Deep learning for image processing

STAT 4710

November 21, 2023

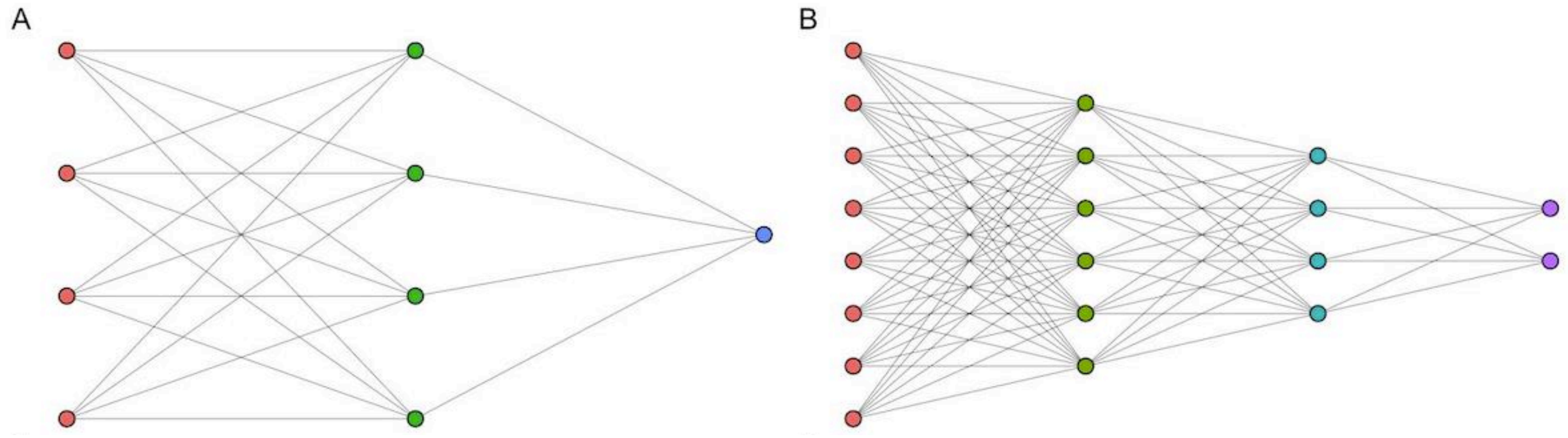
Where we are

- **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
  - $\boxed{\textbf{Lecture 3: } \text{Deep learning for images}}$
  - **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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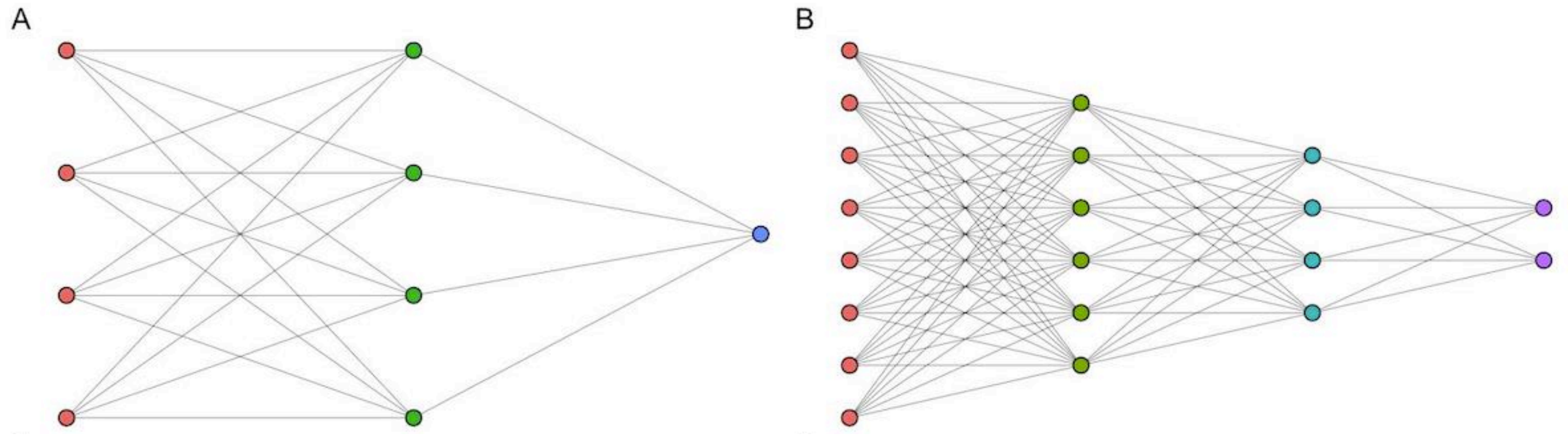

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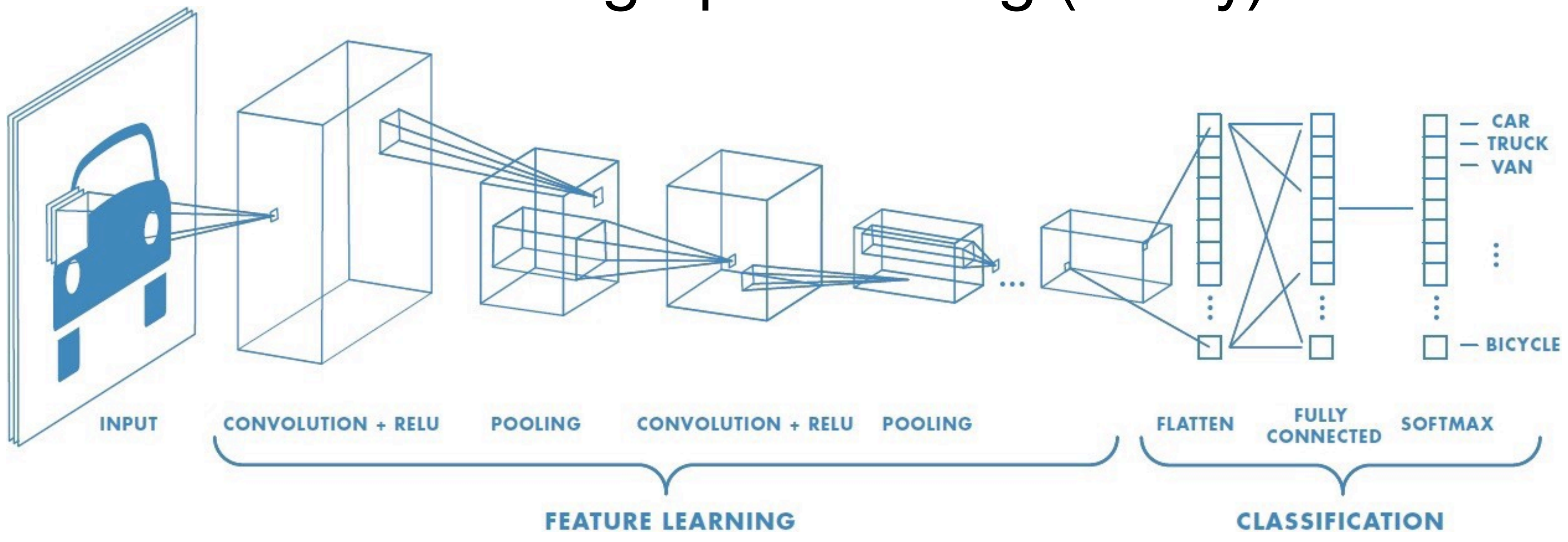
Convolutional neural network (CNN) architectures for image processing (today)



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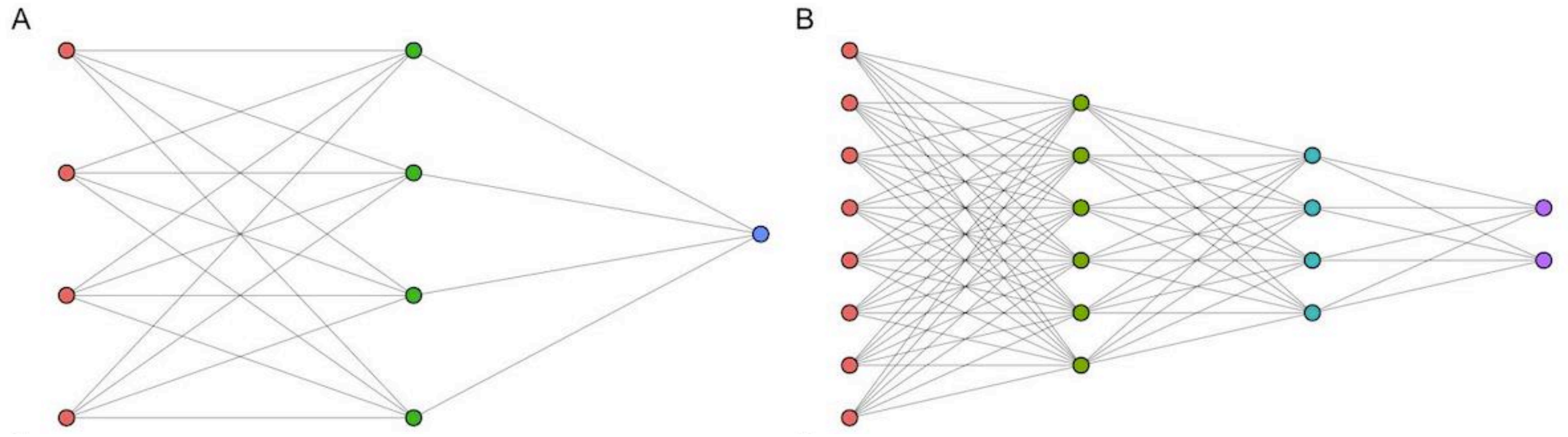

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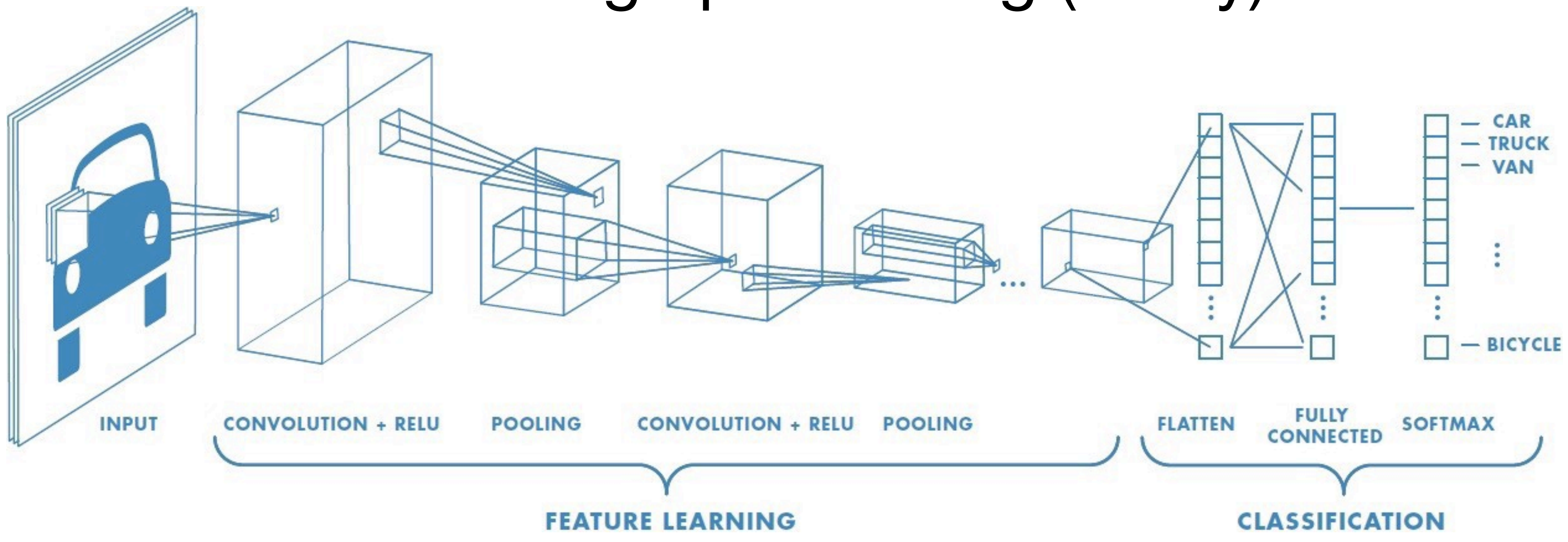

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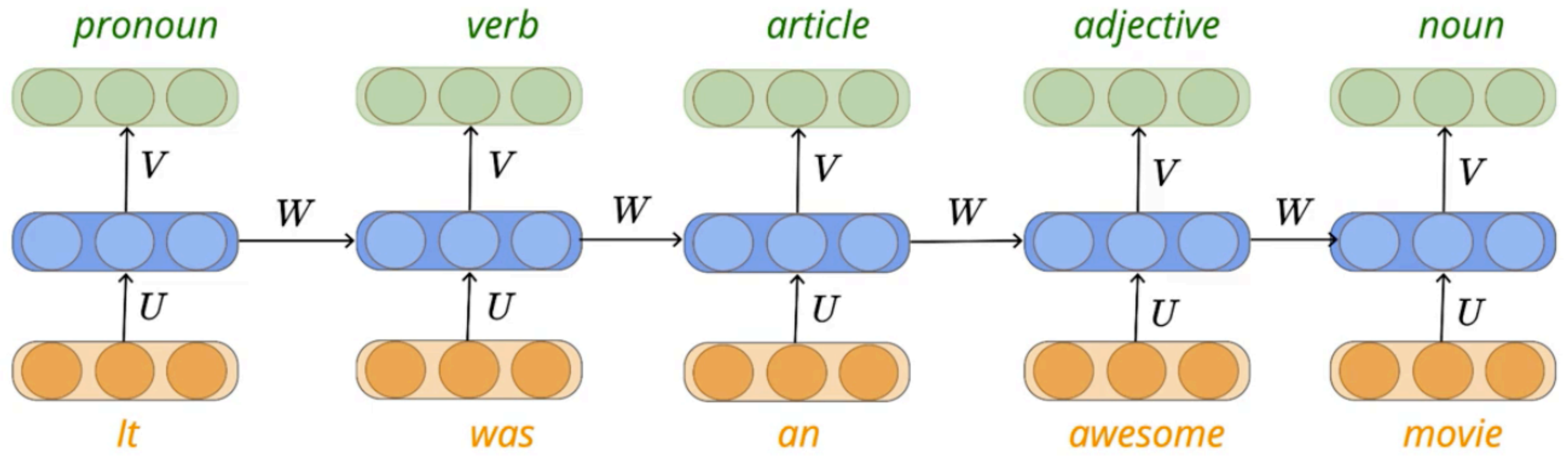
Recurrent neural network architectures for language processing (Thursday)



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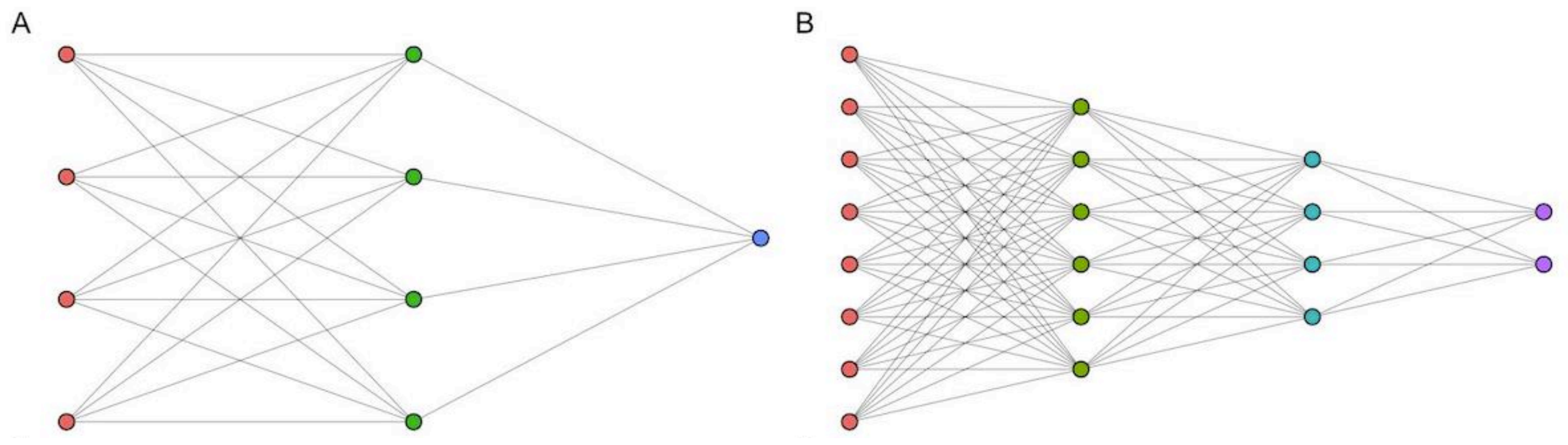

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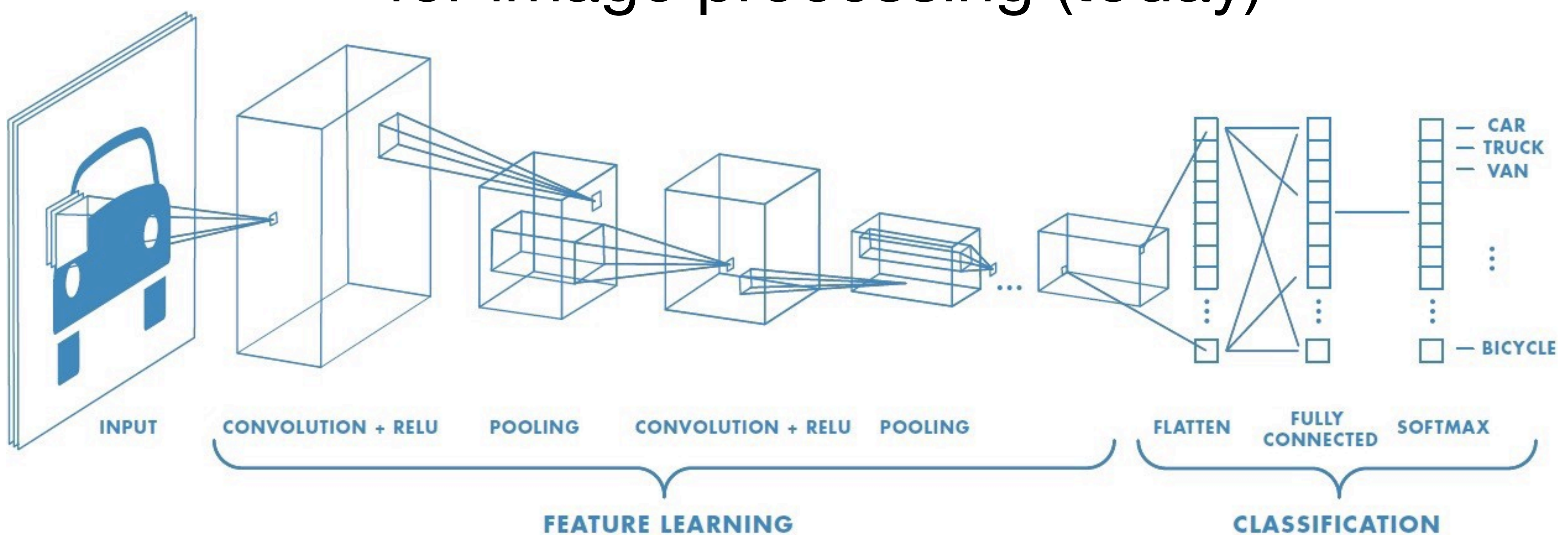

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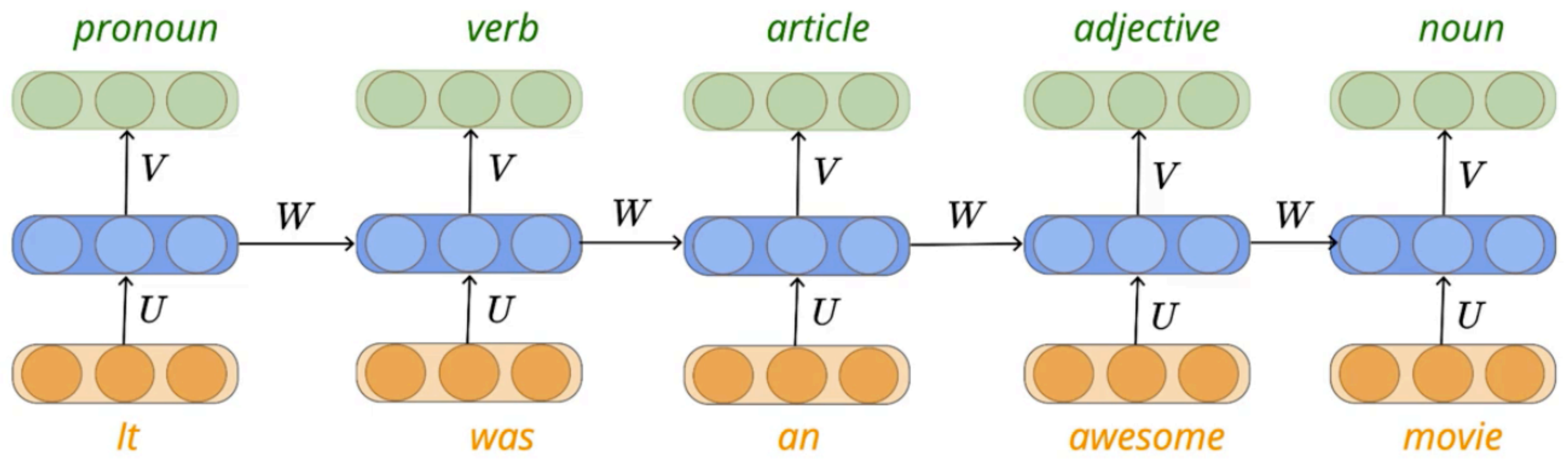

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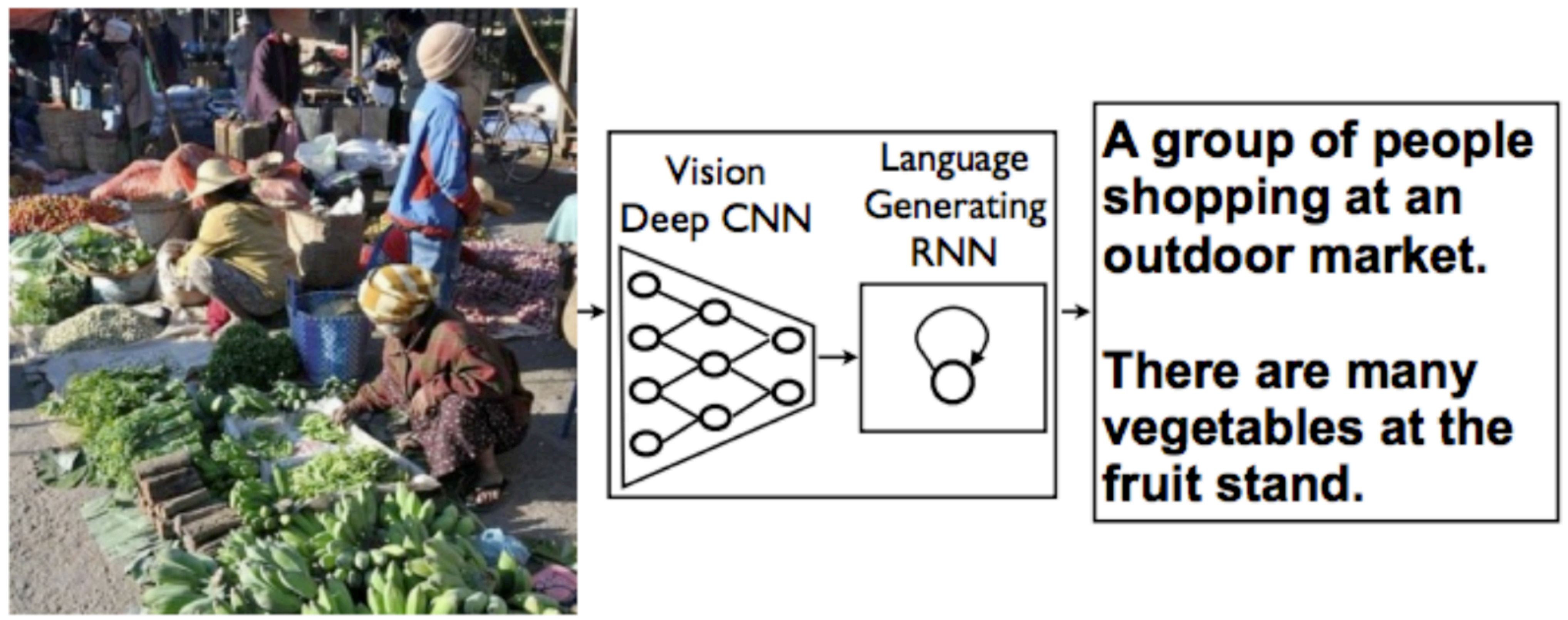
Architecture components are modular and can be composed, e.g. image captioning



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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- Occlusion
- Background clutter
- Intraclass variation

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ImageNet

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.

https://medium.com/syncedreview/sensetime-trains-imagenet-alexnet-in-record-1-5-minutes-e944ab049b2c

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

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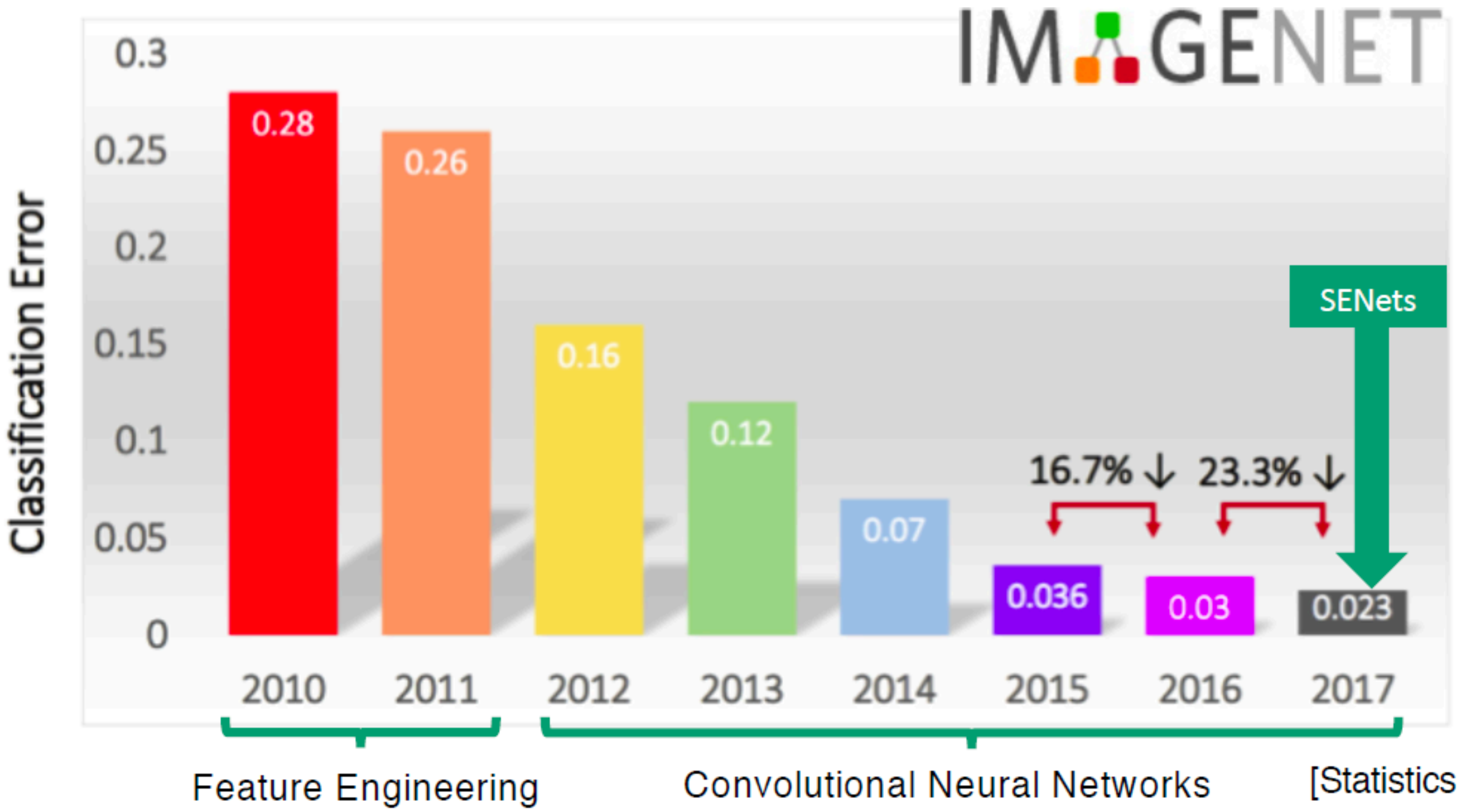
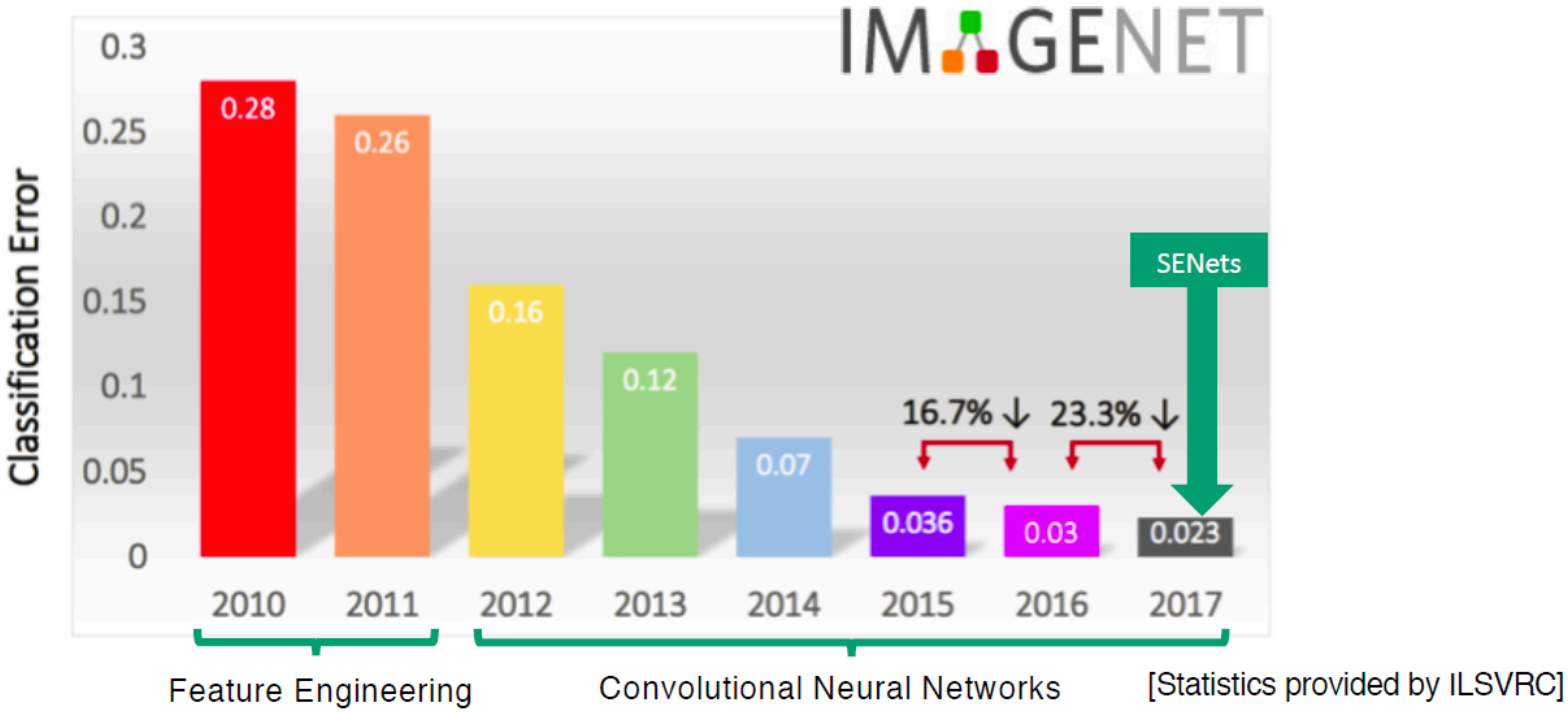
ILSVRC results over the years



[Statistics provided by ILSVRC]

ILSVRC results over the years



Convolutional neural networks (CNNs) have dominated since 2012.

CNNs are built on image-specific properties

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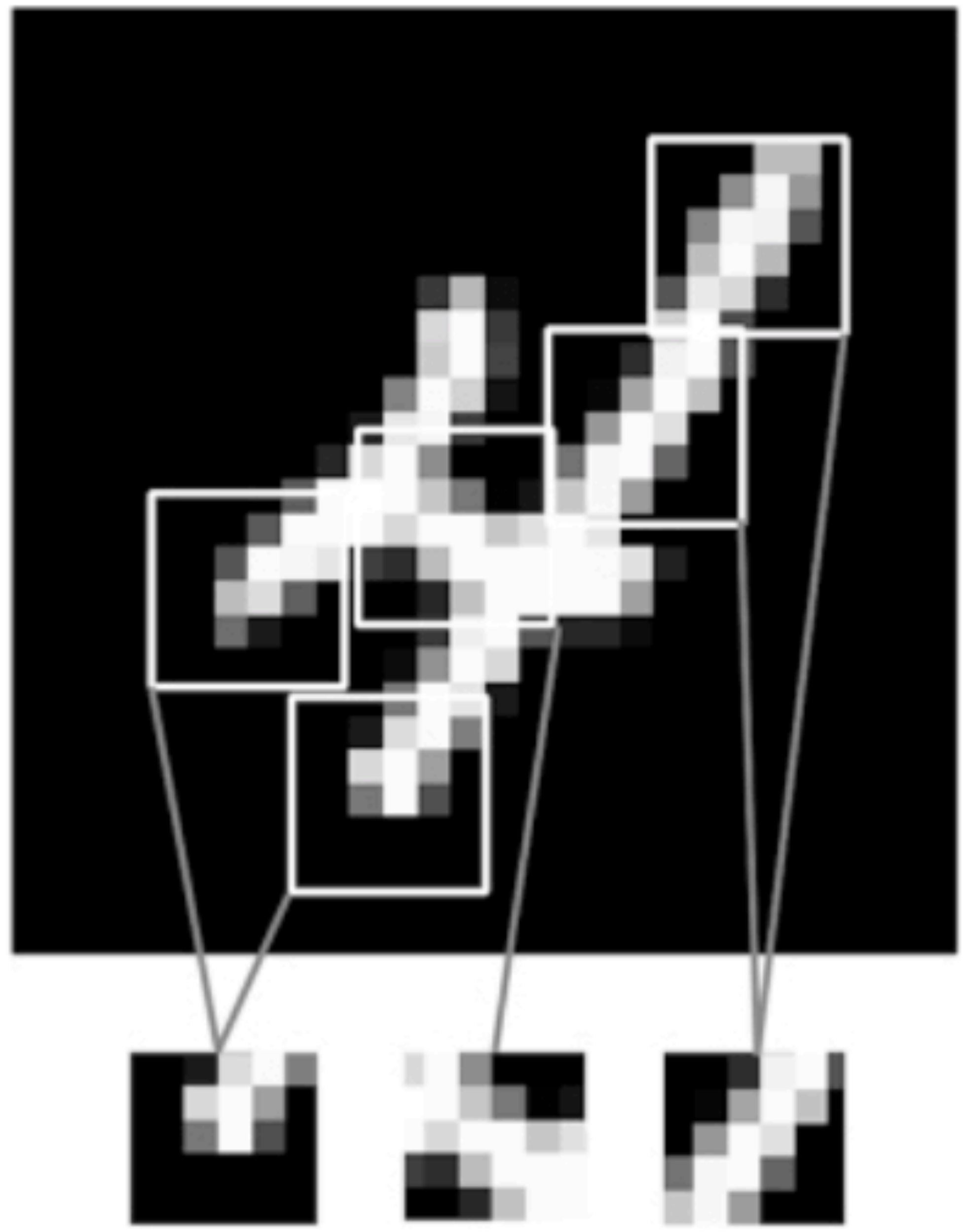
Figure 5.1. Images can be broken into local patterns such as edges, textures, and so on.



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

CNNs are built on image-specific properties

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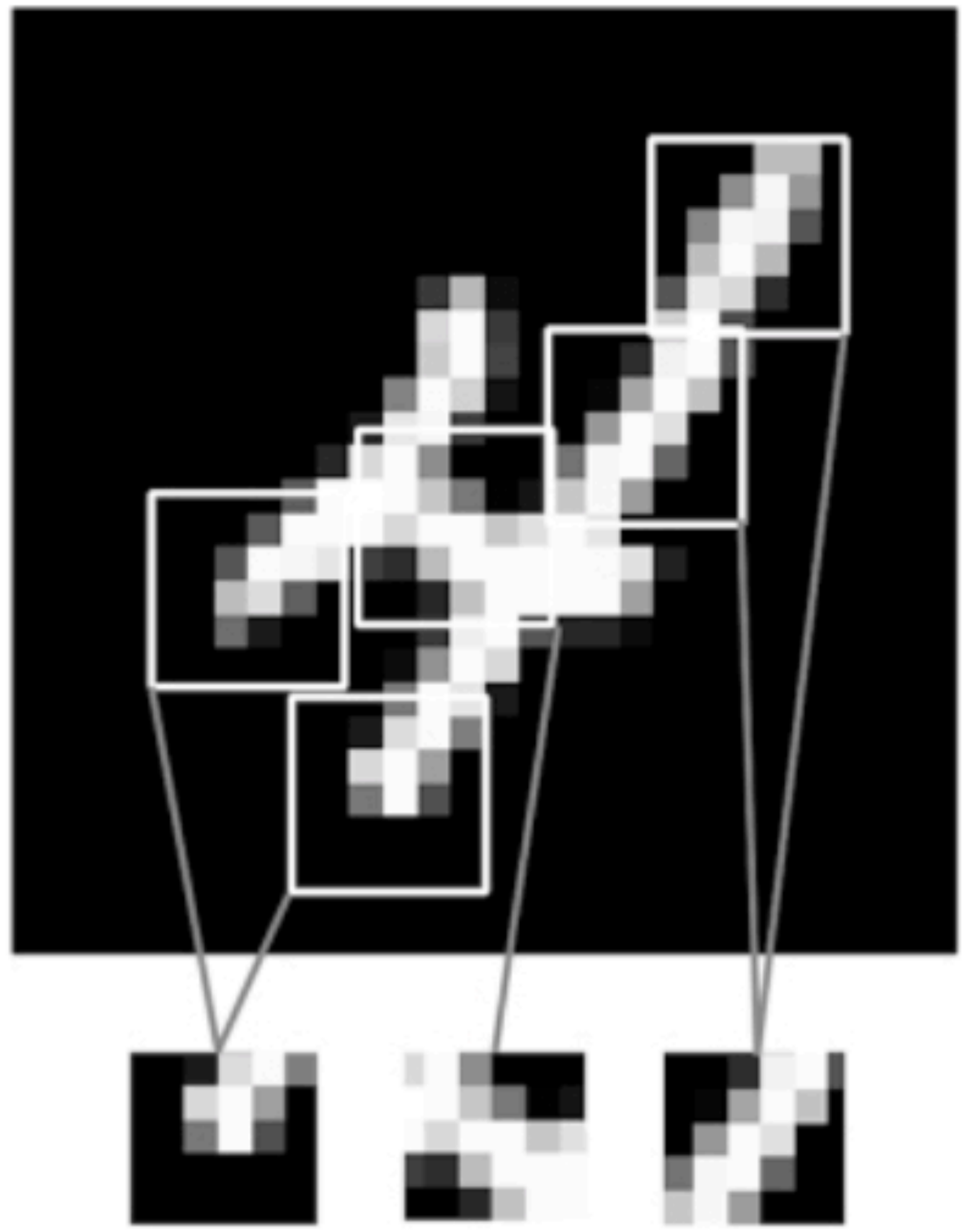
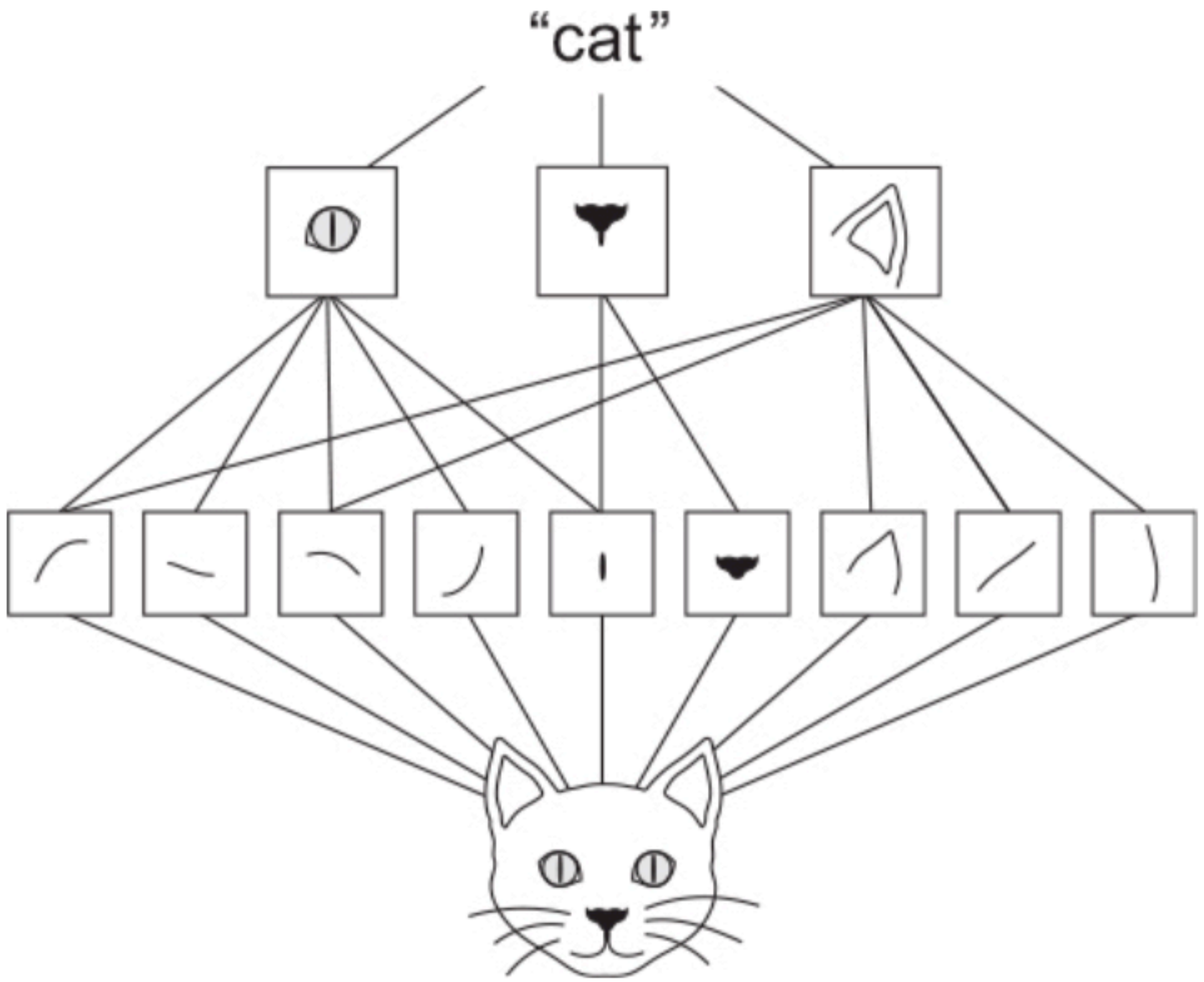


Figure 5.2. The visual world forms a spatial hierarchy of visual modules: hyperlocal edges combine into local objects such as eyes or ears, which combine into high-level concepts such as "cat."



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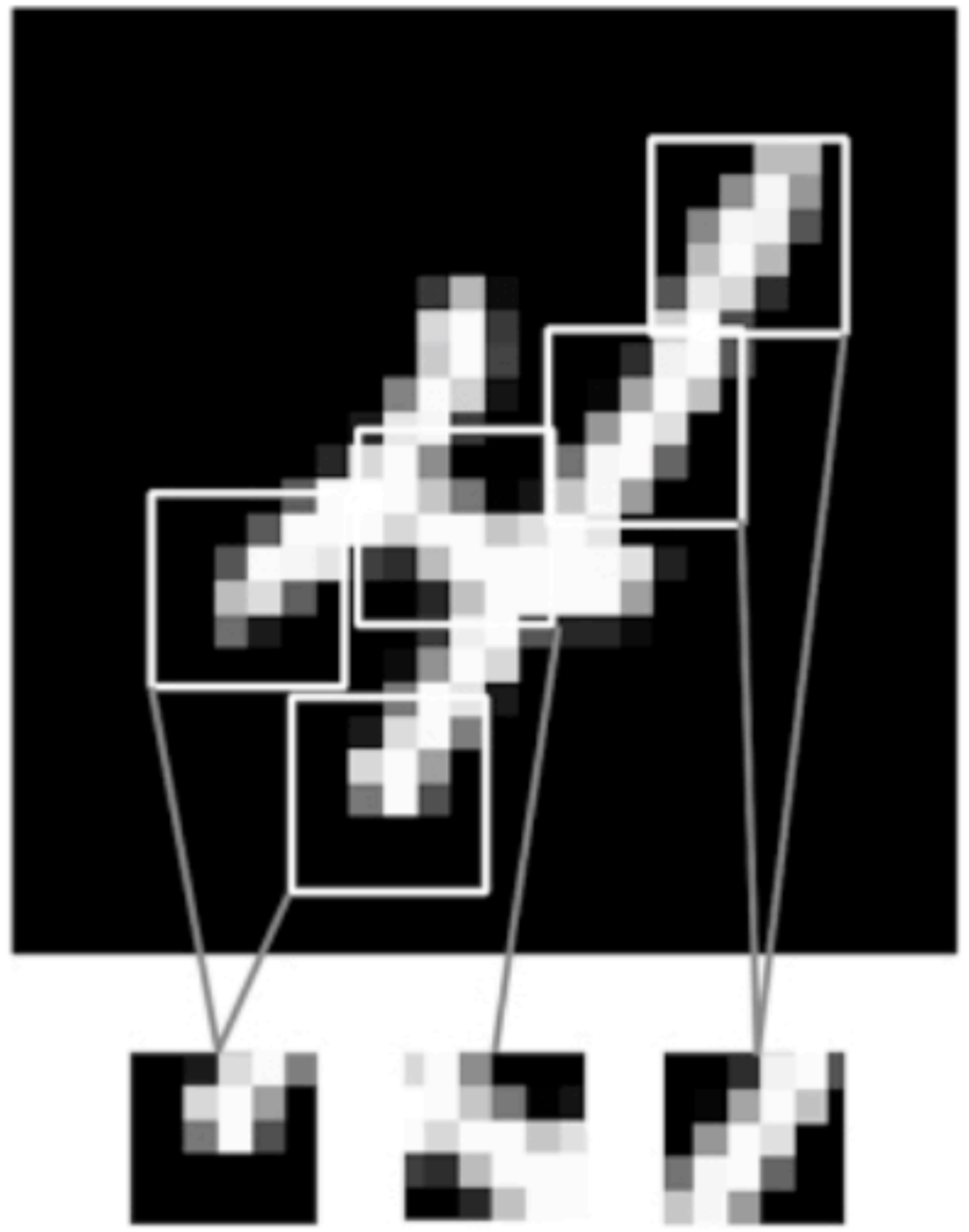

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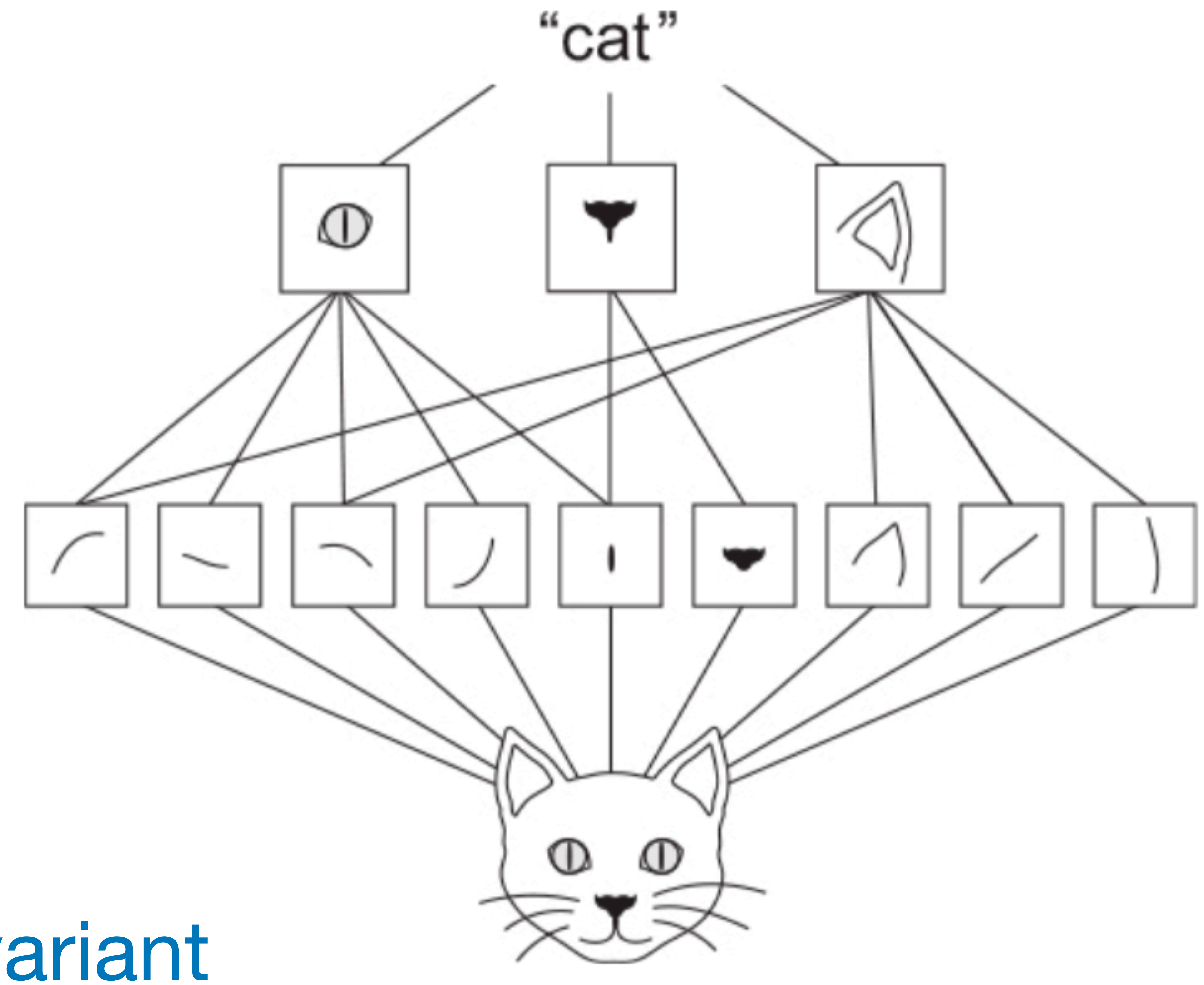


Patterns are

- Local
- Translation-invariant
- Hierarchical

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

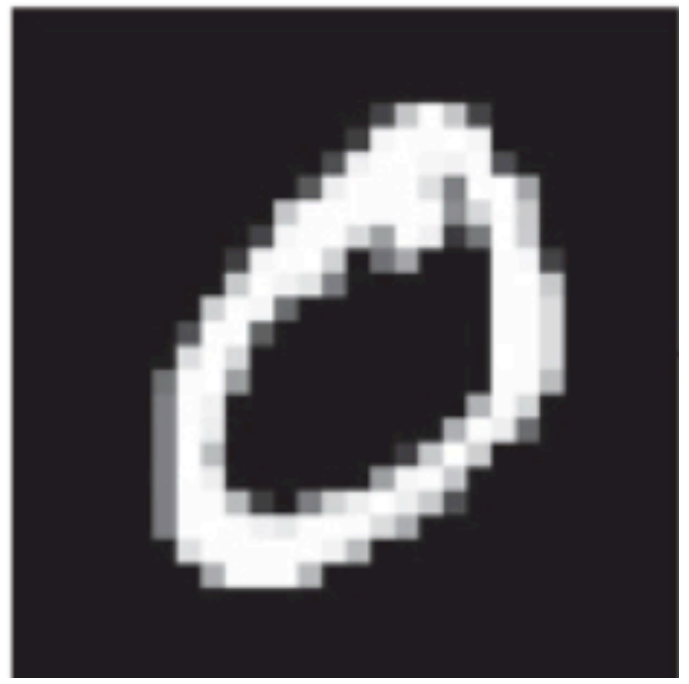
Convolution: Searching for patterns

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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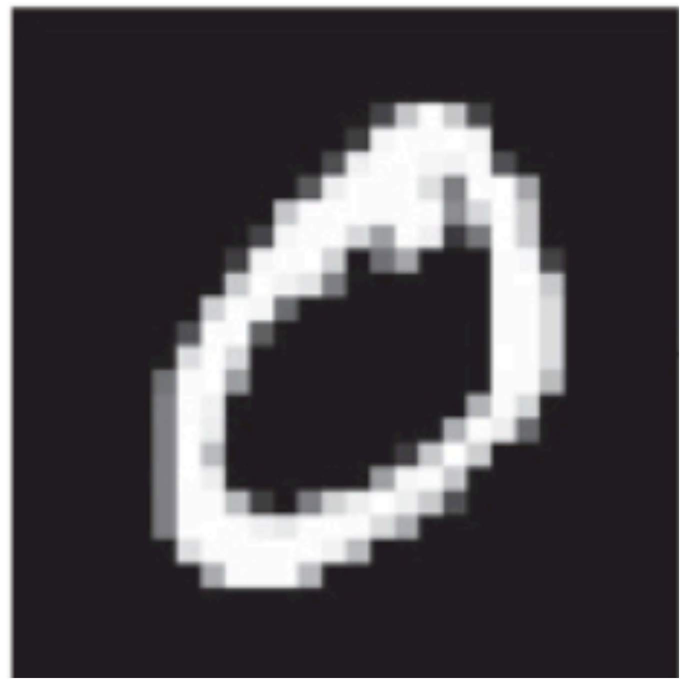

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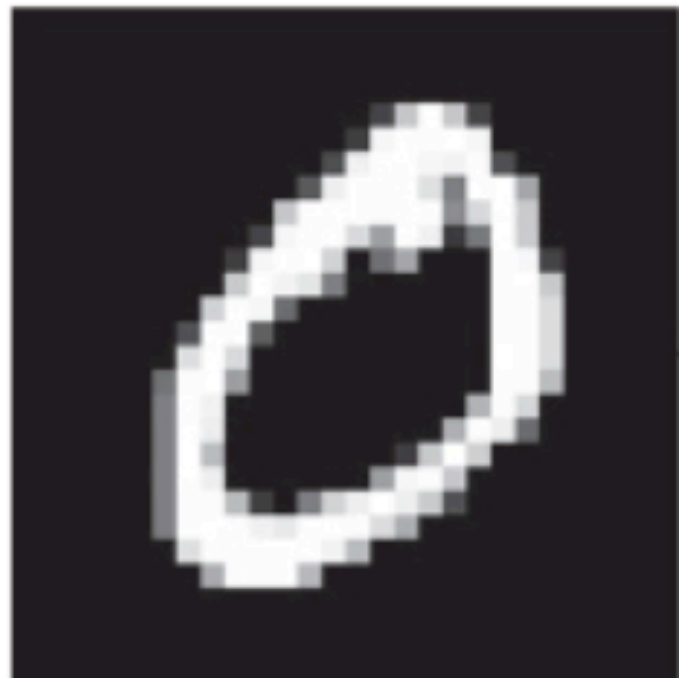

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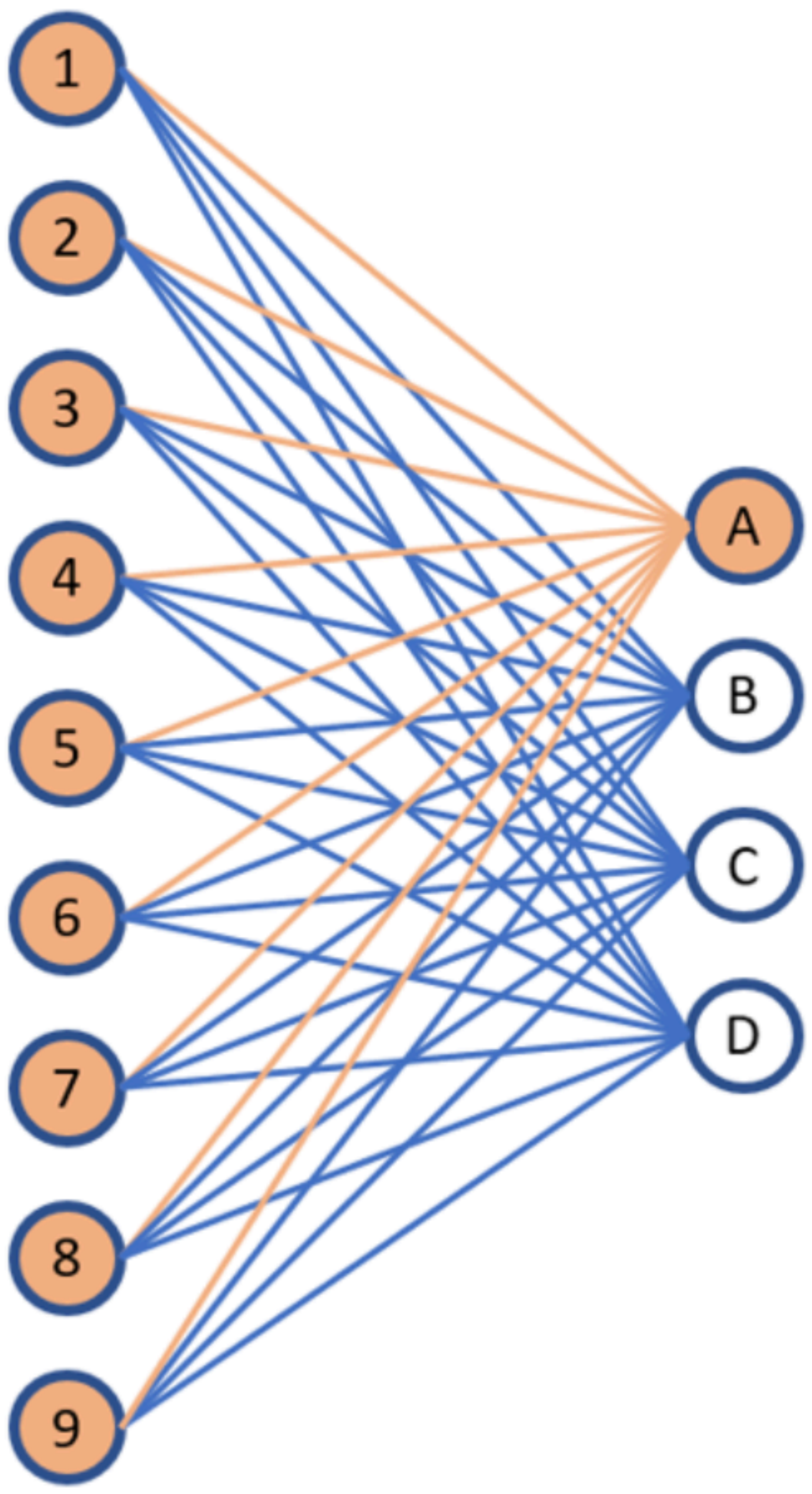
We want to use many filters, each sensitive to a different kind of pattern.

Convolutional layer versus fully-connected layer

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



Fully-connected layer

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

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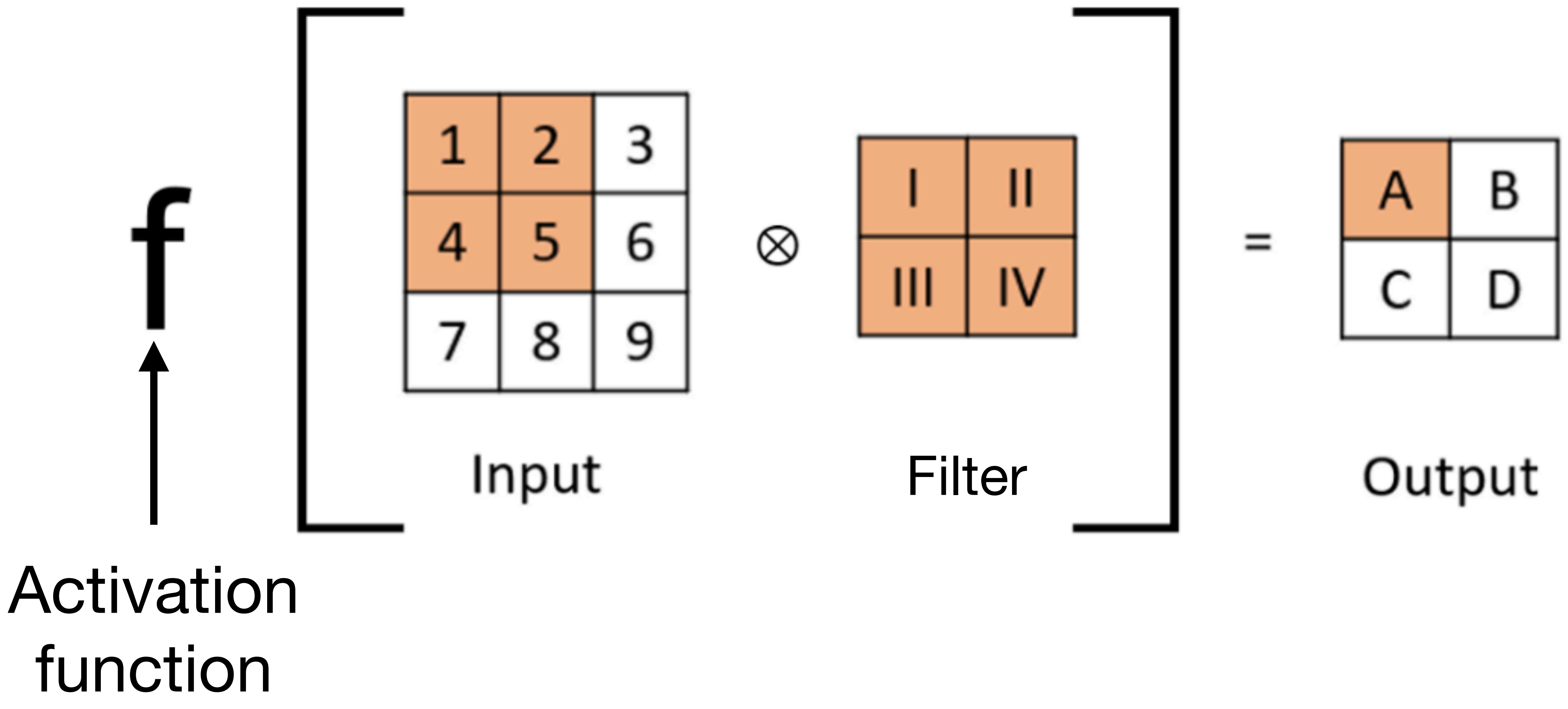

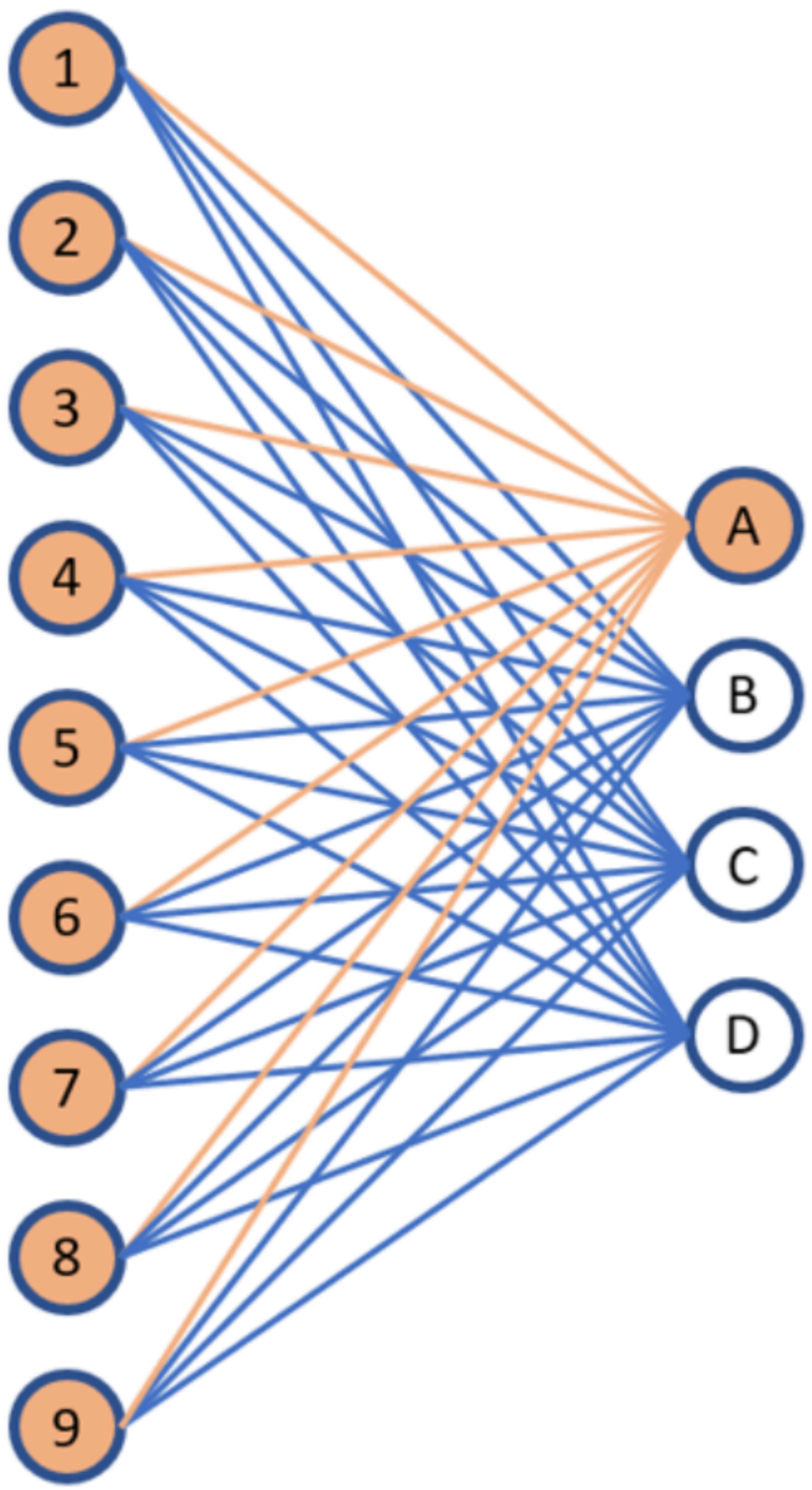

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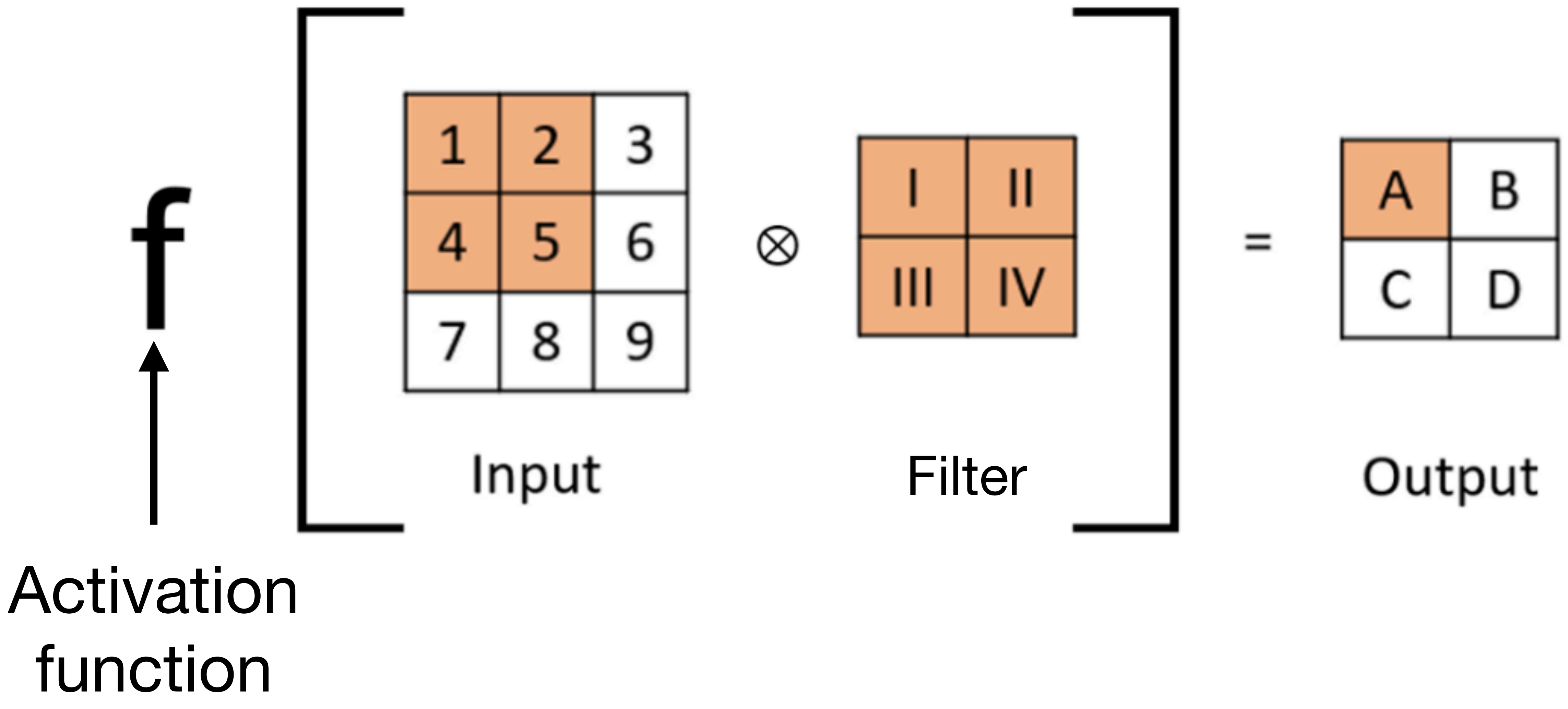

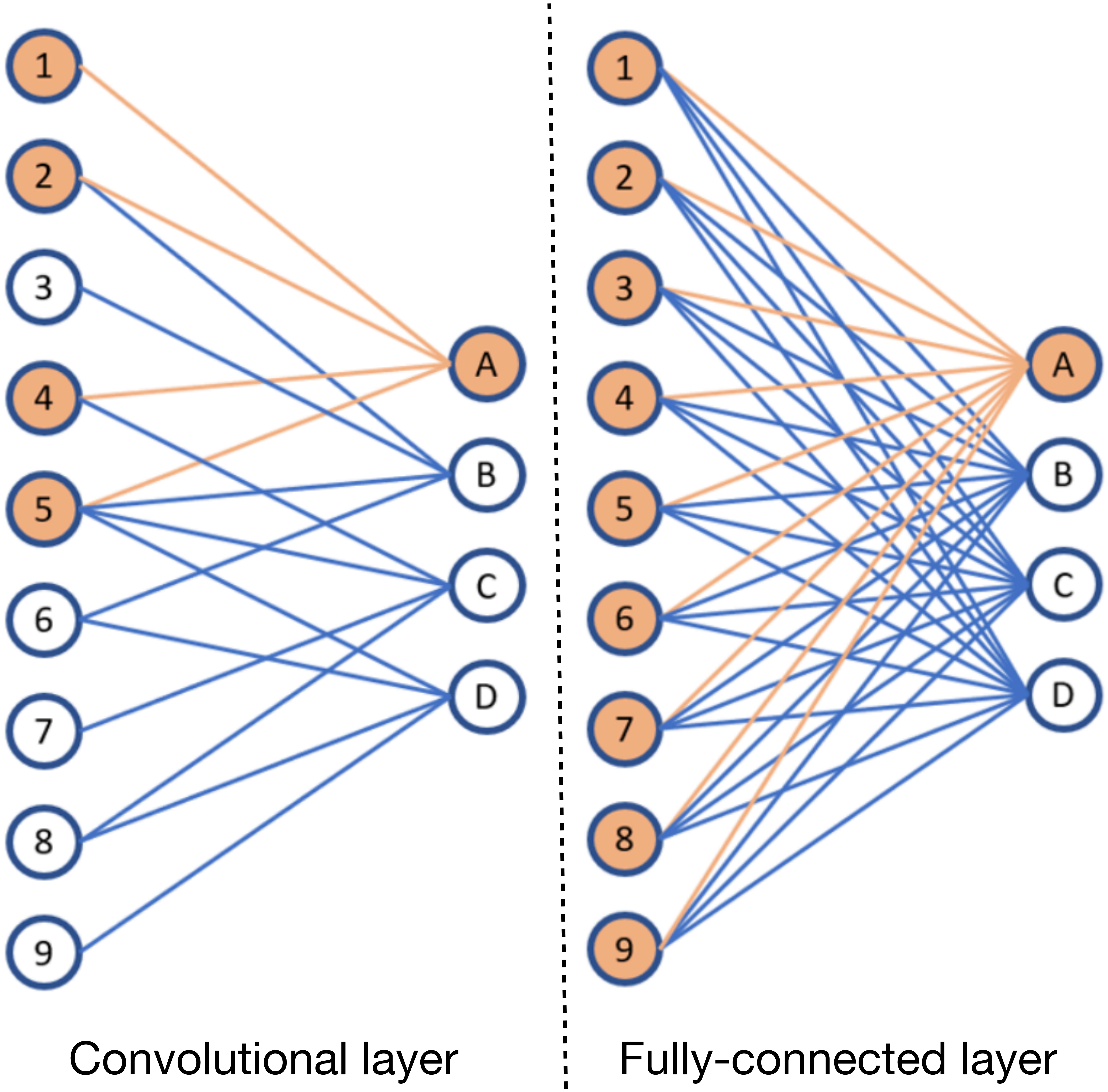

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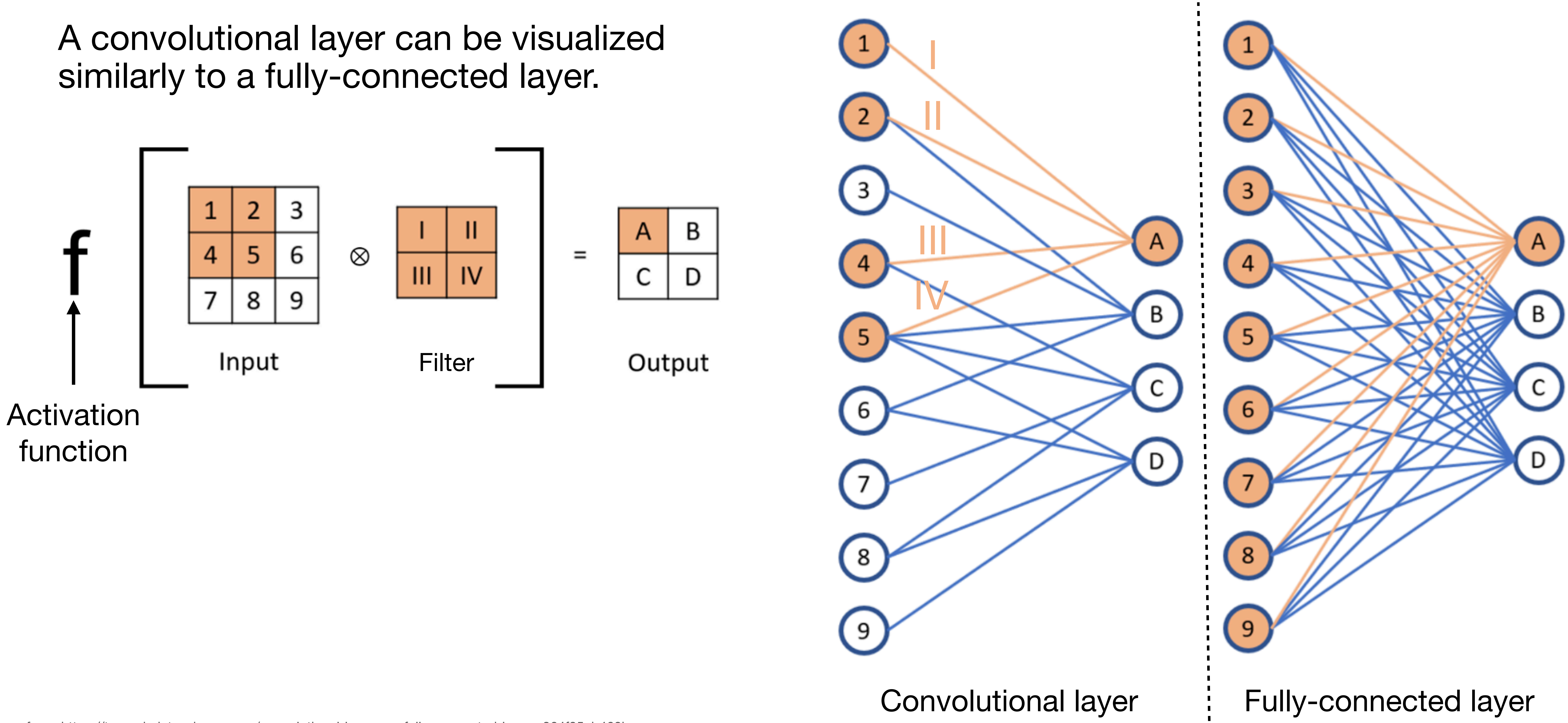

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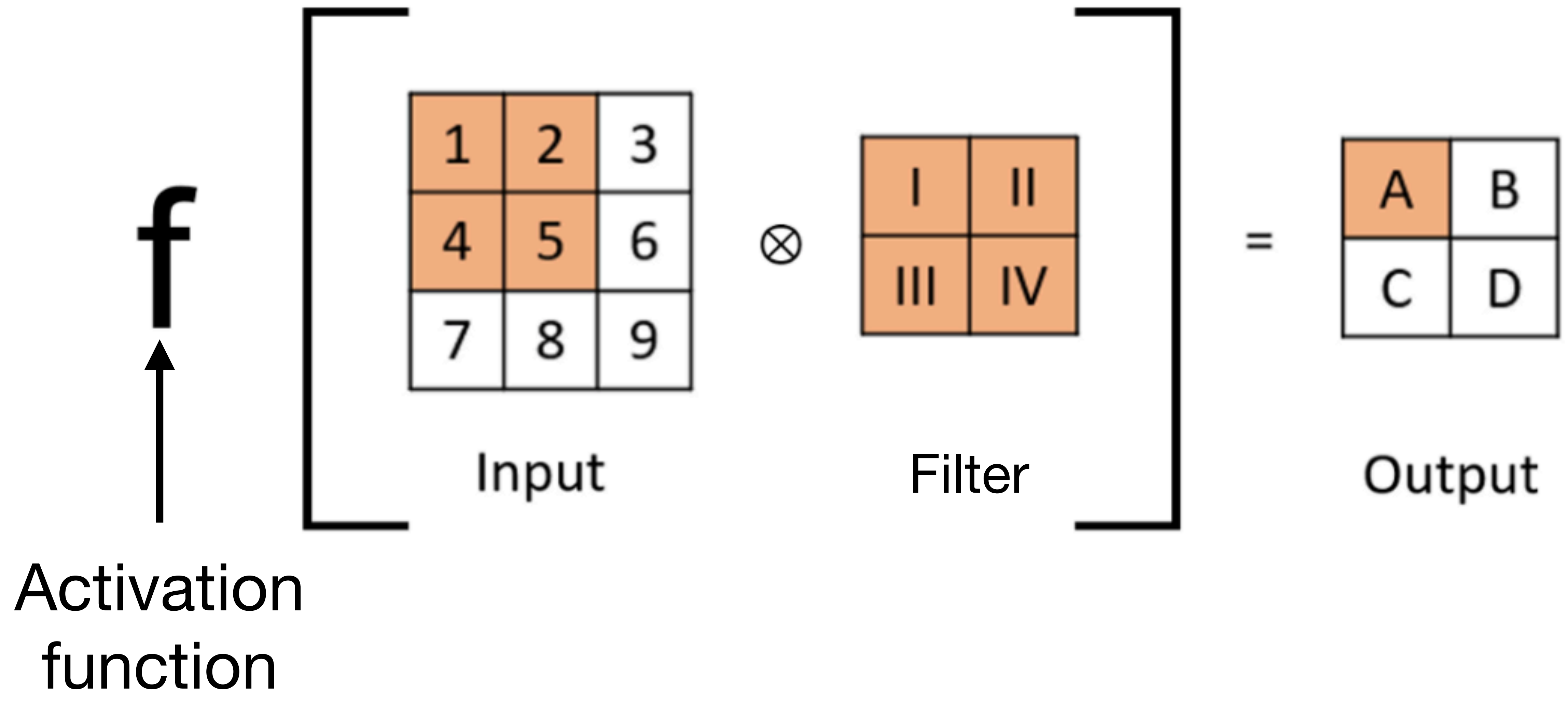

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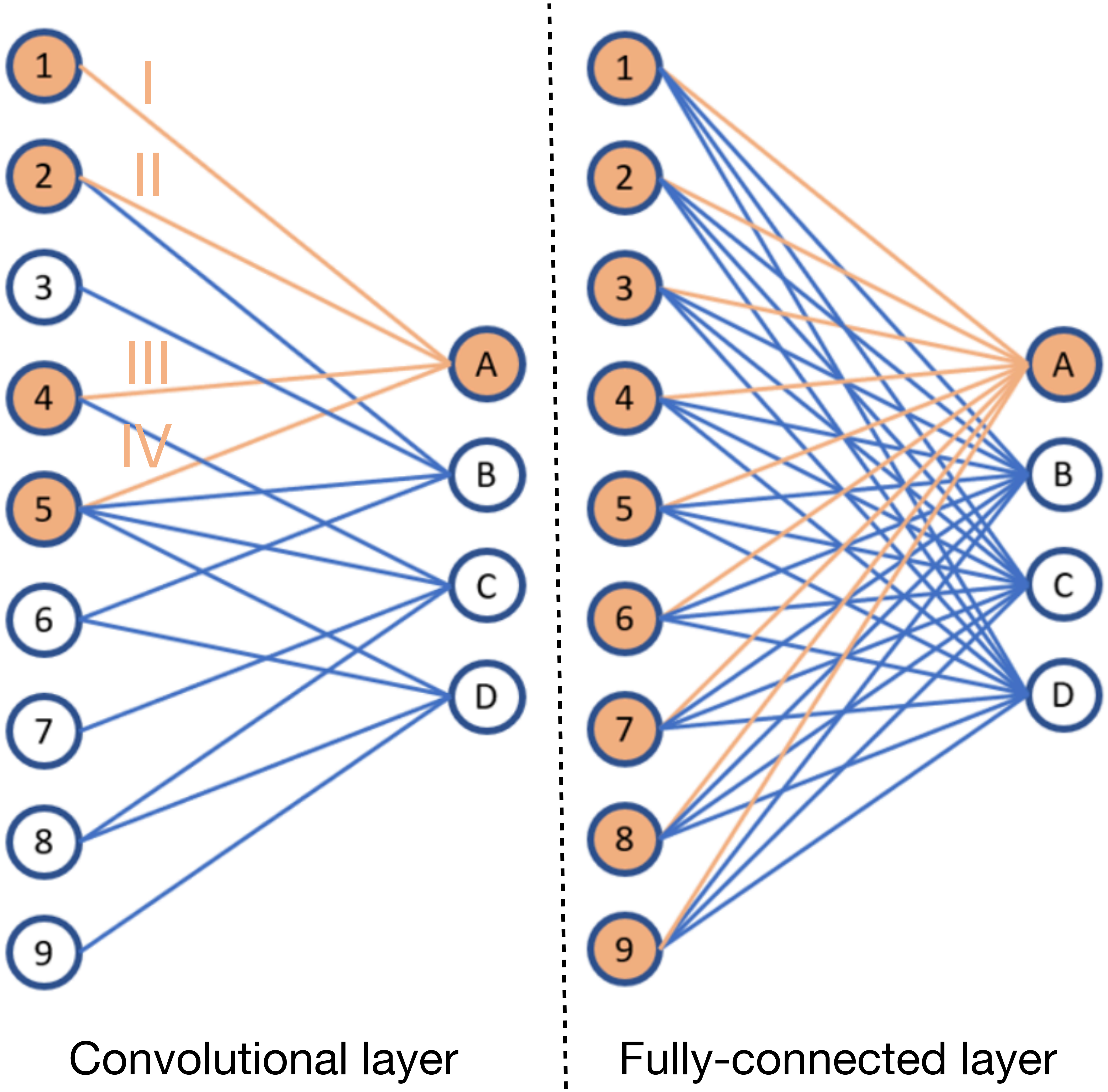

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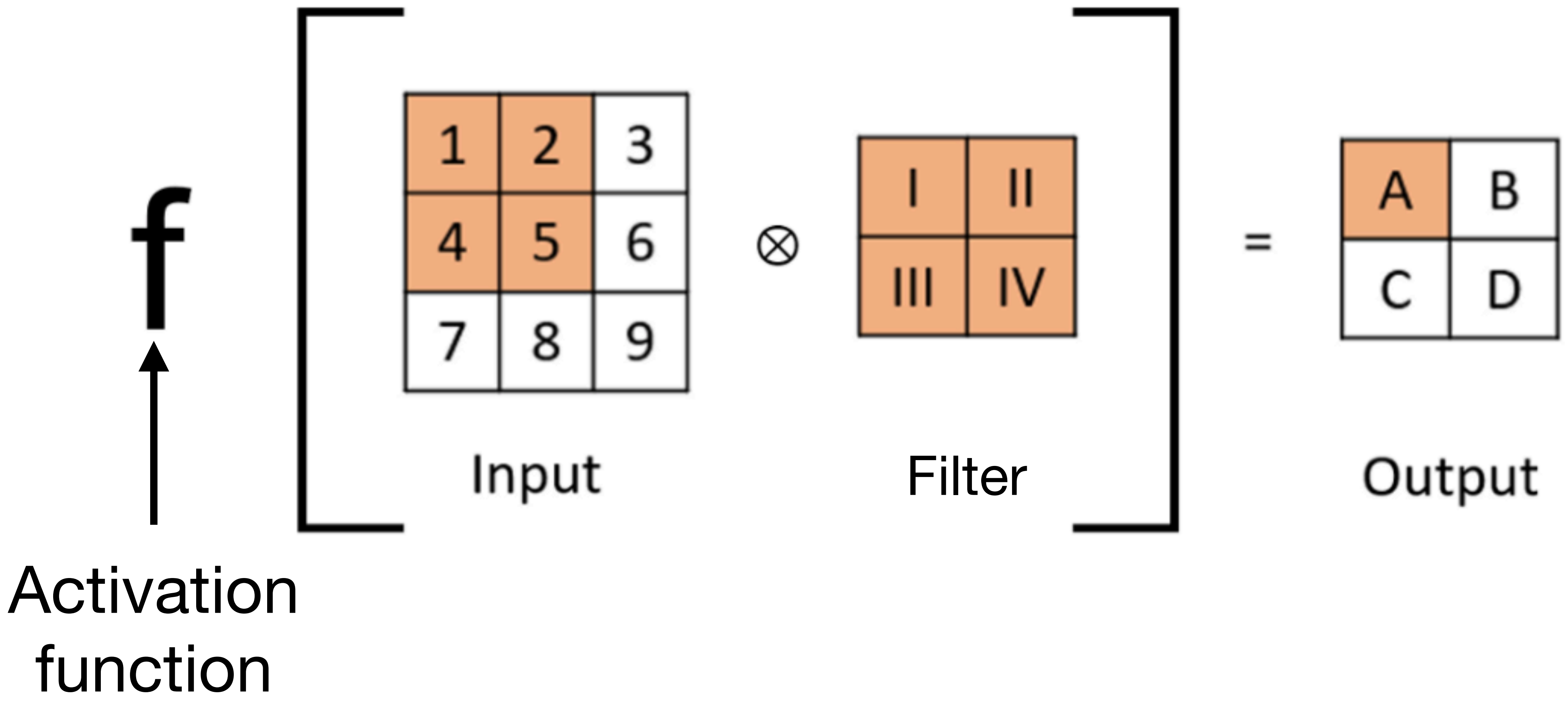
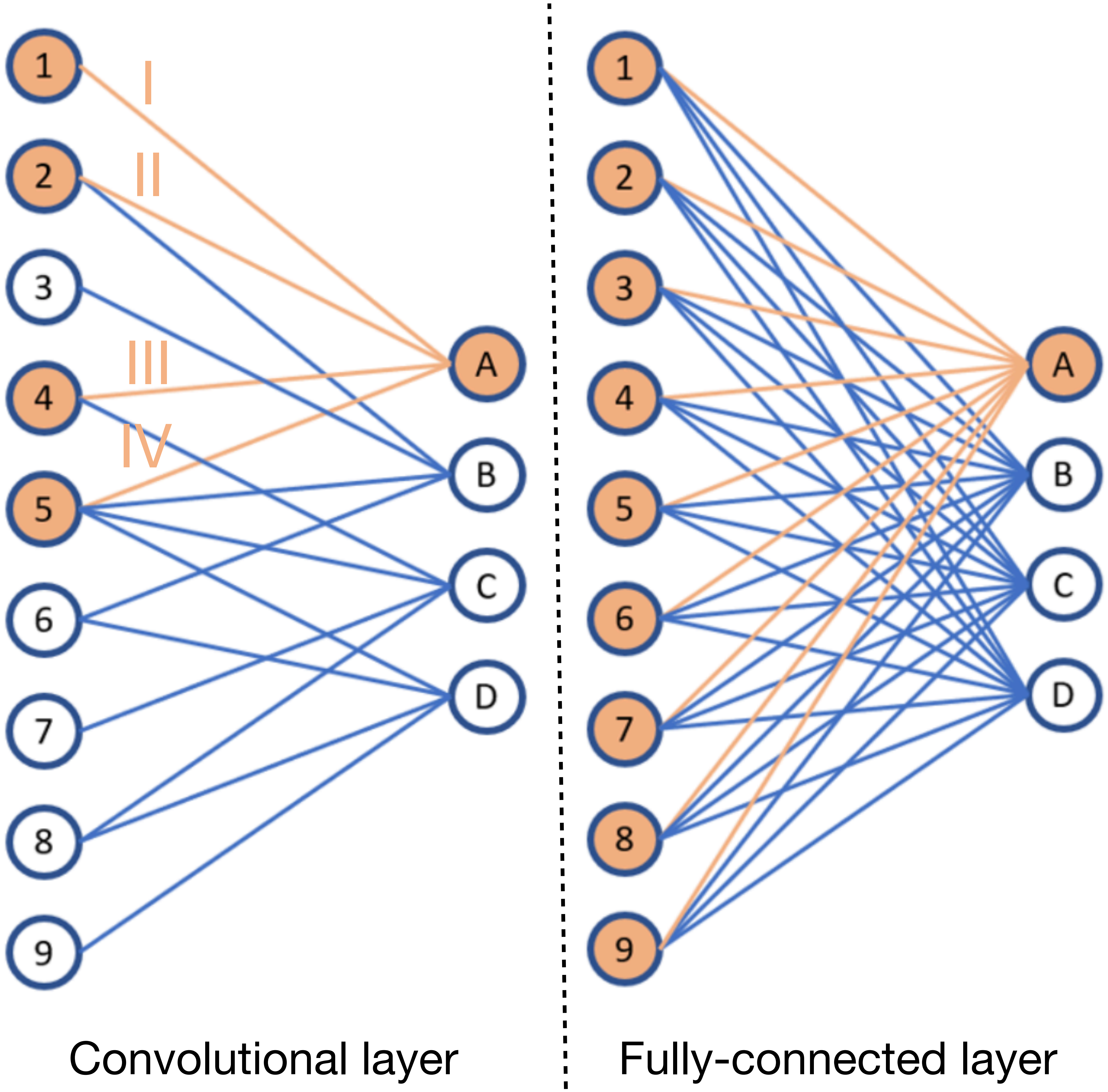


In a convolutional layer:

- Not all node pairs are connected with edges



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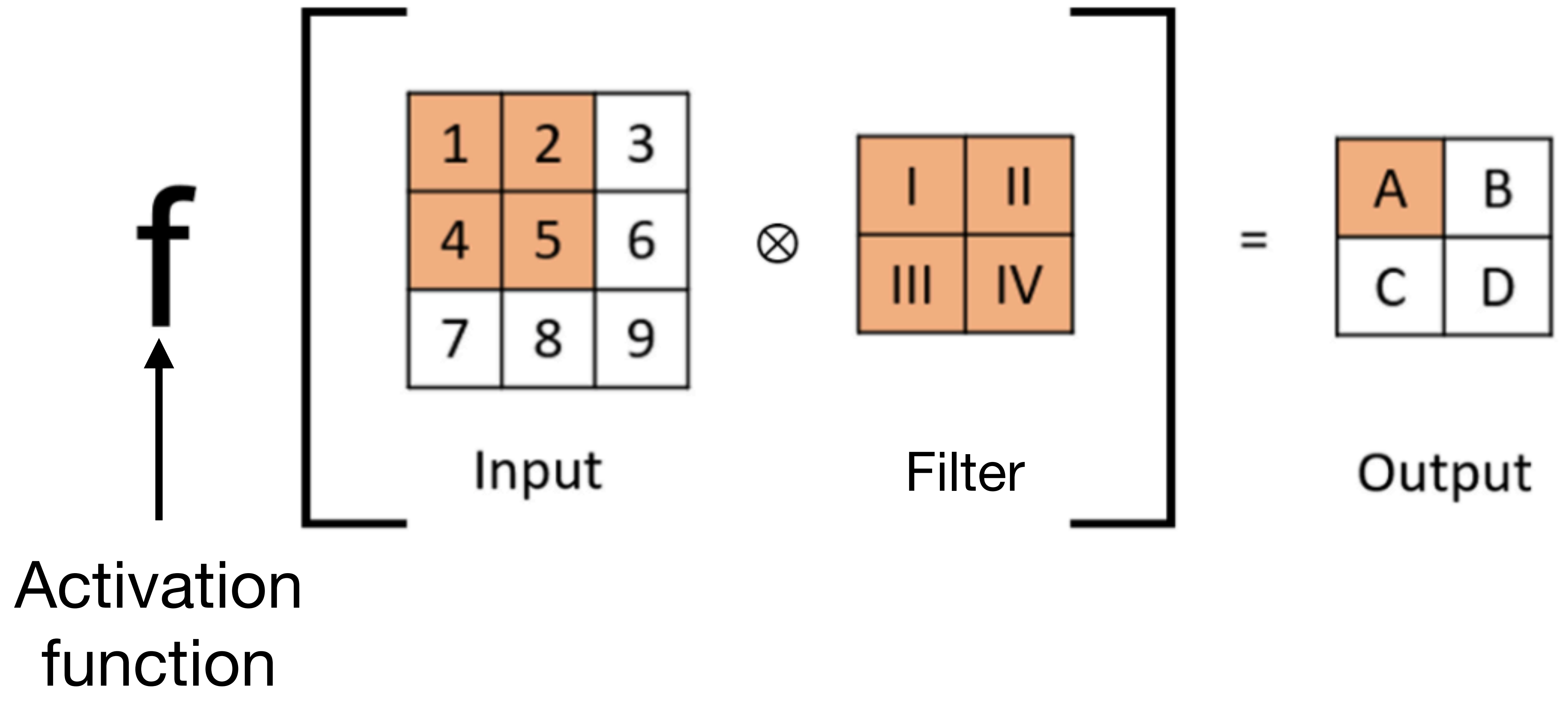
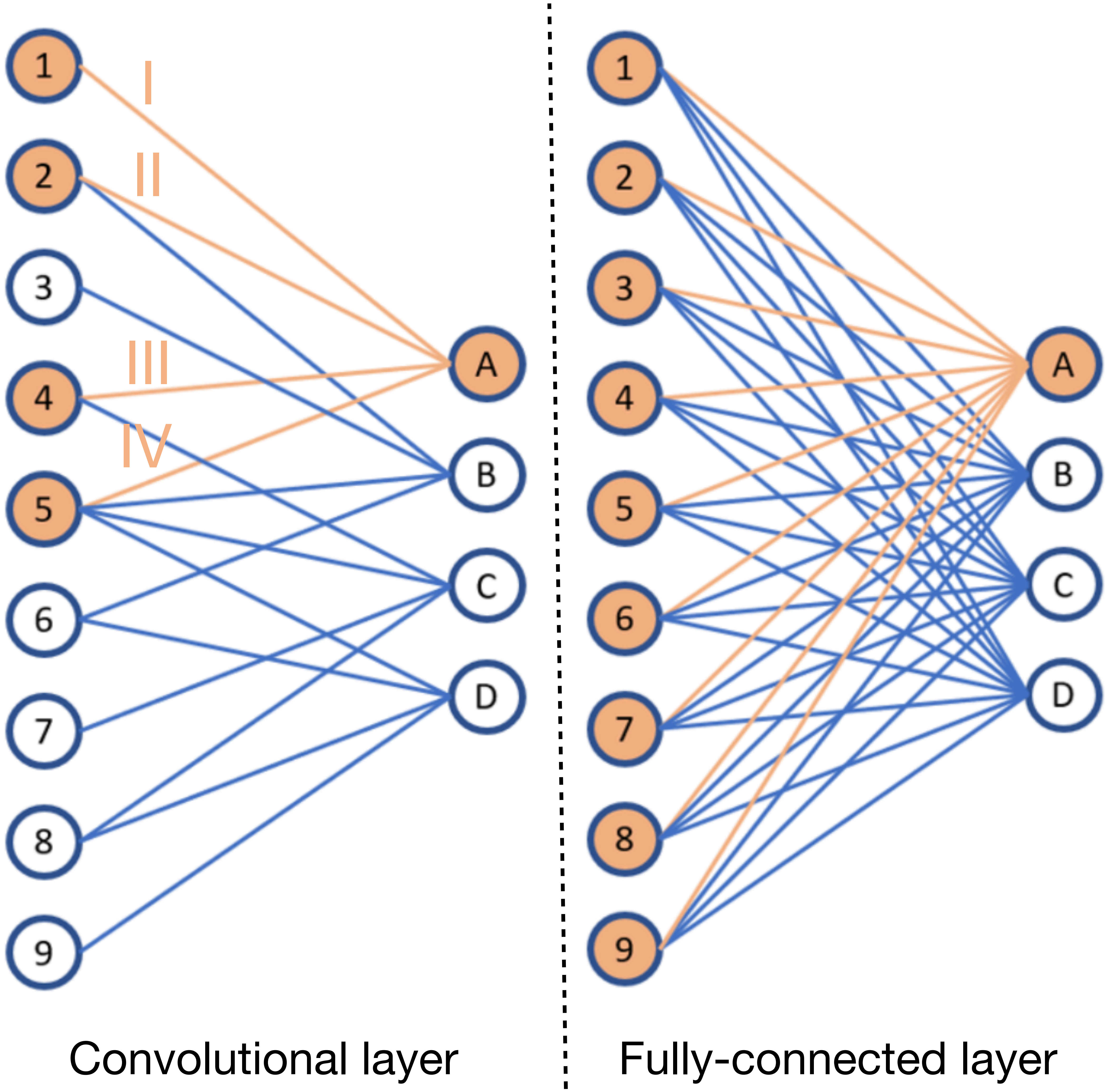


In a convolutional layer:

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



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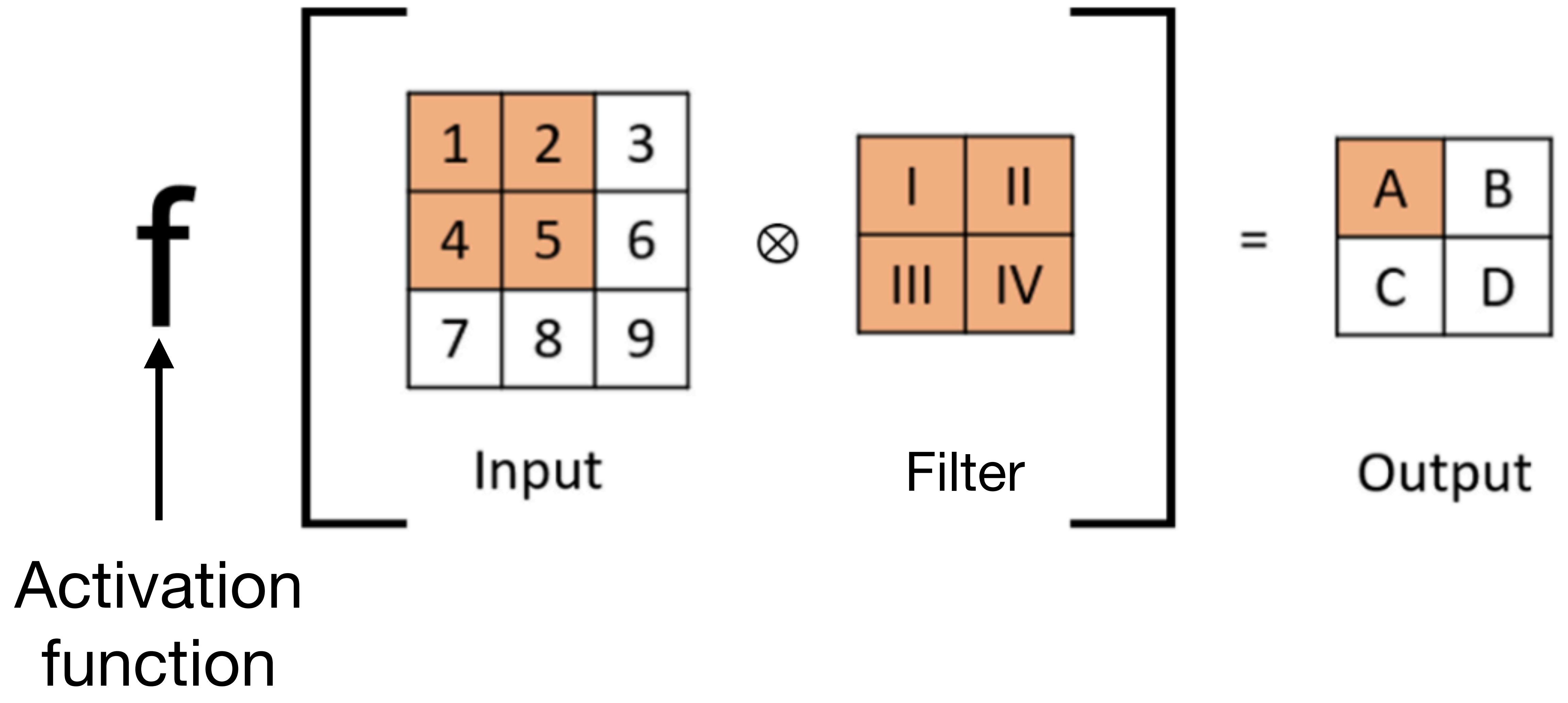

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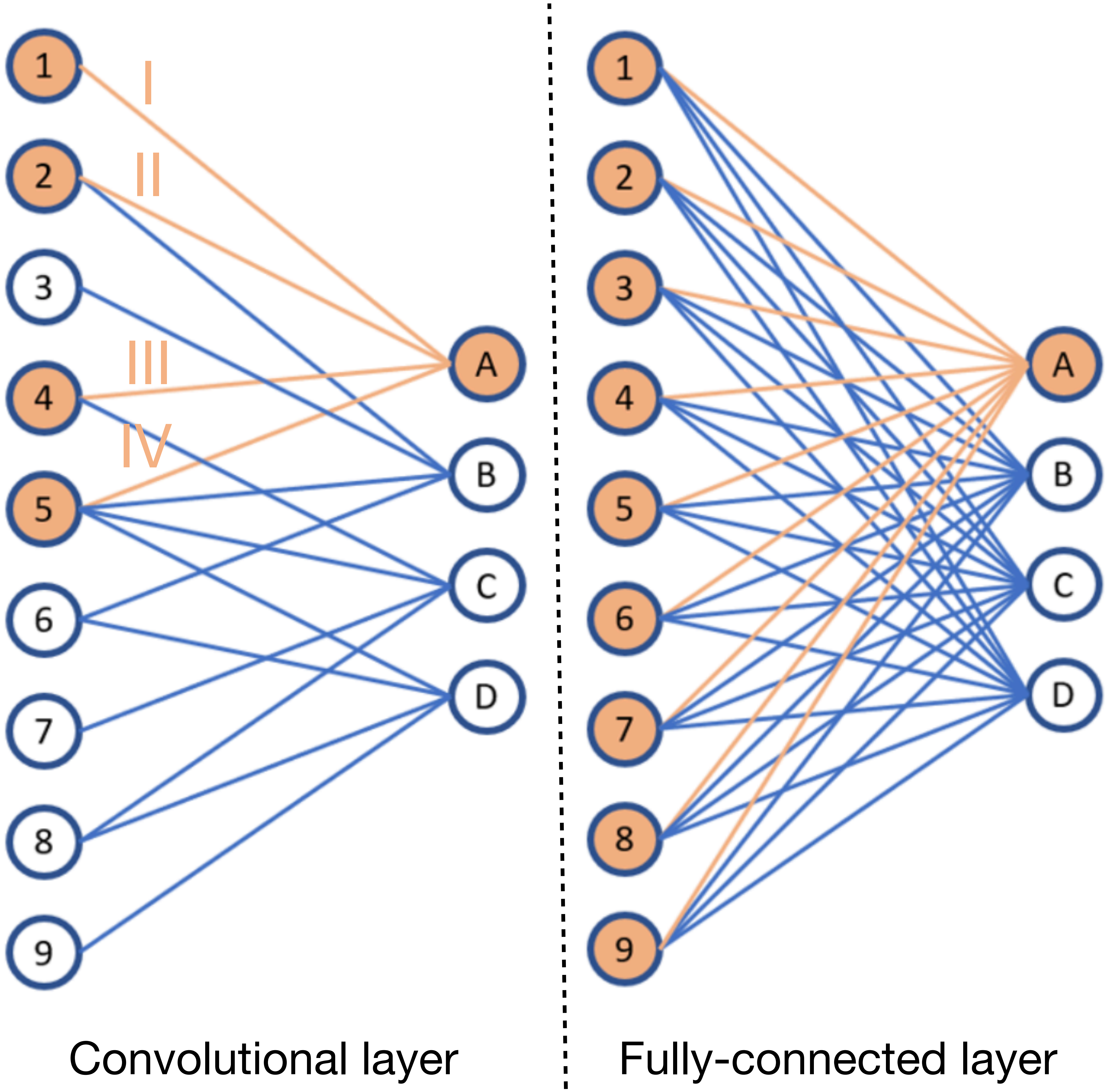
Consequence: Conv layers have fewer parameters!



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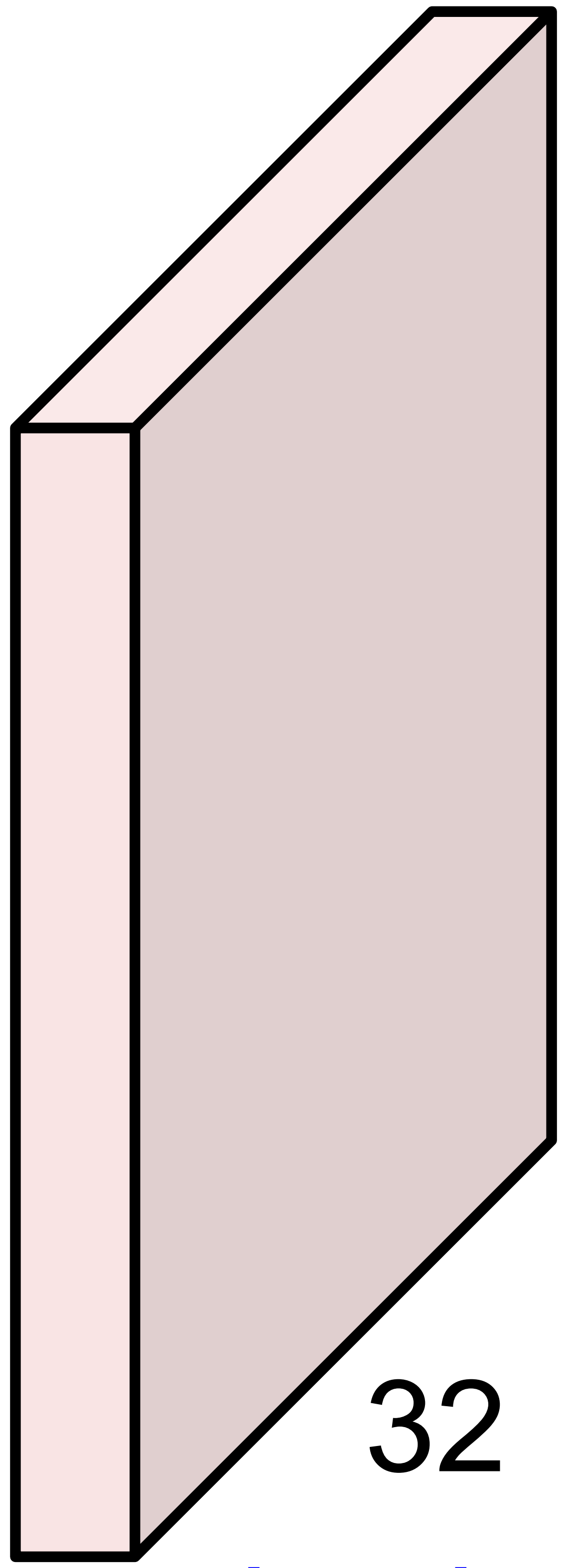
Convolution Layer

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

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



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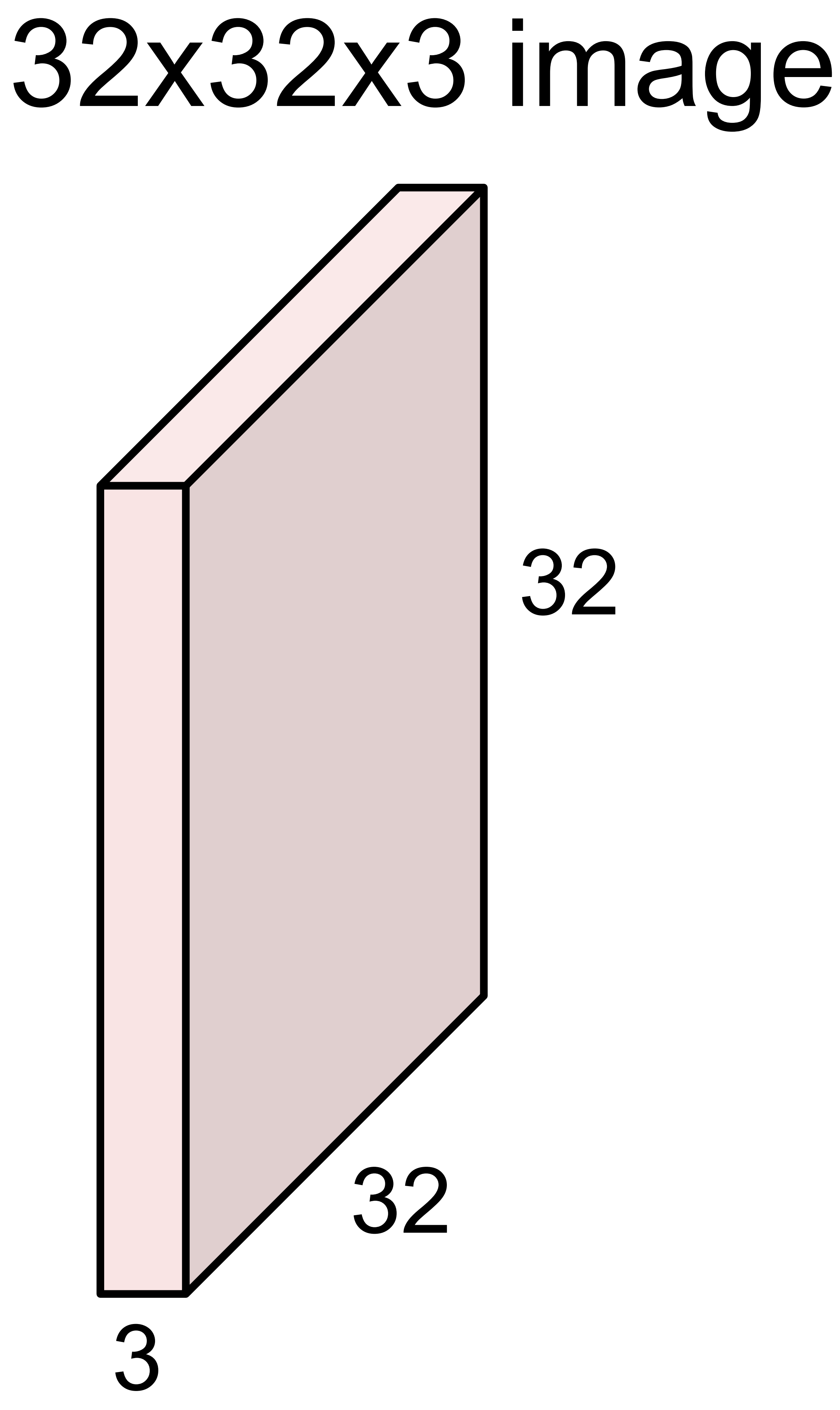
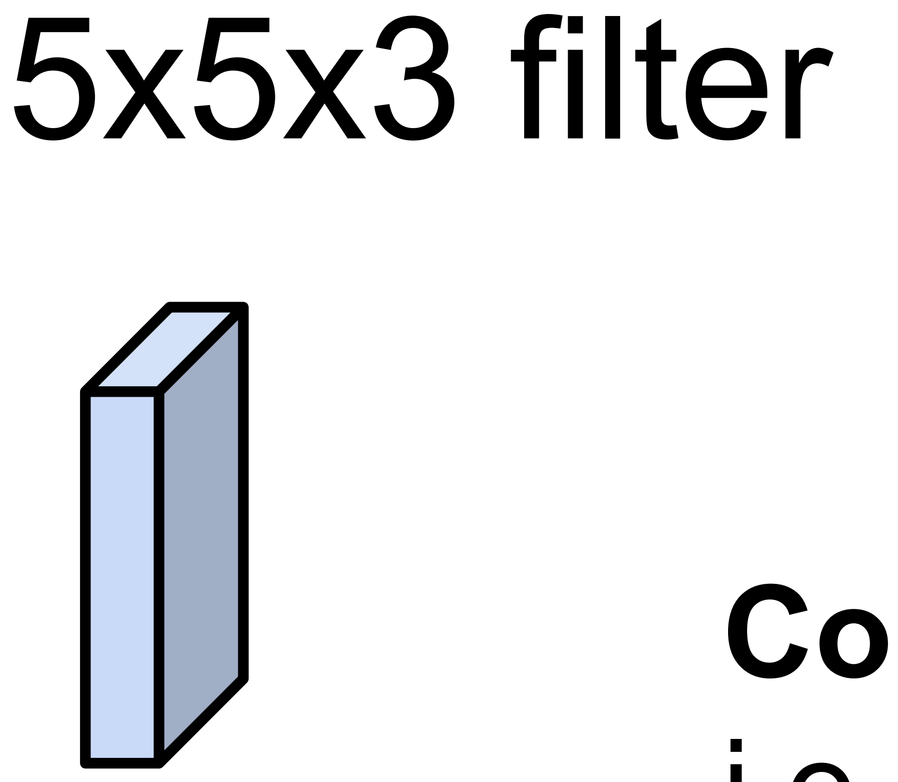


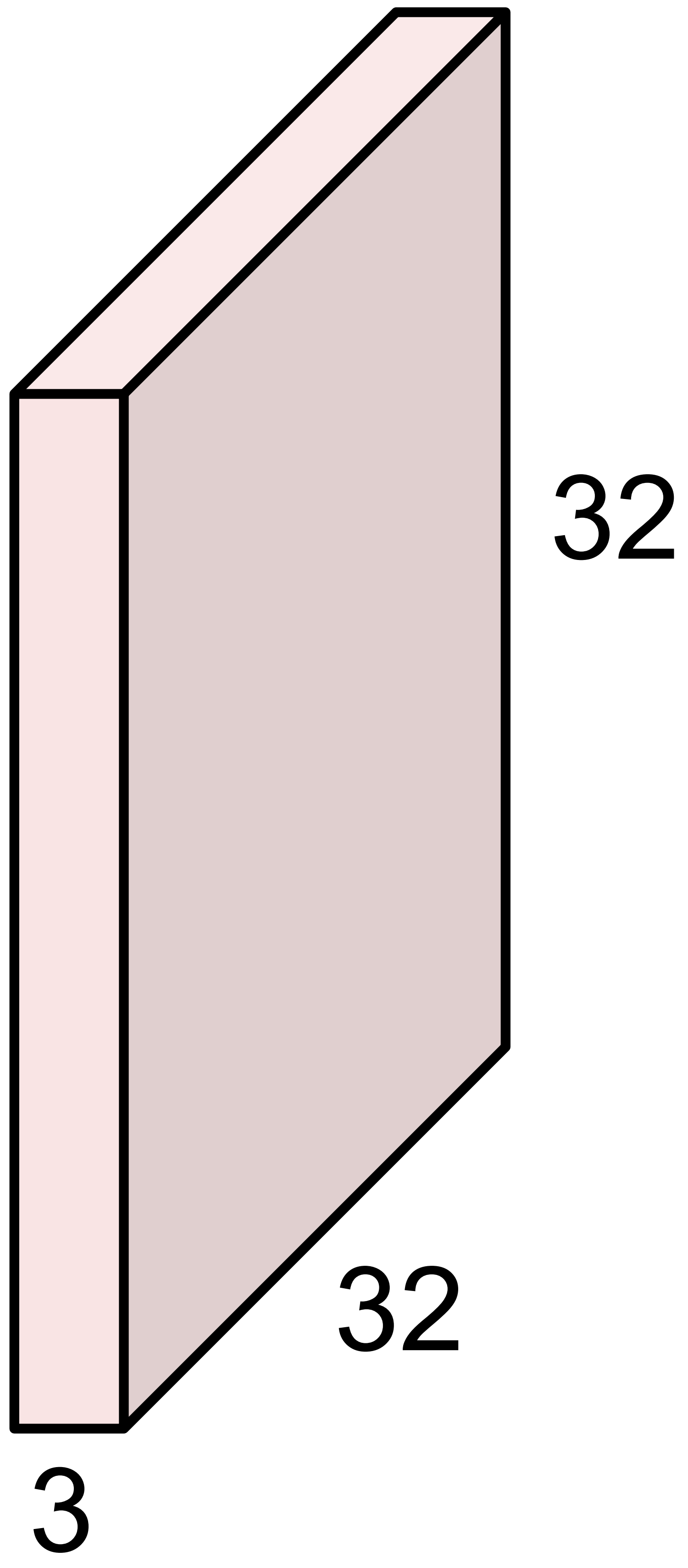


Convolve the filter with the image i.e. "slide over the image spatially, computing dot products"

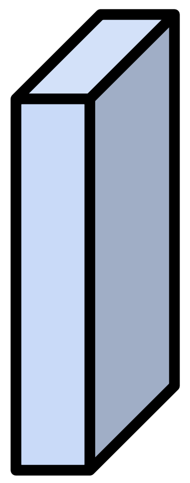
Convolution Layer

Filters always extend the full depth of the input volume

32x32x3 image



5x5x3 filter



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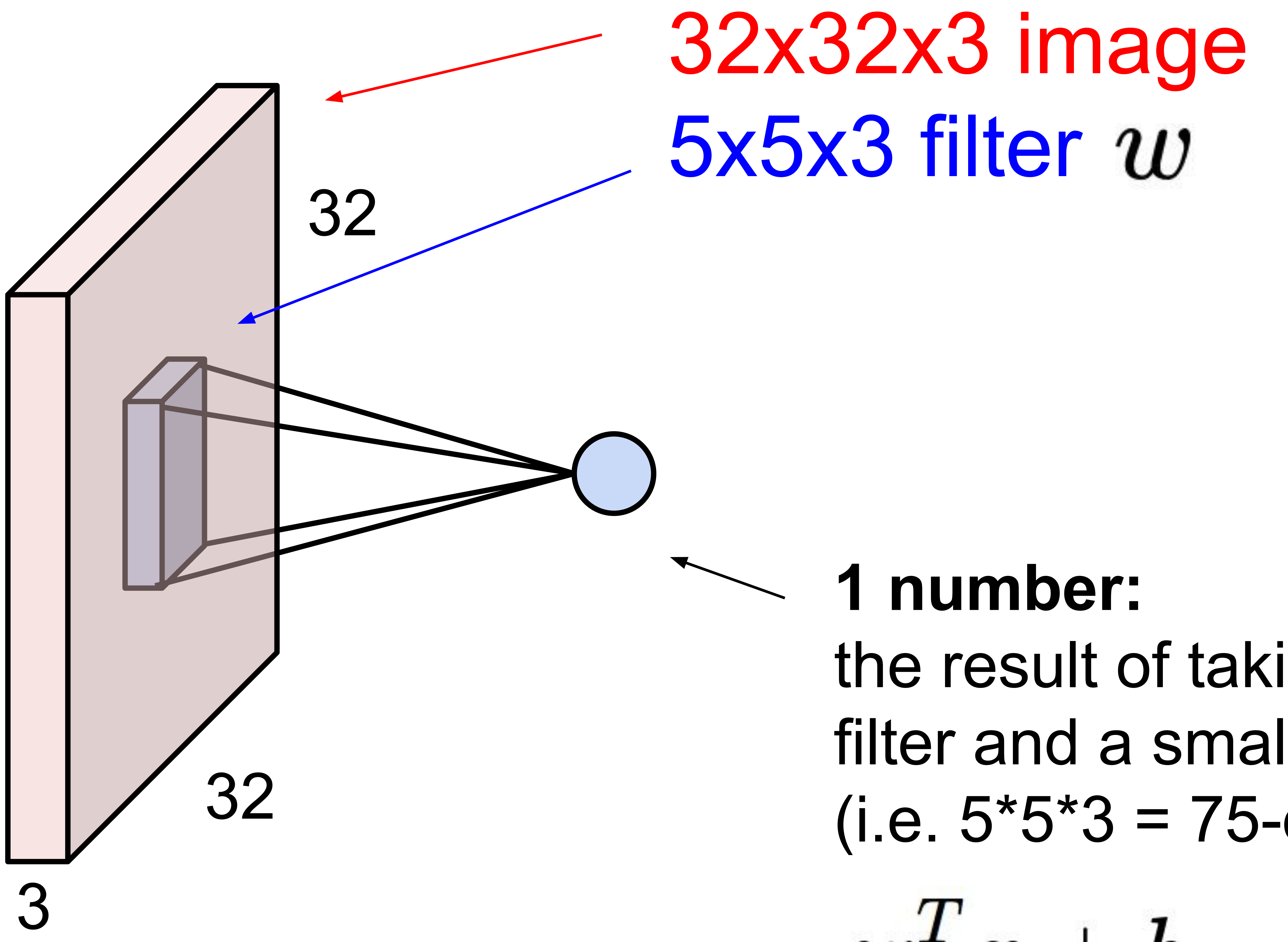
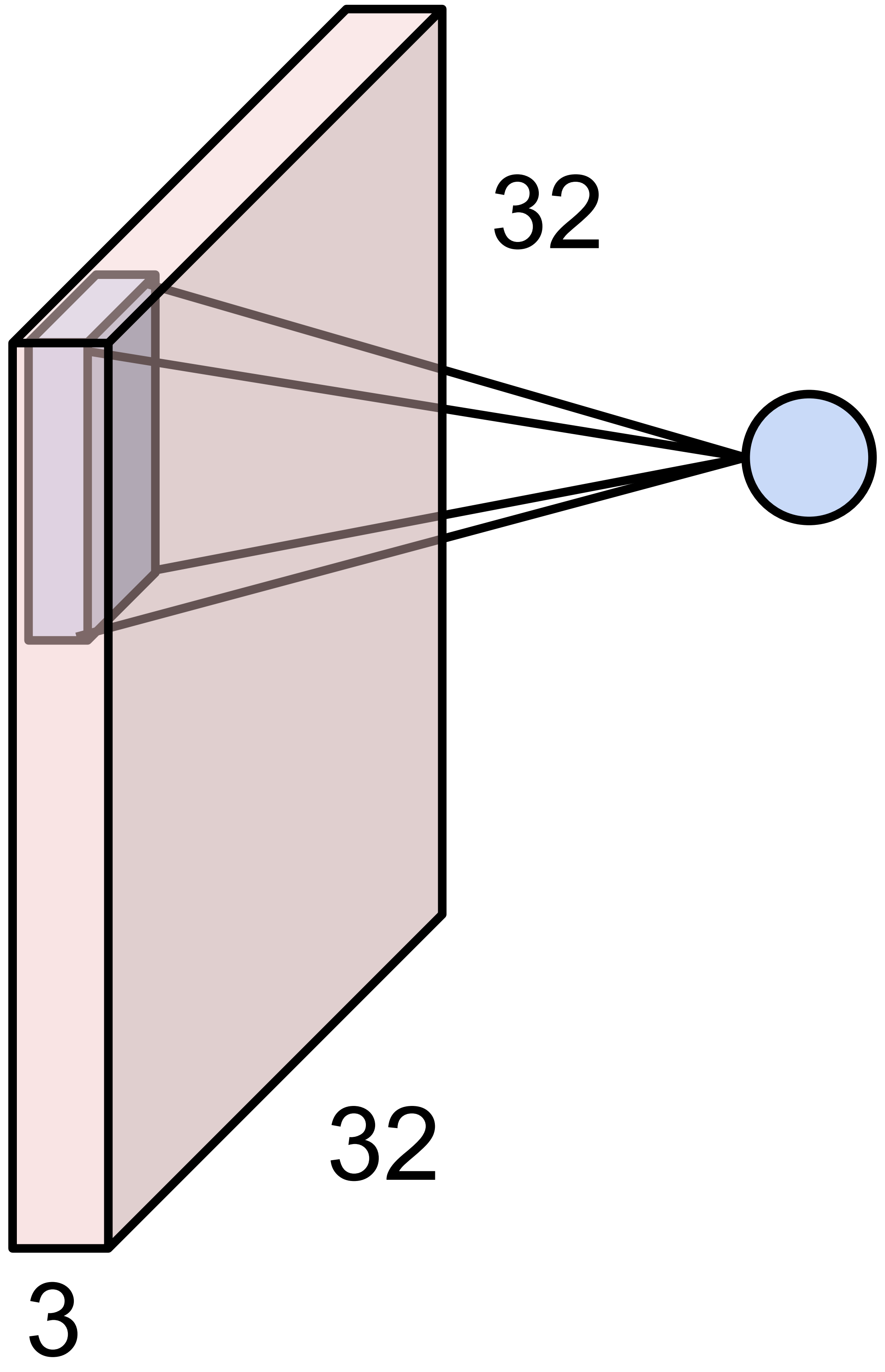


1 number:
the result of taking a dot product between the filter and a small 5x5x3 chunk of the image
(i.e. 5*5*3 = 75-dimensional dot product + bias)

$$w^T x + b$$

Convolution Layer



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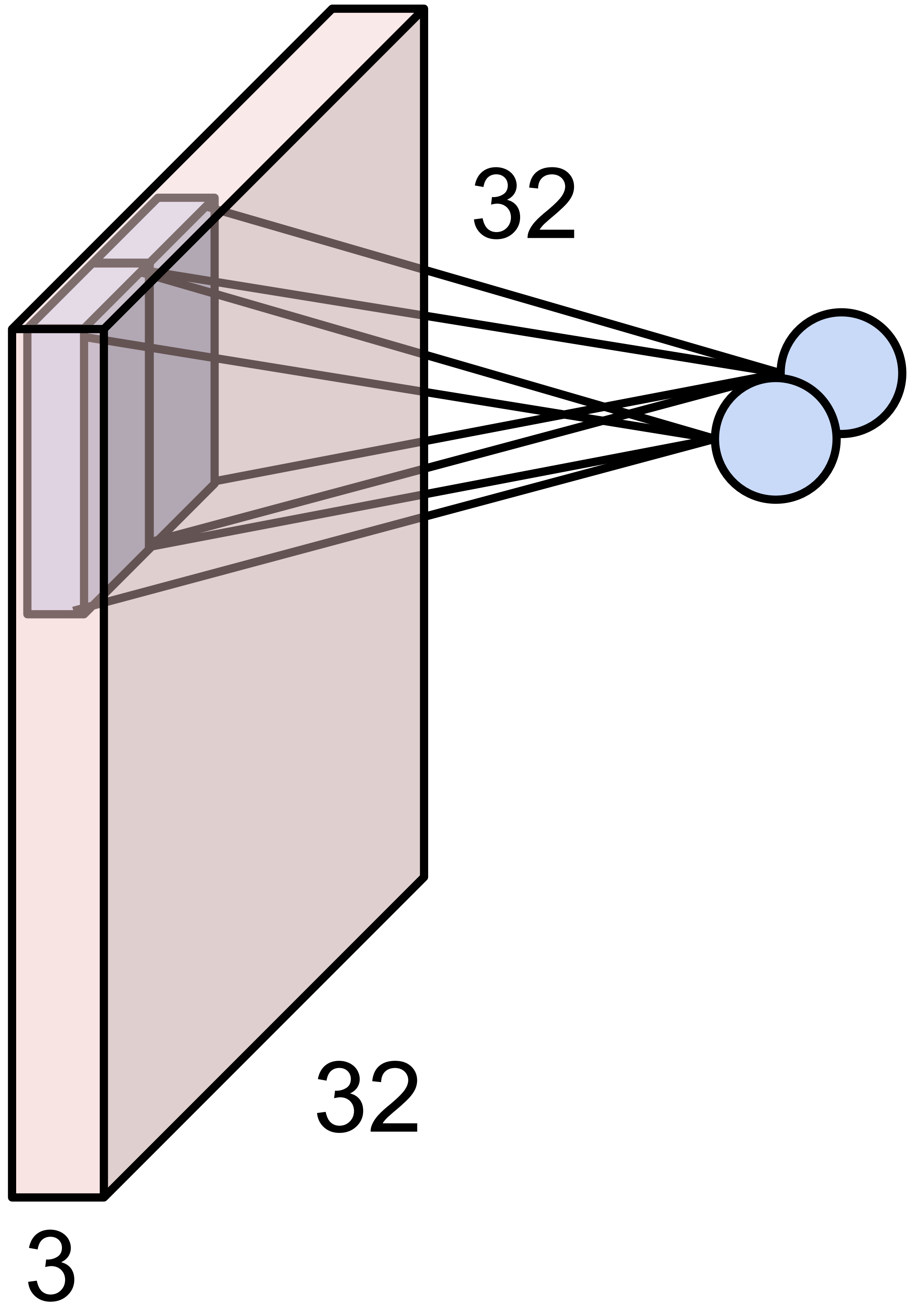

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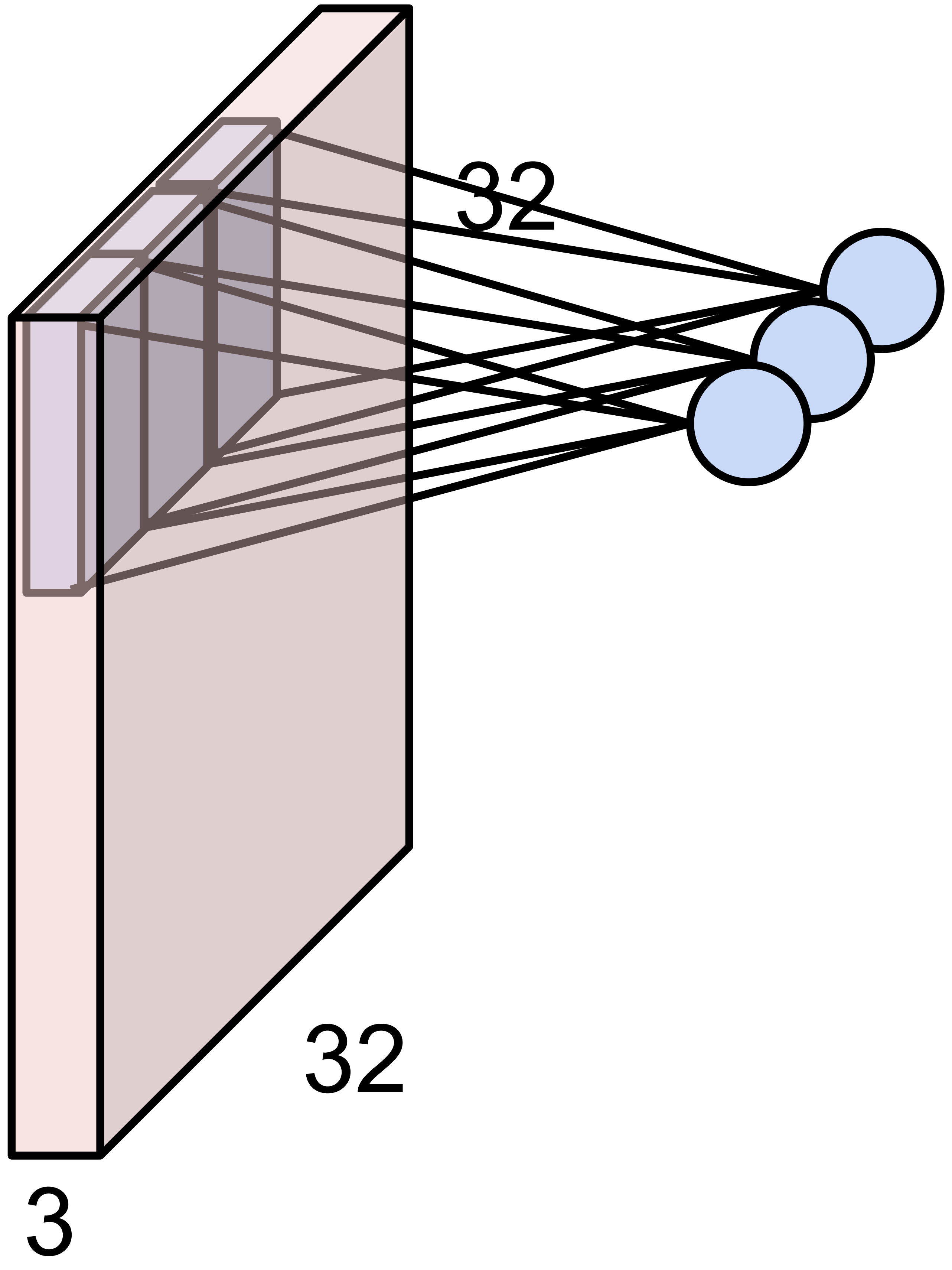

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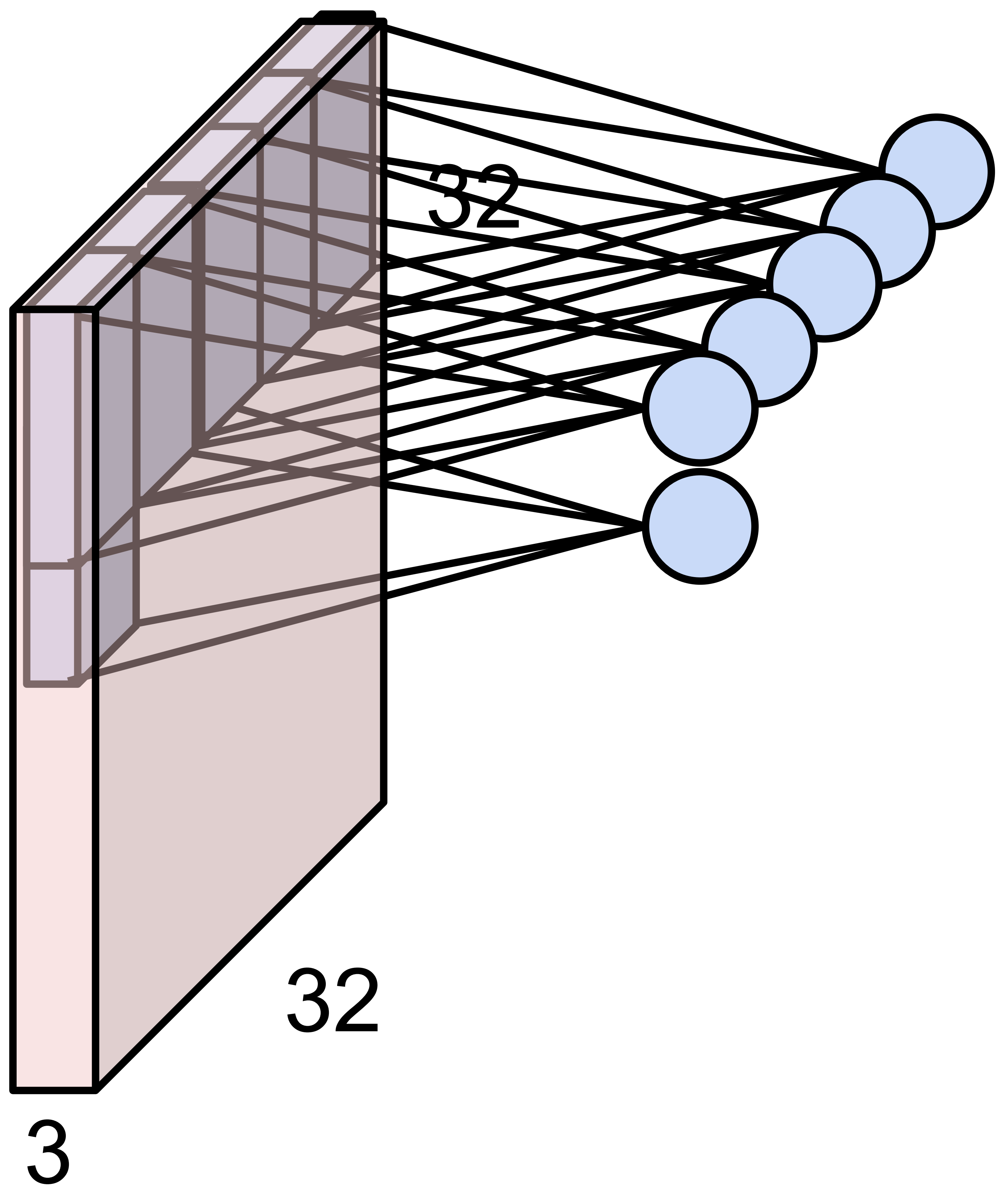

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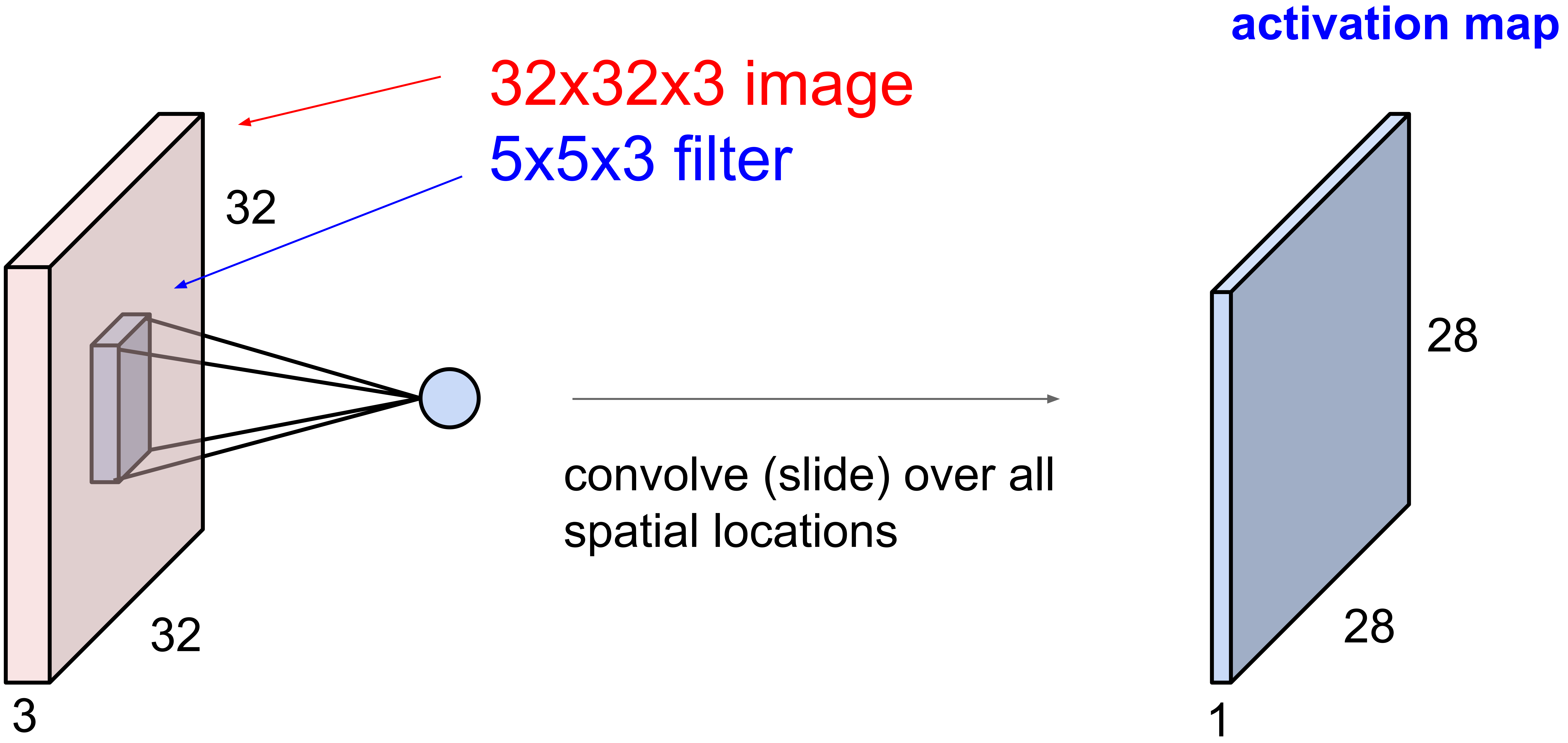

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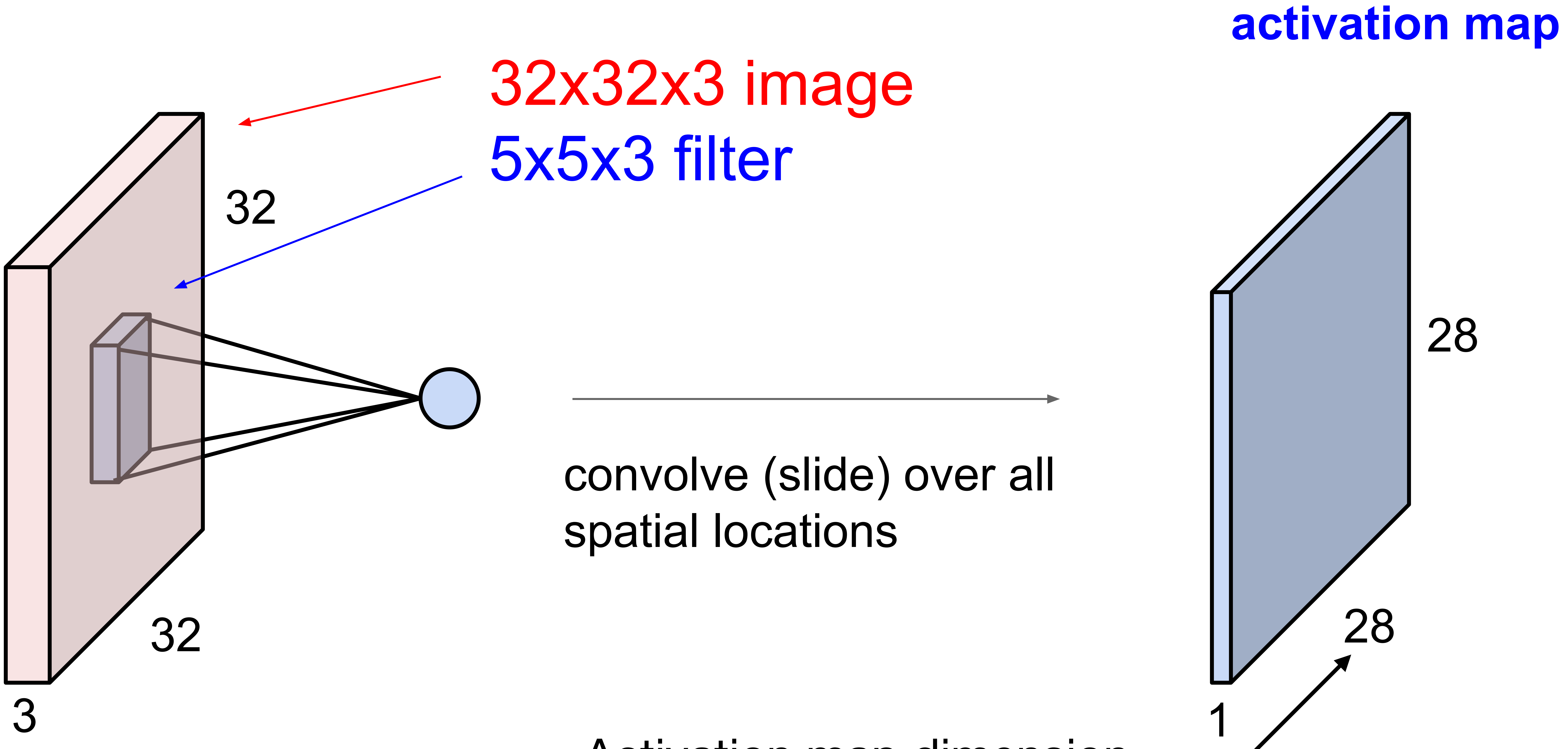
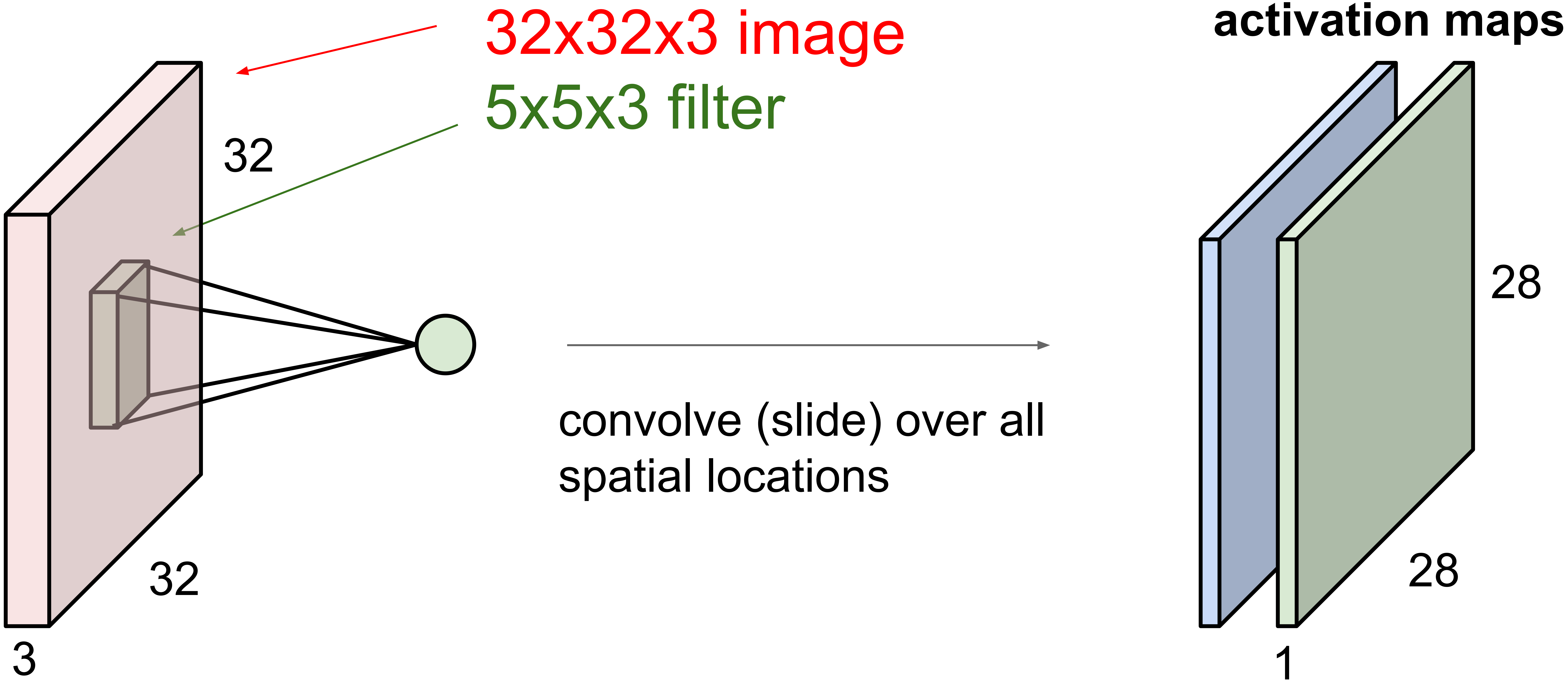


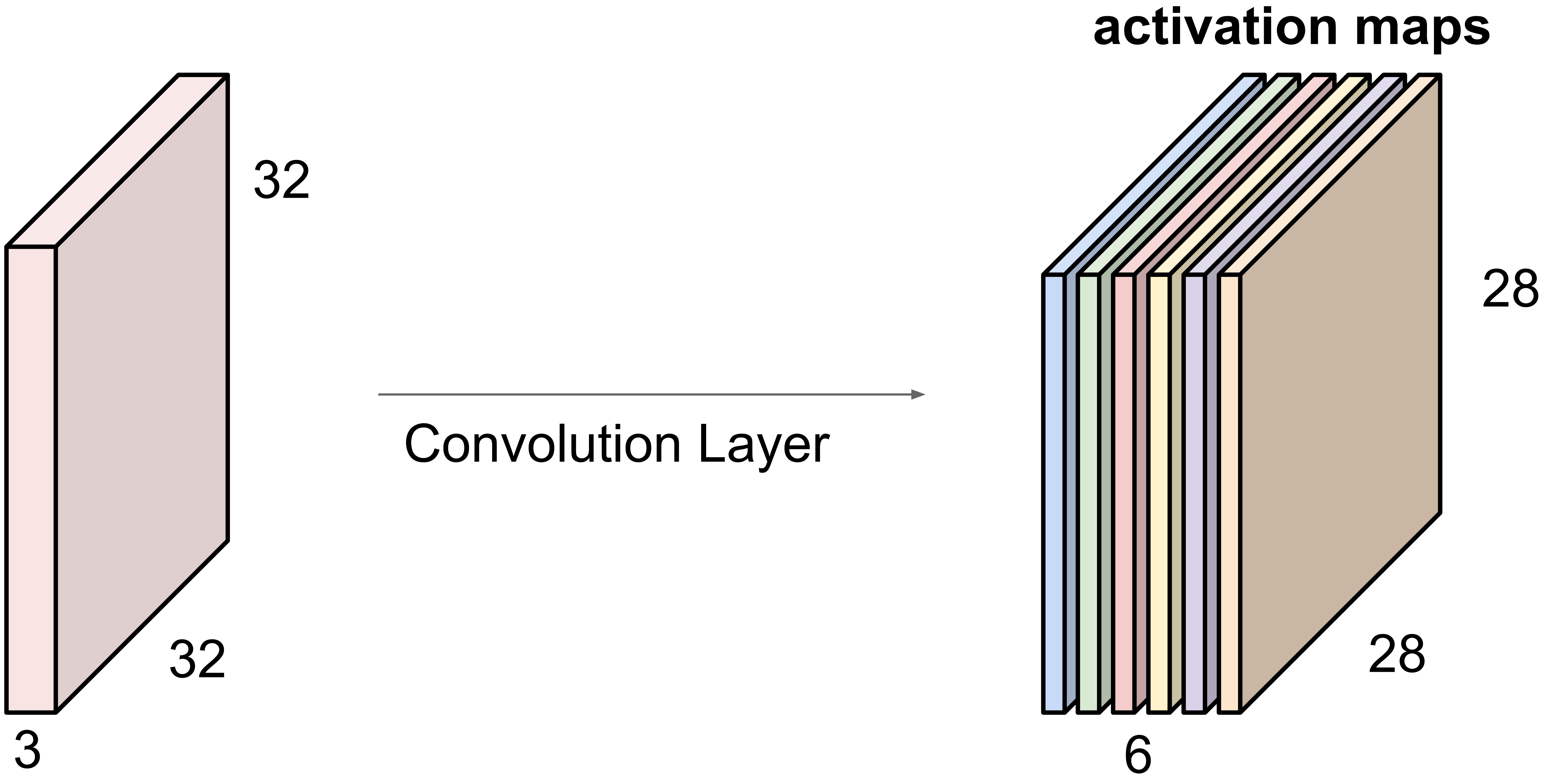
Activation map dimension =
Input image dimension - Filter dimension + 1

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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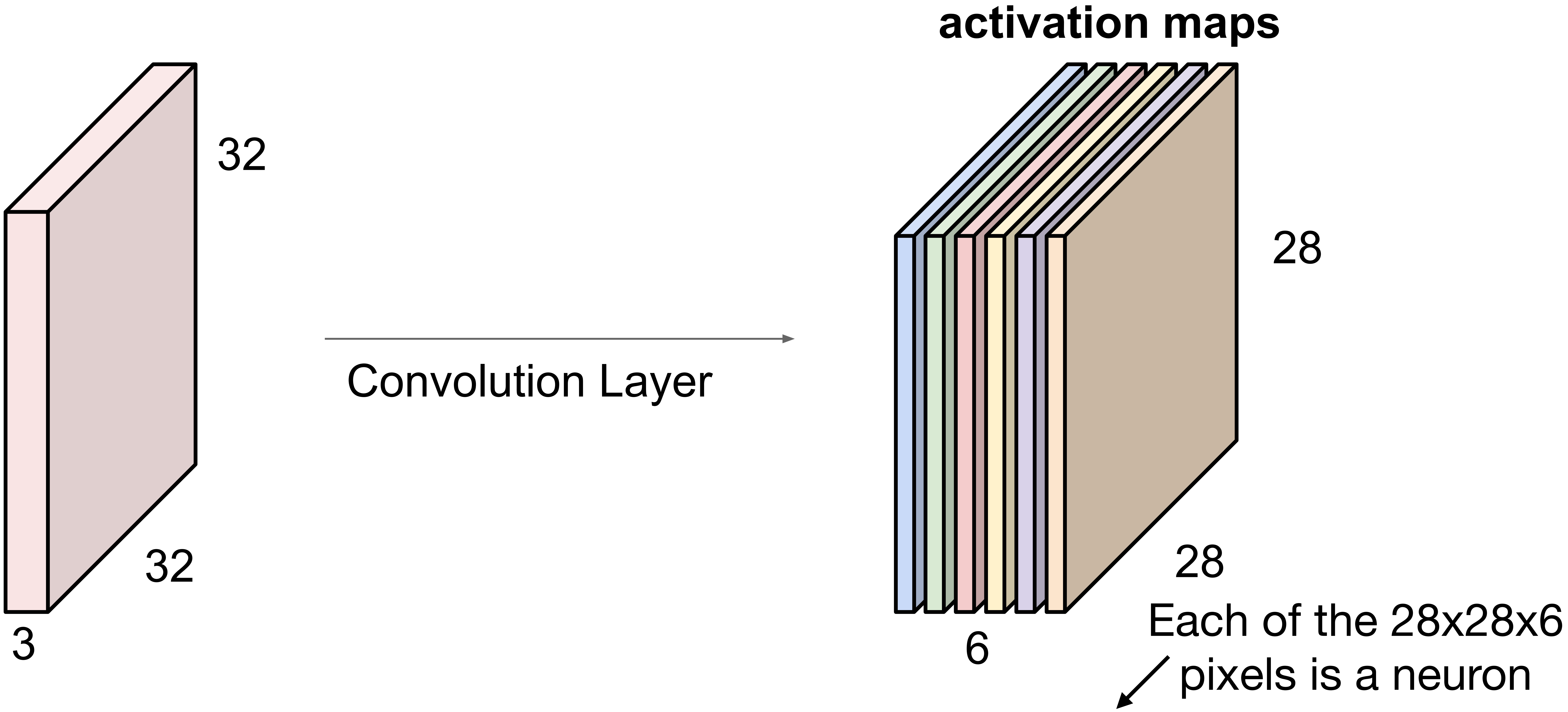

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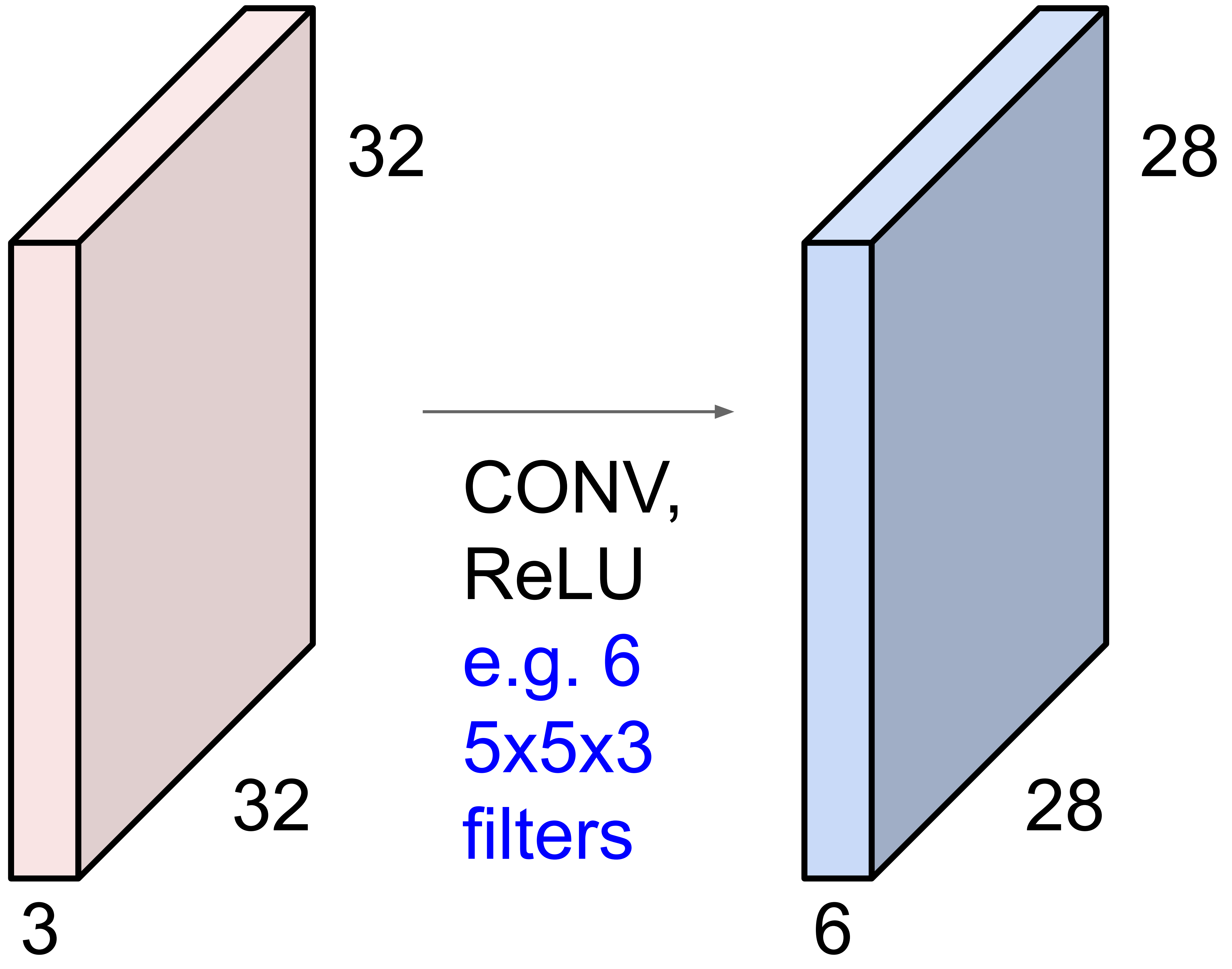
Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



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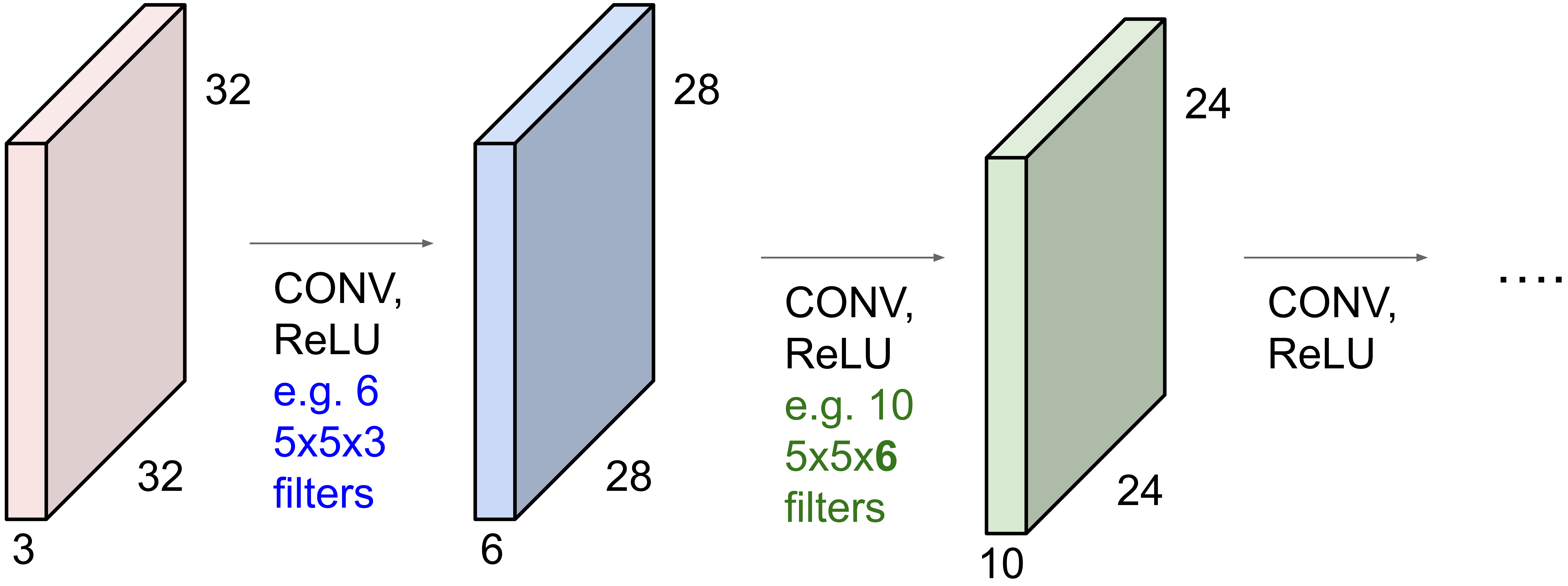

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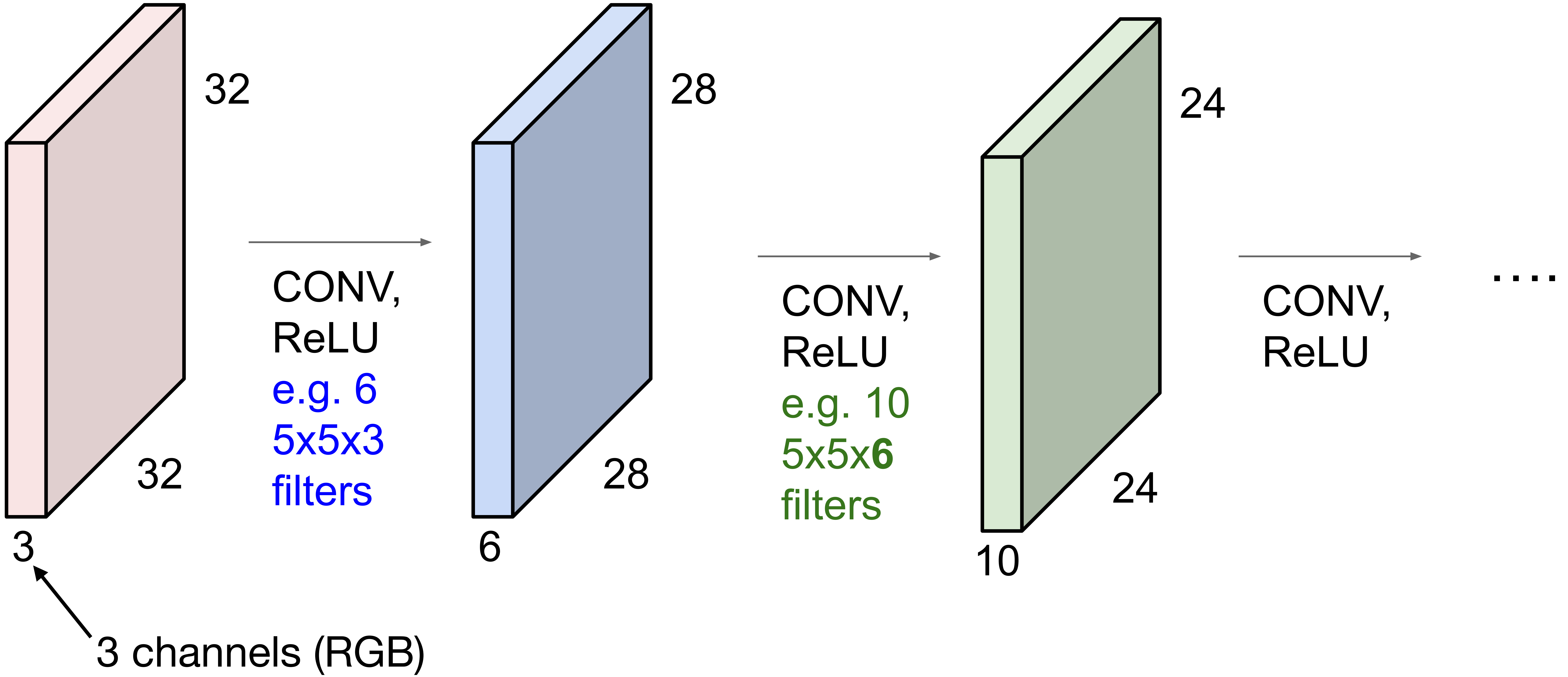

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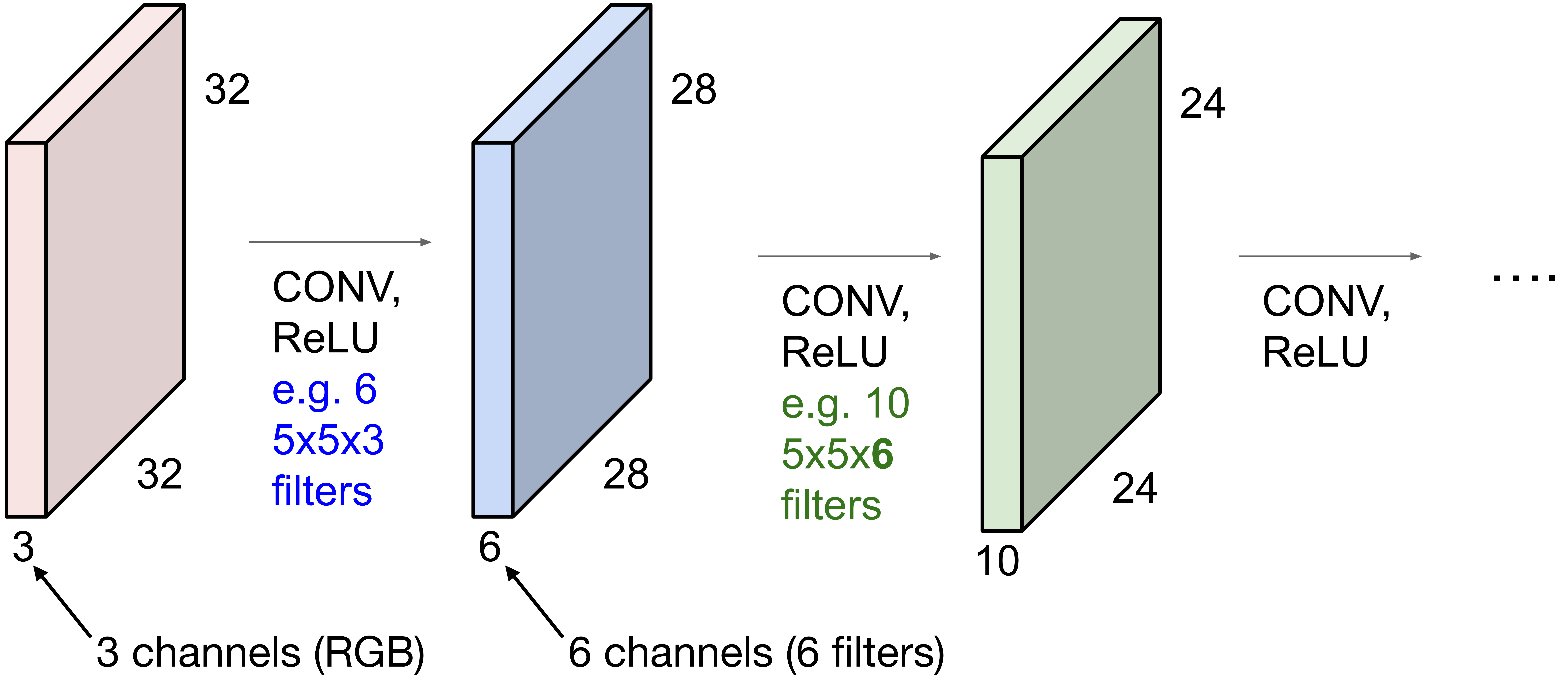

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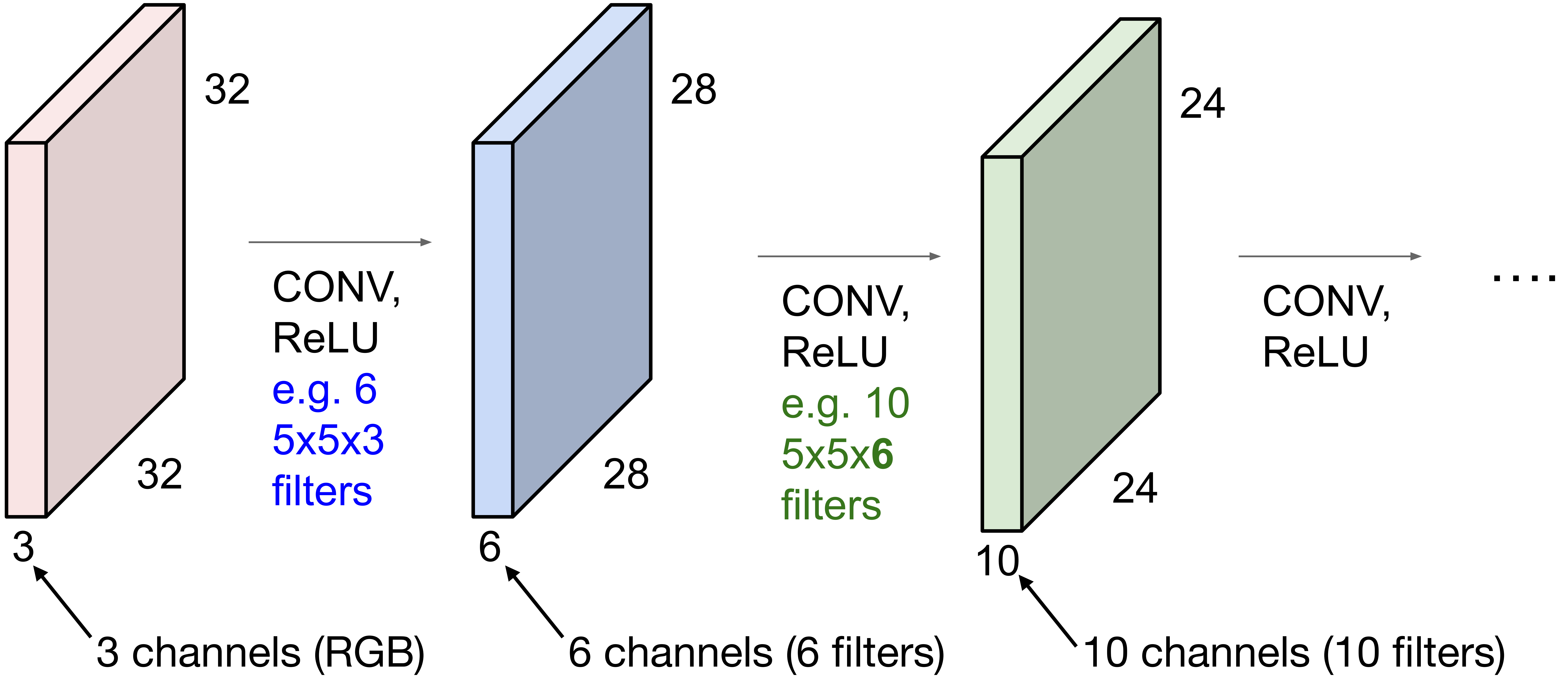
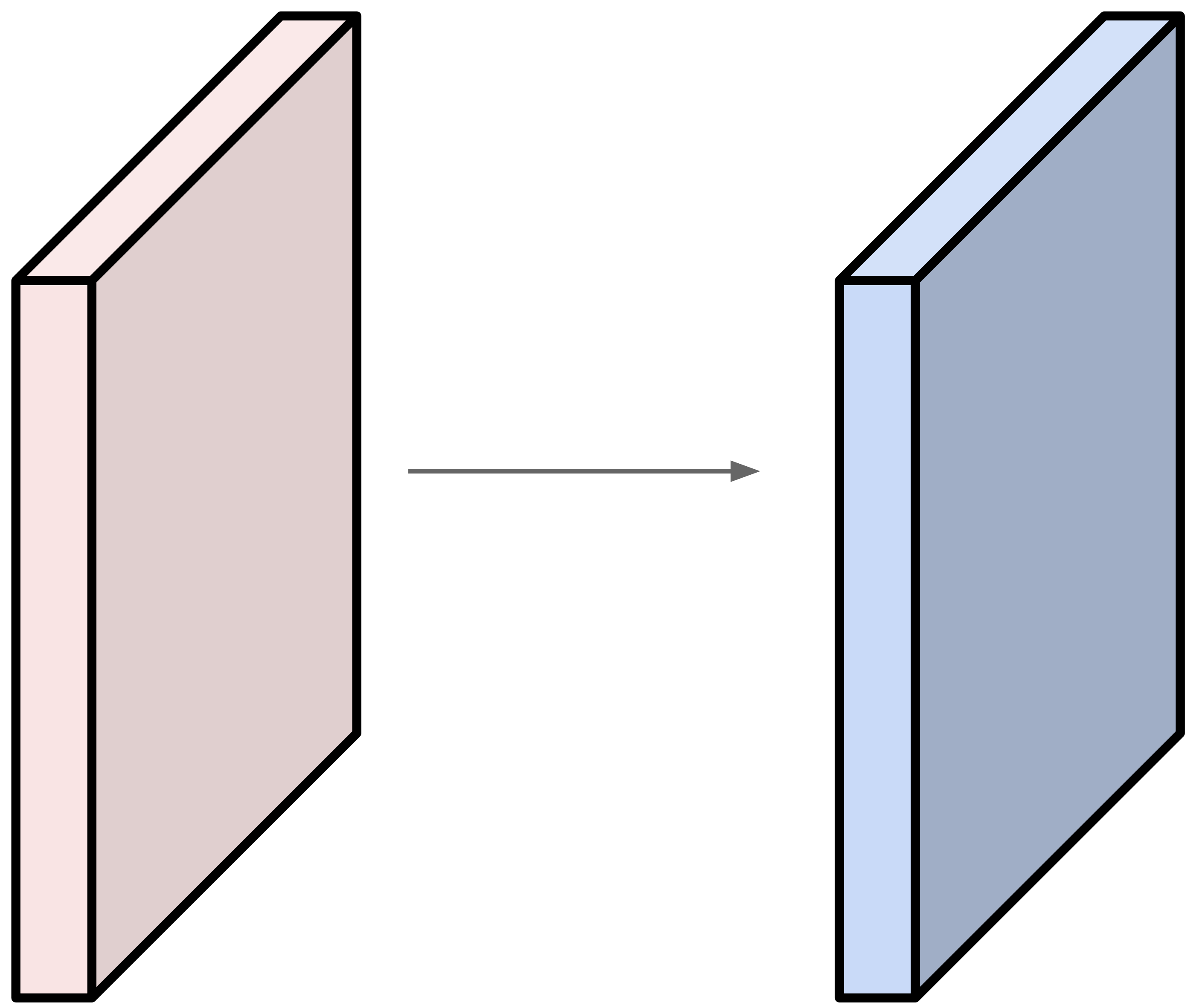
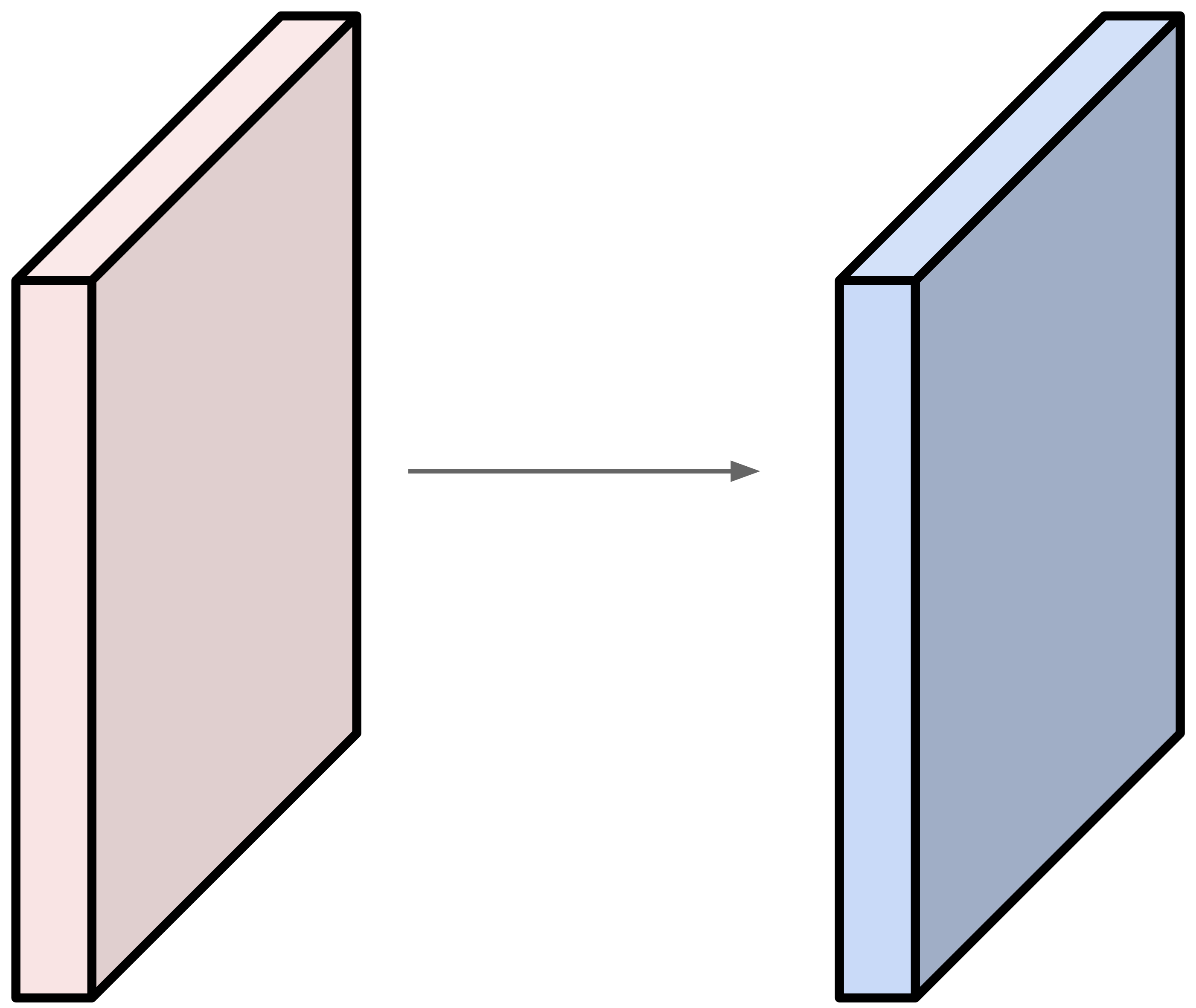


Input volume: **32x32x3**
10 5x5 filters

Number of parameters in this layer?





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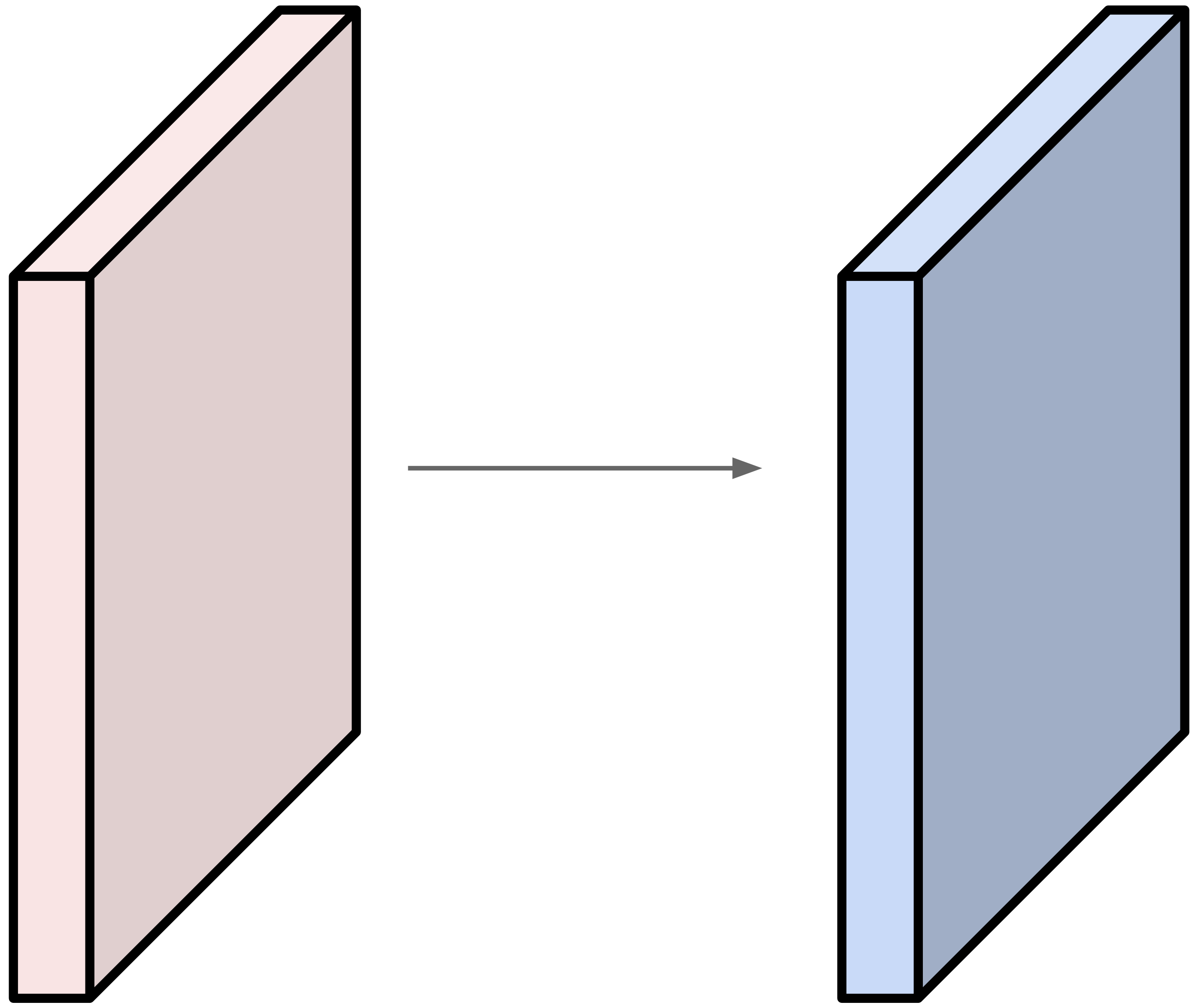
=> 76*10 = **760**



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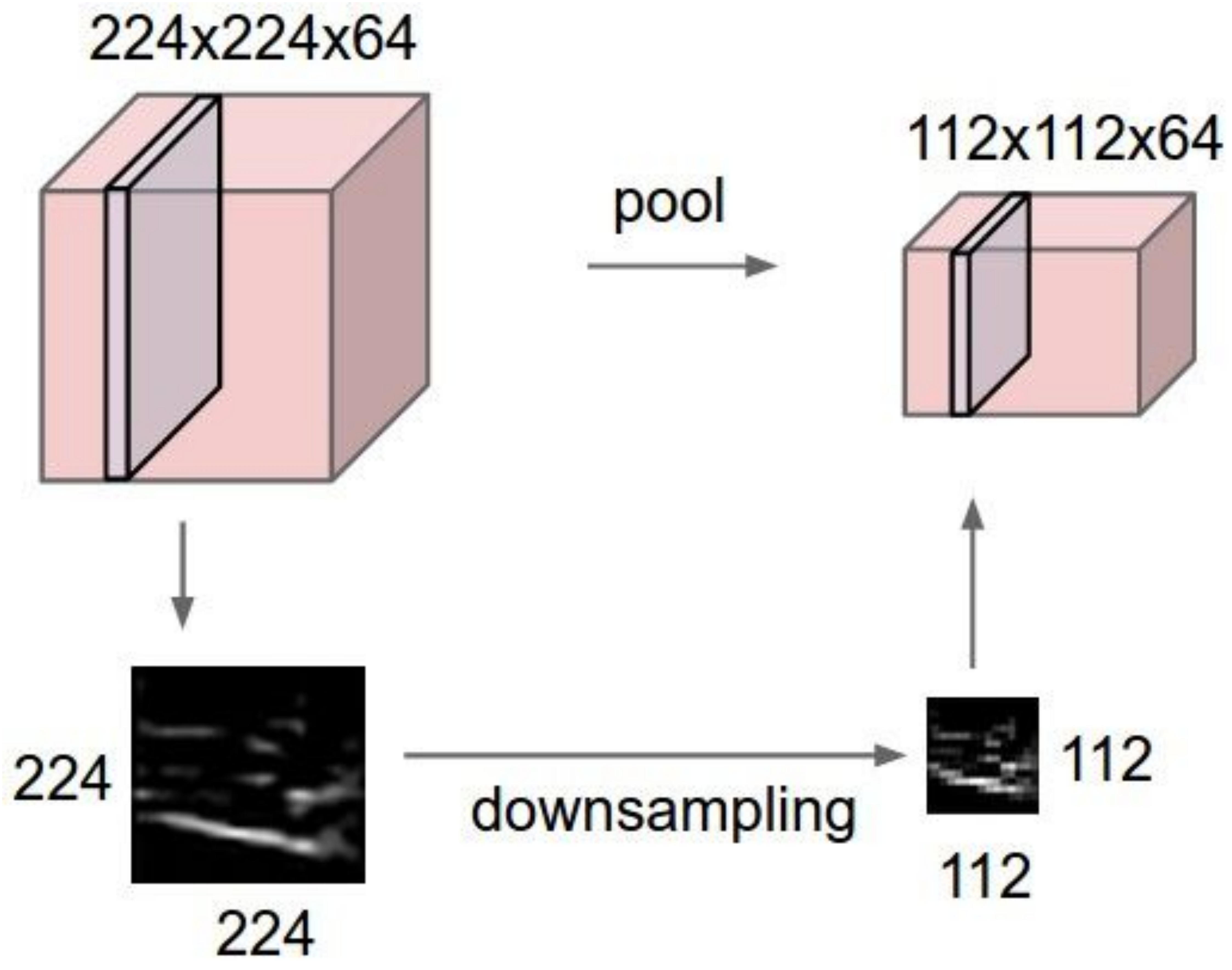
In general, parameters in conv layer =

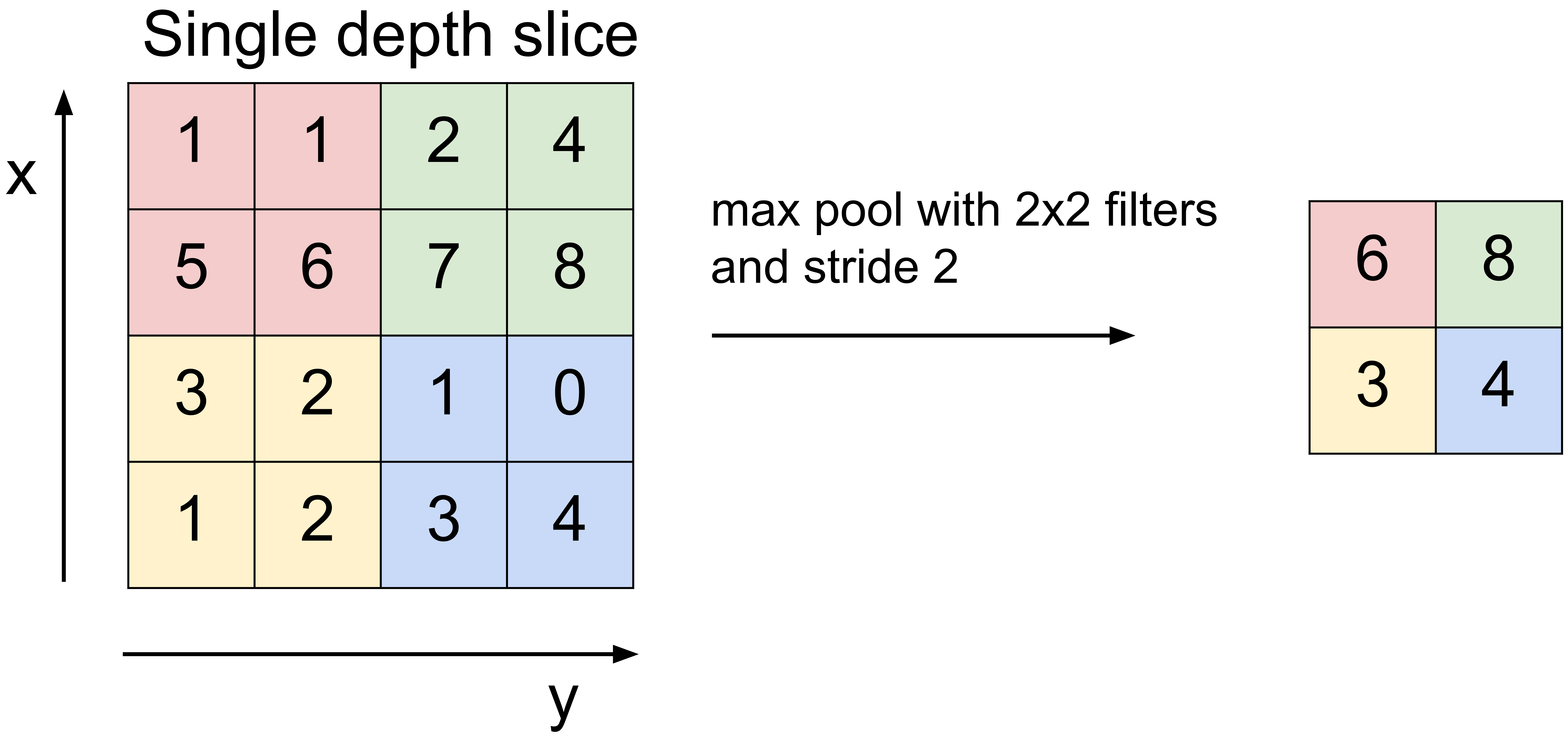
(filter width x filter height x input channels + 1) x number of filters.

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
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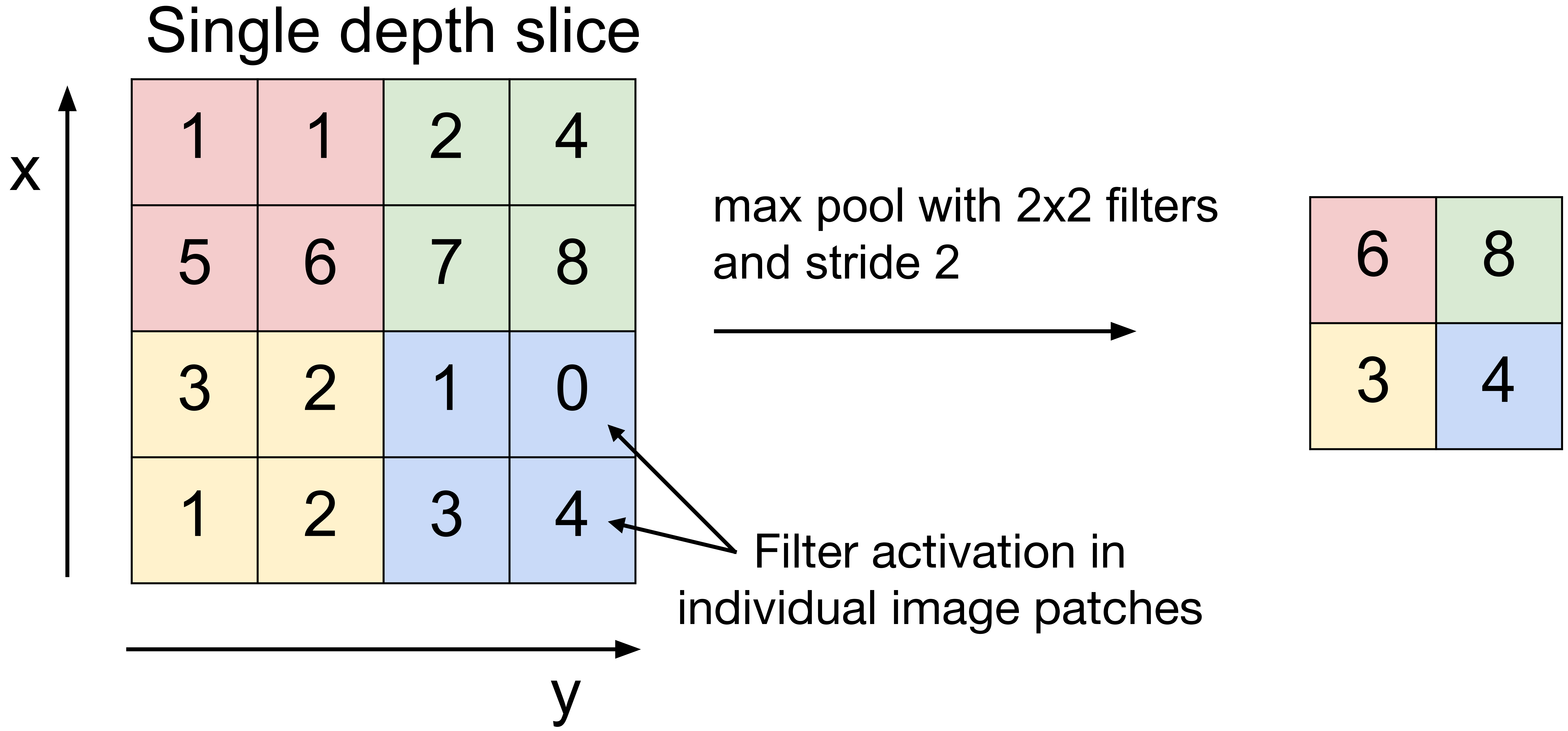
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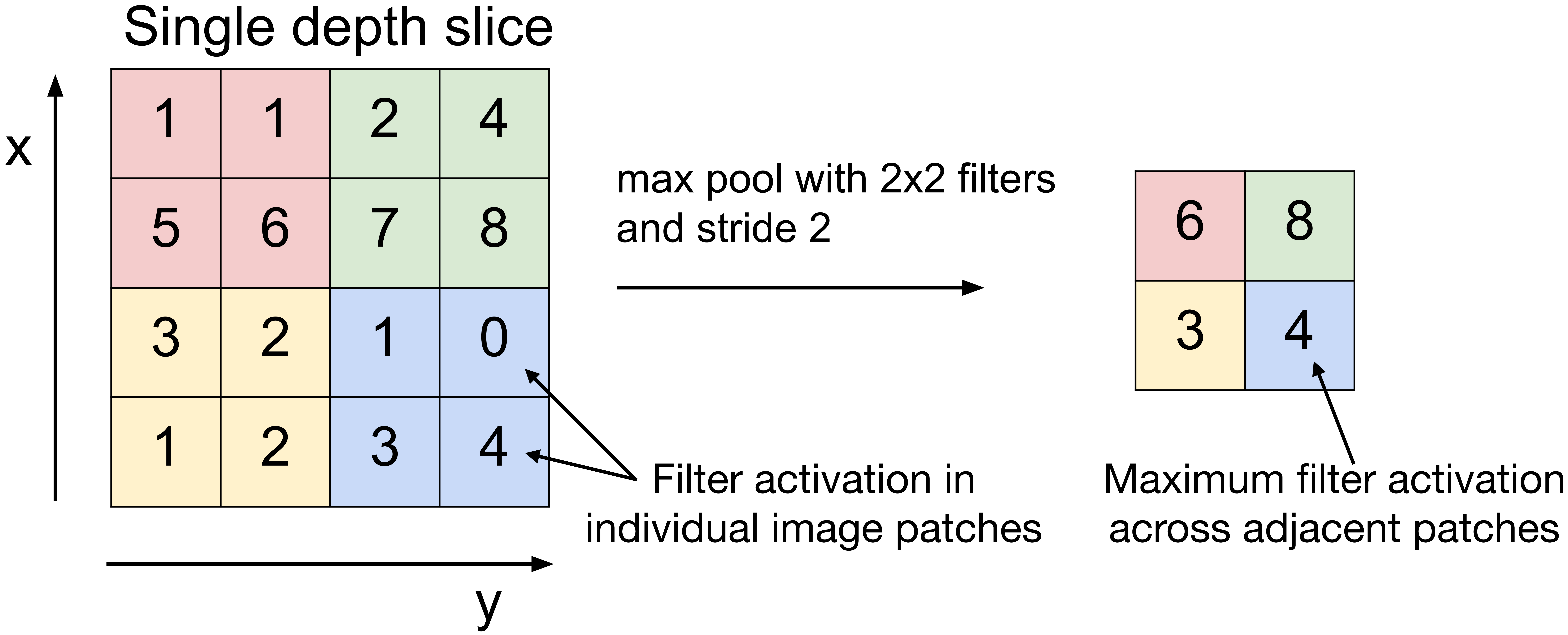
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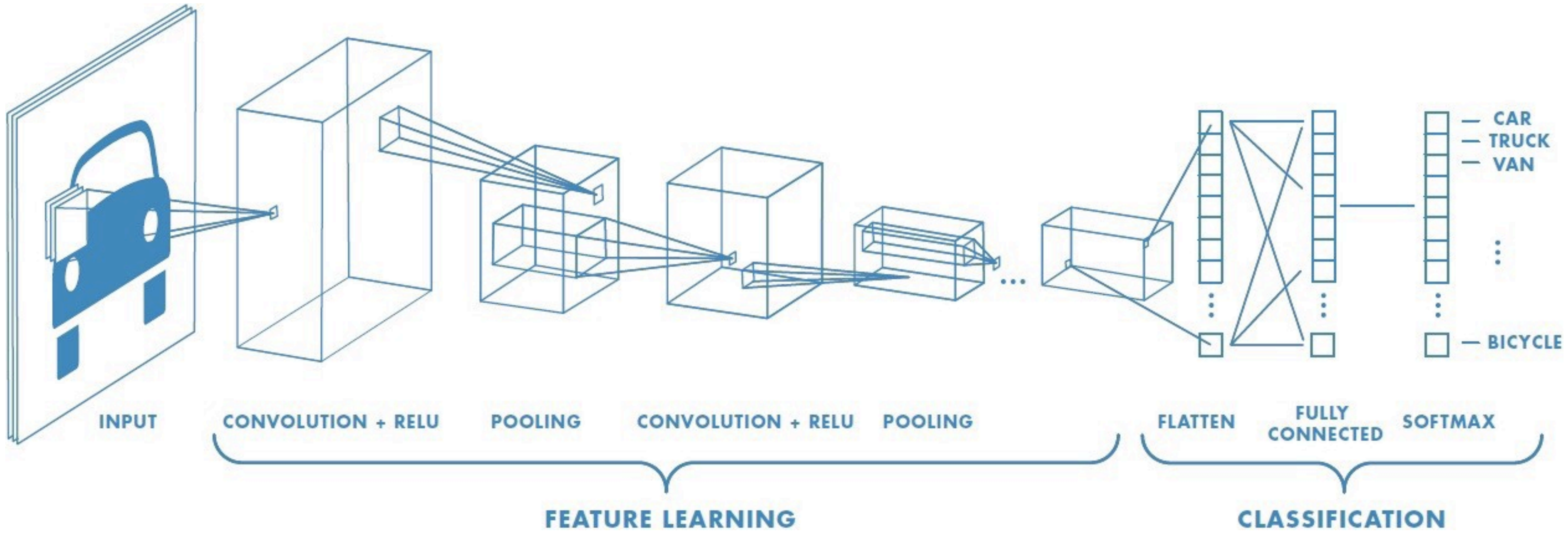
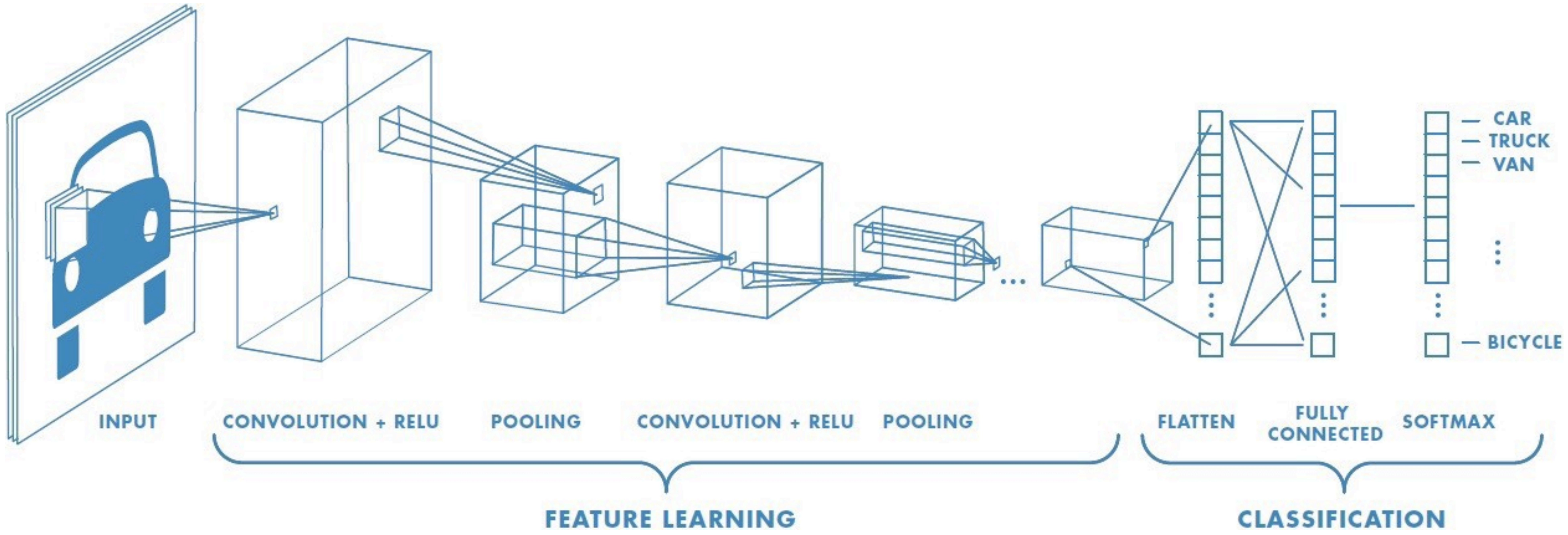
3 4
Filter activation in
individual image patches
Maximum filter activation
across adjacent patches

Convolutional neural networks



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

Convolutional neural networks



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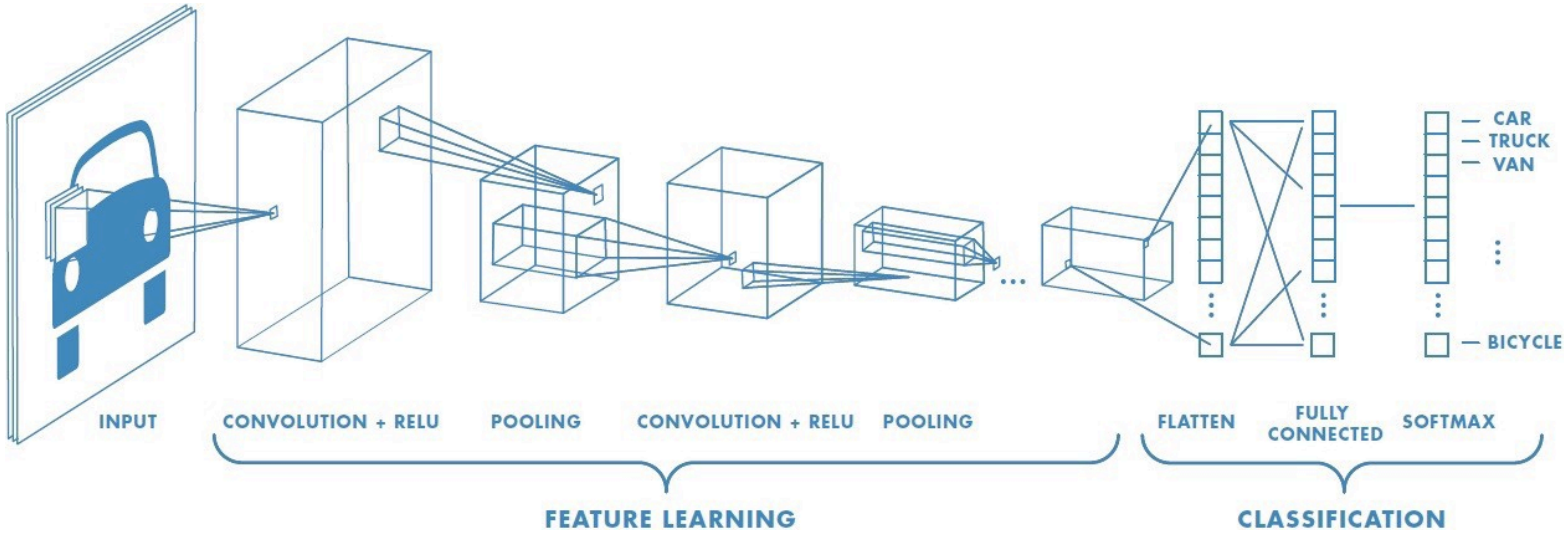
A CNN stacks together several alternating convolution and pooling layers, followed by a fully connected layer and a softmax output.

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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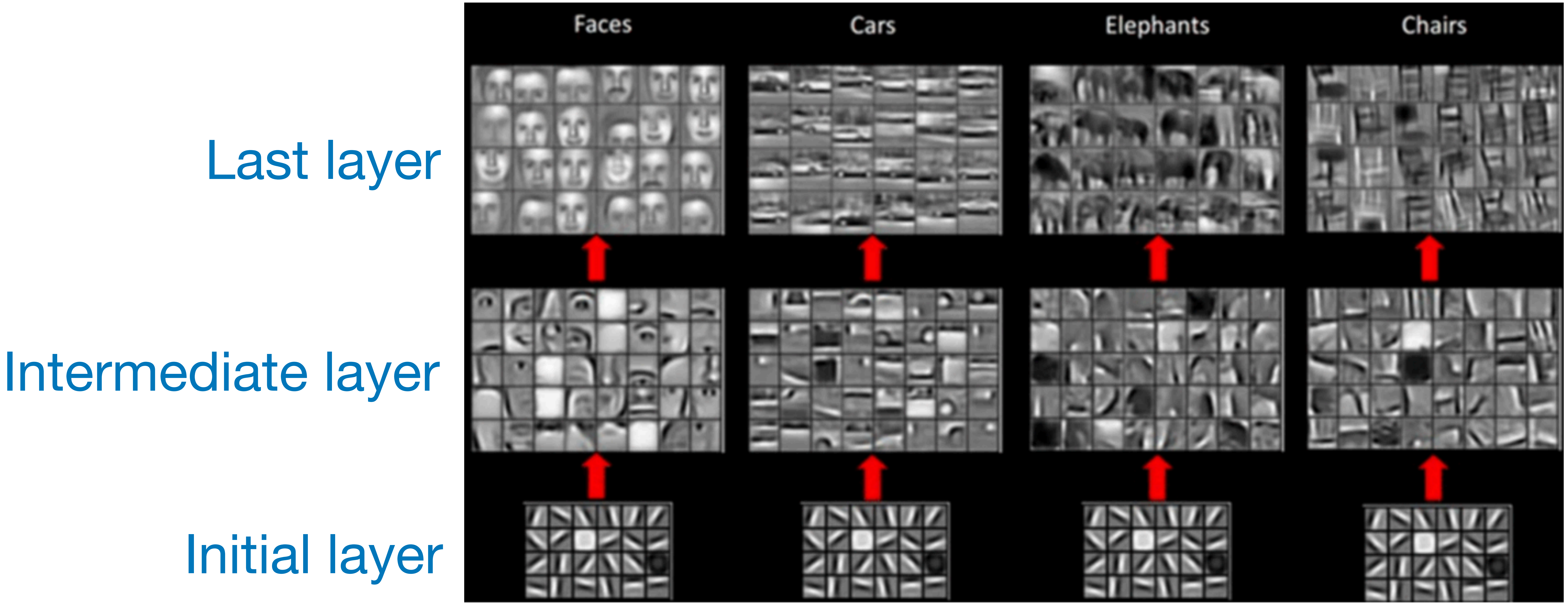

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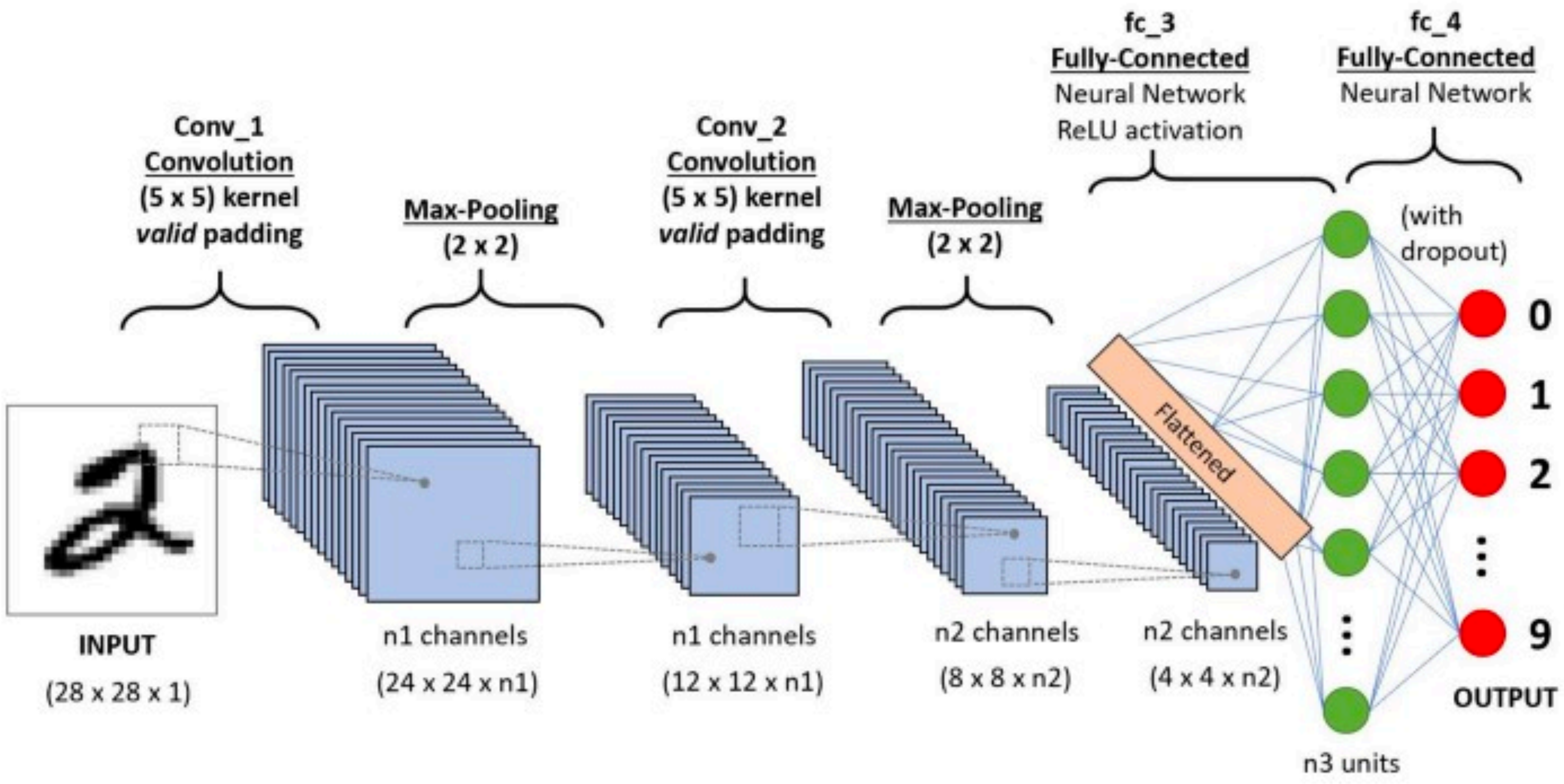

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Yann LeCun

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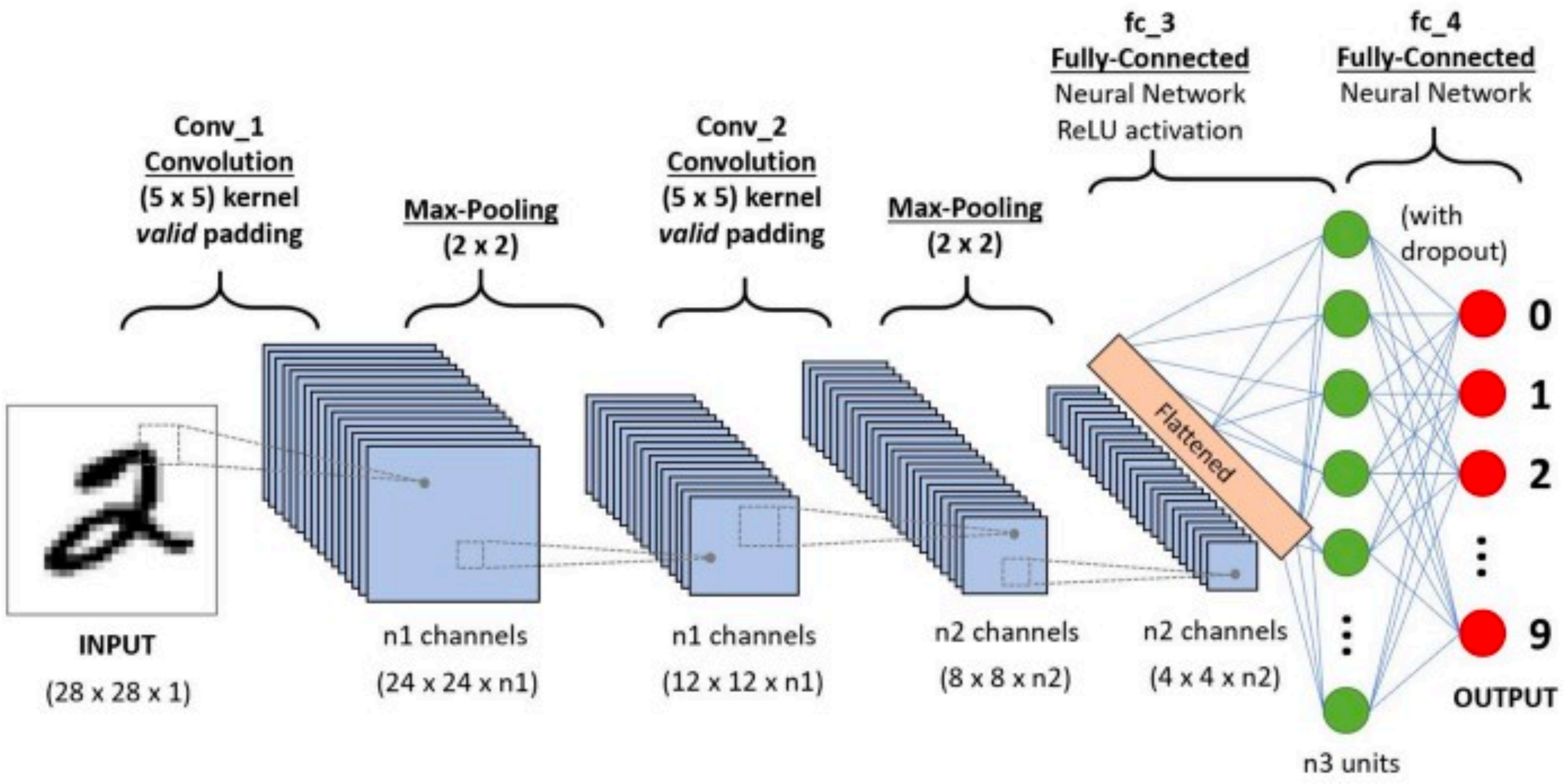
Idea existed decades ago but data and computing power only became available in 2010s.



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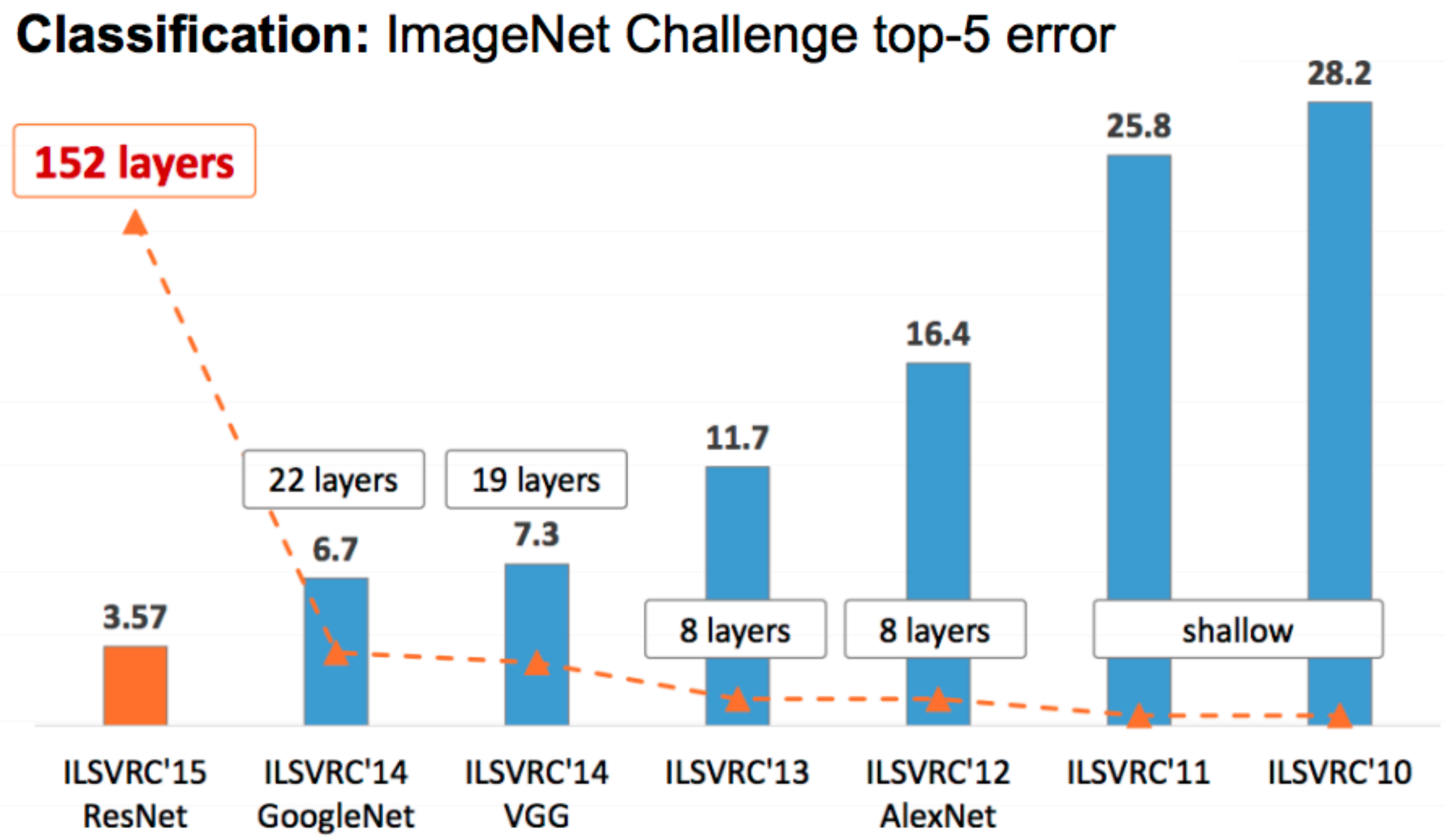
Yann LeCun

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
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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
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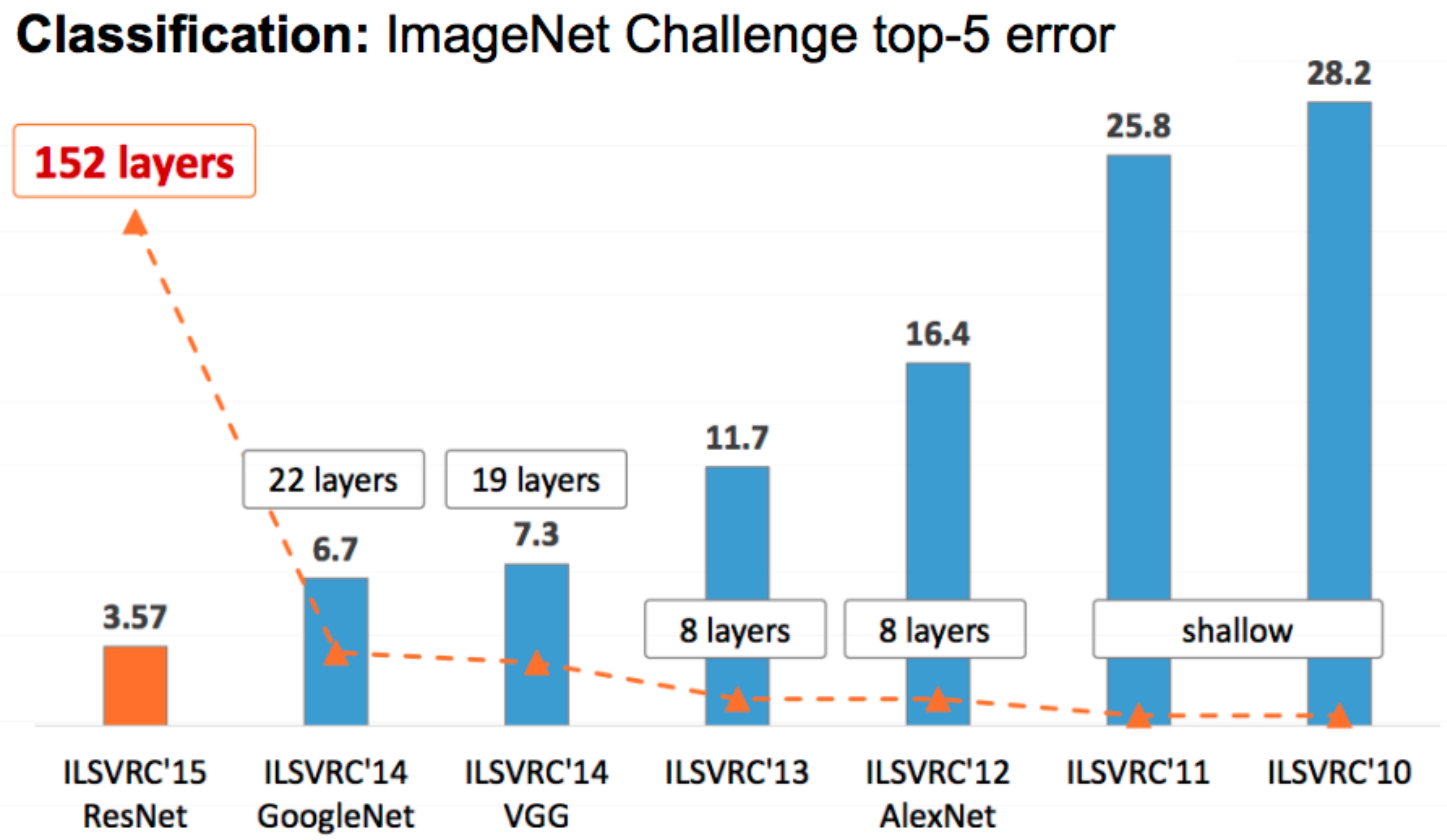

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CNNs are getting progressively deeper with time.

Other applications of CNNs

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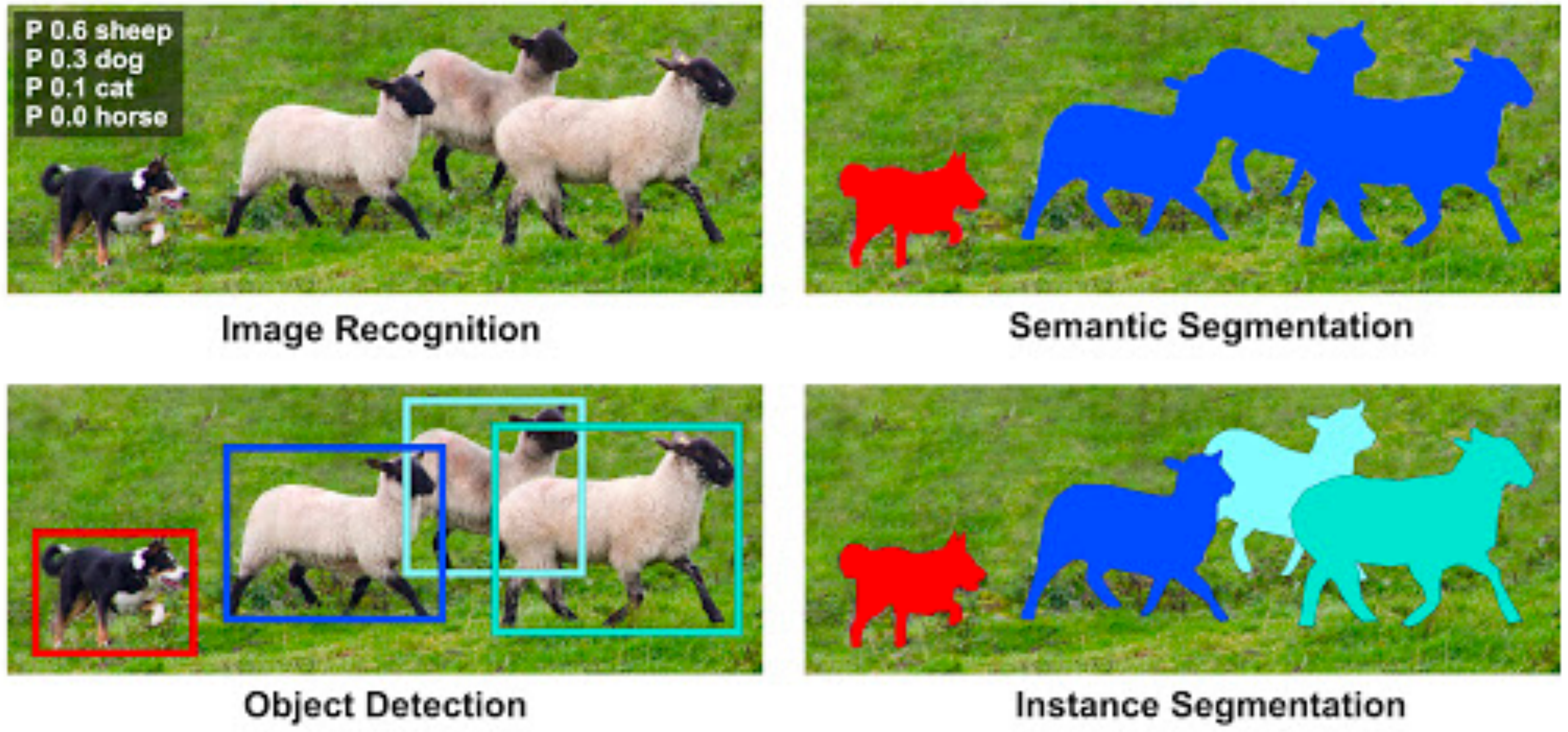

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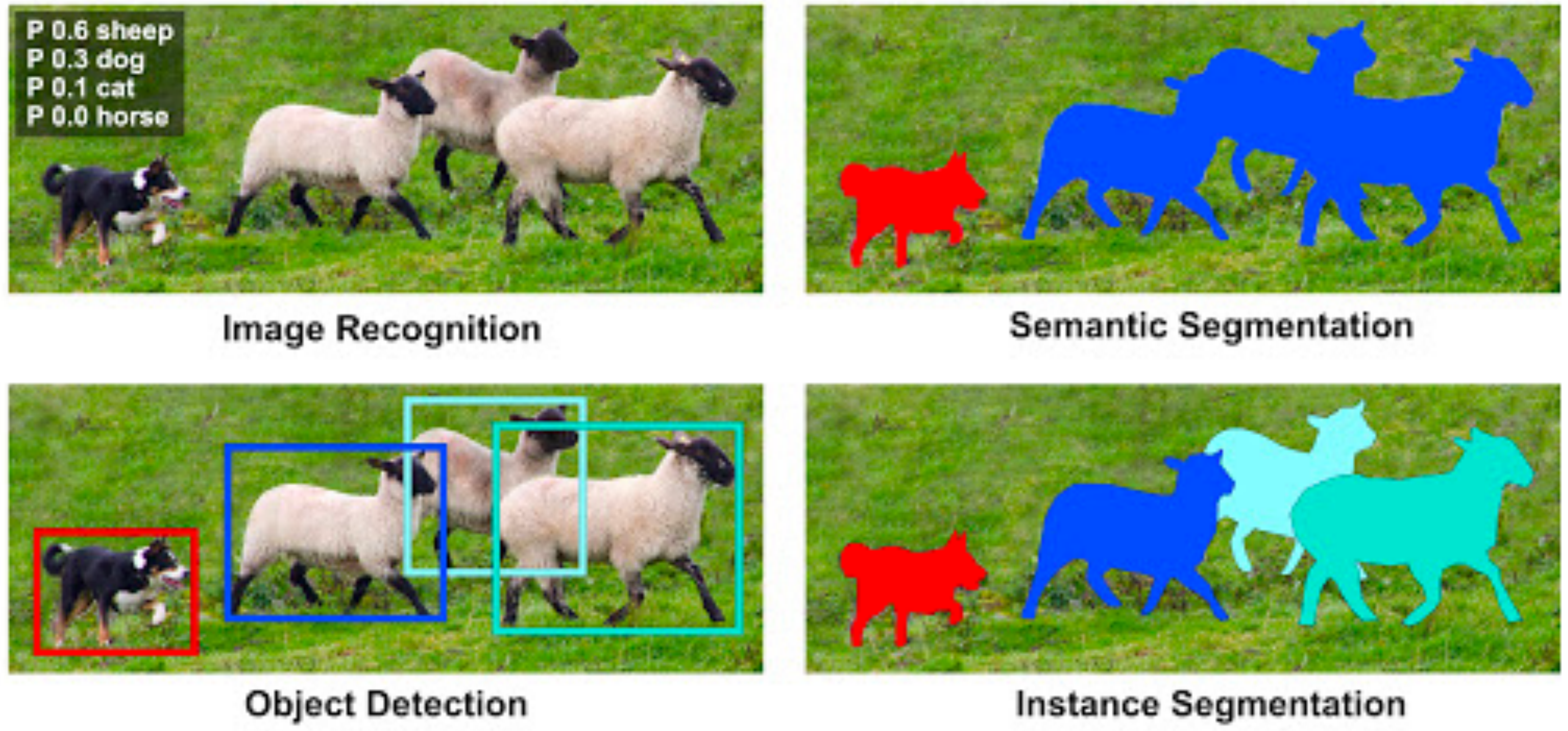

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content image | **style image** | **generated image**

Ancient city of Persepolis

+

The Starry Night (Van Gogh)

=

Persepolis
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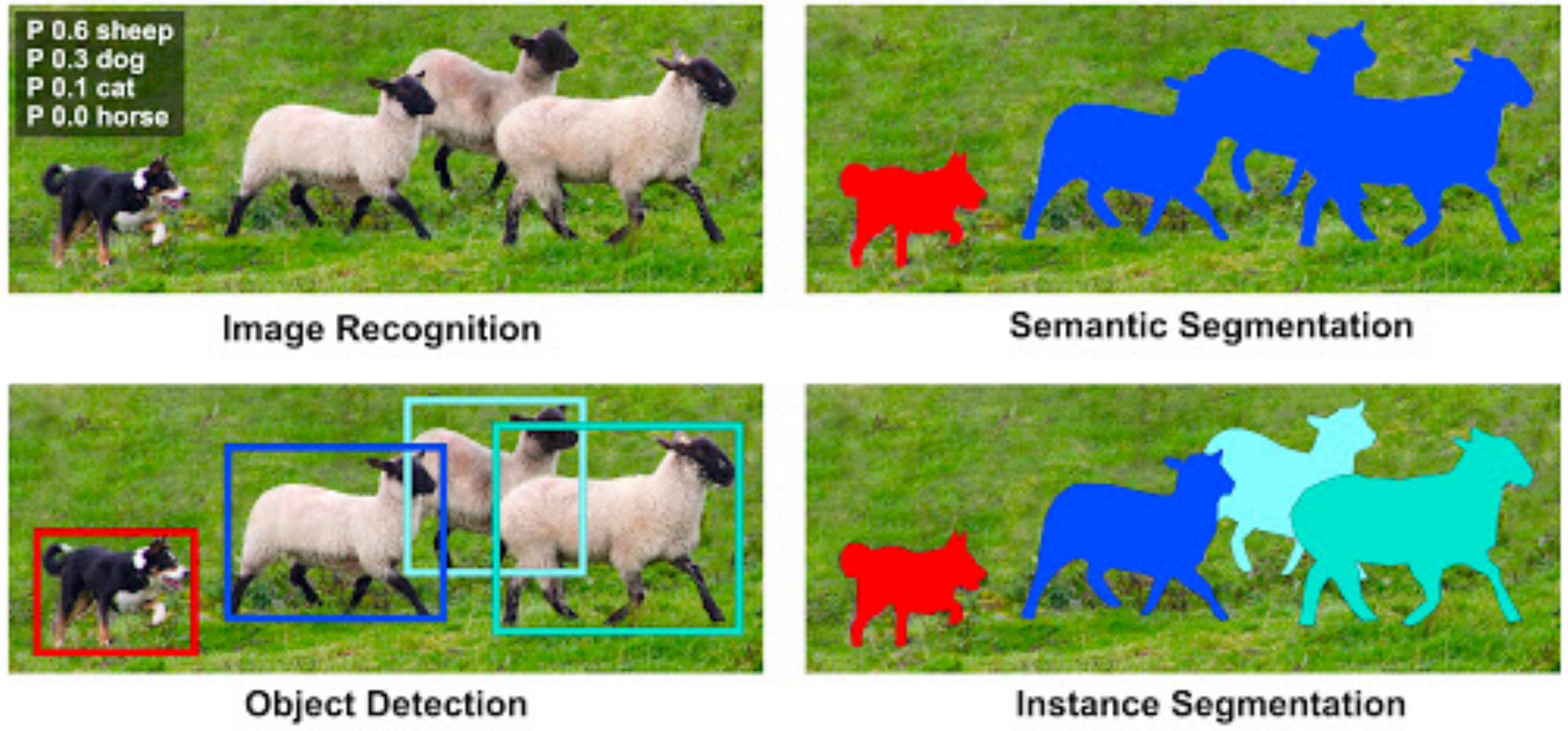
Style Transfer

Other applications of CNNs



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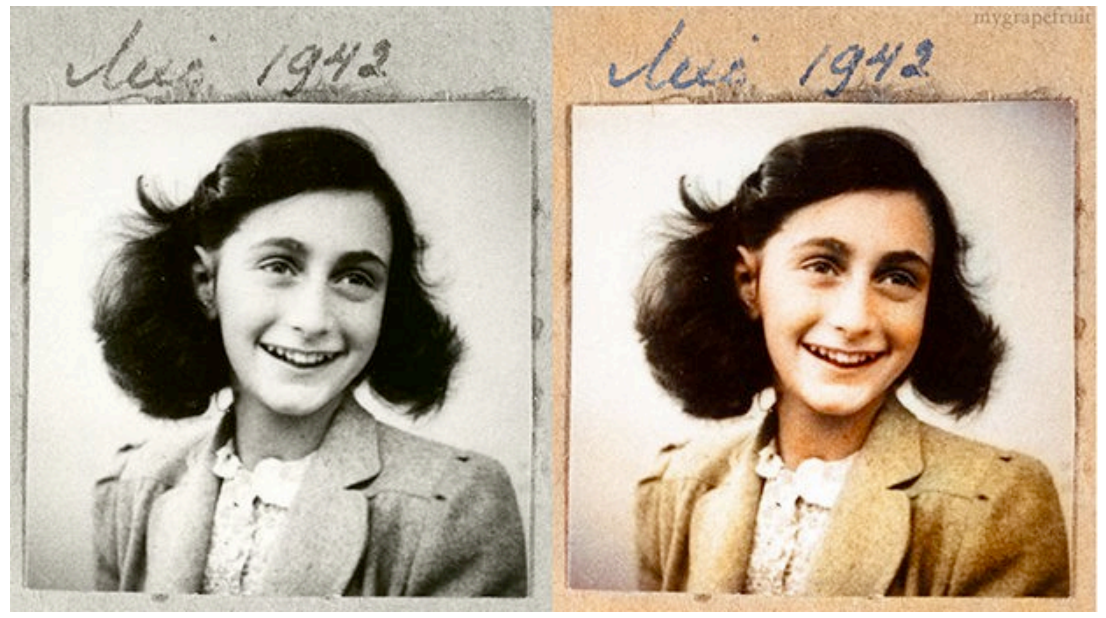

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Image colorization

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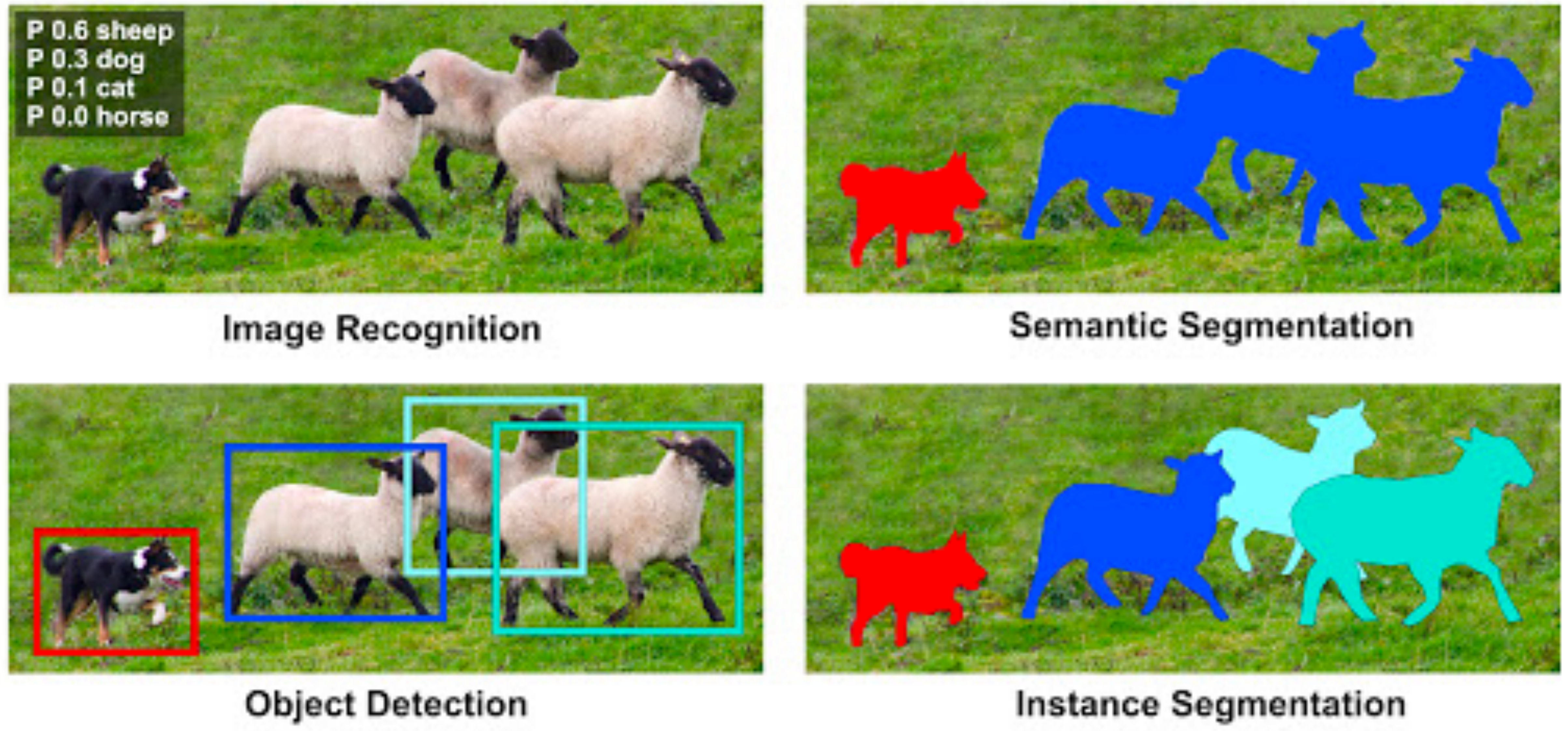

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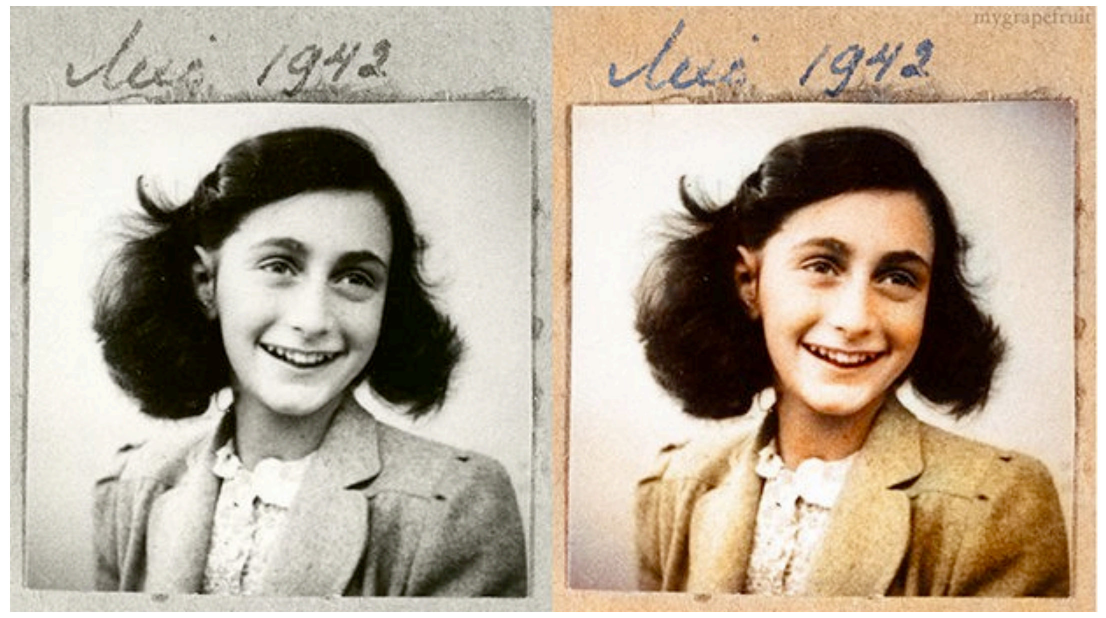

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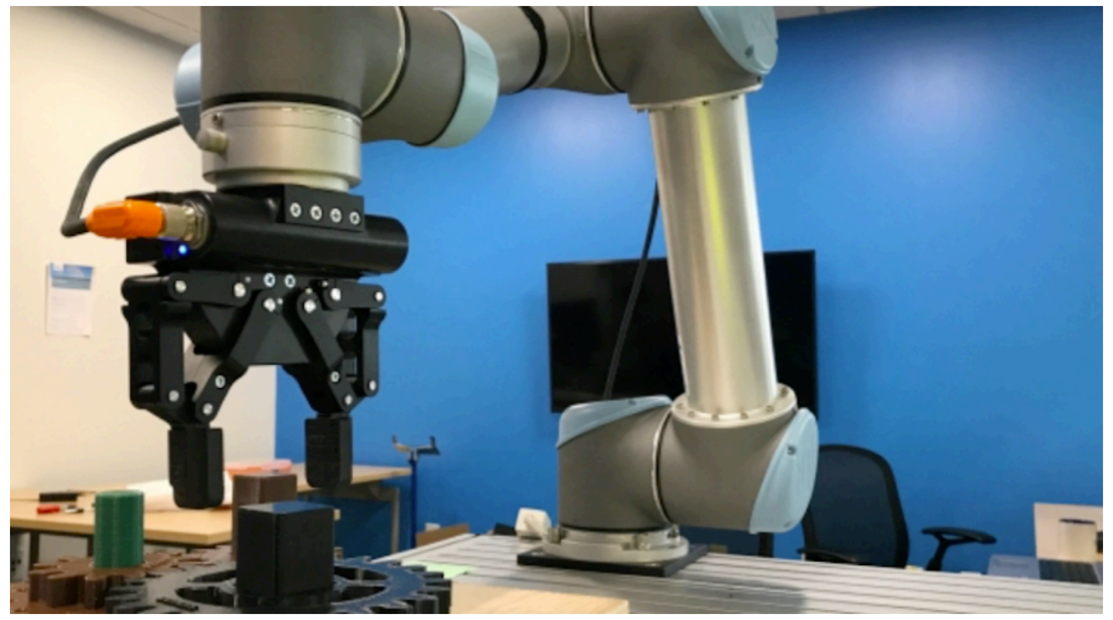

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Reinforcement learning

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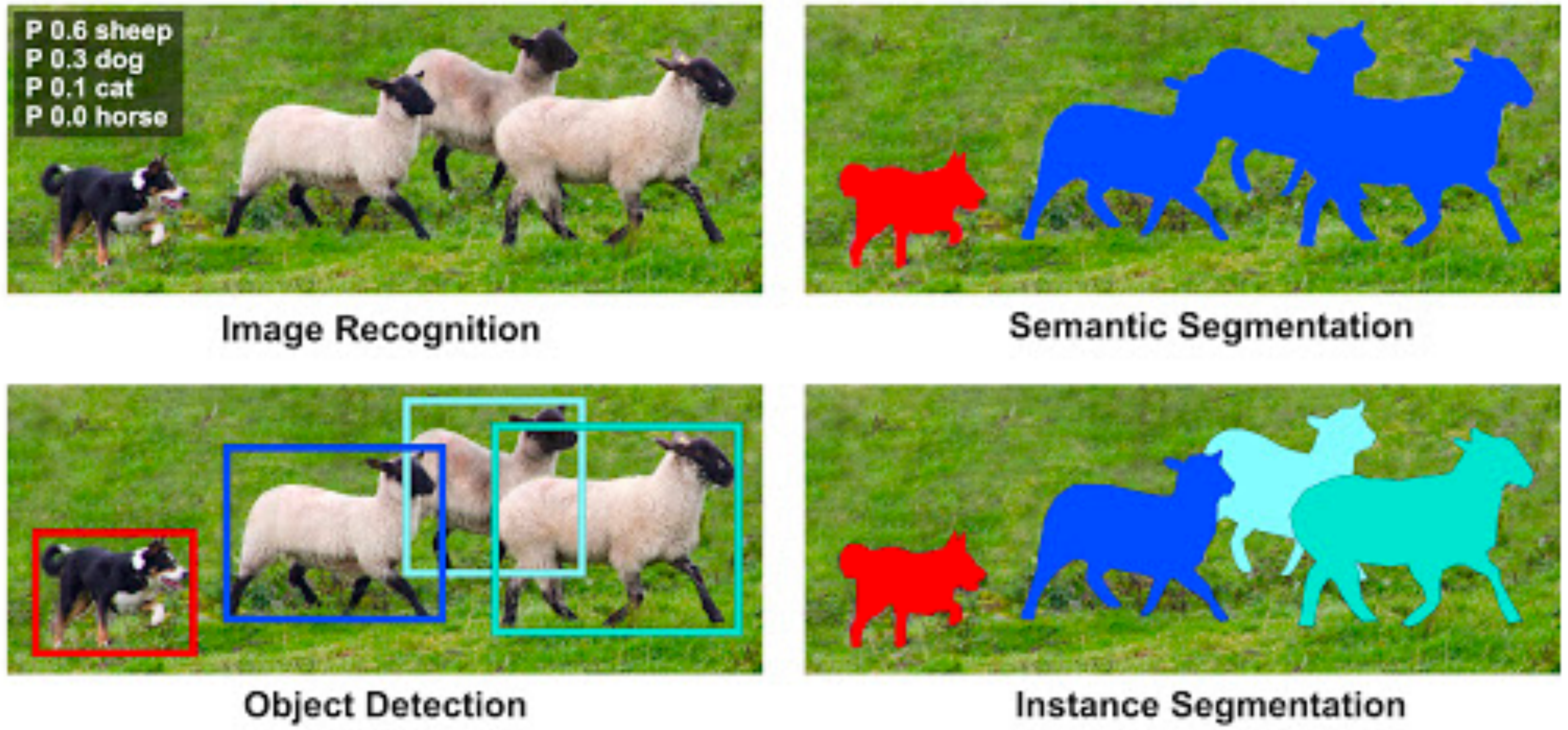

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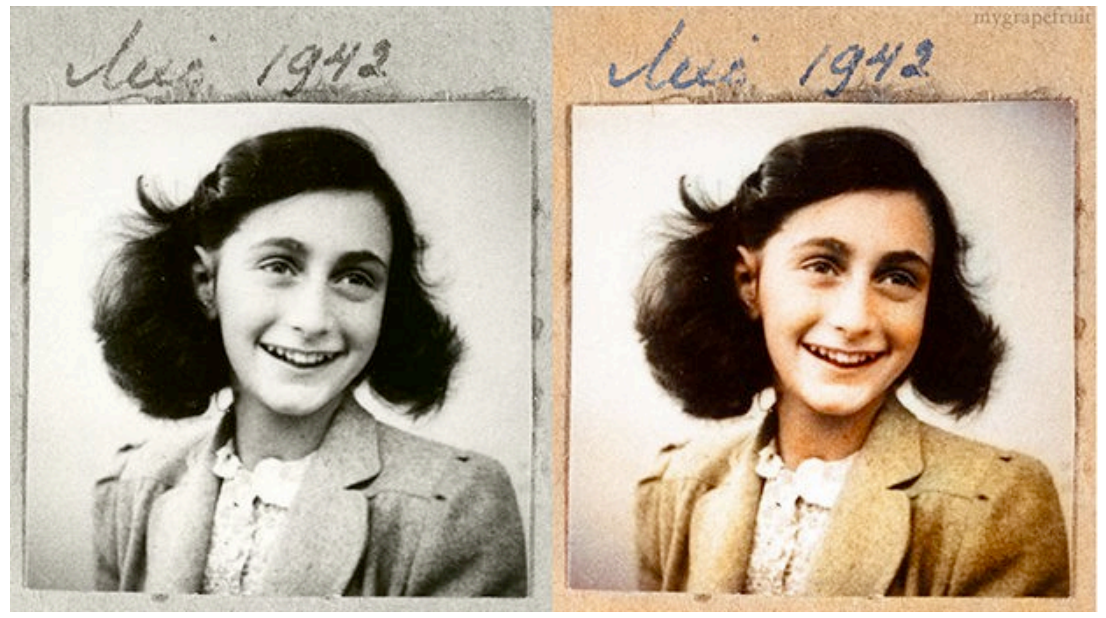

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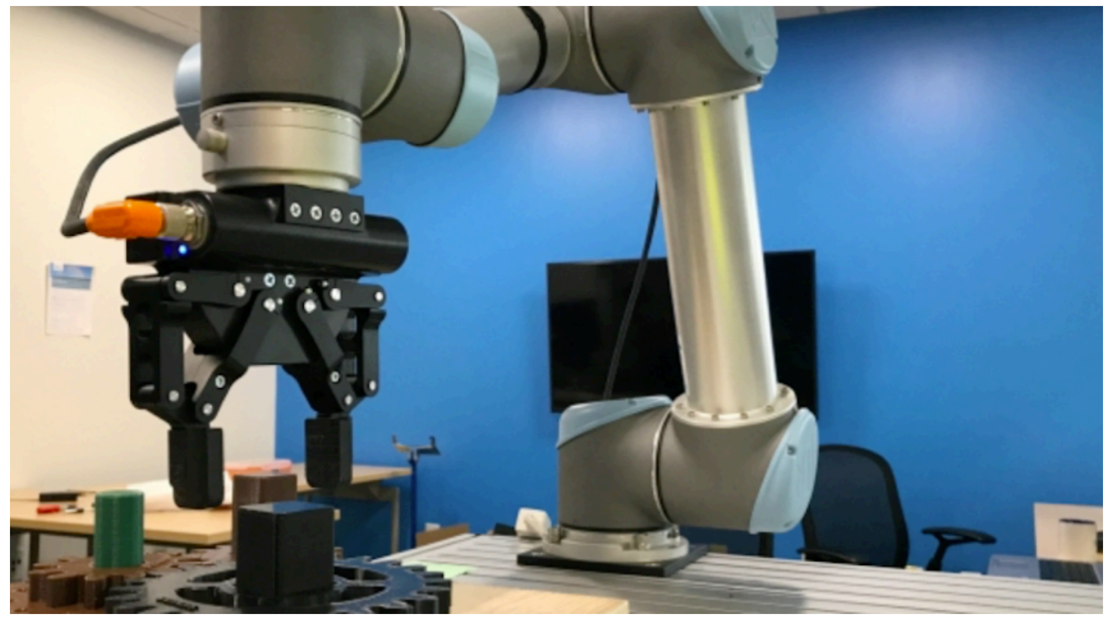

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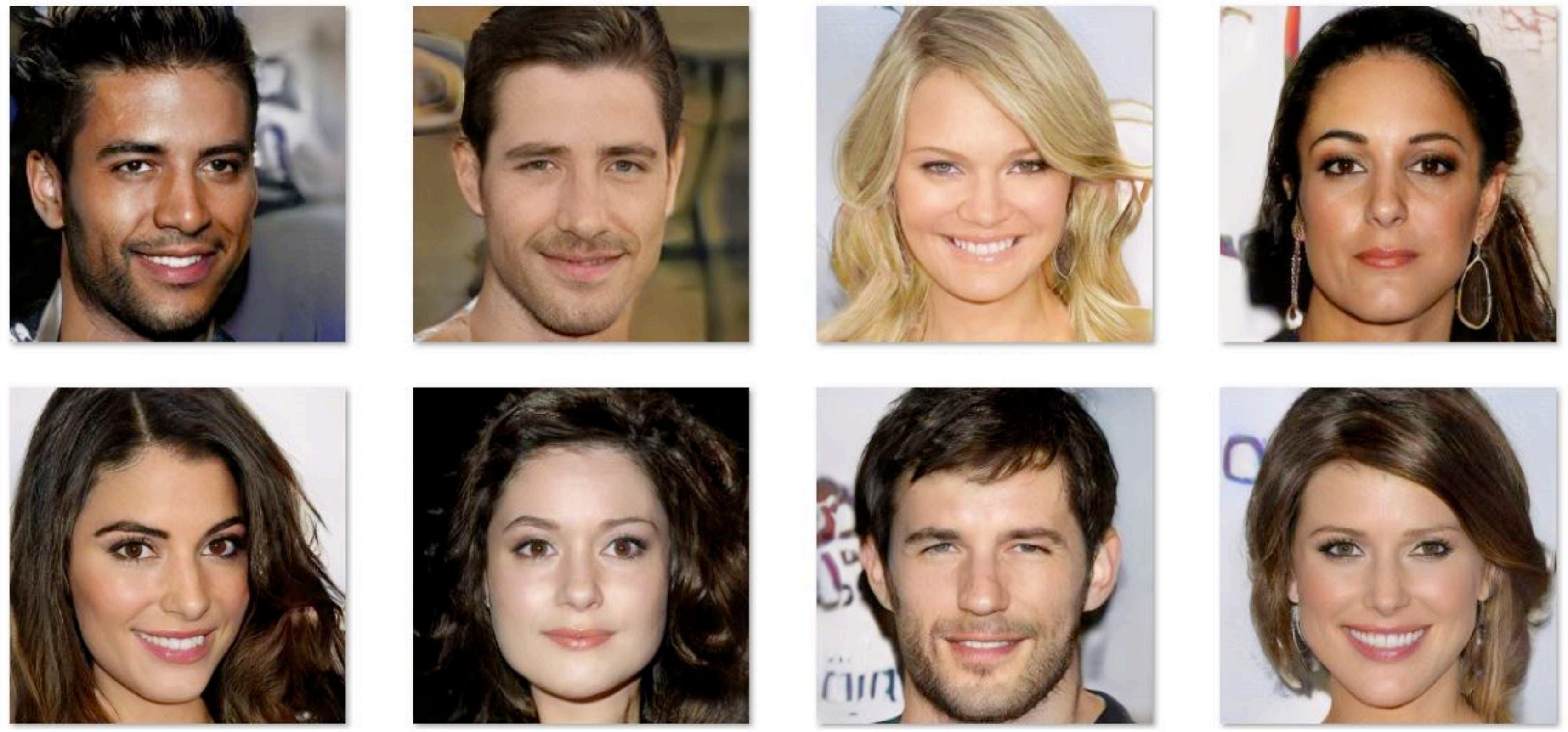

https://medium.datadriveninvestor.com/artificial-intelligence-gans-can-create-fake-celebrity-faces-44fe80d419f7

Generative models

Summary

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