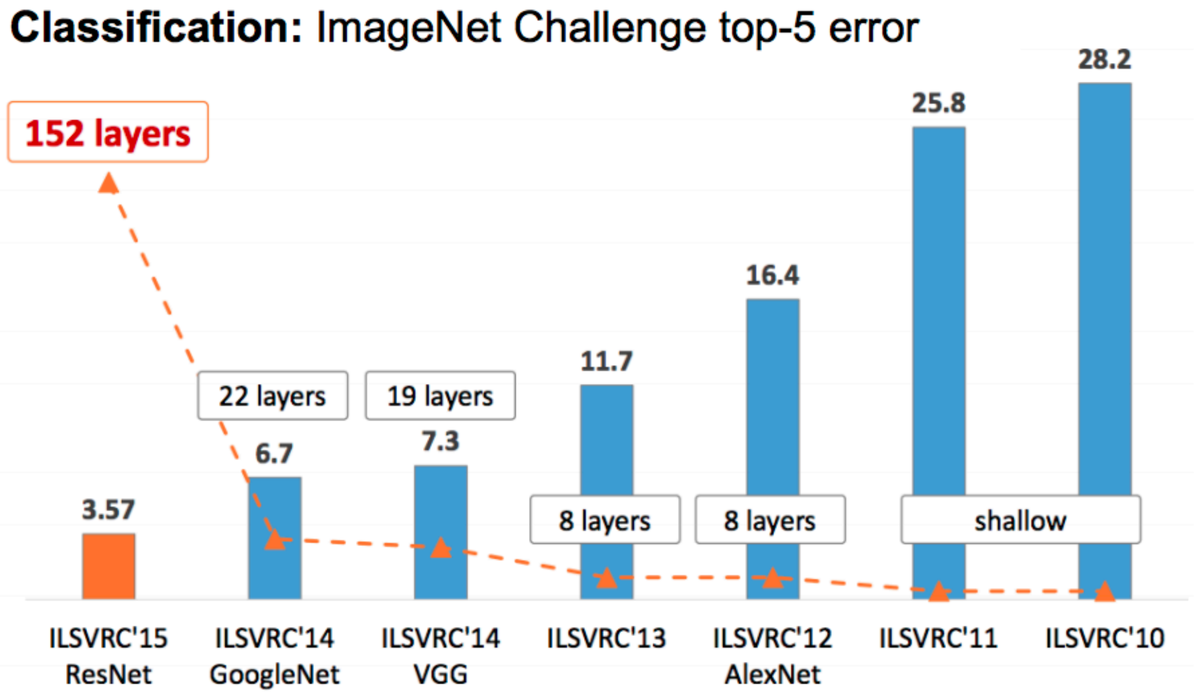


https://medium.com/@RaghavPrabhu/cnn-architectures-lenet-alexnet-vgg-googlenet-and-resnet-7c81c017b848

Model	Size (M)	Top-1/top-5 error (%)	# layers	Model description
AlexNet	238	41.00/18.00	8	5 conv + 3 fc layers
VGG-16	540	28.07/9.33	16	13 conv + 3 fc layers
VGG-19	560	27.30/9.00	19	16 conv + 3 fc layers
GoogleNet	40	29.81/10.04	22	21 conv + 1 fc layers
ResNet-50	100	22.85/6.71	50	49 conv + 1 fc layers
ResNet-152	235	21.43/3.57	152	151 conv + 1 fc layers

https://www.researchgate.net/figure/The-comparison-of-different-CNN-architectures-on-model-size-classification-error-rate_tbl1_320199404

Modern CNN architectures



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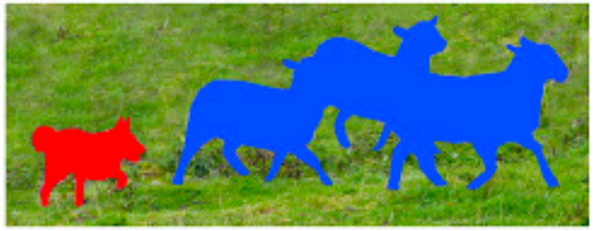
CNNs are getting progressively deeper with time.

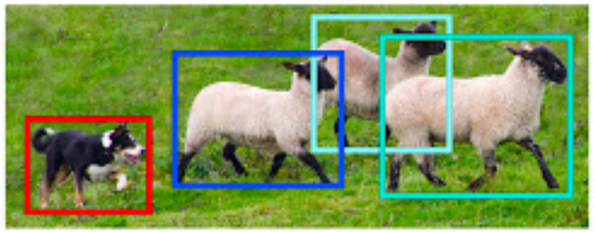
Other applications of CNNs

Other applications of CNNs

Image Recognition



Semantic Segmentation



Object Detection

Instance Segmentation

http://manipulation.csail.mit.edu/segmentation.html

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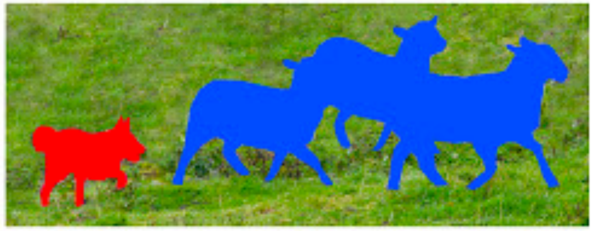

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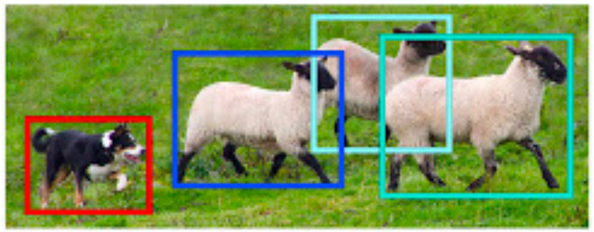

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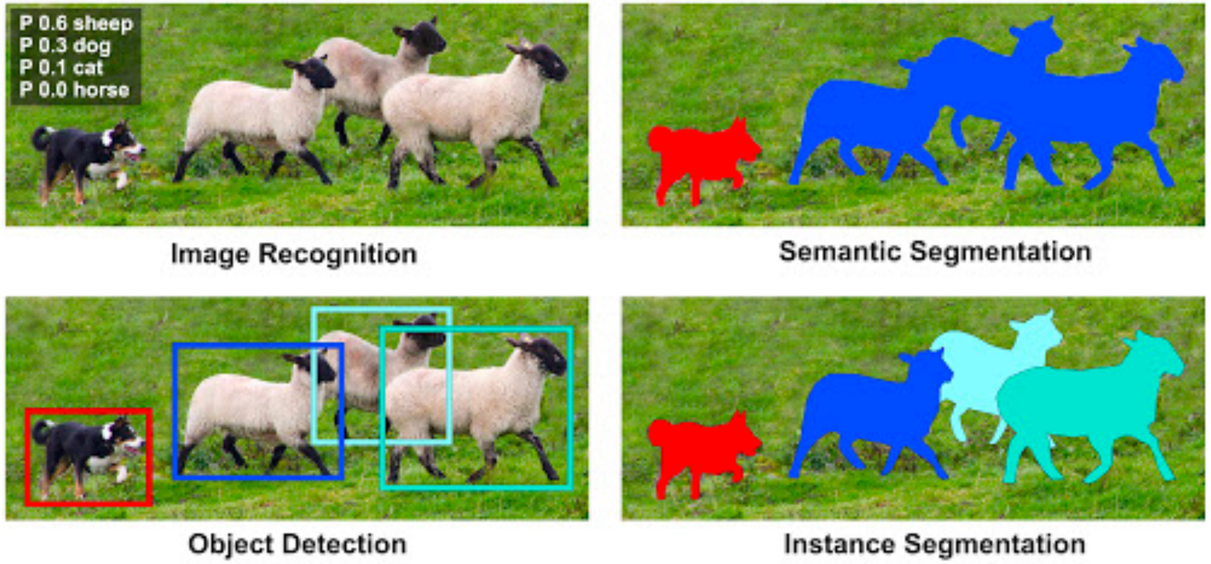
Style Transfer

Other applications of CNNs



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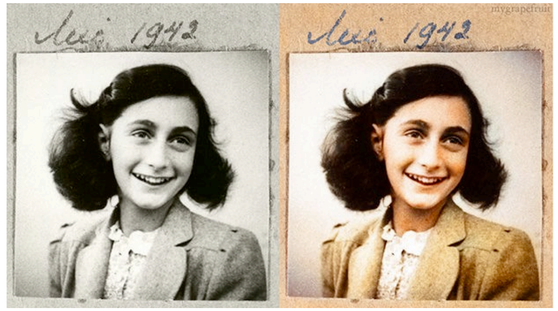

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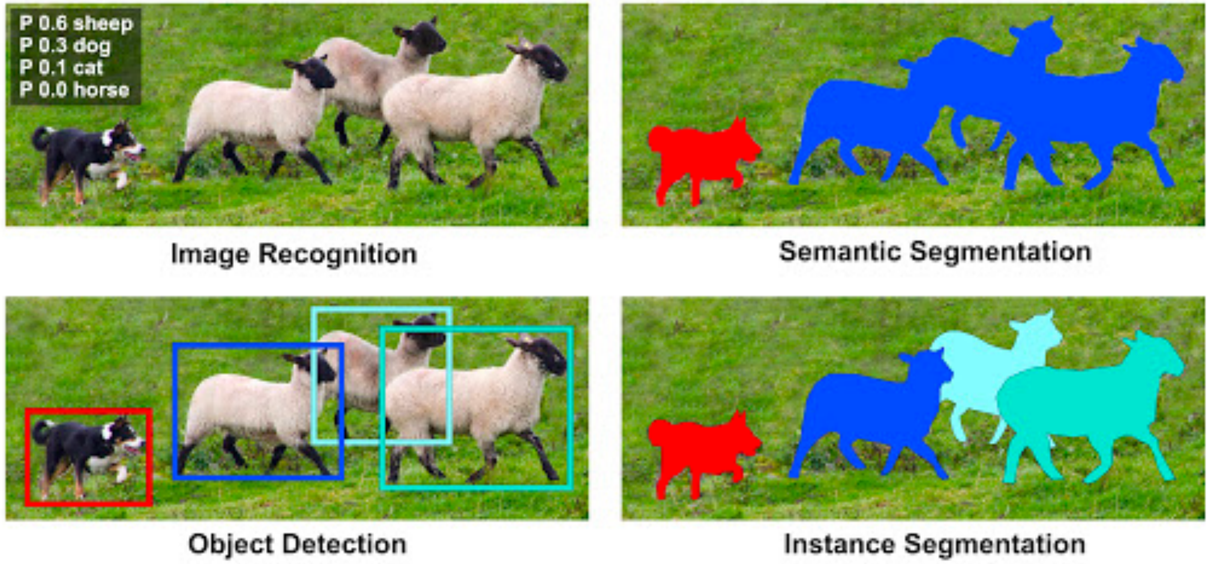

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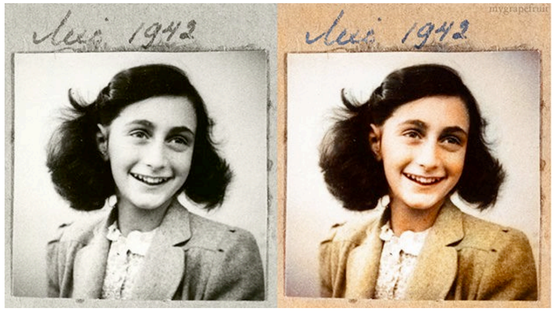

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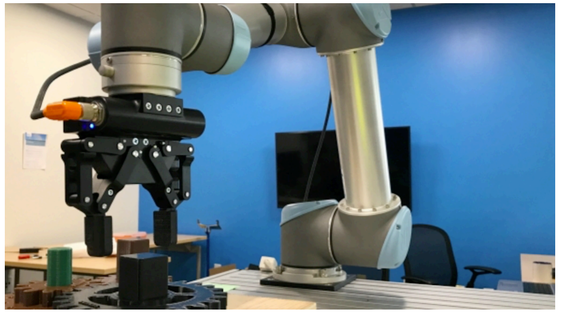

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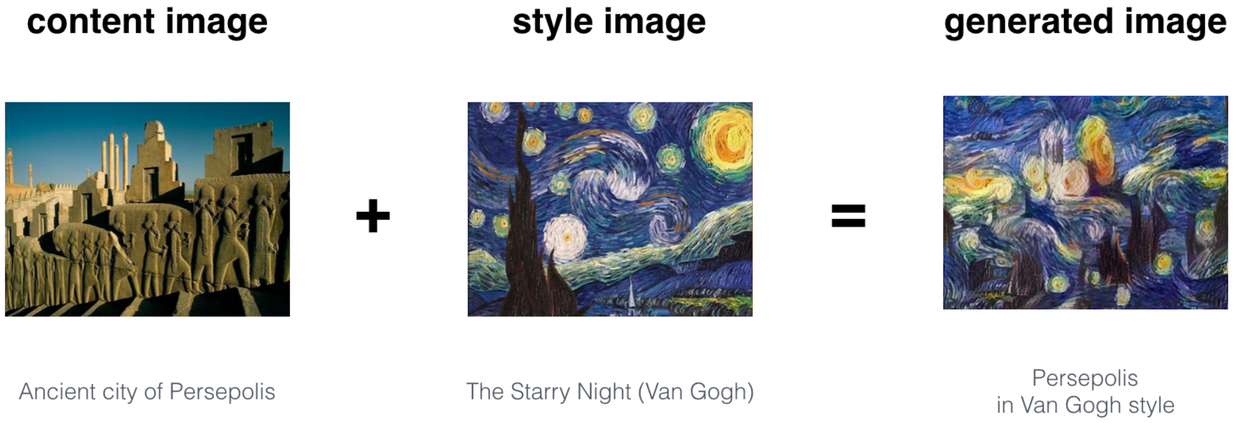
Reinforcement learning



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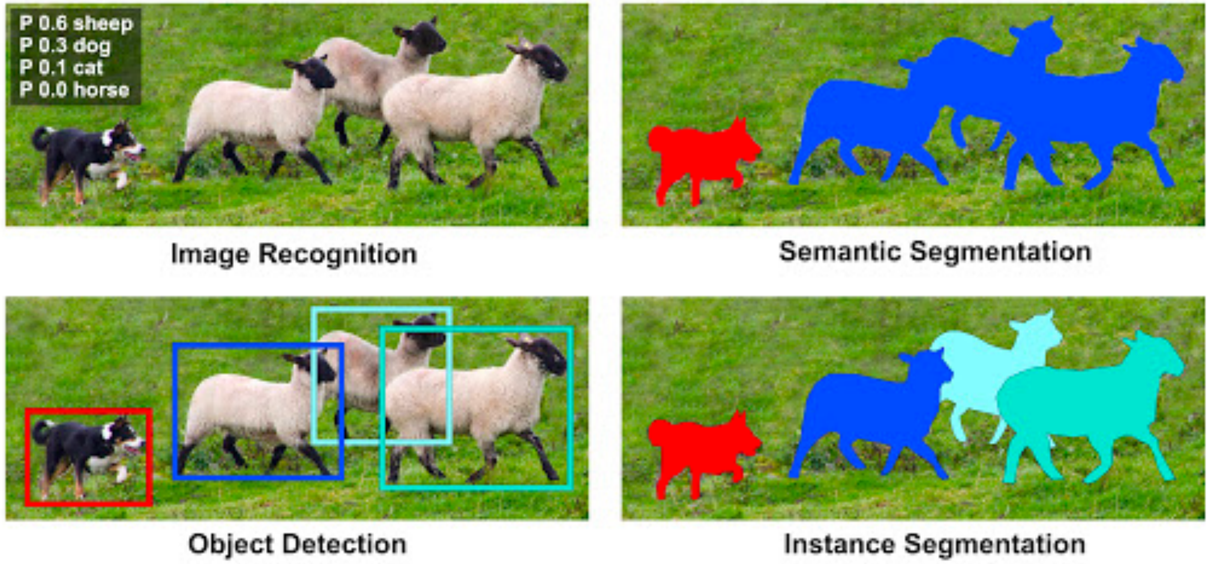

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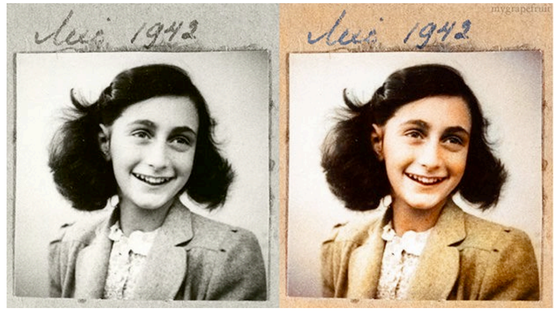

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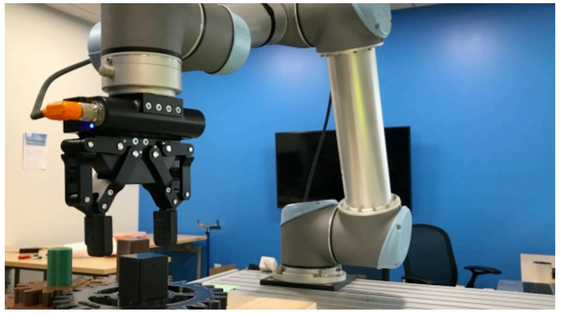

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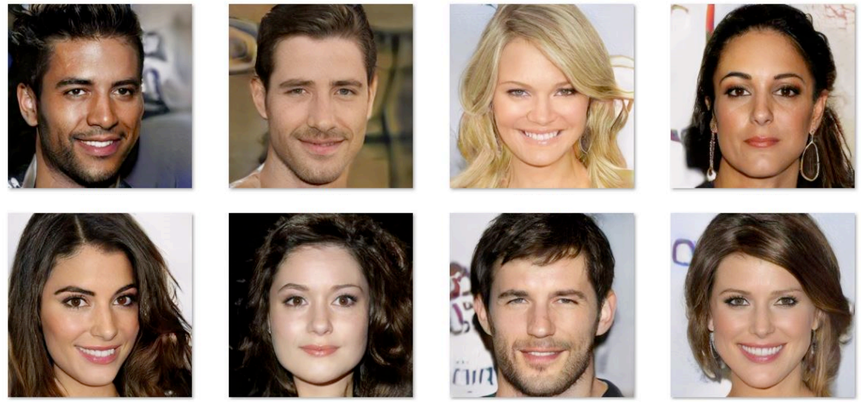

https://medium.datadriveninvestor.com/artificial-intelligence-gans-can-create-fake-celebrity-faces-44fe80d419f7

Generative models

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Quiz Practice