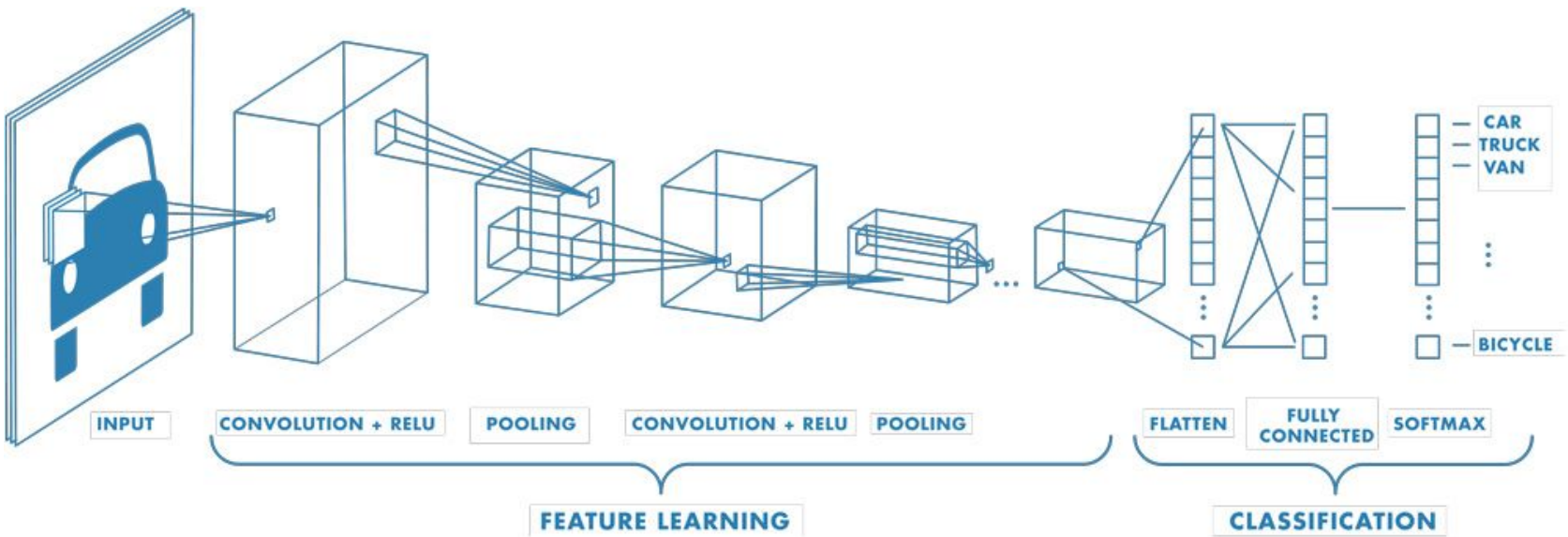
Neural Networks 1 - Convolutional neural networks

18NES1 - Lecture 9, Summer semester 2024/25

Zuzana Petříčková

April 15th, 2025

Today's Lecture: Introduction to Convolutional Neural Networks



Source:

https://matlabacademy.mathworks.com/details/deep-learning-onramp/deeplearning

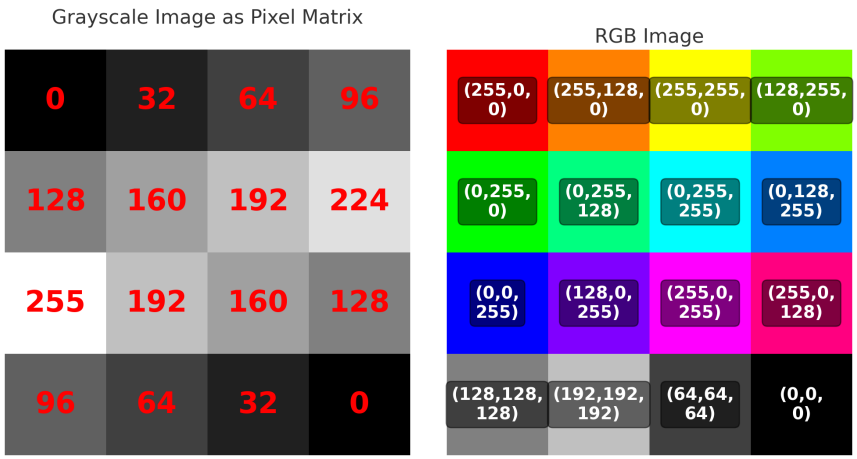
Introduction to Convolutional Neural Networks

Today's Lecture:

- Motivating example: bird species classification
- Convolution operation – intuition, purpose, and parameters
- Convolutional neural network architecture (layers, filters, pooling)
- Classic CNN architecture and MNIST example
- Visualization of learned features (filters, feature maps, saliency maps)

Reminder: Digital Image Representation

- A digital image is a matrix (tensor) of pixels.
- Each pixel (short for "picture element") describes the color at a specific position in the image.



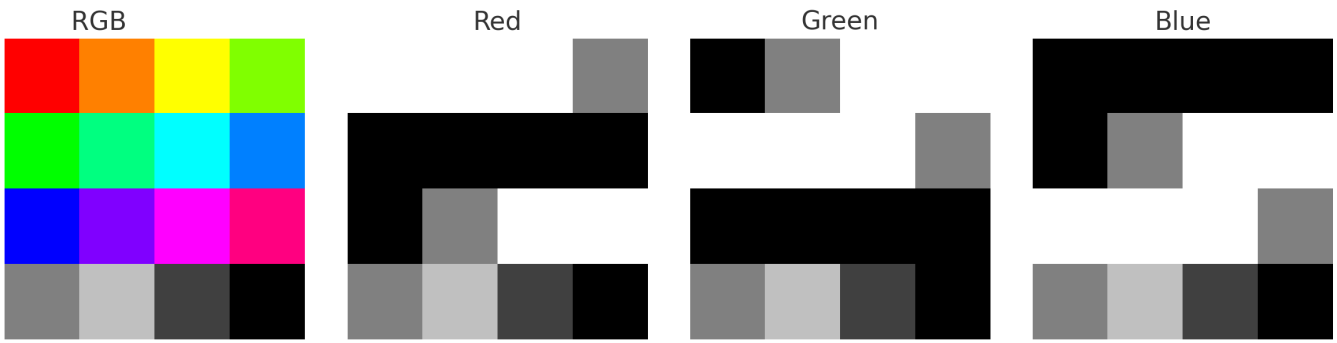
Grayscale Image

- Each pixel is a single value indicating brightness (e.g., 0 = black, 255 = white).
- For machine learning, pixel values are usually normalized to the interval $[0, 1]$.

Reminder: Digital Image Representation

Color Image (RGB)

- Each pixel consists of three components: R (red), G (green), B (blue).
- The image is represented as a 3D tensor of shape (height $\times$ width $\times$ 3).
- These components are called color channels.

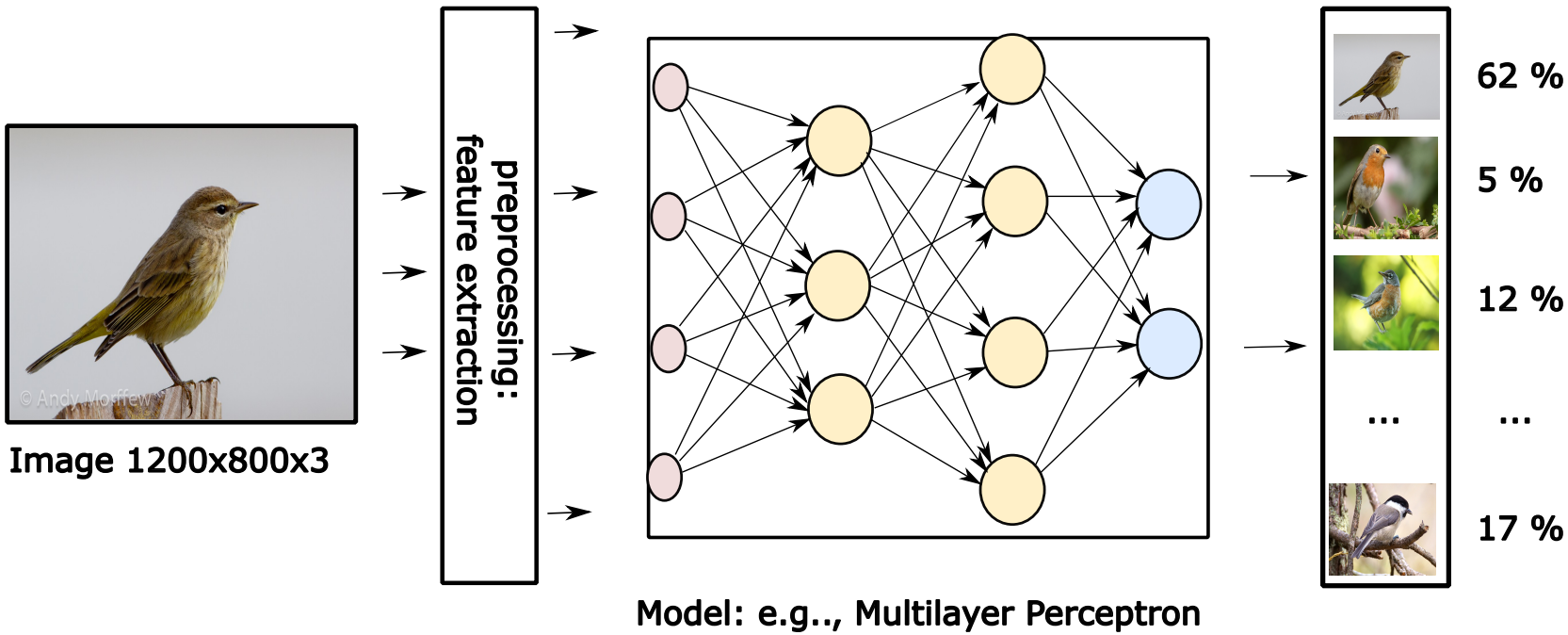


Example: convolution_introduction.ipynb

Motivating Example: Image Classification
Bird Species Recognition

Motivating Example: Bird Species Recognition

Classical Machine Learning Approach

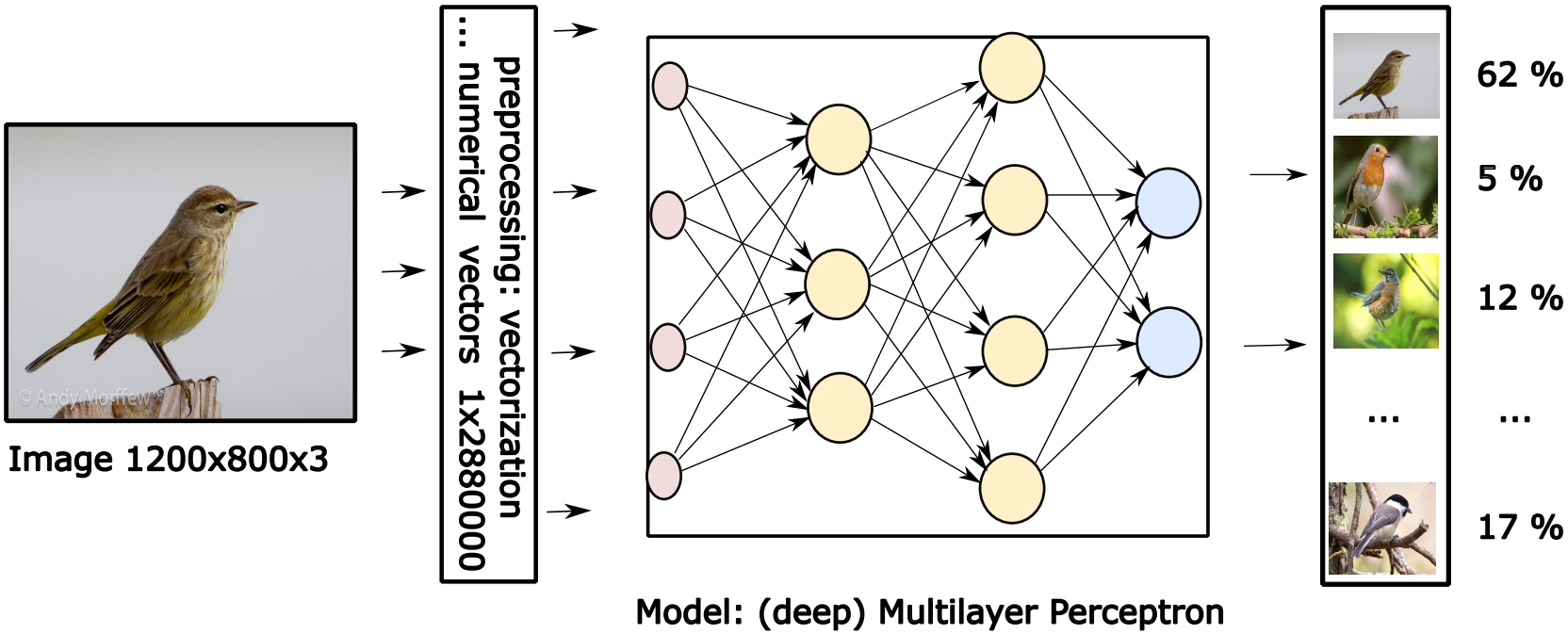


Thorough preprocessing of the data: Feature Extraction

- edge detection, LBP histograms, etc.
- information loss; requires careful feature design

Motivating Example: Bird Species Recognition

What if we train a neural network directly on the data?



Deep Learning Principle

- let the model learn useful features from the data
- preprocess the data just slightly (e.g., vectorization, normalization)

Motivating Example: Bird Species Recognition

What if we train a neural network directly on the data?

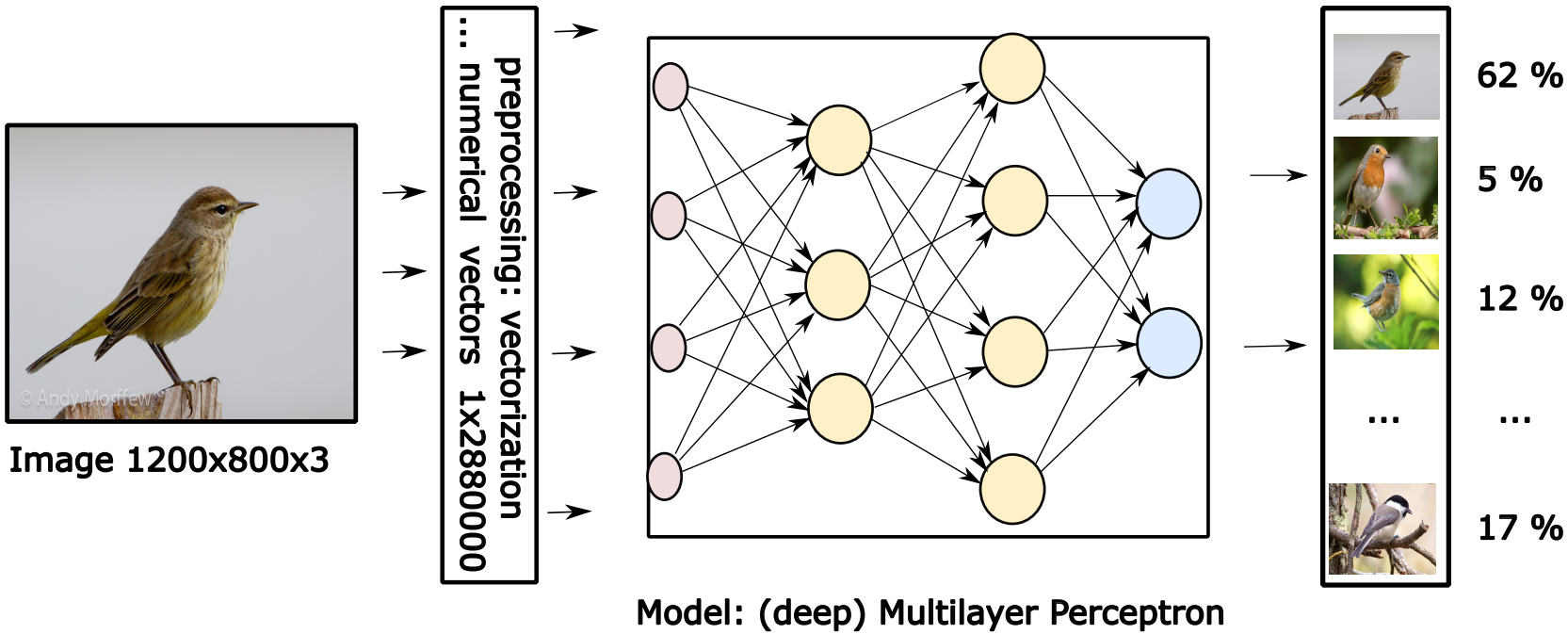


Image 1200x800x3

Model: (deep) Multilayer Perceptron

Drawbacks of the classical approach (fully connected layers only):

- high number of features
- loss of spatial relationships between pixels
- it is difficult to train the model effectively

Motivating Example: Bird Species Recognition

How could we improve this?

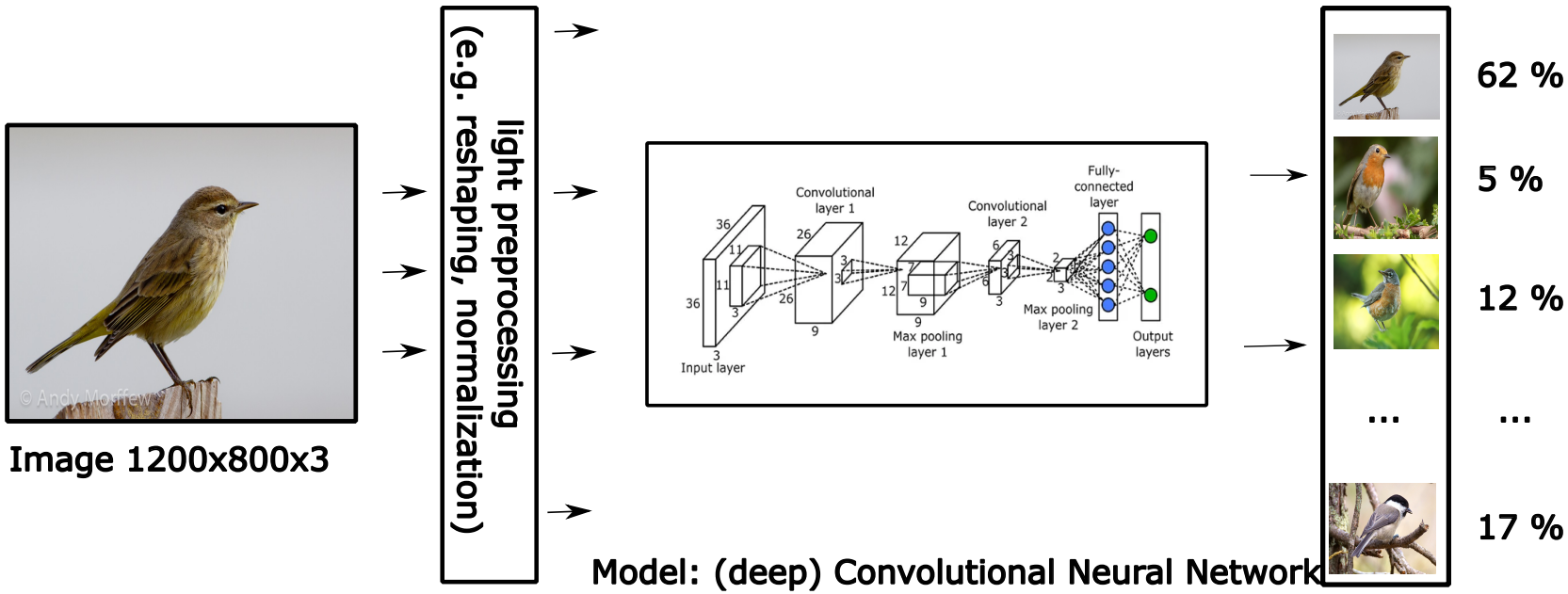


Image 1200x800x3

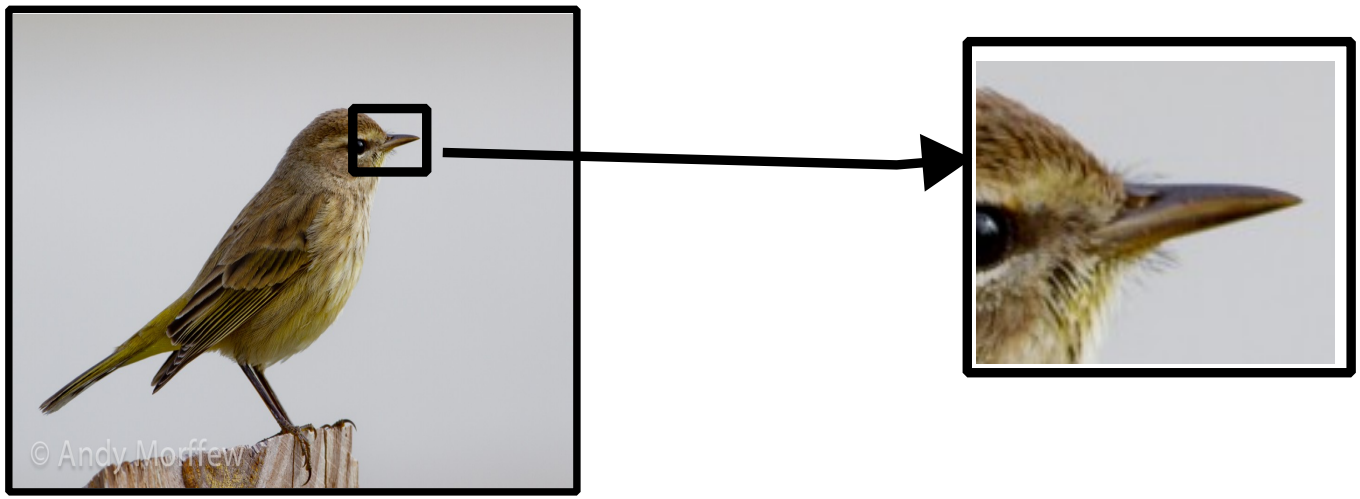
Model: (deep) Convolutional Neural Network

Convolutional Neural Network (CNN):

- a neural network with convolutional layers
- takes spatial arrangement of pixels into account
- fewer parameters, easier to train compared to fully connected networks

Motivating Example: Bird Species Recognition

Patterns in data: for example, beak shape



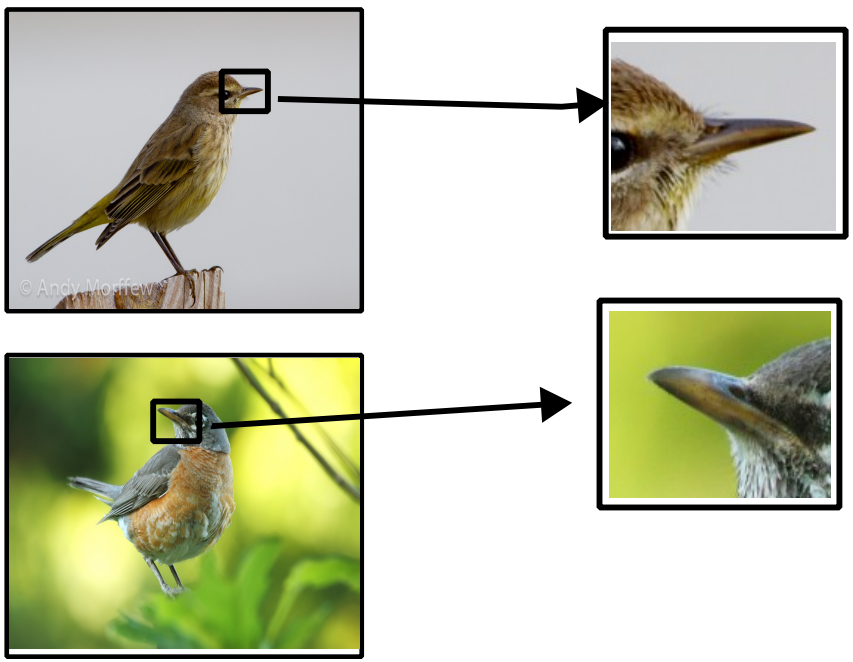
Let's create a beak detector:

- a simple model (e.g., a single-layer neural network) that detects beaks in images

But: the beak may appear in different locations within the image

Motivating Example: Bird Species Recognition

Patterns in data: for example, beak shape

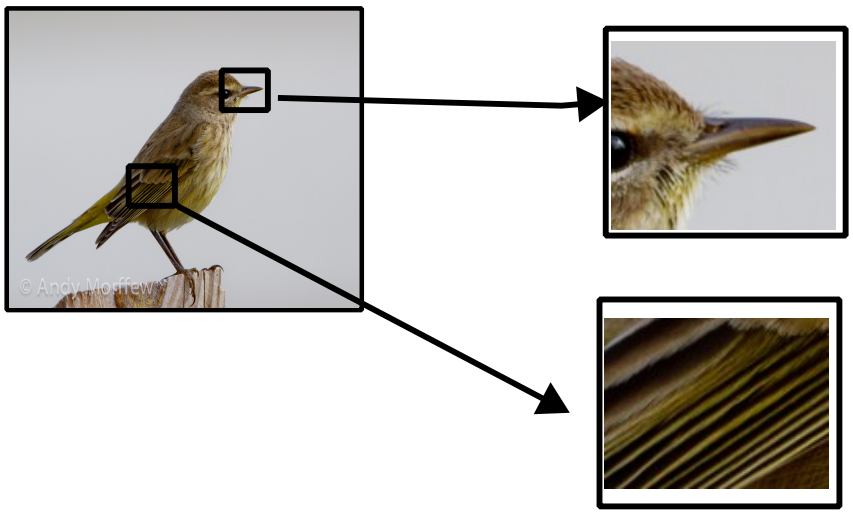


The beak may appear in different image regions

- the detector should find a beak in any image and at any location
  $\rightarrow$ the detector must slide over the input image

Motivating Example: Bird Species Recognition

There are multiple patterns in the data (e.g., beak, feather, eye):



The idea:

- create a set of detectors for different features (patterns)
- detectors should recognize features anywhere in the image
  $\rightarrow$ detectors slide over the image
- these detectors form the initial layers of a convolutional neural network

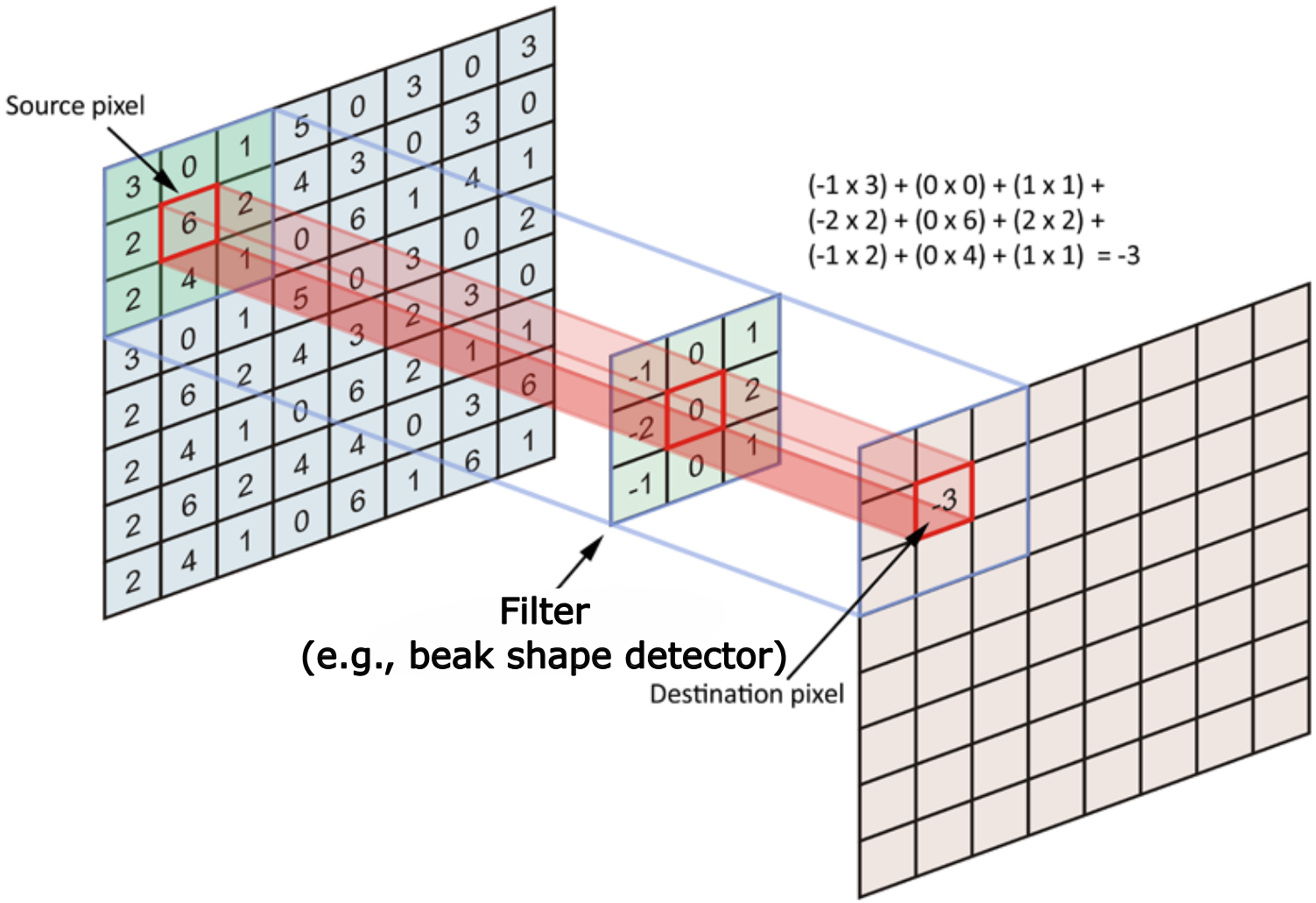
Convolutional Neural Network

- A neural network that includes convolutional layers

Convolutional Layer

- Consists of a set of filters (also called kernels or detectors)
- Each filter performs a convolution operation over the input image
- The output of the convolution (a feature map) is passed to the next layer

Convolution Operation



Source: https://i.stack.imgur.com/YDusp.png

Convolution Operation

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

Image 6x6 (black and white)

Convolutional Layer:

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1 (3x3)

-1	1	-1
-1	1	-1
-1	1	-1

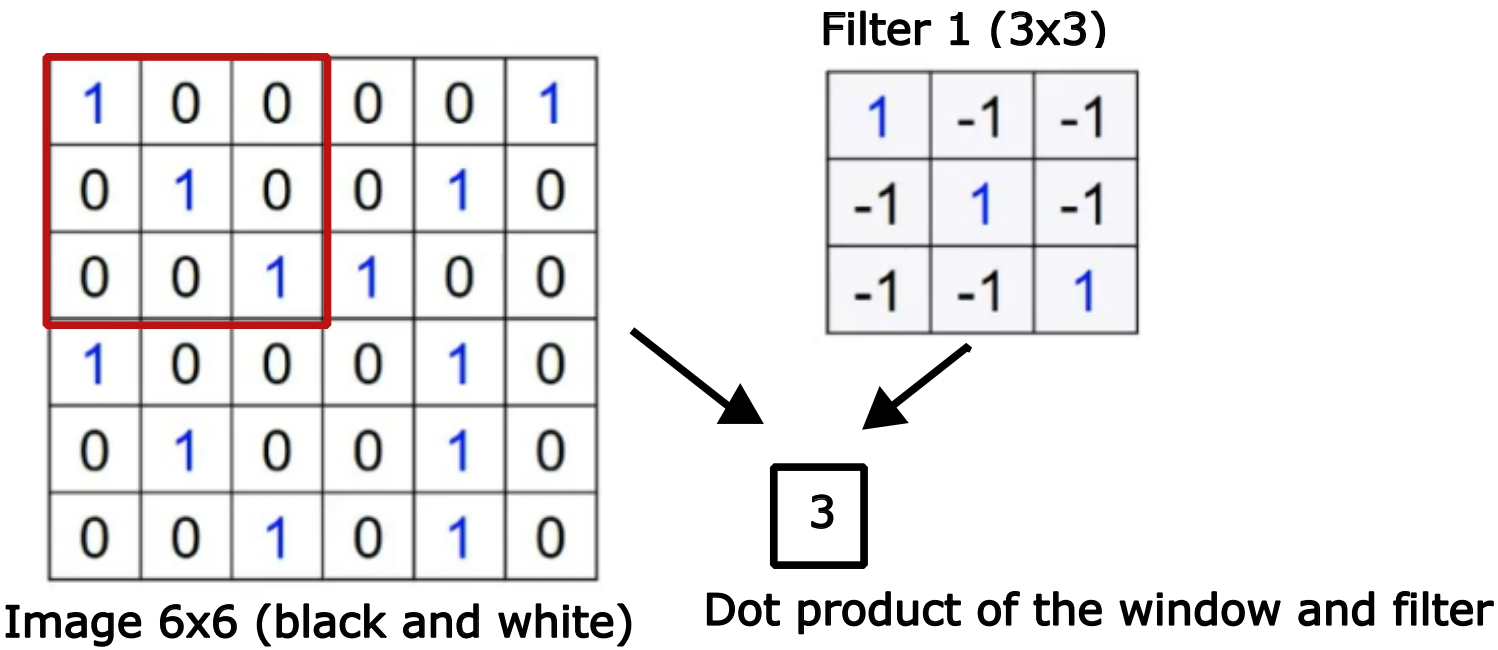
Filter 2 (3x3)

. . .

- The convolutional layer contains several filters
- Each filter detects a pattern (feature) of size 3×3 pixels (e.g., diagonal edge, vertical edge, etc.)

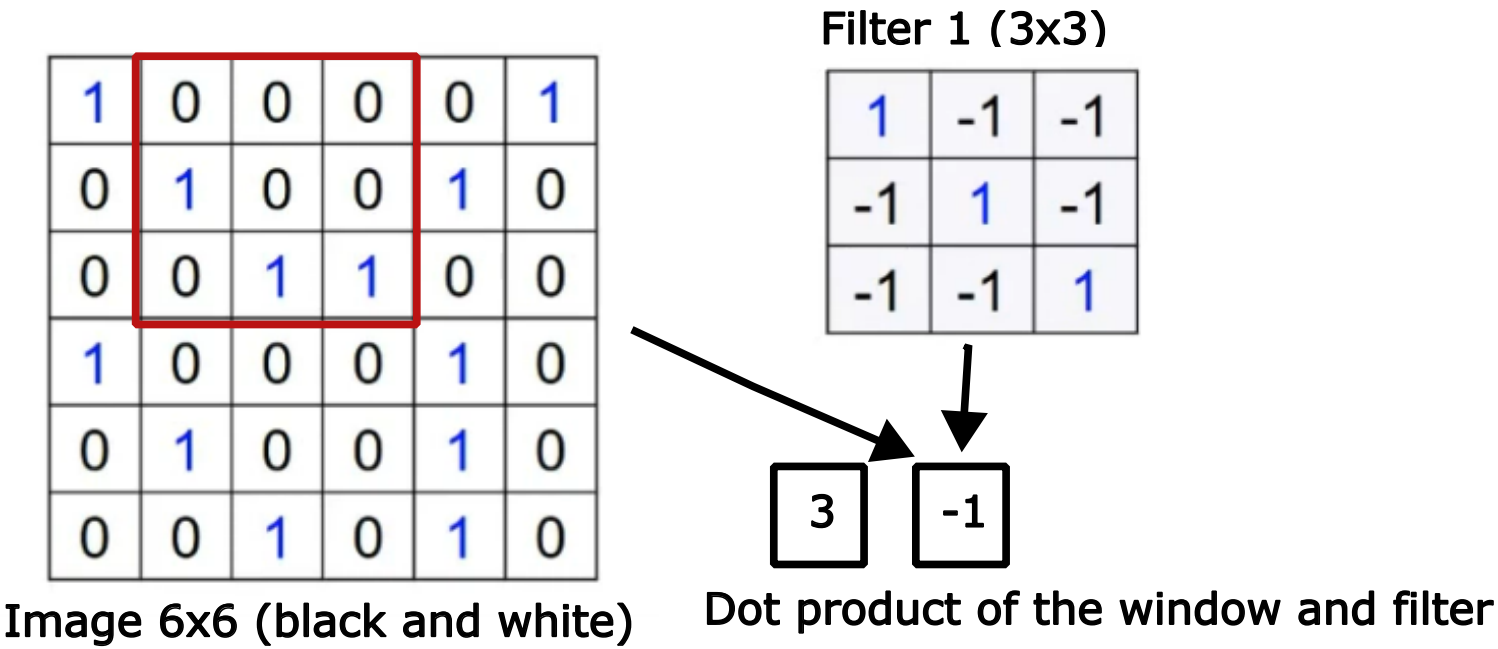
Example source: Petr Doležel – Convolutional Neural Network, https://www.youtube.com/watch?v=-2vEi-Aa0FA

Convolution Operation



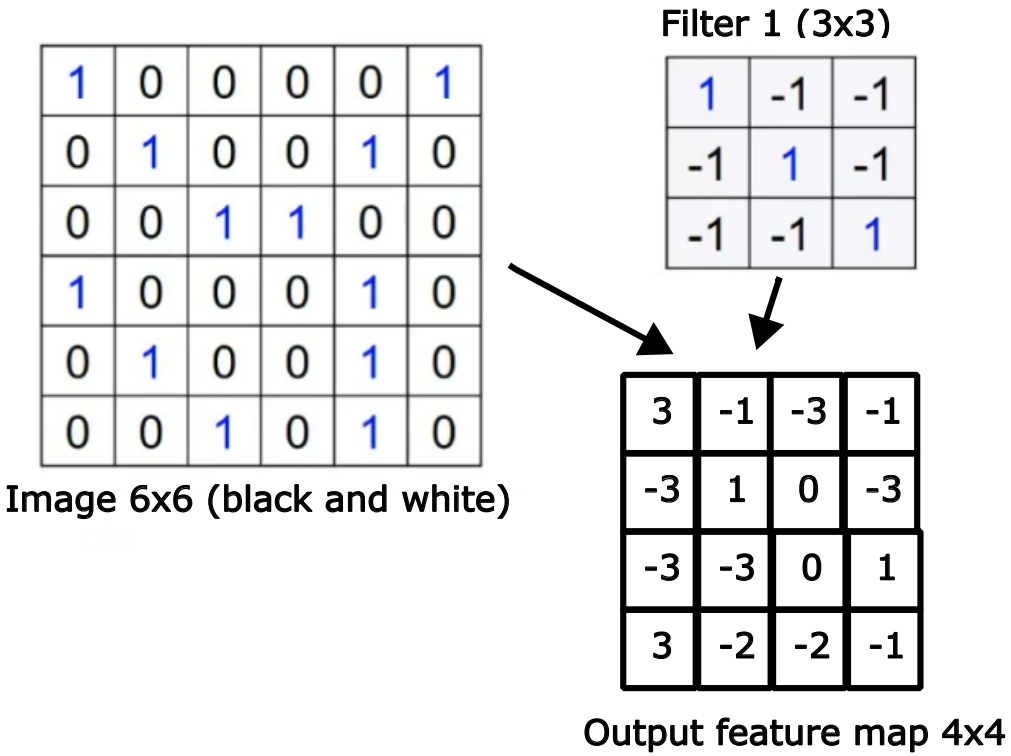
- We compute the dot product:
  $y = \sum_{i=1}^{9} w_i x_i + b$ (for flattened matrices)

Convolution Operation



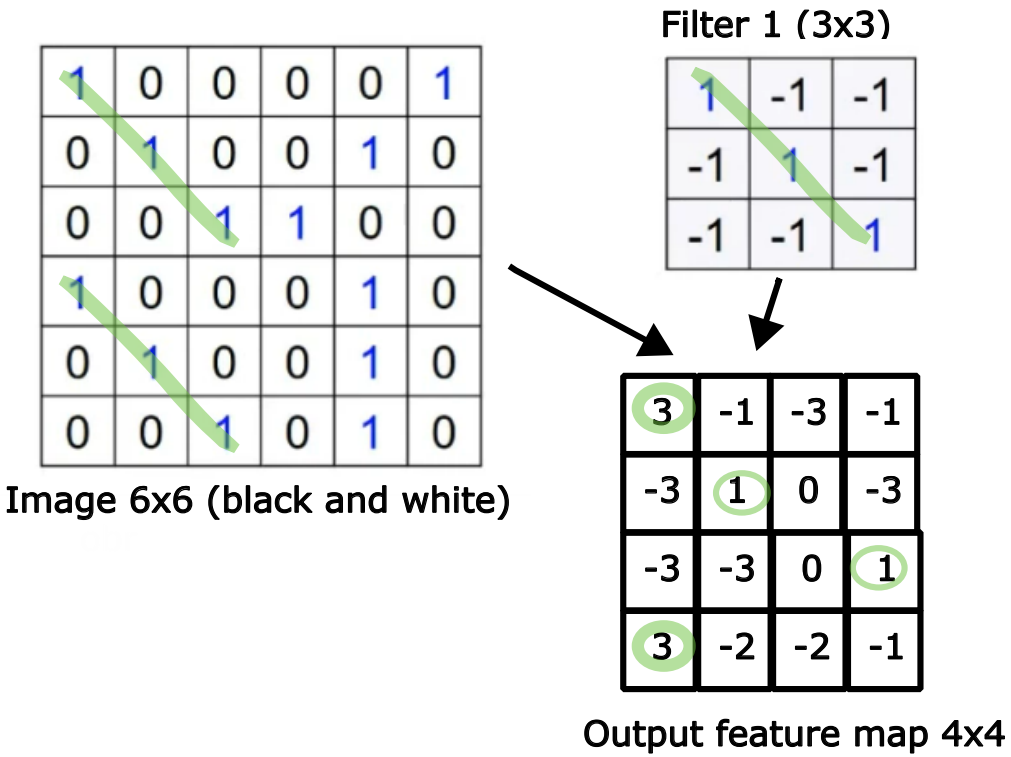
- Move the sliding window and compute another dot product

Convolution Operation



- By sliding the window over the image, we apply the filter to the entire input
- The result is a new 2×2 tensor – a **feature map**

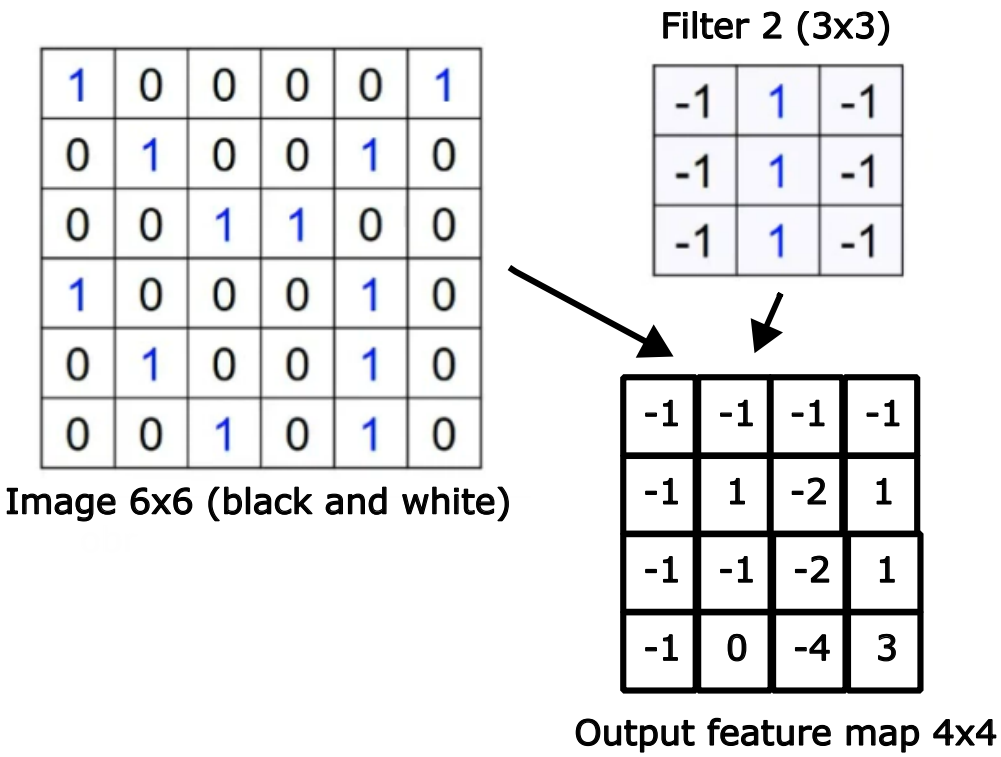
Convolution Operation



Feature Map

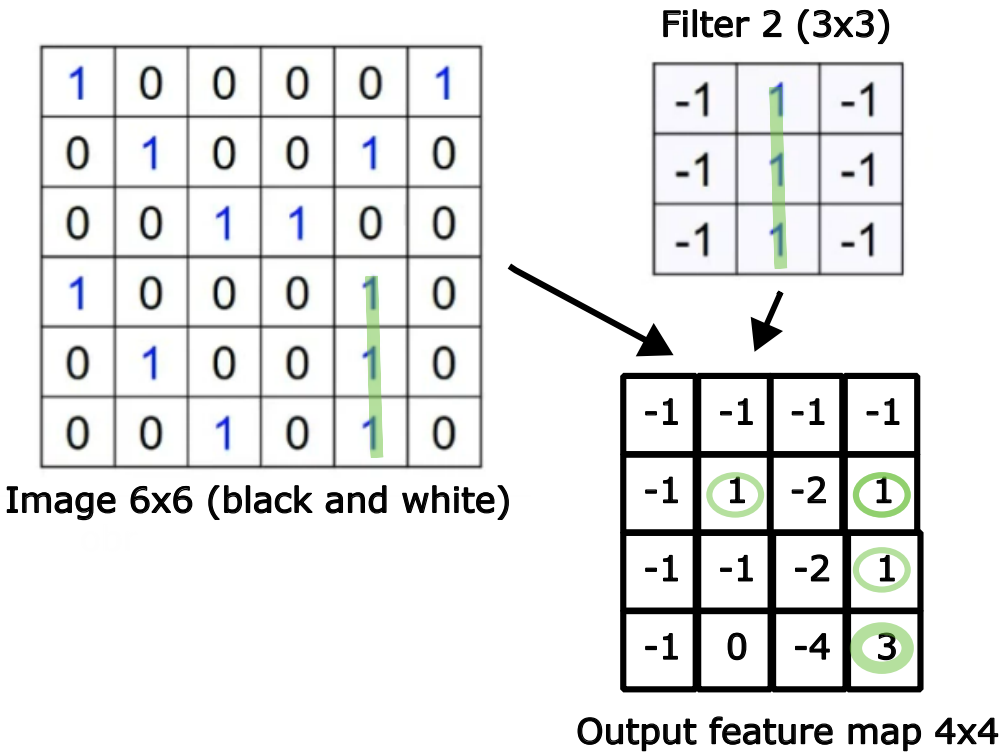
- Indicates where (and how strongly) the pattern represented by the filter appears in the input image
- Example: diagonal edge filter

Convolution Operation



- We can similarly apply a second filter

Convolution Operation

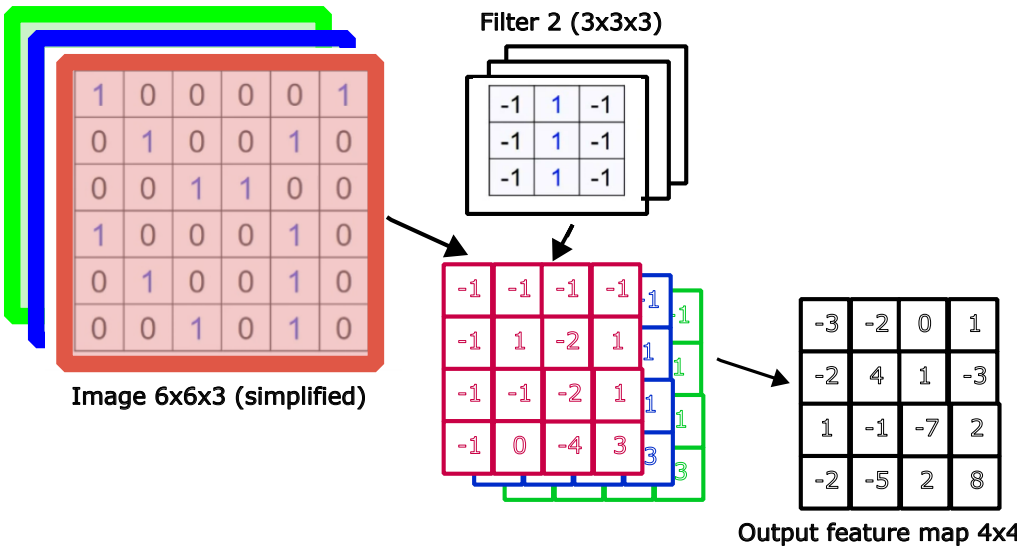


Second Feature Map

- Indicates where (and how strongly) the pattern represented by the second filter appears in the input image
- Example: vertical edge filter

Convolution Operation

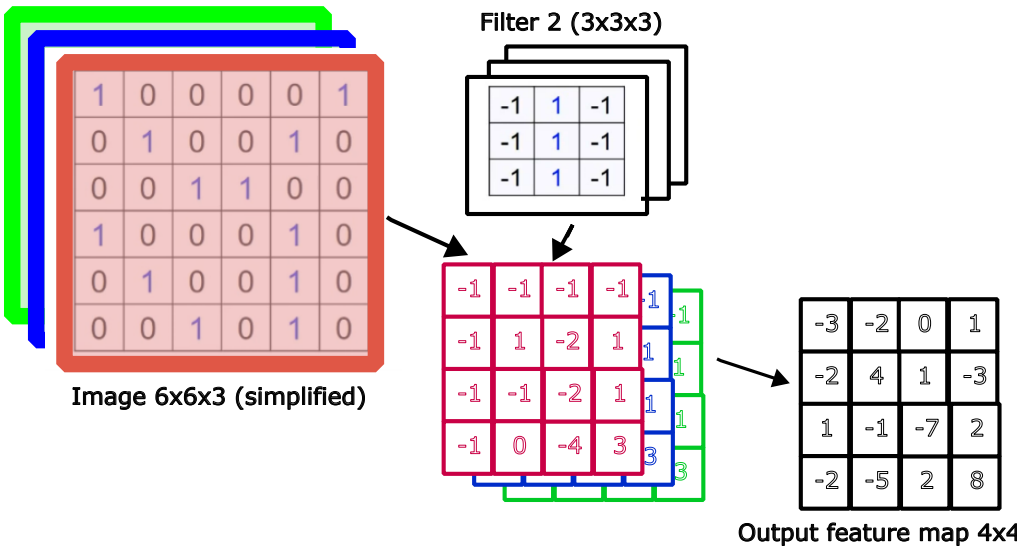
Color Image: 3 input channels – R, G, B



- Each filter has weights for **all input channels (R, G, B)**
- Computation: convolution is performed separately on each channel and the results are **summed**
- Each filter produces **one aggregated** output feature map
- The number of filters defines the **number of output channels**

Convolution Operation

Color Image: 3 input channels – R, G, B



Weight Tensor in a Convolutional Layer:

- A 4-dimensional tensor with shape $u \times u \times c \times f$
  - $u \times u$ – spatial size of each filter (per channel)
  - c – number of input channels (e.g., 3 for RGB)
  - f – number of filters, i.e., number of output channels

Convolution Operation

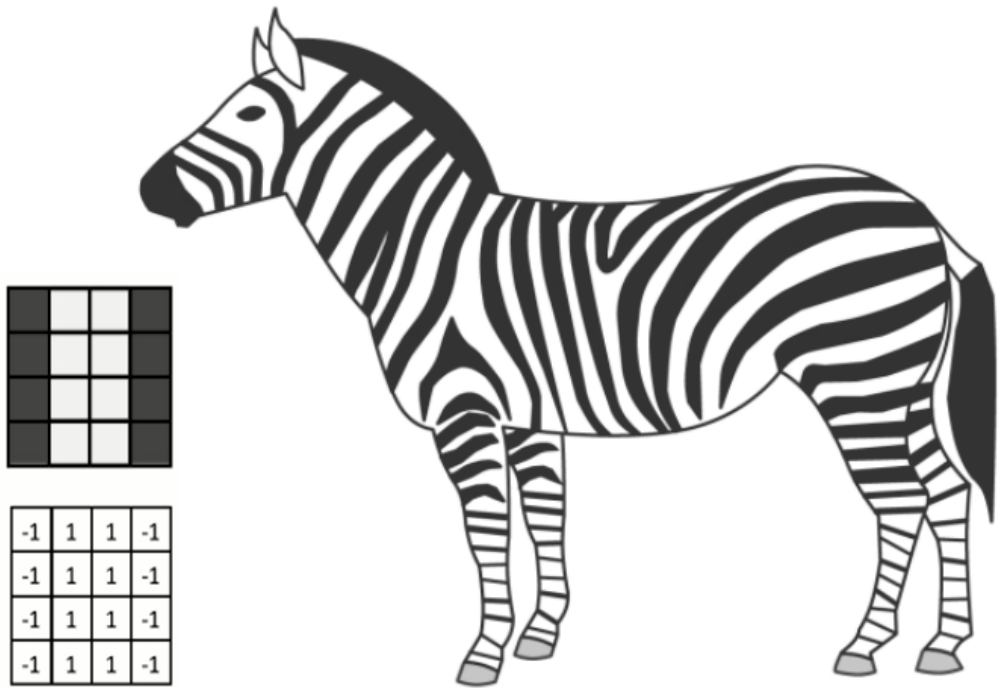
Example: Zebra

Source:

https://matlabacademy.mathworks.com/details/deep-learning-onramp/deeplearning

Convolution Operation

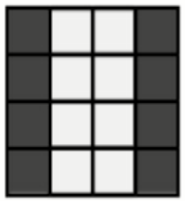
Example: Zebra



- Applying a filter to detect vertical stripes

Convolution Operation

Example: Zebra

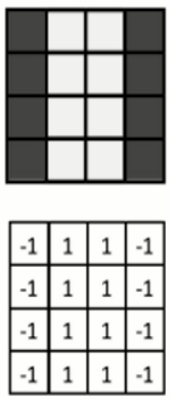


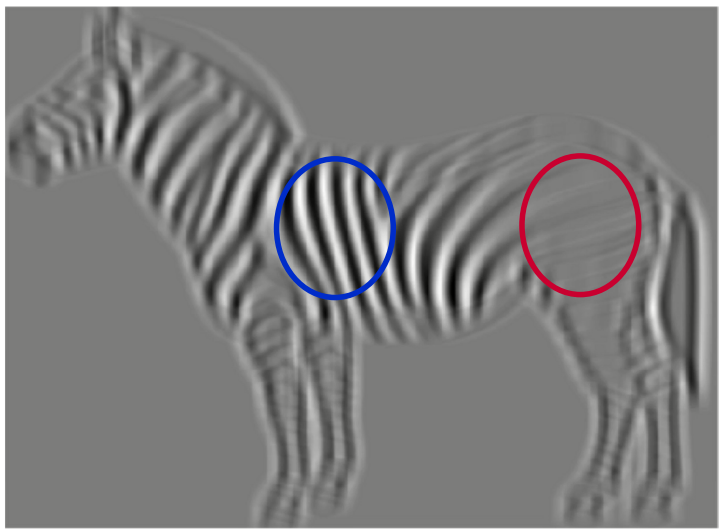
-1	1	1	-1
-1	1	1	-1
-1	1	1	-1
-1	1	1	-1

- Output after applying the vertical stripe filter

Convolution Operation

Example: Zebra

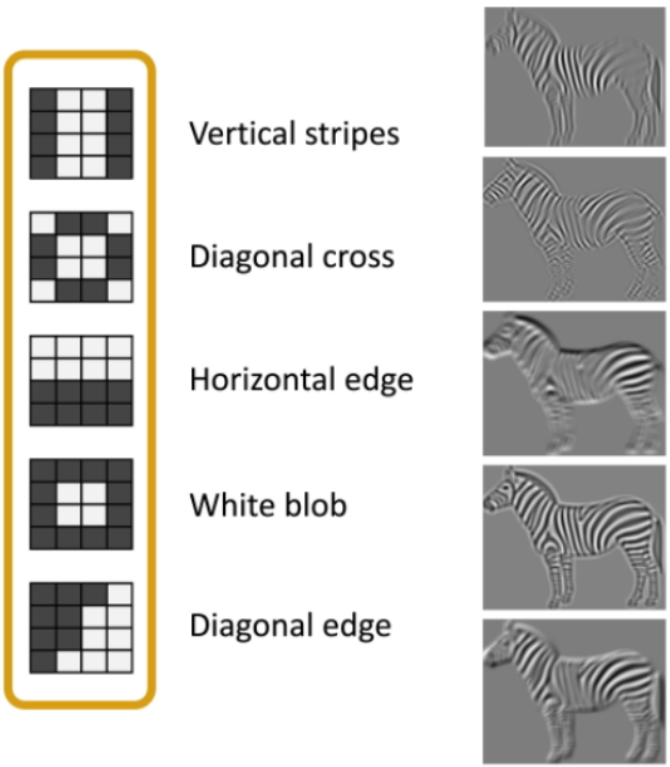




- Clearly shows where the pattern is strongly present and where it is not

Convolution Operation

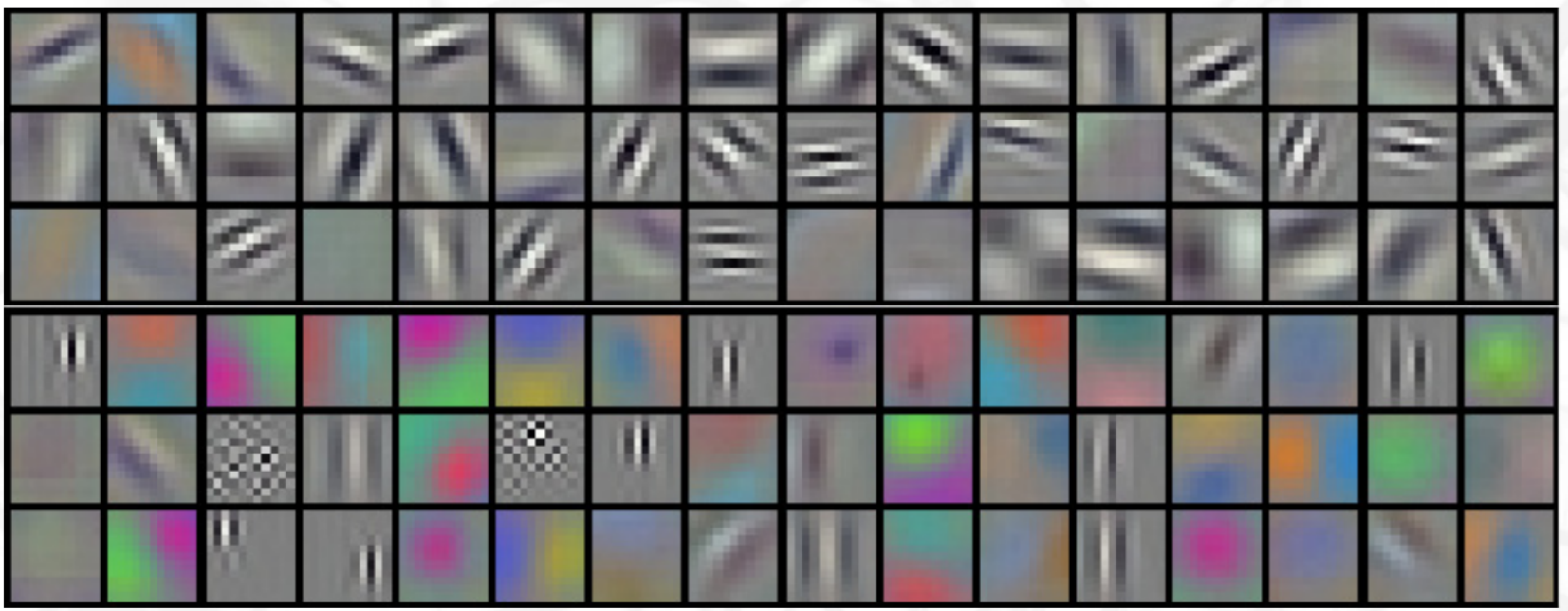
Example: Zebra



- Examples of other filters and their resulting feature maps

Convolution Operation

- **Example:** 96 filters of size $11 \times 11 \times 3$ in the first convolutional layer of AlexNet



Source: Alex Krizhevsky et al., "ImageNet Classification with Deep Convolutional Neural Networks", 2012, Figure 3

Convolution Operation beyond neural networks

What happens when we apply different filters to the same image?

- Each filter is designed to highlight specific features in the image
  - edge filters (e.g., vertical, horizontal, diagonal edges)
  - blur filter – suppresses details and noise
  - sharpen filter – enhances details and edges
  - texture filters – highlight repetitive patterns

0	0	0
0	1	0
0	0	0

Identity filter

1/8	1/8	1/8
1/8	1/8	1/8
1/8	1/8	1/8

Blur filter

Convolution Operation beyond neural networks

What happens when we apply different filters to the same image?

- **The same input image** produces different feature maps depending on the filter
- Deep learning: filters are learned from data to detect the most useful patterns

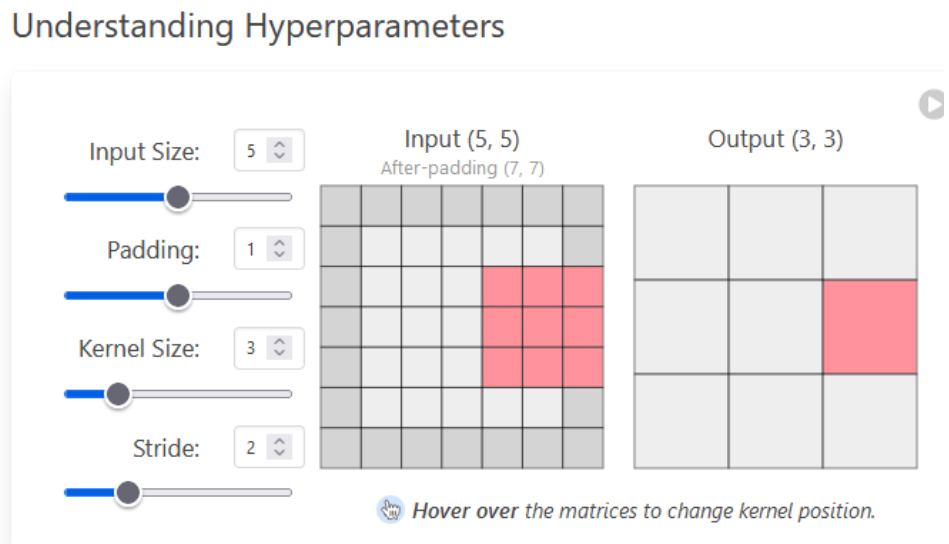
Tip: Try it yourself in https://generic-github-user.github.io/Image-Convolution-Playground/src/

Example notebook: convolution_introduction.ipynb

Convolution Operation

Convolution Operation Parameters

- Dimensions of the input image
- Padding – how borders are handled
- Filter size
- Stride – the step used to move the filter across the image



Great interactive visualization:
https://poloclub.github.io/cnn-explainer/

Convolution Parameters: Padding and Stride

Padding

- Adds extra border pixels around the input image
- Common options:
  - **Valid** – no padding (output shrinks)
  - **Same** – padding added to keep output size the same as input
- Helps preserve spatial size and improve edge detection

Stride

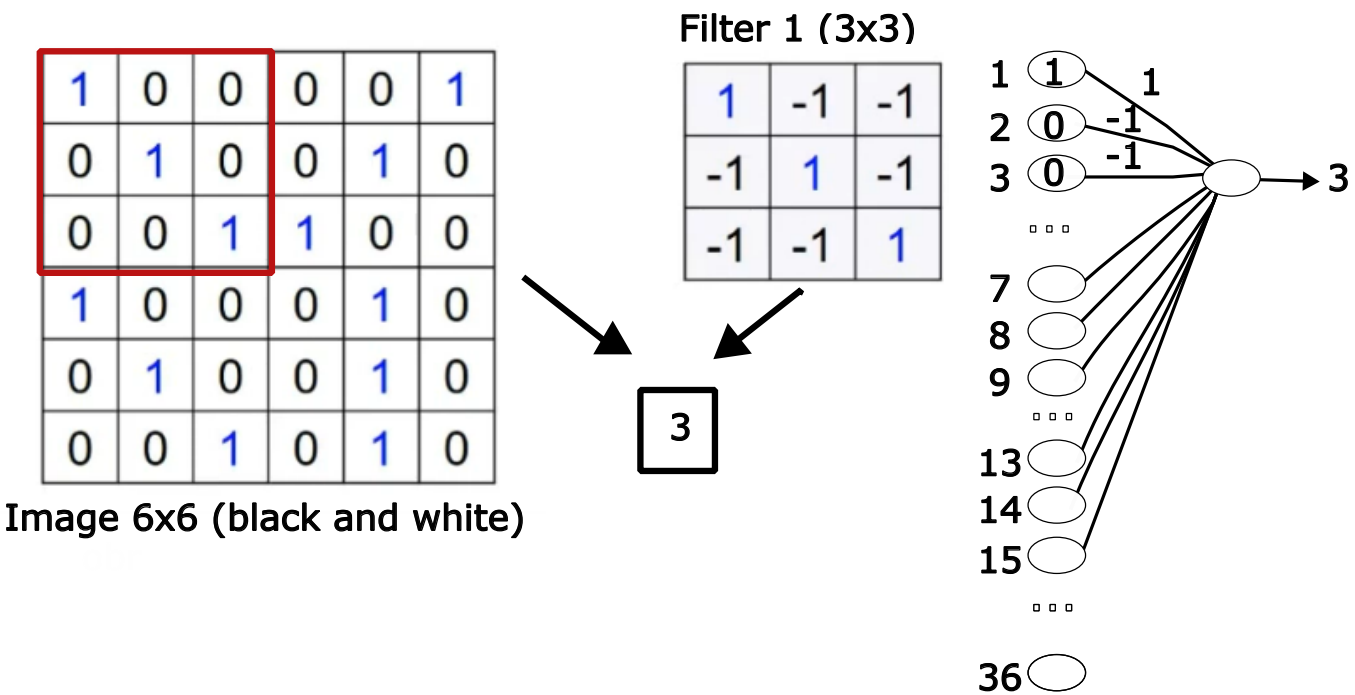
- Controls how far the filter moves at each step
- **Stride = 1**: typical setting, dense coverage
- **Stride ¿ 1**: reduces output size, performs downsampling

Tip: Try out different values in CNN Explainer

Convolutional Layer vs. Fully Connected Layer

- A convolutional layer can be viewed as a regular neural network layer (without activation function)
- However, neurons are **not fully connected**

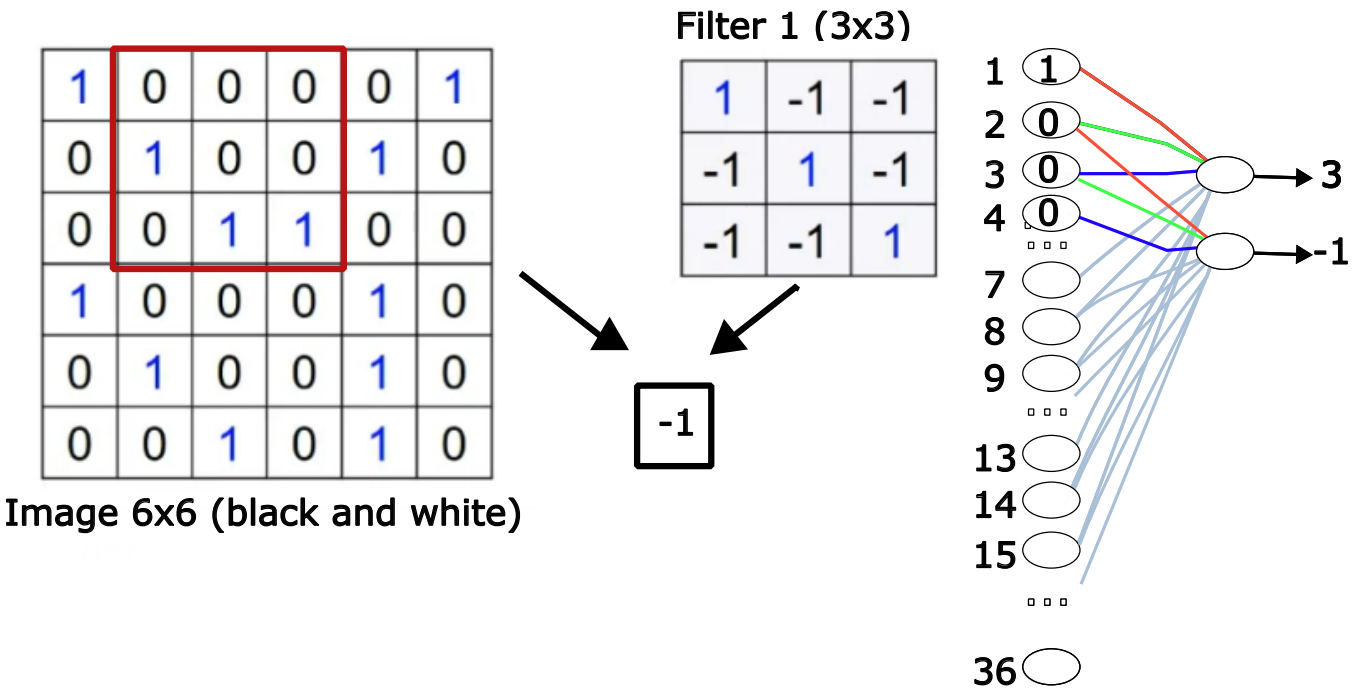
$\Rightarrow$ much fewer parameters



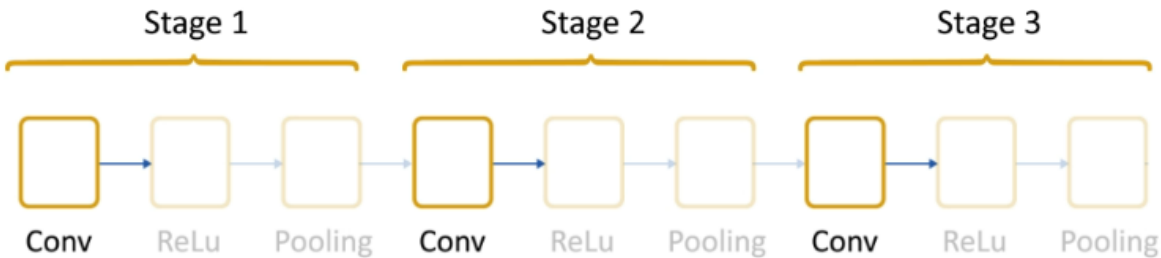
Convolutional Layer vs. Fully Connected Layer

- A convolutional layer can be viewed as a regular neural network layer
- Hidden units (neurons) share the **same set of weights**

$\Rightarrow$ even fewer parameters, more efficient learning



Classic CNN Architecture

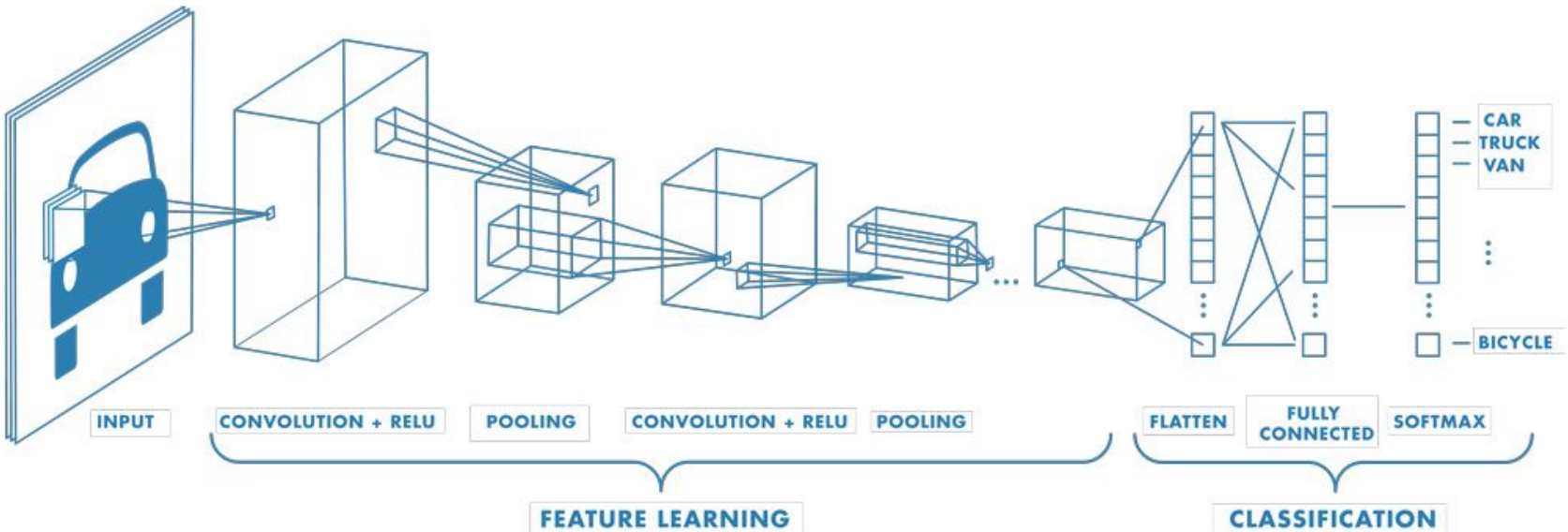


Core idea: stack convolutional layers (or blocks) on top of each other

- The first convolutional layer detects simple features (e.g., edges, blobs)
- Each following layer extracts higher-level features

Hierarchical structure of features:
edges $\rightarrow$ shapes $\rightarrow$ object parts $\rightarrow$ whole objects

Classic CNN Architecture



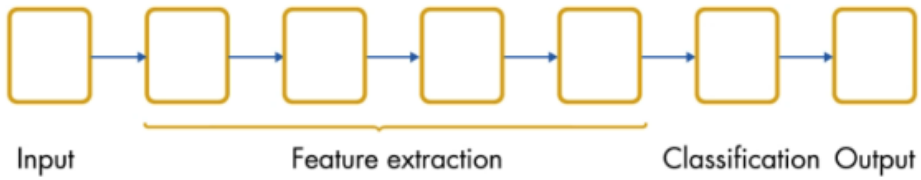
Main components of a CNN:

- Convolutional blocks for feature extraction
- Flattening layer – converts the feature maps into a 1D vector
- Fully connected neural network for classification

Image source: `https:`

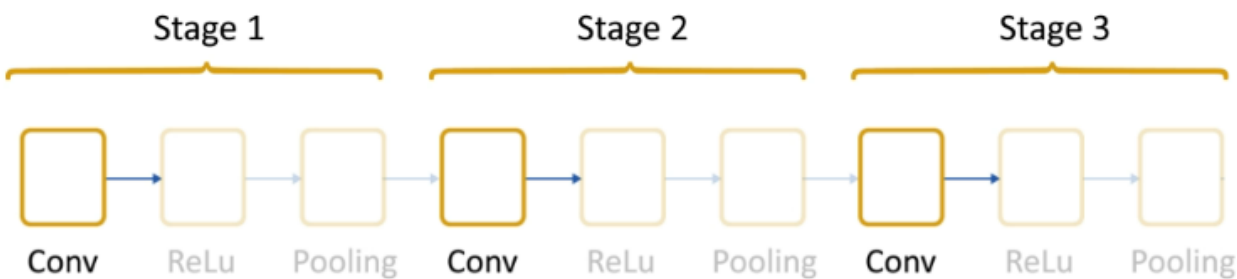
`//matlabacademy.mathworks.com/details/deep-learning-onramp/deeplearning`

Classic CNN Architecture



Typical structure of a convolutional block:

- Convolutional layer
- Nonlinear activation function (e.g., ReLU)
- Pooling layer



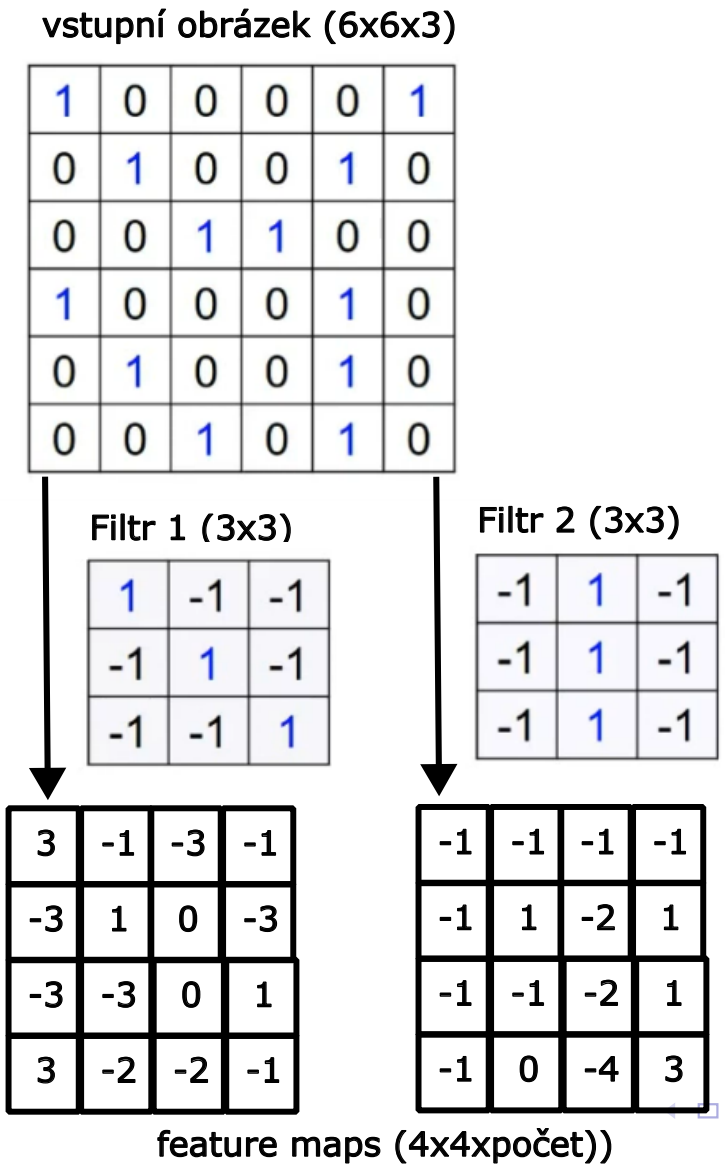
Pooling (Subsampling) Layer

- Reduces spatial resolution while preserving most of the relevant information
- A sliding window (e.g., 2×2) moves across the feature map, often with stride $= 2$
- Common operations: MAX (max pooling), AVERAGE (average pooling); no weights involved

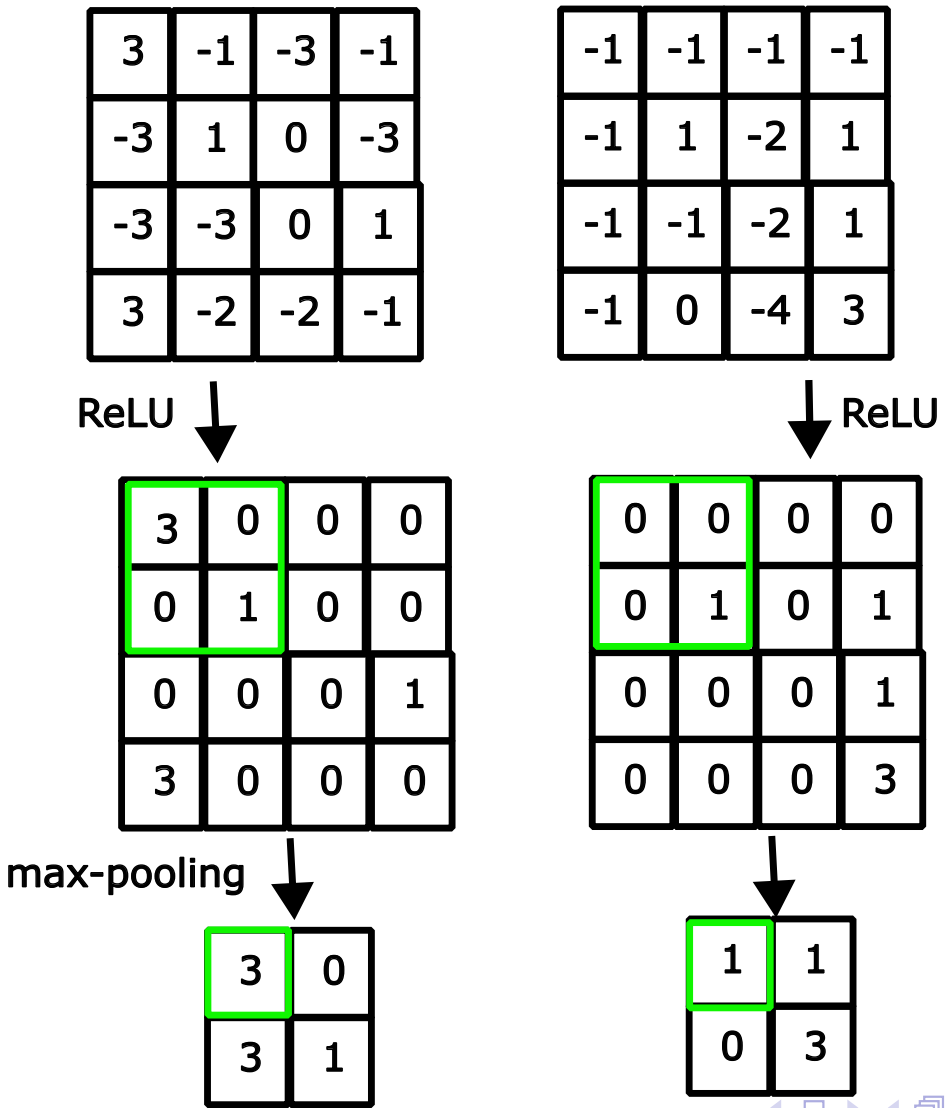
Why pooling?

- Condenses the information stored in the feature map
- Keeps track of where and how strongly a feature occurs
- Reduces the data size (e.g., $2 \times 2 \rightarrow 1$ value $= 75\%$ reduction)

Convolutional Block – Example: Convolutional Layer



Convolutional Block – Example: Pooling Layer



Convolutional Block

Why not just stack convolutional layers without pooling?

- The number of parameters grows with each added layer
- Image size stays (almost) the same, especially with "same" padding
  $\Rightarrow$ the size of the feature maps (and computation) keeps growing

Pooling layer:

- Reduces data size while preserving information about feature presence and strength
- e.g., $2 \times 2 \rightarrow 1$ value = quarter size

Alternating convolution and pooling – bipyramidal effect:

- Spatial size decreases, number of feature maps increases

Bipyramidal Architecture

- One of the oldest architecture types: wide and shallow, with a deeper fully connected part – close to the basic layered schema

LeNet-5

- One of the original CNN architectures (Yann LeCun, 1998), relatively simple, trained on the MNIST dataset

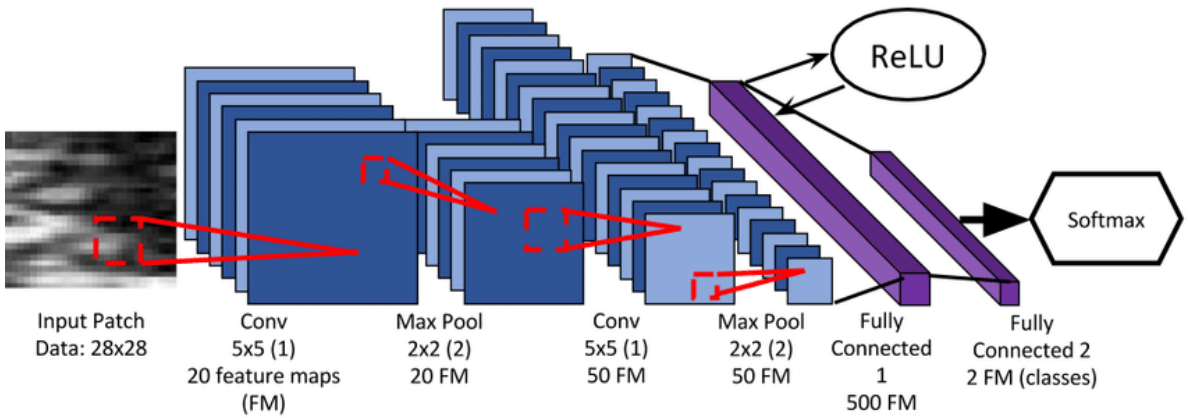


Image source: M. H. Yap et al., "Automated Breast Ultrasound Lesions Detection Using Convolutional Neural Networks," IEEE Journal of Biomedical and Health Informatics, vol. 22, 2018.

Bipyramidal Architecture

Typical structure of a bipyramidal architecture:

- The number of filters typically doubles in deeper layers (e.g., 32, 64, 128, ...)
- Most commonly used filter size: 3×3
- ReLu activation
- Max-pooling 2×2 is often paired with filter doubling
- When using several convolutional layers, we may not need many fully connected layers
- (Optionally) One or more fully connected layers are added for classification

visualize_cnn_mnist.ipynb

- Practical example: MNIST dataset (handwritten digits)