



Deep Learning for Computer Vision

MIT 6.S191

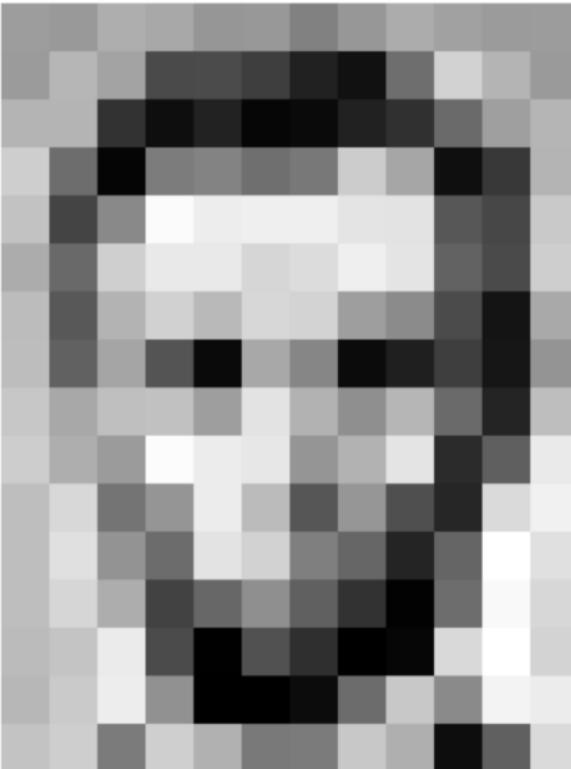
Ava Soleimany

January 29, 2019



What Computers “See”

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	84	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
189	97	165	84	10	168	134	11	31	62	22	148
199	168	191	193	158	227	178	143	182	105	36	190
205	174	155	252	236	251	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	35	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

What the computer sees

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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	35	101	255	224
190	214	173	66	103	143	95	50	2	109	249	215
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183	202	237	145	0	0	12	108	200	138	243	236
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An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Tasks in Computer Vision



Input Image



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155	182	163	74	75	62	33	17	110	210	180	154
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183	202	237	145	0	0	12	108	200	138	243	236
195	206	123	207	177	121	123	200	175	13	96	218

Pixel Representation

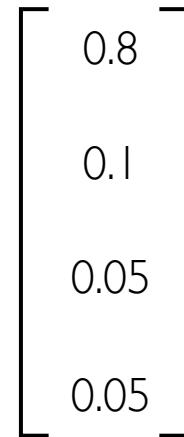
classification

Lincoln

Washington

Jefferson

Obama

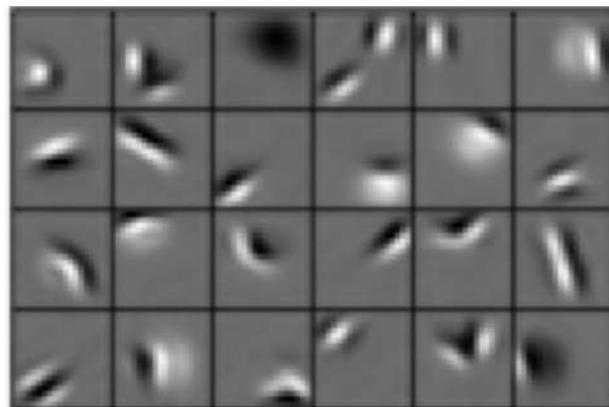


- **Regression:** output variable takes continuous value
- **Classification:** output variable takes class label. Can produce probability of belonging to a particular class

Learning Feature Representations

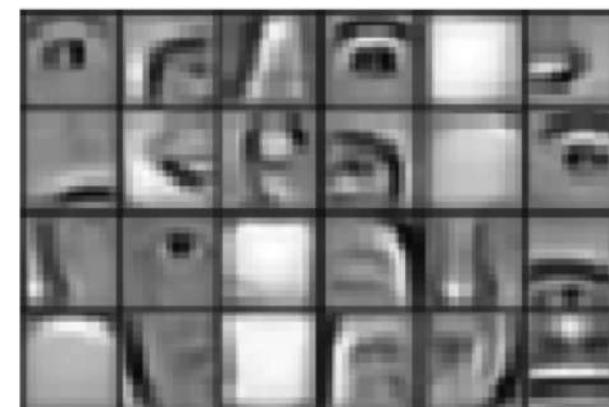
Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

Mid level features



Eyes, ears, nose

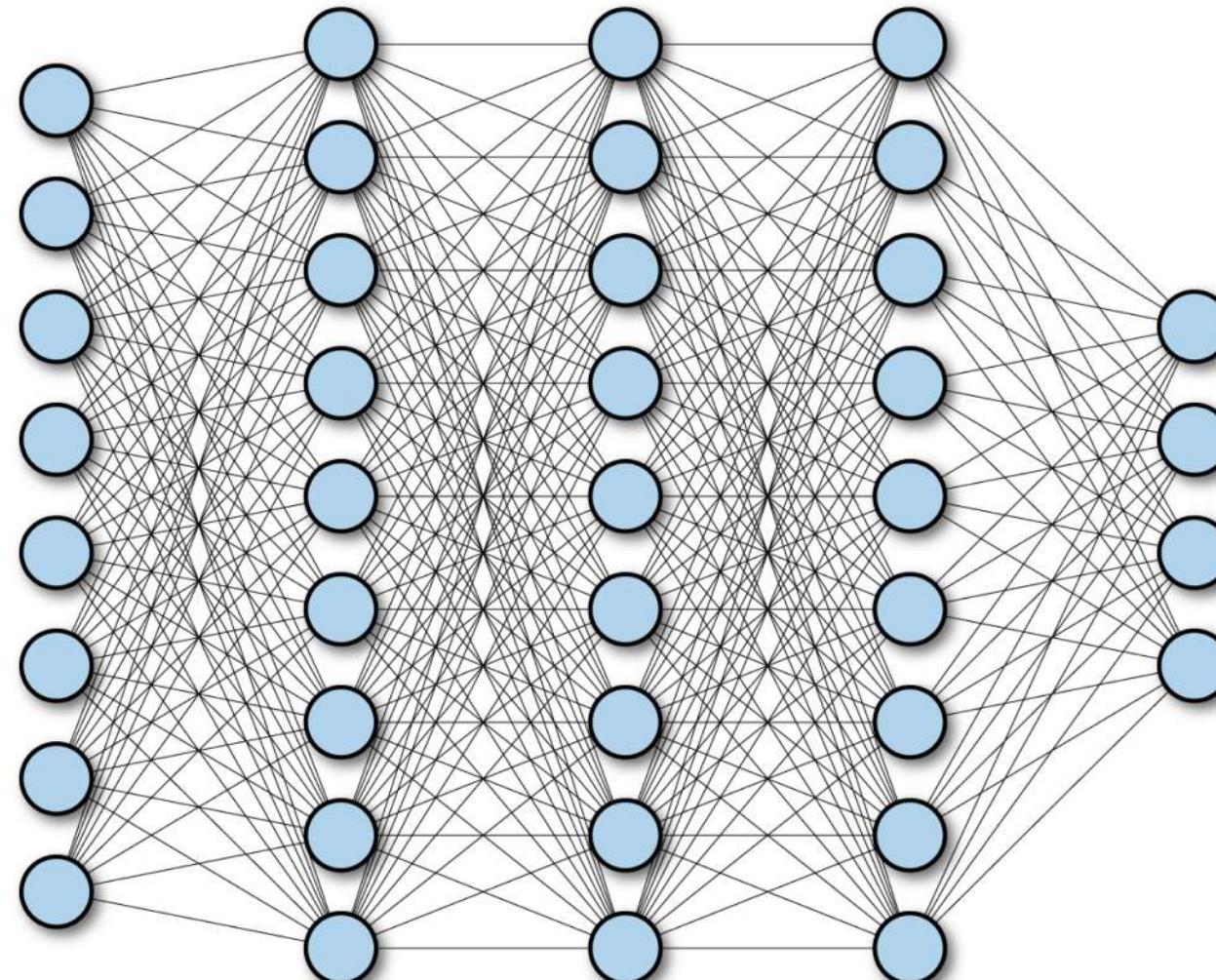
High level features



Facial structure

Learning Visual Features

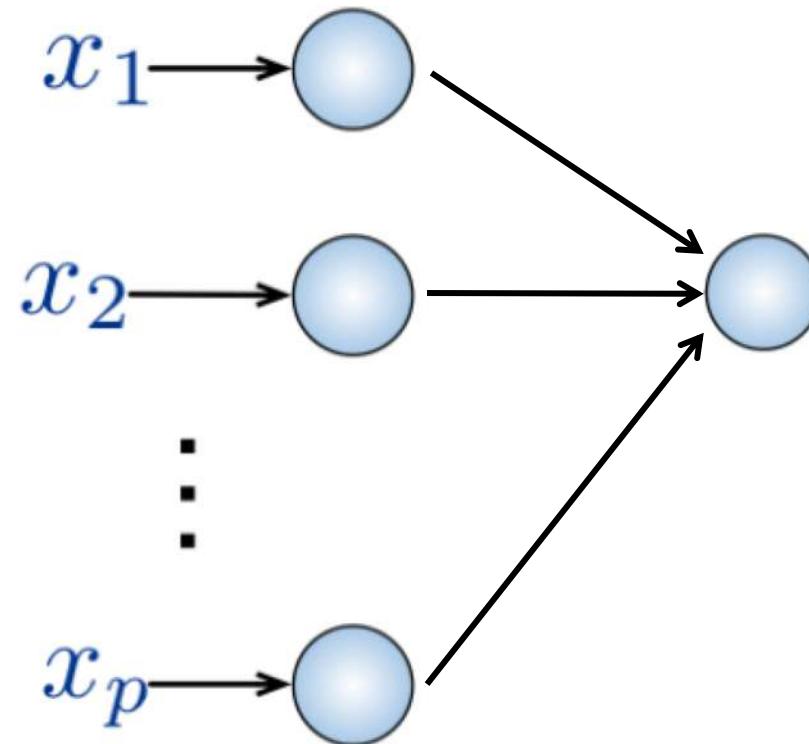
Fully Connected Neural Network



Fully Connected Neural Network

Input:

- 2D image
- Vector of pixel values



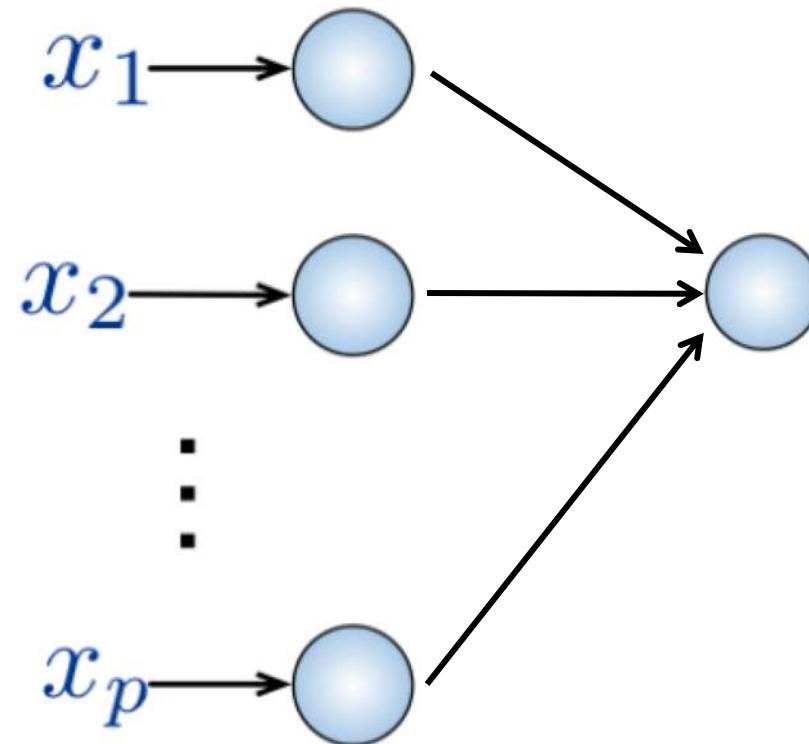
Fully Connected:

- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

Fully Connected Neural Network

Input:

- 2D image
- Vector of pixel values



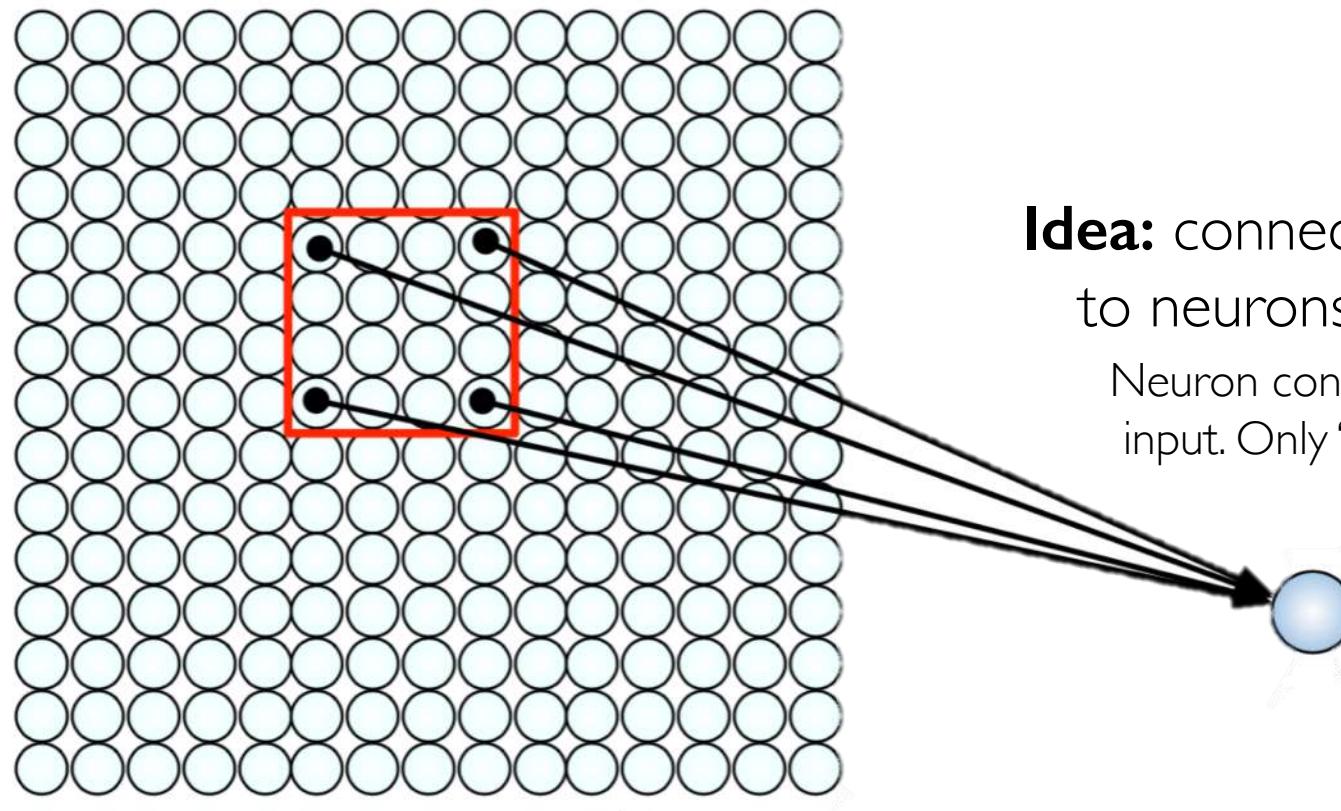
Fully Connected:

- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

How can we use **spatial structure** in the input to inform the architecture of the network?

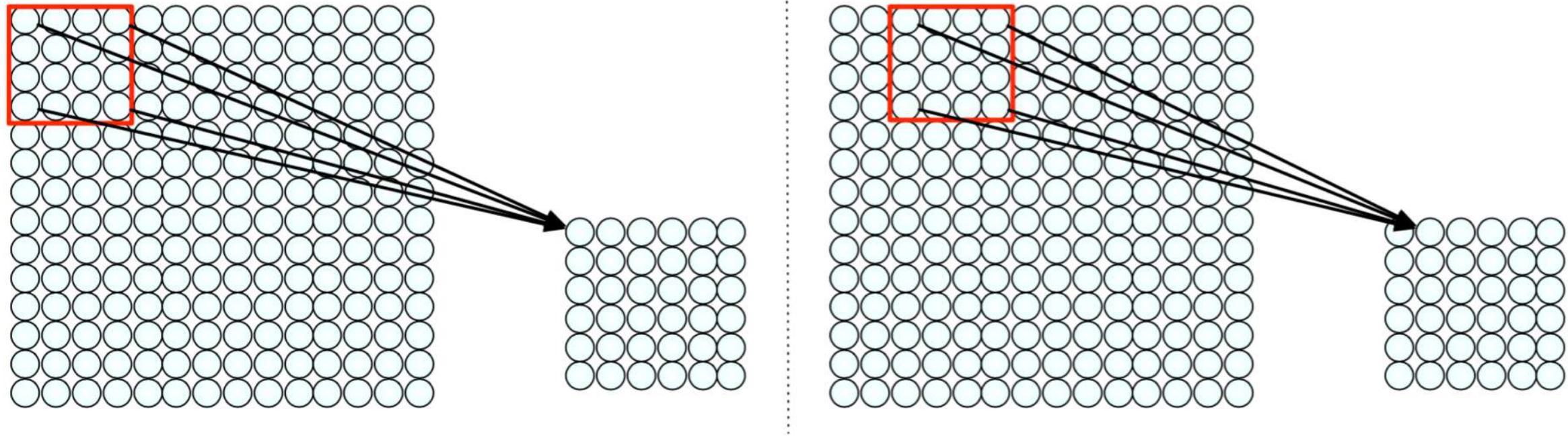
Using Spatial Structure

Input: 2D image.
Array of pixel values



Idea: connect patches of input
to neurons in hidden layer.
Neuron connected to region of
input. Only “sees” these values.

Using Spatial Structure



Connect patch in input layer to a single neuron in subsequent layer.

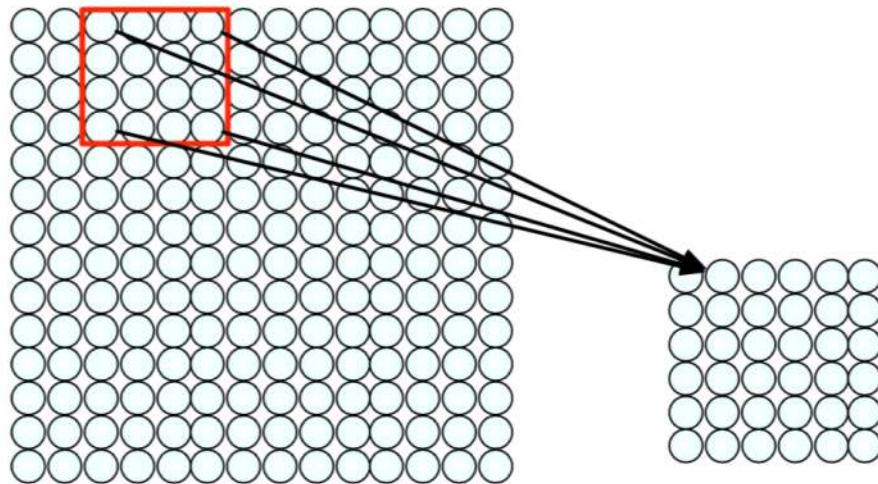
Use a sliding window to define connections.

*How can we **weight** the patch to detect particular features?*

Applying Filters to Extract Features

- I) Apply a set of weights – a filter – to extract **local features**
- 2) Use **multiple filters** to extract different features
- 3) Spatially **share** parameters of each filter
(features that matter in one part of the input should matter elsewhere)

Feature Extraction with Convolution



- Filter of size 4×4 : 16 different weights
- Apply this same filter to 4×4 patches in input
- Shift by 2 pixels for next patch

This “patchy” operation is **convolution**

- 1) Apply a set of weights – a filter – to extract **local features**
- 2) Use **multiple filters** to extract different features
- 3) **Spatially share** parameters of each filter

Feature Extraction and Convolution

A Case Study

X or X?

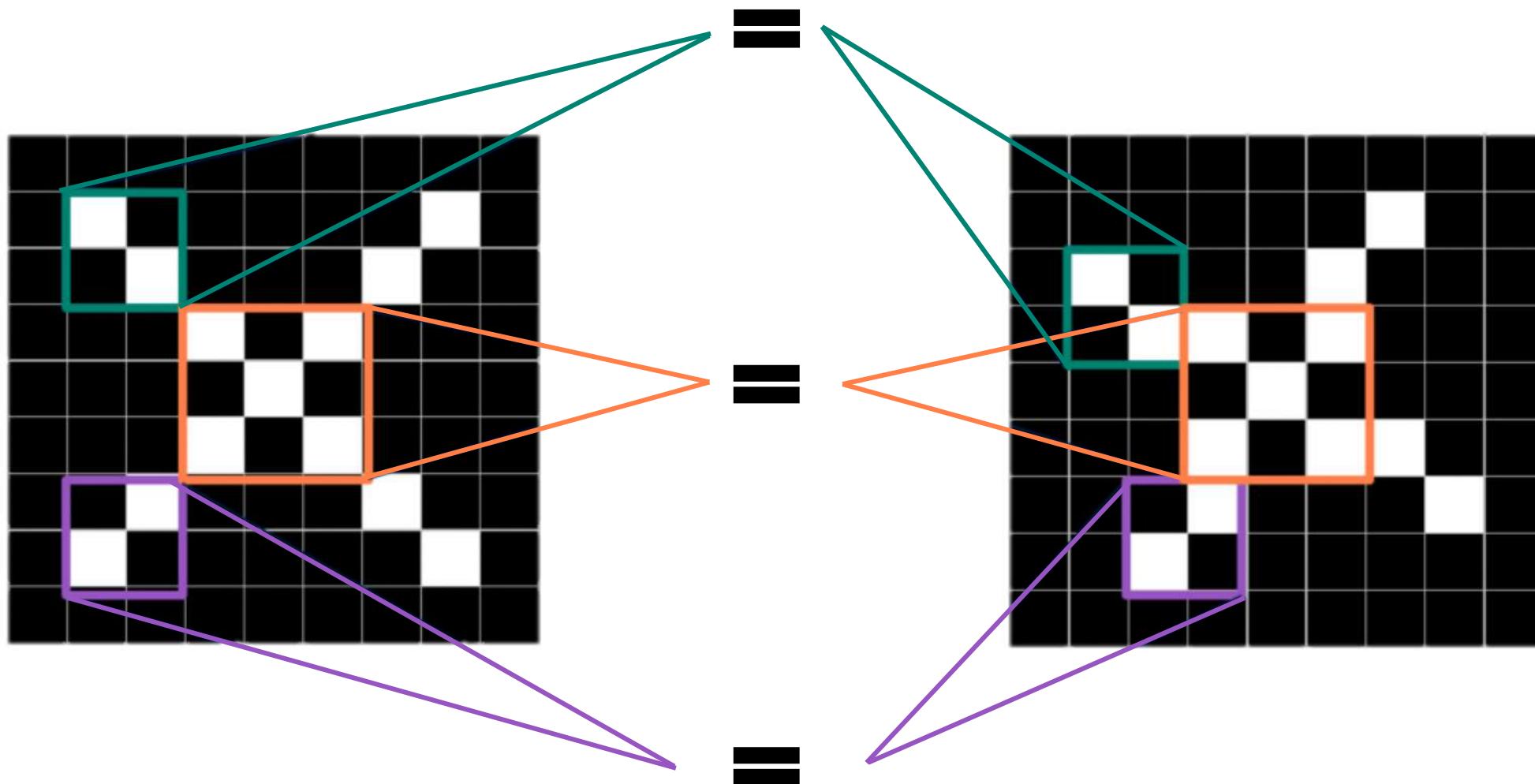


-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	-1	-1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	-1	-1	-1
-1	-1	1	-1	-1	-1	1	-1	-1
-1	1	-1	-1	-1	-1	1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

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

Image is represented as matrix of pixel values... and computers are literal!
We want to be able to classify an X as an X even if it's shifted, shrunk, rotated, deformed.

Features of X



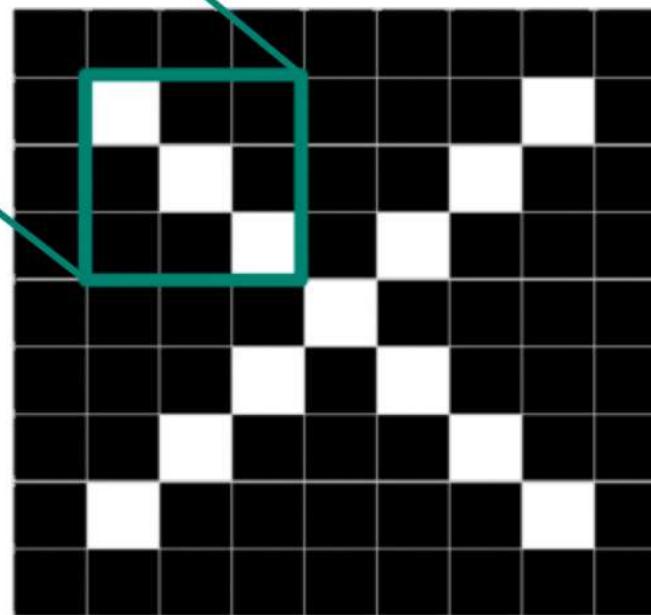
Filters to Detect X Features

filters

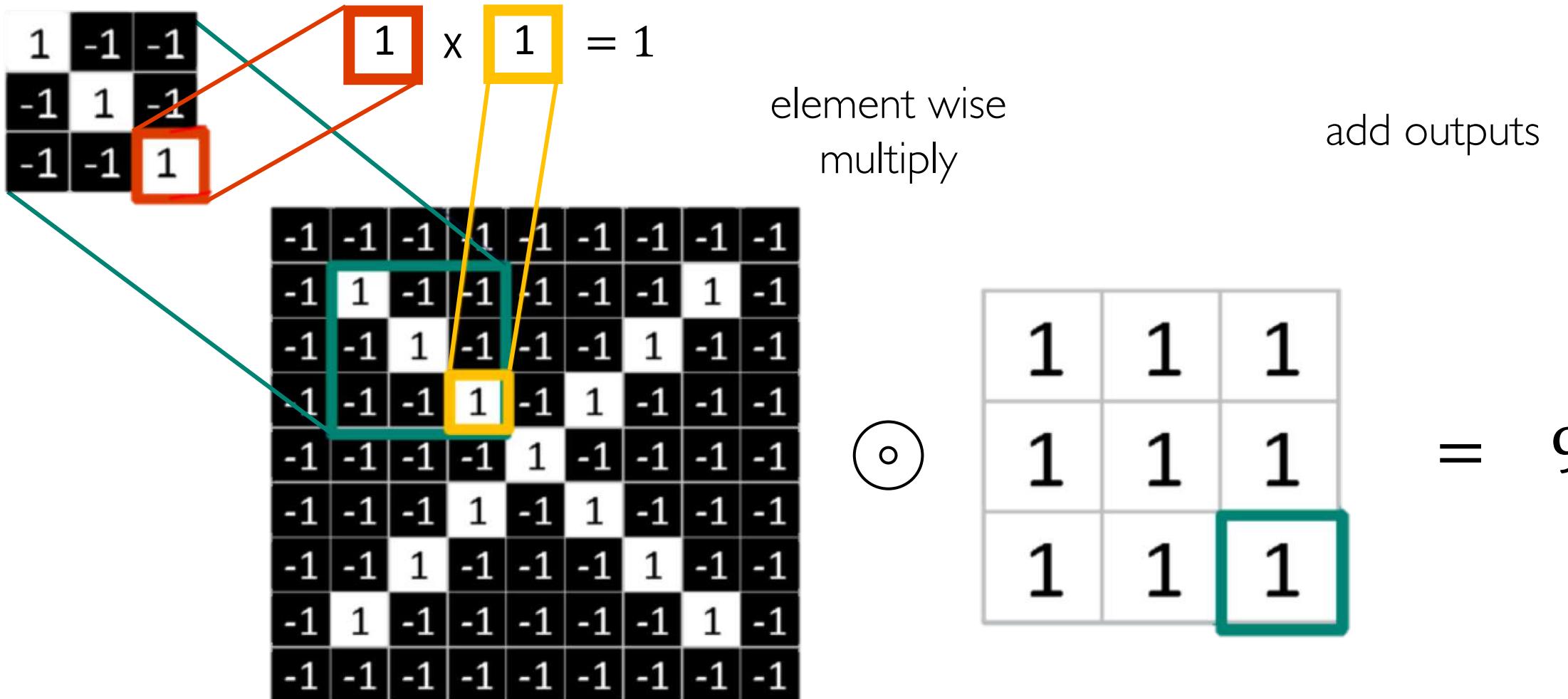
$$\begin{bmatrix} 1 & -1 & -1 \\ -1 & 1 & -1 \\ -1 & -1 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & 1 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -1 & 1 \\ -1 & 1 & -1 \\ 1 & -1 & -1 \end{bmatrix}$$



The Convolution Operation

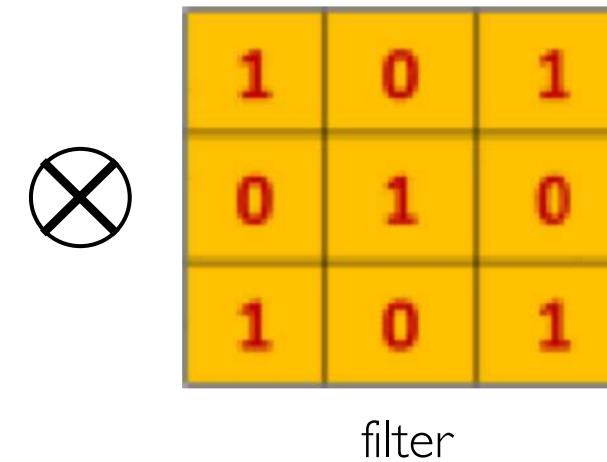


The Convolution Operation

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

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

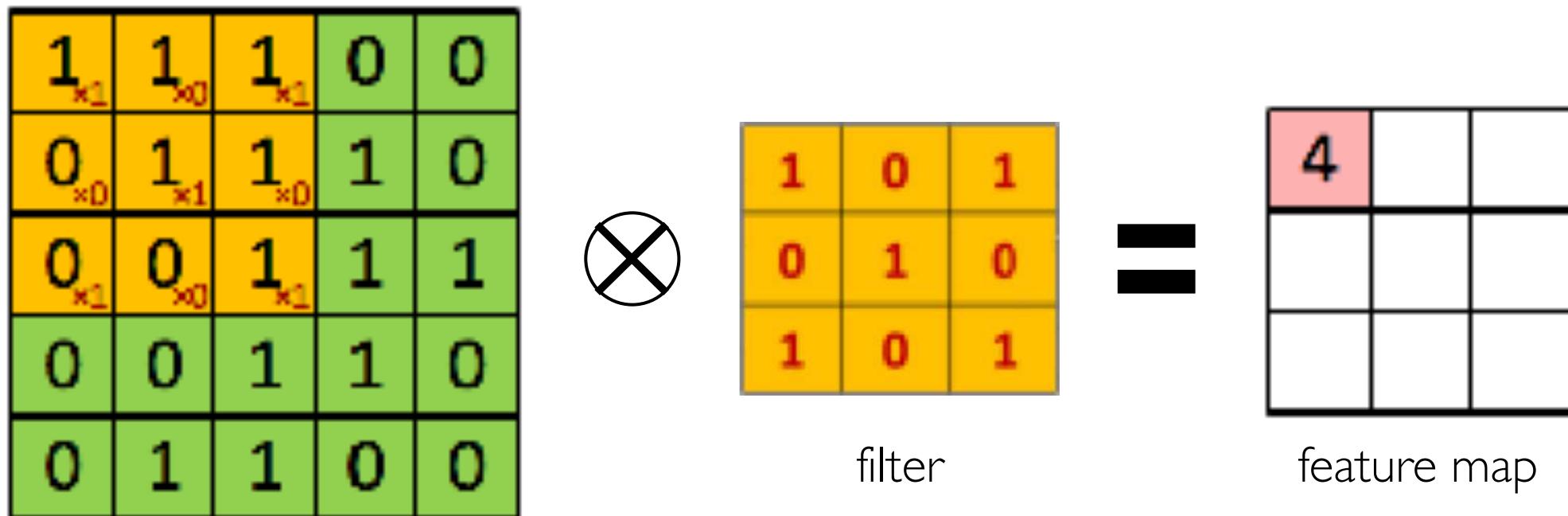
image



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

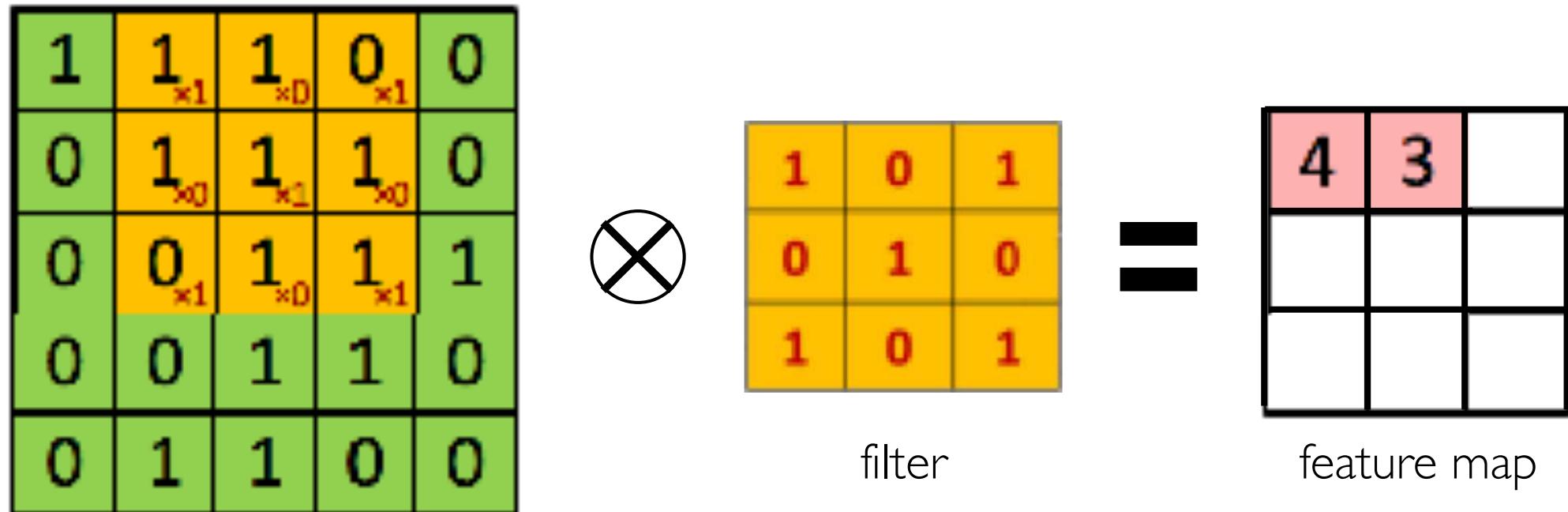
The Convolution Operation

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



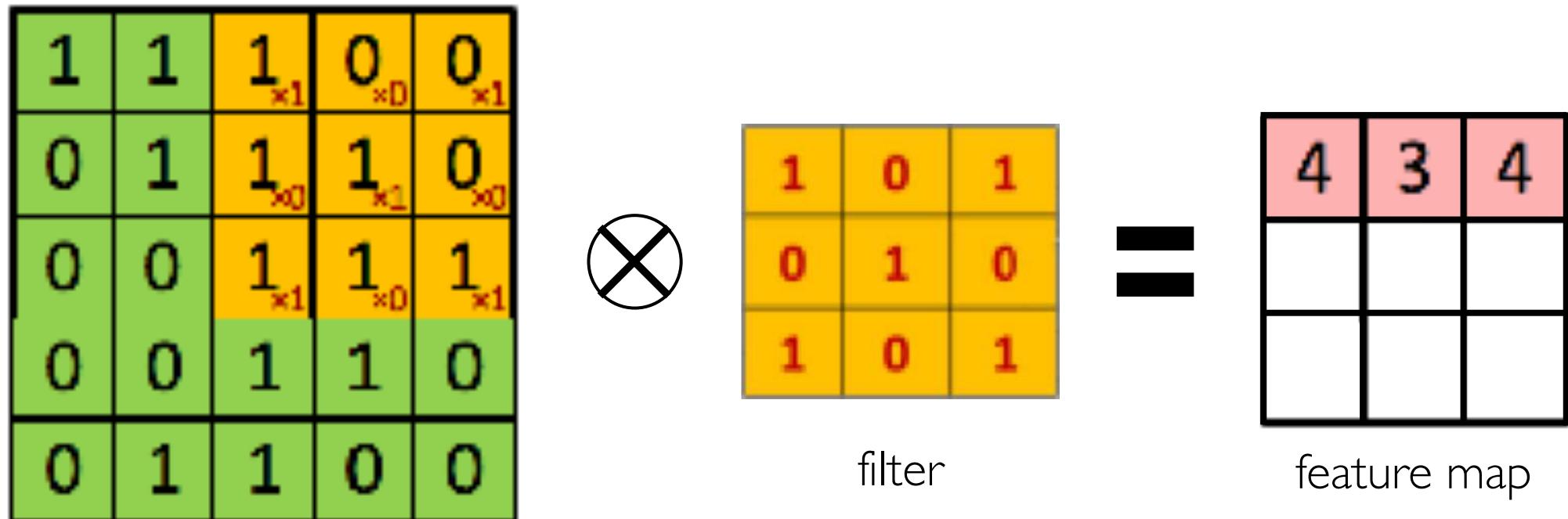
The Convolution Operation

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



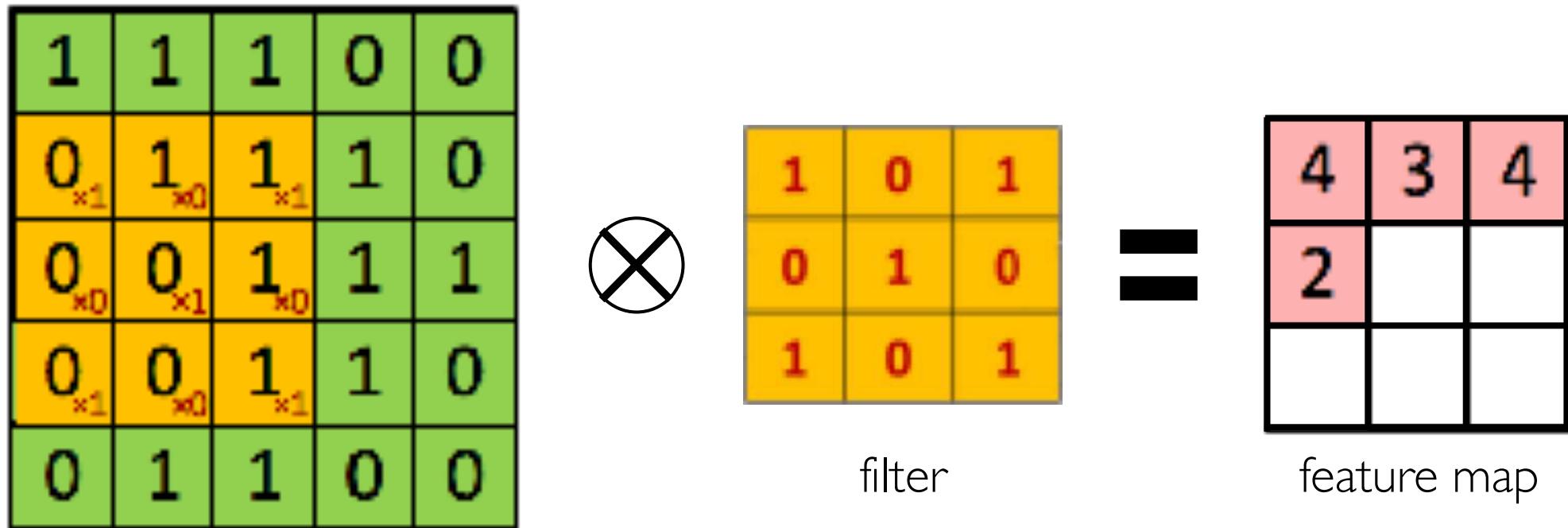
The Convolution Operation

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



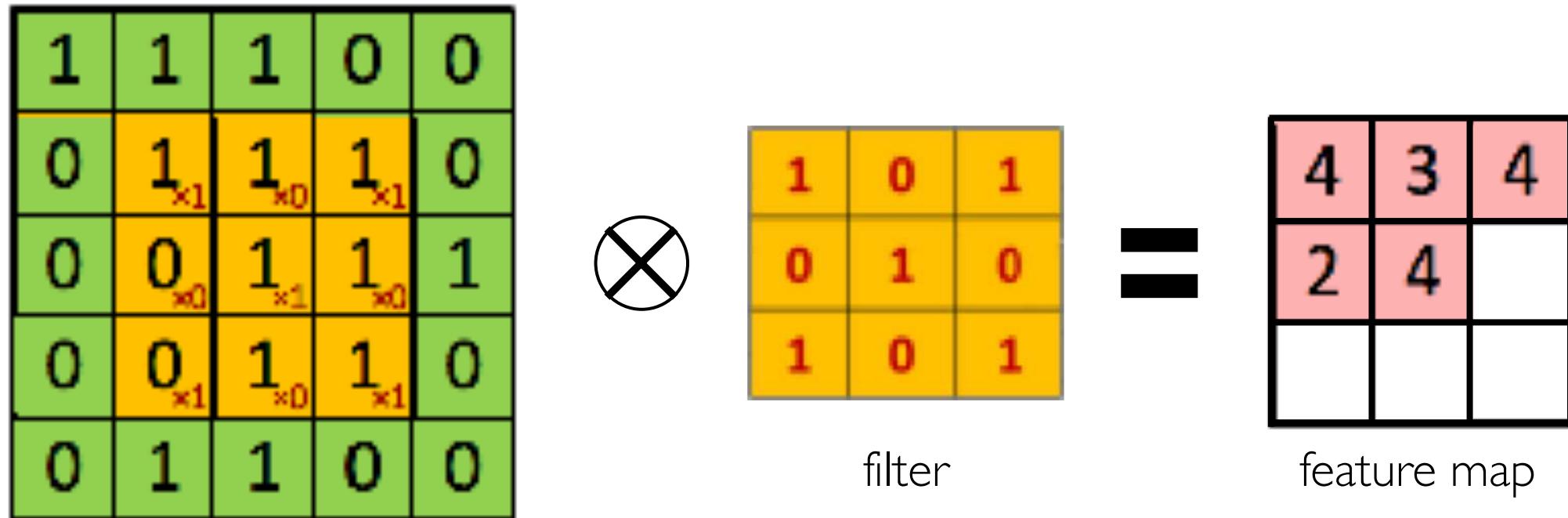
The Convolution Operation

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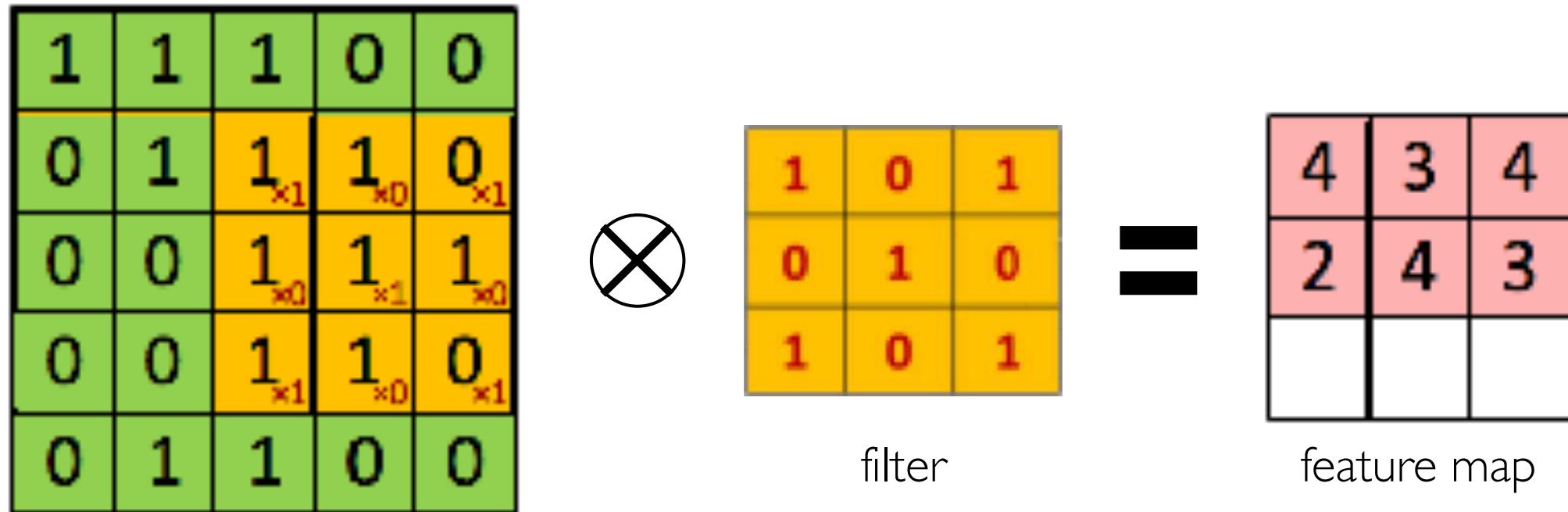
The Convolution Operation

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



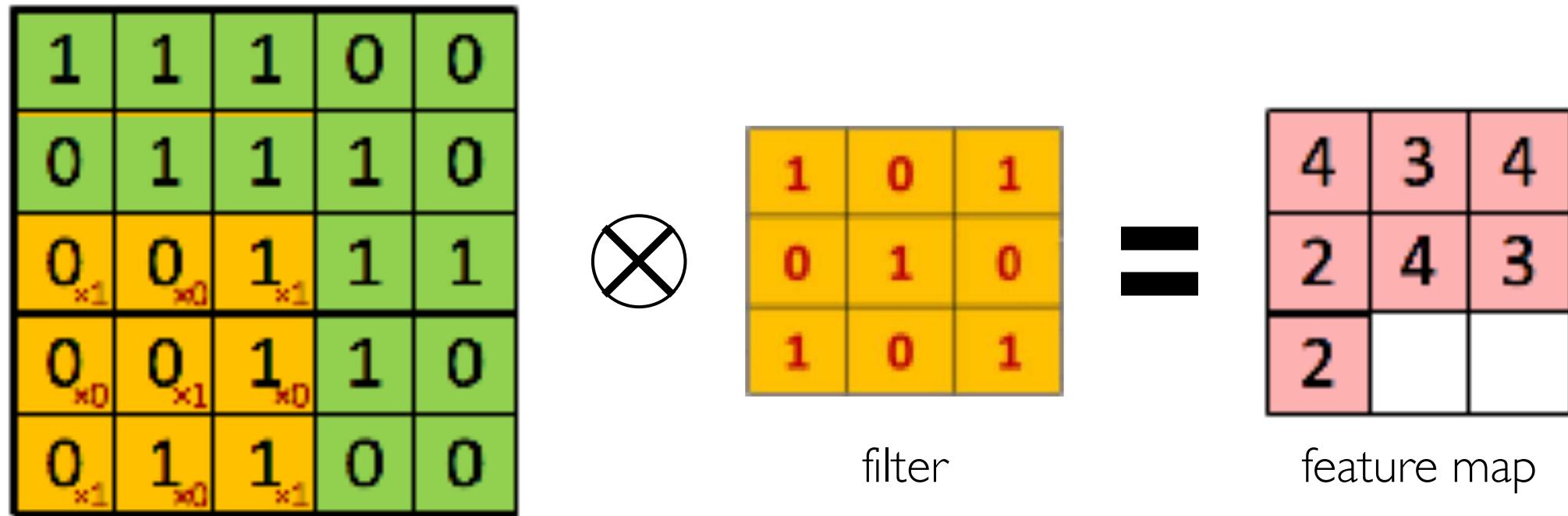
The Convolution Operation

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



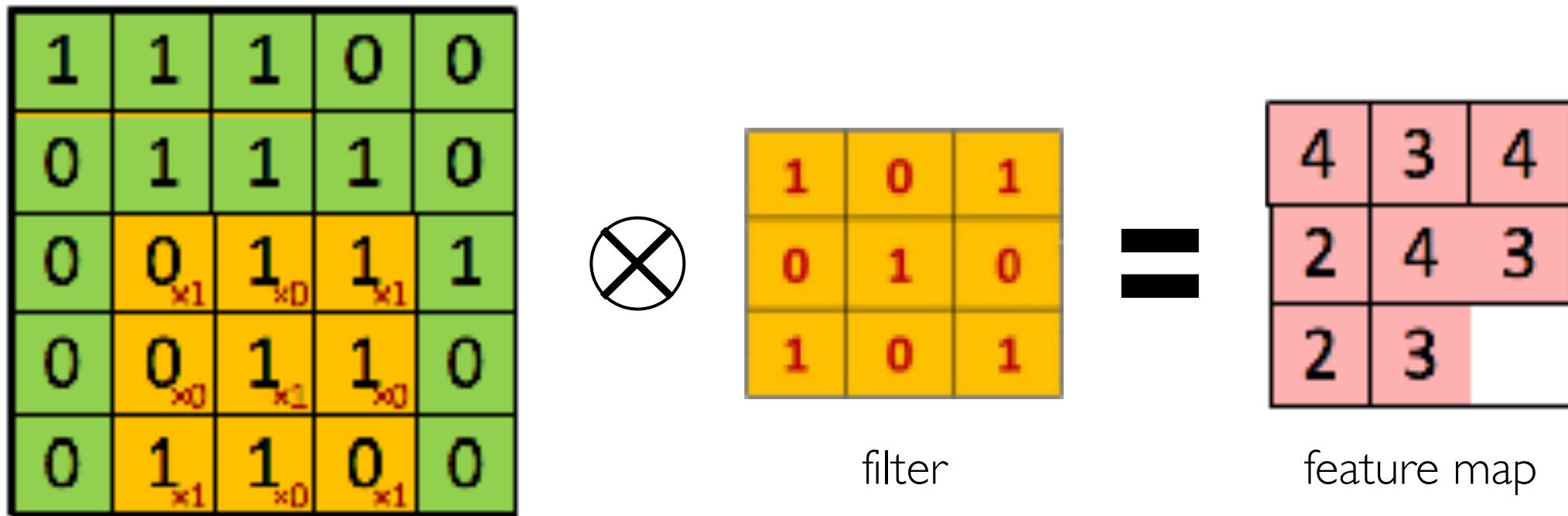
The Convolution Operation

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



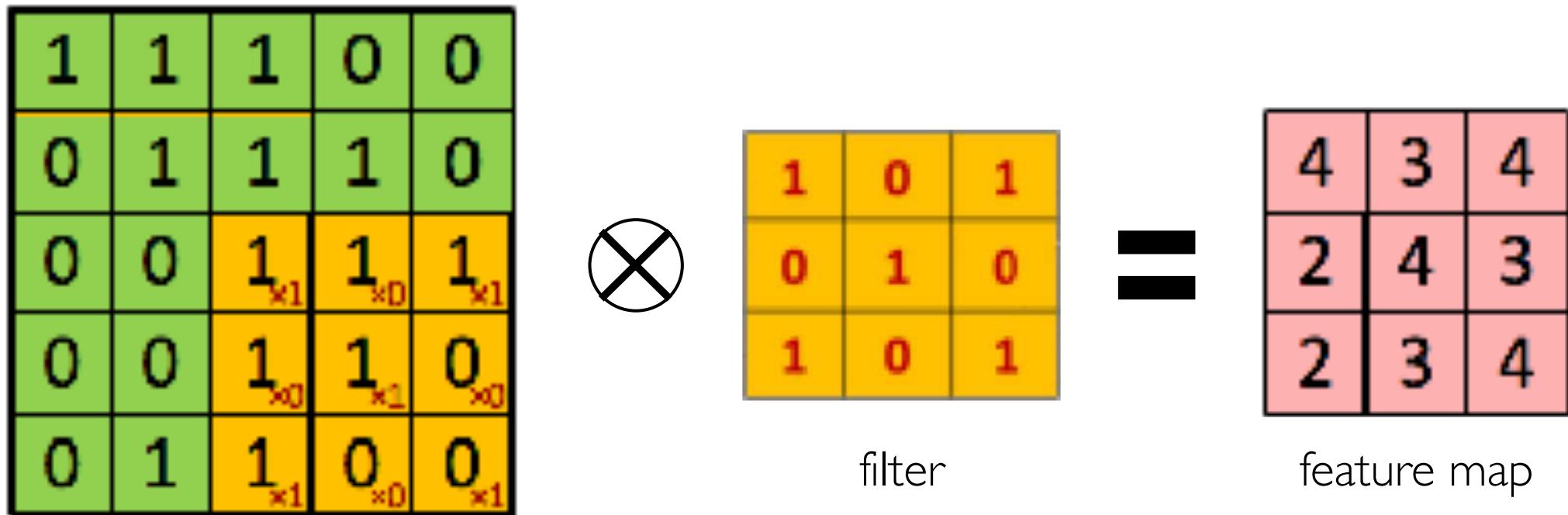
The Convolution Operation

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



The Convolution Operation

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



Producing Feature Maps



Original



Sharpen

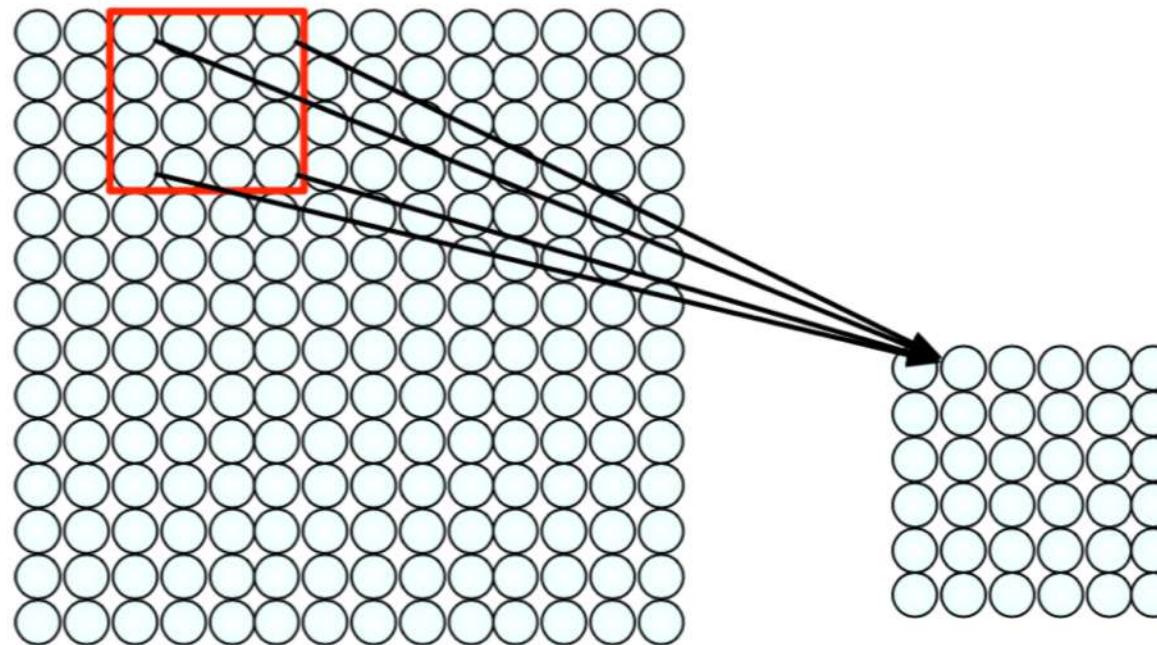


Edge Detect



“Strong” Edge
Detect

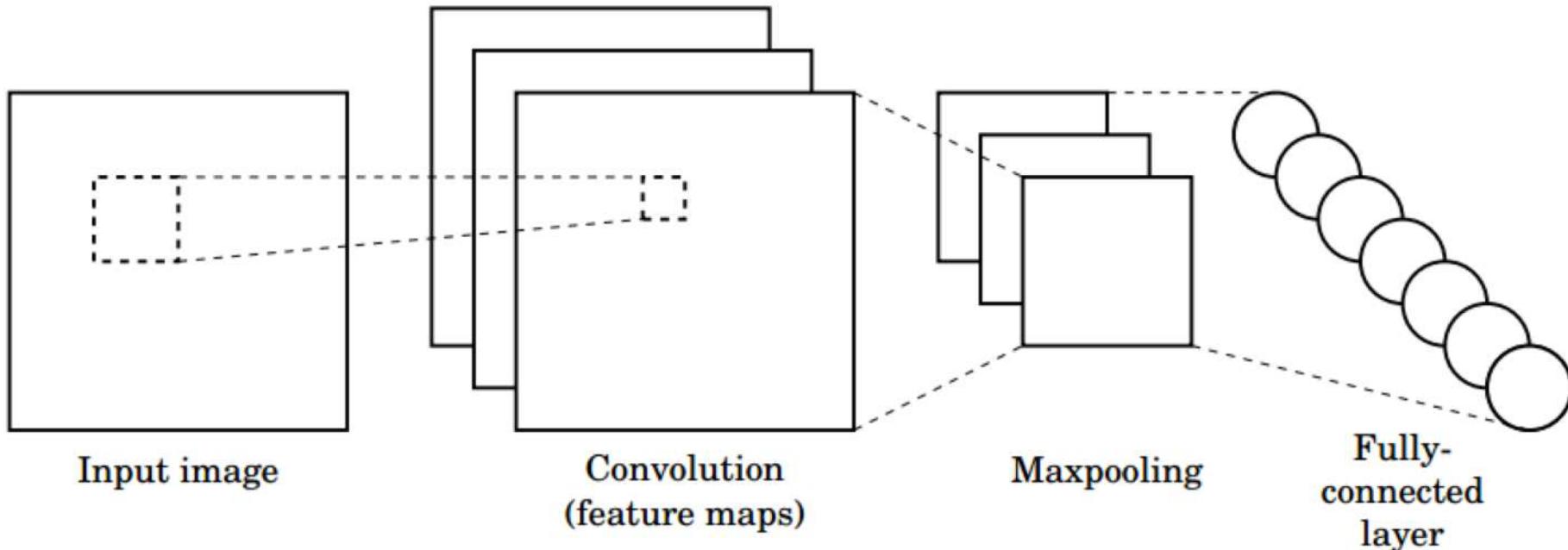
Feature Extraction with Convolution



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Convolutional Neural Networks (CNNs)

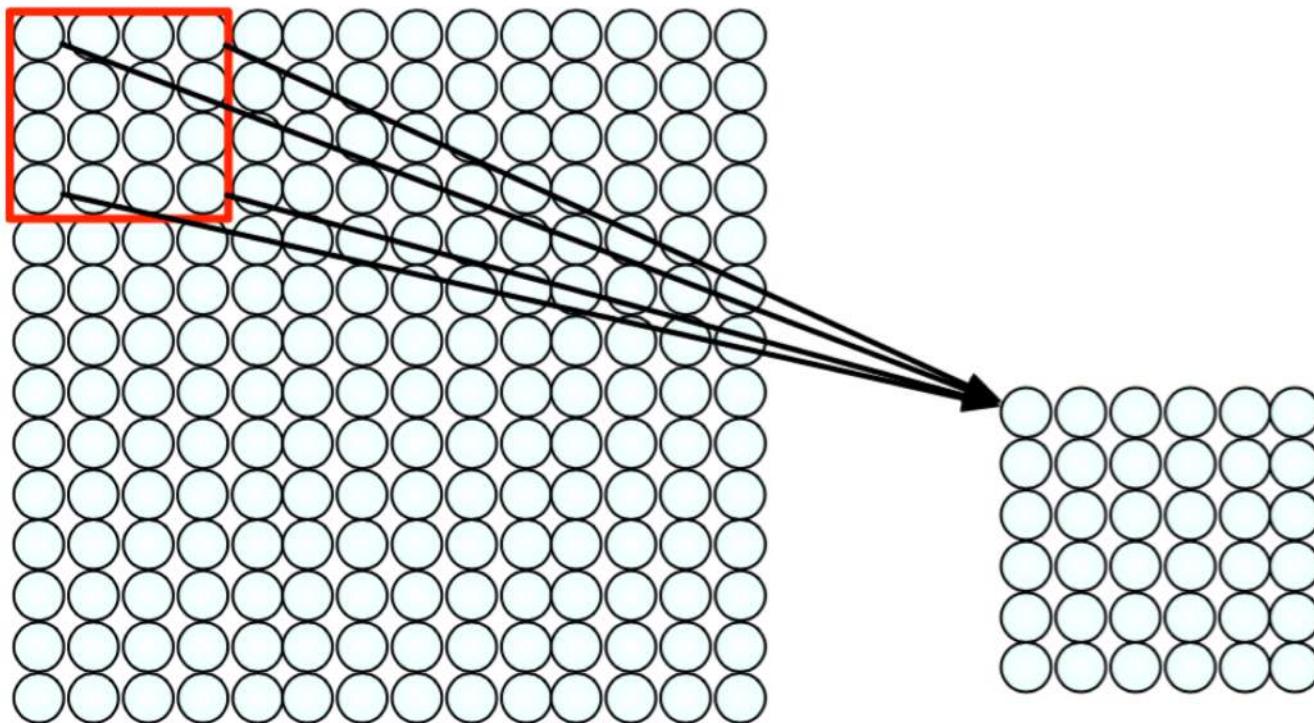
CNNs for Classification



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

Train model with image data.
Learn weights of filters in convolutional layers.

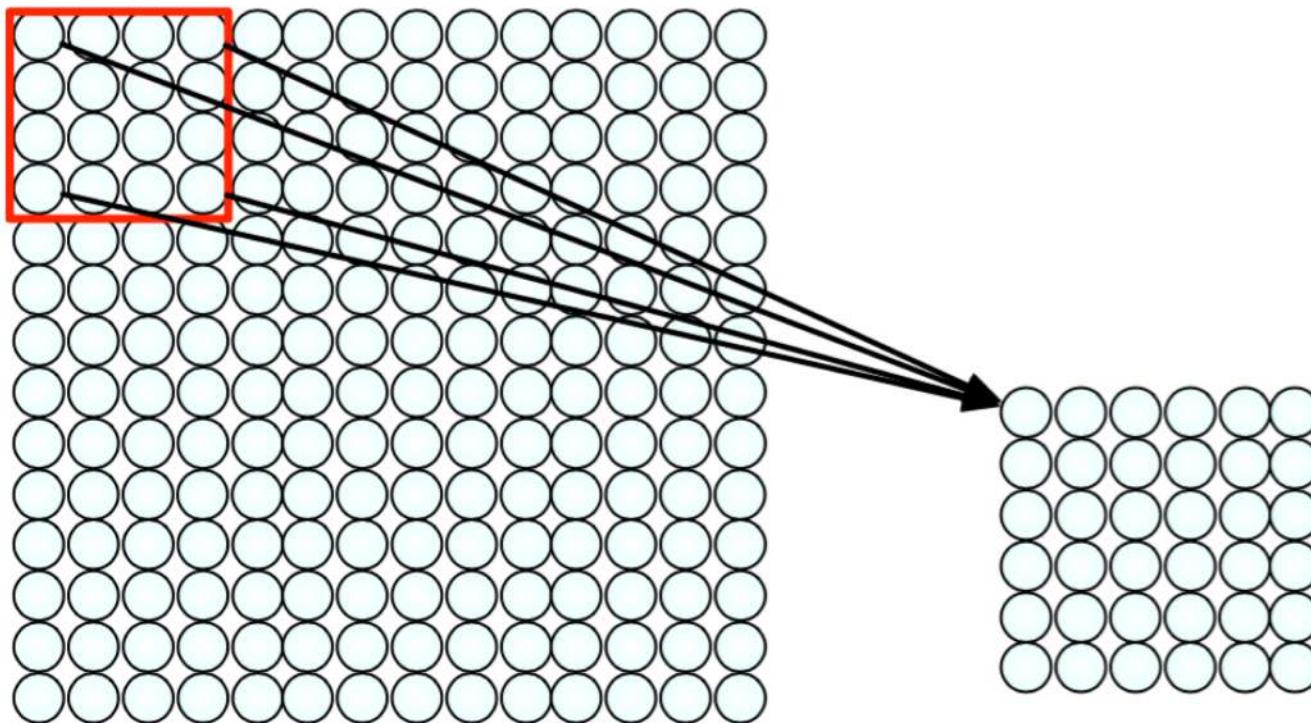
Convolutional Layers: Local Connectivity



For a neuron in hidden layer:

- Take inputs from patch
- Compute weighted sum
- Apply bias

Convolutional Layers: Local Connectivity



4x4 filter: matrix
of weights w_{ij}

$$\sum_{i=1}^4 \sum_{j=1}^4 w_{ij} x_{i+p,j+q} + b$$

for neuron (p,q) in hidden layer

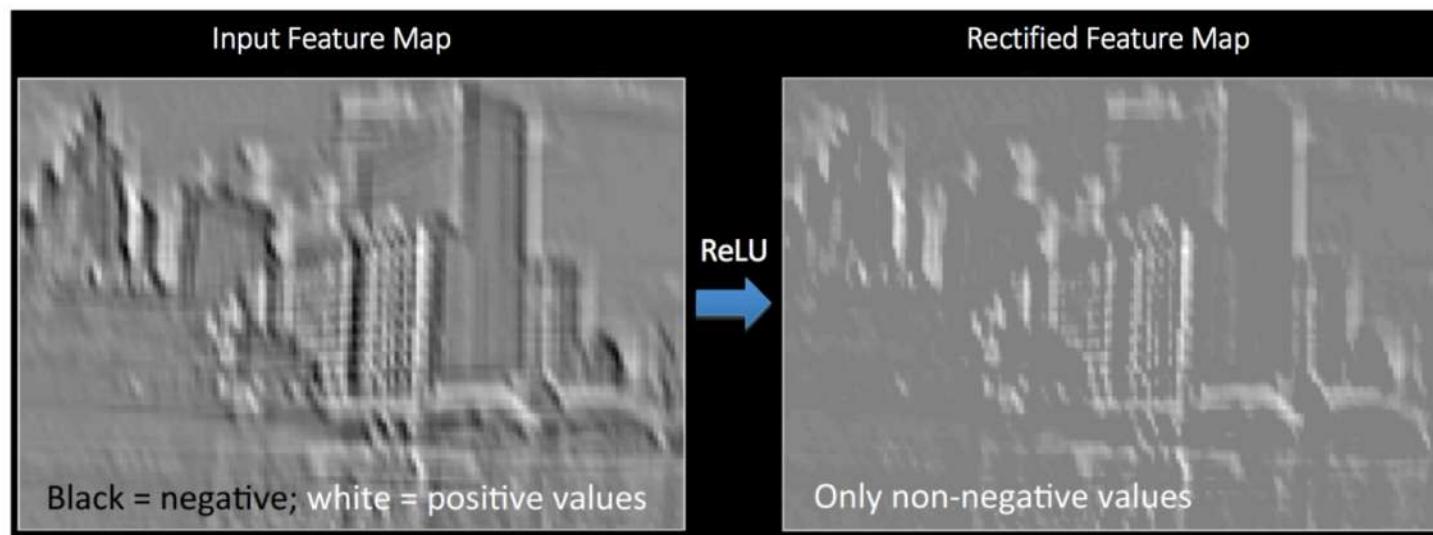
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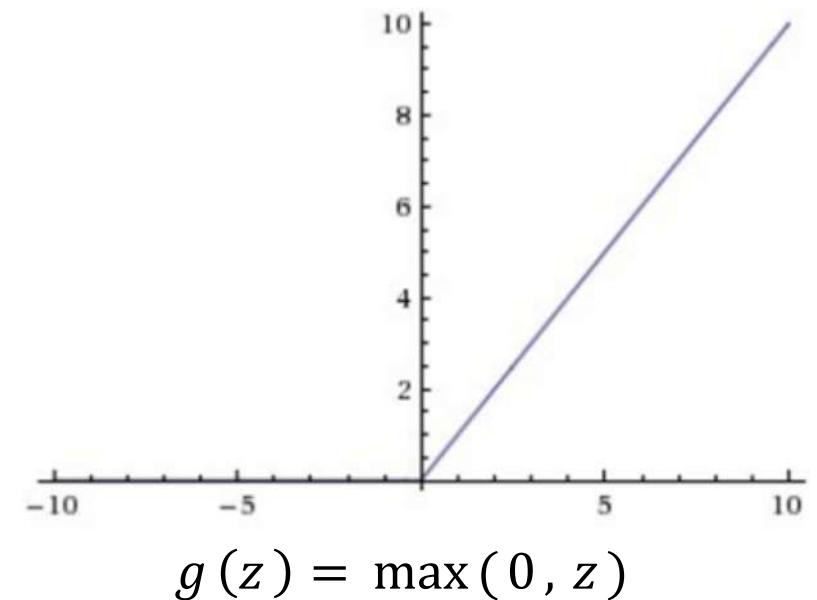
- 1) applying a window of weights
- 2) computing linear combinations
- 3) activating with non-linear function

Introducing Non-Linearity

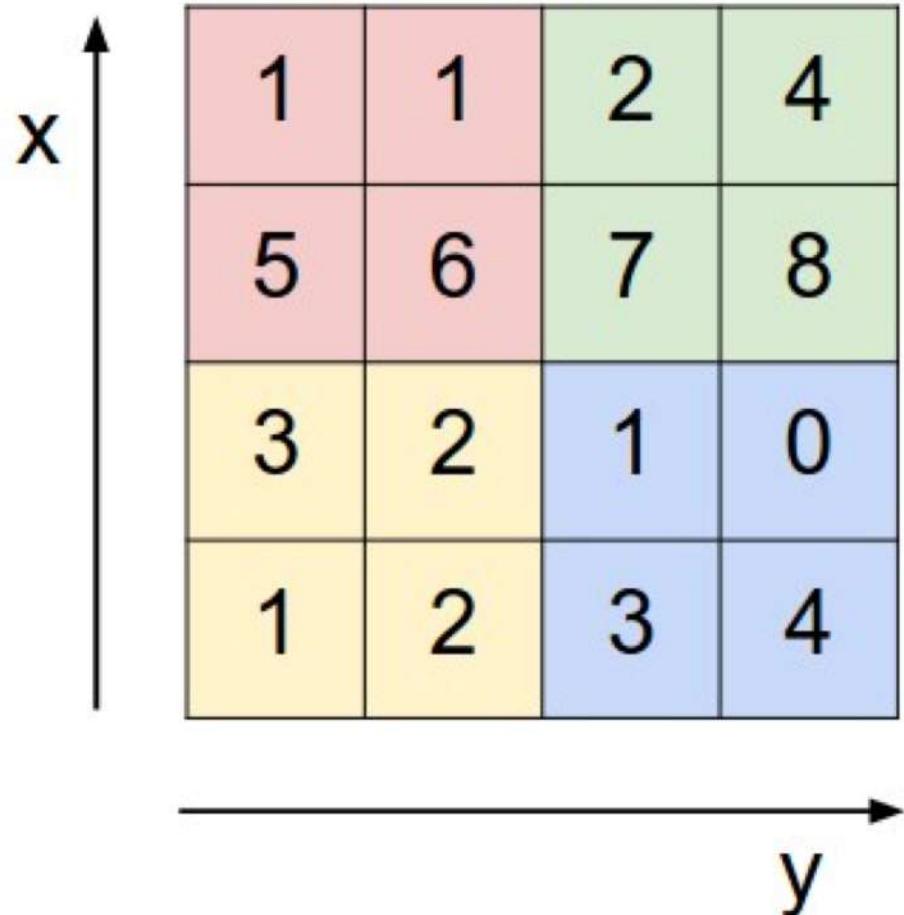
- Apply after every convolution operation (i.e., after convolutional layers)
- ReLU: pixel-by-pixel operation that replaces all negative values by zero. **Non-linear operation!**



Rectified Linear Unit (ReLU)



Pooling



max pool with 2x2 filters
and stride 2

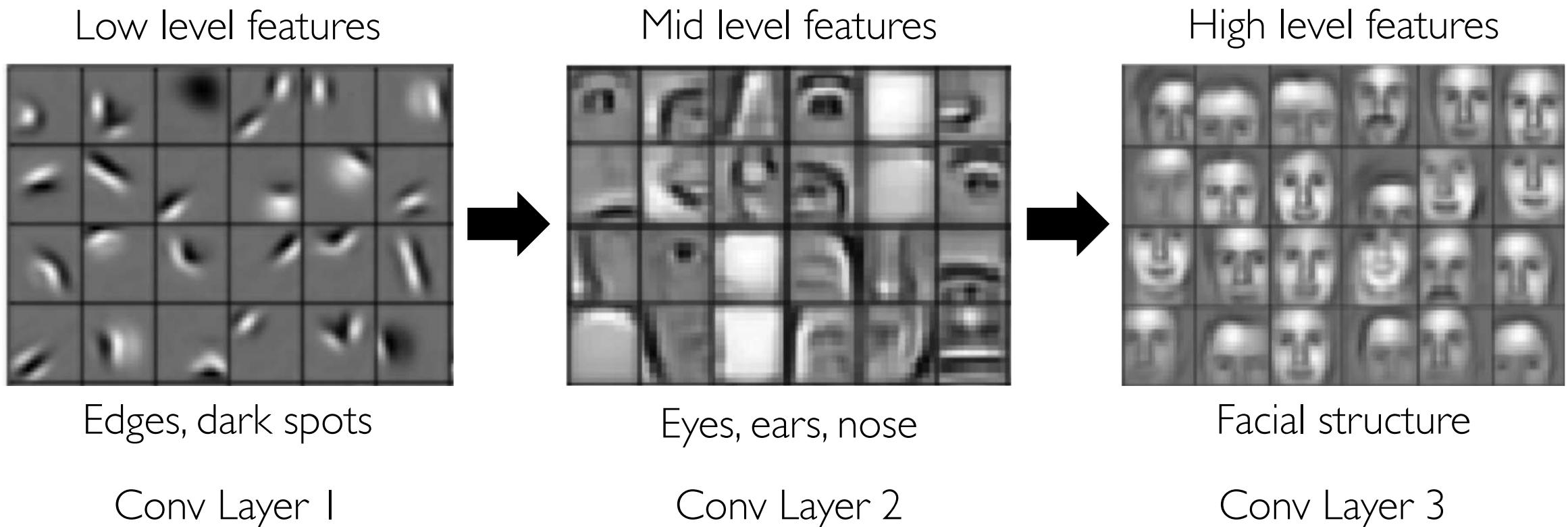


6	8
3	4

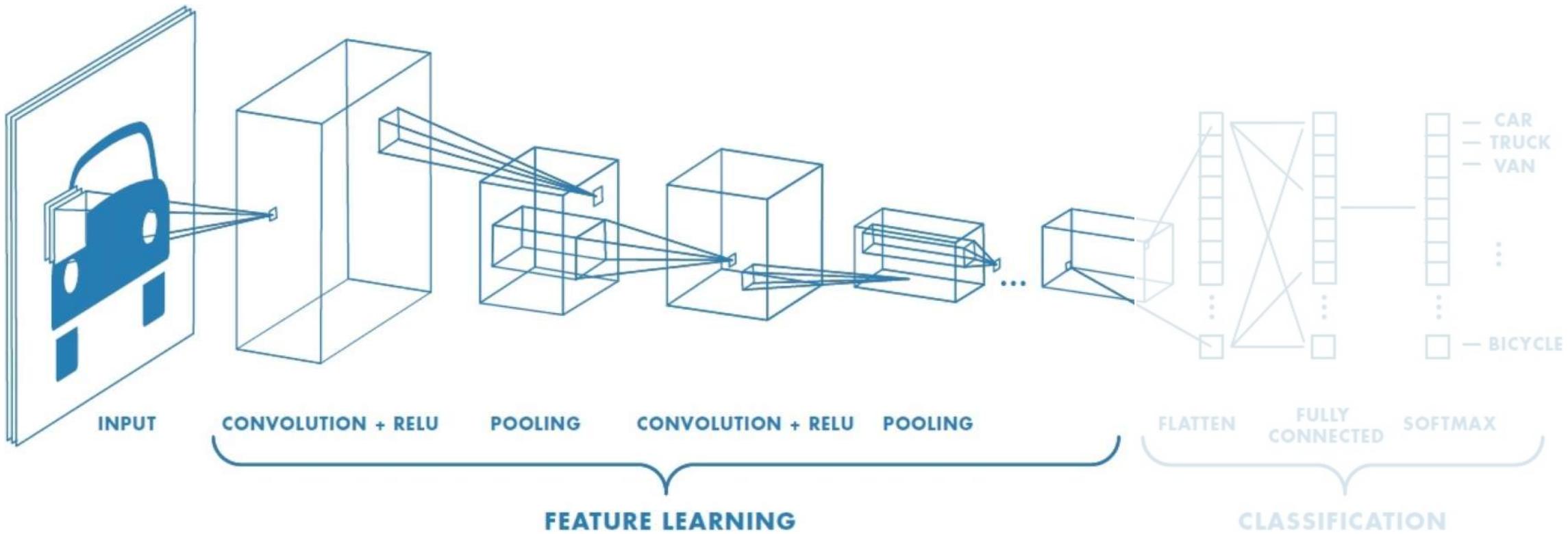
- 1) Reduced dimensionality
- 2) Spatial invariance

How else can we downsample and preserve spatial invariance?

Representation Learning in Deep CNNs

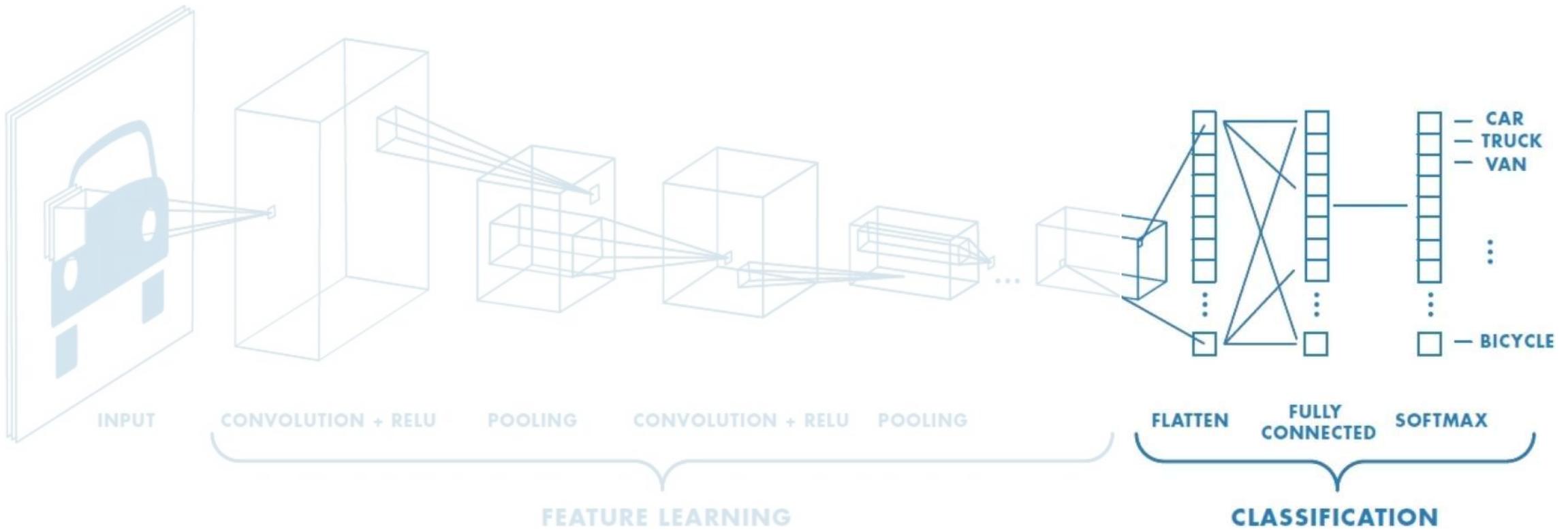


CNNs for Classification: Feature Learning



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**

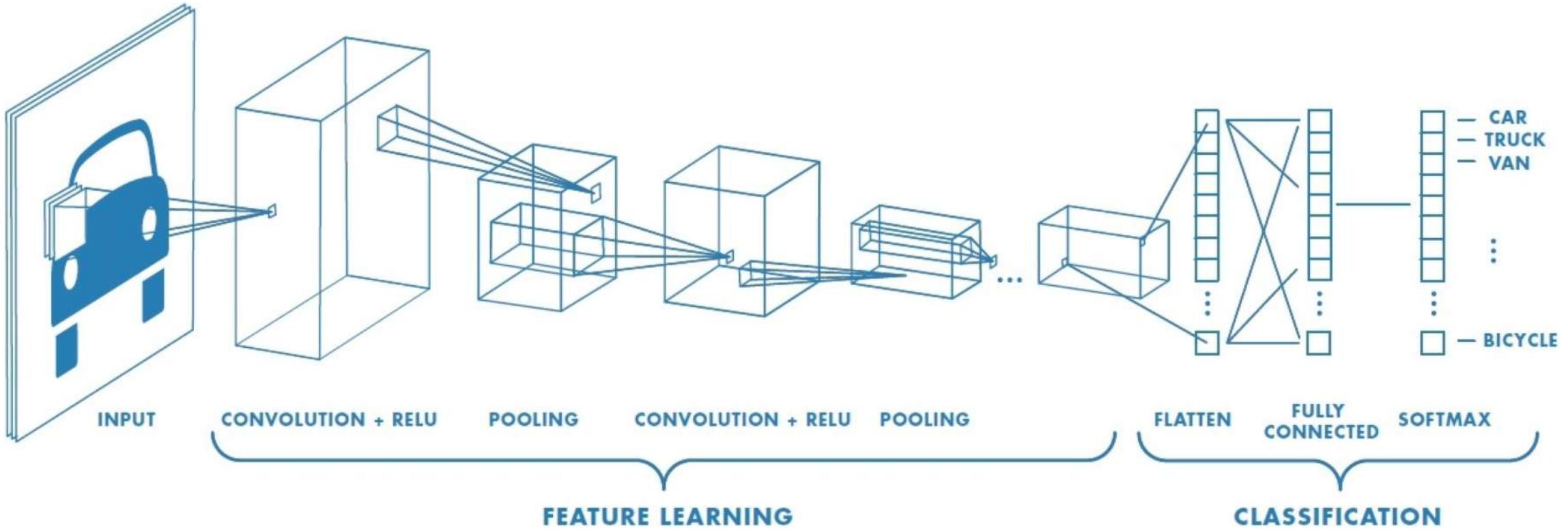
CNNs for Classification: Class Probabilities



- 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

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

CNNs: Training with Backpropagation



Learn weights for convolutional filters and fully connected layers

Backpropagation: cross-entropy loss

$$J(\theta) = \sum_i y^{(i)} \log(\hat{y}^{(i)})$$

CNNs for Classification: ImageNet

ImageNet Dataset

Dataset of over 14 million images across 21,841 categories

“Elongated crescent-shaped yellow fruit with soft sweet flesh”



1409 pictures of bananas.

ImageNet Challenge



ImageNet Large Scale Visual Recognition Challenges



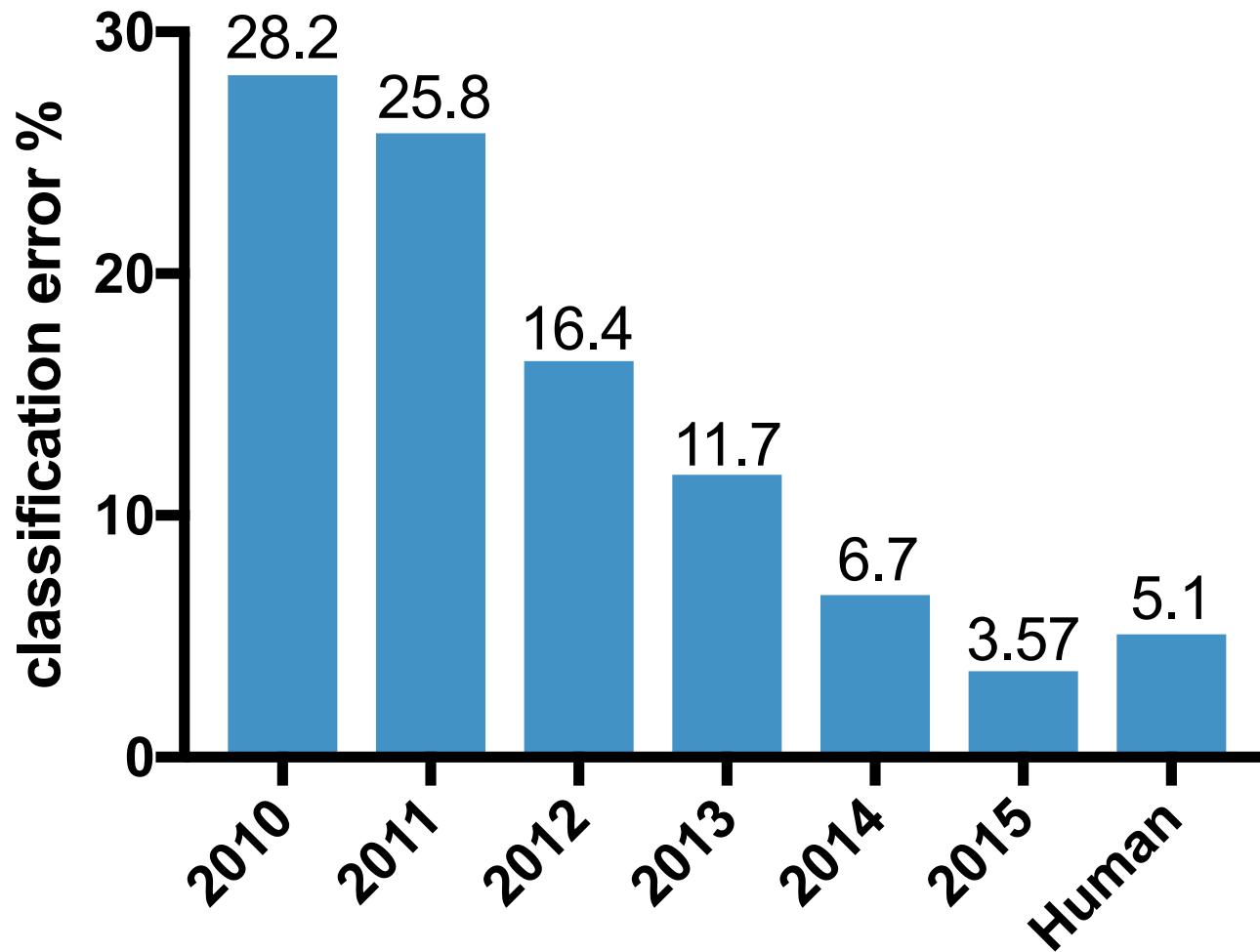
Classification task: produce a list of object categories present in image. 1000 categories.

“Top 5 error”: rate at which the model does not output correct label in top 5 predictions

Other tasks include:

single-object localization, object detection from video/image, scene classification, scene parsing

ImageNet Challenge: Classification Task



2012: AlexNet. First CNN to win.

- 8 layers, 61 million parameters

2013: ZFNet

- 8 layers, more filters

2014: VGG

- 19 layers

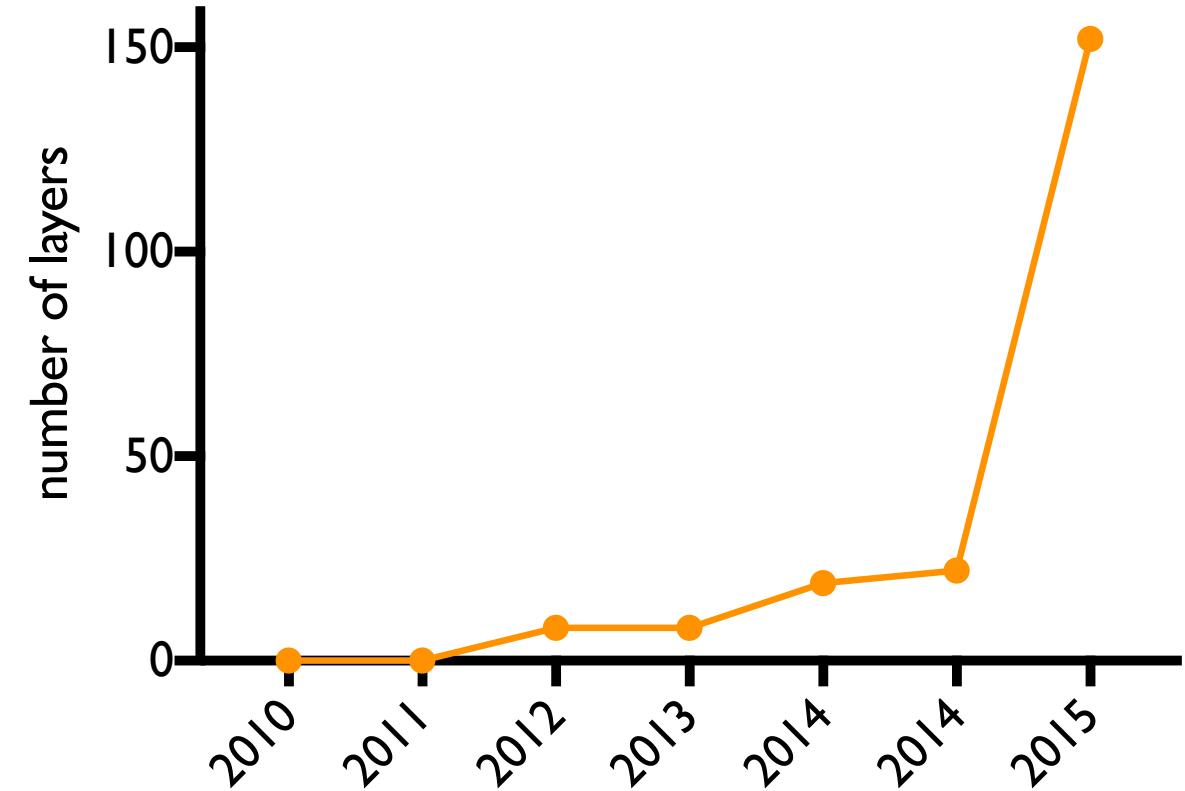
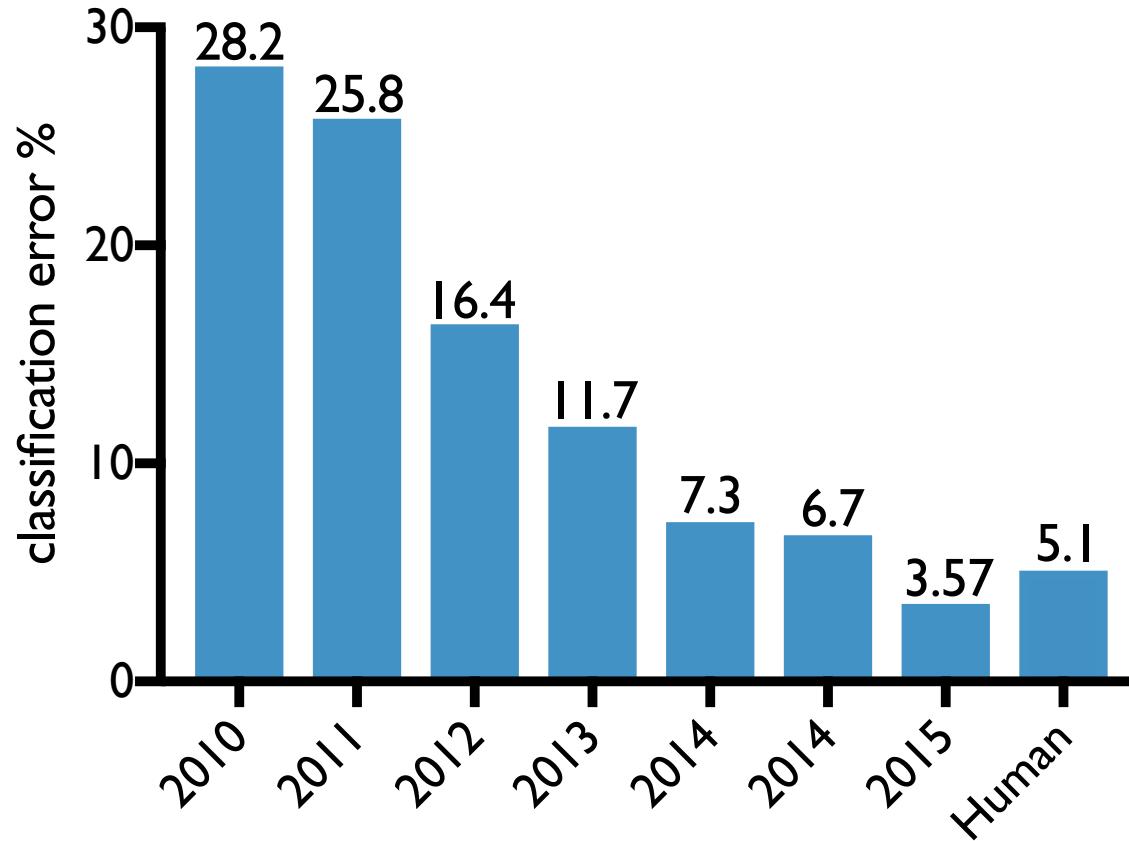
2014: GoogLeNet

- “Inception” modules
- 22 layers, 5 million parameters

2015: ResNet

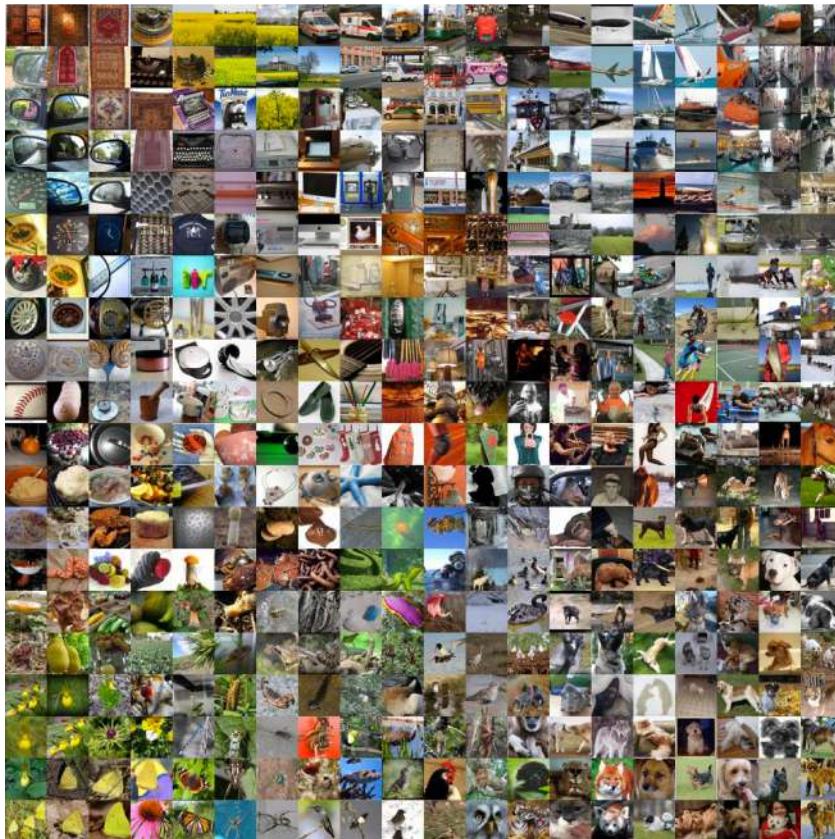
- 152 layers

ImageNet Challenge: Classification Task



Deep Learning for Computer Vision: Impact and Summary

Data, Data, Data



ImageNet:
22K categories. 14M images.

Airplane

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

Automobile

Bird

Cat

Deer

Dog

Frog

Horse

Ship

Truck

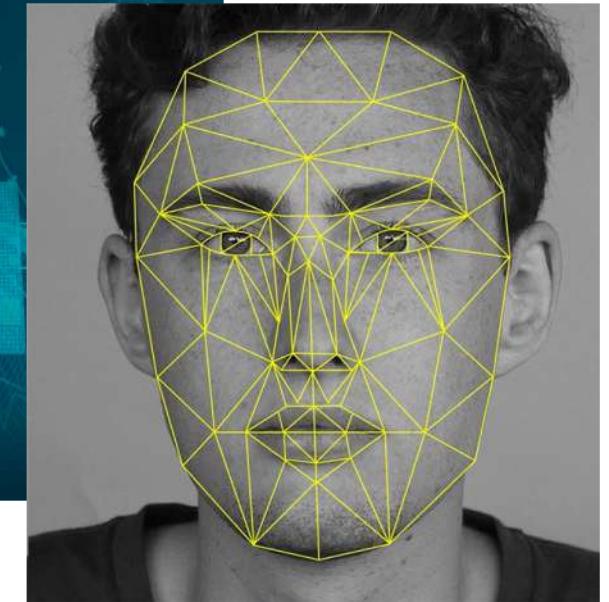
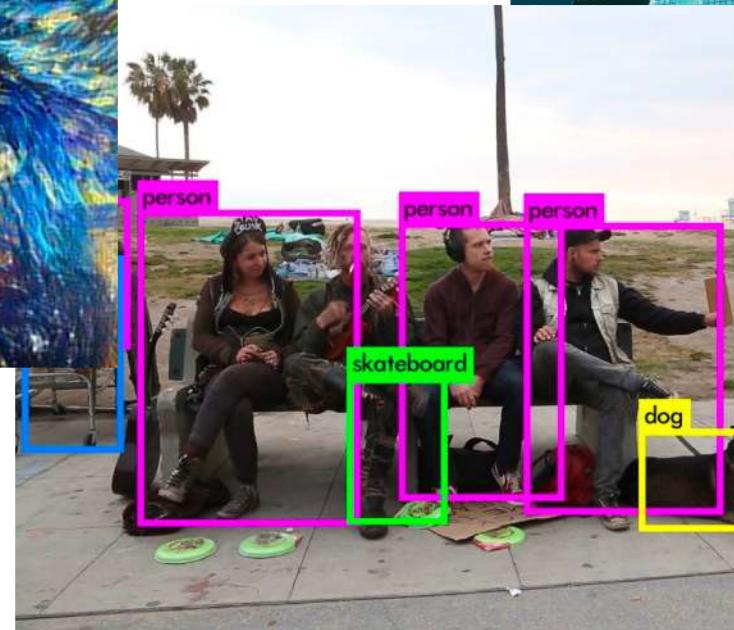
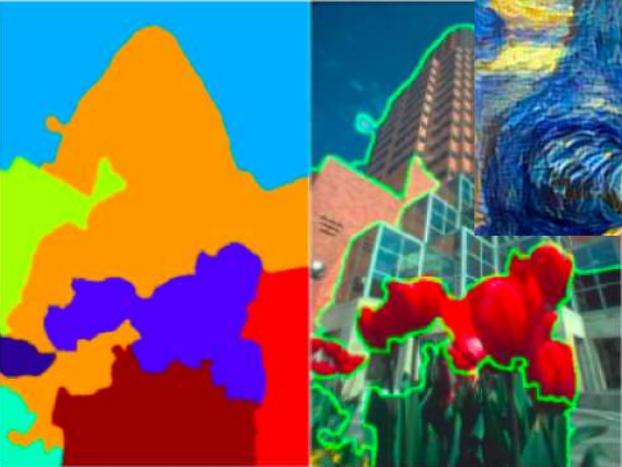
CIFAR-10

MNIST: handwritten digits

places 
THE SCENE RECOGNITION DATABASE

places: natural scenes

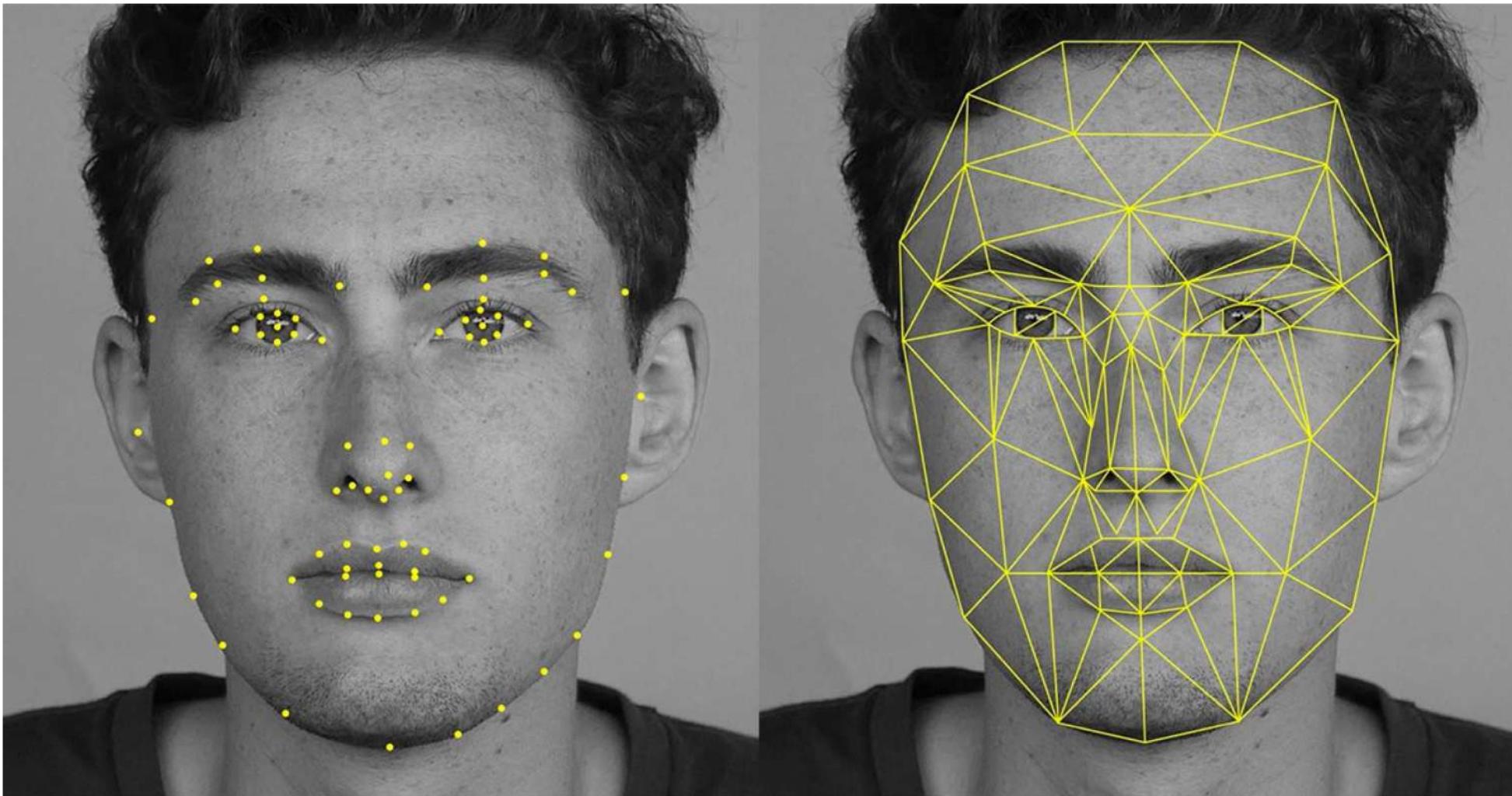
Deep Learning for Computer Vision: Impact



Impact: Face Detection



6.SI91 Lab!



Impact: Self-Driving Cars

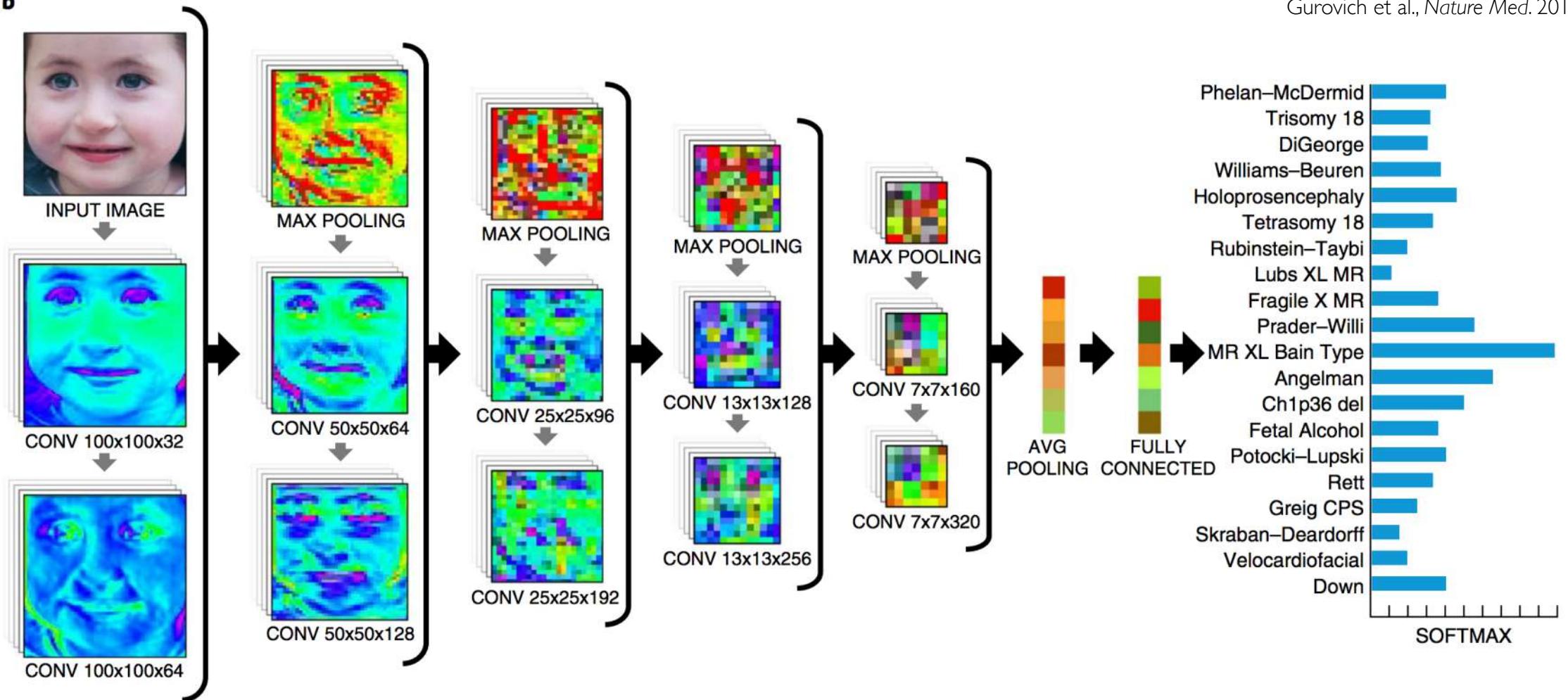


Impact: Healthcare

Identifying facial phenotypes of genetic disorders using deep learning

Gurovich et al., *Nature Med.* 2019

b



Deep Learning for Computer Vision: Summary

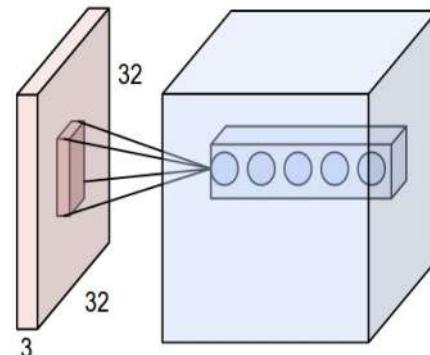
Foundations

- Why computer vision?
- Representing images
- Convolutions for feature extraction



CNNs

- CNN architecture
- Application to classification
- ImageNet



Applications

- Segmentation, object detection, image captioning
- Visualization



References

goo.gl/hbLkF6

End of Slides