Convolutional Neural Network

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ChatGPT 4.0

Disclaimer

Adopted from

6.390

Introduction to Machine Learning
(Fall 2024)

https://introml.mit.edu/fall24

Outline

- Recap, fully-connected net
- Vision problem structure
- Convolutional network structure
- Convolution
  - 1-dimensional and 2-dimensional *convolution*
  - 3-dimensional *tensors*
- Max pooling
- Case studies

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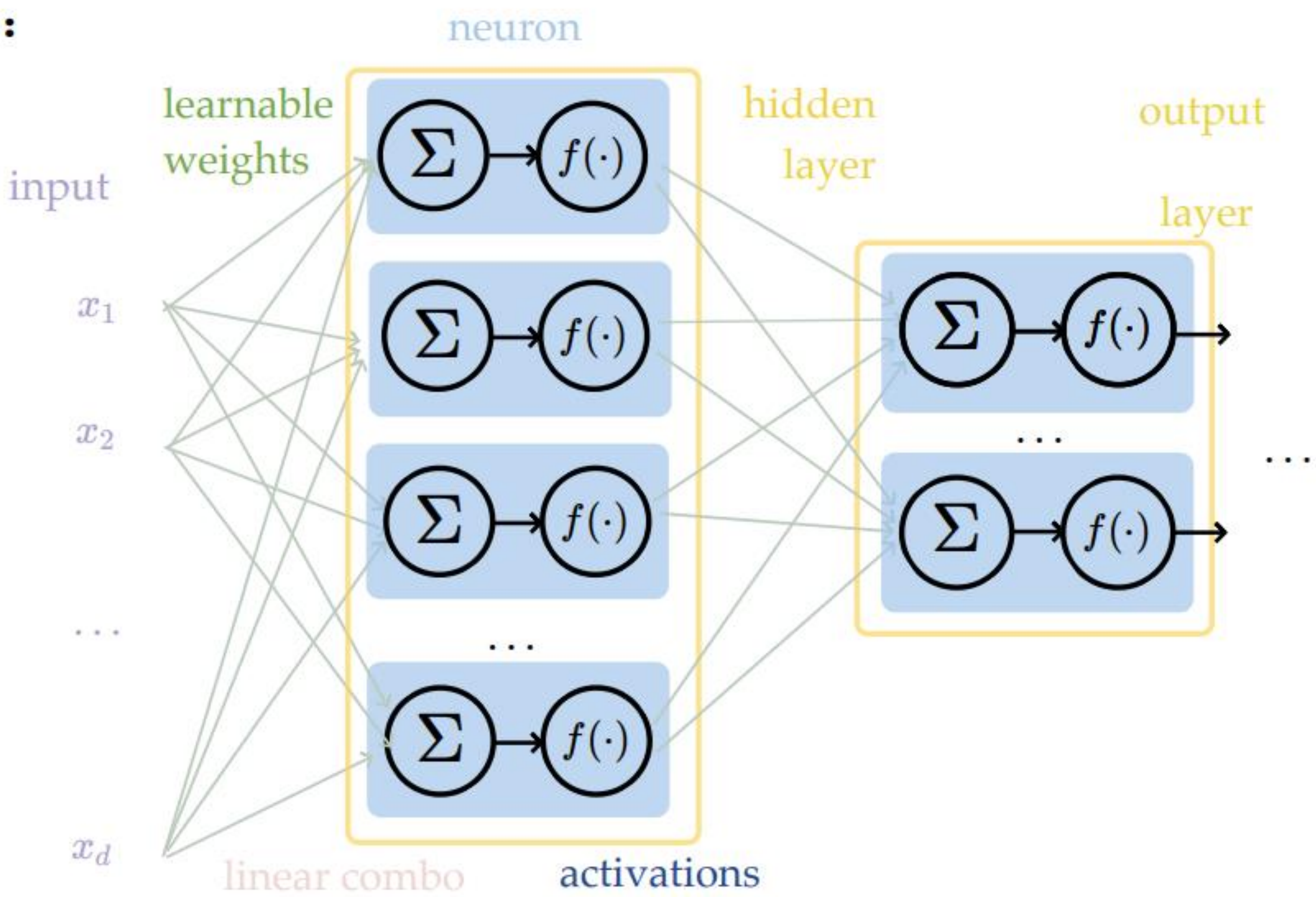
Recap:



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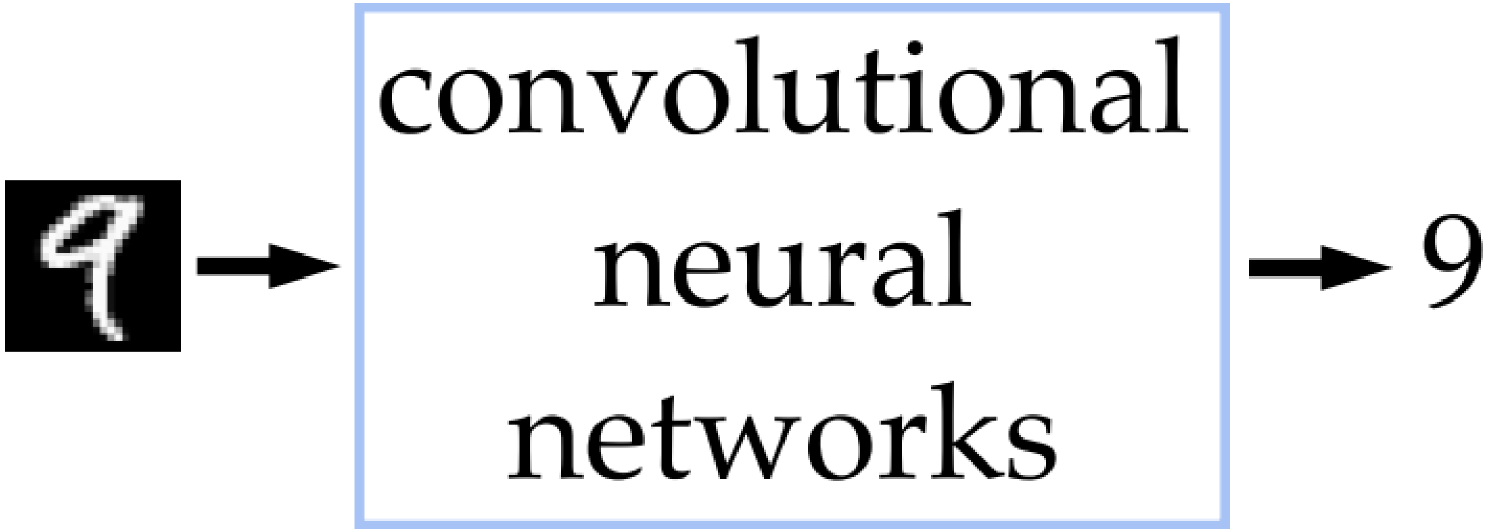

1. Why do we need a special network for images?
2. Why is CNN (the) special network for images?

Why do we need a special net for images?

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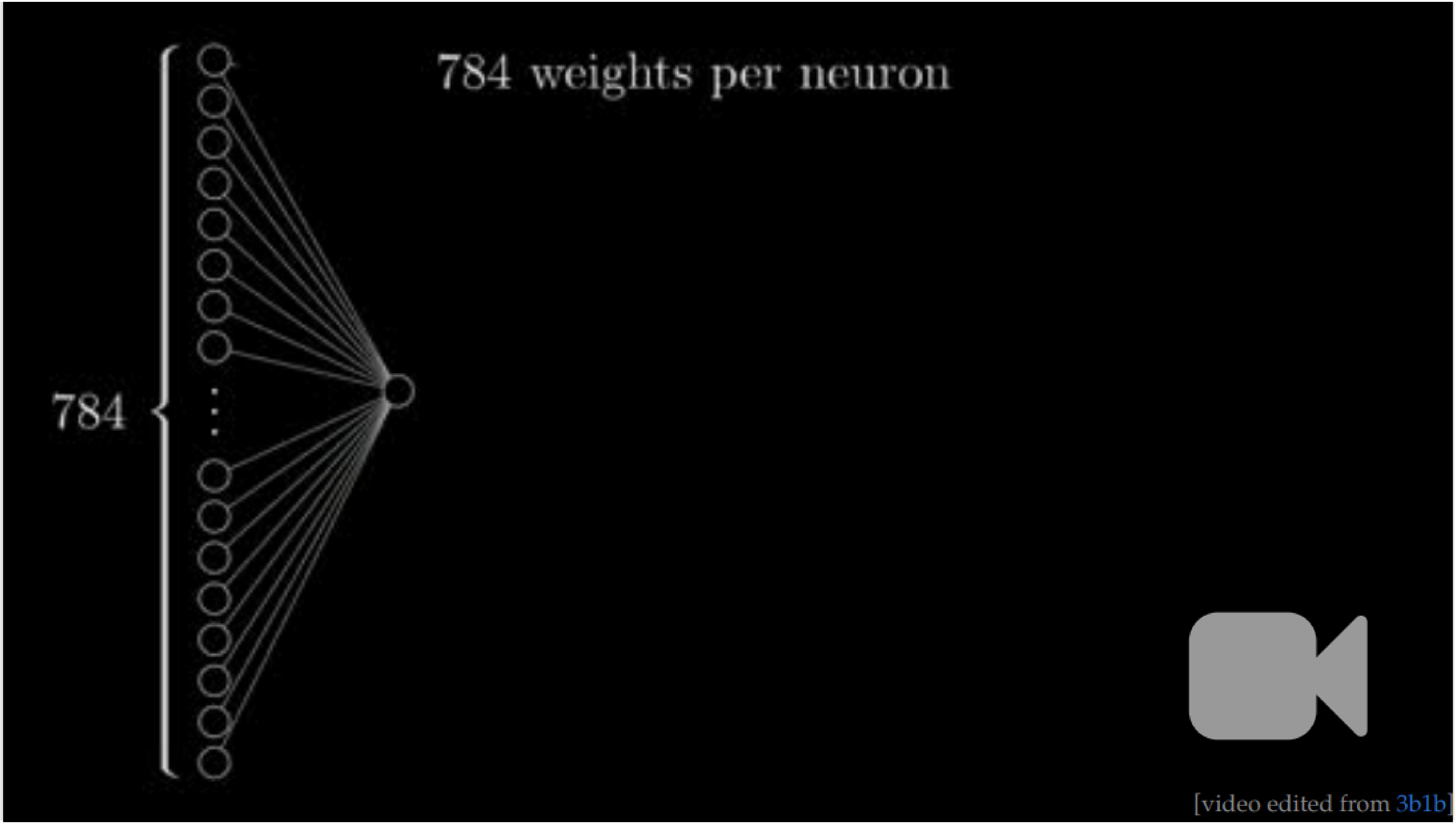

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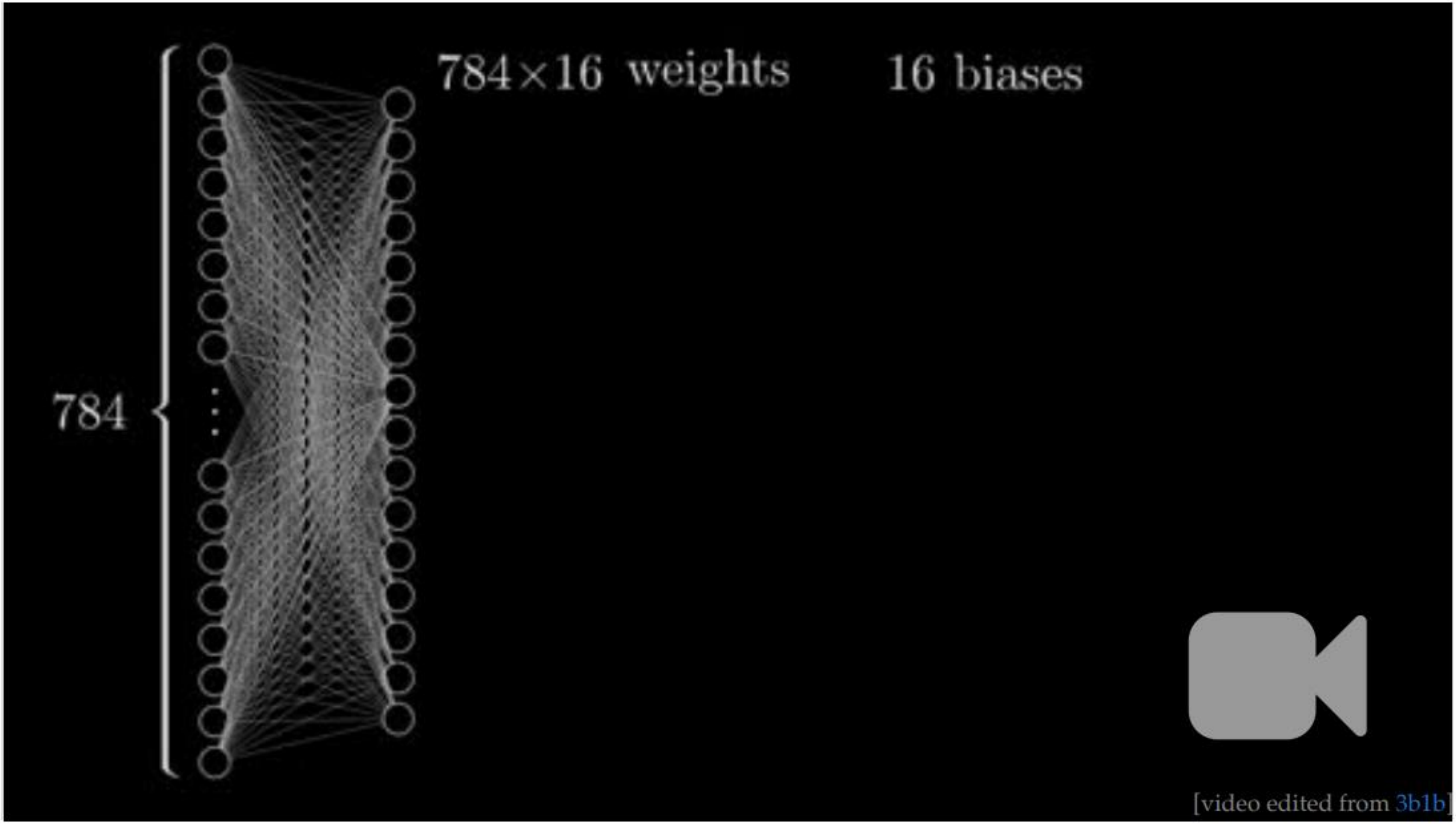


426-by-426
grayscale image

Use the same small 2-layer network, need to learn ~3M parameters

Imagine even higher-resolution images (e.g. 1024-1024 already leads to 1-million dimensional as input), or more complex tasks, the number of parameters can just grow very fast.

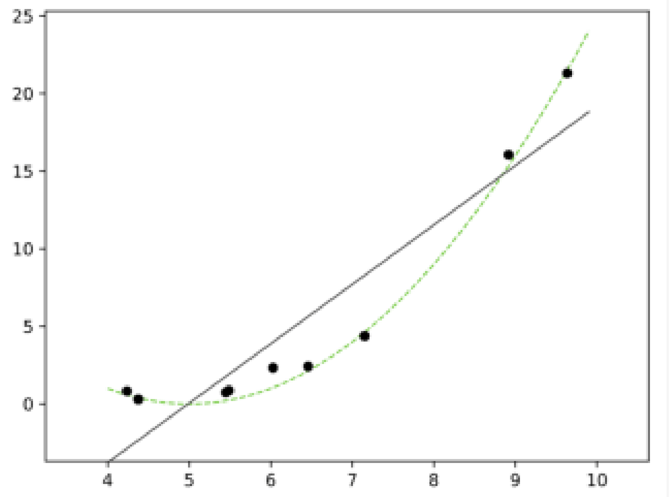
Q: Why do we need a specialized network?

A: fully-connected nets don't scale well for vision tasks

Recall, more powerful models also has the pitfall of overfitting

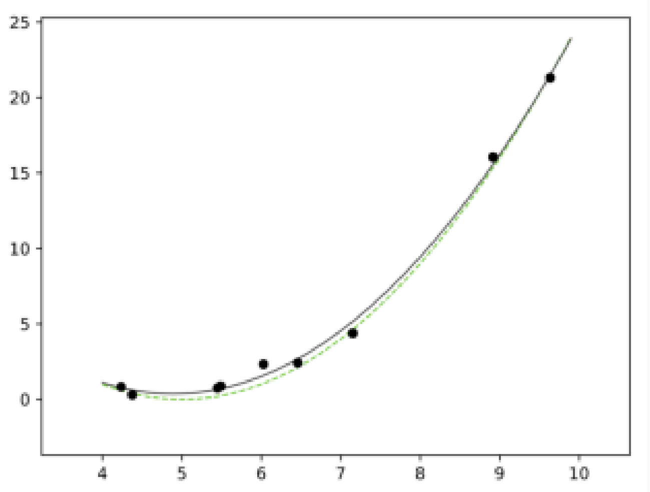
Underfitting

$k = 1$



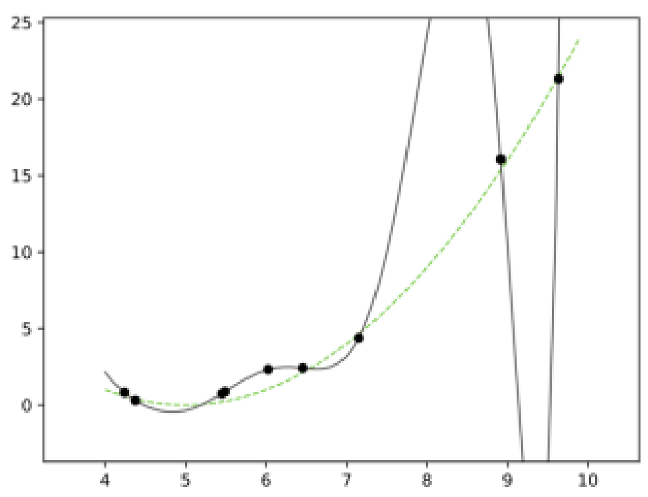
Appropriate model

$k = 2$

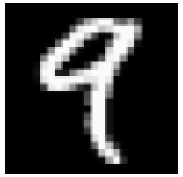


Overfitting

$k = 10$



Why do we think



is 9?

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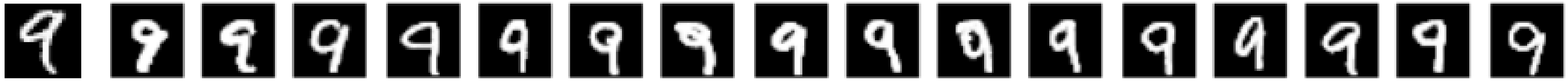
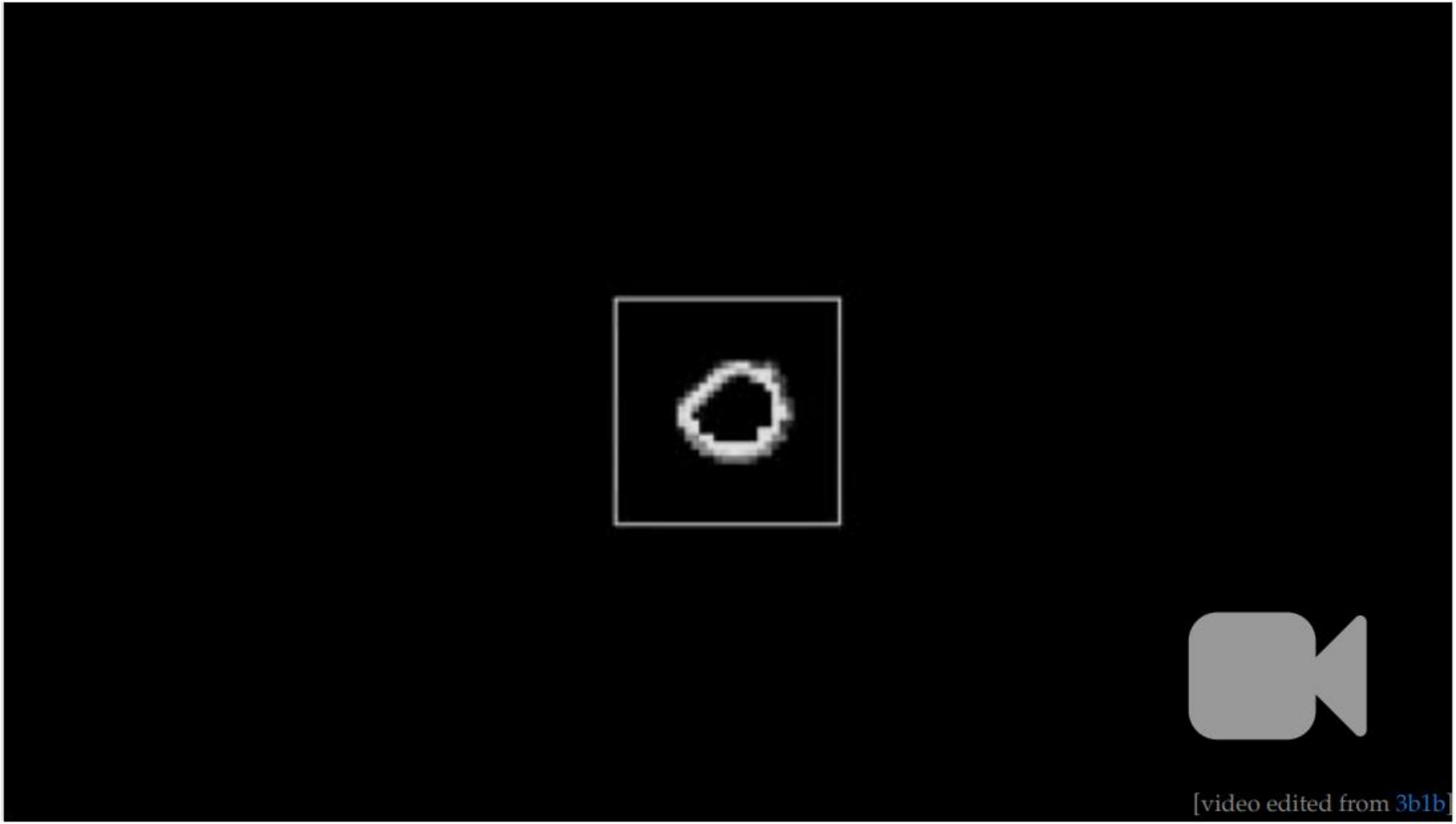
Why do we think any of

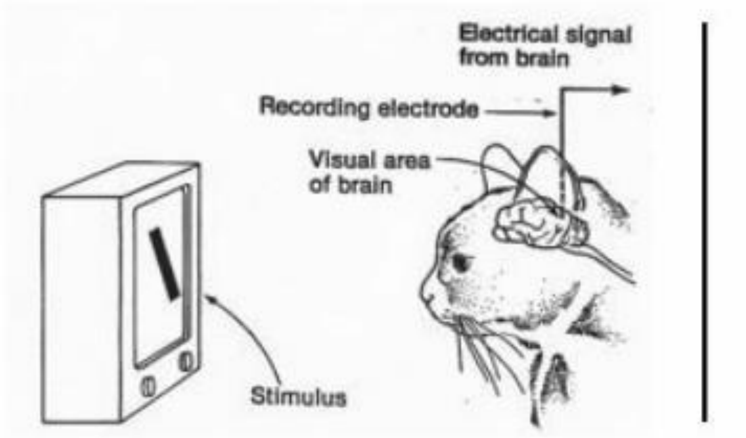


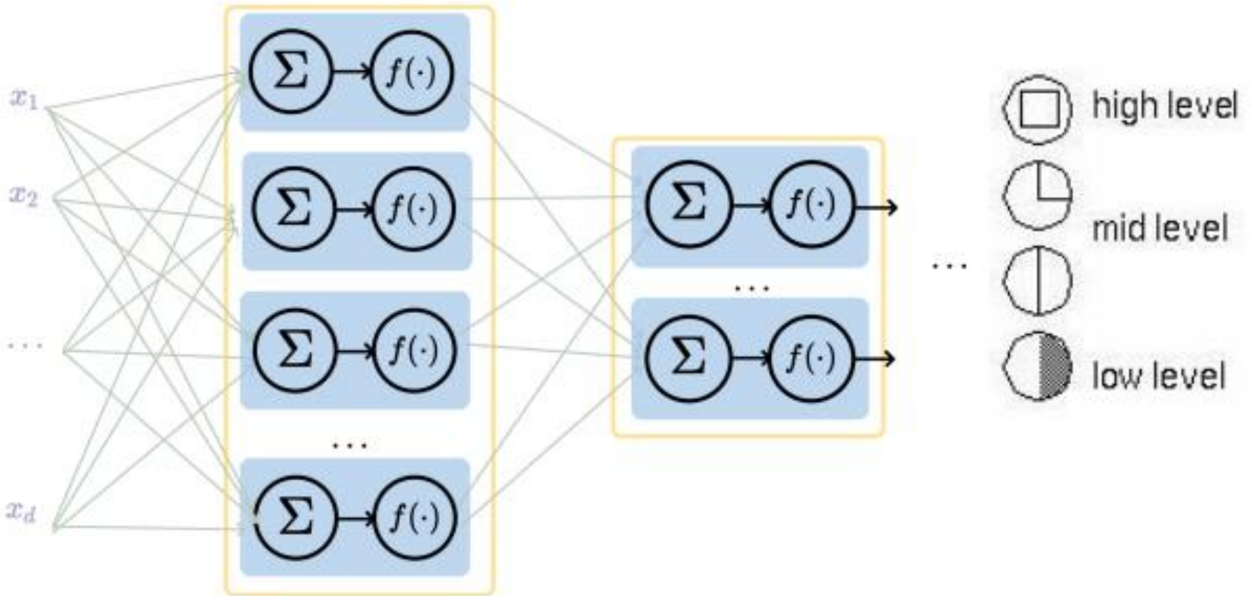
is 9?


[video edited from 3b1b]


[video edited from 3b1b]

- Visual hierarchy





layering is compatible with hierarchical structure

- Visual hierarchy

- Spatial locality

- Translational invariance

CNN cleverly exploits

- Visual hierarchy
- Spatial locality
- Translational invariance

via

- layering (with nonlinear activations)
- convolution
- pooling

to handle images efficiently and sensibly.

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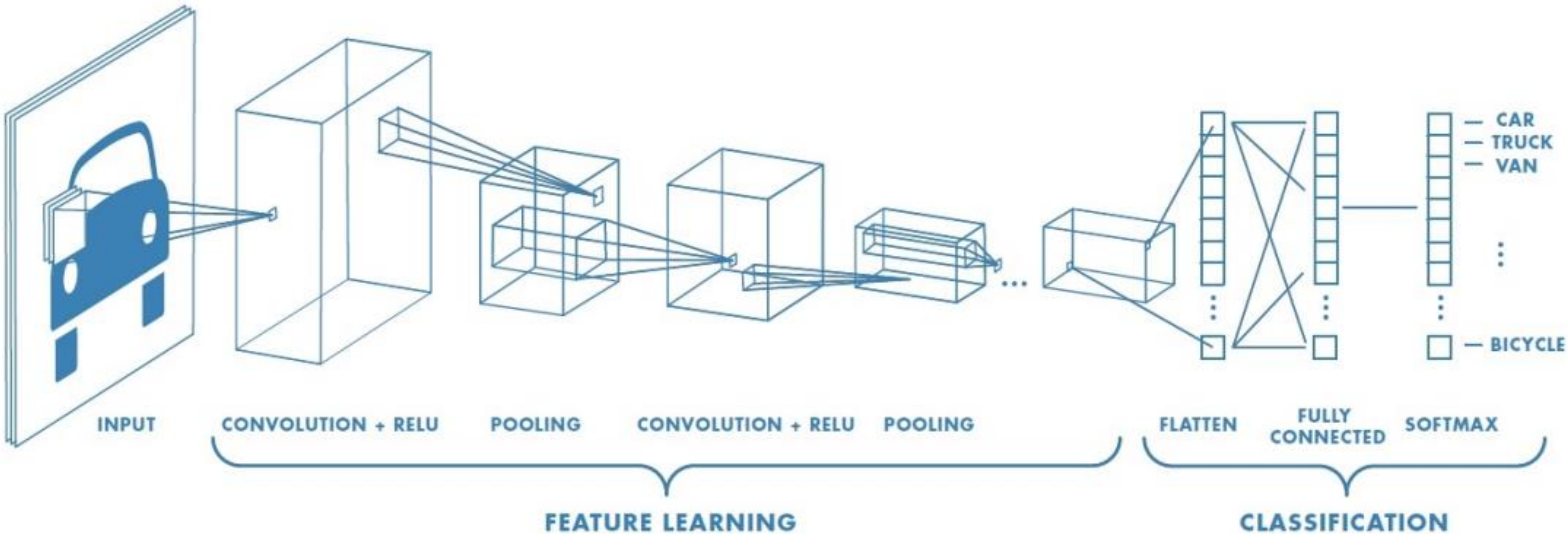
typical CNN structure for image classification



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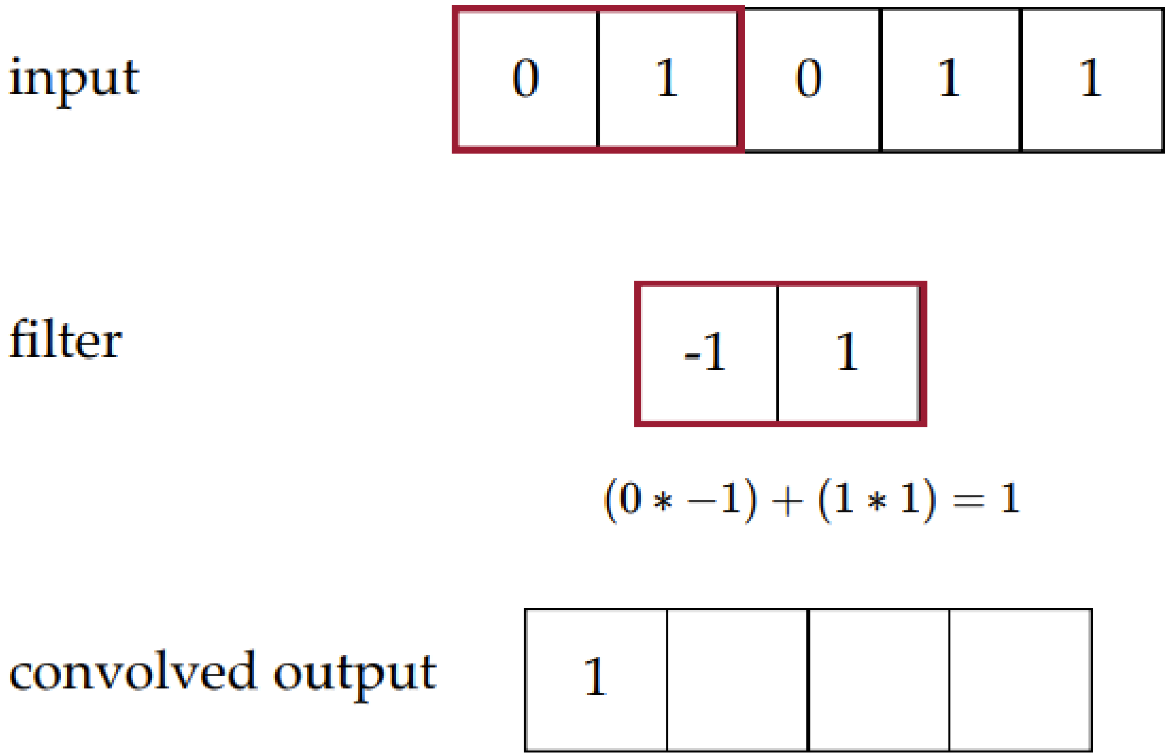
Convolutional layer might sound foreign, but it's very similar to fully connected layer

Layer	Forward pass, *do*	Backward pass, *learn*
fully-connected	dot-product	neuron weights
convolutional	convolution	filter (kernels) weights

convolution with filters do these things:

example: 1-dimensional convolution



$$(0 * -1) + (1 * 1) = 1$$

Adopted from : https://introml.mit.edu

example: 1-dimensional convolution

input	0	1	0	1	1

filter	-1	1

$$(1 * -1) + (0 * 1) = -1$$

convolved output	1	-1		

Adopted from : https://introml.mit.edu

example: 1-dimensional convolution

input

0	1	0	1	1

filter

-1	1

$$(0 * -1) + (1 * 1) = 1$$

convolved output

1	-1	1	

Adopted from : https://introml.mit.edu

example: 1-dimensional convolution

input

0	1	0	1	1

filter

-1	1

$$(1 * -1) + (1 * 1) = 0$$

convolved output

1	-1	1	0

Adopted from : https://introml.mit.edu

convolution interpretation: template matching

input

0	1	-1	1	1

filter

-1	1

convolved output

1	-2	2	0

Adopted from : https://introml.mit.edu

convolution interpretation: "look" locally

input

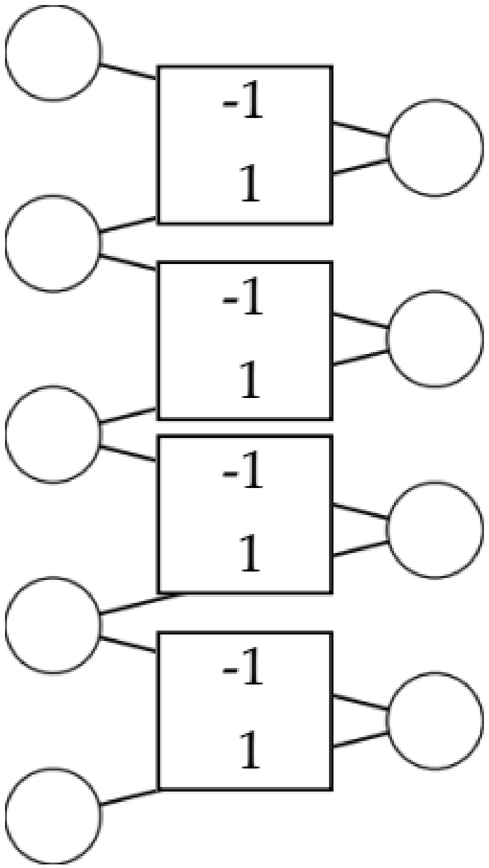
0	1	-1	1	1

filter

-1	1

convolved output

1	-2	2	0



convolution interpretation: parameter sharing

0	1	-1	1	1

convolve with

-1	1

dot product with

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

=

1	-2	2	0

Adopted from : https://introml.mit.edu

0	1	0	1	1

convolve with

1

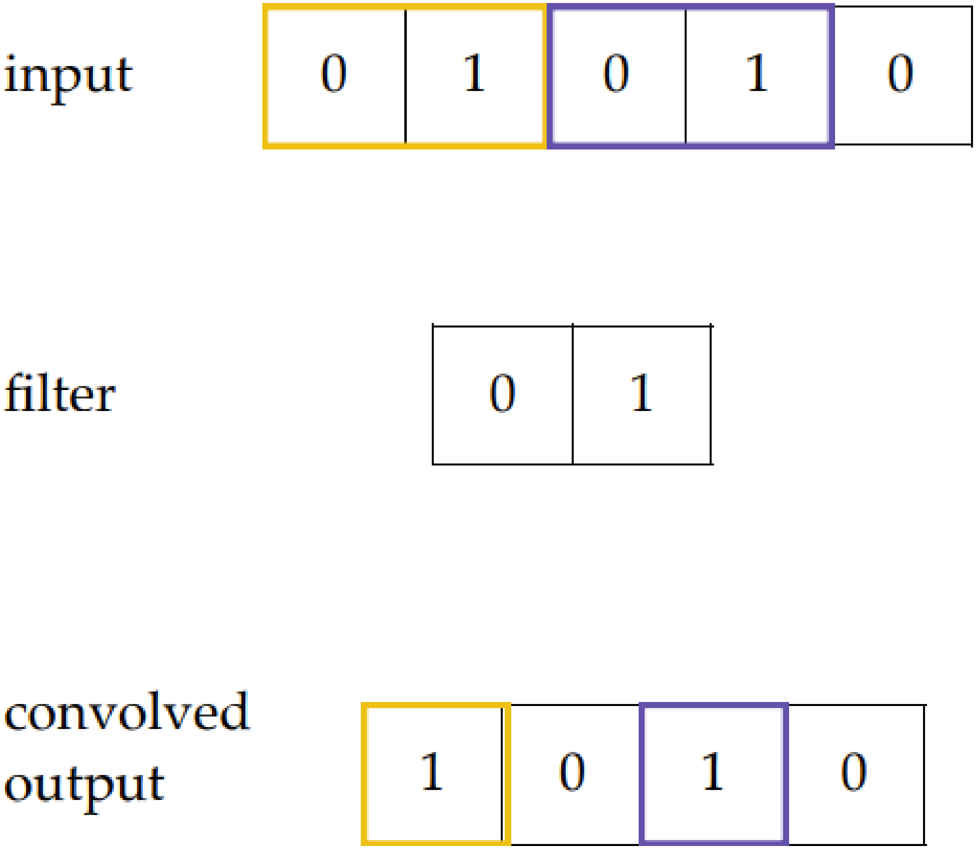
dot product with

$I_{5\times5}$

0	1	0	1	1

Adopted from : https://introml.mit.edu

convolution interpretation: translational equivariance



hyperparameters

- Zero-padding input

0	0	1	0	1	1	0

- Stride (e.g. stride of 2)

0	0	1	0	1	1	0

- Filter size (e.g. we saw these two)

-1	1

1

these weights are what
CNN learn eventually

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2-dimensional convolution

input

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

filter

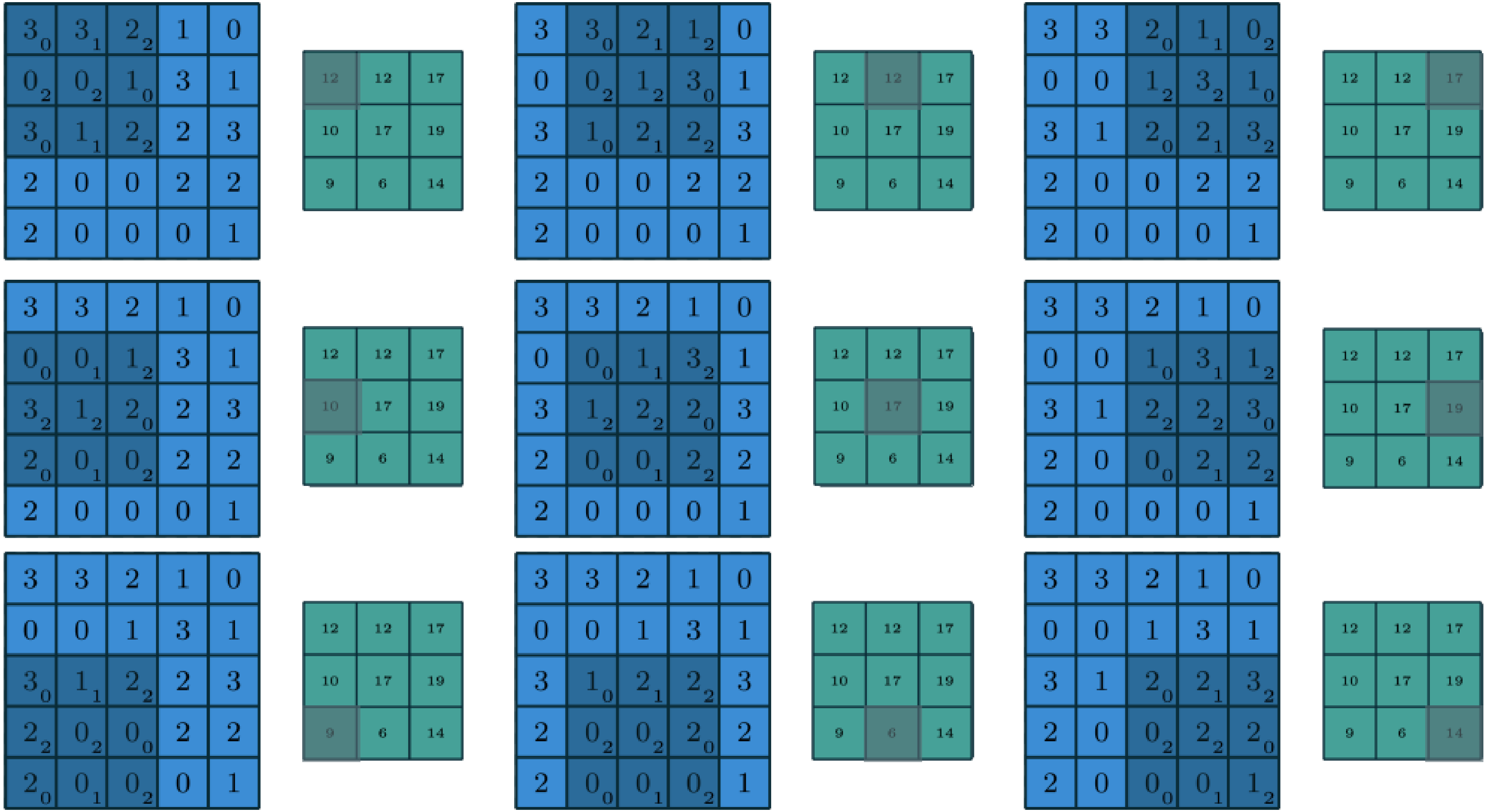
0	1	2
2	2	0
0	1	2

output

12	12	17
10	17	19
9	6	14

[image edited from vdumoulin]

Adopted from : https://introml.mit.edu



[image edited from vdumoulin]

Adopted from : https://introml.mit.edu

stride of 2

input

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

filter

0	1	2
2	2	0
0	1	2

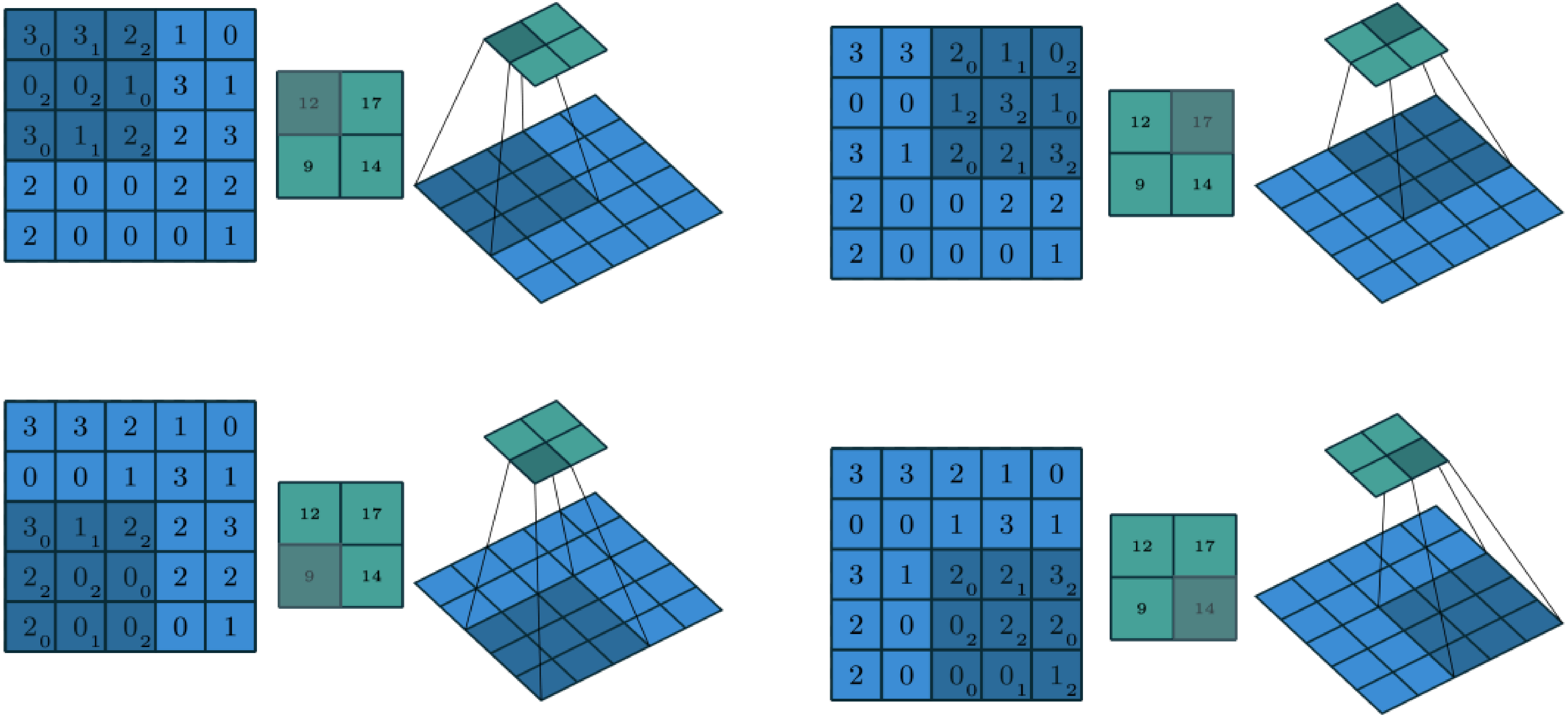
output

12	17
9	14

[image edited from vdumoulin]

Adopted from : https://introml.mit.edu

stride of 2



[image edited from vdumoulin]

stride of 2, with padding of size 1

input

3	3	2	1	0
0	0	1	3	1
3	1	2	2	3
2	0	0	2	2
2	0	0	0	1

filter

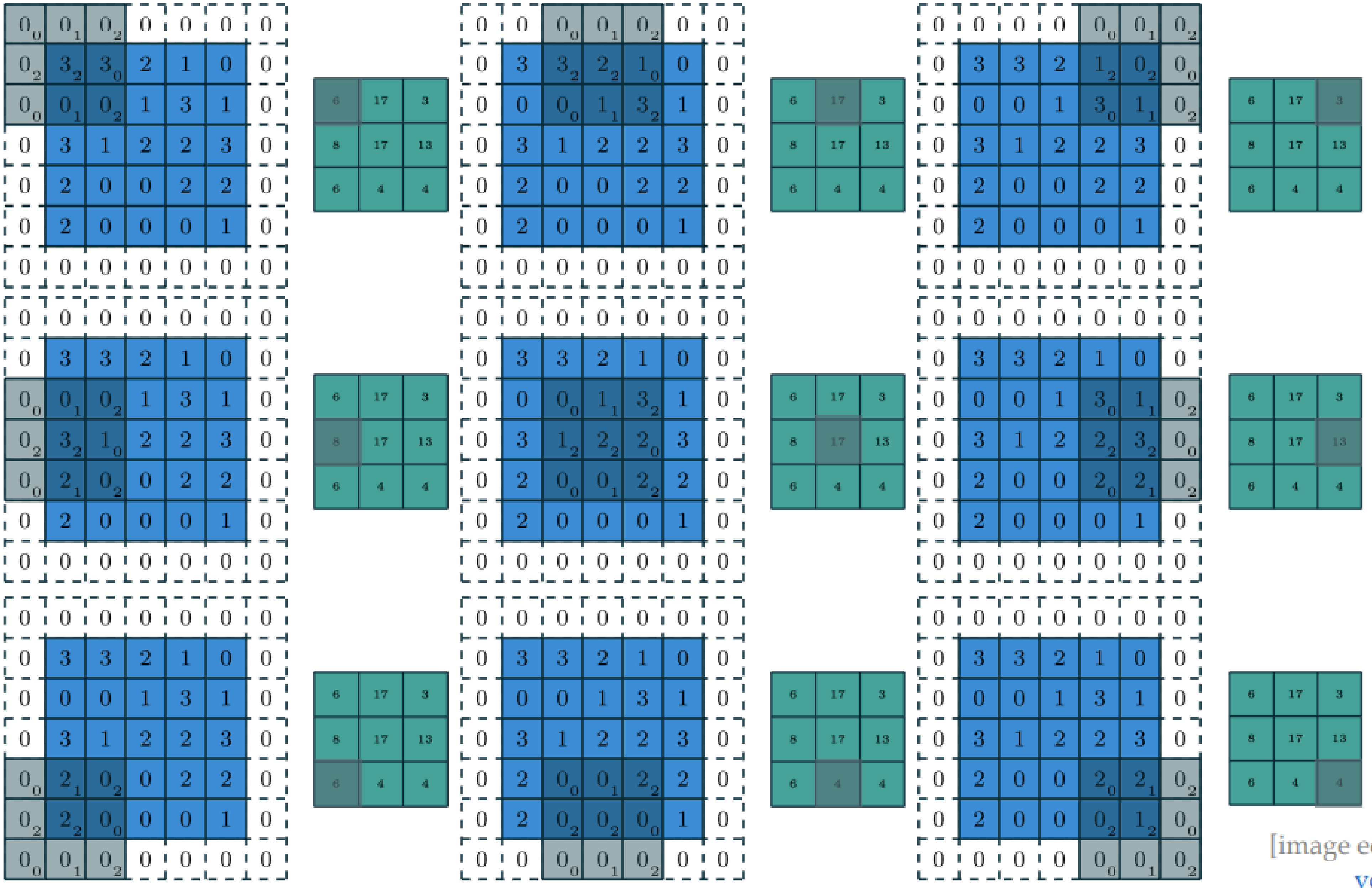
0	1	2
2	2	0
0	1	2

output

6	17	3
8	17	13
6	4	4

[image edited from vdumoulin]

Adopted from : https://introml.mit.edu



[image edited from vdumoulin]

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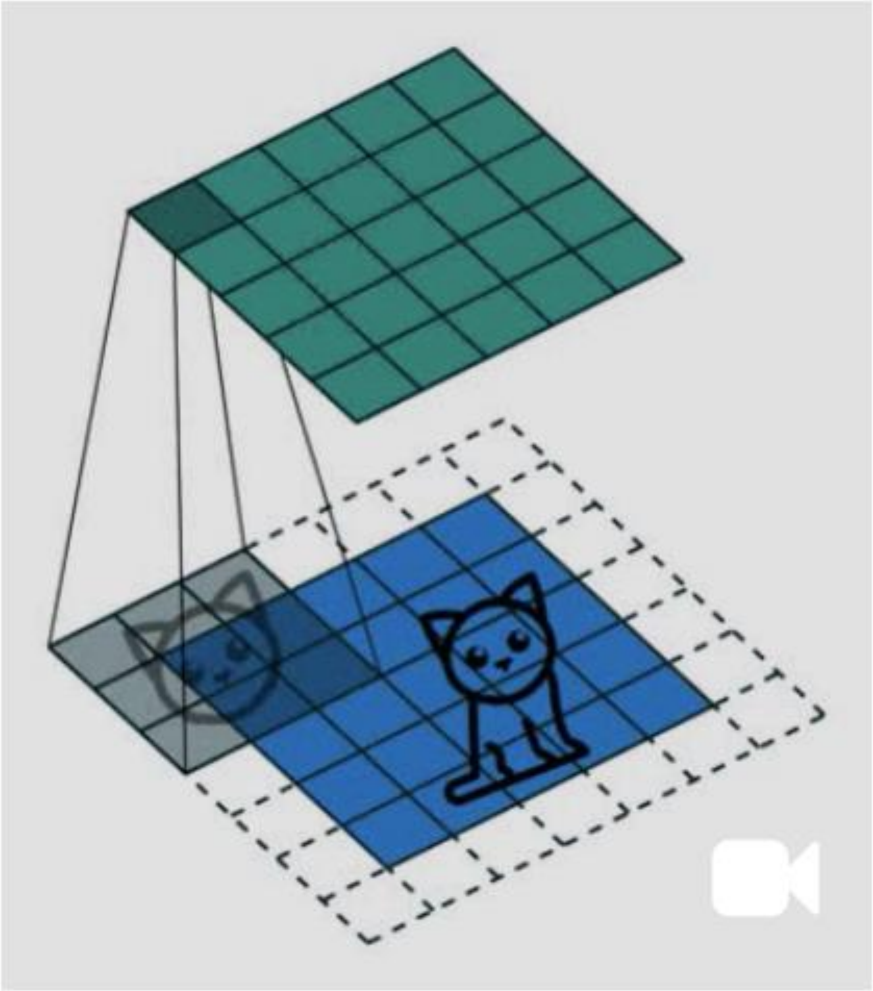
convolution interpretation:

- Looking locally
- Parameter sharing
- Template matching
- Translational equivariance



[video credit Lena Voita]

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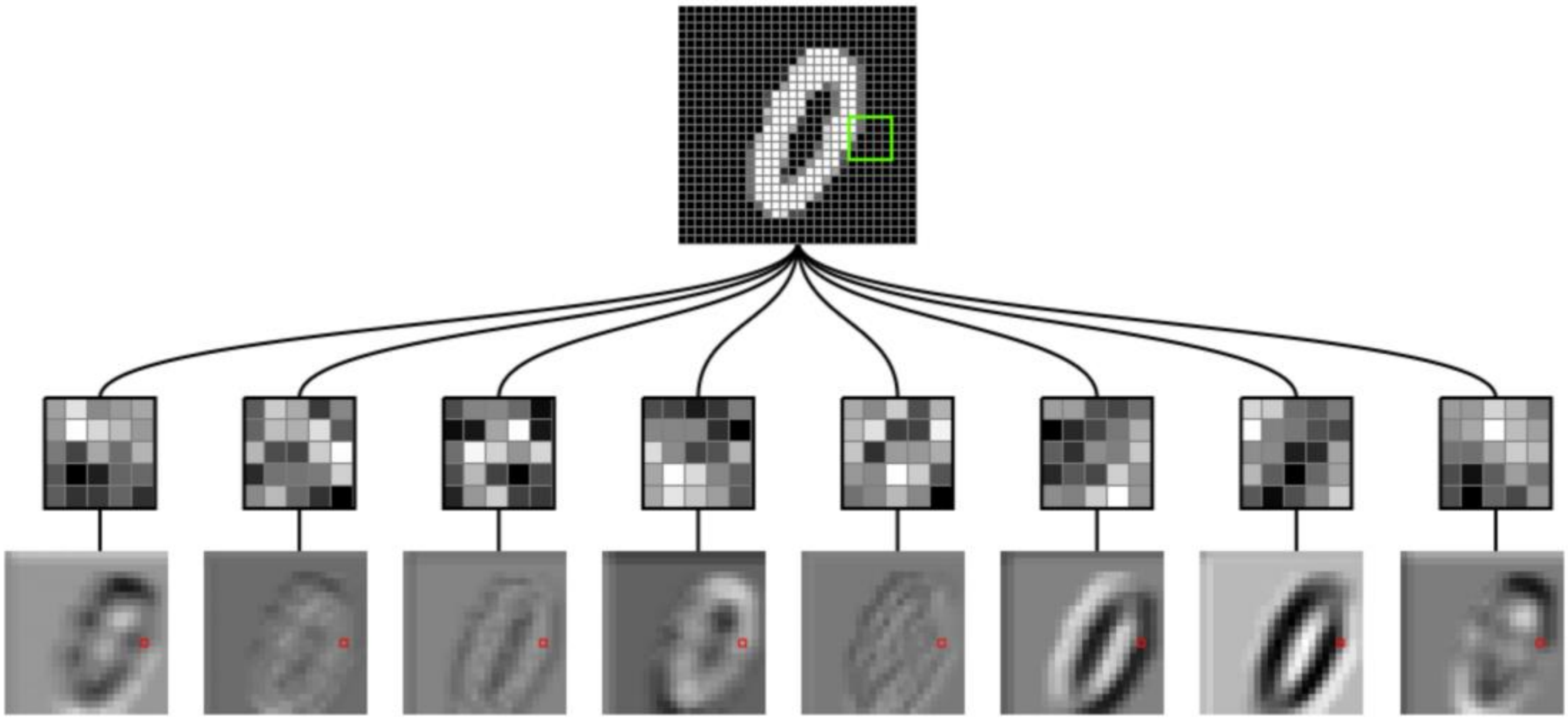

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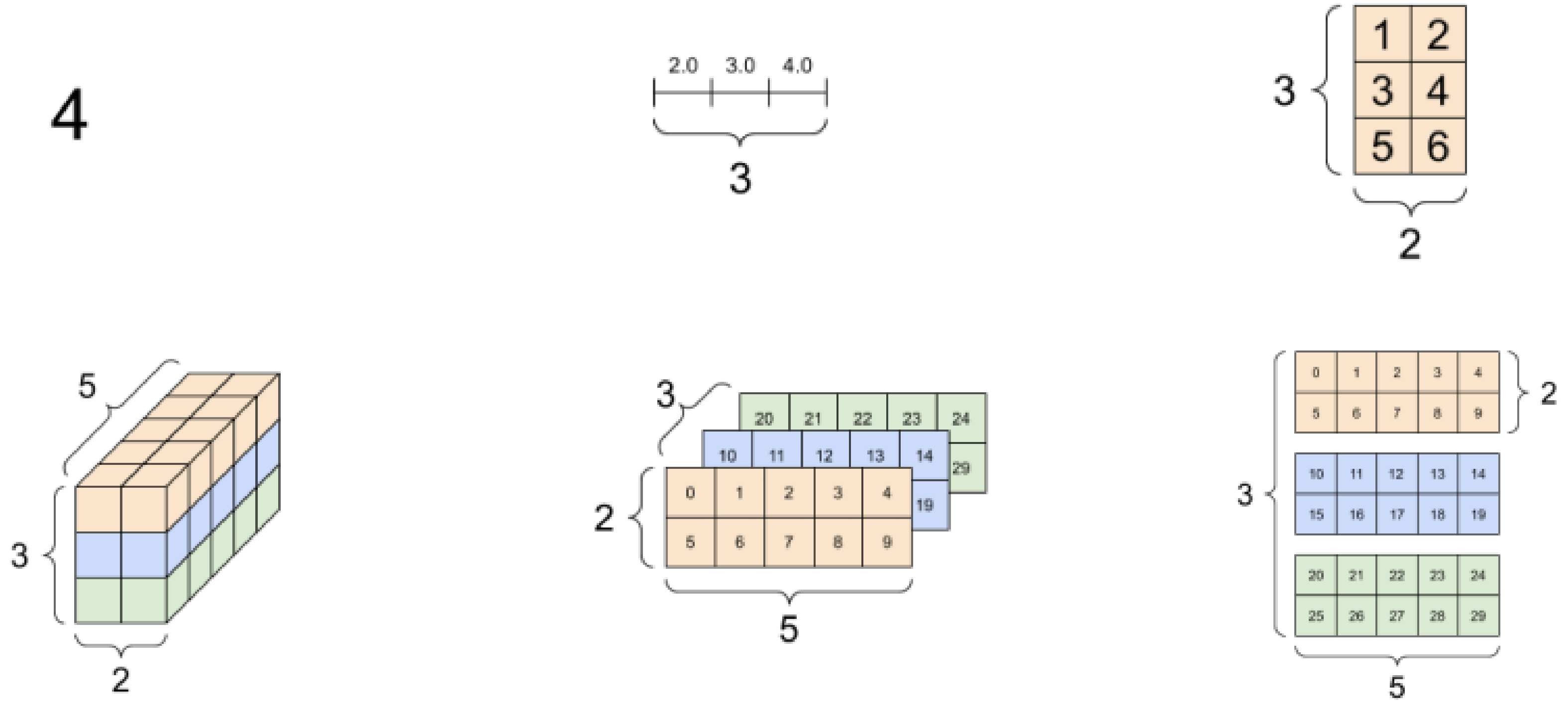
A tender intro to tensor:



[image credit: tensorflow]

We'd encounter 3d tensor due to:

1. color input

blue

green

red

[Photo by Zayn Shah, Unsplash]

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[Photo by Zayn Shah, Unsplash]

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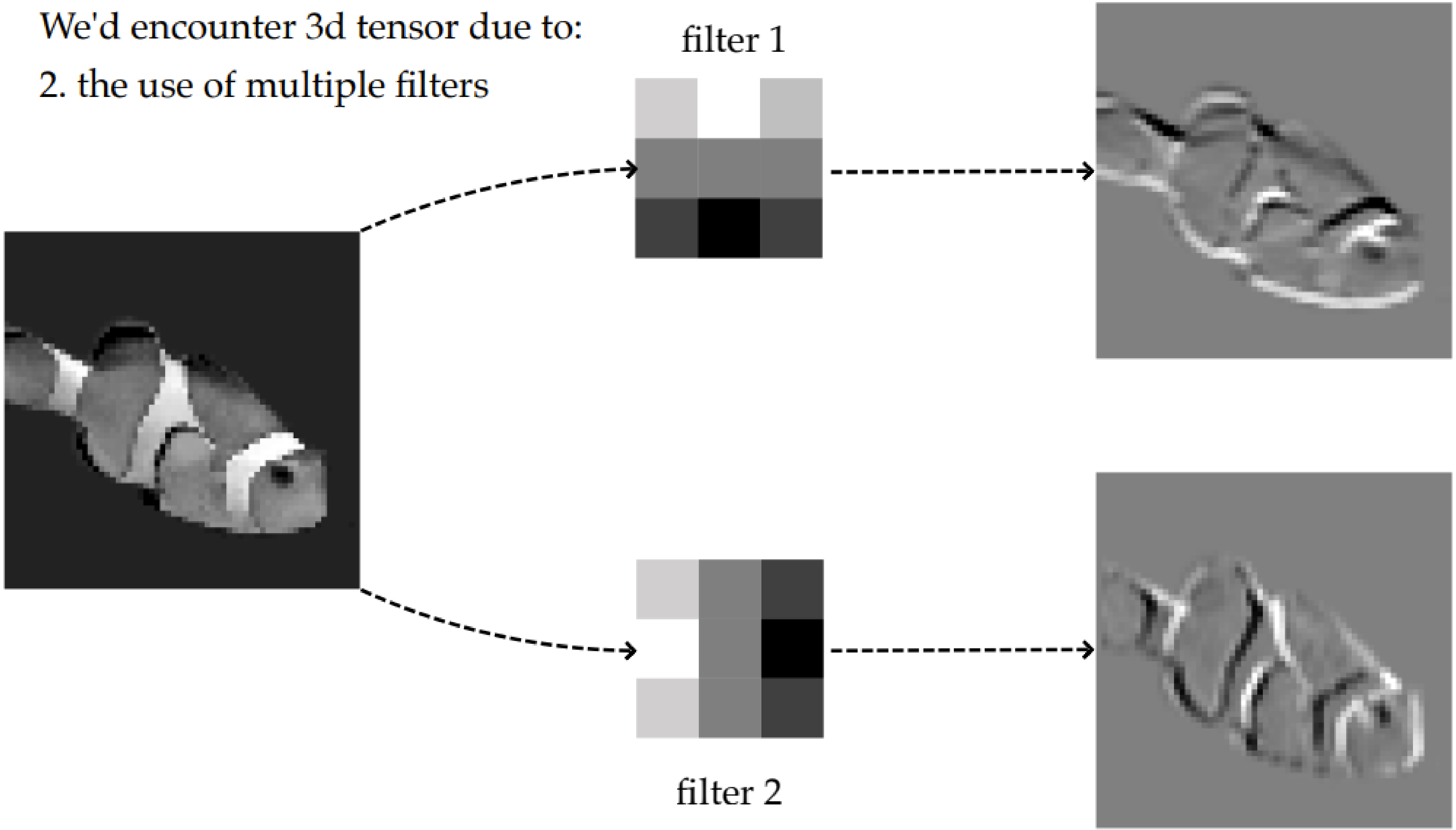
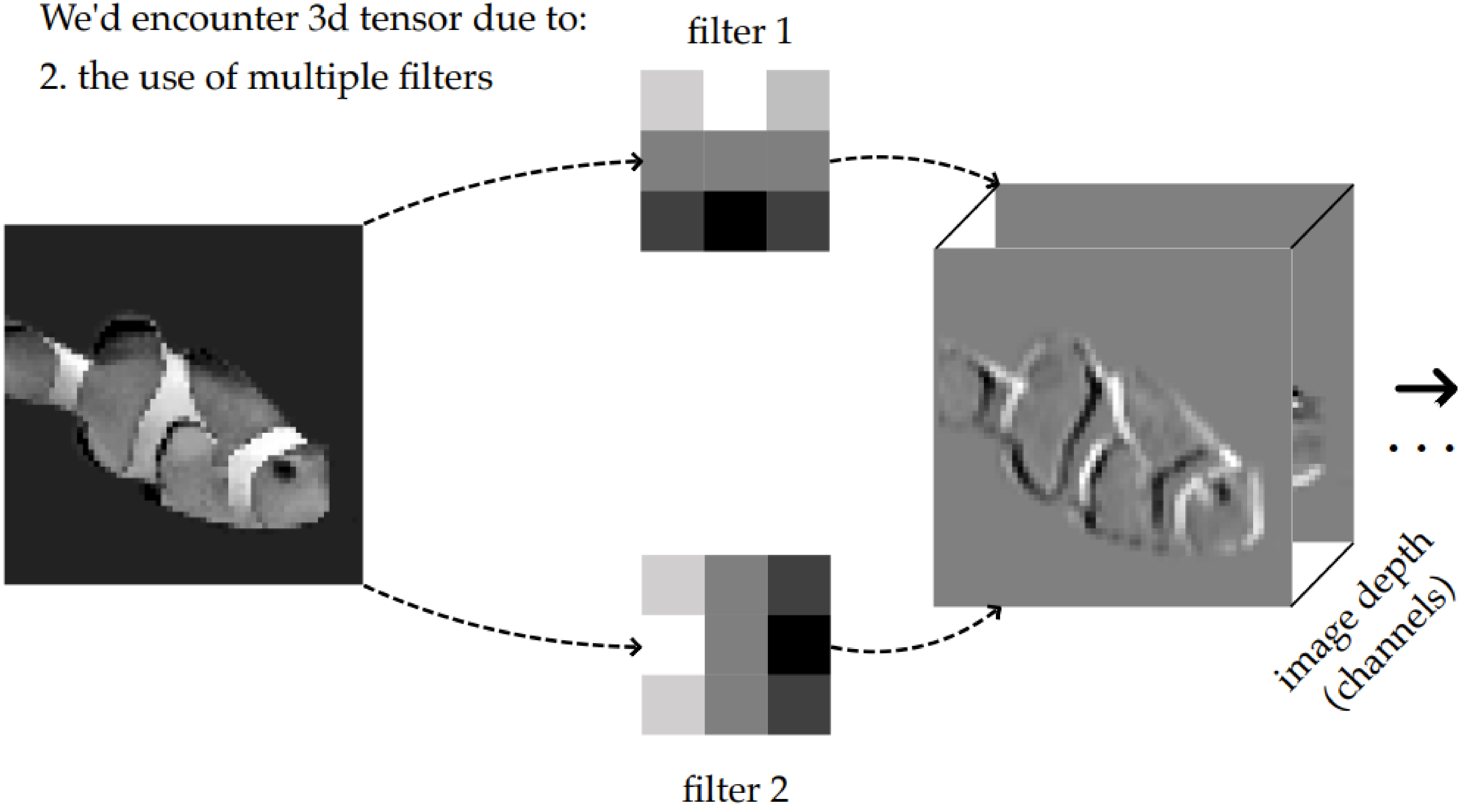
We'd encounter 3d tensor due to:

2. the use of multiple filters



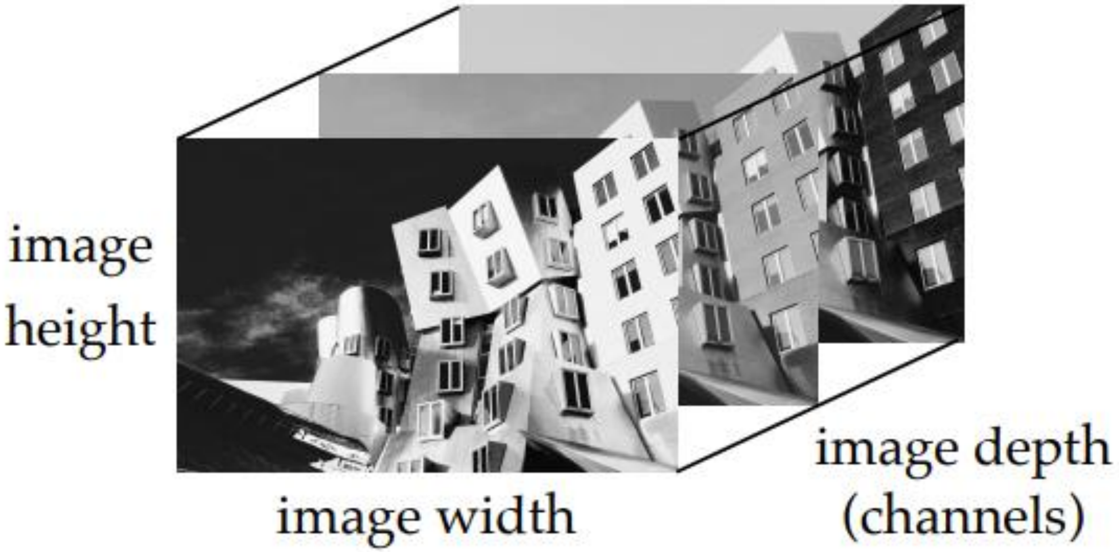
We'd encounter 3d tensor due to:

2. the use of multiple filters

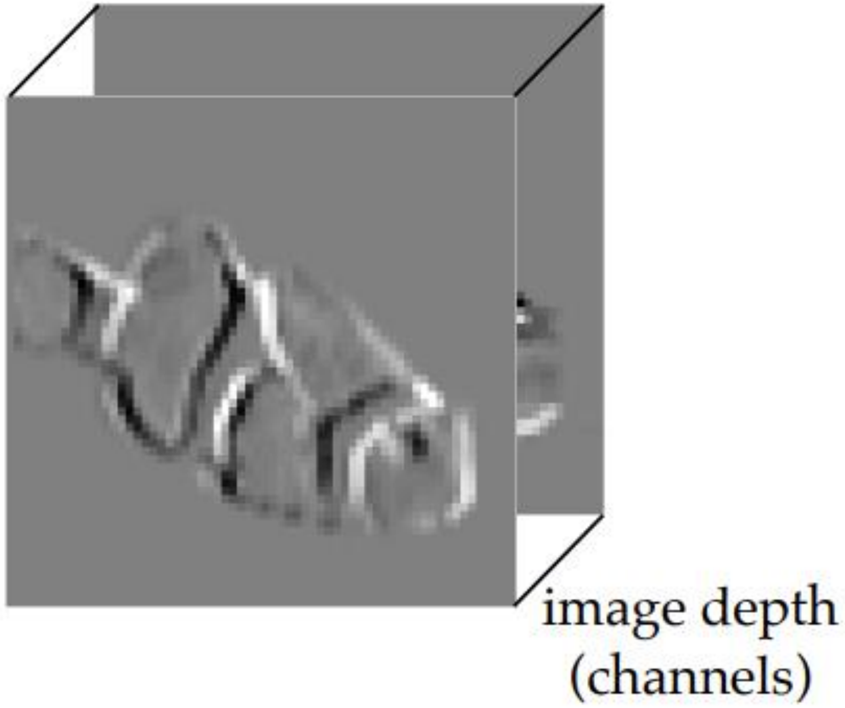


We'd encounter 3d tensor due to

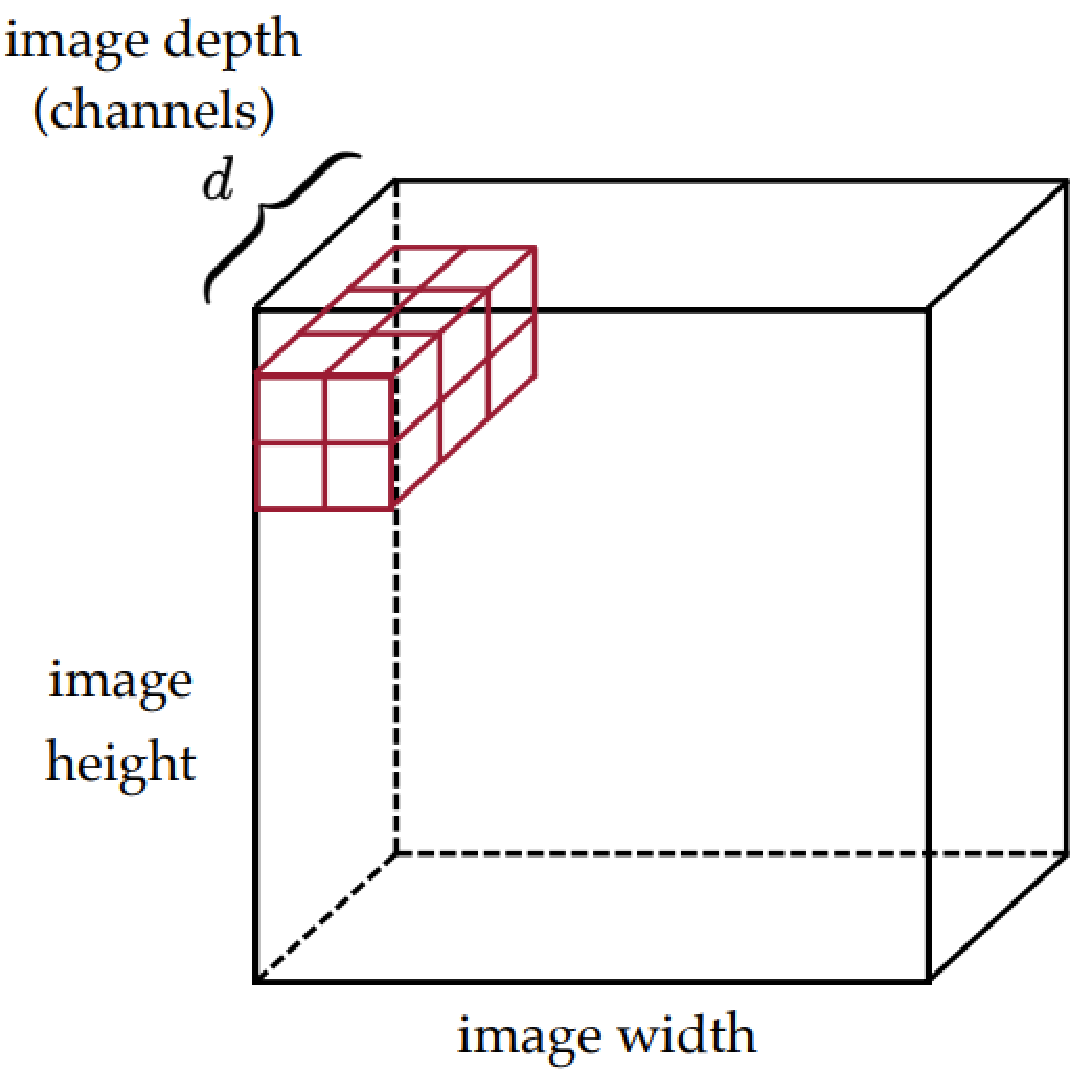
1. color input



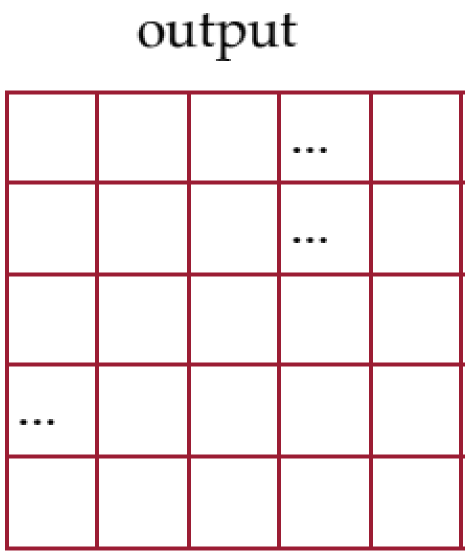
2. the use of multiple filters



But, we *don't* typically do 3-dimensional convolution. Instead:



- 3d tensor input, depth d
- 3d tensor filter, depth d
- 2d convolution, 2d output



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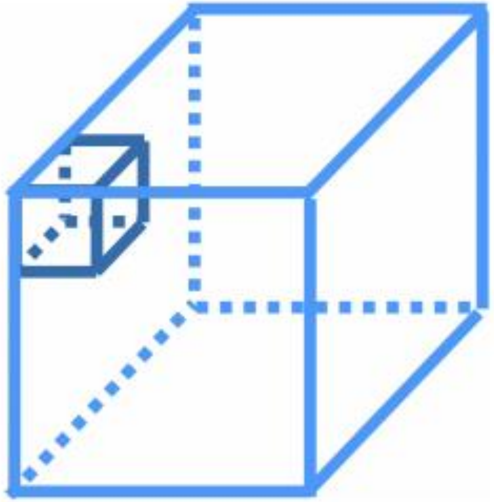
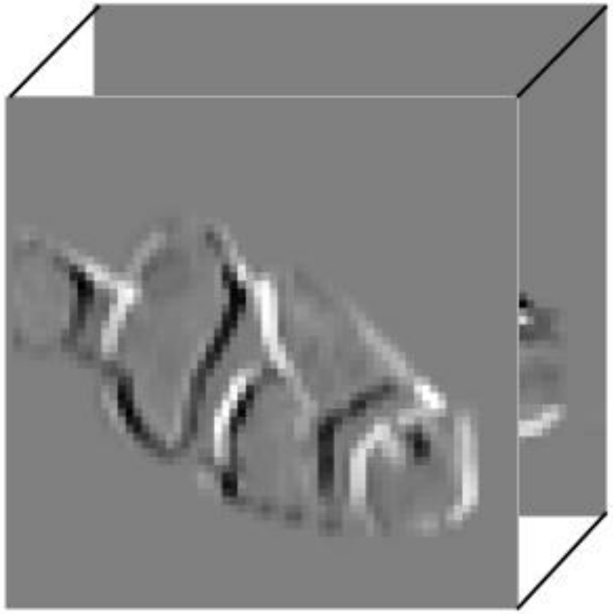
We *don't* typically do 3-dimensional convolution, because





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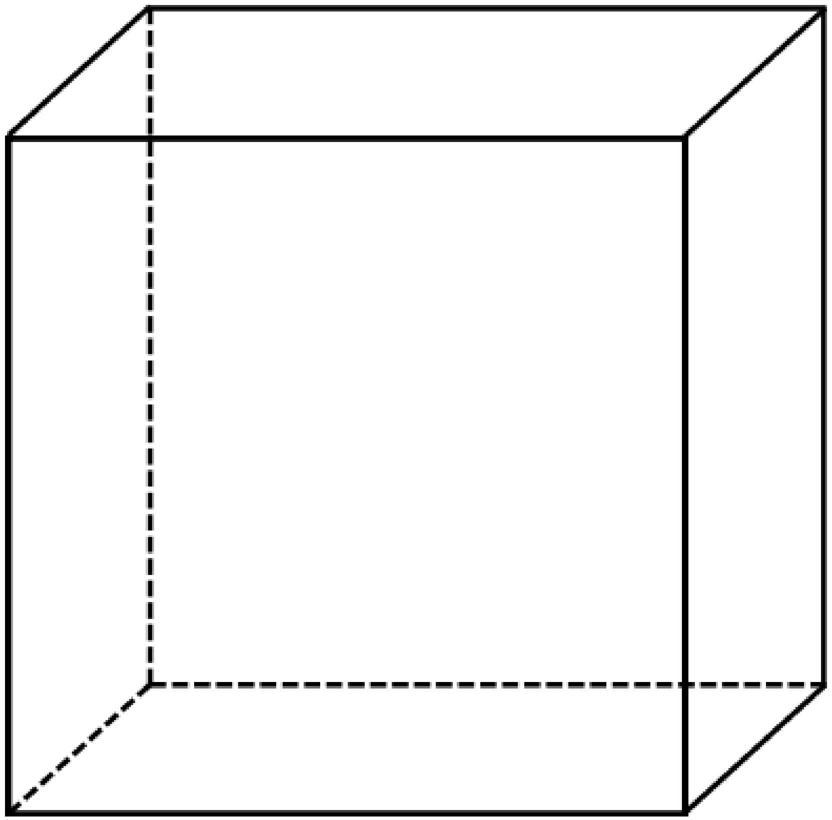
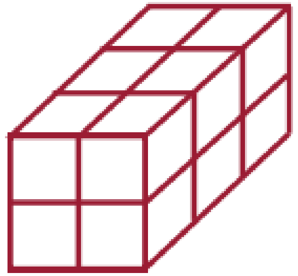
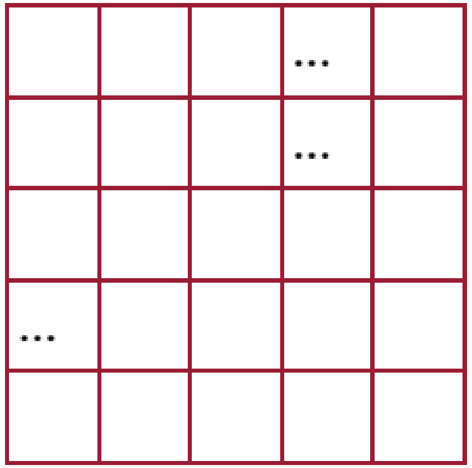
input tensor



one filter

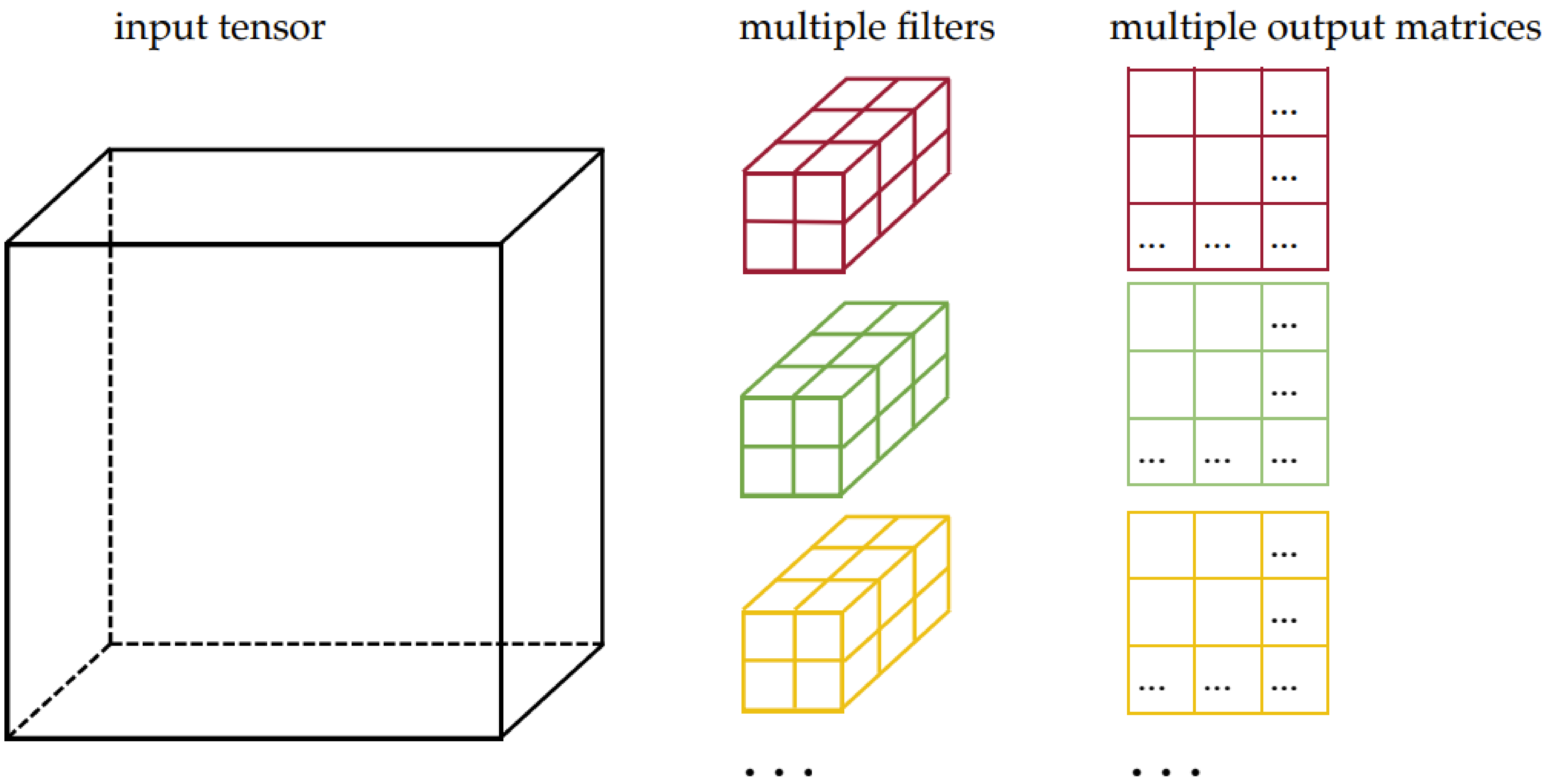


2d output



- 3d tensor input, depth d
- 3d tensor filter, depth d
- 2d tensor (matrix) output

Adopted from : https://introml.mit.edu



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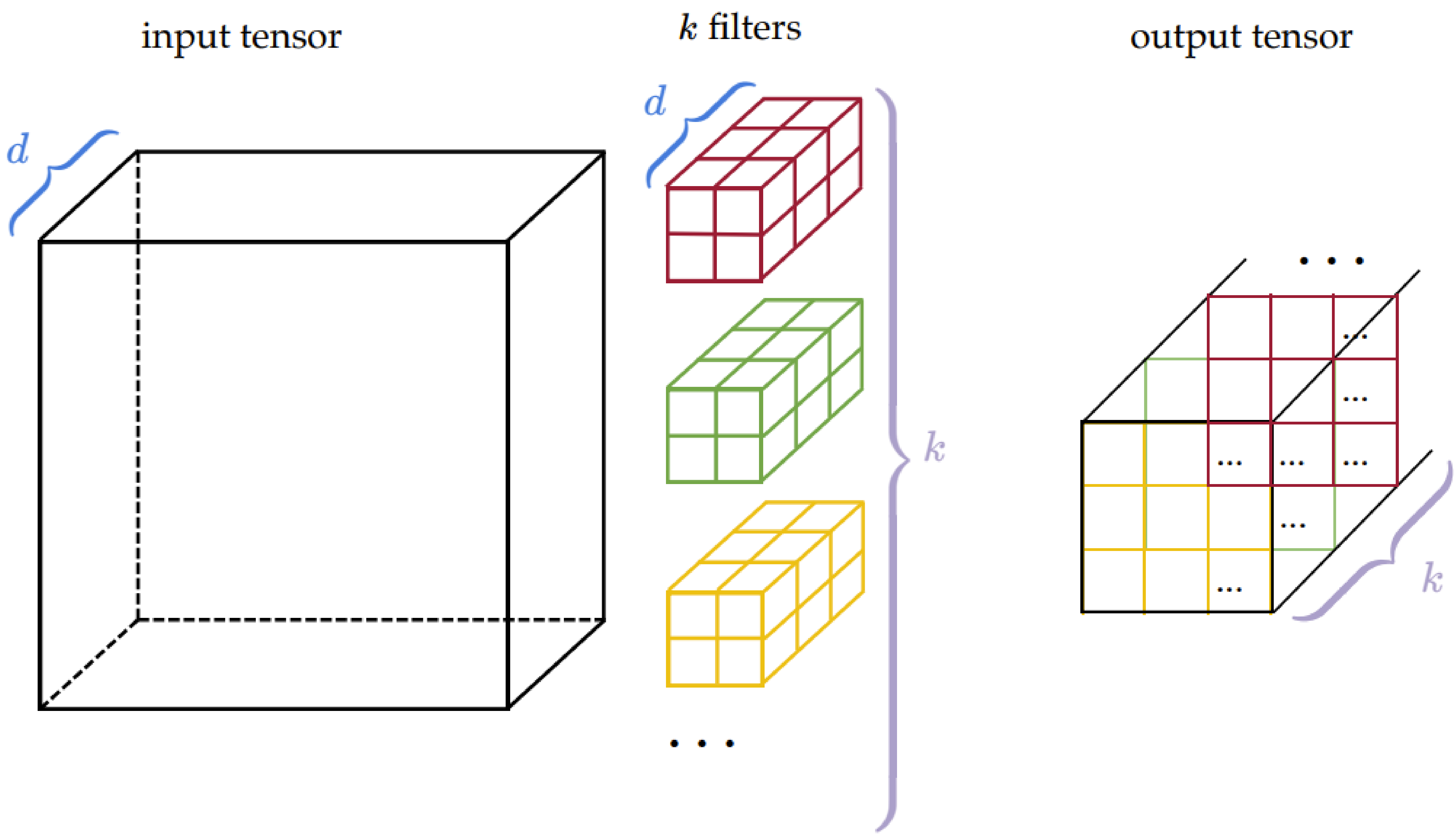
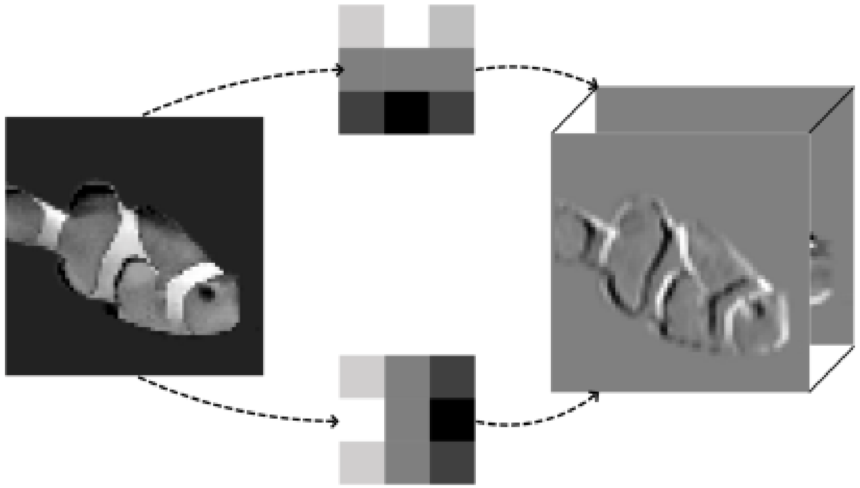
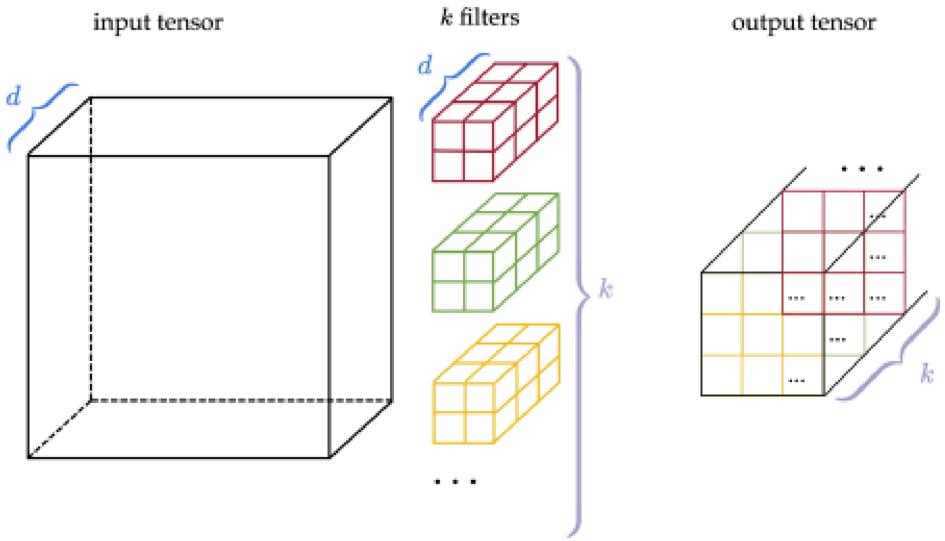


We'd encounter 3d tensor due to:

1. color input

2. the use of multiple filters -- in doing 2-dimensional convolution





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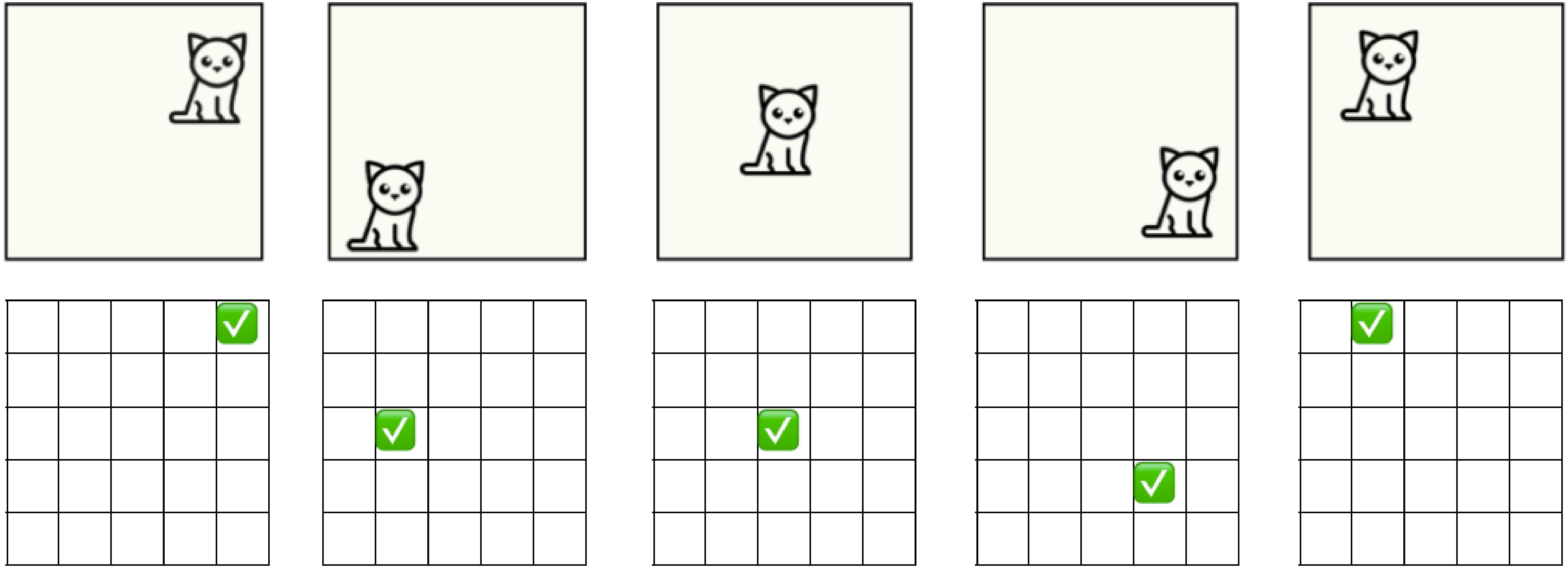
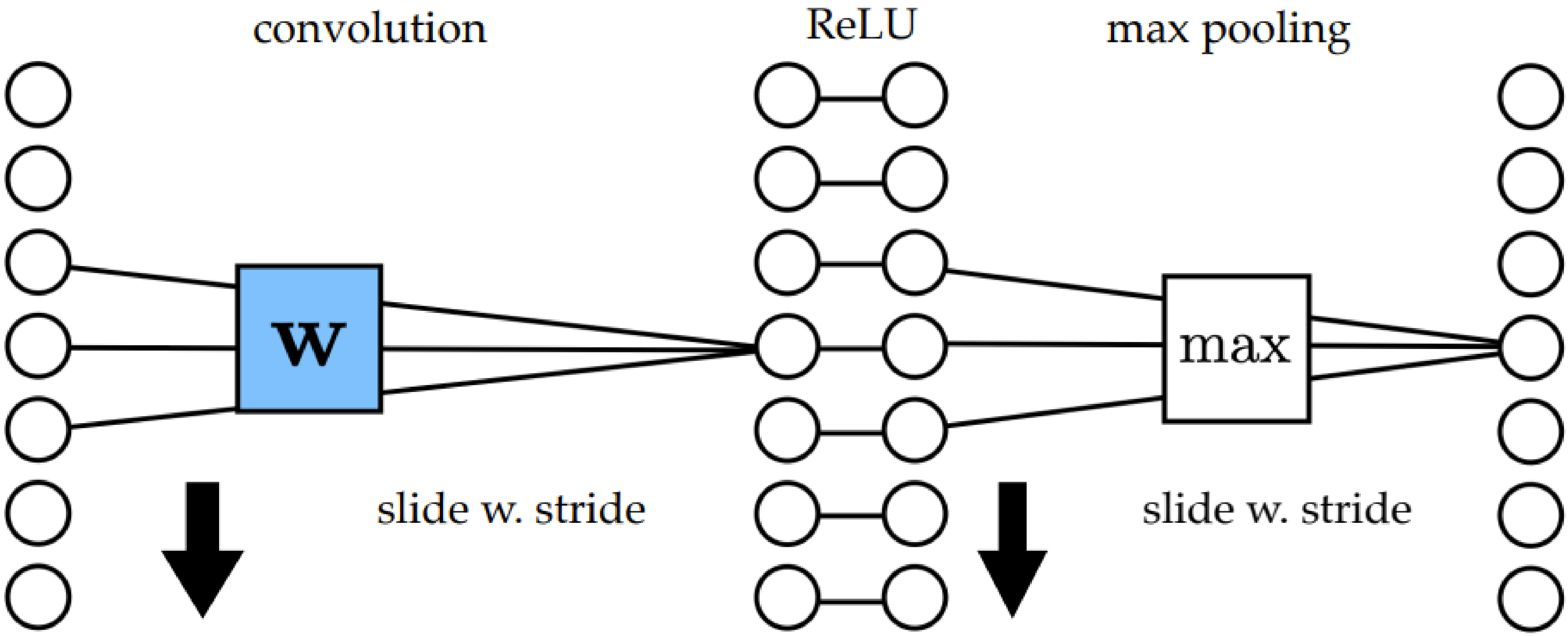


1-dimensional pooling

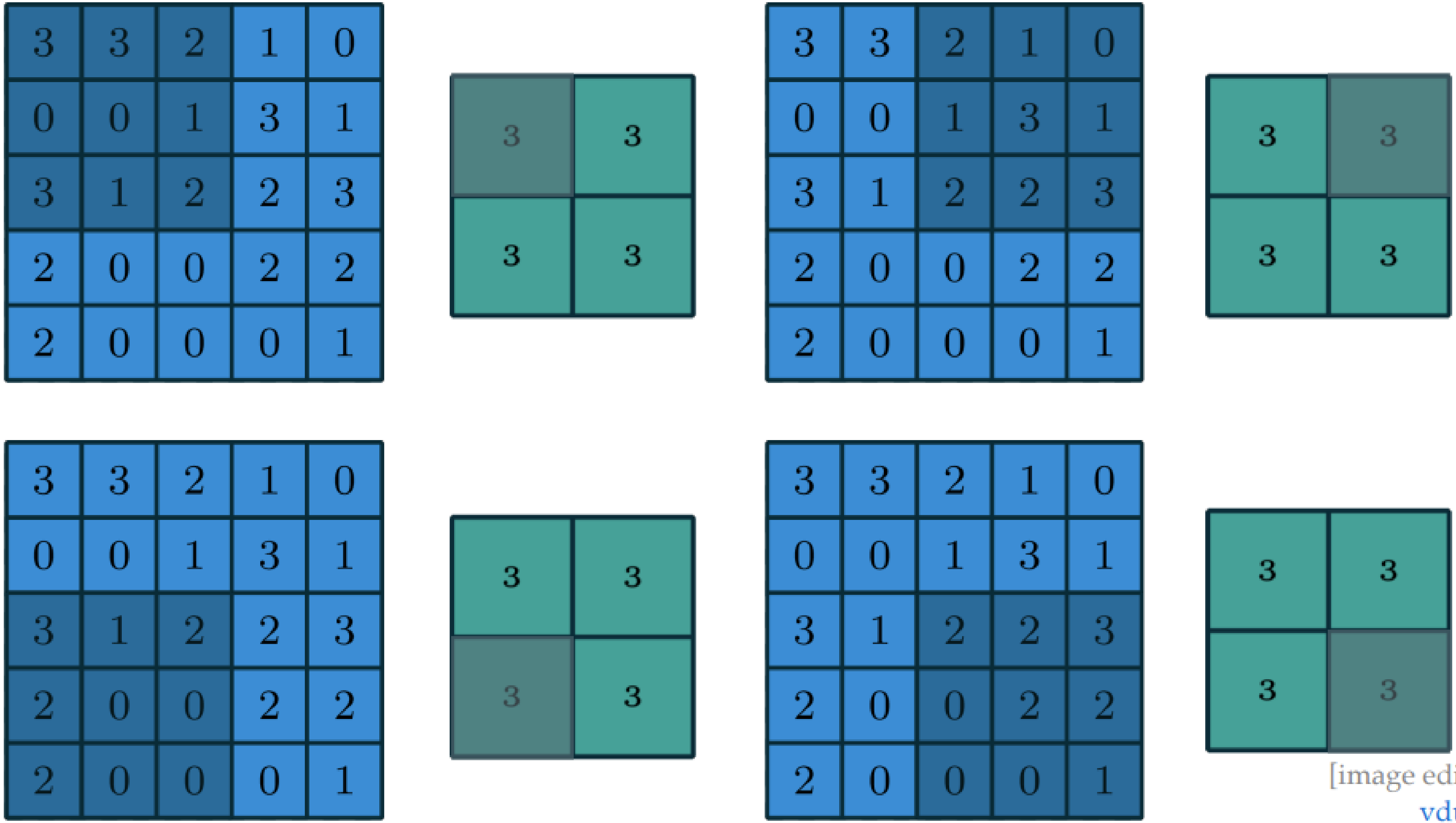


filter weights are the learnable parameter

no learnable parameter

Adopted from : https://introml.mit.edu

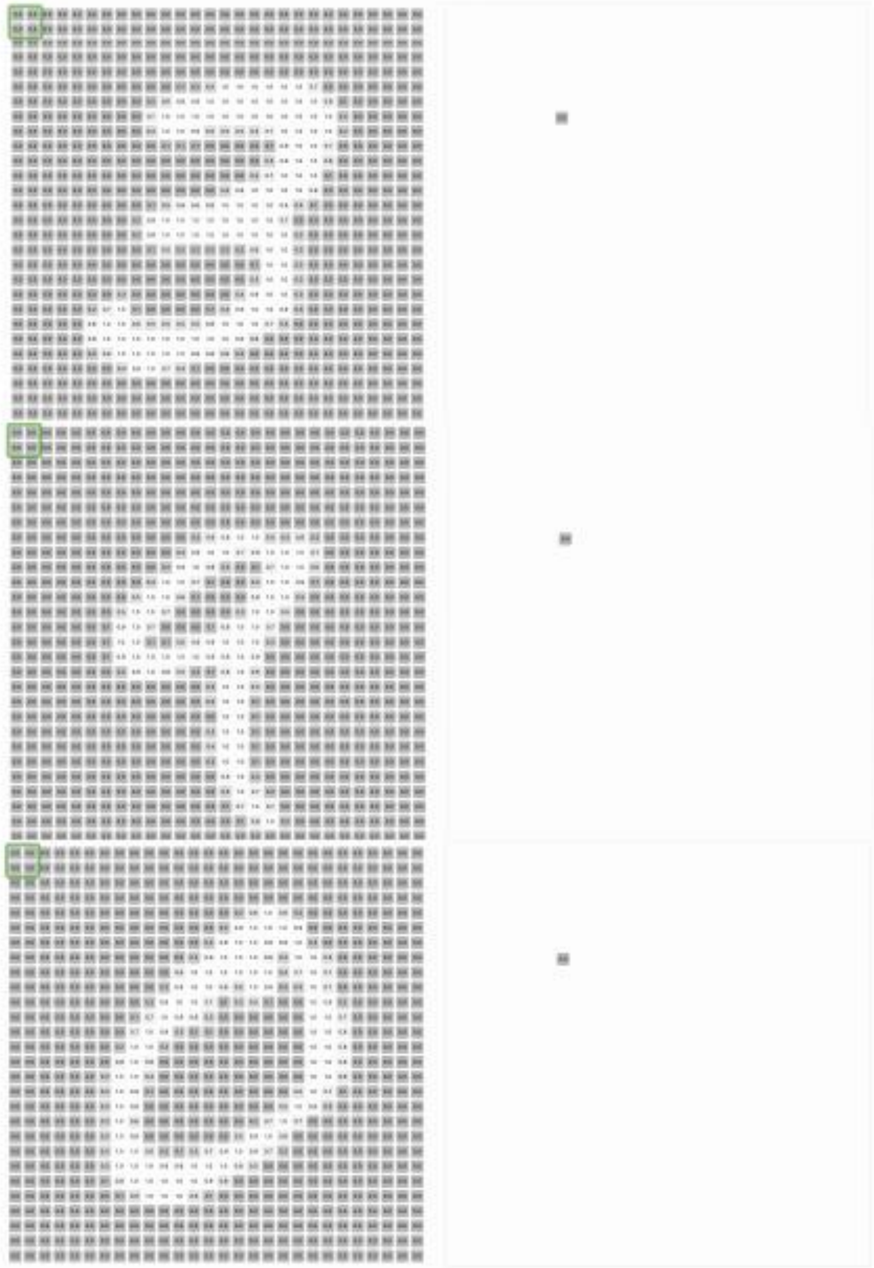
2-dimensional max pooling (example)



[image edited from vdumoulin]

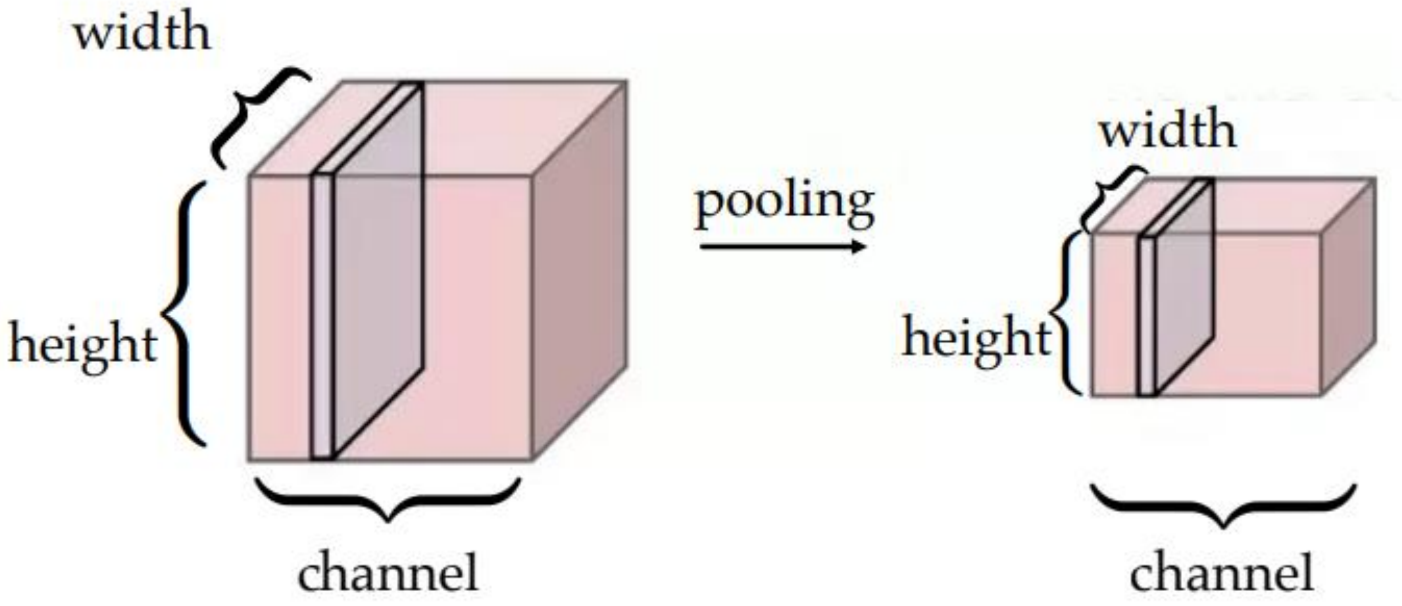
2-dimensional max pooling (example)

- can choose filter size
- typically choose to have no padding
- typically a stride >1
- reduces spatial dimension



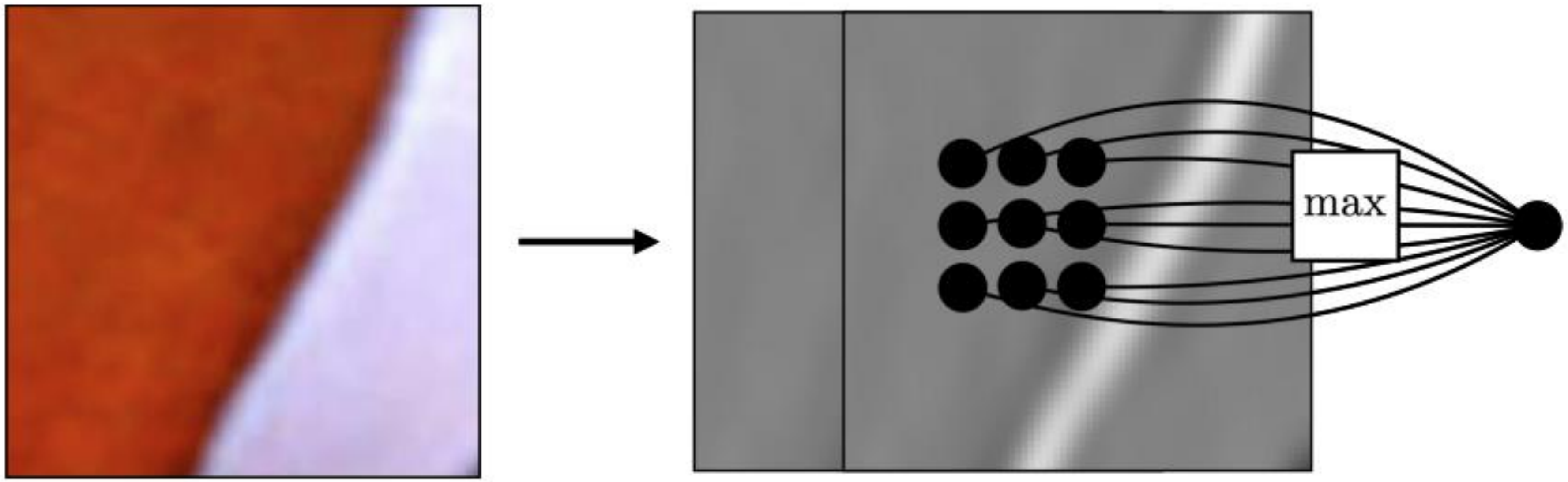
[gif adapted from demo source]

Pooling across *spatial* locations achieves invariance w.r.t. small translations:



so the *channel* dimension remains *unchanged* after pooling.

Pooling across *spatial* locations achieves invariance w.r.t. small translations:



large response regardless of exact position of edge

[image credit Philip Isola]

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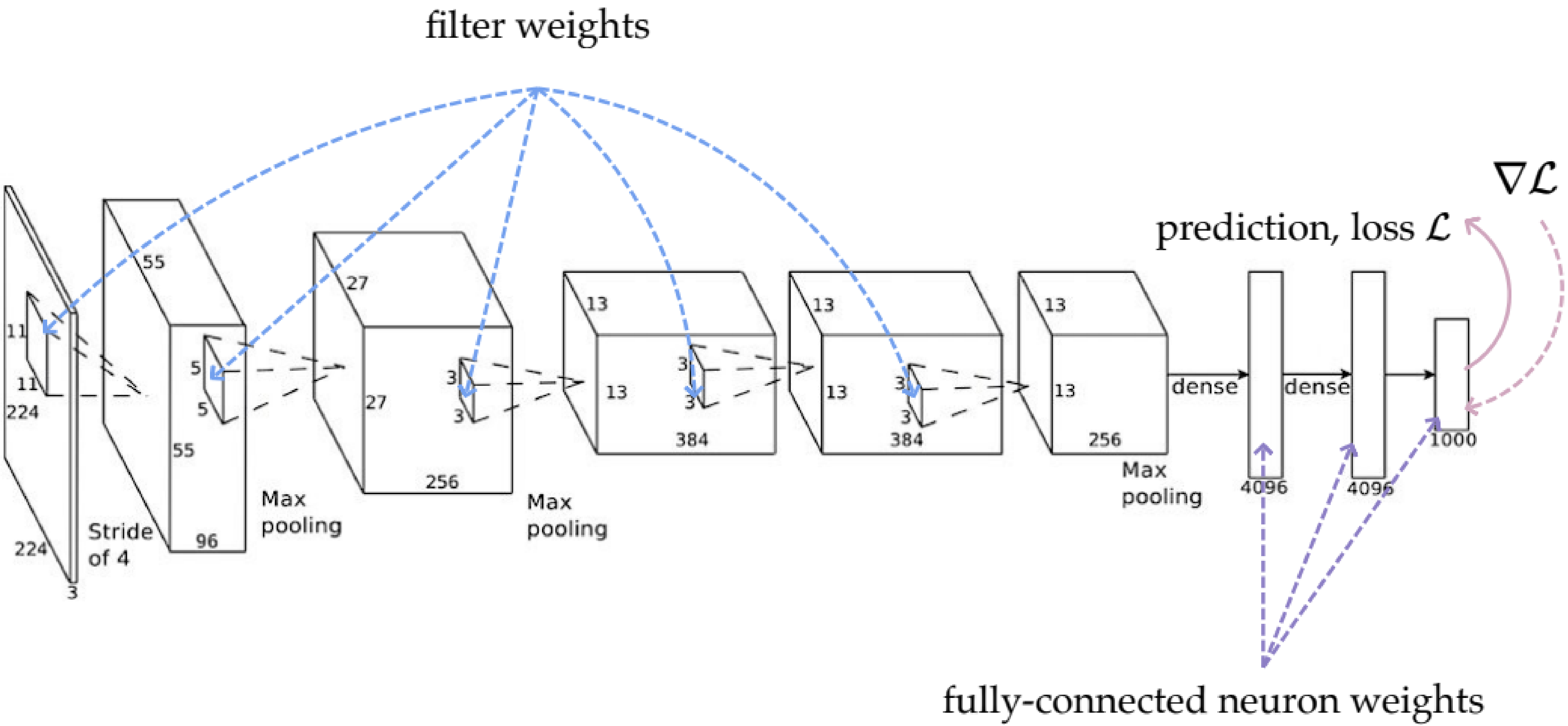

[AlexNet paper]

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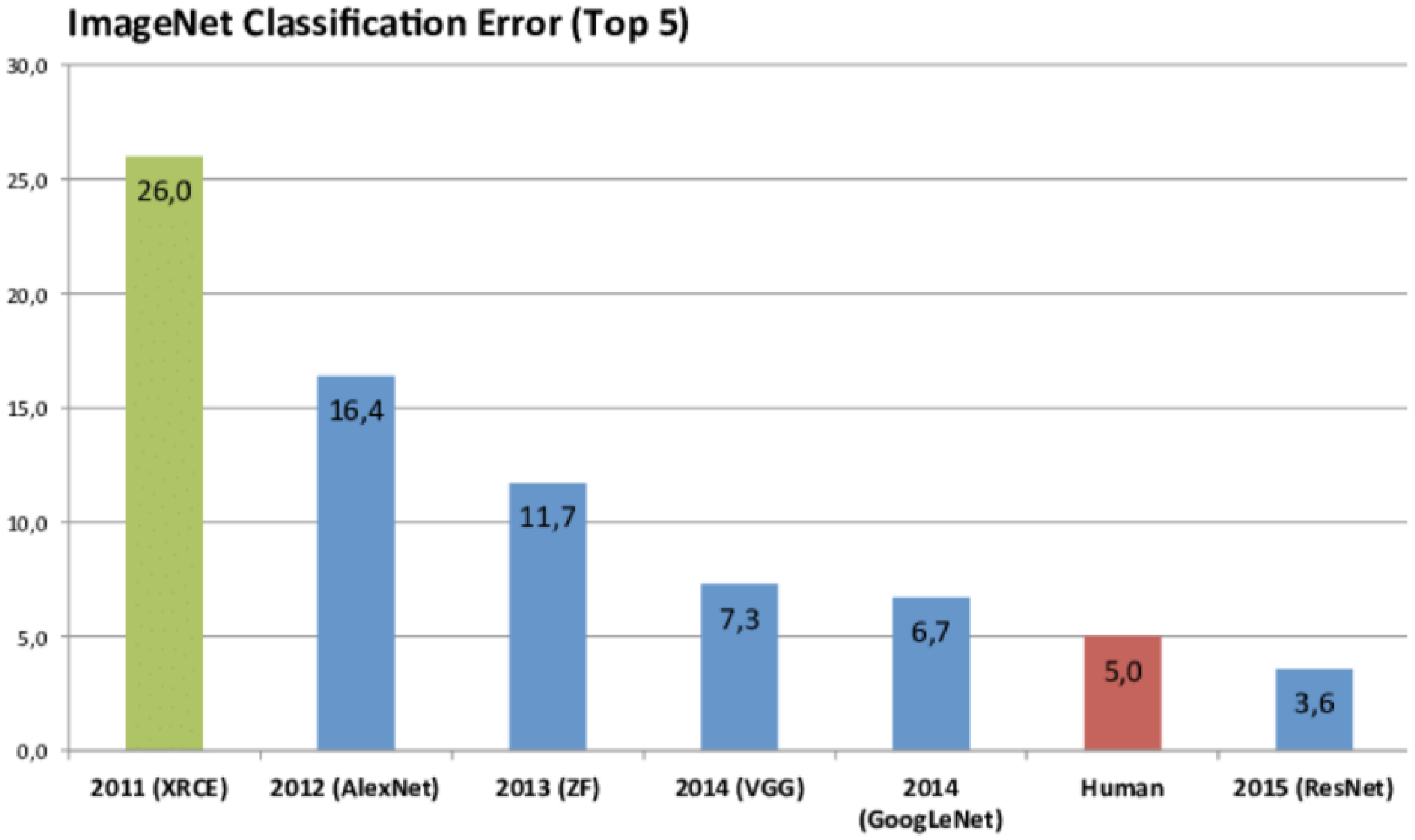

[image credit Philip Isola]

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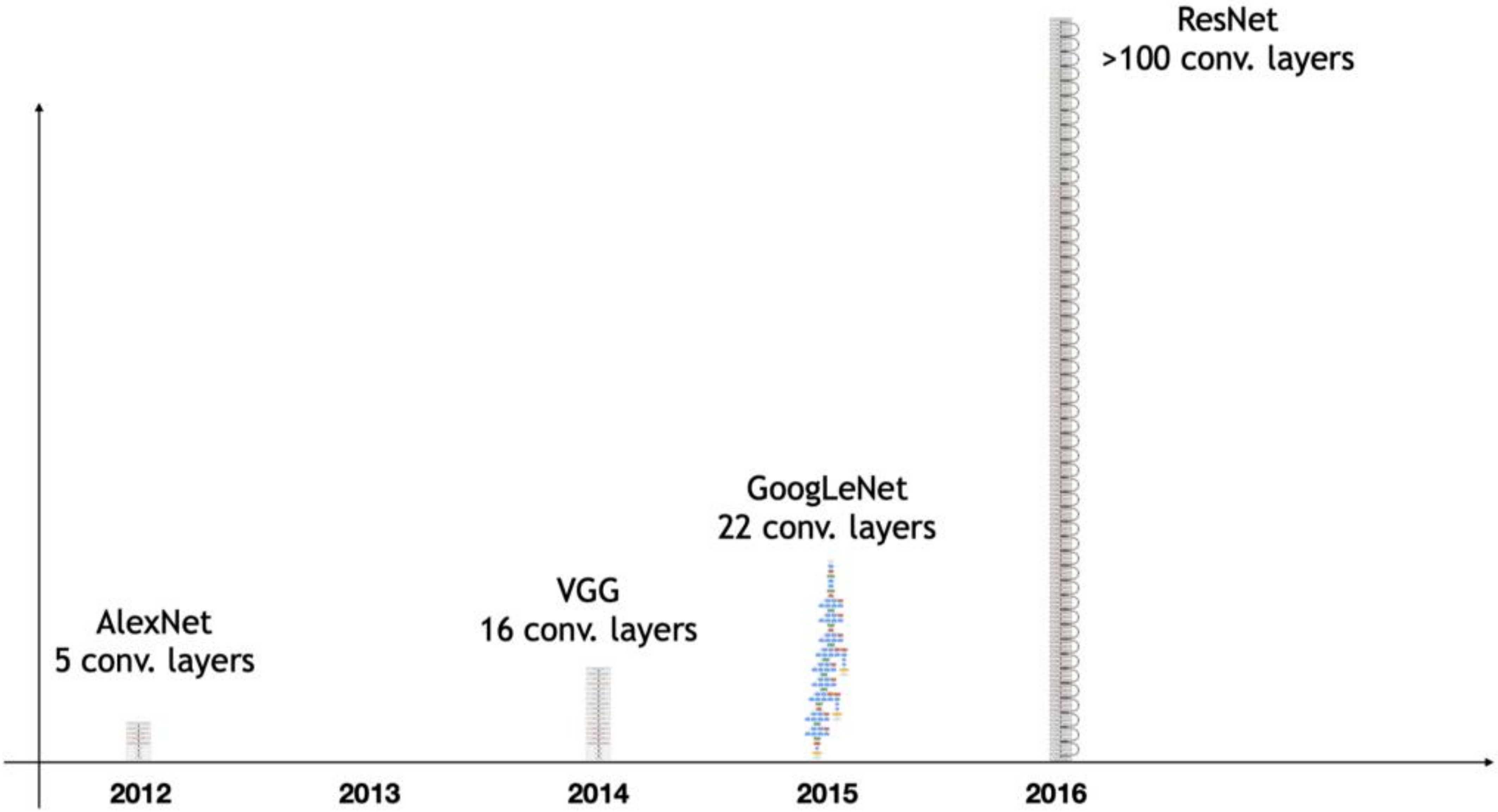
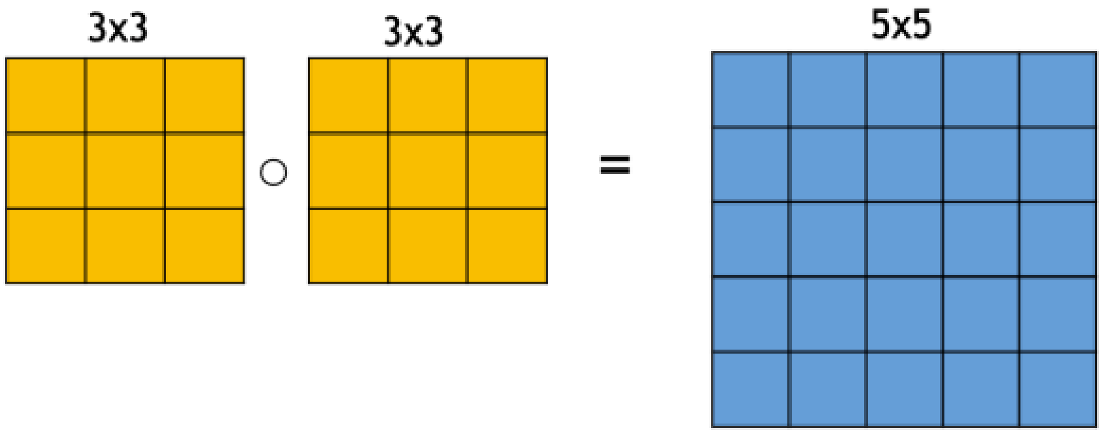


[image credit Philip Isola]

VGG 16

Main developments:

- small convolutional kernels: only 3x3



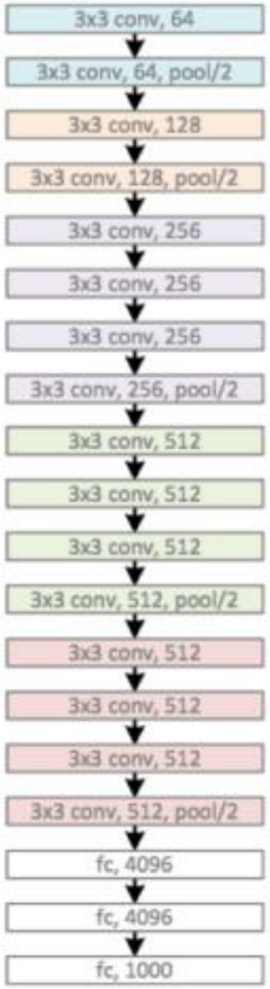
- increased depth: about 16 or 19 layers
- stack the same modules

"Very Deep Convolutional Networks for Large-Scale Image Recognition", Simonyan & Zisserman. ICLR 2015

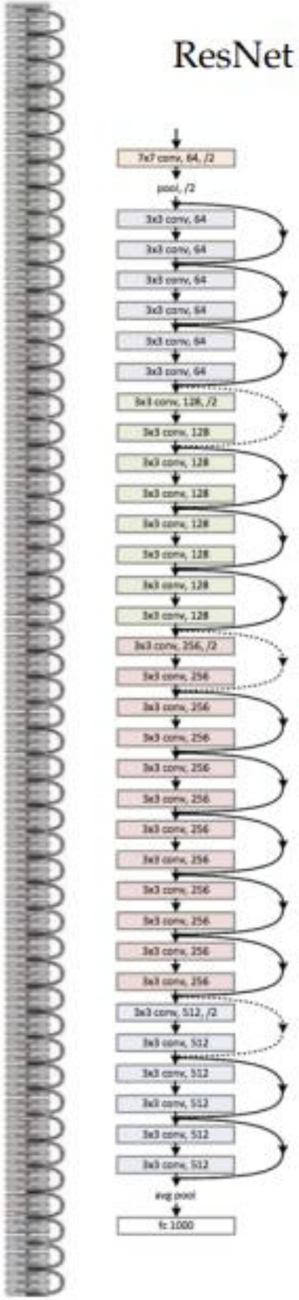
[image credit Philip Isola and Kaiming He]

Adopted from : https://introml.mit.edu

VGG '14

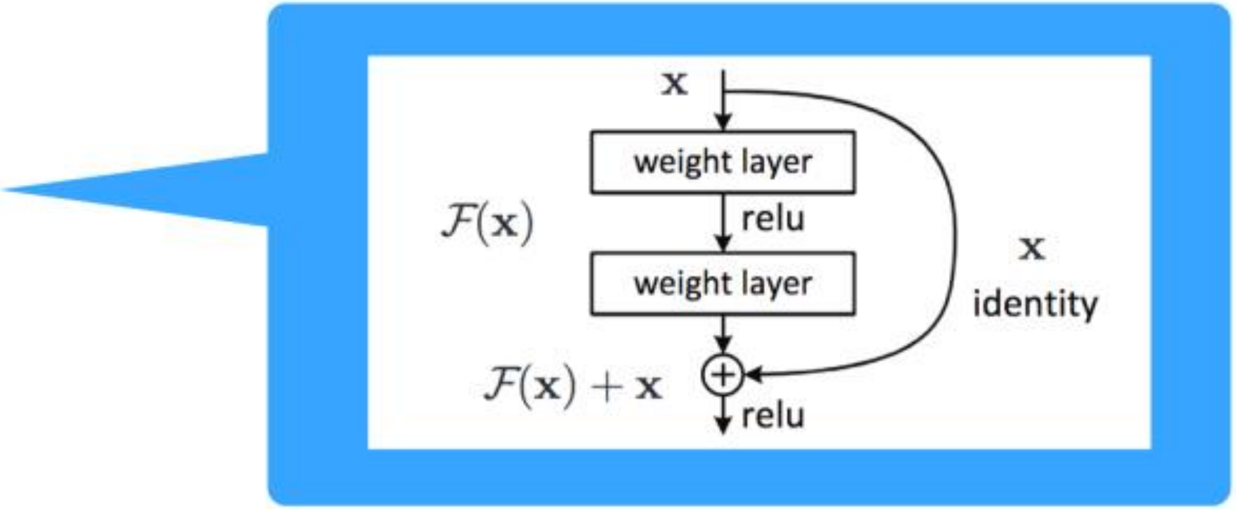


ResNet '16



Main developments:

- Residual block -- gradients can propagate faster (via the identity mapping)
- increased depth: > 100 layers



[He et al: Deep Residual Learning for Image Recognition, CVPR 2016]

[image credit Philip Isola and Kaiming He]

Summary

- Though NN are technically “universal approximators”, designing the NN structure so that it matches what we know about the underlying structure of the problem can substantially improve generalization ability and computational efficiency.
- Images are a very important input type and they have important properties that we can take advantage of: visual hierarchy, translation invariance, spatial locality.
- Convolution is an important image-processing technique that builds on these ideas. It can be interpreted as locally connected network, with weight-sharing.
- Pooling layer helps aggregate local info effectively, achieving bigger receptive field.
- We can train the parameters in a convolutional filtering function using backprop and combine convolutional filtering operations with other neural-network layers.