Deep Learning

Lecture 3
Application to Computer Vision

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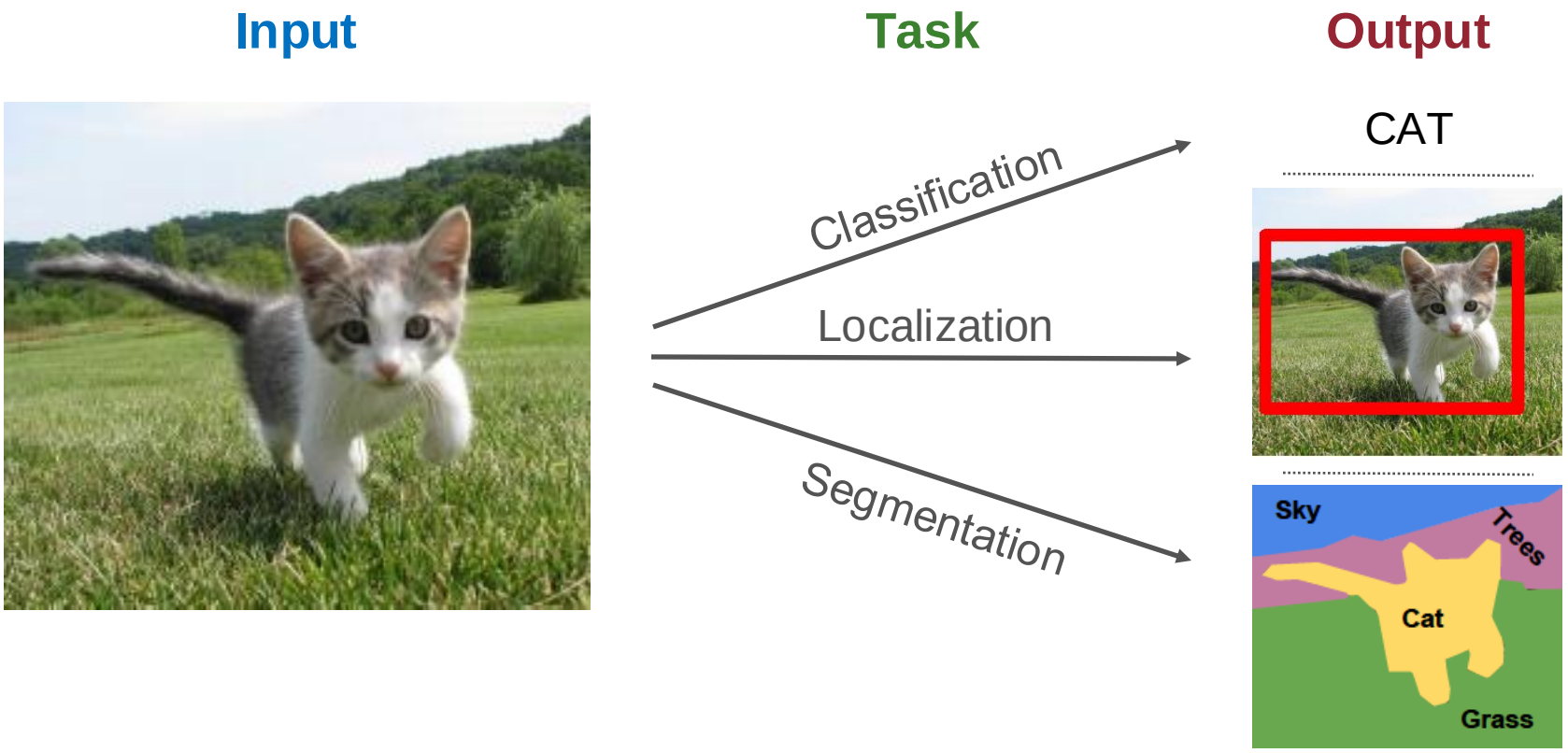
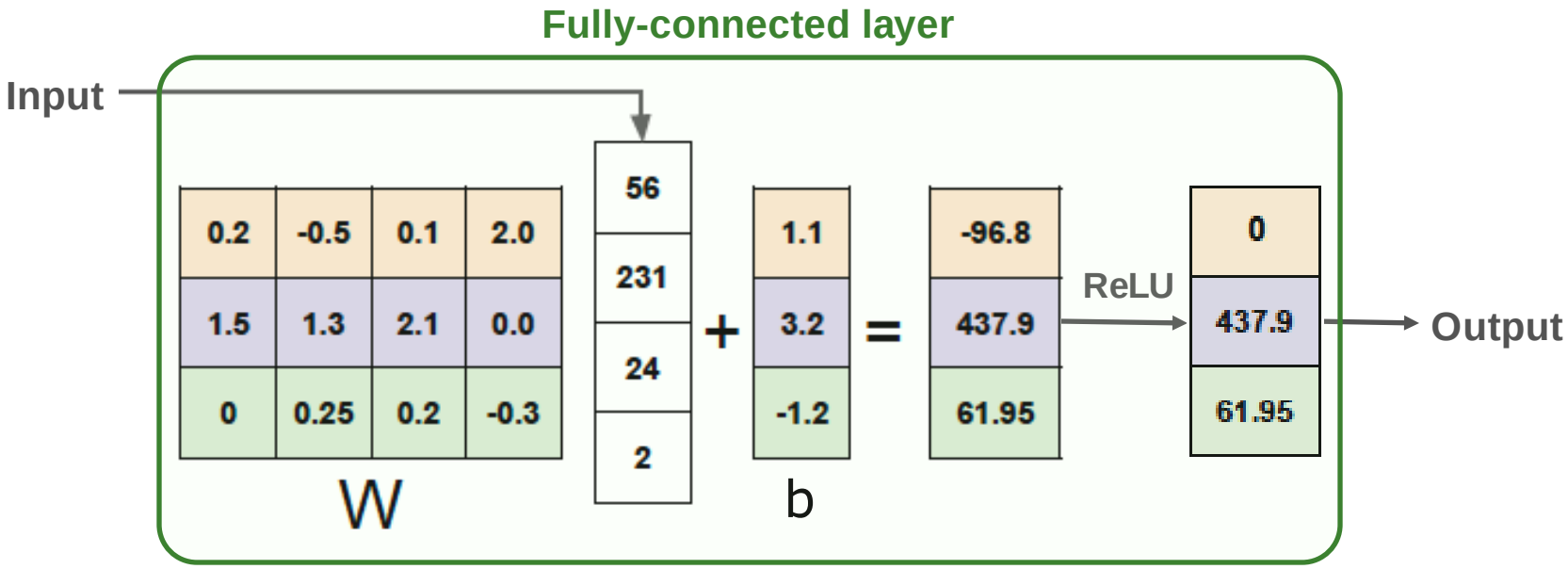
Image-related tasks

- Neural networks can be used for many things…



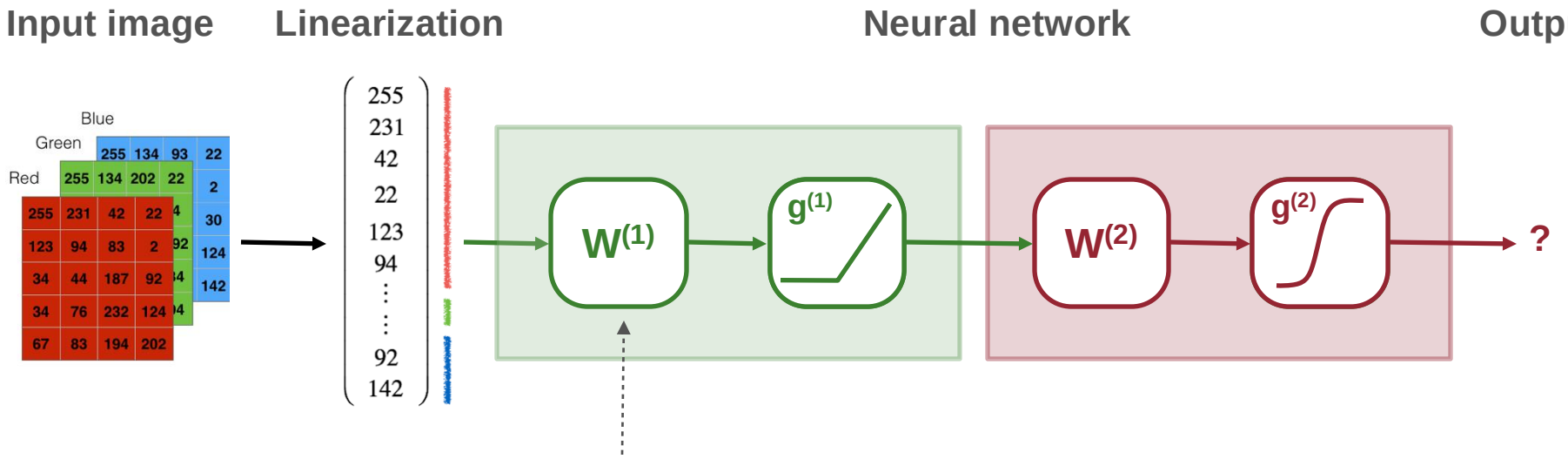
Fully-connected layer

- Standard networks are made of **fully-connected layers**
  - *Each layer is a matrix multiplication*
  - *Each layer contains **"(input dim. + 1) x hidden dim."** parameters*



Bottleneck of standard networks

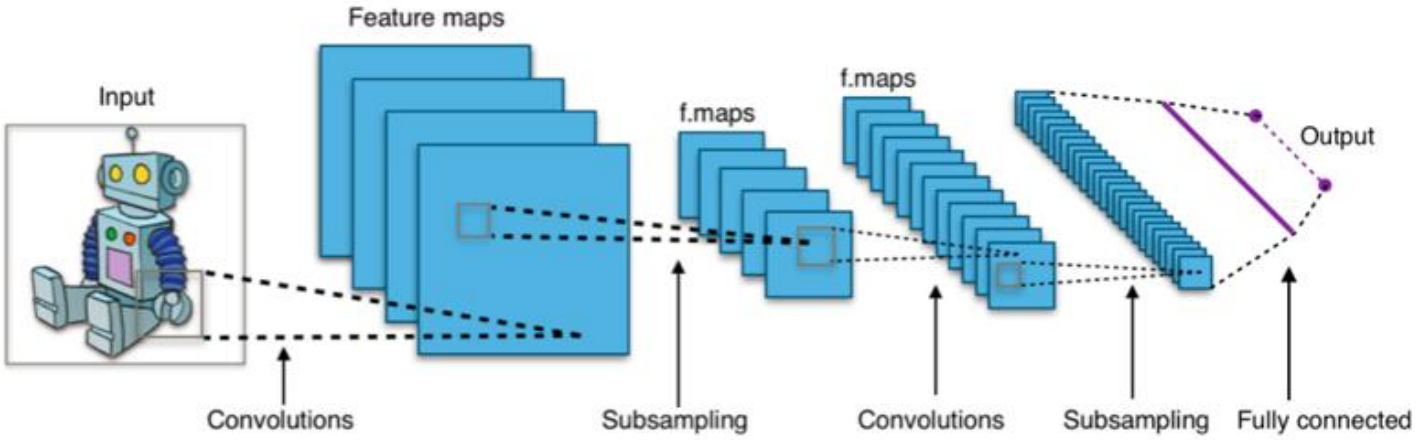
- Fully-connected layers are **unsuitable for images**
  - *Too many parameters to train*
  - *Difficult to prevent overfitting*



Coming up…

- Standard networks are limited to **low-dimensional data**
  - *Too many parameters when the input is high-dimensional*
  - *How to deal with high-resolution images?*

- Solution for image inputs → **Convolutional networks**



Convolution

Convolution in 1D/2D/3D

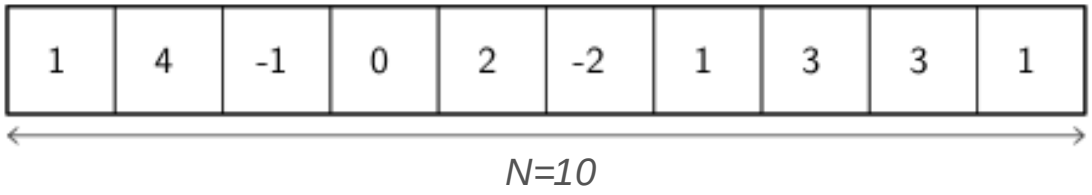
Edge detection

Convolution 1D (1/2)

- Convolution with **vectors**

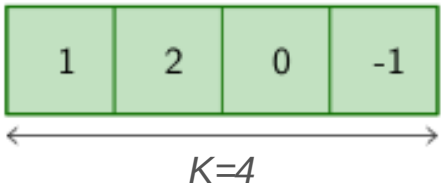
Input

*(vector of size **N**)*



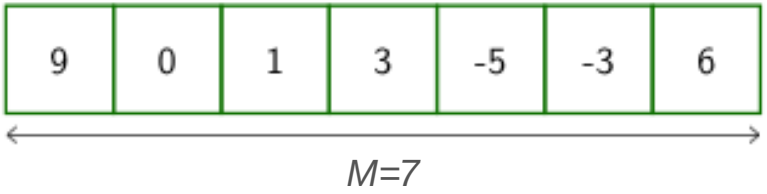
Kernel

*(vector of size **K<N**)*



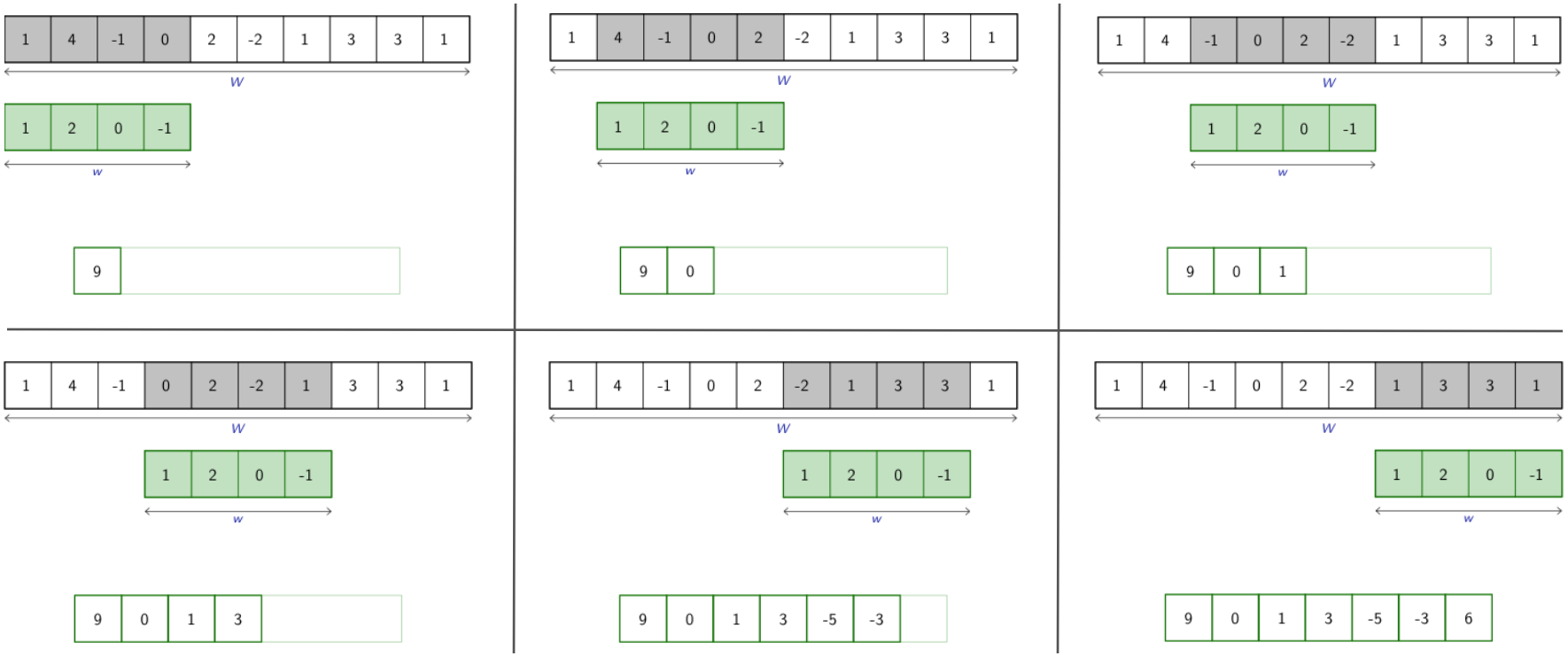
Output

*(vector of size **N-K+1**)*



Convolution 1D (2/2)

- Visual explanation of convolution in 1D
  - *At each step, the kernel is multiplied to a chunk of the input…*
  - *… and the resulting coefficients are summed*



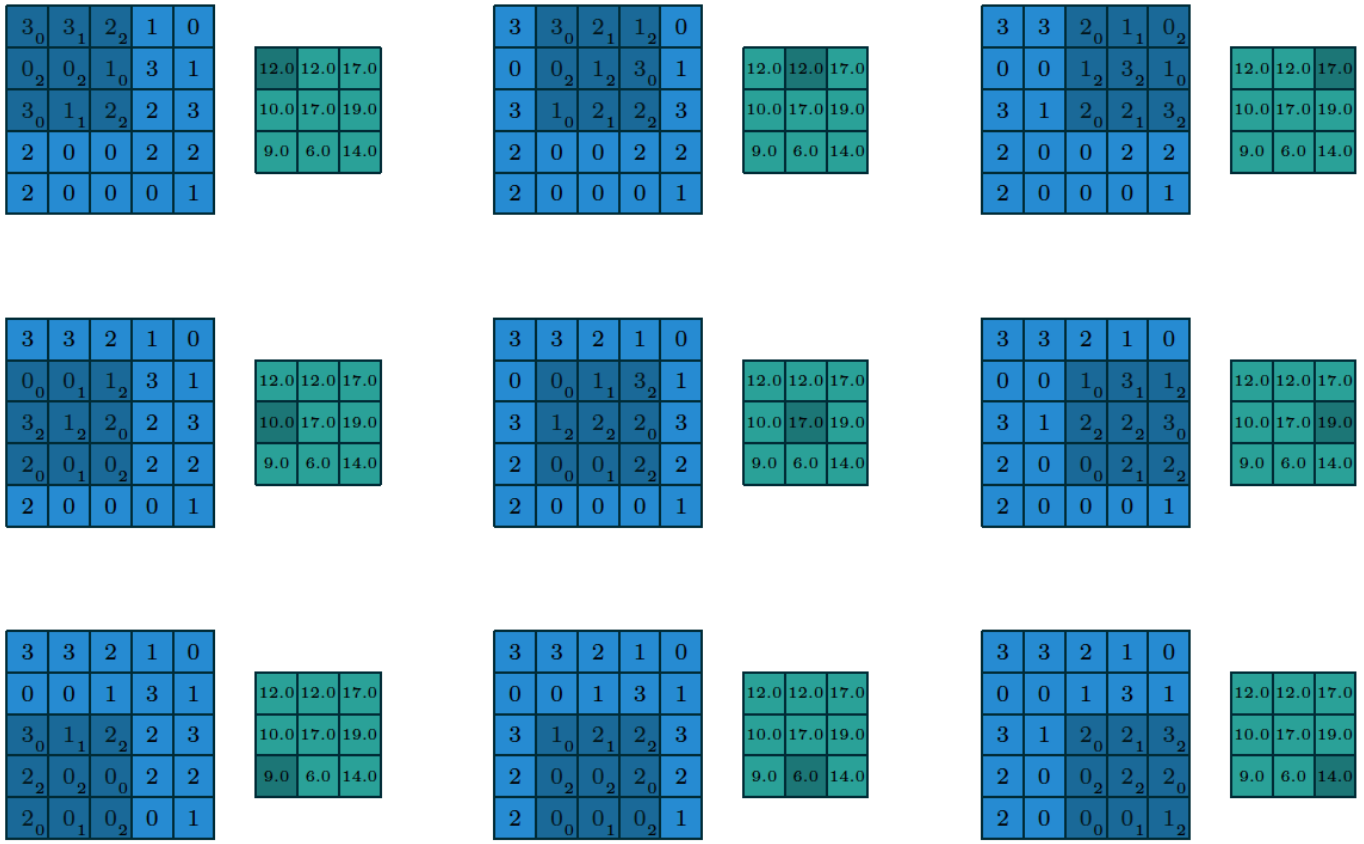
Convolution 2D (1/2)

- Convolution with **single-channel images**

Input *(size N_1 x N_2)*							***Kernel*** *(size K_1 x K_2)*				***Output*** *(size N_1-K_1+1 x N_2-K_2+1)*			
3	0	1	2	7	4		1	0	-1		-5	-4	0	8
1	5	8	9	3	1		1	0	-1		-10	-2	2	3
2	7	2	5	1	3	*	1	0	-1	=	0	-2	-4	-7
0	1	3	1	7	8						-3	-2	-3	-16
4	2	1	6	2	8									
2	4	5	2	3	9									

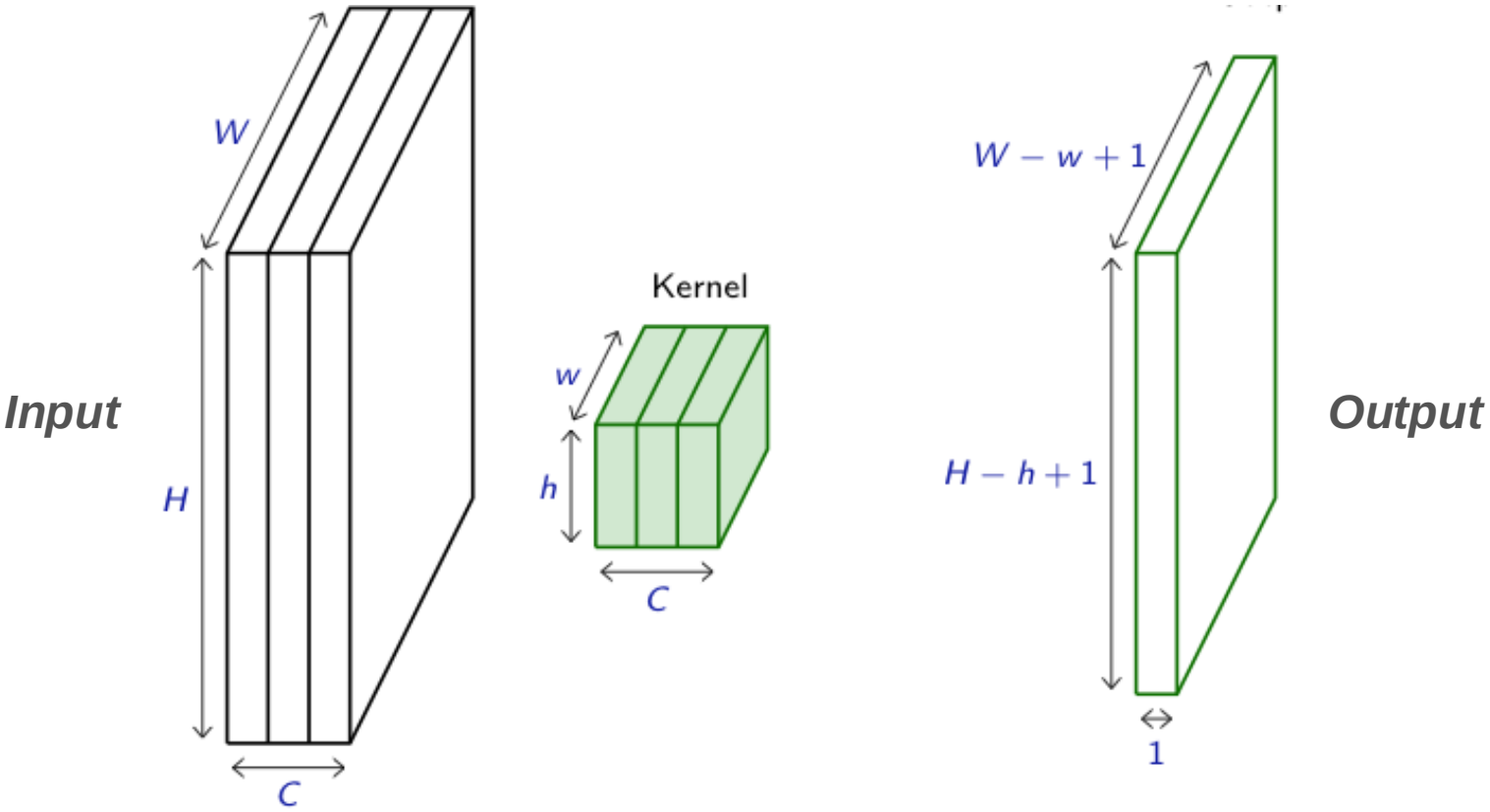
Convolution 2D (2/2)

- Visual explanation of convolution in 2D



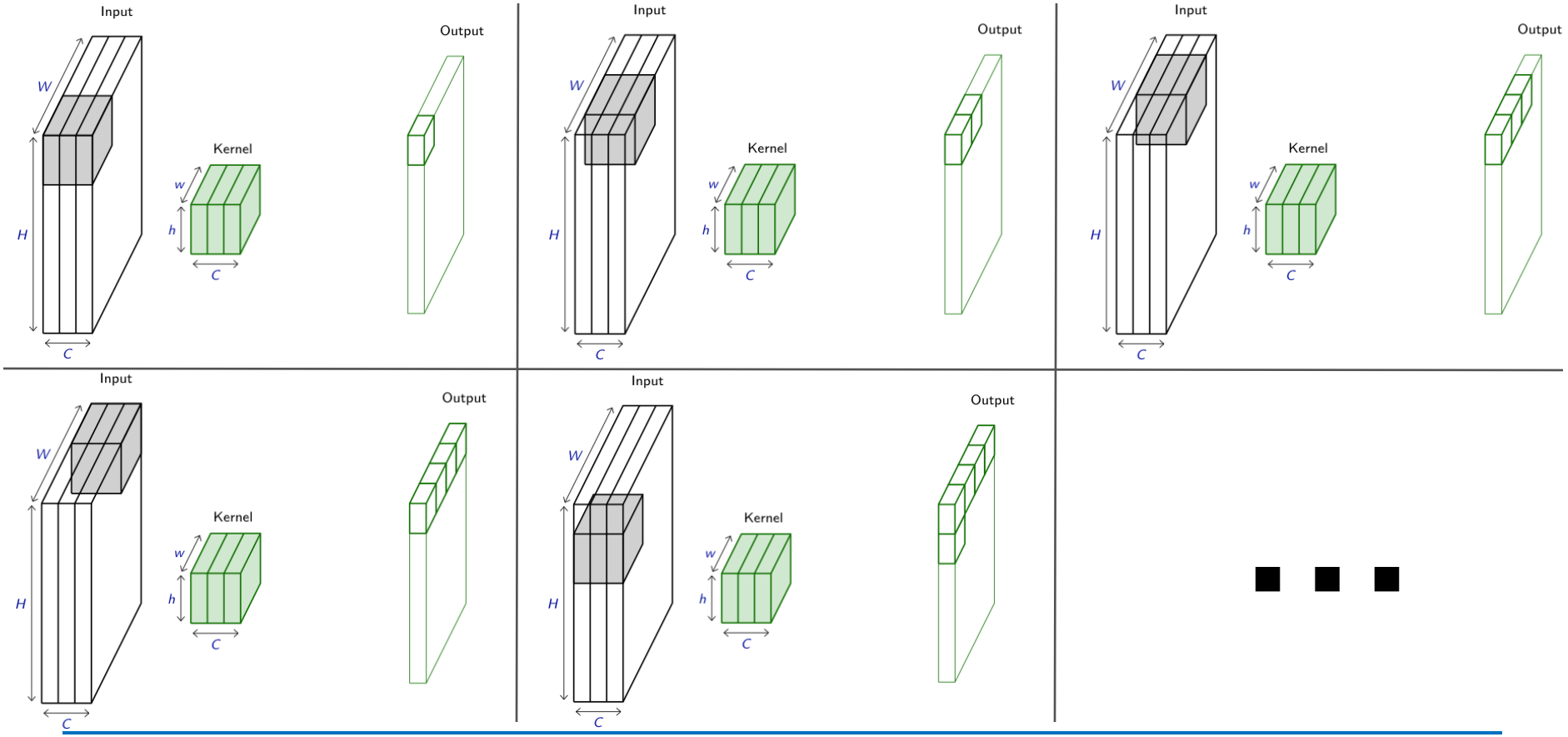
Convolution 3D (1/2)

- Convolution with **multi-channel images**



Convolution 3D (2/2)

- Visual explanation of convolution in 3D



Edge detection (1/3)

- **Vertical edge detection**

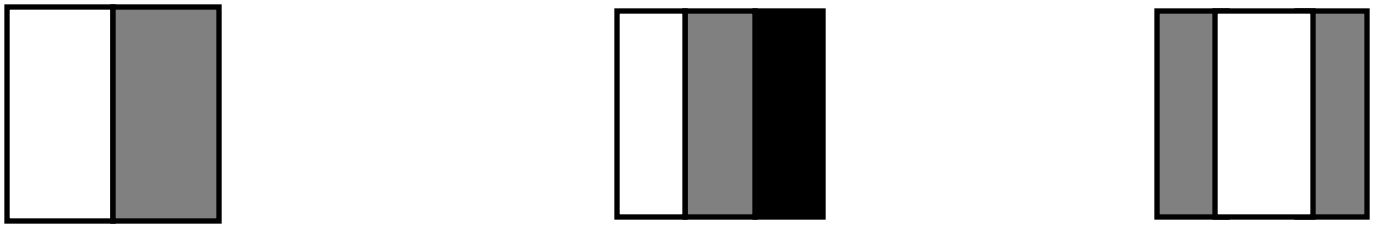
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

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

=

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0



Edge detection (2/3)

- **Horizontal edge detection**

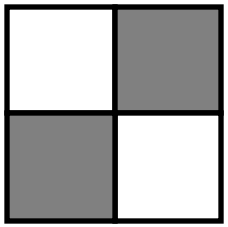
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

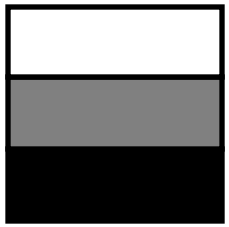
*

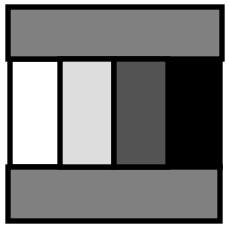
1	1	1
0	0	0
-1	-1	-1

=

0	0	0	0
30	10	-10	-30
30	10	-10	-30
0	0	0	0



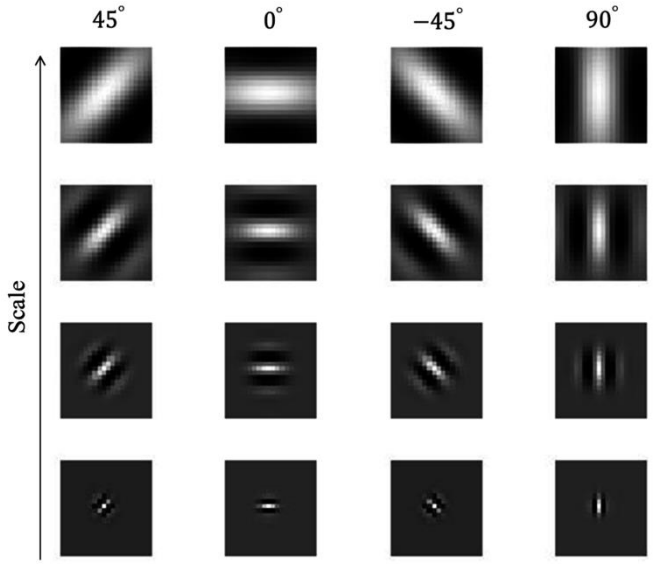




Edge detection (3/3)

- **Putting all together**
  - *A different kernel for each orientation and scale*

Kernels



Convolutions

Output

(Combination of all the convolved images)

Quiz

1) What is the output size of the following convolutions?
   - ***10x12*** *matrix convolved by* ***5x5*** *kernel*
   - ***15x15x10*** *volume convolved by* ***3x3x3*** *kernel*

2) Compute the following convolution.

3	0	1	2	7	4
1	5	8	9	3	1
2	7	2	5	1	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

*

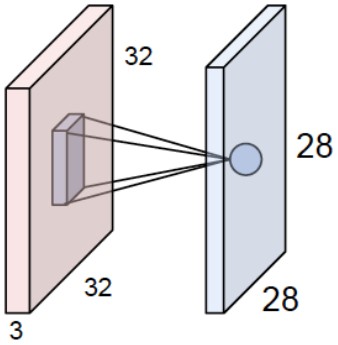
1	1	1
1	1	1
1	1	1

=

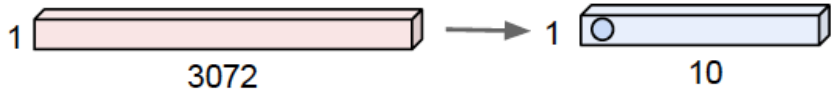
Summary so far…

- **Convolution** → Spatially-invariant operation
  - *The same weights are used for computing the output coefficients*
- **Matrix multiplication** → General operation
  - *Different weights are used for computing the output coefficients*

Convolution
(5x5 kernel)



Matrix multiplication
(10x3072 matrix)



Convolutional layer

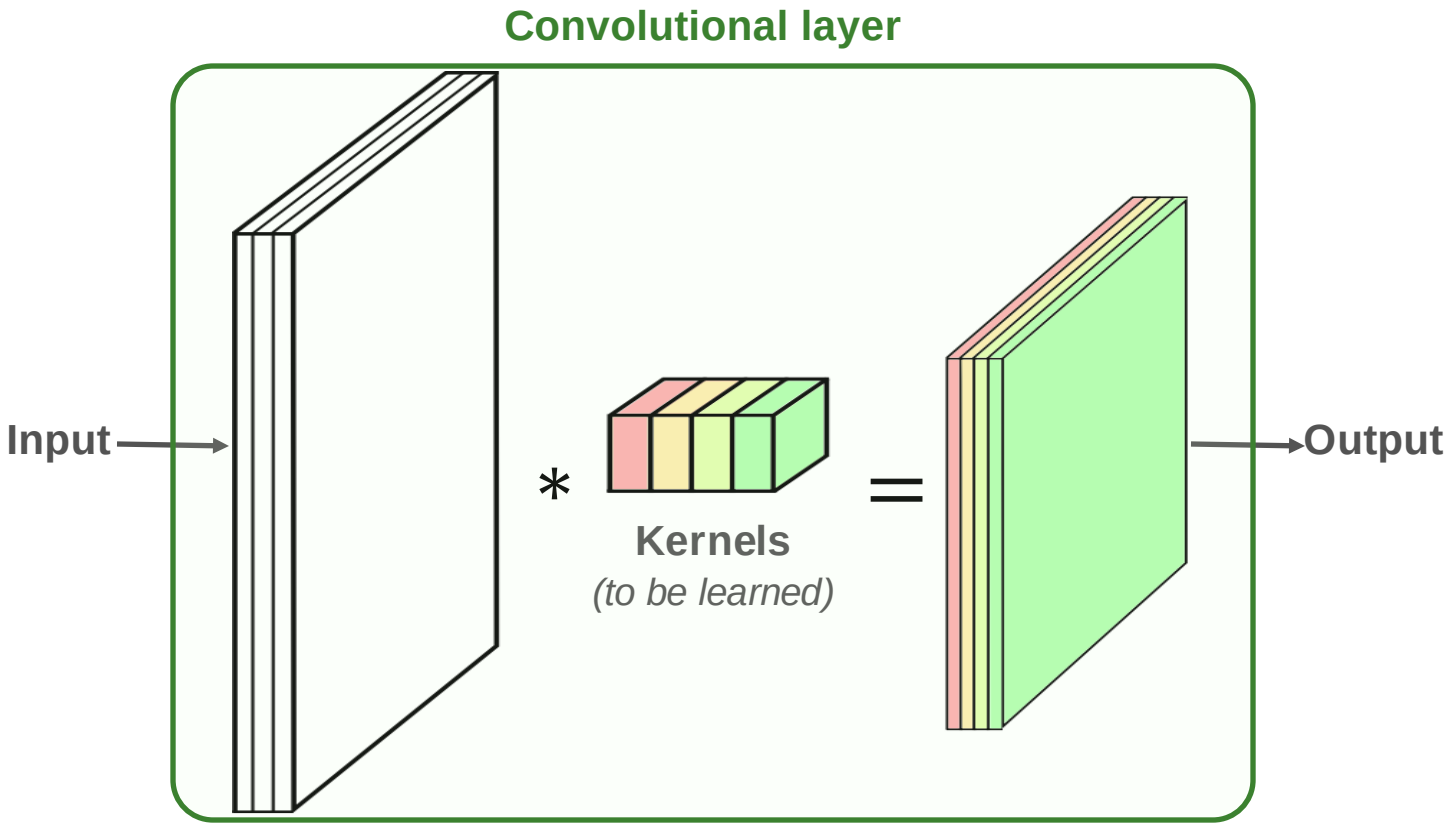
Multiple kernels

Hyper-parameters

Padding & Stride

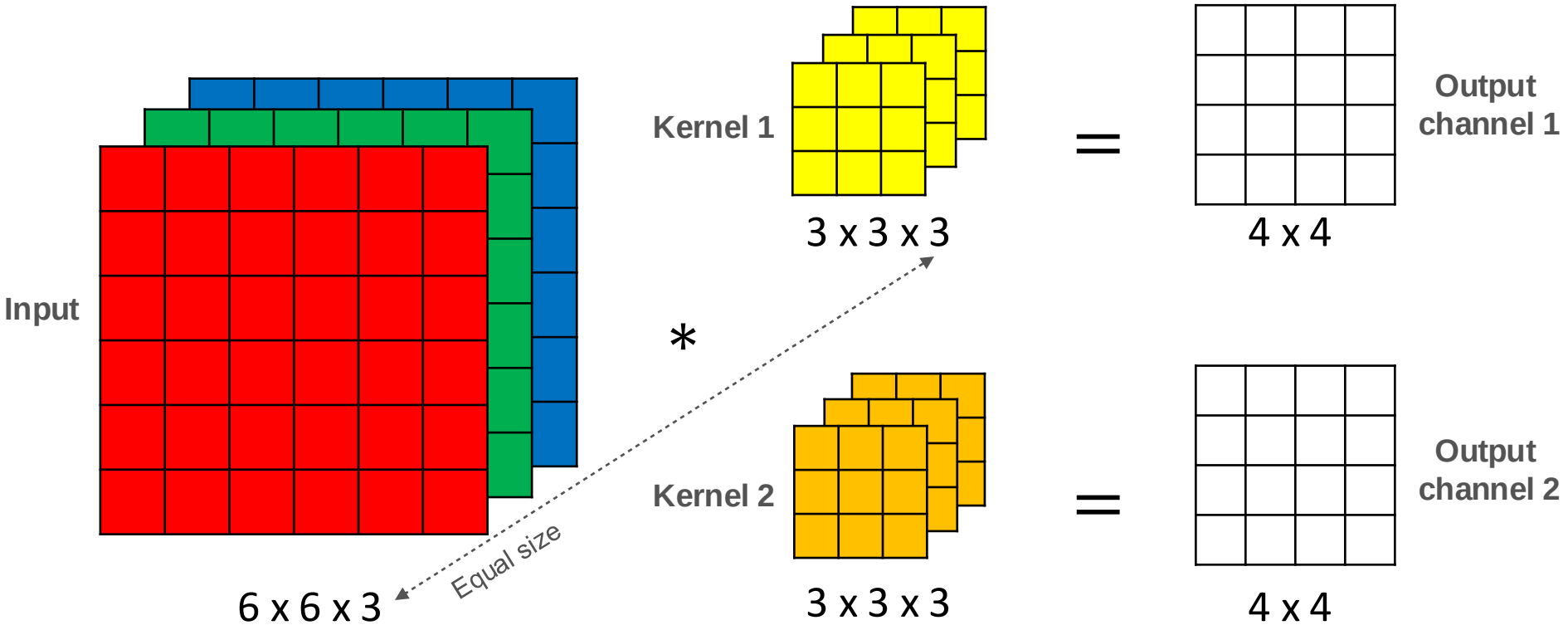
Multiple kernels (1/2)

- The input is convolved with **multiple kernels**



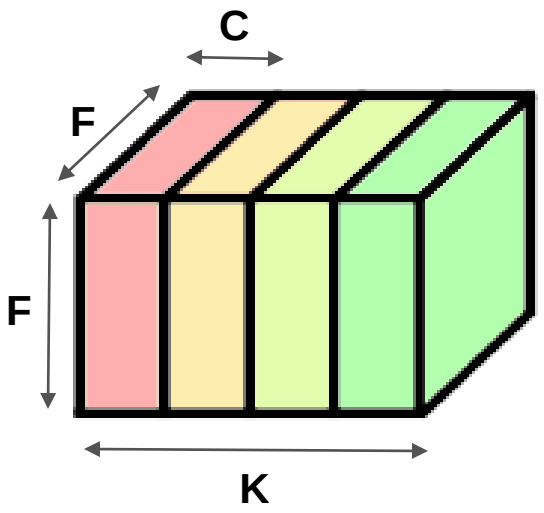
Multiple kernels (2/2)

- Each convolution produces a channel for the output
  - *The **kernel depth** must be equal to the number of **input channels***



Hyper-parameters

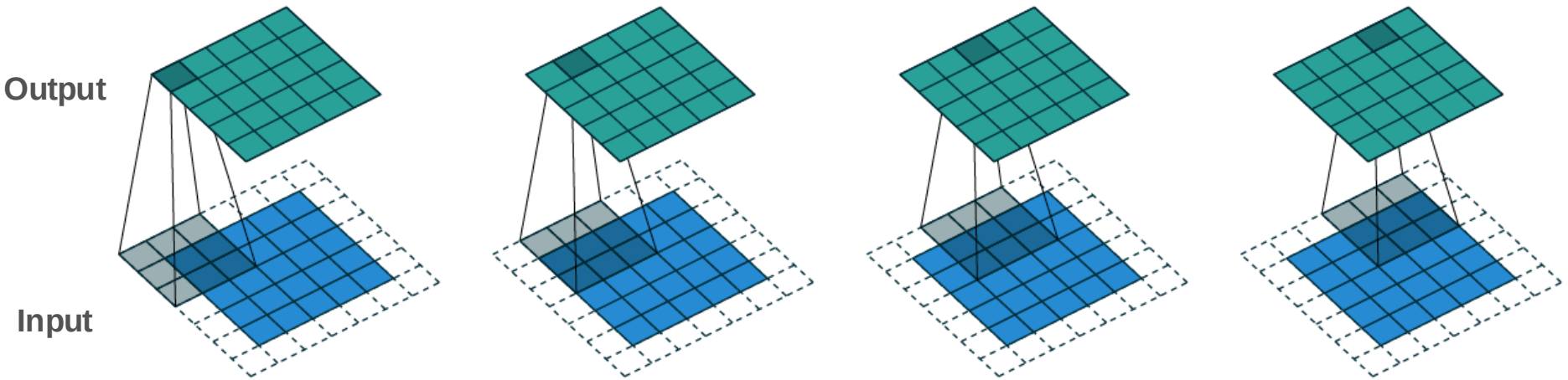
- Main hyper-parameters
  - ***F*** ➜ ***Spatial size of kernels***
  - ***K*** ➜ ***Number of kernels***
- Other hyper-parameters
  - ***P*** ➜ ***Padding***
  - ***S*** ➜ ***Stride***
- Fixed value
  - ***C*** ➜ ***Kernel depth*** *(equal to the number of input channels)*



Padding & stride (1/3)

- The input can be **padded** with zero rows/columns
  - *The output size is extended by **P > 0***

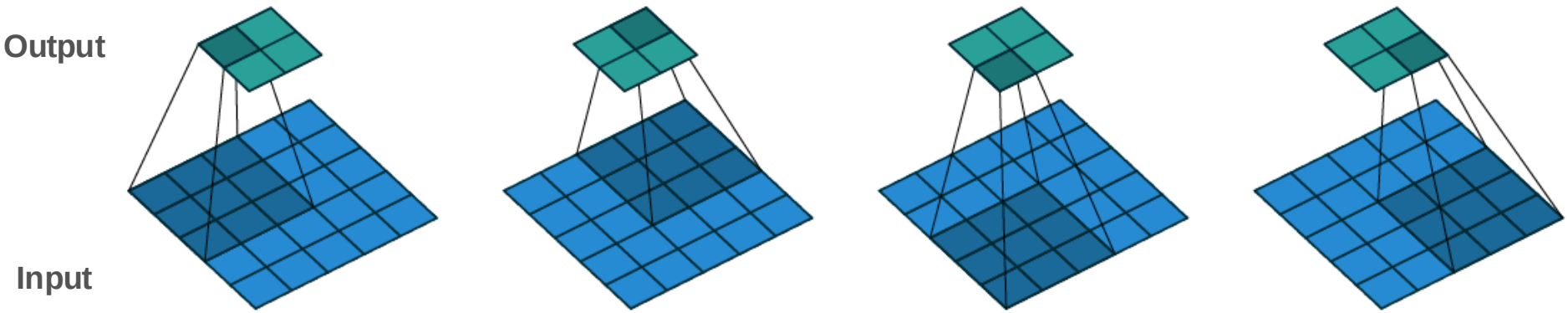
Example with **P=1**



Padding & stride (2/3)

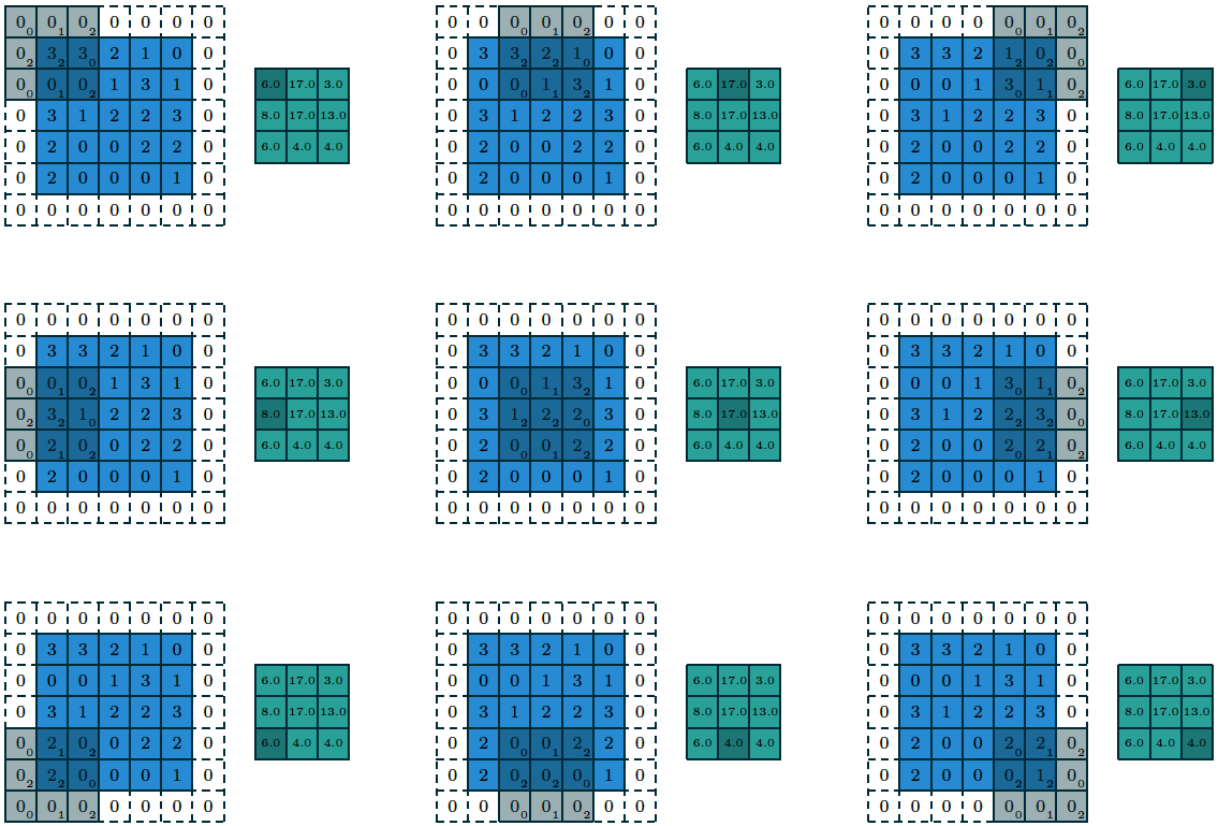
- The output can be **downsampled** along the rows/columns
  - *The output size is reduced by a factor **S > 1***

Example with **S=2**



Padding & stride (3/3)

- Example with **padding (P=1)** and **stride (S=2)**

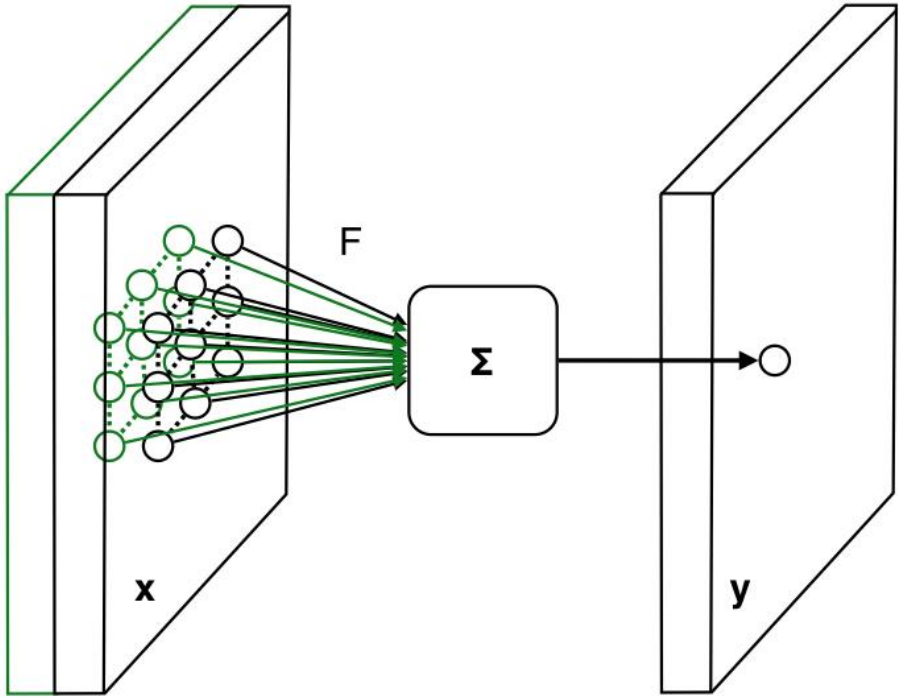


Neural interpretation

- A convolution is a neuron with limited reception field
  - *The field limit is defined by the kernel size*
  - *The same neuron is "fired" over multiple areas from the input.*

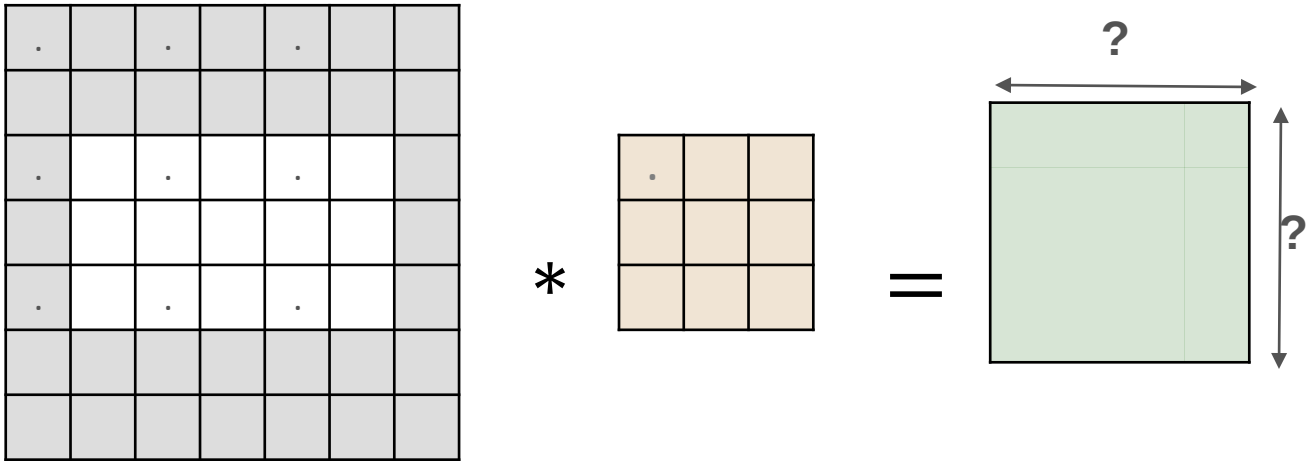
Local
Filters look locally

Translation invariant
Filters act the same everywhere



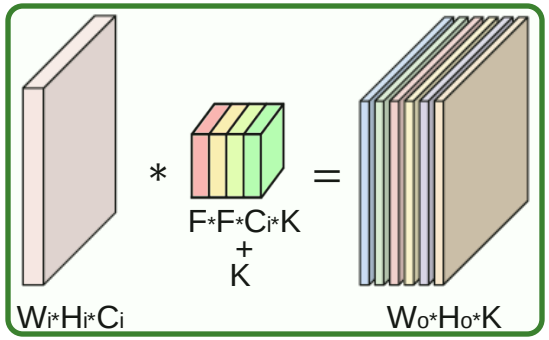
Quiz

- Compute the output shape of a convolutional layer with
  - ***Input*** ➔ *3 x 5 x C*
  - ***Kernel*** ➔ *3 x 3 x C x 2*
  - ***Padding*** ➔ *2 x 1*
  - ***Stride*** ➔ *2 x 2*



Summary so far…

- **Convolutional layer**
  - The input is a volume of size $\mathbf{W_i}$ x $\mathbf{H_i}$ x $\mathbf{C_i}$
  - Four hyper-parameters are required
    - ***K*** ➜ *Number of kernels*
    - ***F*** ➜ *Spatial size*
    - ***S*** ➜ *Stride*
    - ***P*** ➜ *Padding*
  - The output is a volume of size $\mathbf{W_o}$ x $\mathbf{H_o}$ x $\mathbf{C_o}$
    - $W_o = (W_i - F + 2P) / S + 1$
    - $H_o = (H_i - F + 2P) / S + 1$
    - $C_o = K$
  - The number of parameters to be learned is $(\mathbf{F} \times \mathbf{F} \times \mathbf{C_i} + \mathbf{1}) \times \mathbf{K}$



Pooling layer

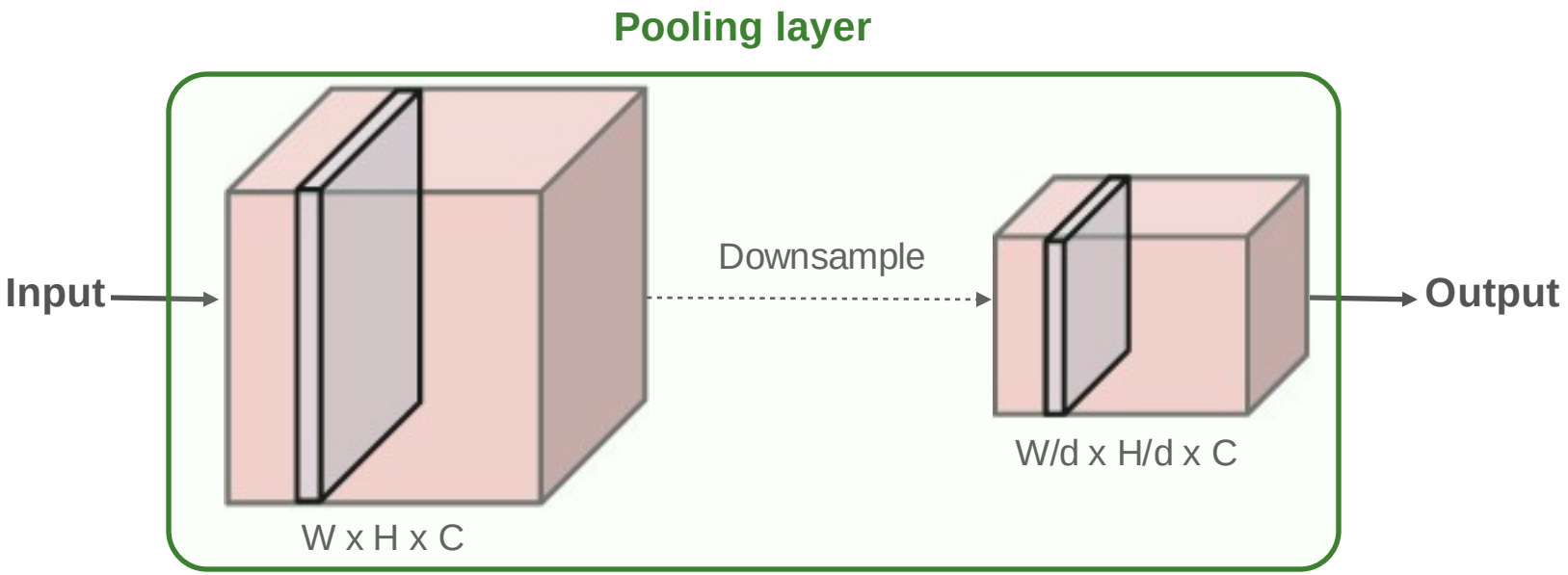
Downsampling

Max-pooling

Translation invariance

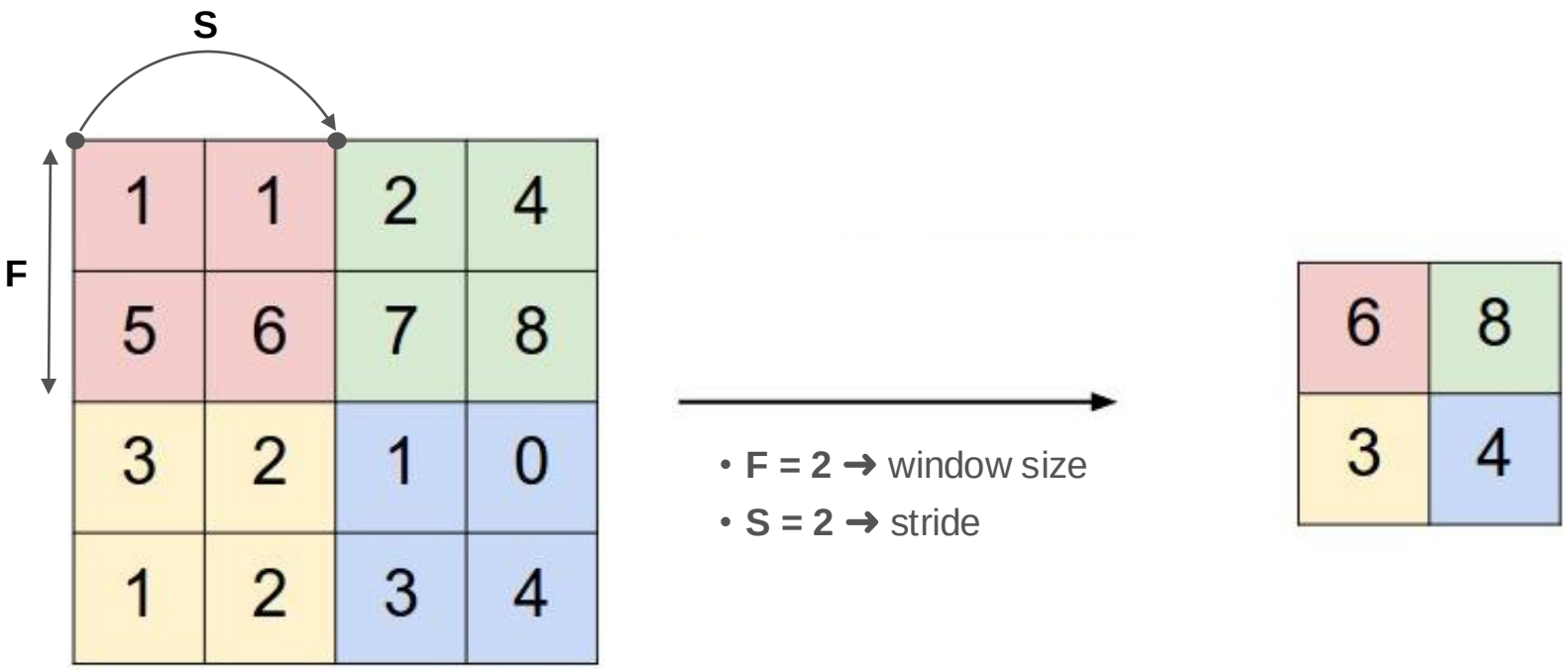
Downsampling

- The **pooling layer** reduces the spatial size of the input
  - *It operates over each channel map independently*
  - *It has no parameter to be learned*



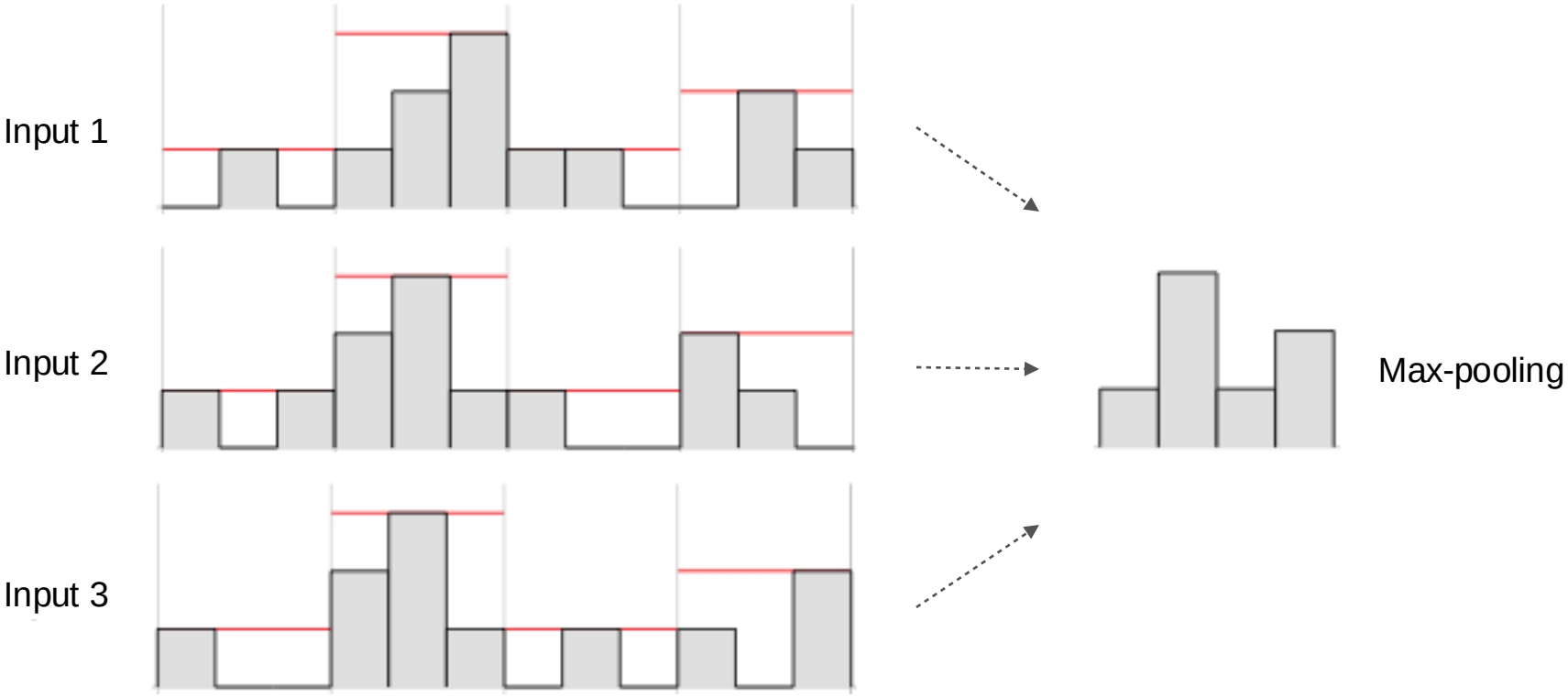
Max-pooling

- The most-common variant is **max-pooling**
  - *It computes the max over a sliding window*
  - ***Hyper-parameters*** ➜ *window size (**F**) & stride (**S**)*



Translation invariance

- Pooling and convolution are **translation invariant**
  - *A spatial shift in the input doesn't change the output*



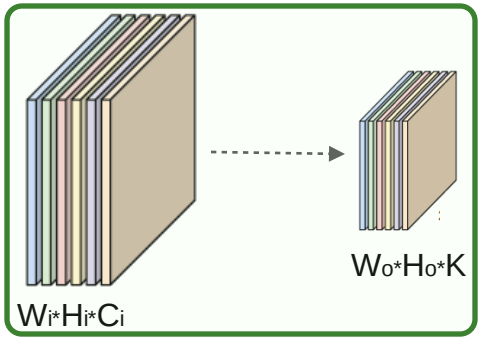
Quiz

1) Because pooling layers do not have parameters, they do not affect the gradient calculation.
   A. *True*
   B. *False*

2) You have an input volume that is **32x32x16**, and apply max-pooling with a **stride of 2** and a **window size of 2**. What is the output volume?
   A. *16x16x8*
   B. *32x32x8*
   C. *16x16x16*
   D. *15x15x16*

Summary so far…

- **Pooling layer**
  - The input is a volume of size W_i x H_i x C_i
  - Two hyper-parameters are required
    - ***F*** ➜ *Window size*
    - ***S*** ➜ *Stride*
  - The output is a volume of size W_o x H_o x C_o
    - $W_o = (W_i - F) / S + 1$
    - $H_o = (H_i - F) / S + 1$
    - $C_o = C_i$
  - No parameters to be learned



- **Note** ➜ Pooling can be replaced with a stride in convolutional layers!

Convolutional network

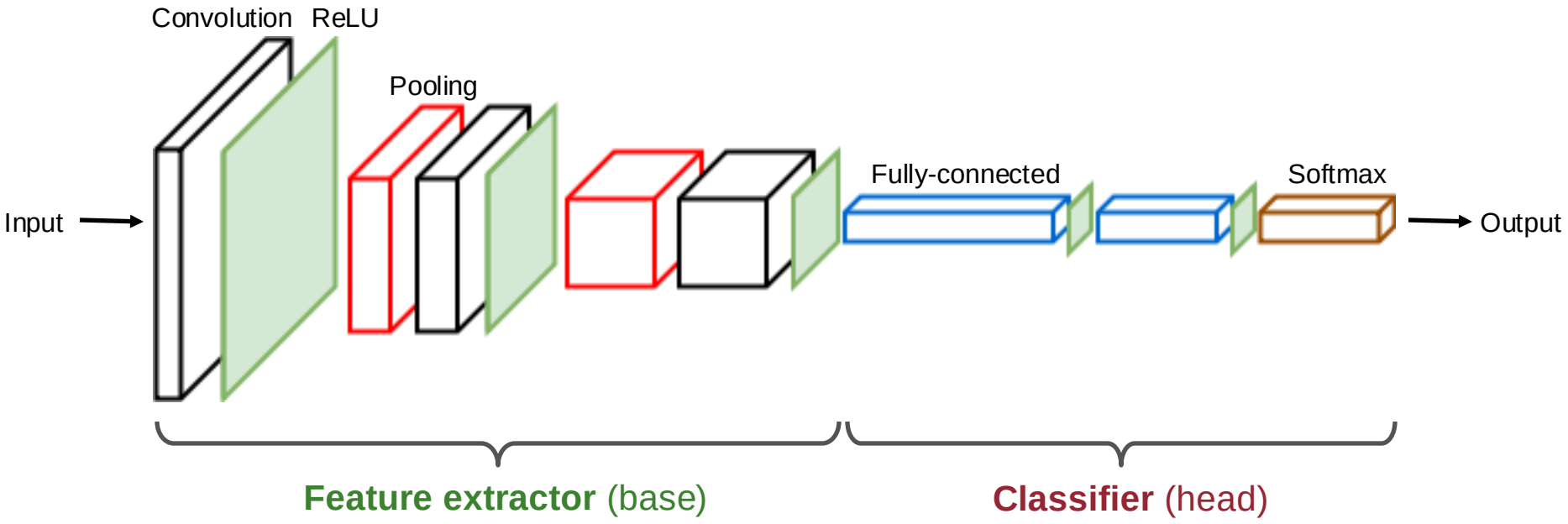
Building blocks

Classic architectures

Modern architectures

Building blocks (1/2)

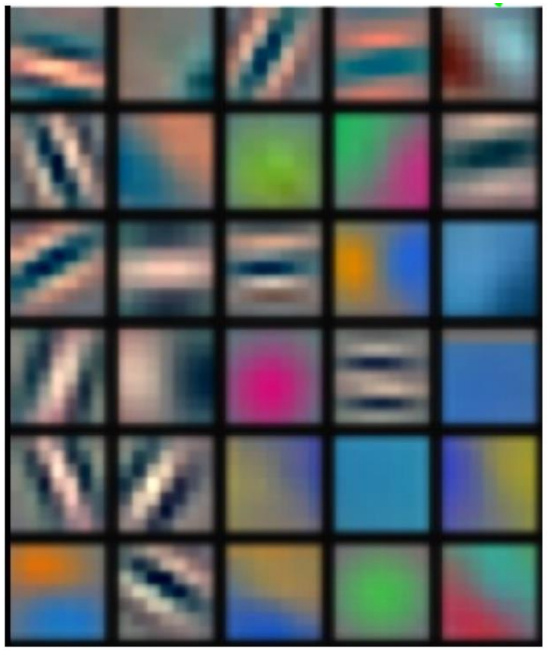
- Architecture of a **convolutional neural network**
  - ***Base*** ➜ *Convolution + pooling*
  - ***Head*** ➜ *Fully-connected + output layer*



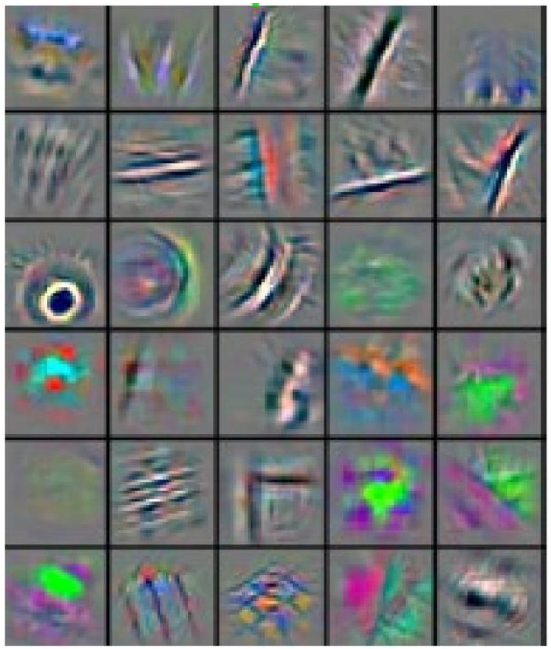
Building blocks (2/2)

- ConvNets learn spatial **hierarchies of patterns**

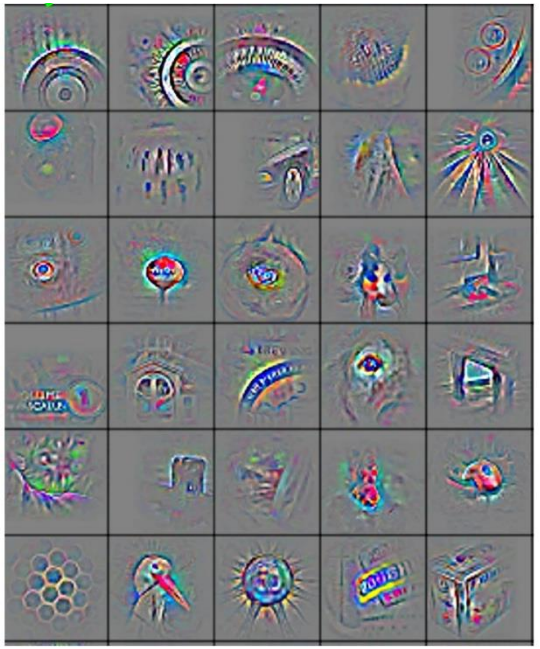
Low-level patterns
(conv. layers in the front)



Mid-level patterns
(conv. layers in the middle)

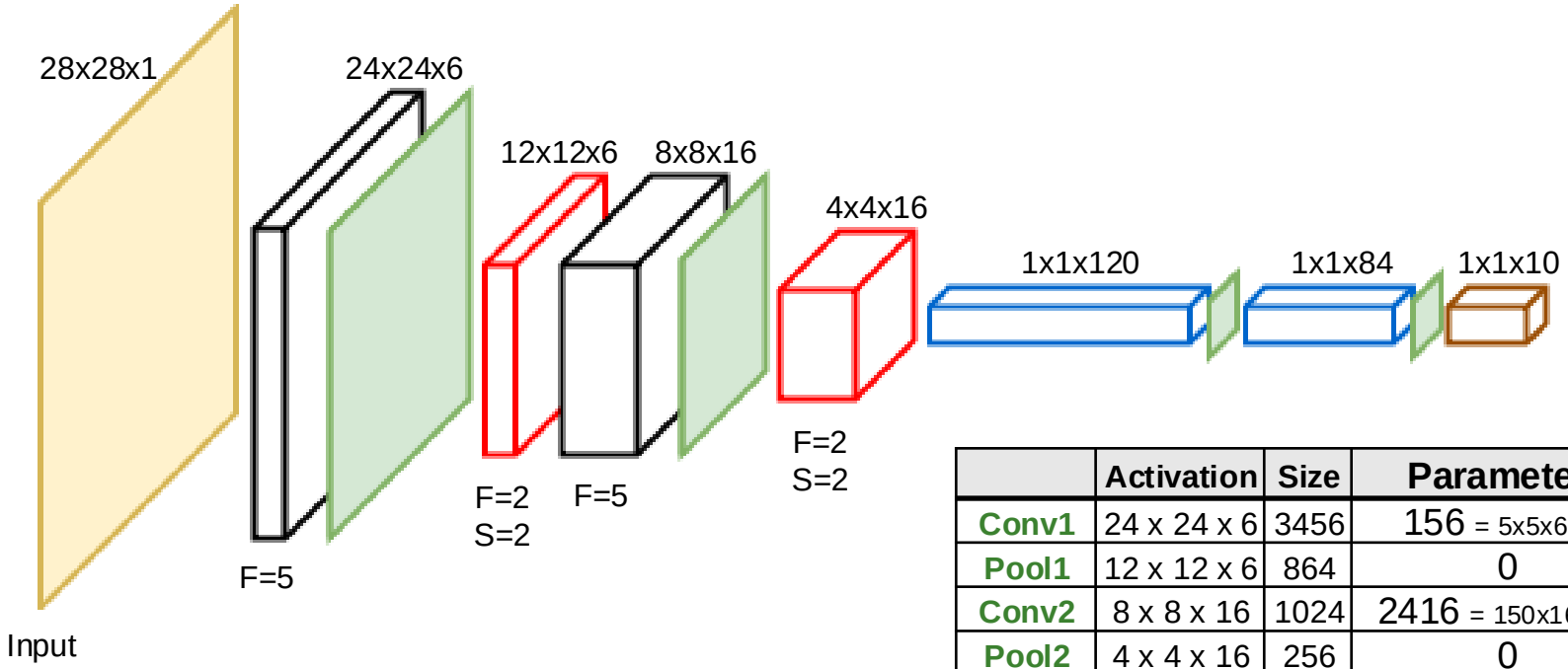


High-level patterns
(conv. layers in the end)



Classic architectures (1/3)

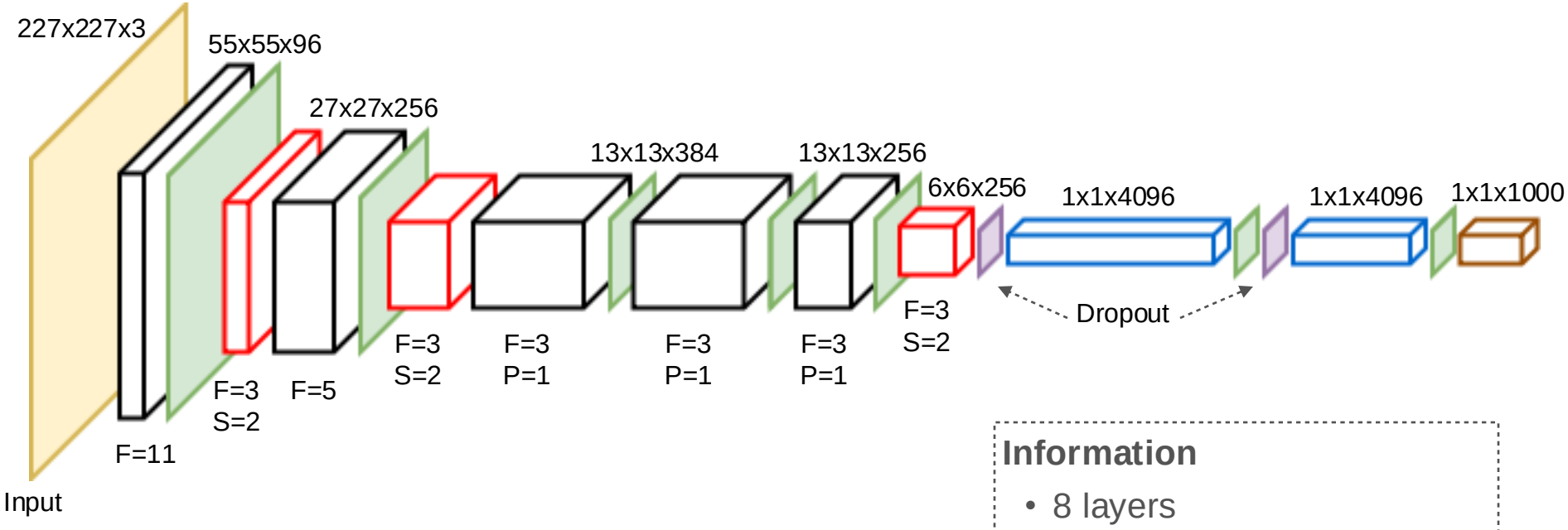
- **LeNet-5** (1998) ➜ *0.05 millions of parameters*



	Activation	Size	Parameters
Conv1	24 x 24 x 6	3456	156 = 5x5x6 + 6
Pool1	12 x 12 x 6	864	0
Conv2	8 x 8 x 16	1024	2416 = 150x16 + 16
Pool2	4 x 4 x 16	256	0
Flatten	1 x 1 x 256	256	0
FC1	1 x 1 x 120	120	30840 = (256+1)x120
FC2	1 x 1x 84	84	10164 = (120+1)x84
Softmax	1 x 1 x 10	10	850 = (84+1)x10

Classic architectures (2/3)

- **AlexNet** (2012)

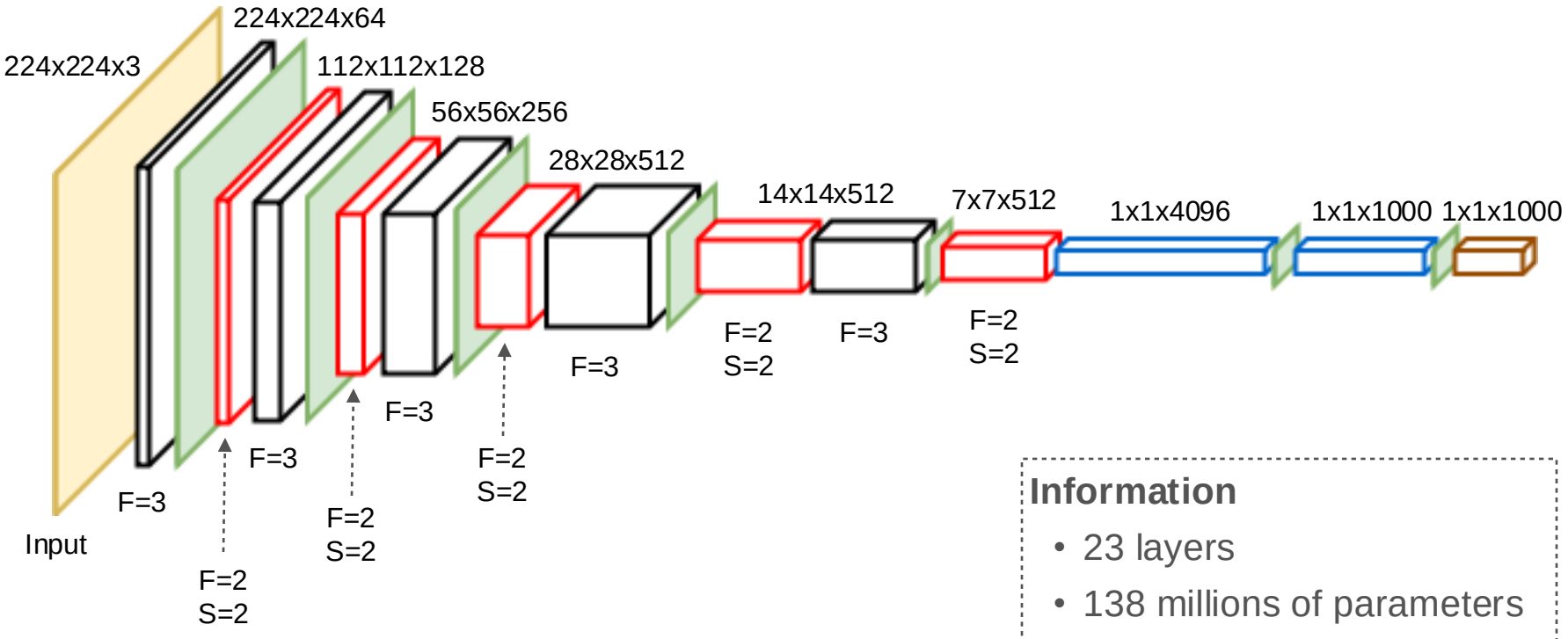


Information

- 8 layers
- 60 millions of parameters
- 84% accuracy on ImageNet

Classic architectures (3/3)

- **VGG-16** (2015)

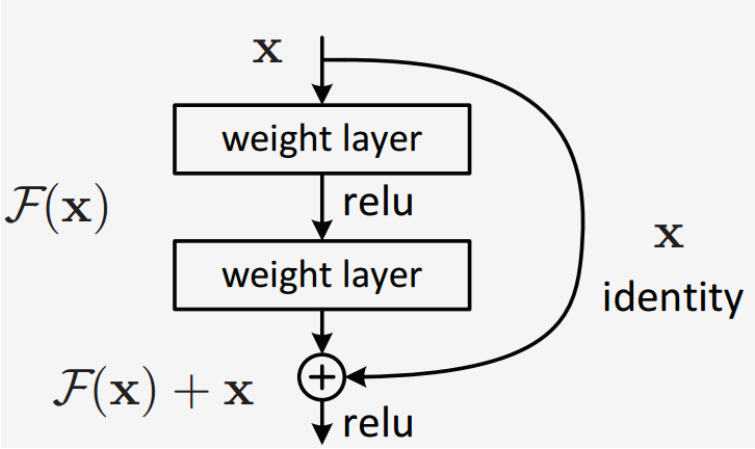


Information

- 23 layers
- 138 millions of parameters
- 90% accuracy on ImageNet

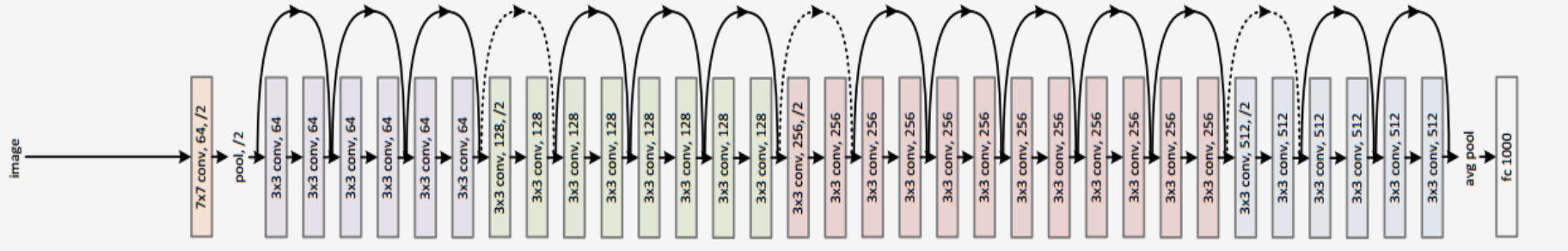
Modern architectures (1/2)

- **Residual network** (2016)



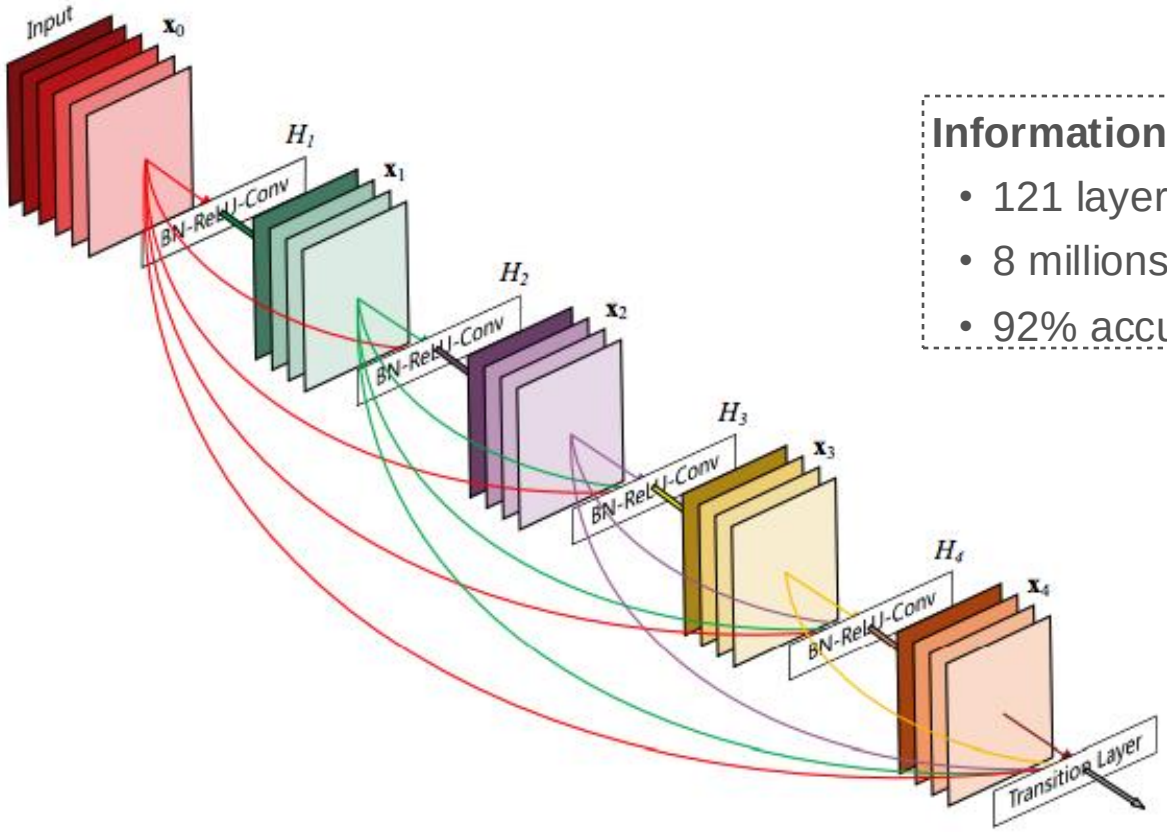
Information

- 168 layers
- 25 millions of parameters
- 93% accuracy on ImageNet



Modern architectures (2/2)

- **Dense network** (2017)



Information

- 121 layers
- 8 millions of parameters
- 92% accuracy on ImageNet

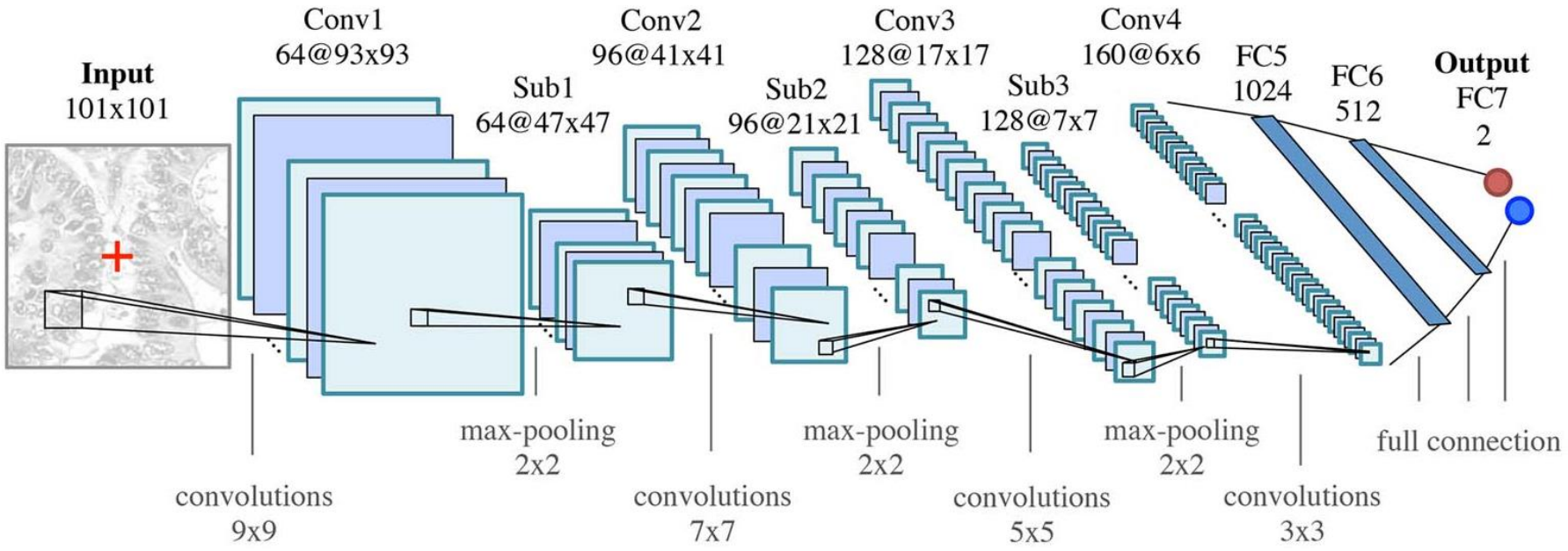
Quiz

1) Which of the following do you typically see as you move to deeper layers in a ConvNet? *(**W**x**H**x**C** is the layers' output size)*
   - ***A.*** ***W*** *and* ***H*** *decreases, while* ***C*** *also decreases*
   - ***B.*** ***W*** *and* ***H*** *increases, while* ***C*** *decreases*
   - ***C.*** ***W*** *and* ***H*** *decreases, while* ***C*** *increases*
   - ***D.*** ***W*** *and* ***H*** *increases, while* ***C*** *also increases*

2) Which of the following do you typically see in a ConvNet?
   - *A. Multiple CONV layers follows by a POOL layer*
   - *B. Multiple POOL layers follows by a CONV layer*
   - *C. FC layers in the* ***last*** *few layers*
   - *D. FC layers in the* ***first*** *few layers*

Summary so far…

- ConvNets make the assumption that the **inputs are images**
  - ***New layers*** ➜ *Convolution & Pooling*
  - ***Architecture*** ➜ *Feature extractor + Classifier*



Practical advice

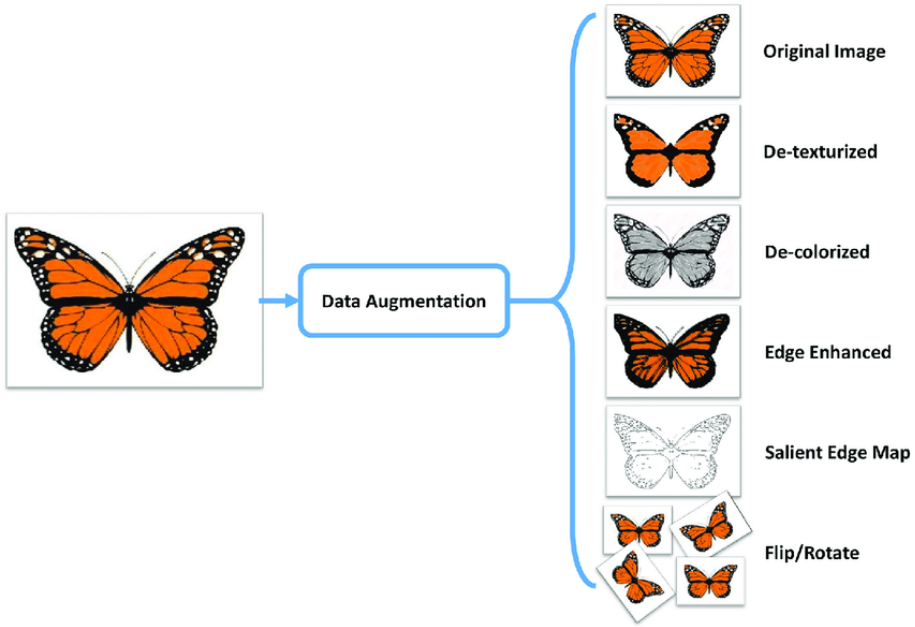
- **Use whatever works best on ImageNet**
  - If you're feeling a bit of a fatigue in thinking about the architectural decisions, you'll be pleased to know that in 90% or more of applications you should not have to worry about these. Instead of rolling your own architecture for a problem, you should look at whatever architecture currently works best on ImageNet, download a pretrained model and fine-tune it on your data. You should rarely ever have to train a CNN from scratch or design one from scratch.

- **Prefer a stack of small CONV layers to one large CONV layer**
  - Suppose that you stack three 3x3 CONV layers on top of each other (with non-linearities in between, of course). In this arrangement, each neuron on the first CONV layer has a 3x3 view of the input volume. A neuron on the second CONV layer has a 3x3 view of the first CONV layer, and hence by extension a 5x5 view of the input volume. Similarly, a neuron on the third CONV layer has a 3x3 view of the 2nd CONV layer, and hence a 7x7 view of the input volume. Suppose that instead of these three layers of 3x3 CONV, we only wanted to use a single CONV layer with 7x7 receptive fields. These neurons would have a receptive field size of the input volume that is identical in spatial extent (7x7). However, the neurons would be computing a linear function over the input, while the three stacks of CONV layers contain non-linearities that make their features more expressive.

Data augmentation

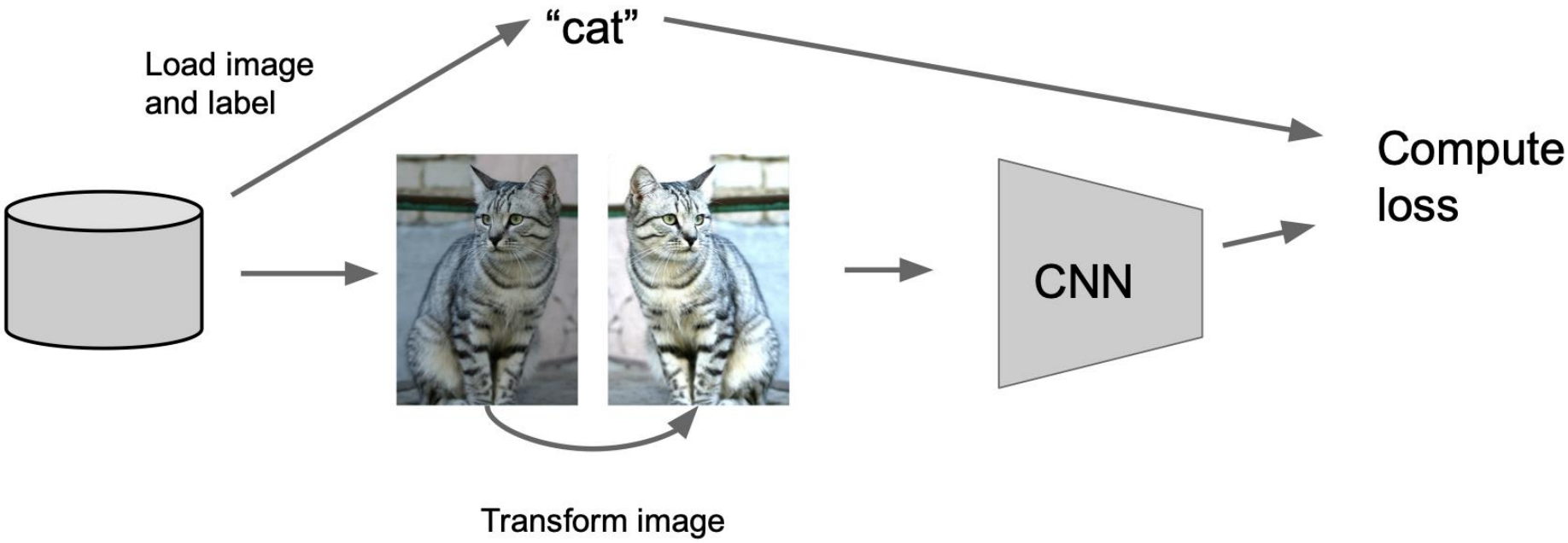
Introduction (1/2)

- **Data augmentation**
  - Technique to increase the amount of data *during* ***training***
  - Add slightly modified copies of already existing data
  - It is a form of regularization that helps reducing overfitting



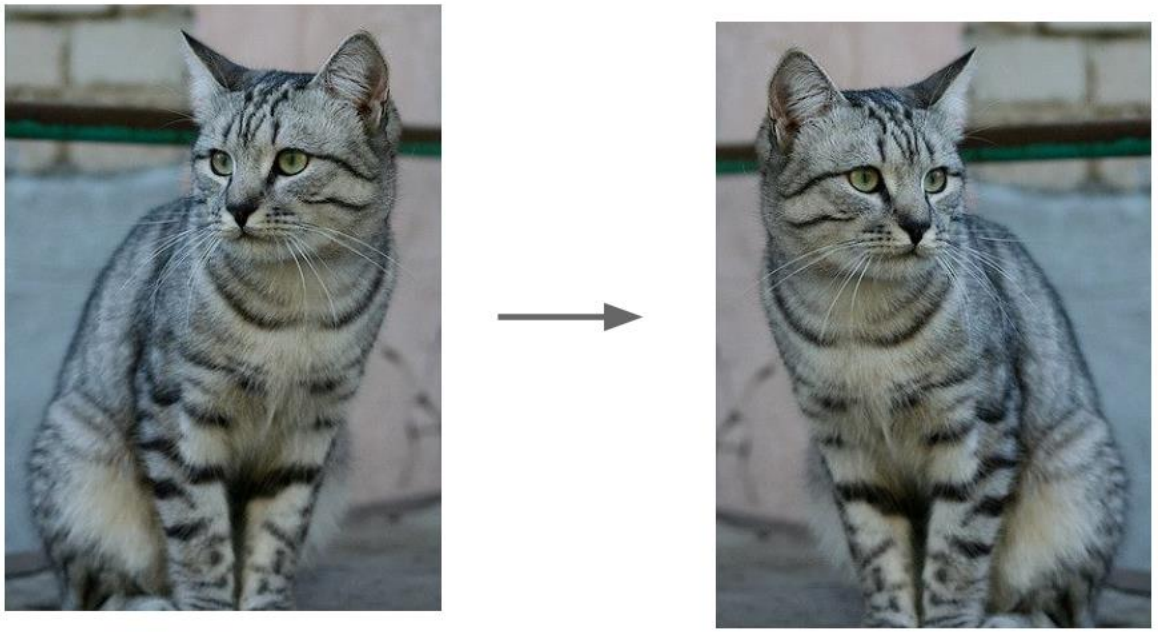
Introduction (2/2)

- Where does data augmentation occur in the ML pipeline?
  - Before a mini-batch of data is input to the neural network
  - The transformation is performed on the fly (nothing is stored)



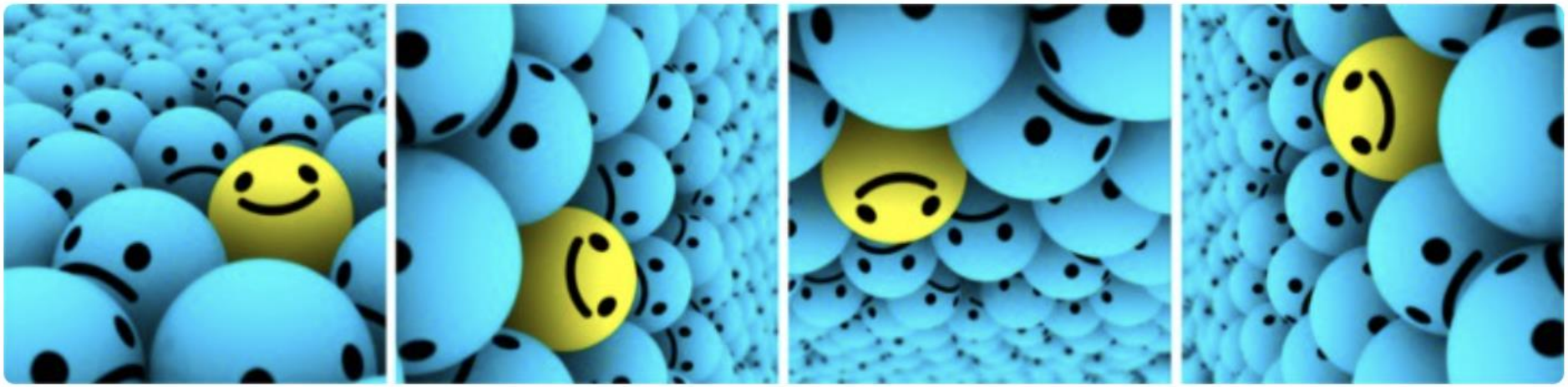
Transformations (1/)

- **Horizontal or vertical flip**



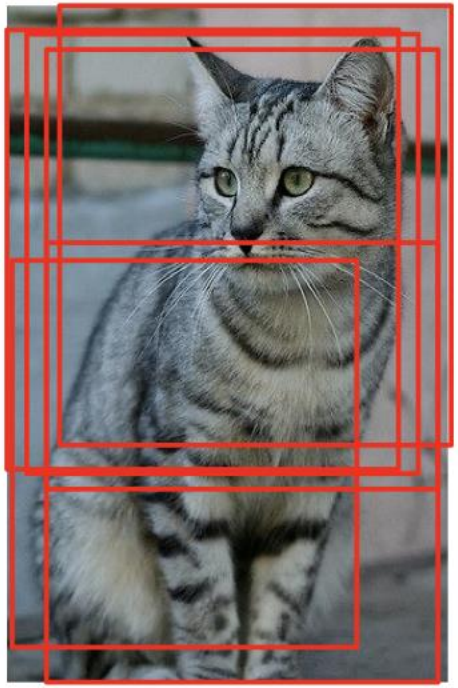
Transformations (2/)

- **Rotation**



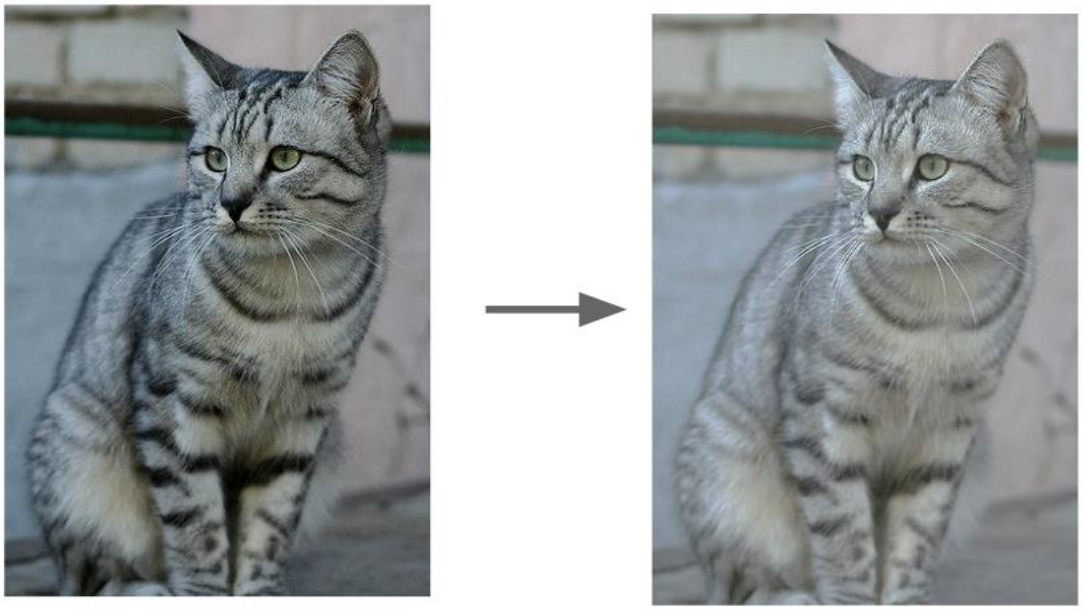
Transformations (3/)

- **Crop and scale**



Transformations (4/)

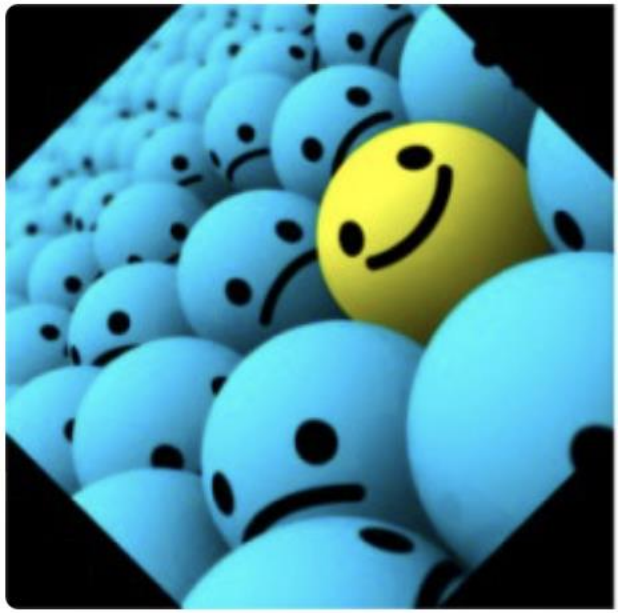
- **Color jitter**



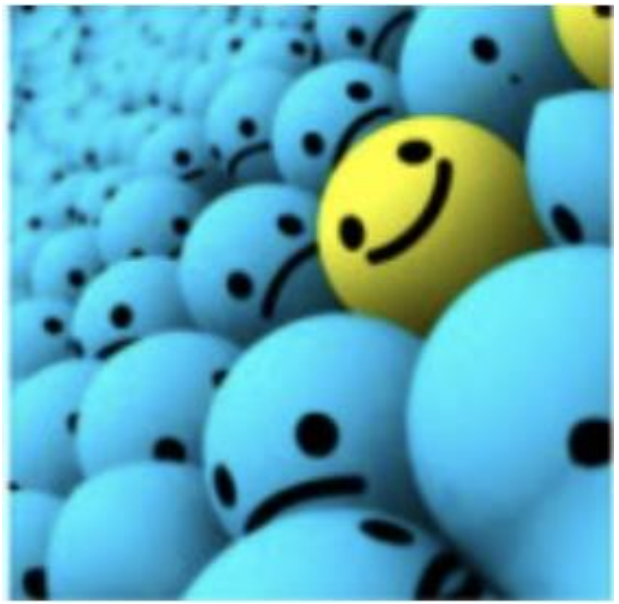
Discussion

- There are many types of augmentation… **but be careful**
  - Always preserve the image size
  - Do **not** “zero pad” the space beyond the image boundary

Wrong



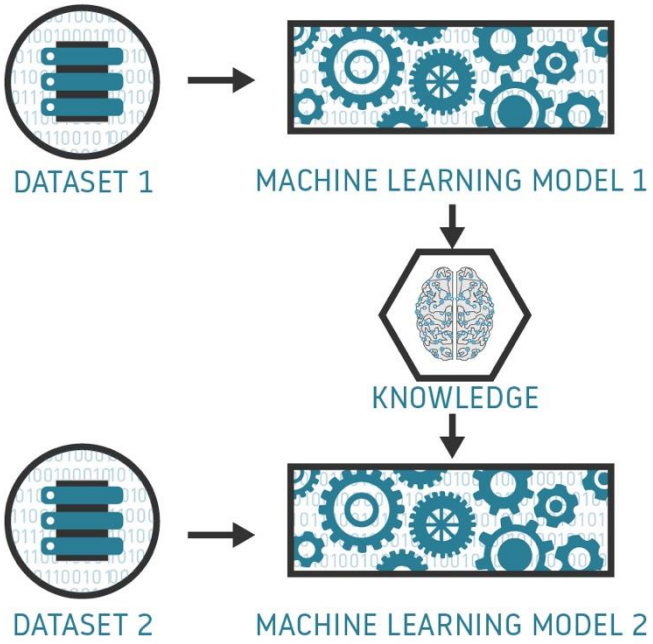
Correct



Transfer learning

Introduction (1/2)

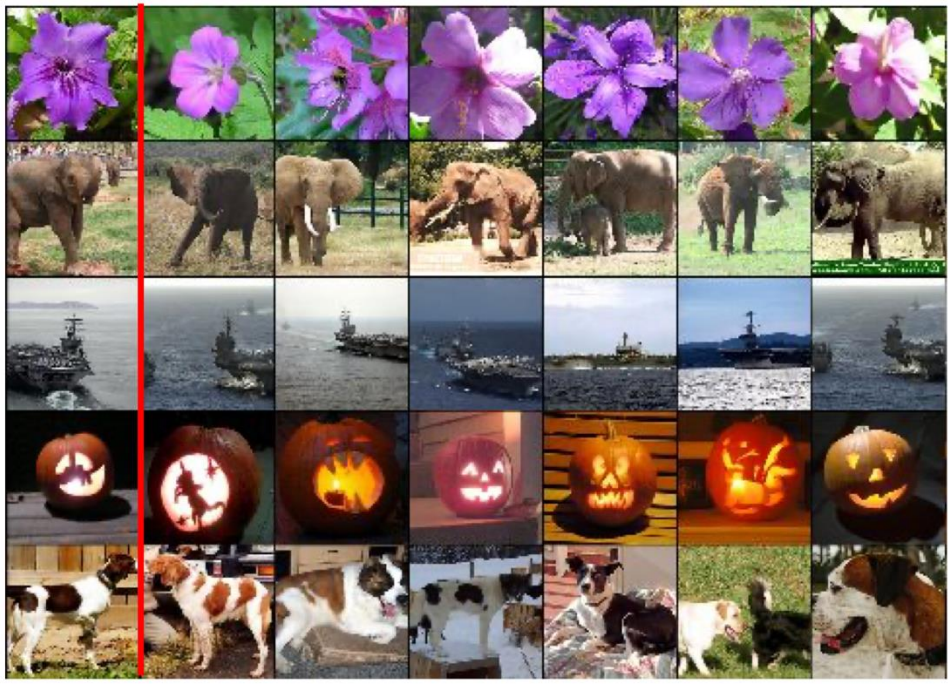
- **Transfer learning**
  - Reusing knowledge from previously learned tasks
  - Help in learning new tasks on small datasets



Introduction (2/2)

- A convolutional networks learns to extract features
  - If the training dataset is sufficiently varied, the learned features are generic enough to be useful with similar images

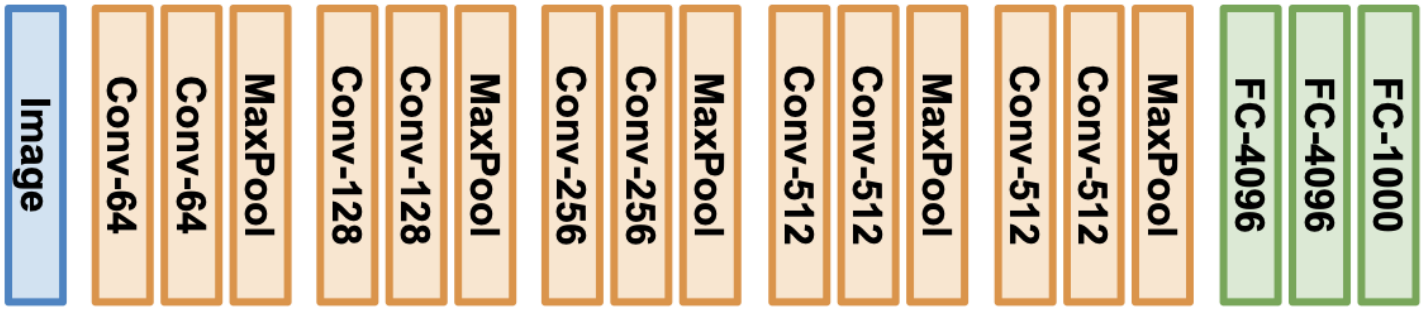
Test images



Images with similar features from a CNN trained on “ImageNet”

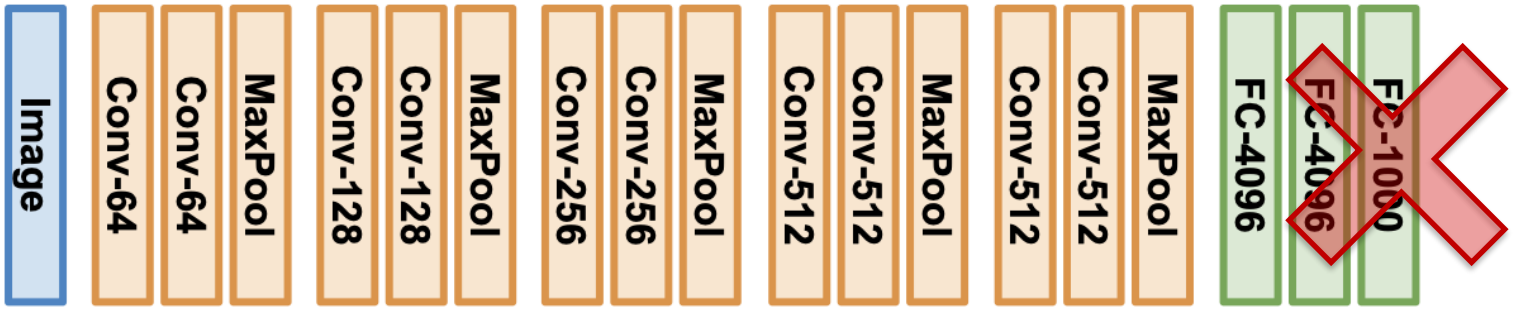
Feature extraction (1/3)

- **Step 1** → Take a pre-trained CNN
  - Any network trained on “ImageNet” dataset will do



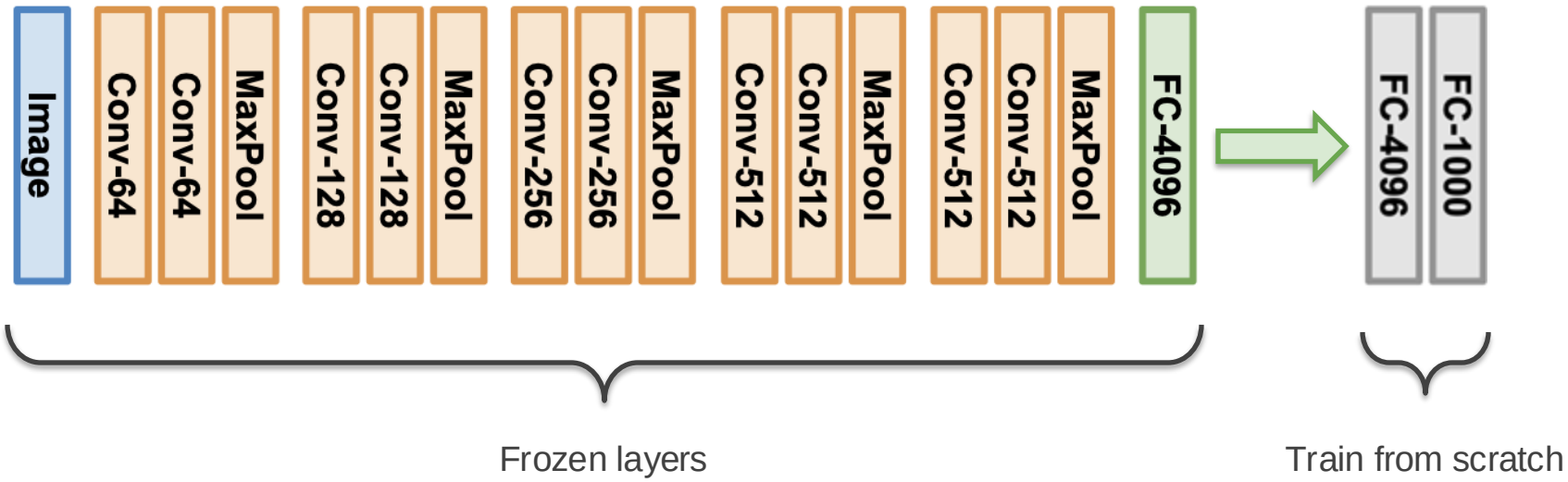
Feature extraction (2/3)

- **Step 2** → Remove the last few layers
  - Always remove the output layer, as it's too specific for the old task
  - Remove more layers based on the new task (more on this later)



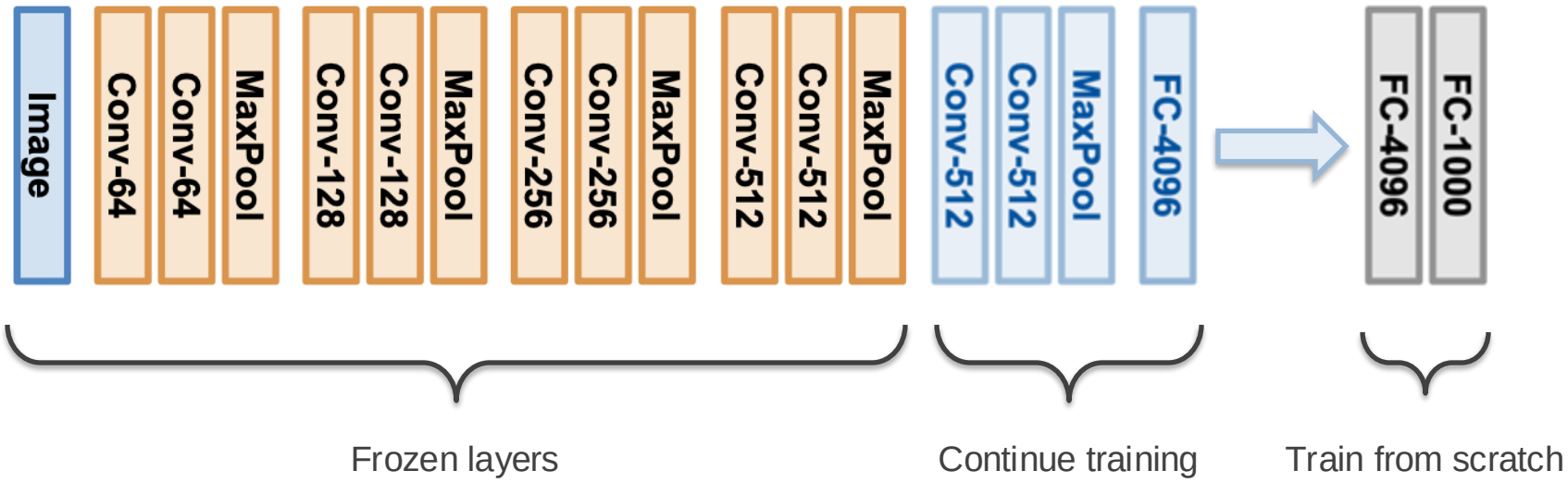
Feature extraction (3/3)

- **Step 3** → Train a new classifier
  - Run the new dataset through the pretrained CNN
  - Use the extracted features to train the classifier for the new task



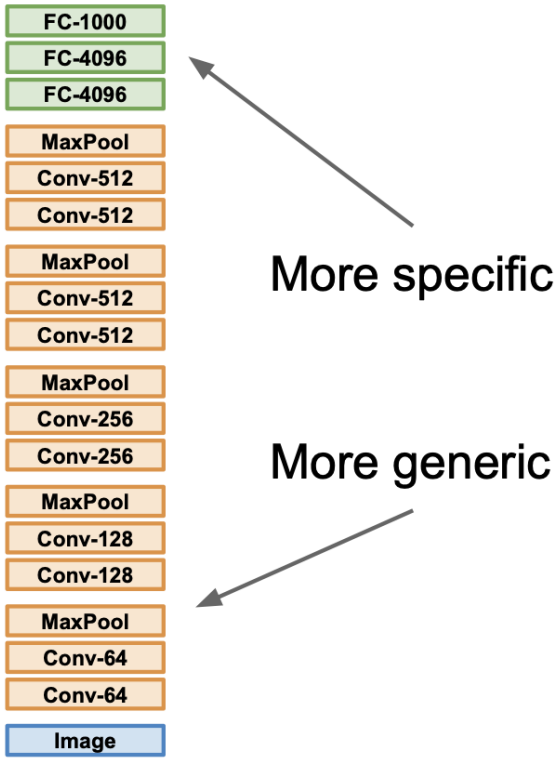
Fine tuning

- **Step 3 (bis)** → Allow the last few layers to be trained
  - Let the weights of these layers change during training
  - Use a small learning rate to avoid catastrophic cancellation



Discussion

- How to decide which layers to freeze?



	very similar dataset	very different dataset
very little data	Use Linear Classifier on top layer	You're in trouble… Try linear classifier from different stages
quite a lot of data	Finetune a few layers	Finetune a larger number of layers

Summary so far…

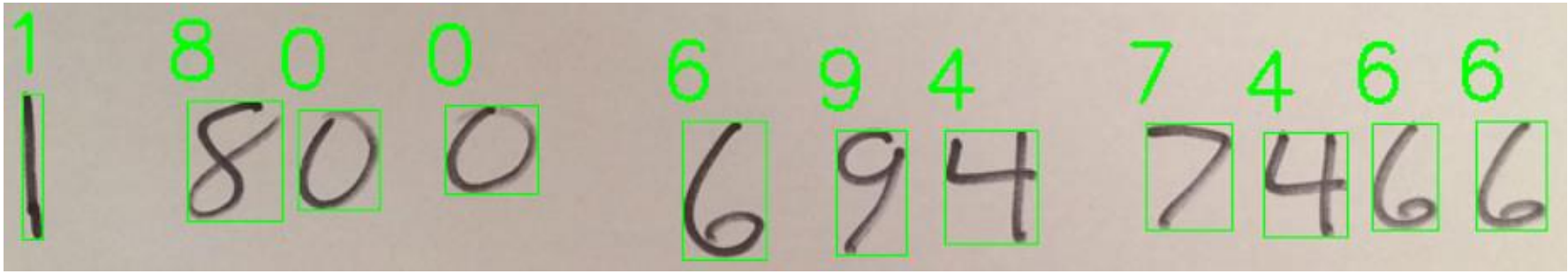
- **Takeaway for your projects and beyond**
  - Find a very large dataset that is similar to your problem
  - Train a big CNN there (or find a pretrained CNN online)
  - Transfer learn to your dataset

- Deep learning frameworks provide a zoo of pretrained models !!!

Assignment

Introduction

- **Create a deep learning framework from scratch**
  - Implement the building blocks of multilayer neural networks
  - Train a neural network on classification tasks
  - Implement several types of regularization
  - Implement the building blocks of convolutional neural networks
  - Build a CNN for handwritten image classification



Grading

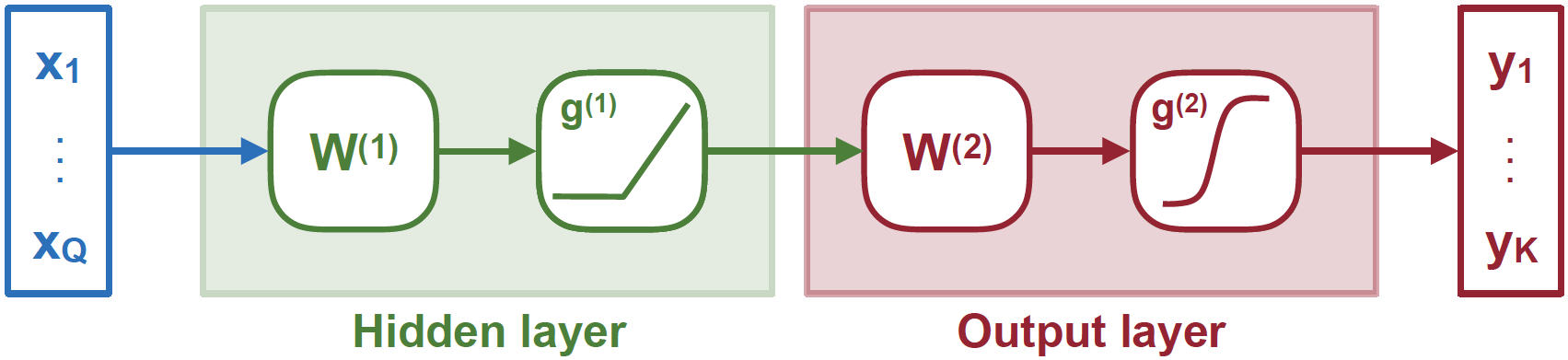
- The assignment requires to
  - solve the exercises in the **notebook**
  - add **more functions** to the basic framework
  - write a **report** that explains all the work done

- Grading is based **both on** the notebook **and** the report
  - *The **grade will be 0** if you don't submit a well-written report*

Activity	Points
Quiz 1-10	1,25 x quiz
More work	0 to 8
Total	***20** (**zero** if the report is not submitted)*

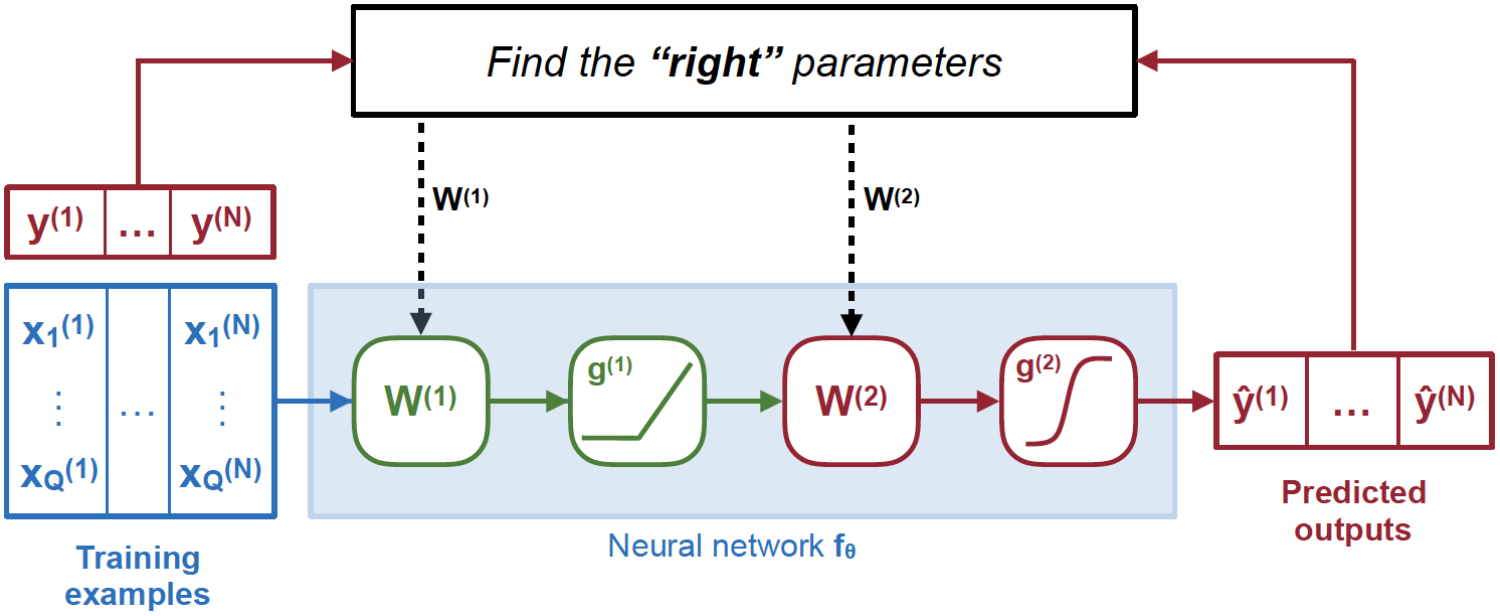
Exercises (1/4)

- **Part 1 ➜** Build the neural network
  - **Quiz 1 –** *Implement the "SoftMax" and "ReLU" activations*
  - **Quiz 2 –** *Define a fully-connected layer*
  - **Quiz 3 –** *Randomly initialize the layer parameters*
  - **Quiz 4 –** *Assemble a two-layer network*



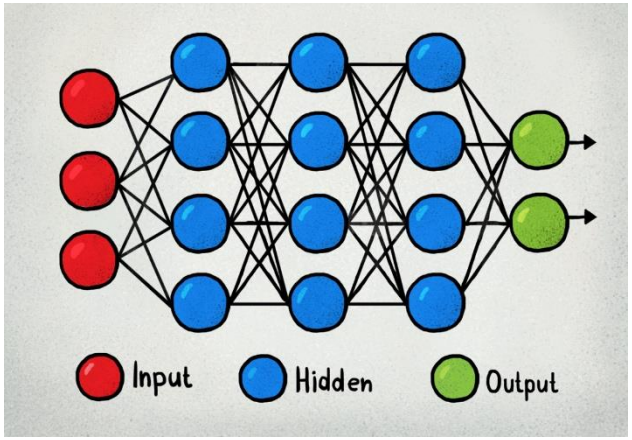
Exercises (2/4)

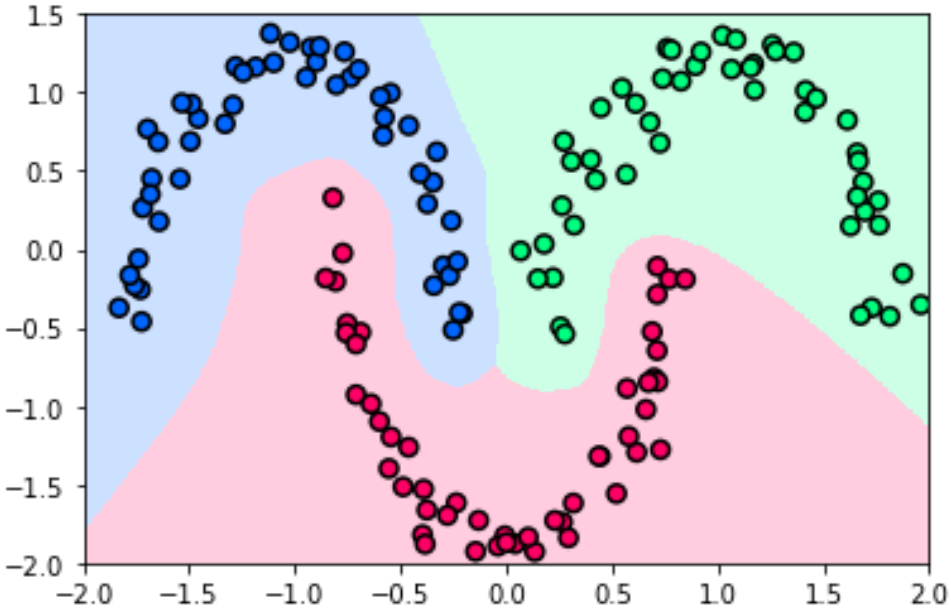
- **Part 2 ➜** Train the neural network
  - **Quiz 5 –** *Encode the labels as "one-hot" vectors*
  - **Quiz 6 –** *Compute the cross-entropy between the outputs and targets*
  - **Quiz 7 –** *Define the optimization problem to adjust the network weights*



Exercises (3/4)

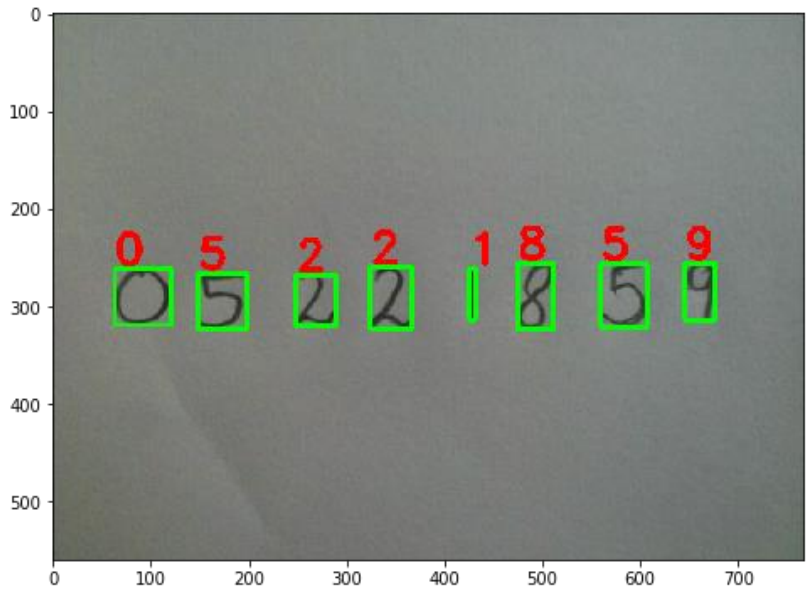
- **Part 3 ➜** Test the neural network on a toy example
  - **Quiz 8** – *Use the network to classify data points*

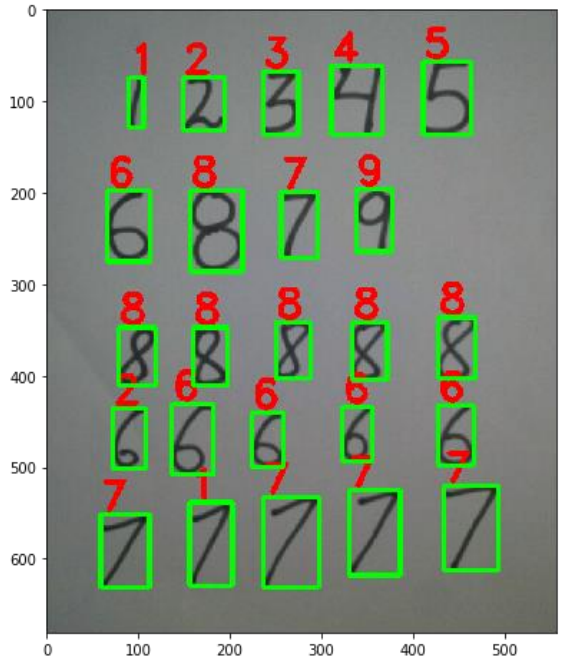




Exercises (4/4)

- **Part 4 ➜** Handwritten digit classification
  - **Quiz 9** – *Train the network on MNIST with stochastic gradient descent*
  - **Quiz 10** – *Use the network to classify images of handwritten digits*





Add more to the framework

- **Multilayer neural networks (4 points)**
  - Allow the creation of networks with any number of layers
  - Implement more activation functions: tanh, leaky relu, elu, selu
  - Implement “dropout” layer
  - Use the network on new datasets

- **Convolutional neural networks (4 points)**
  - Implement “convolutional” and “max-pooling” layers
  - Build the architecture “LeNet-5” (see previous slide)
  - Use “LeNet-5” on MNIST dataset