Machine learning

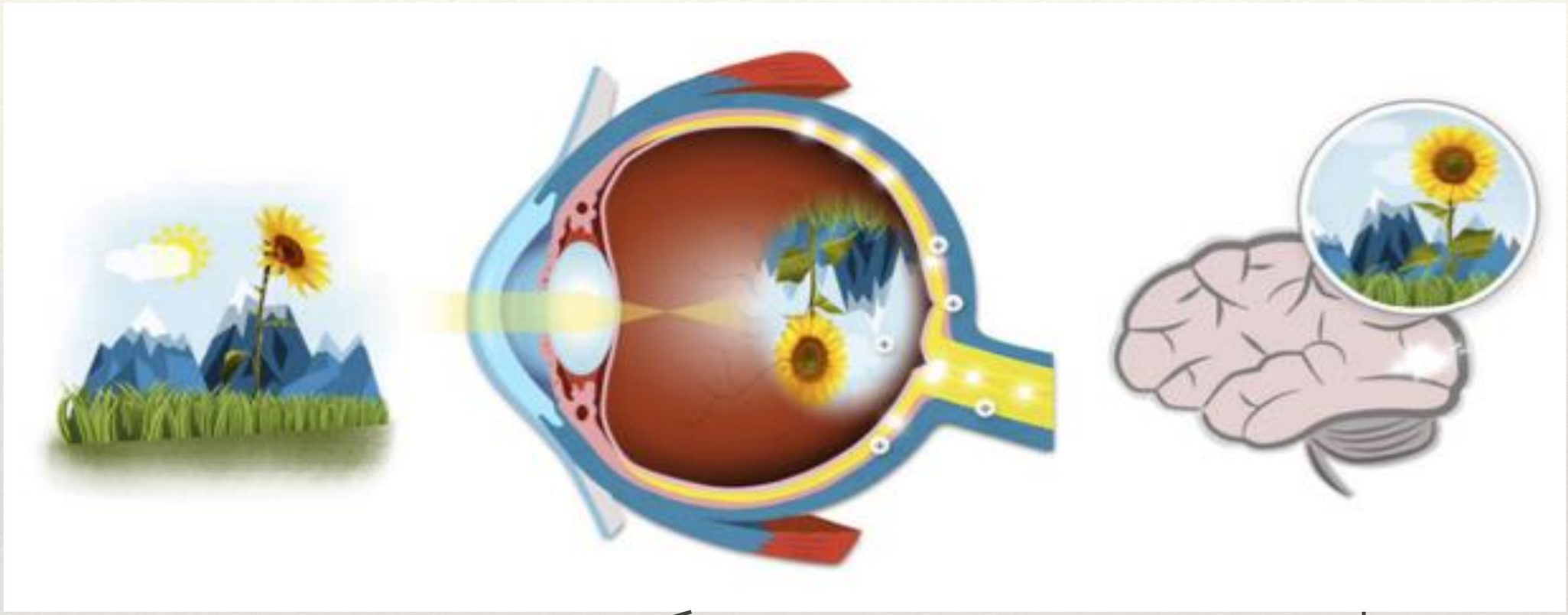
Introduction to Computer Vision

Lecture XI

פיתוח:
להב יפת

Based on Alexaner Amini @ MIT slides

Human Vision

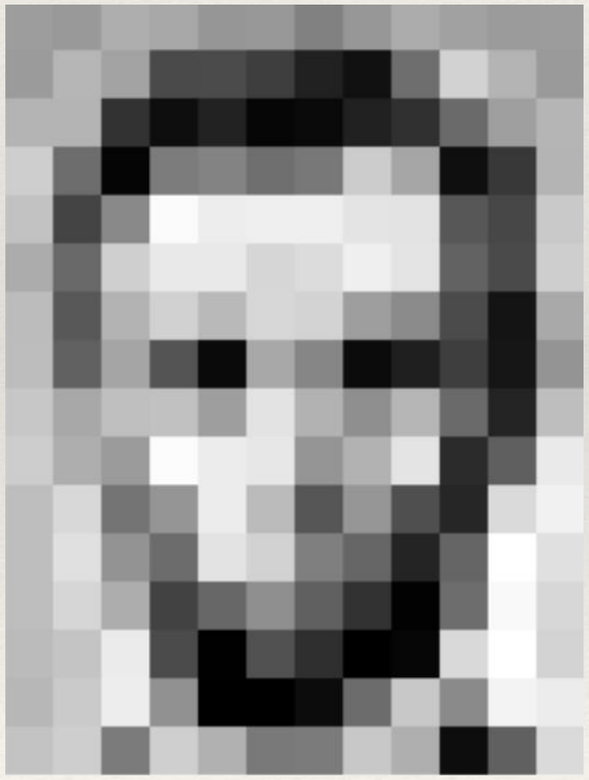


The eye Translates visual information into electric information

The brain’s visual cortex interprets the electrical form of the image

Computer Vision

What computers “see”?



Images are numbers

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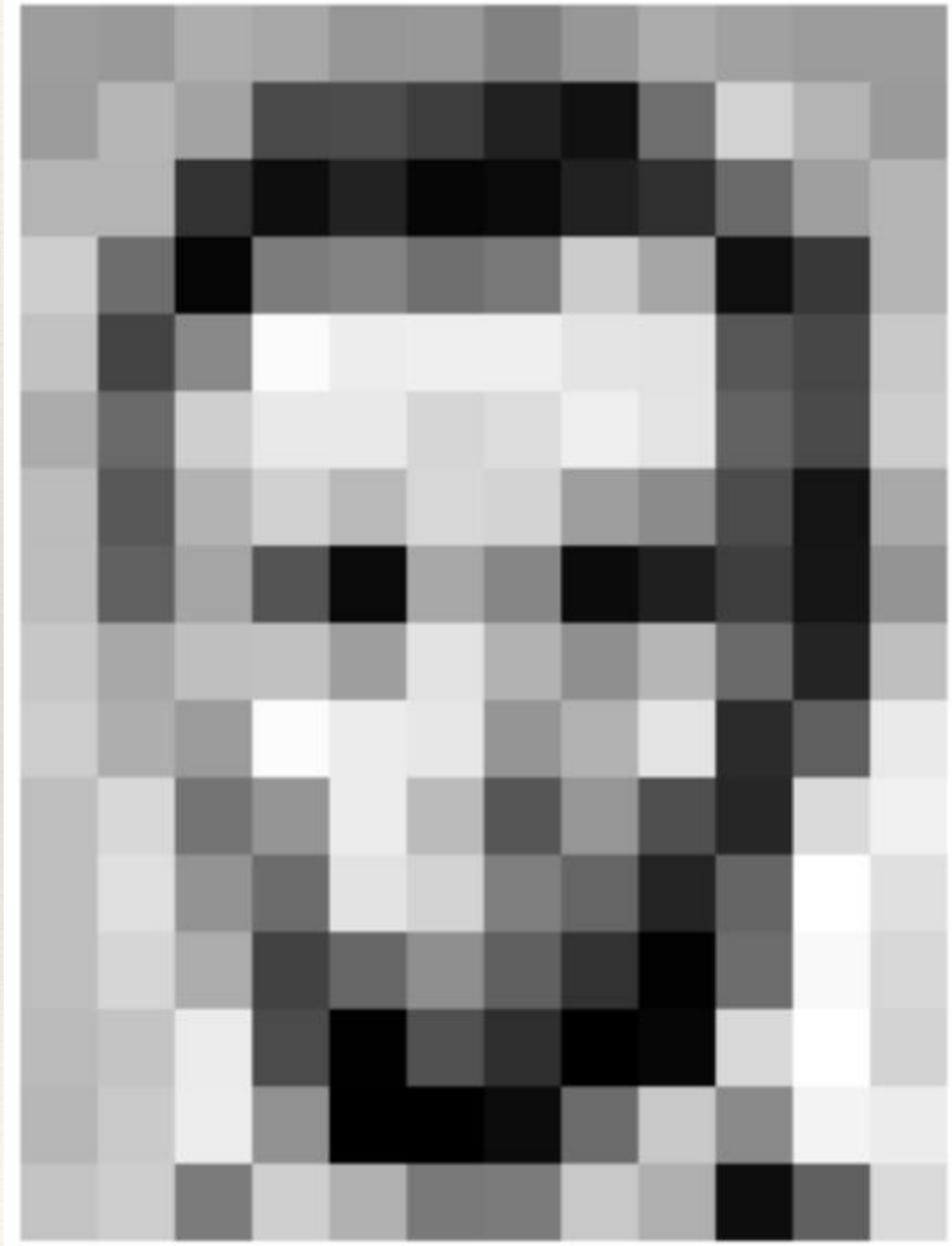
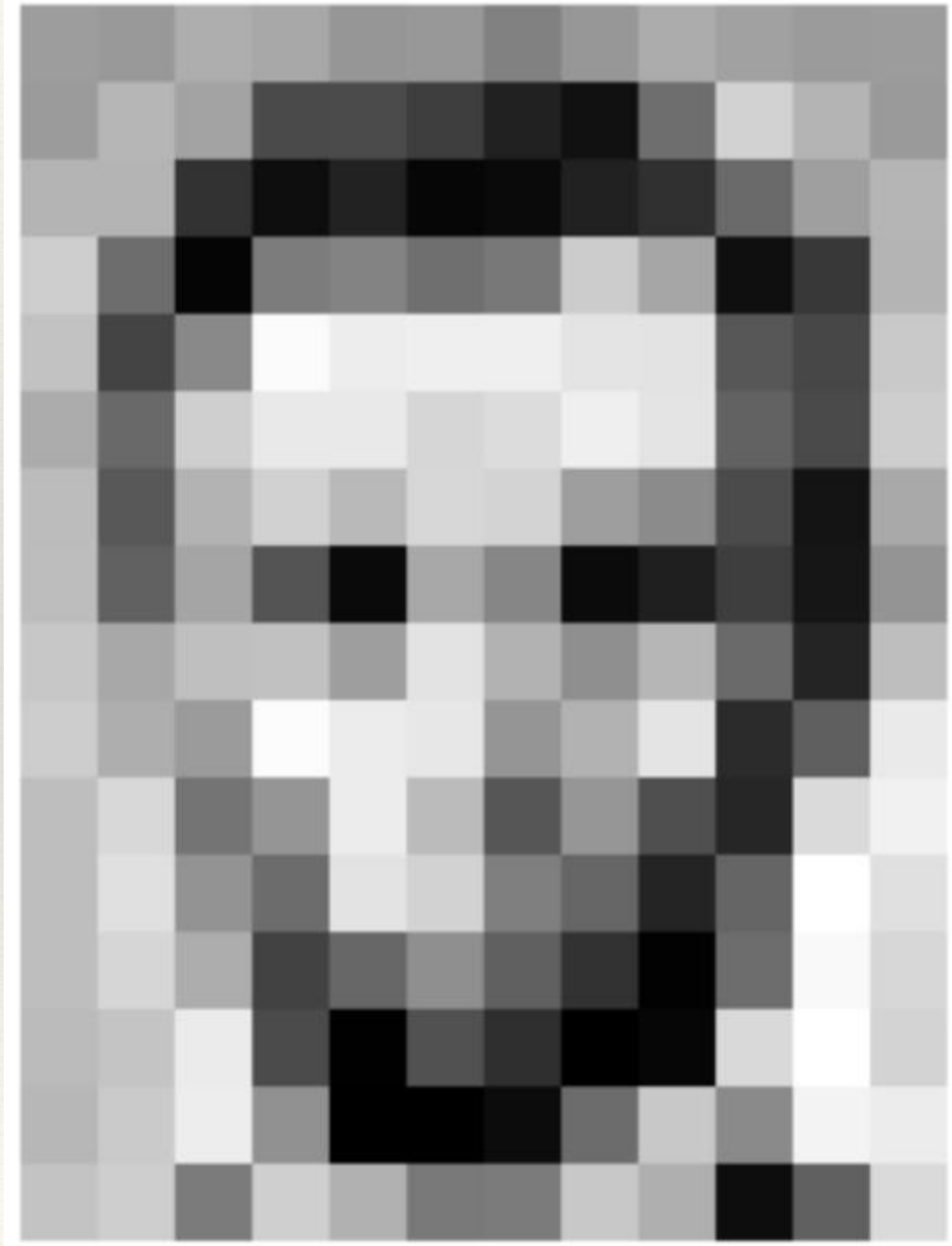


157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	105	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	106	36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

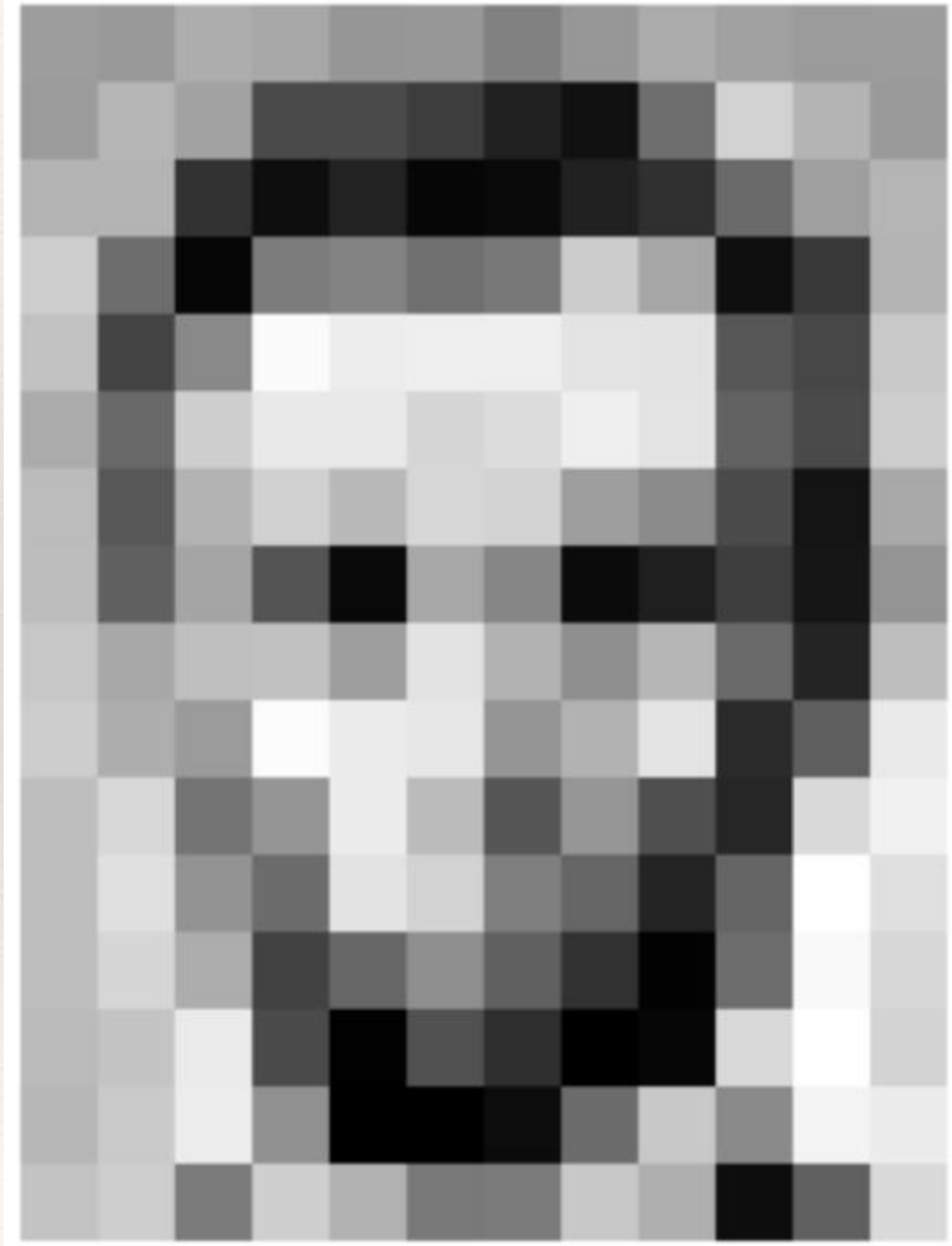
Images are numbers

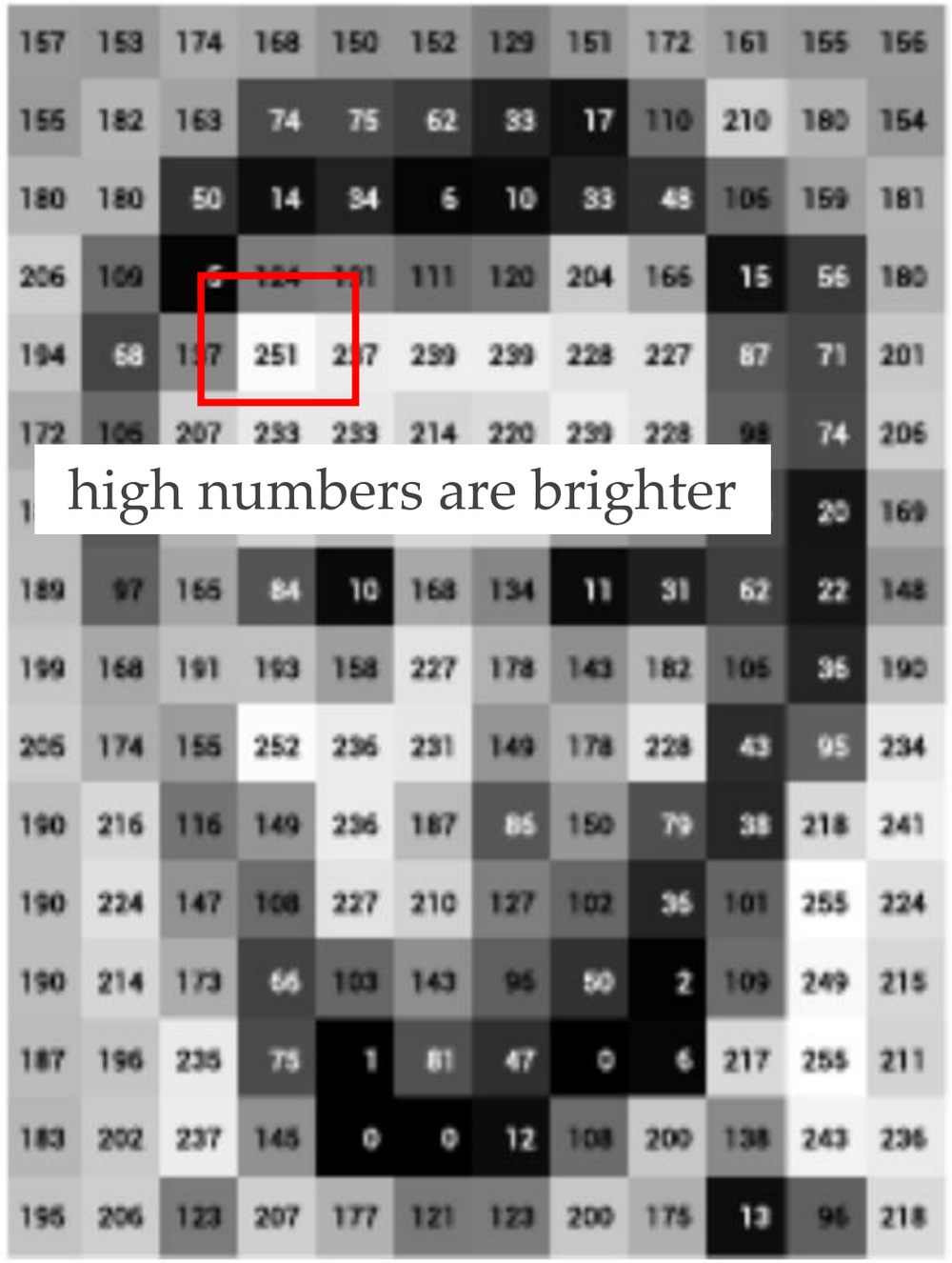


157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	105	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
										22	148
										36	190
205	174	155	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	86	150	79	38	218	241
190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	95	50	2	109	249	215
187	196	235	75	1	81	47	0	6	217	255	211
183	202	237	145	0	0	12	108	200	138	243	236
196	206	123	207	177	121	123	200	175	13	96	218

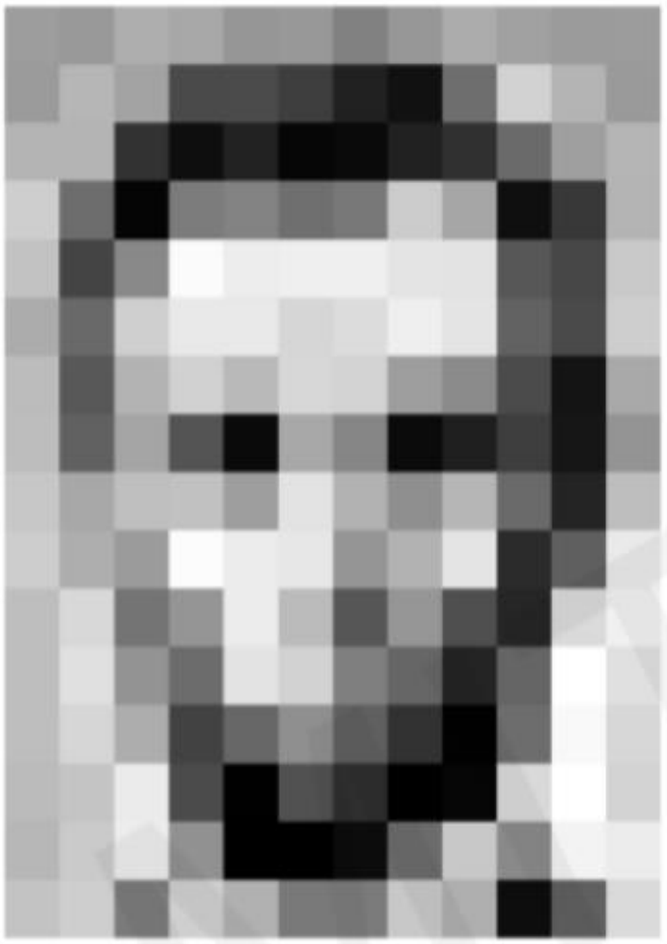
Low numbers are darker

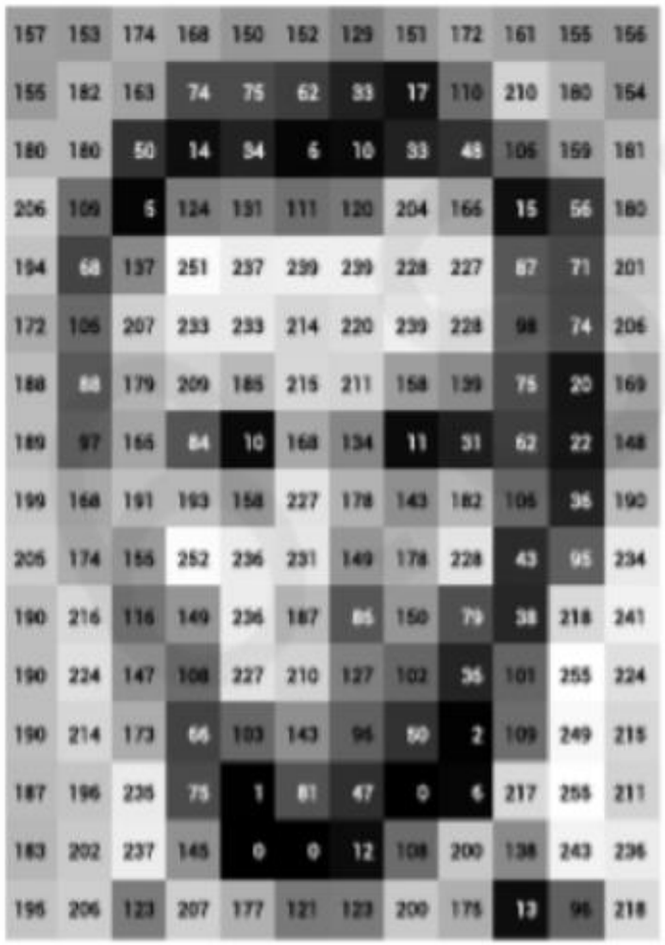
Images are numbers

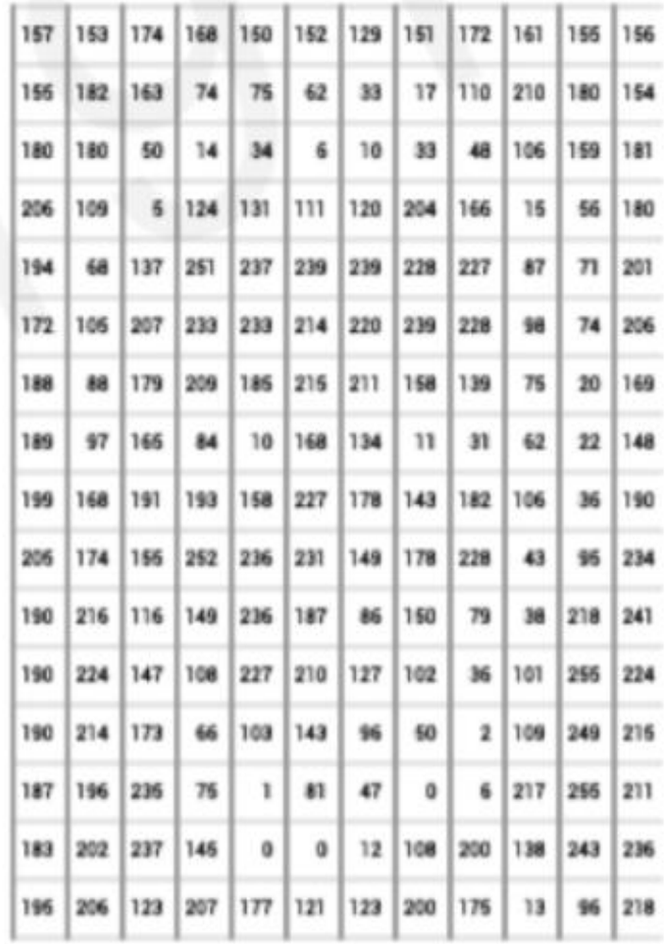




Images are numbers

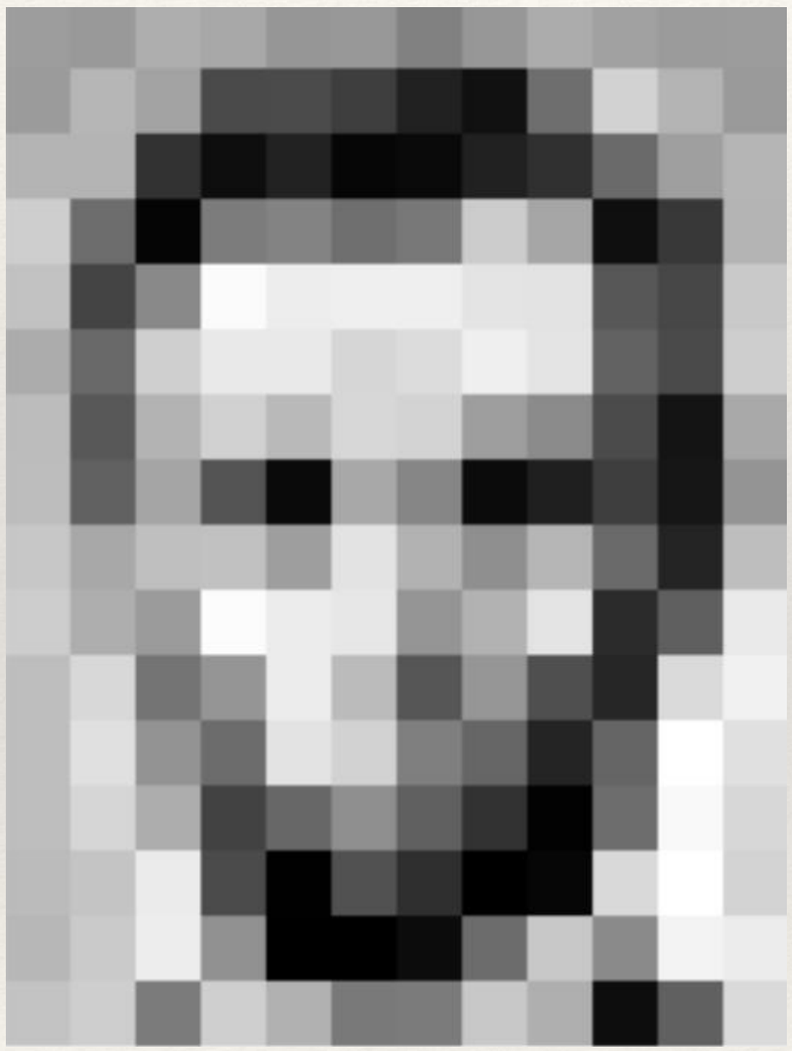






An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Grey level image



1 b/w band

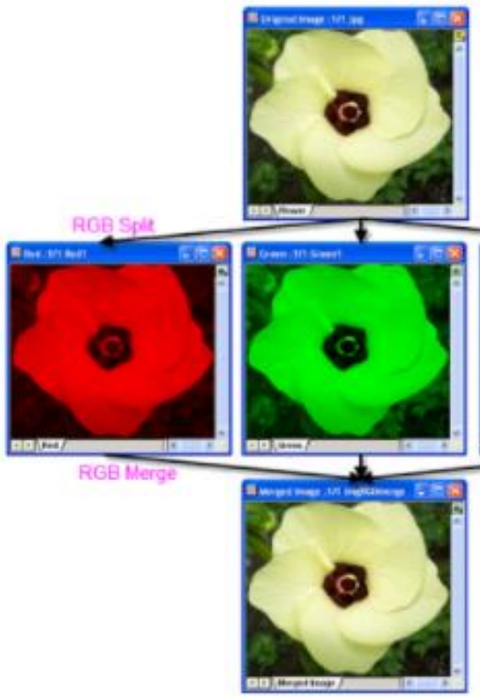
0-255

0 = black

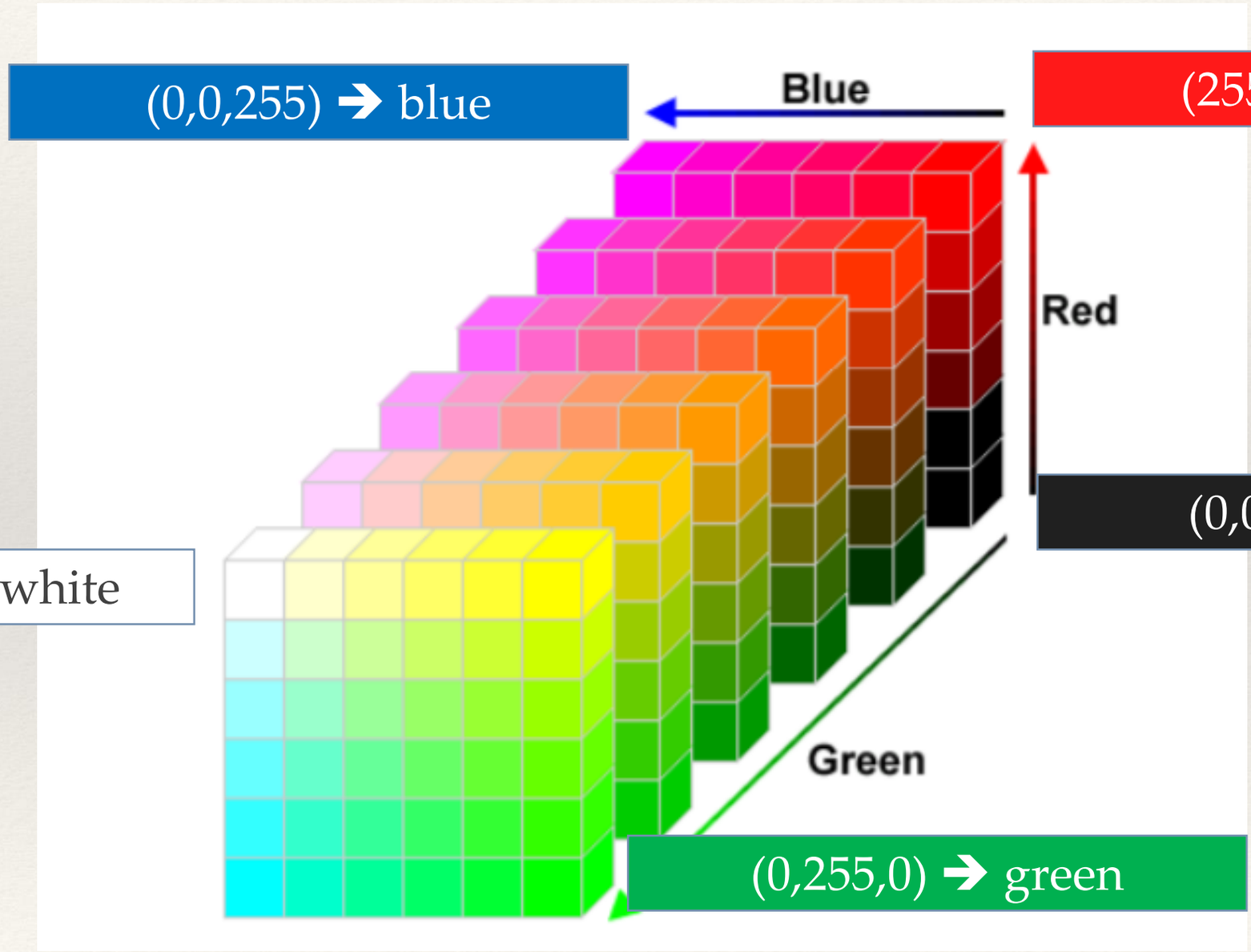
255 = white

Color image

תמונה צבעונית היא הרכבה של 3 תמונות



RGB Pallet


(0,0,255) ➔ blue
Blue
(255,0,0) ➔ red
Red
(0,0,0) ➔ black
(255,255,255) ➔ white
Green
(0,255,0) ➔ green

Tasks in computer vision – example 1

Classification

Dog	0.8
Cat	0.1
…	…
Horse	0.01

What is in the picture?

Tasks in computer vision – example 2

Regression #1

x,y,w,h

Where is the object?

Tasks in computer vision – example 3

Regression #2

X

How many cars in the parking lot?

Tasks in computer vision – example 4

Segmentation

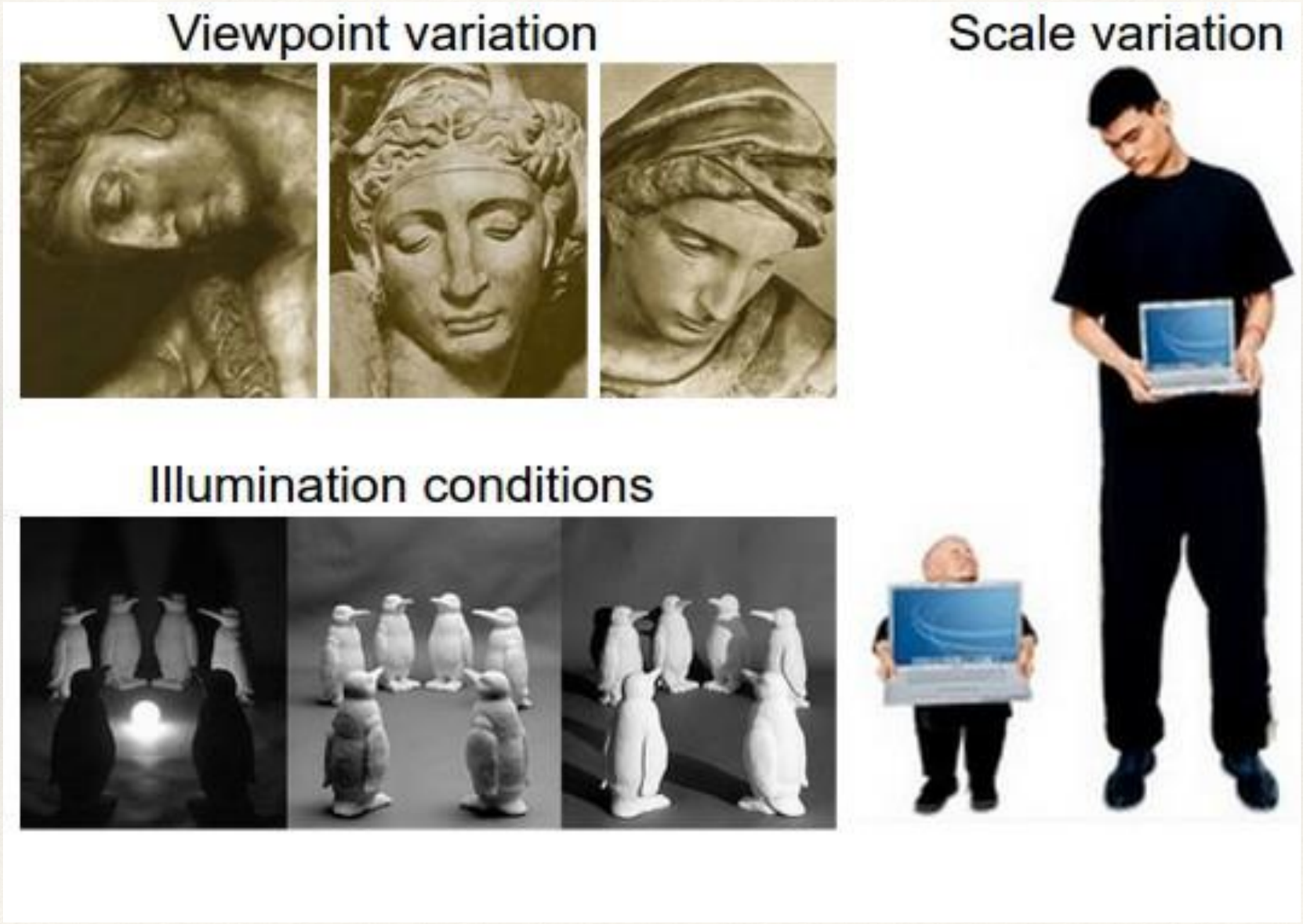
Pixel (i,j) ➔ segment

Tasks in computer vision

Many other tasks:

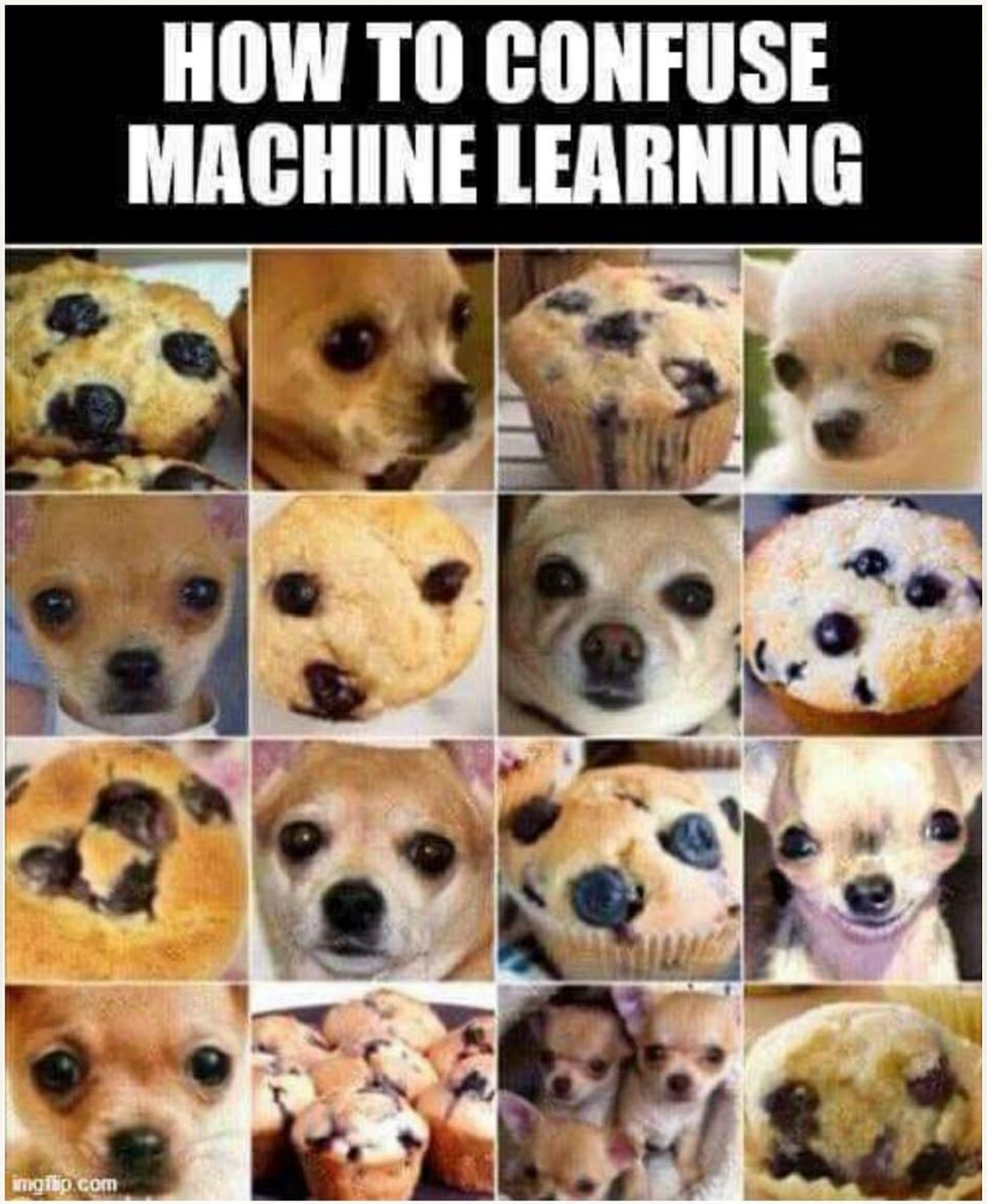
- Action Recognition
- Pose estimation
- Facial recognition
- 3d reconstruction
- …

Challenges in computer vision



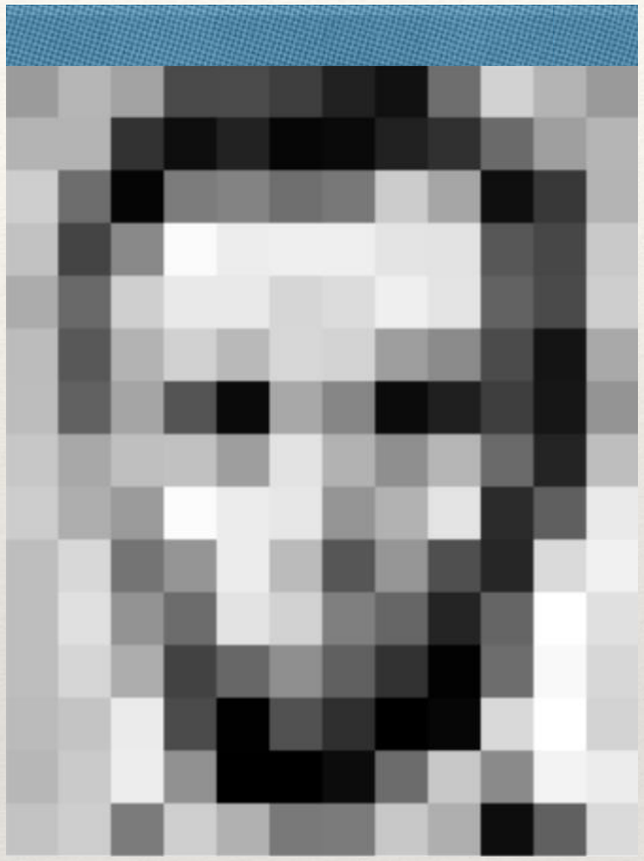
Challenges in computer vision

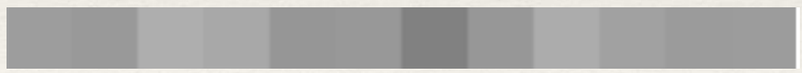
Challenges in computer vision



From image to features

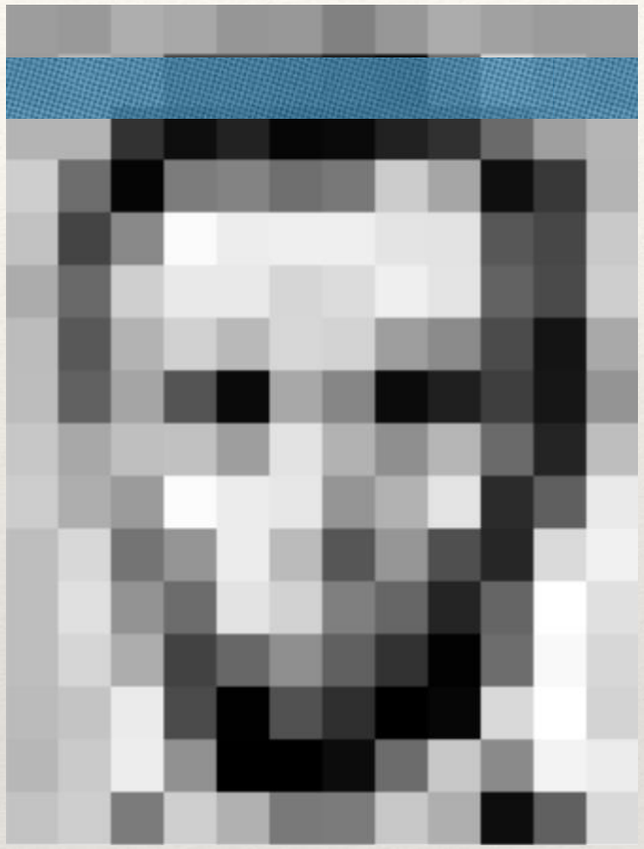
Raw Pixels

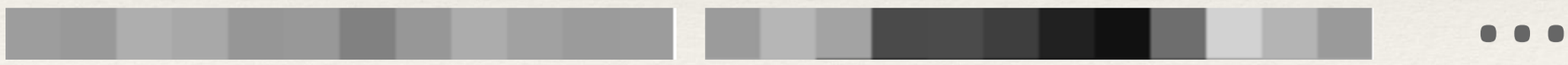




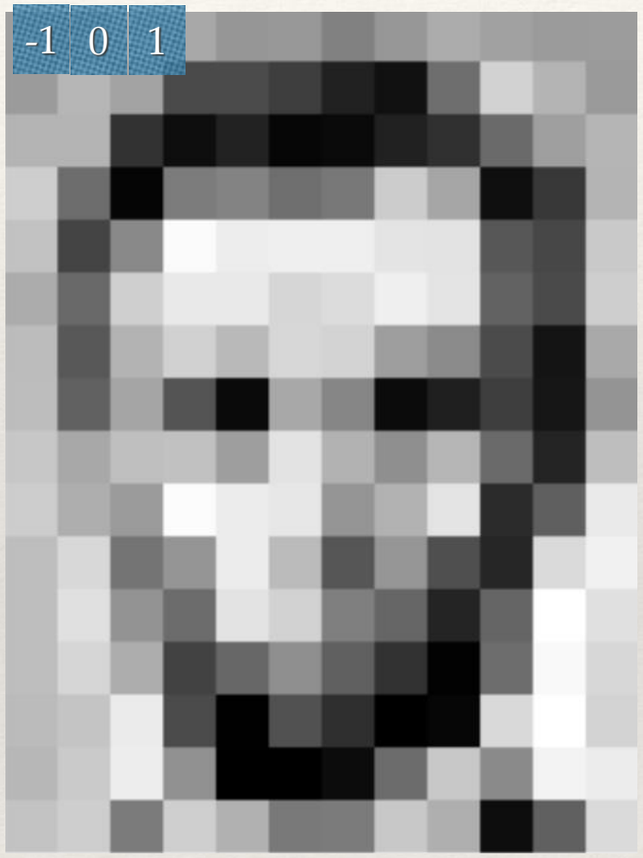
From image to features

Raw Pixels





From image to features



Horizontal Gradients

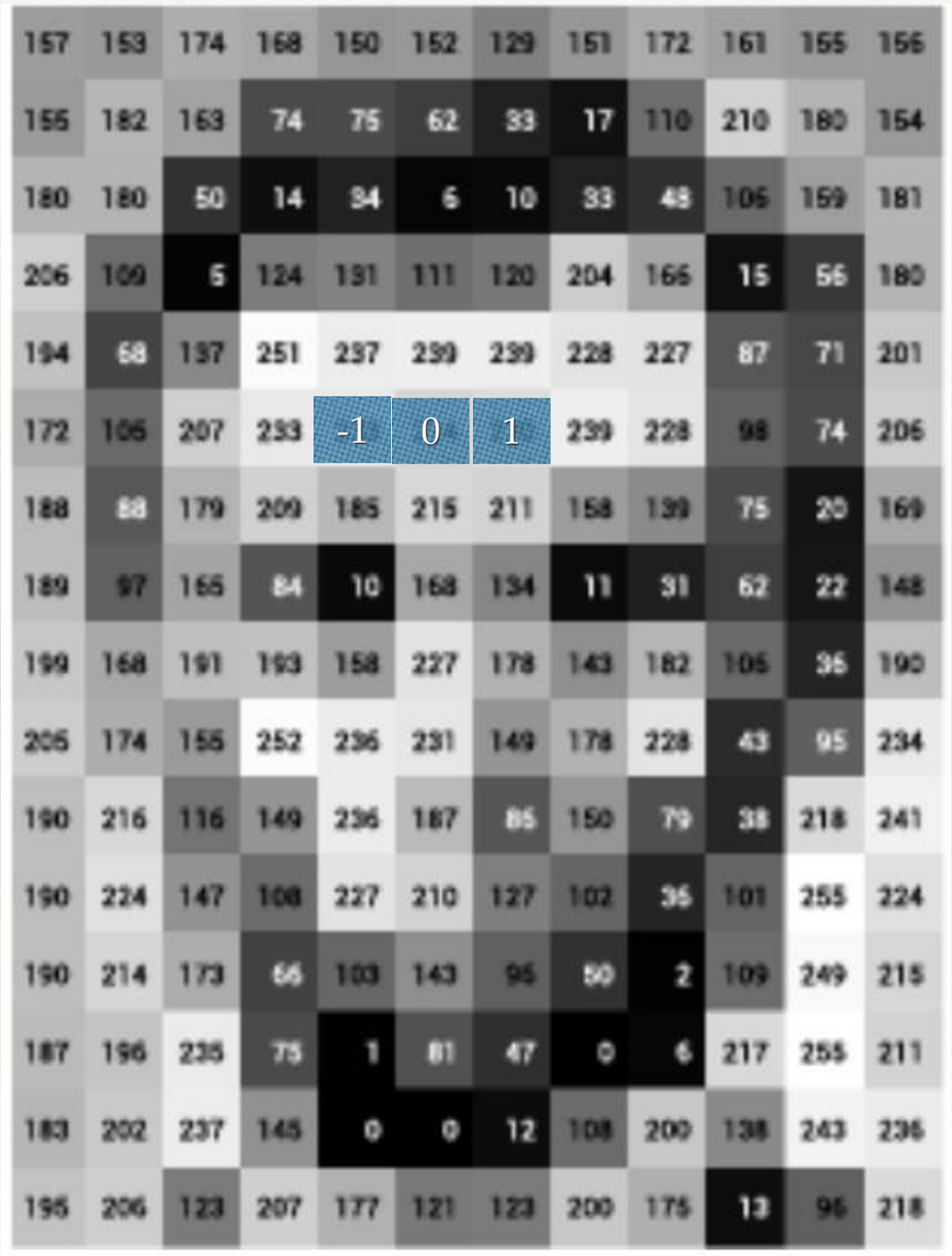
From image to features

Horizontal Gradients

233 214 220

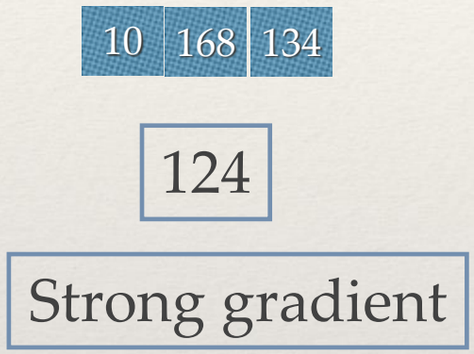
-13

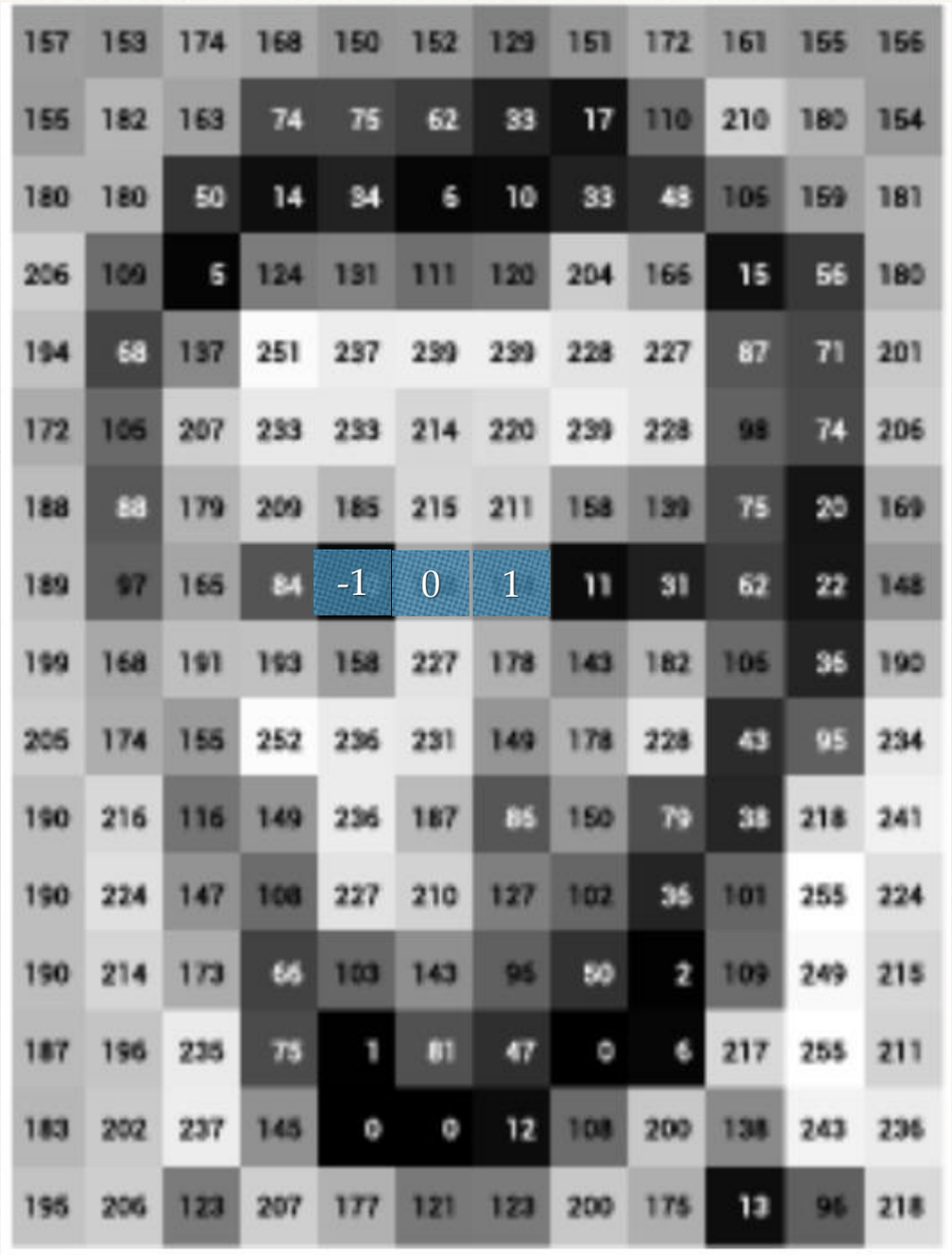
Weak gradient



From image to features

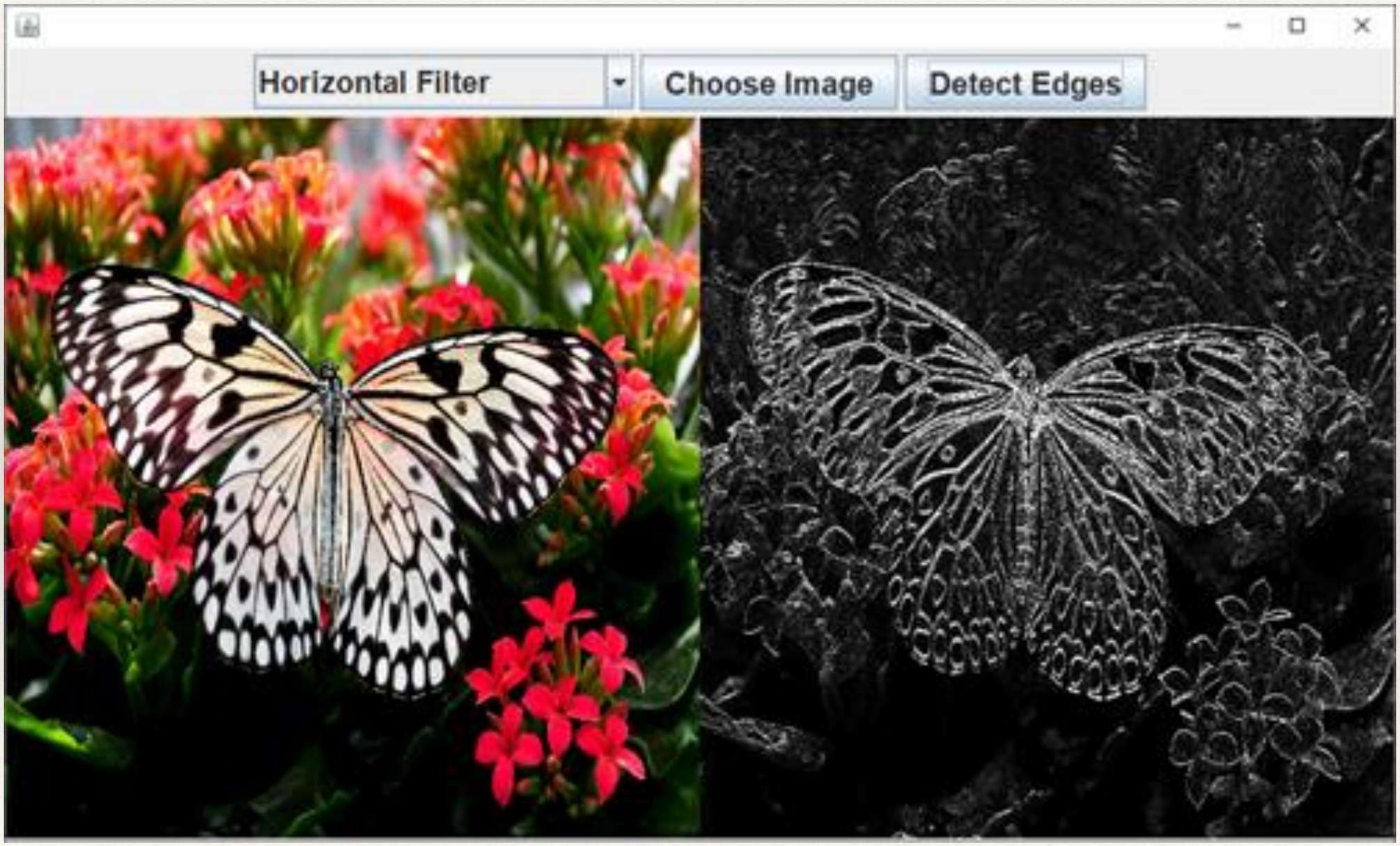
Horizontal Gradients





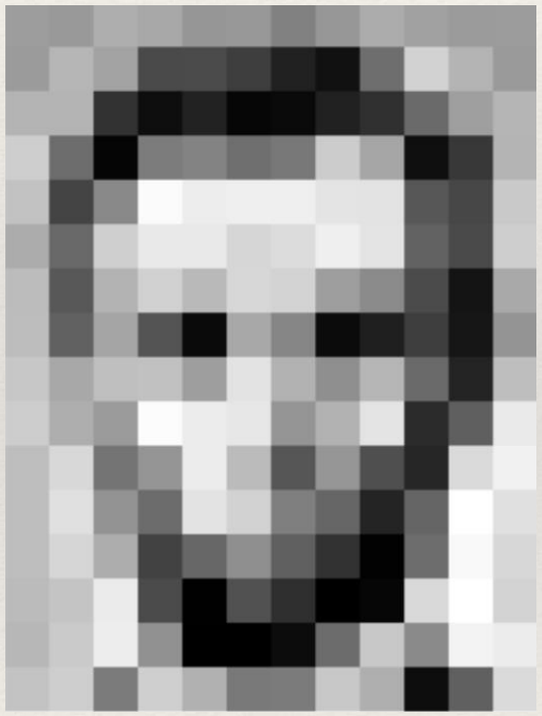
From image to features

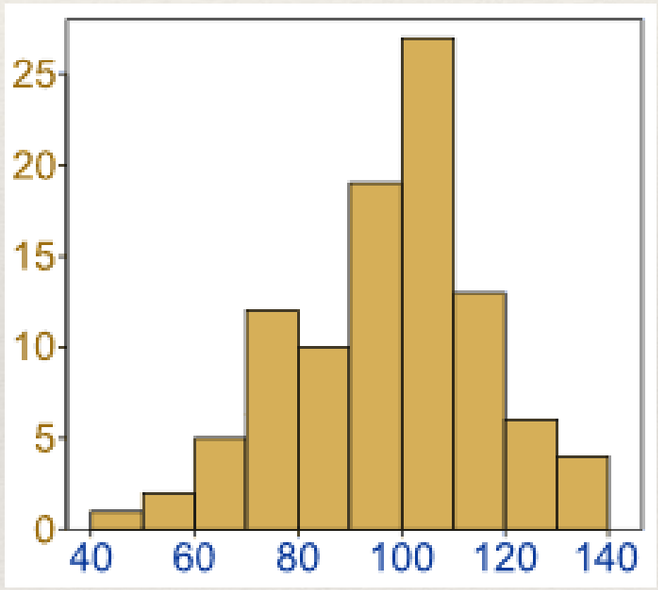
Horizontal Gradients - example



From image to features

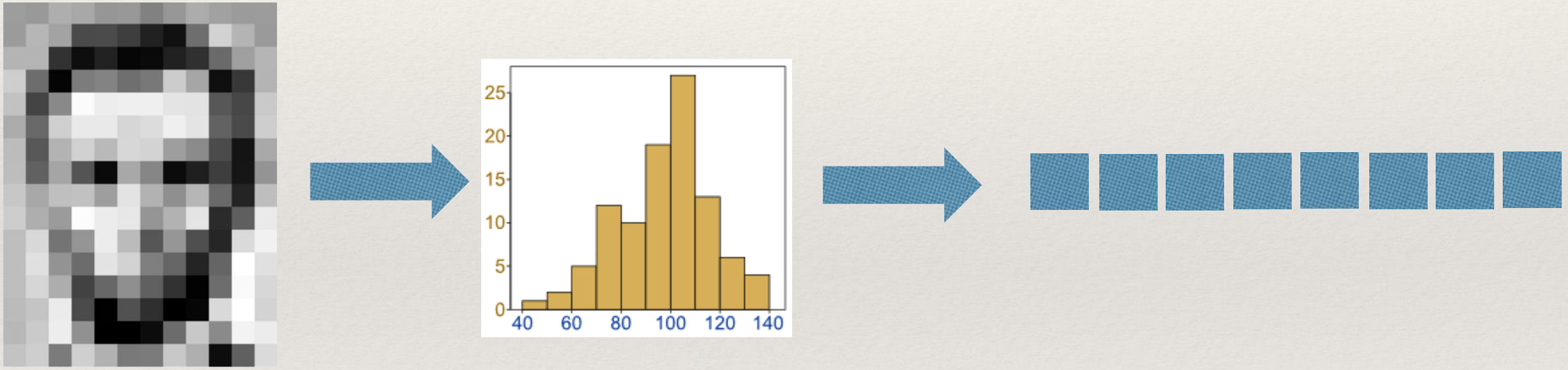
Image Descriptors, e.g. Histograms





From image to features

Image Descriptors, e.g. Histograms



Traditional approach

Manually Identify key features in each category.

Nose
Eyes
Mouth

Wheels
License Plate
Headlights

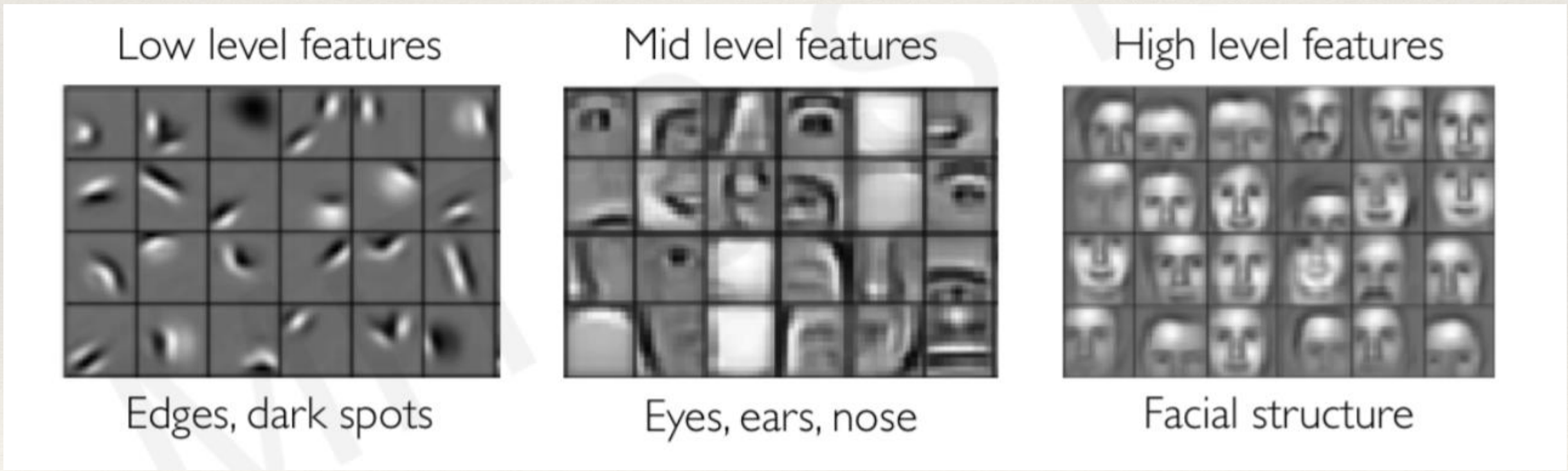
Train ML classifier on these features.

Traditional approach

- This was the traditional computer vision approach
- Engineers handcrafted new features & handed them as vectors to ML algorithms
- Better features / combinations of features improved performance

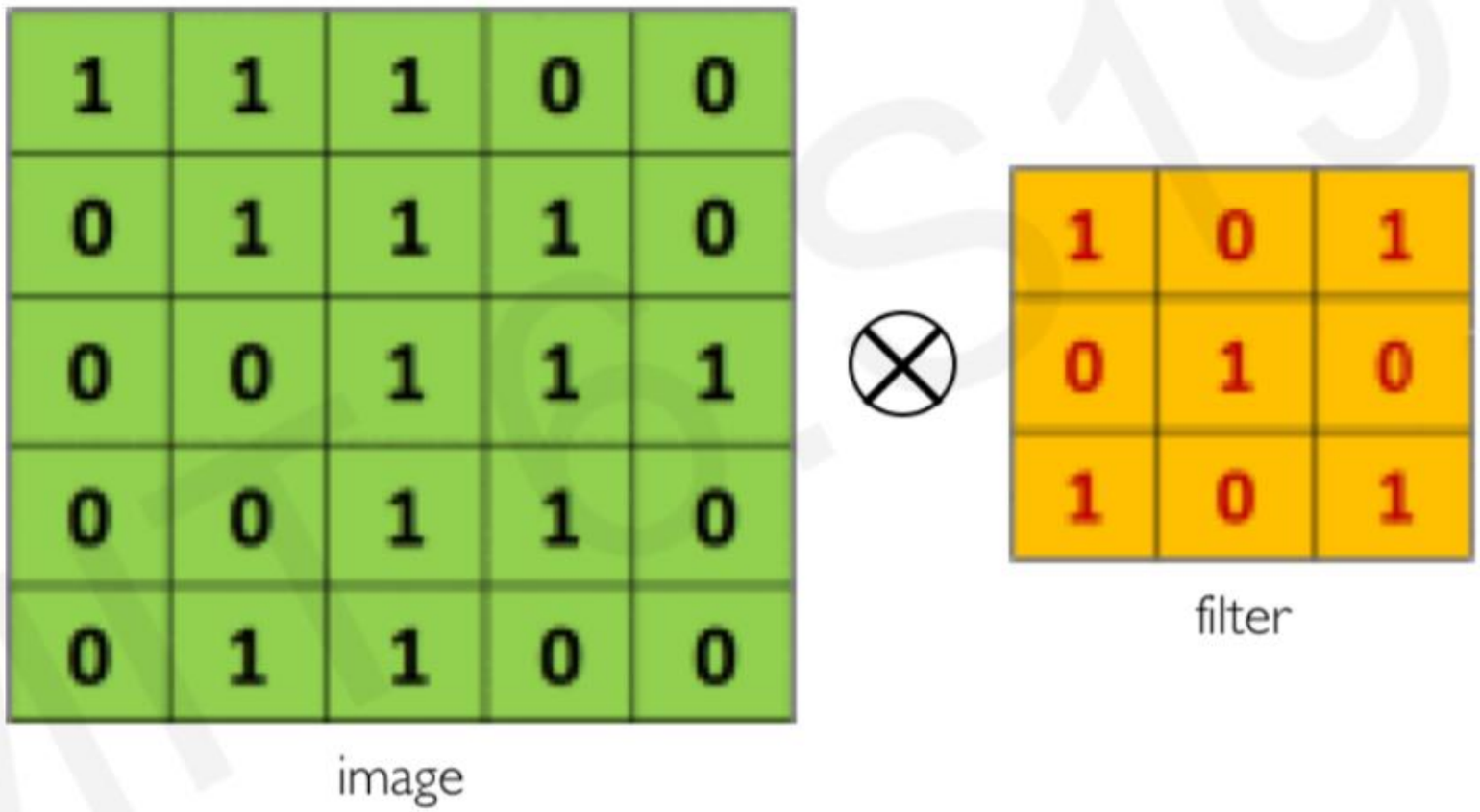
Automatic feature extraction

Can we learn hierarchy of features directly from the data?



convolutions

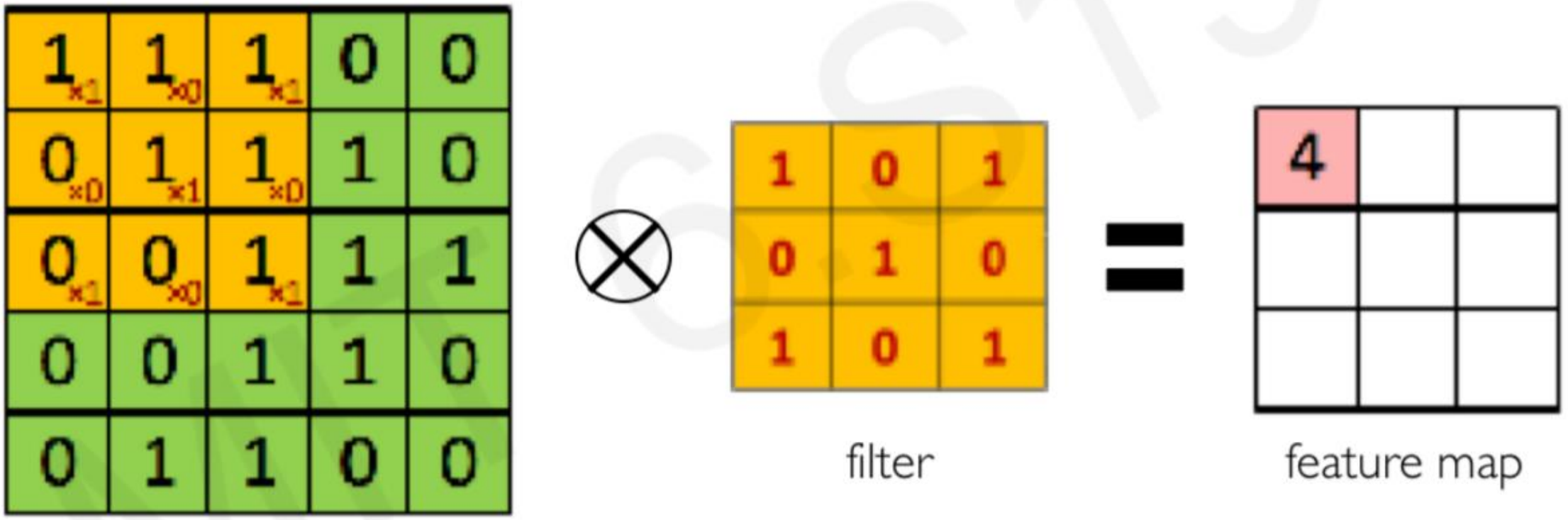
Suppose we want to compute the convolution of a 5x5 image and a 3x3 filter:



We slide the 3x3 filter over the input image, element-wise multiply, and add the outputs...

convolutions

We slide the 3x3 filter over the input image, element-wise multiply, and add the output



convolutions

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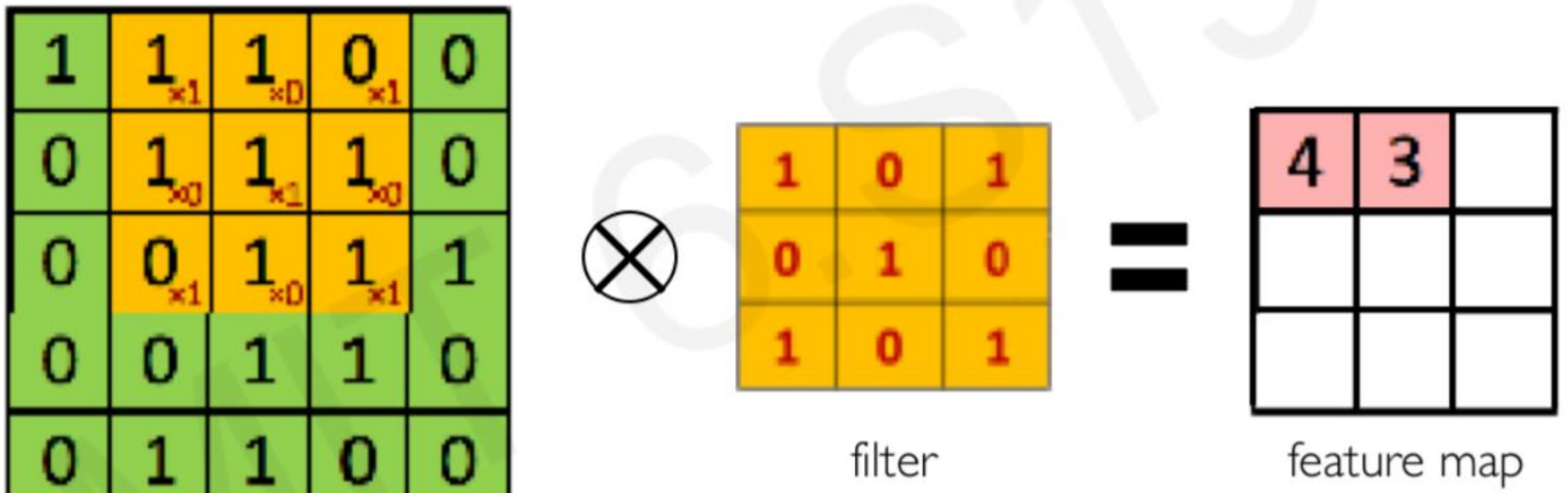

convolutions

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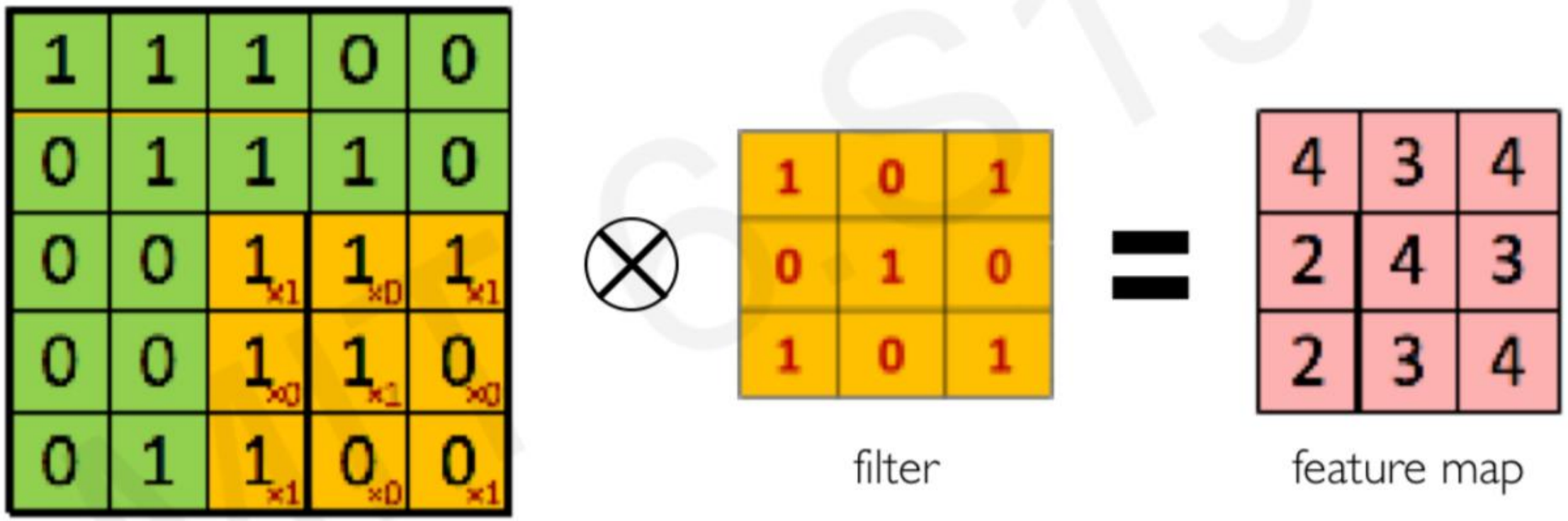

convolutions

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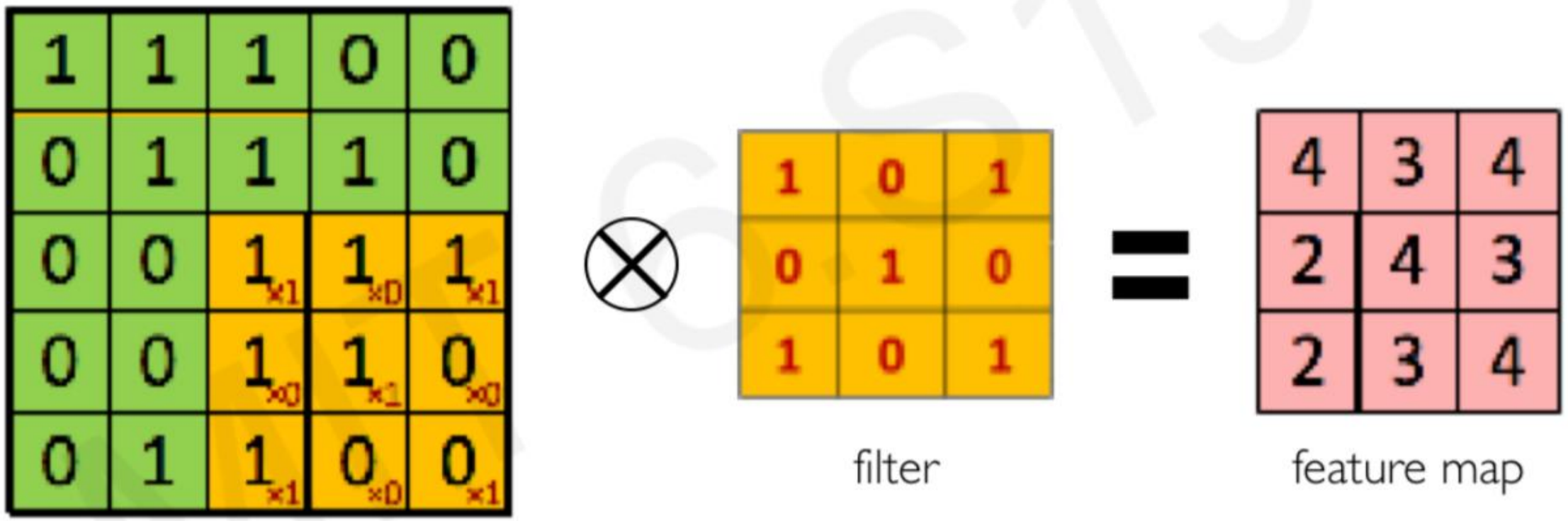
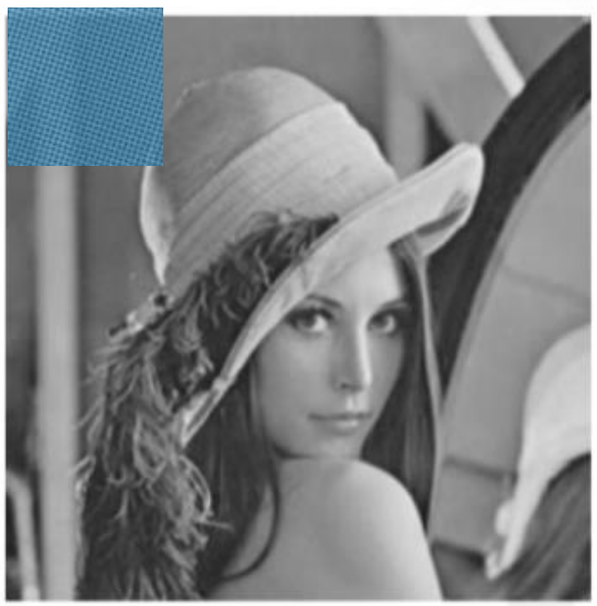


Convolutions produce feature maps



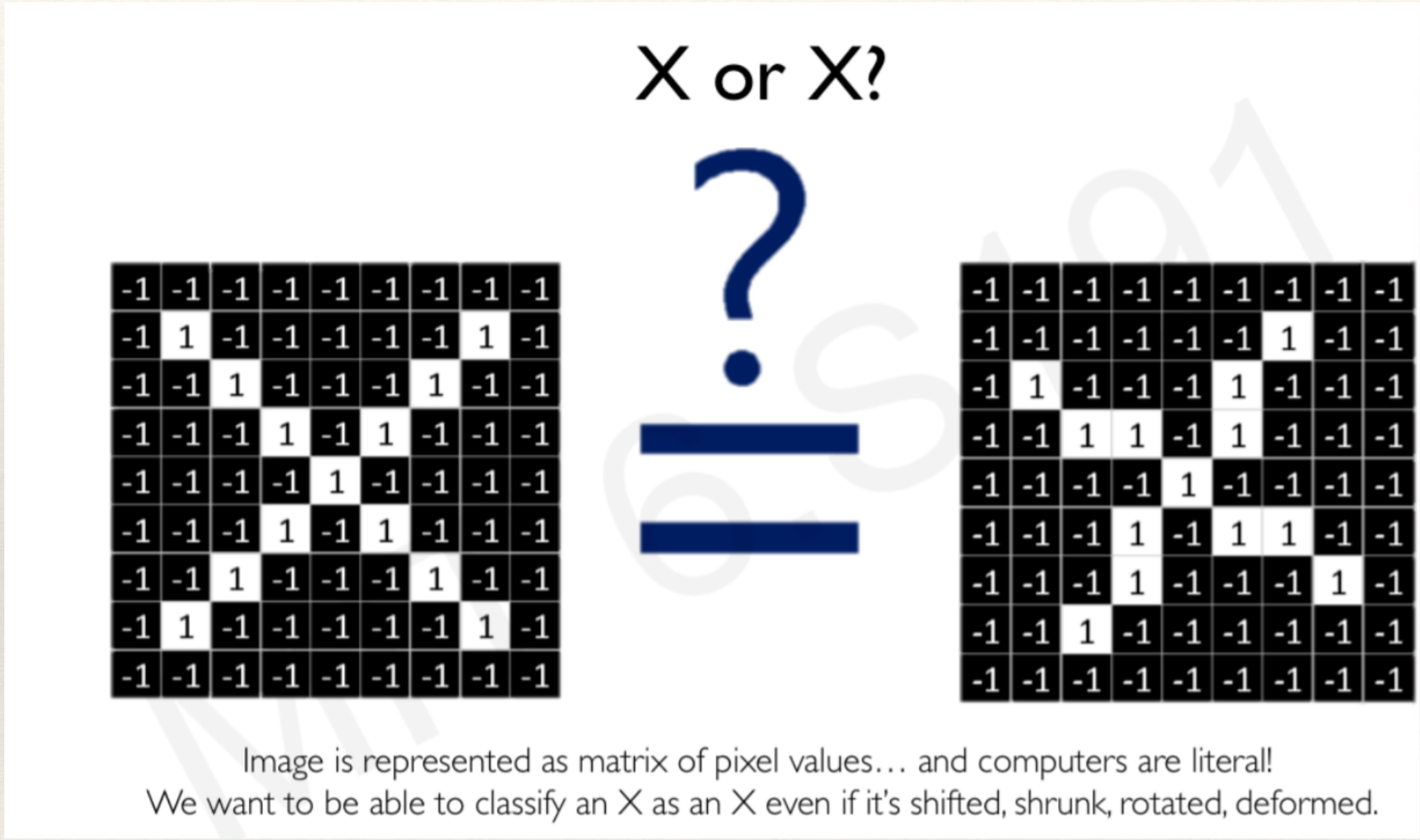
Original

Sharpen

Edge Detect

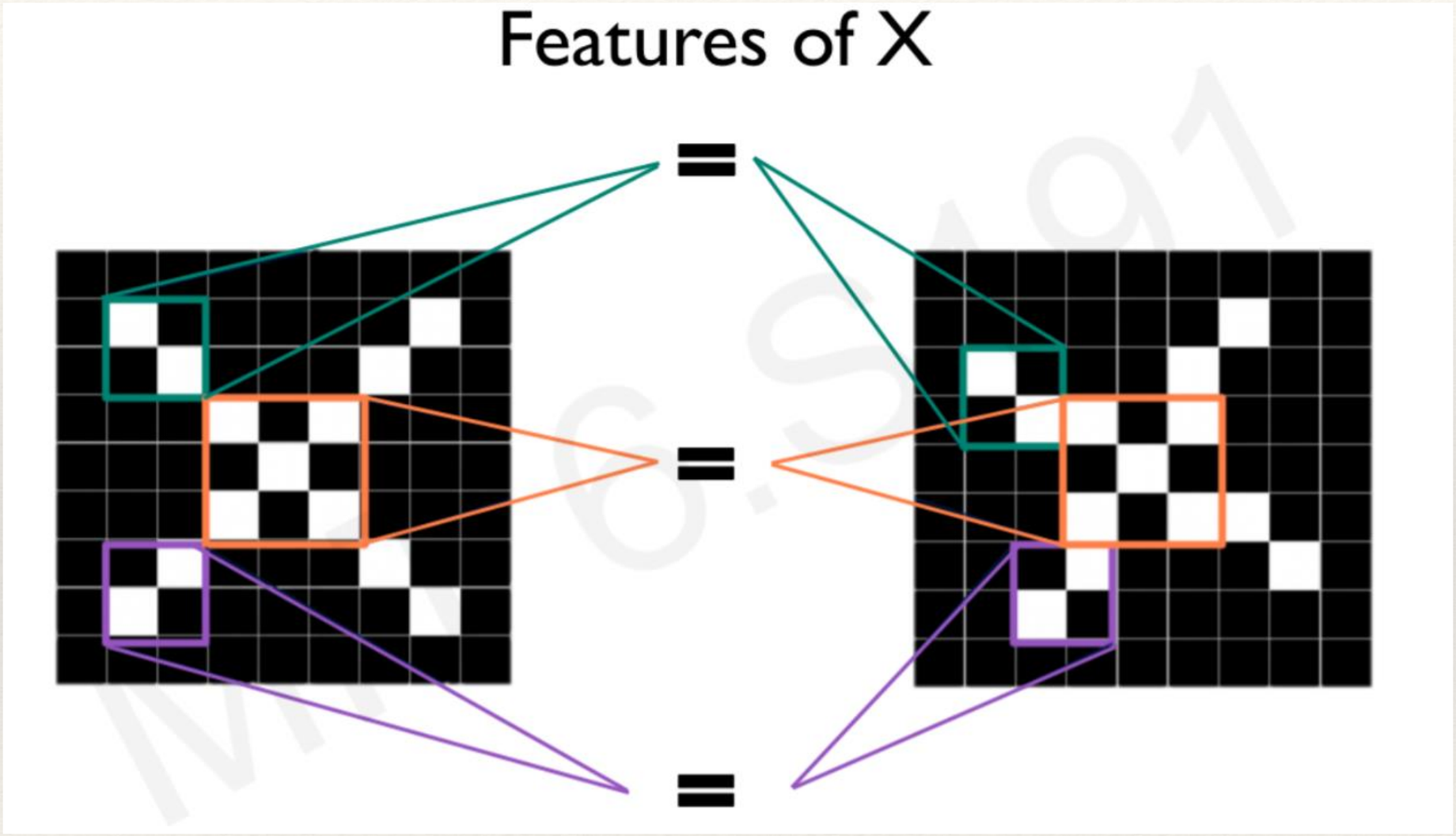
"Strong" Edge Detect

Convolutions large or small?



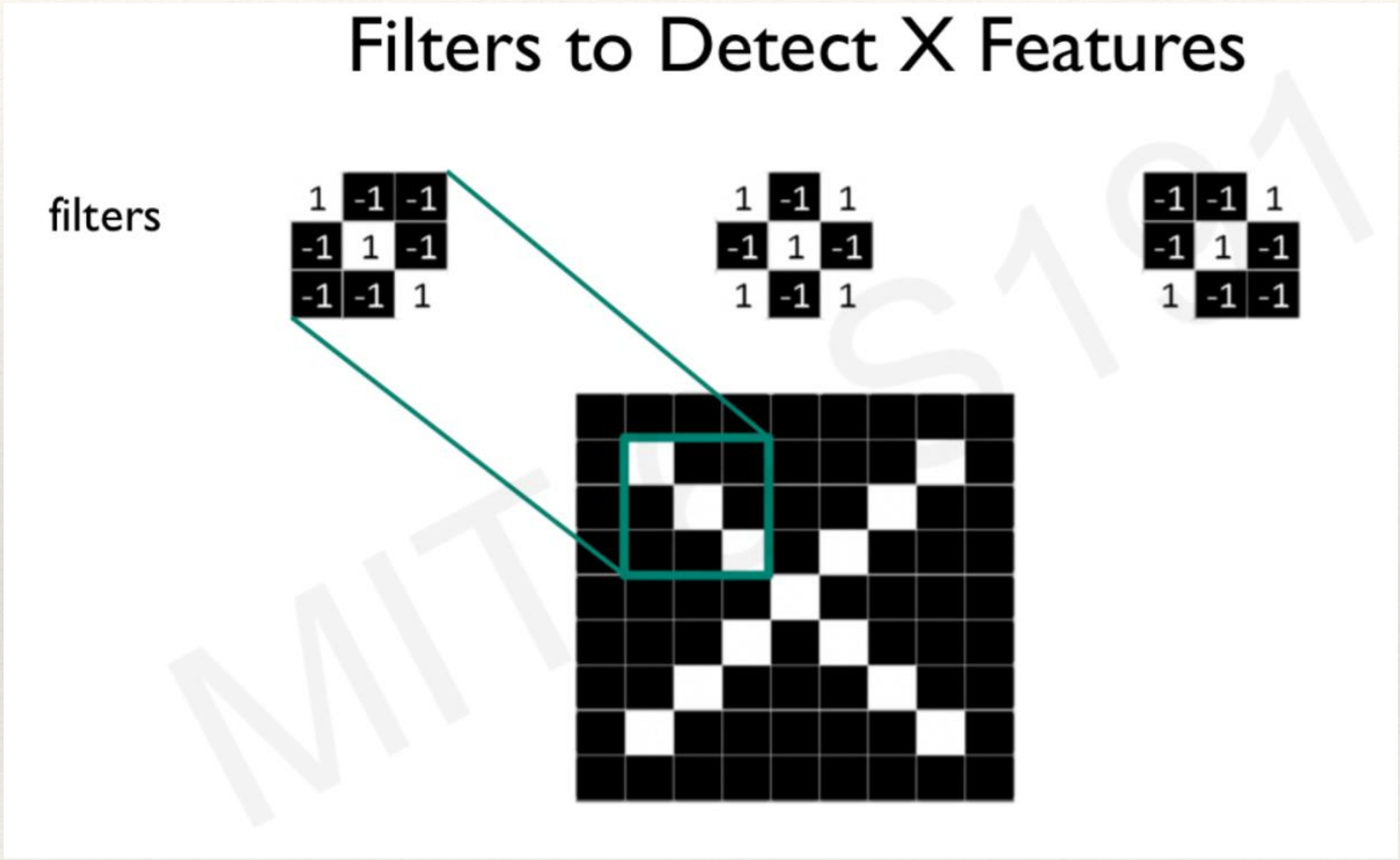
Large convolutions will often fail to capture these variations

Convolutions large or small?



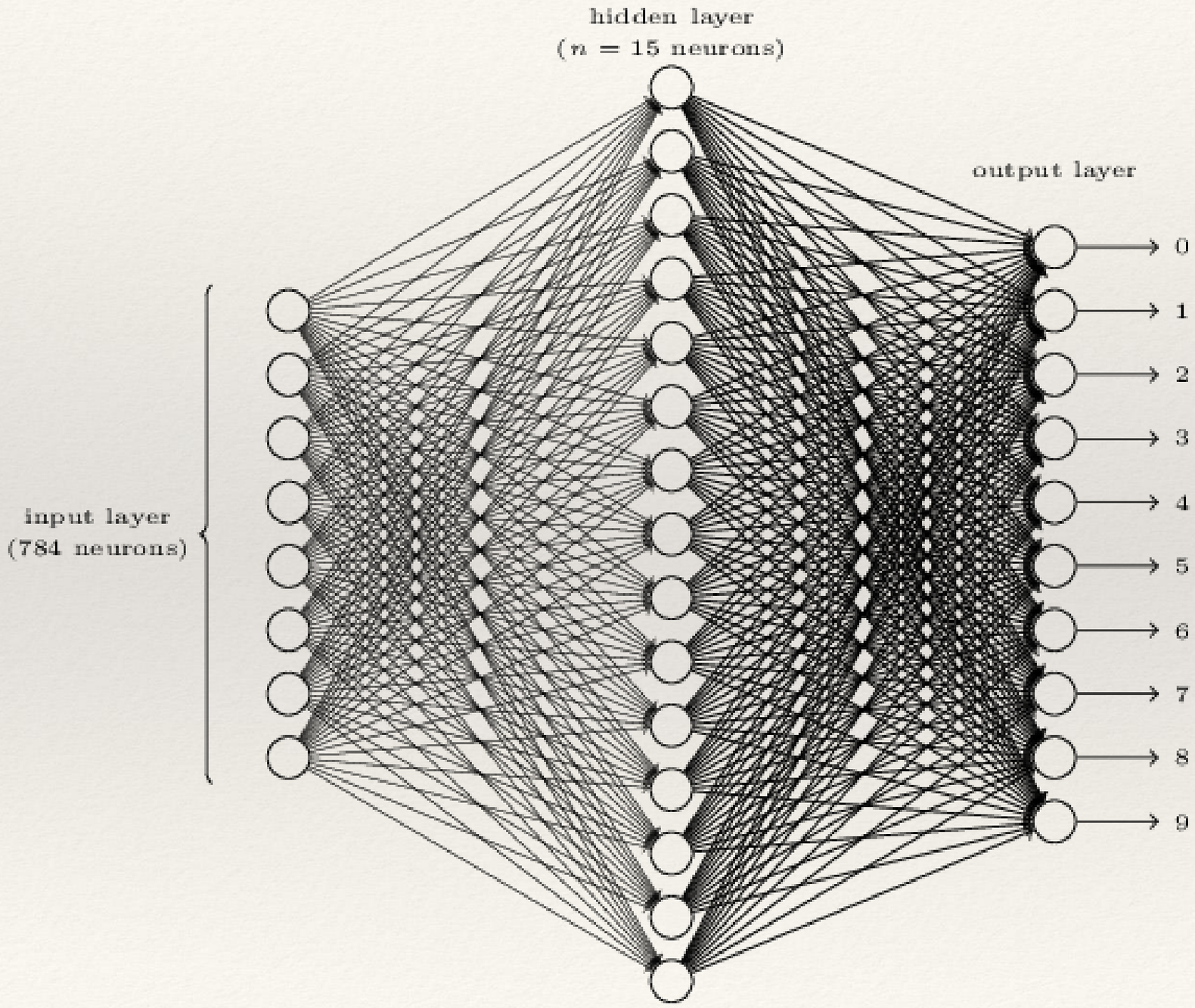
Small convolutions can identify low level features

Convolutions large or small?

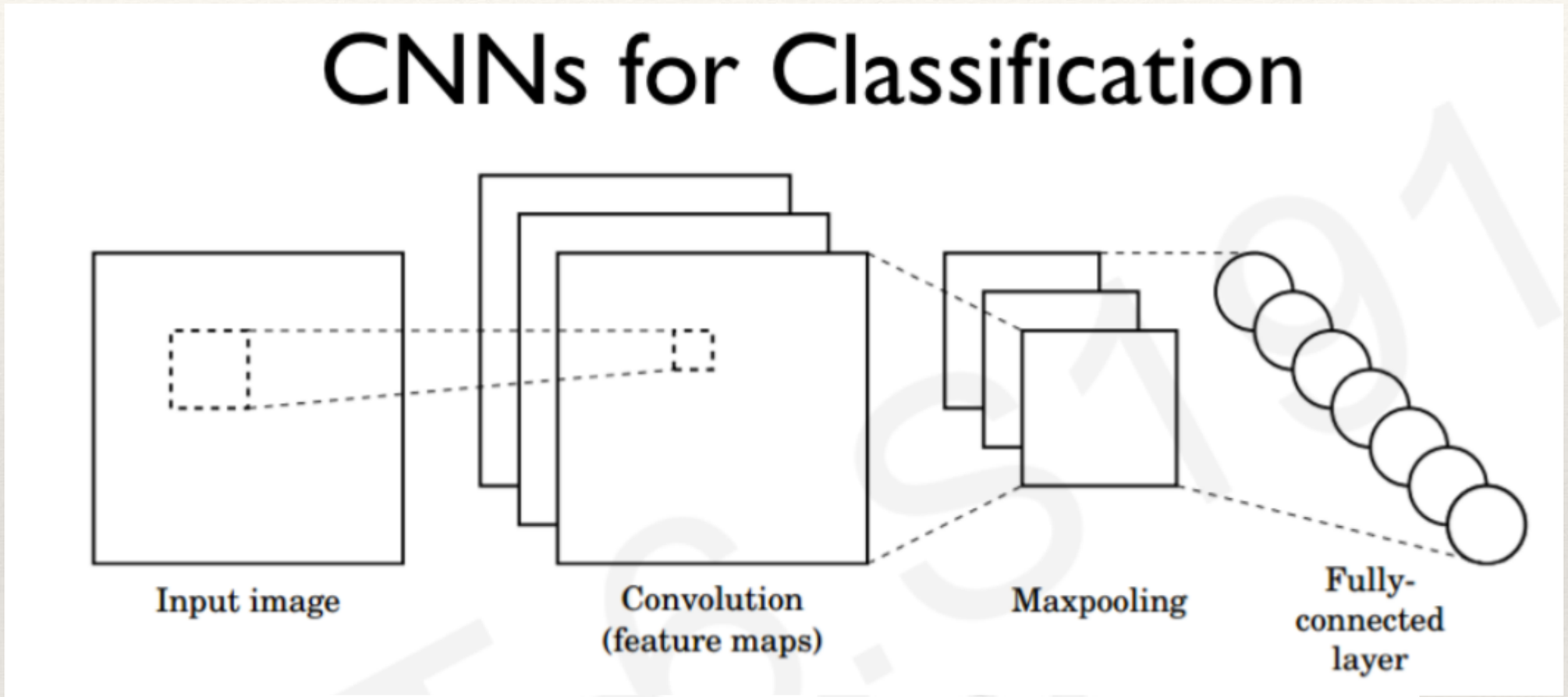


Convolutions on the low-level feature map produce mid-level features and so on

Fully connected NN - reminder

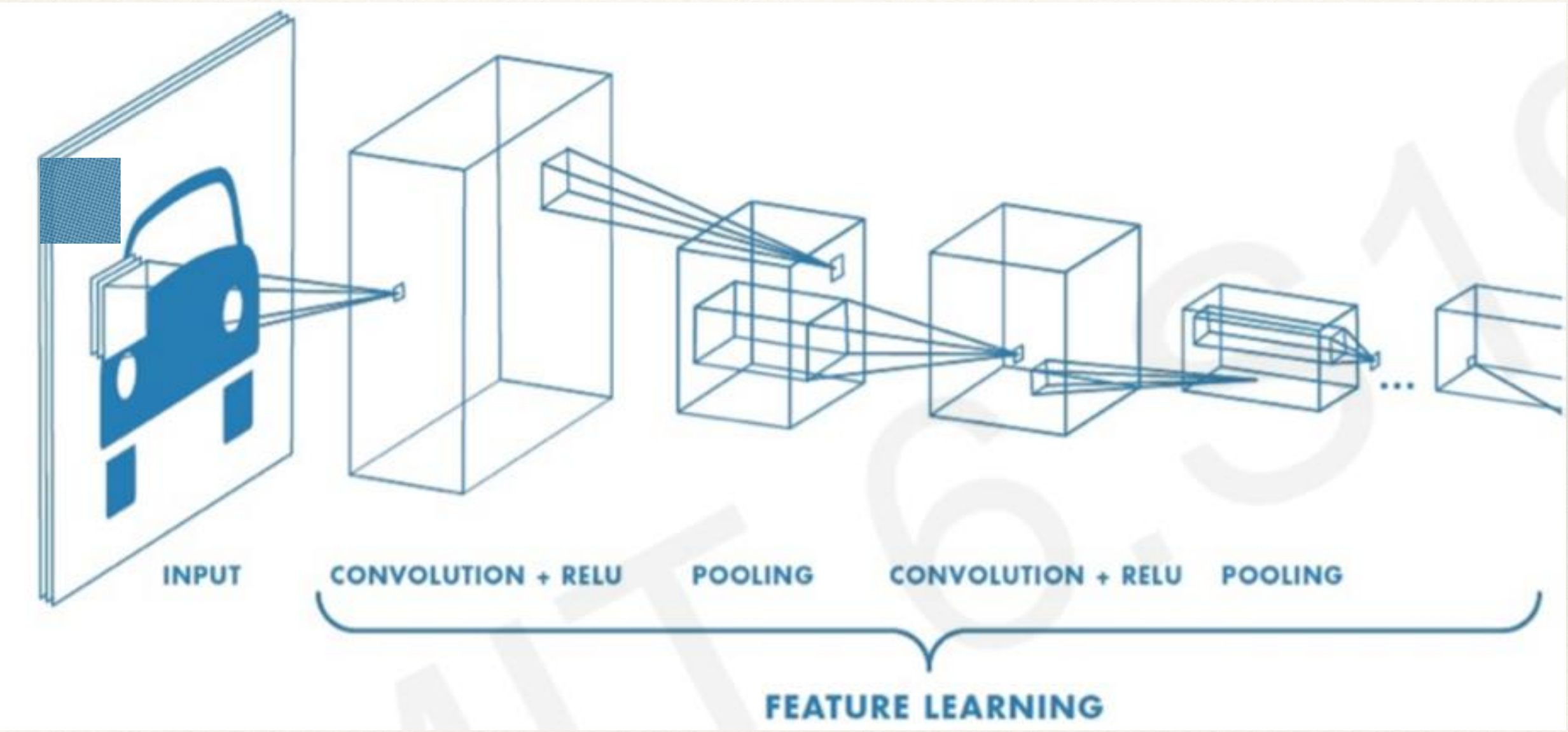


Convolutional Neural Networks
Deep Learning



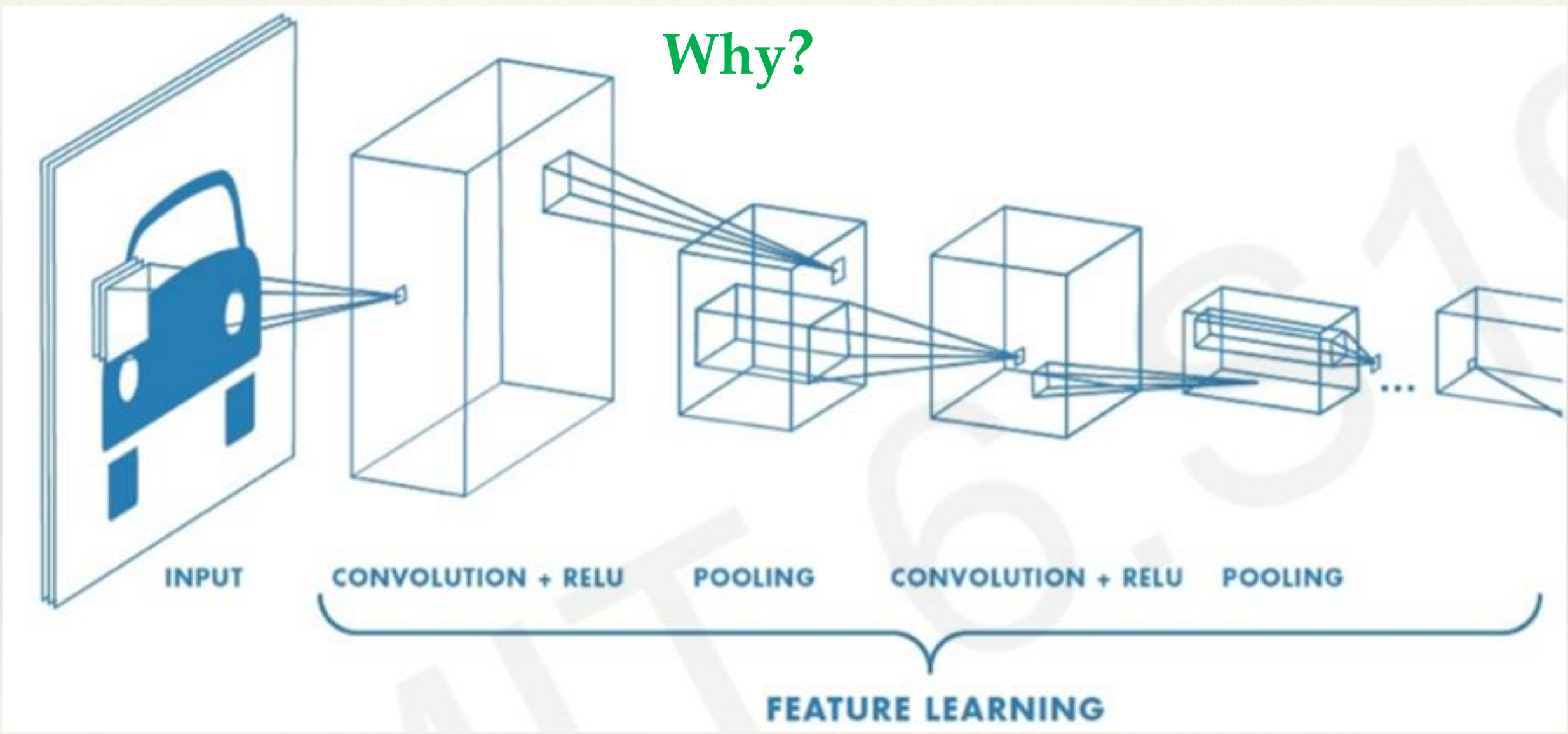
1. **Convolution**: Apply filters to generate feature maps.
2. **Non-linearity**: Often ReLU.
3. **Pooling**: Downsampling operation on each feature map.

Convolution



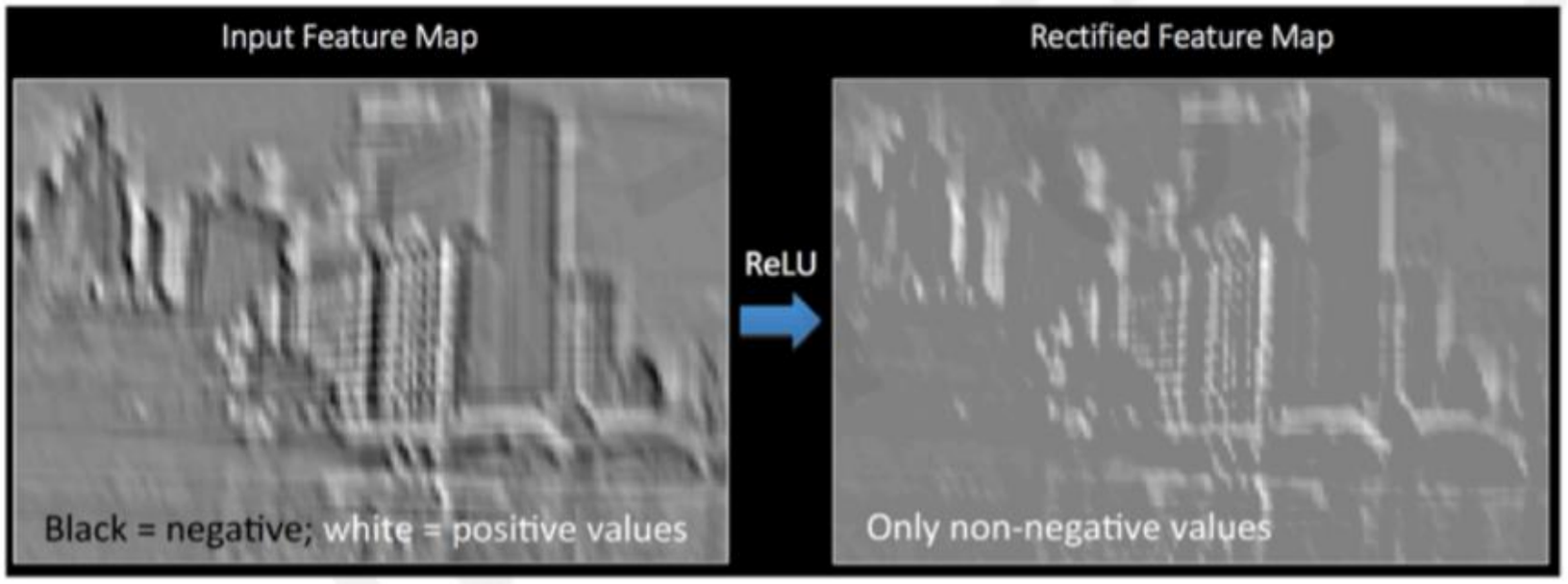
Convolution

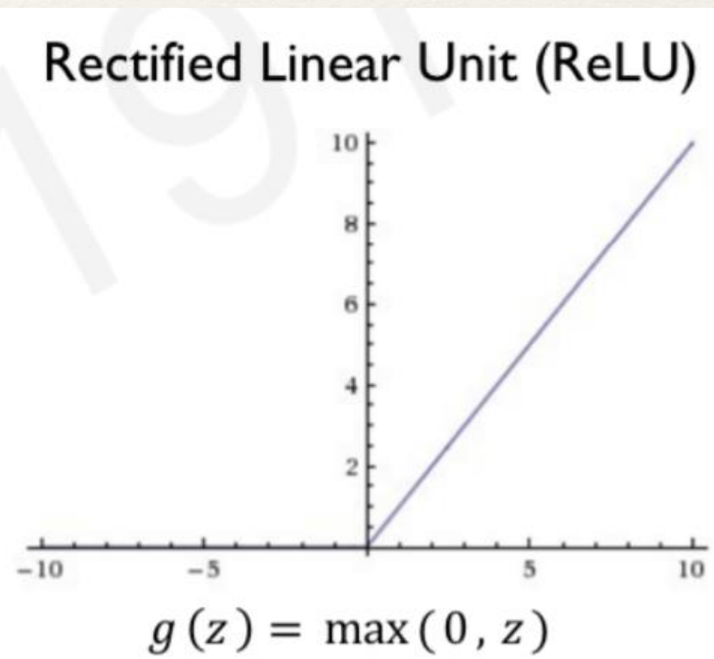
Input: w * h * 3 **w * h * k**



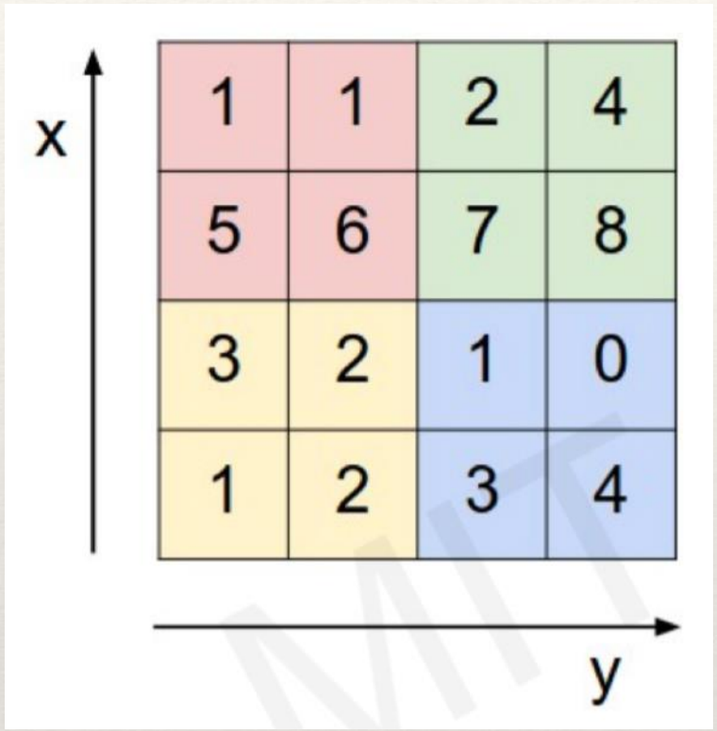
ReLU - activation

- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**

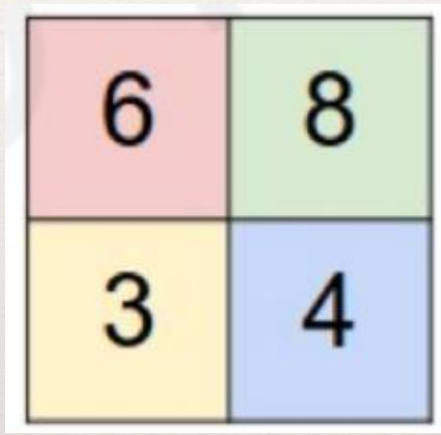




Pooling



Max Pooling Filter (2,2), stride 2



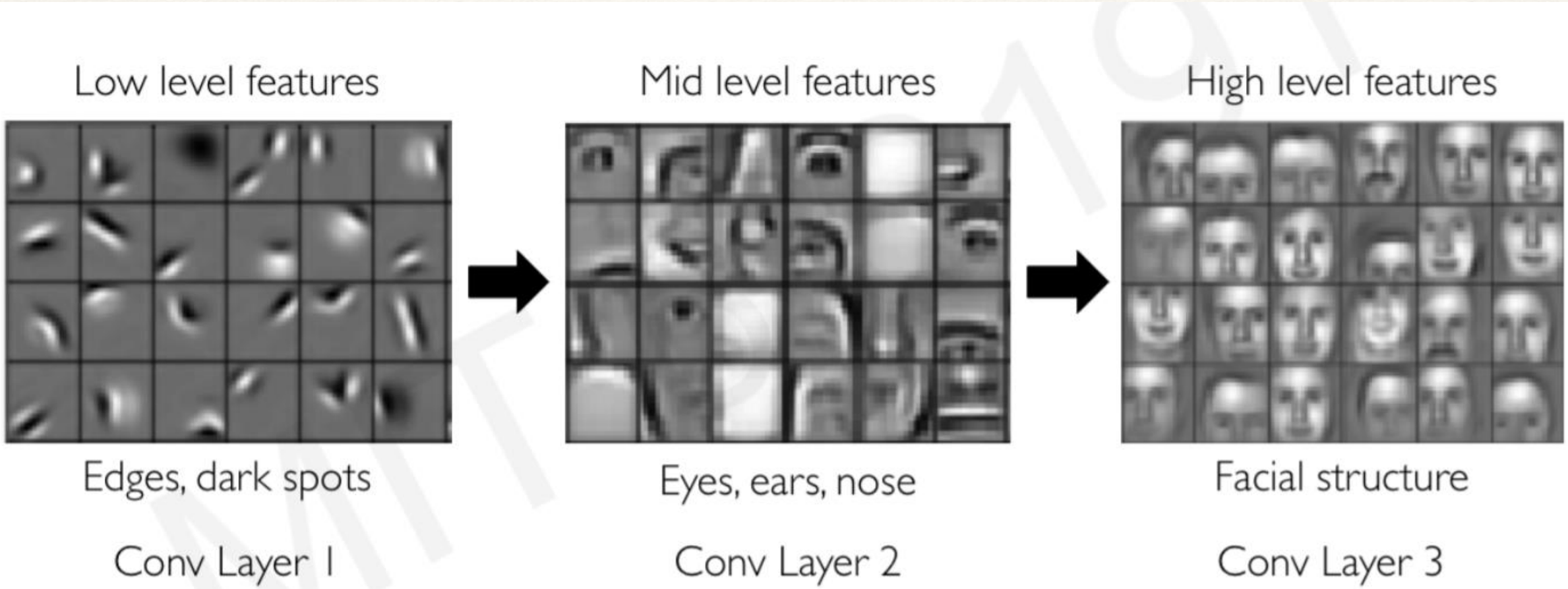
Max pooling helps convolutions on the next layer to enlarge the spatial surrounding. Why?

Pooling

Convolutions of constant size (typically 3x3)

Feature map is scaled down

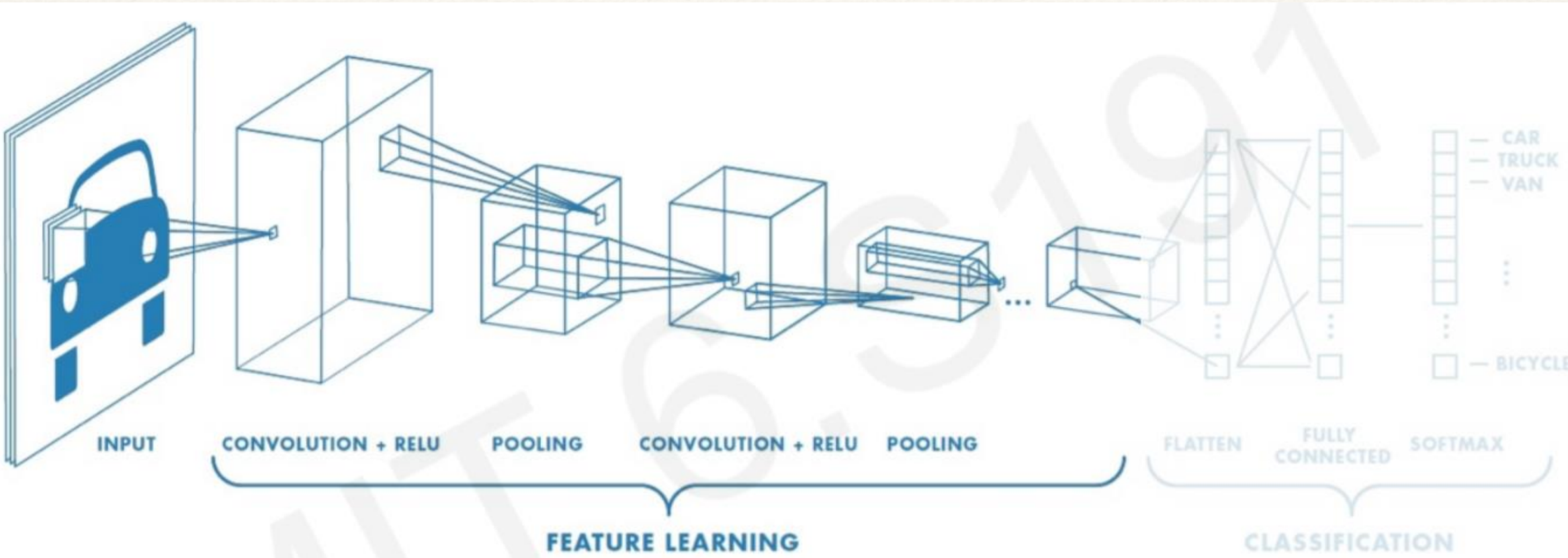
Representation learning with CNNs



Each layer (Convolution + Relu + pooling) works on the previous layer's output

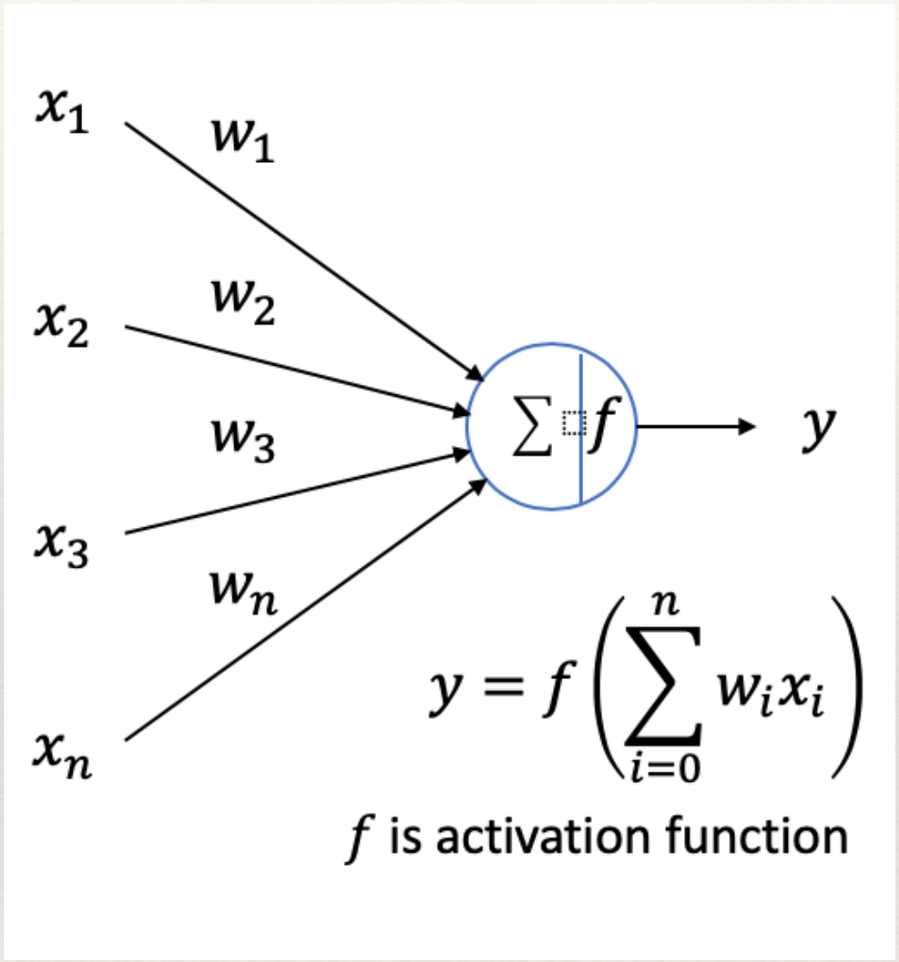
Produces higher level features

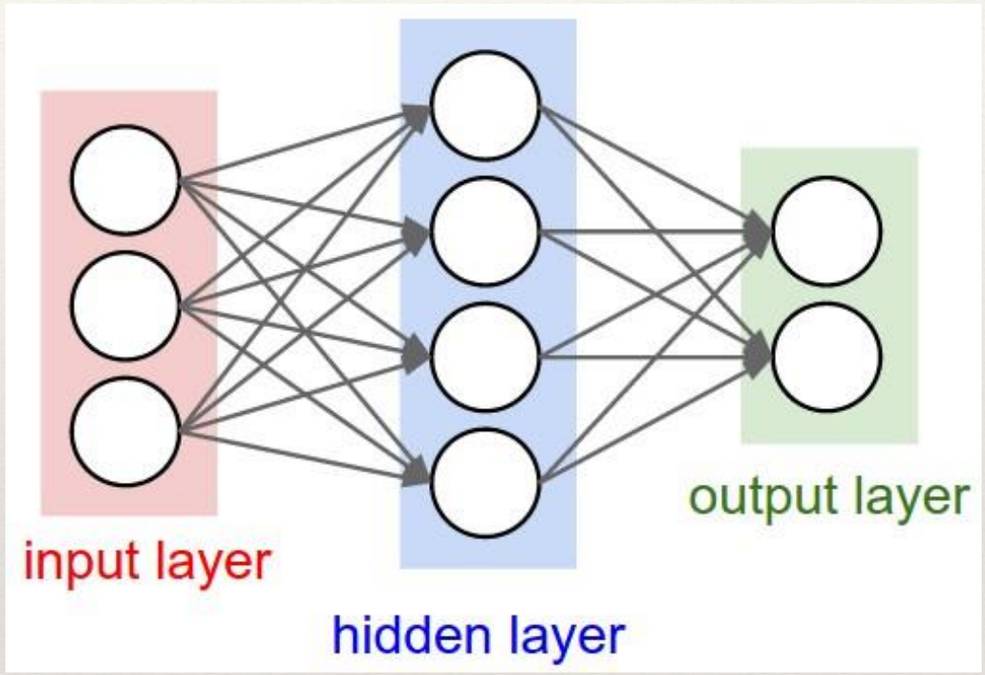
CNNs for classification – Features learning



1. Learn features in input image through **convolution**
2. Introduce **non-linearity** through activation function (real-world data is non-linear!)
3. Reduce dimensionality and preserve spatial invariance with **pooling**

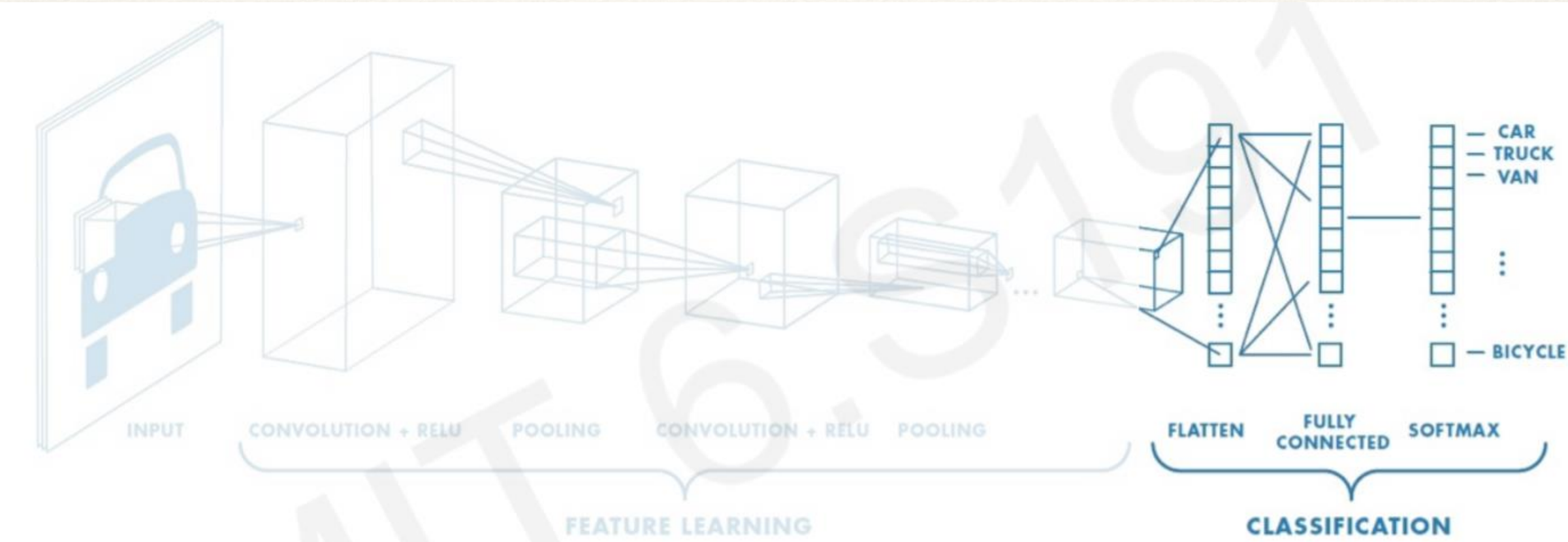
Fully connected layer





Use fully connected layer to predict classification output

CNNs for classification – Class probabilities



- CONV and POOL layers output high-level features of input
- Fully connected layer uses these features for classifying input image
- Express output as **probability** of image belonging to a particular class

$$\text{softmax}(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$$

An architecture for many applications

Convolutional layer produces strong features automatically. connect the fully connected layer, and learn the appropriate weights

Summary

- Computers “see” image as a matrix of numbers
- Traditionally, ML specialists generated handcrafted features for each problem, and then applied machine learning techniques to solve classification \ regression problems.
- Nowadays, feature representation is learned automatically using CNNs
- CNNs generates powerful features, which can represent image data.
- The feature layers are then connected to a fully connected layer, to make a classification \ regression decision.