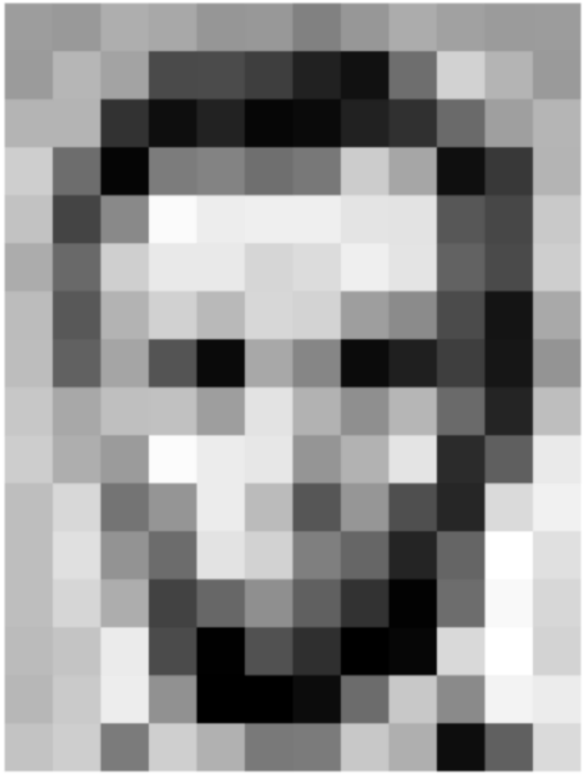
# Deep Learning for Computer Vision
# MIT 6.S191

Ava Soleimany

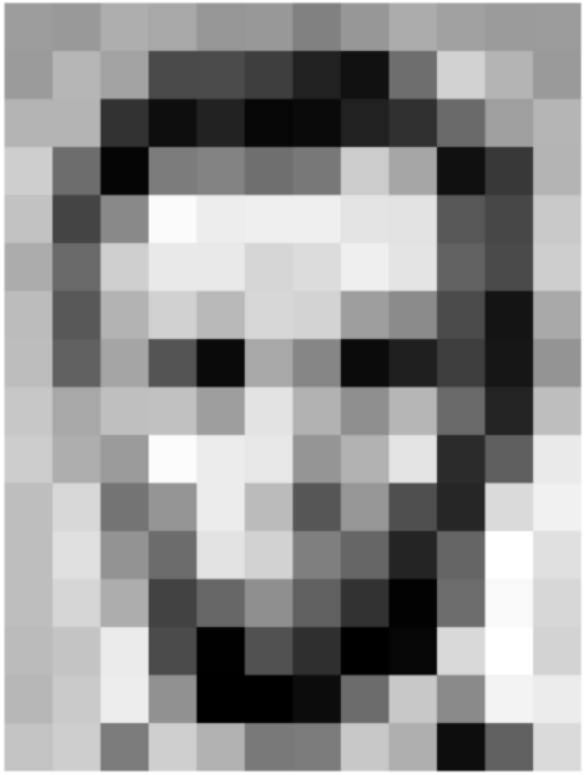
January 29, 2019

# What Computers “See”

# Images are Numbers

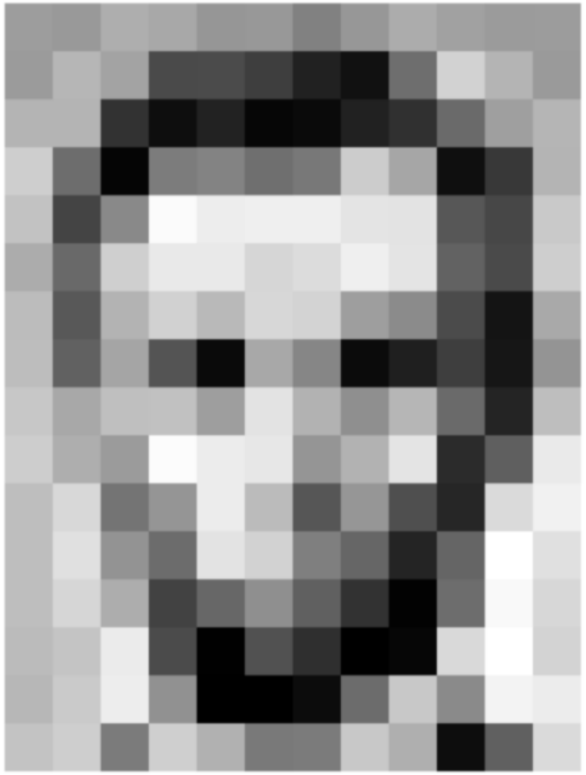


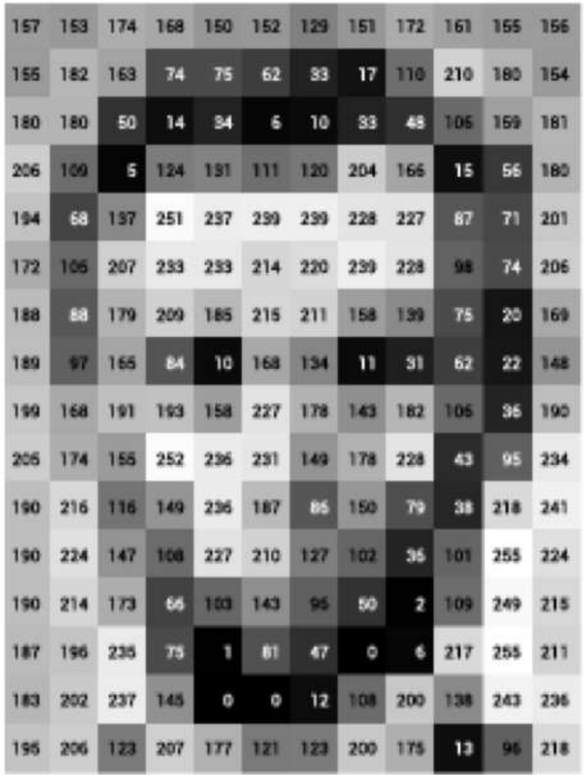
# Images are Numbers



| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| 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 | 85 | 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



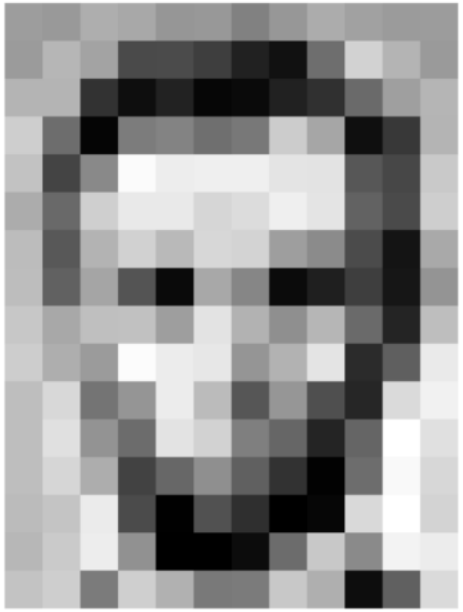



What the computer sees

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| 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 | 96 | 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 |

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

# Tasks in Computer Vision



Input Image

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 |
| 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 | 96 | 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 |

Pixel Representation

classification

$$\begin{array}{l} \text{Lincoln} \\ \text{Washington} \\ \text{Jefferson} \\ \text{Obama} \end{array} \begin{bmatrix} 0.8 \\ 0.1 \\ 0.05 \\ 0.05 \end{bmatrix}$$

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

# High Level Feature Detection

Let's identify key features in each image category

Nose,
Eyes,
Mouth

Wheels,
License Plate,
Headlights

Door,
Windows,
Steps

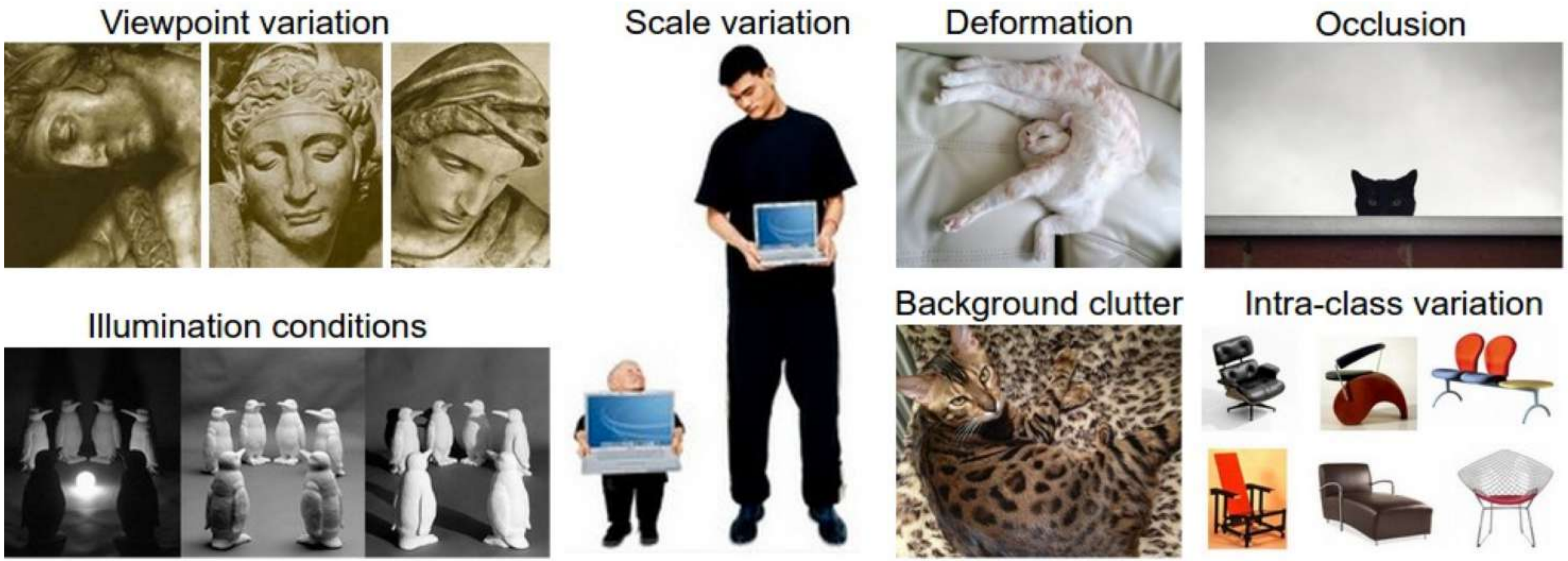
# Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify

Problems?

# Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify

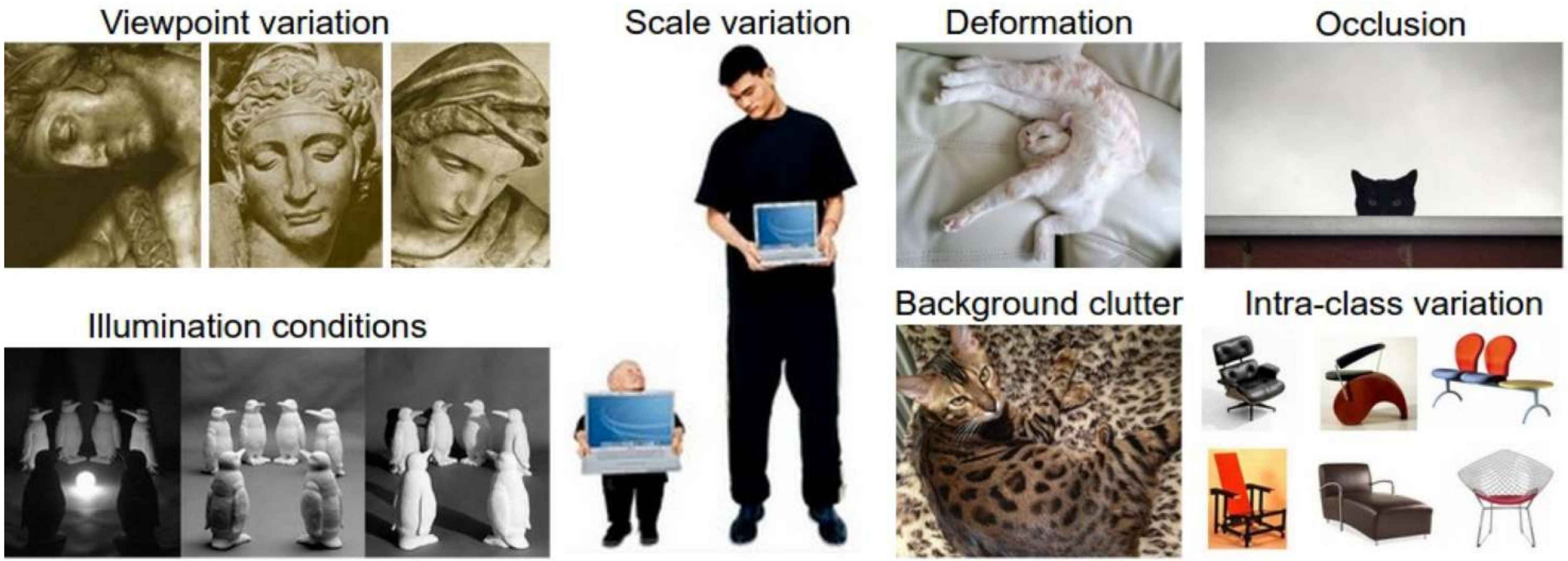


# Manual Feature Extraction

Domain knowledge

Define features

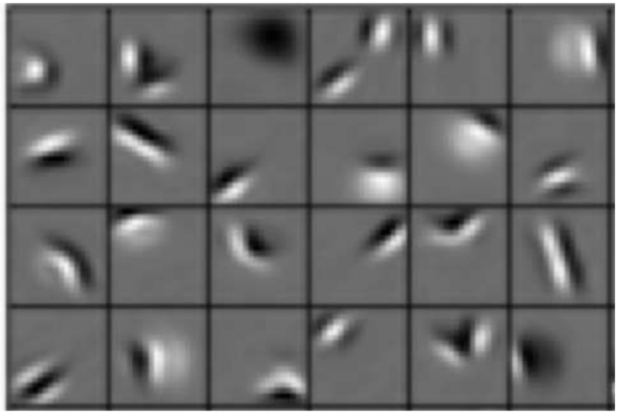
Detect features to classify



# Learning Feature Representations

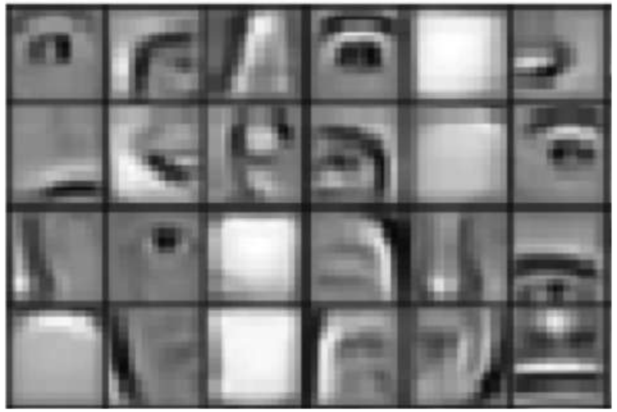
Can we learn a **hierarchy of features** directly from the data instead of hand engineering?

Low level features



Edges, dark spots

Mid level features



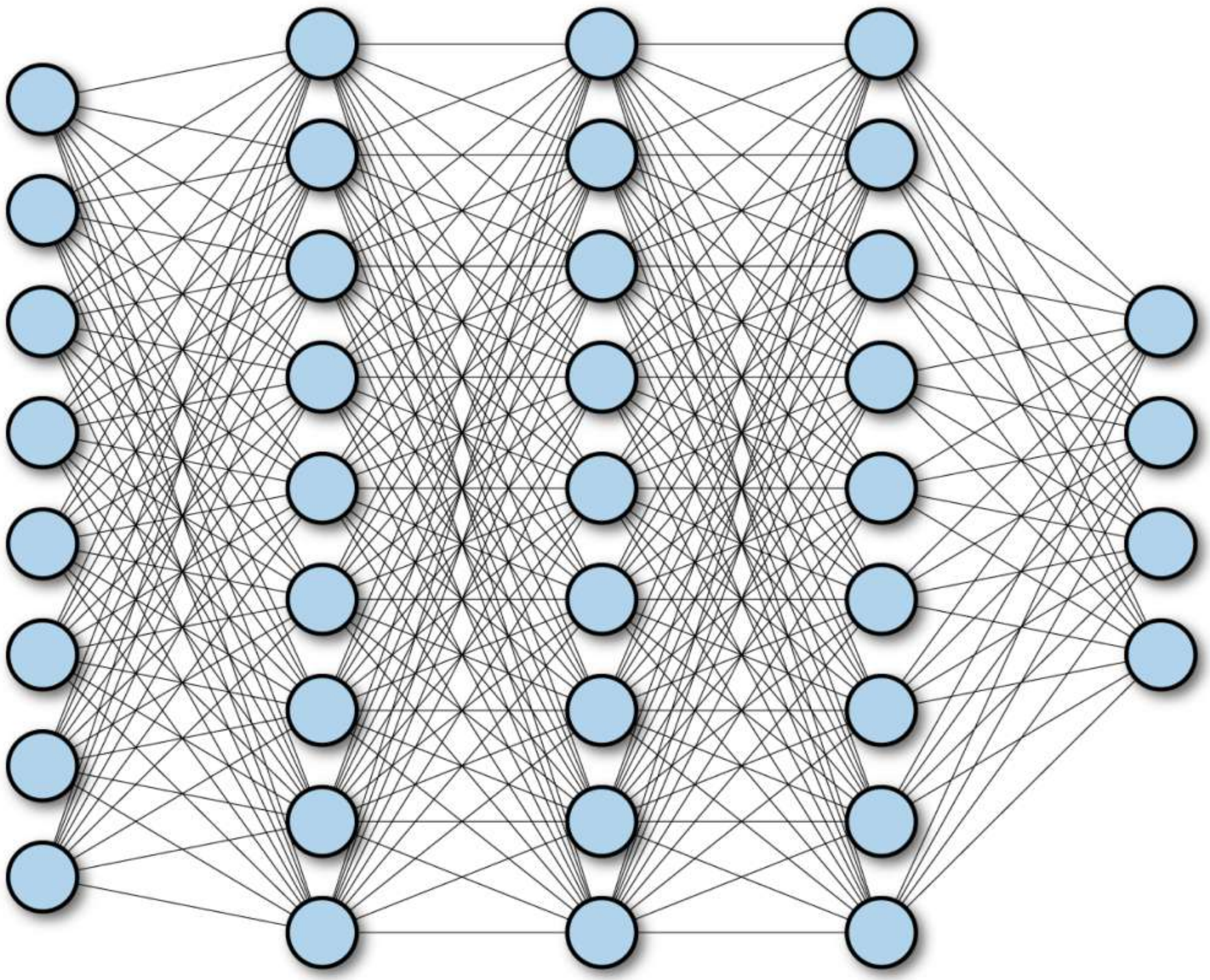
Eyes, ears, nose

High level features

Facial structure

# Learning Visual Features

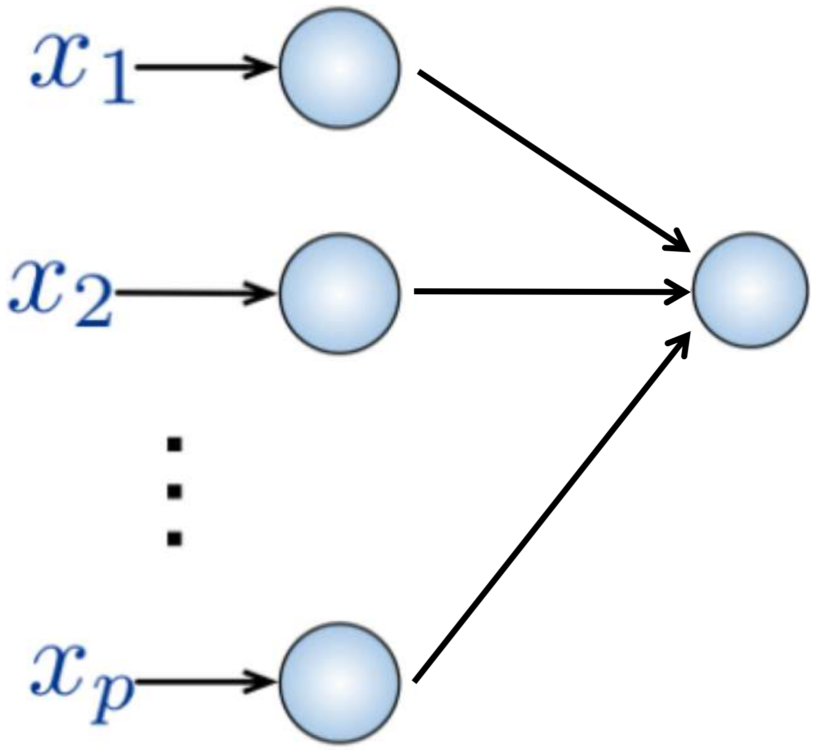
# Fully Connected Neural Network



# Fully Connected Neural Network

**Input:**

- 2D image
- Vector of pixel values

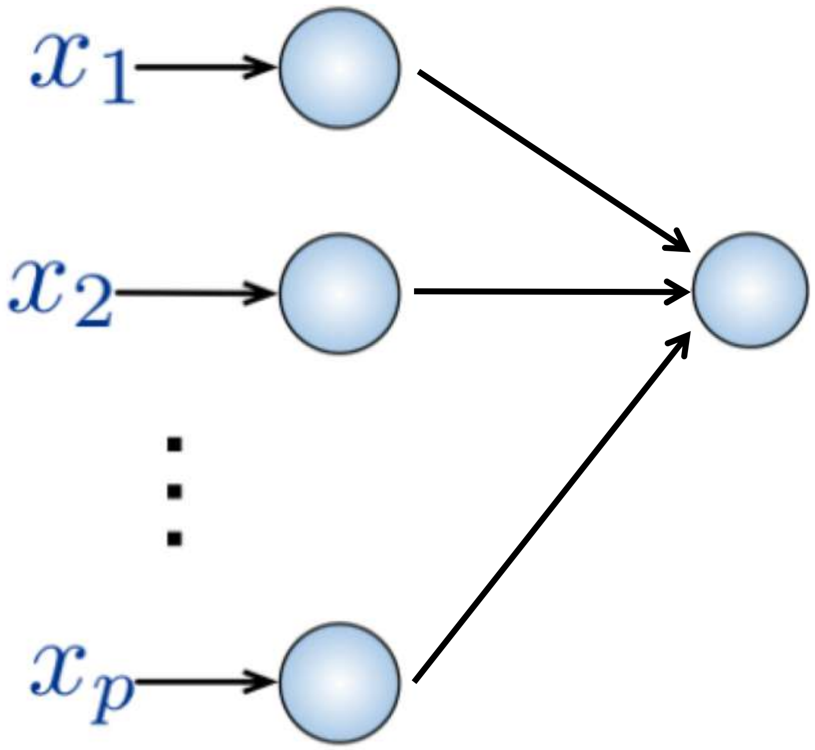



**Fully Connected:**

- 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

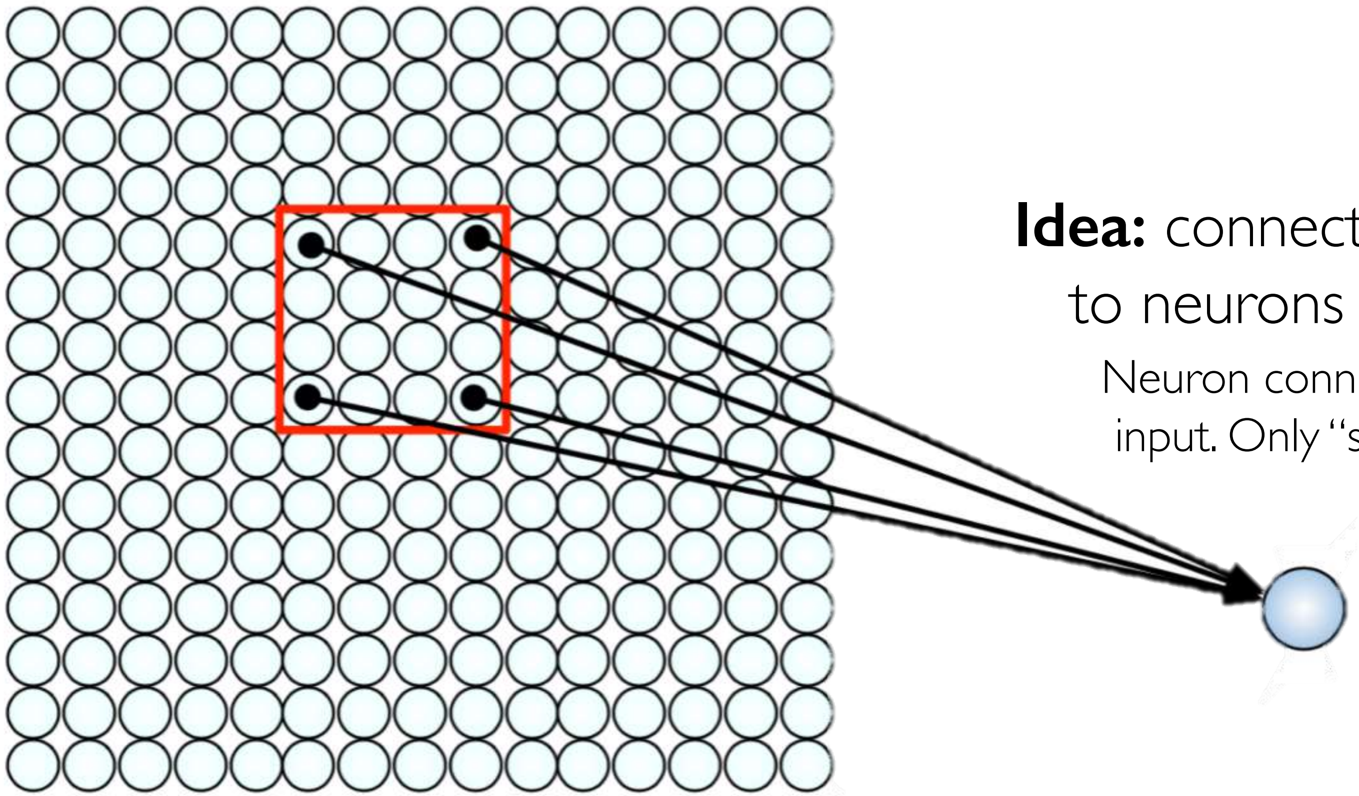



**Fully Connected:**
- Connect neuron in hidden layer to all neurons in input layer
- No spatial information!
- And many, many parameters!

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

# Using Spatial Structure

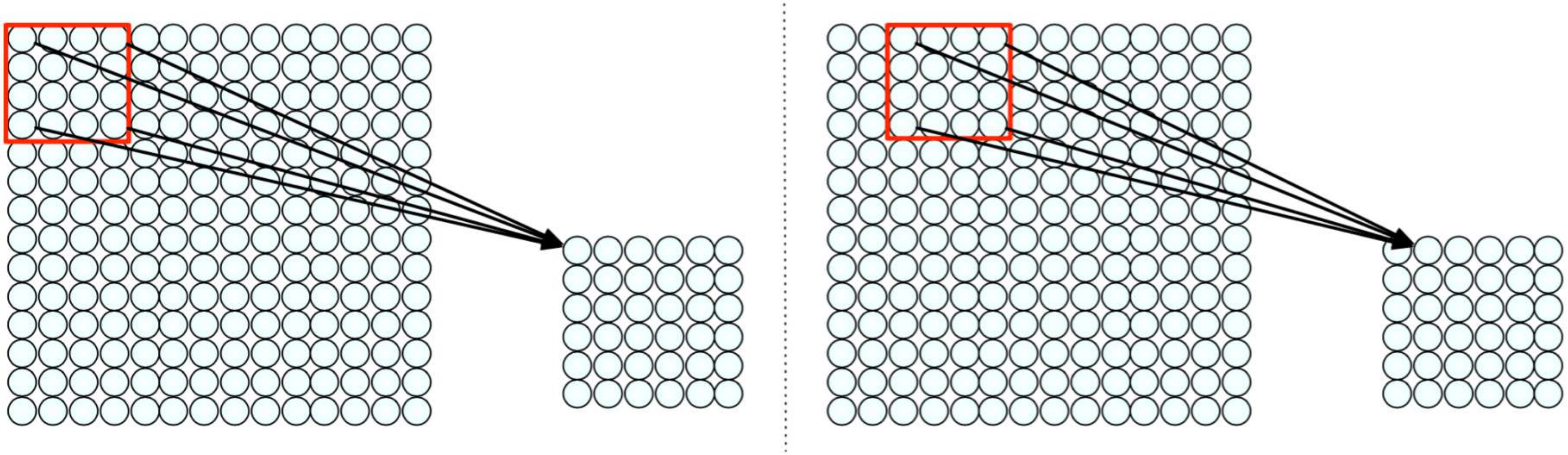
**Input:** 2D image.
Array of pixel values



**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?*

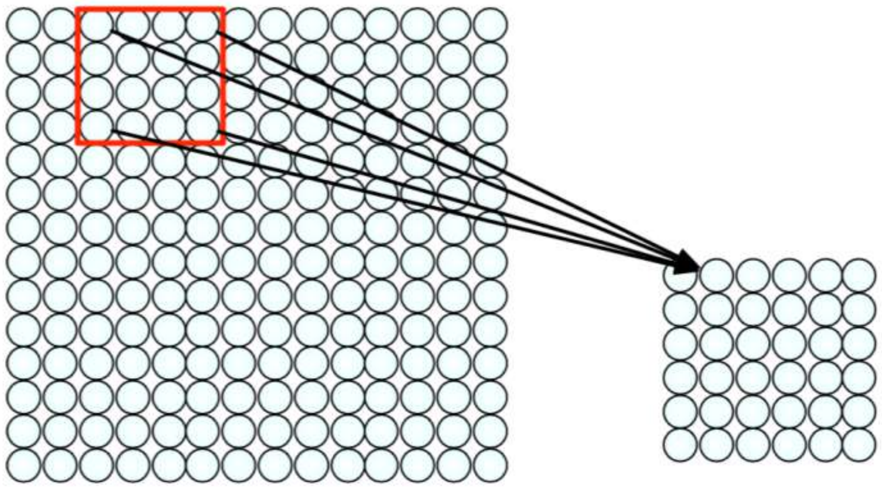
# Applying Filters to Extract Features

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
(features that matter in one part of the input should matter elsewhere)

# Feature Extraction with Convolution



- Filter of size 4x4 : 16 different weights
- Apply this same filter to 4x4 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?

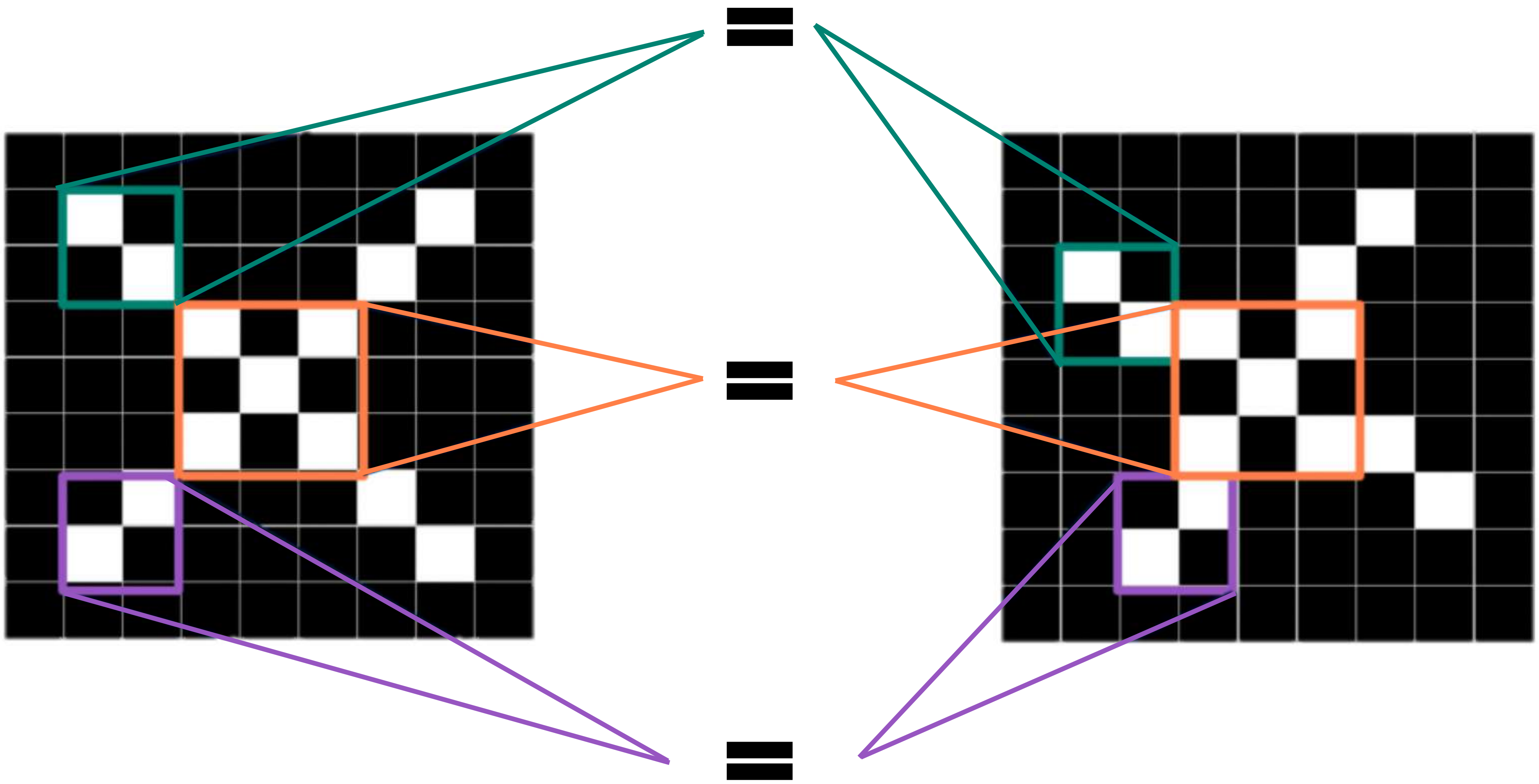
| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 | -1 |
| -1 | 1 | -1 | -1 | -1 | -1 | -1 | 1 | -1 |
| -1 | -1 | 1 | -1 | -1 | -1 | 1 | -1 | -1 |
| -1 | -1 | -1 | 1 | -1 | 1 | -1 | -1 | -1 |
| -1 | -1 | -1 | -1 | 1 | -1 | -1 | -1 | -1 |
| -1 | -1 | -1 | 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 |

$\stackrel{?}{=}$

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| -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 |

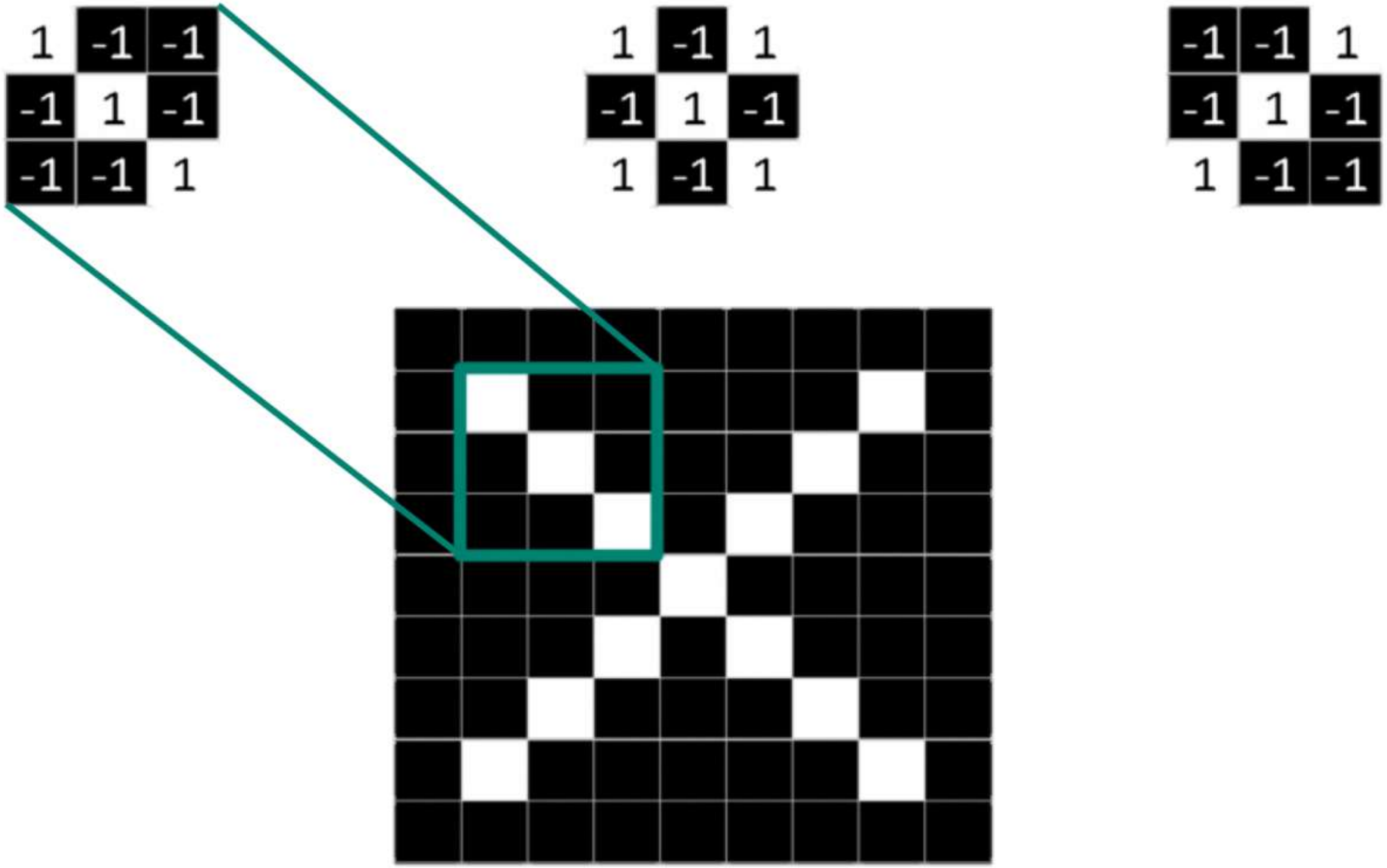
Image is represented as matrix of pixel values… and computers are literal!
We want to be able to classify an X as an X even if it's shifted, shrunk, rotated, deformed.

# Features of X

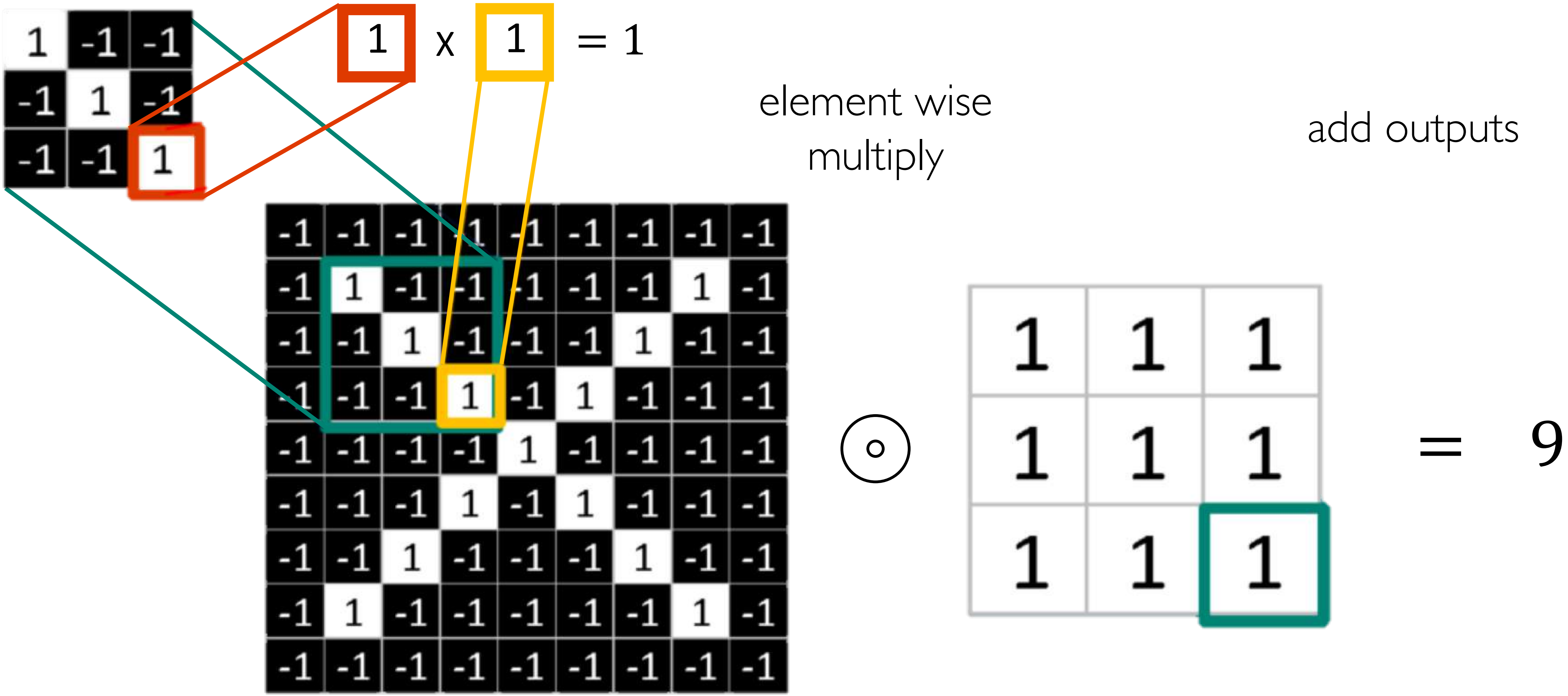


# Filters to Detect X Features

filters



# The Convolution Operation



# The Convolution Operation

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

$$\begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} \otimes \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{bmatrix}$$

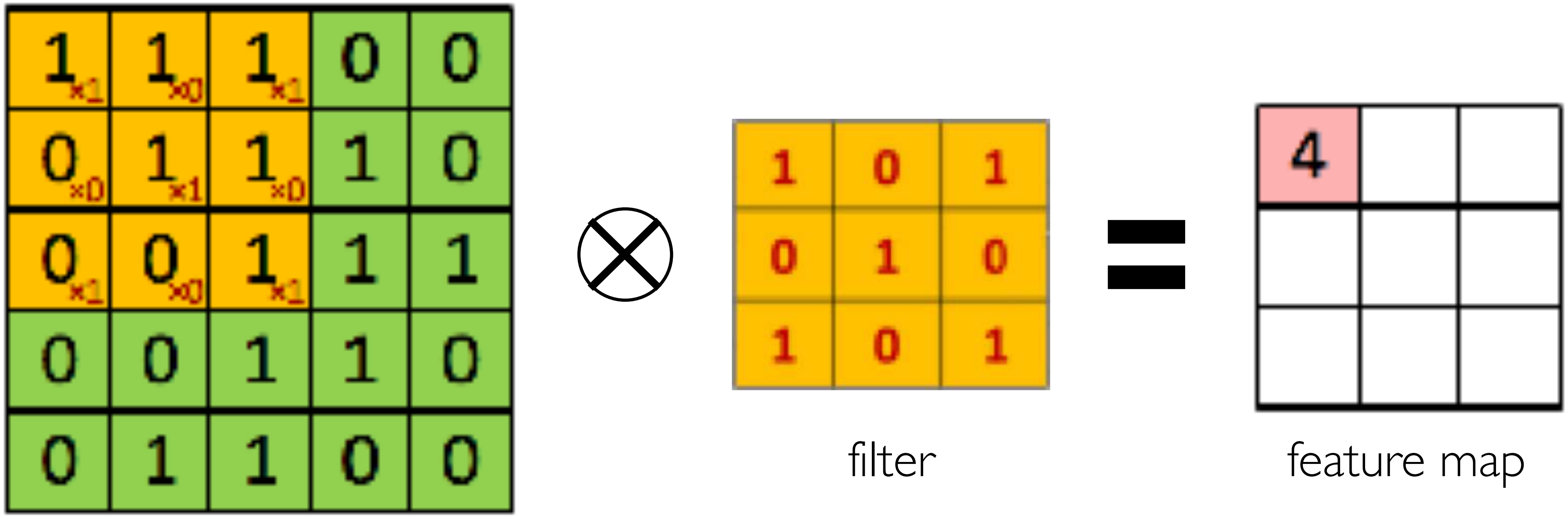
image

filter

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

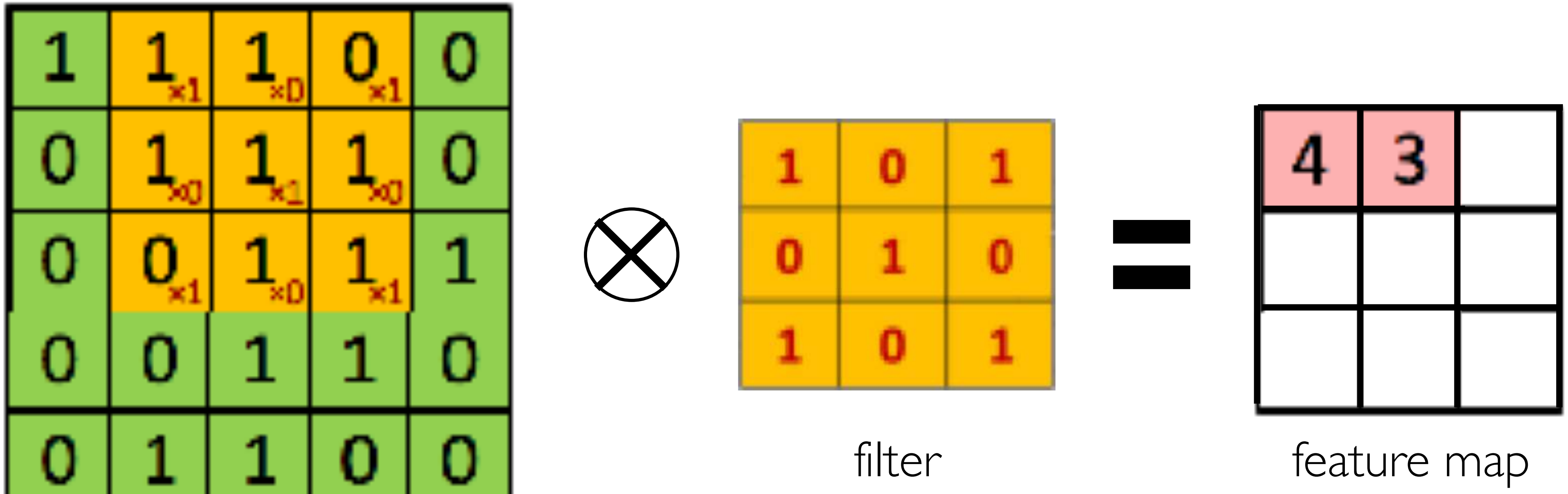
# The Convolution Operation

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



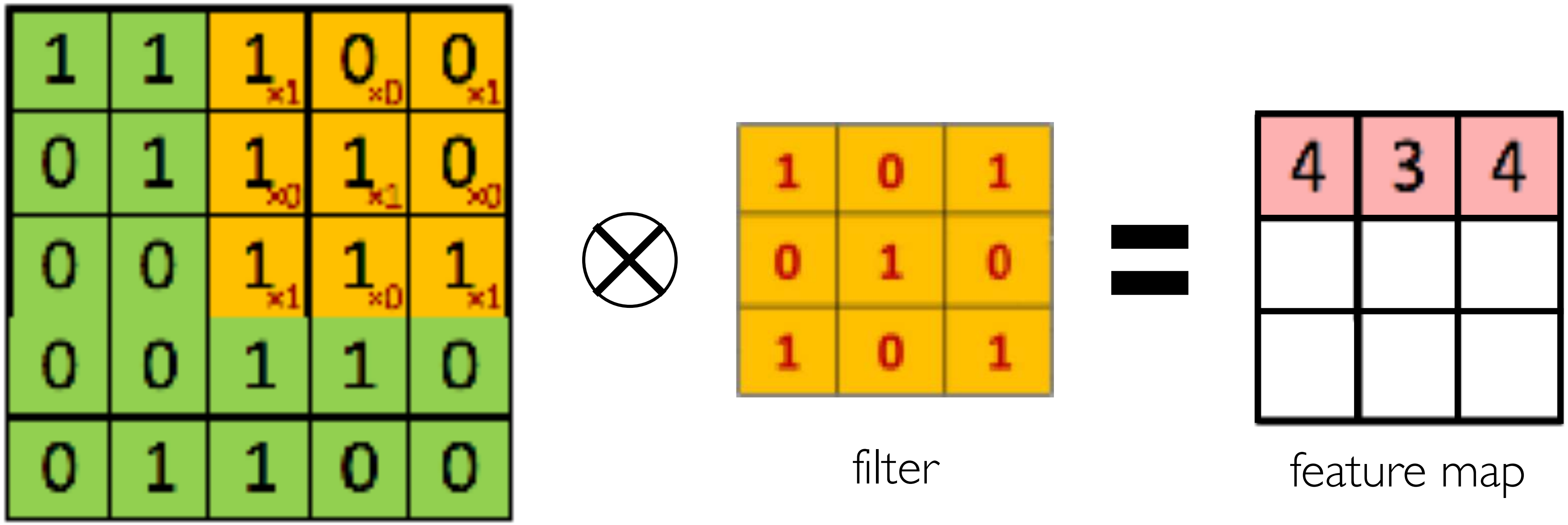
# The Convolution Operation

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



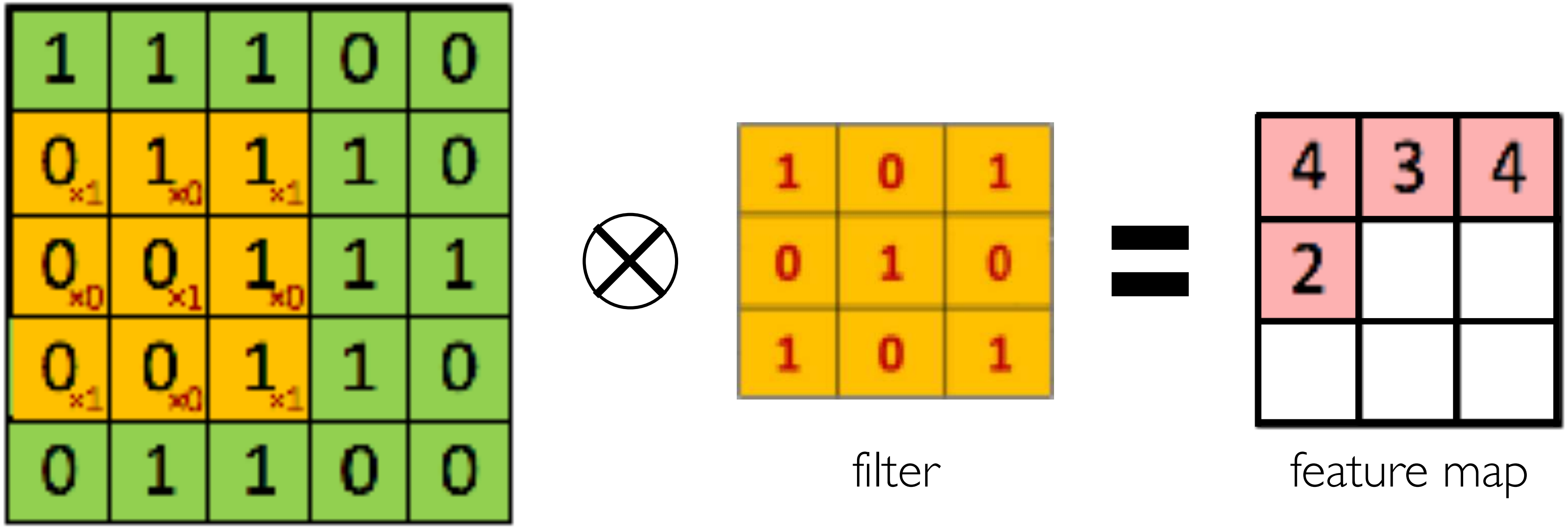
# The Convolution Operation

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



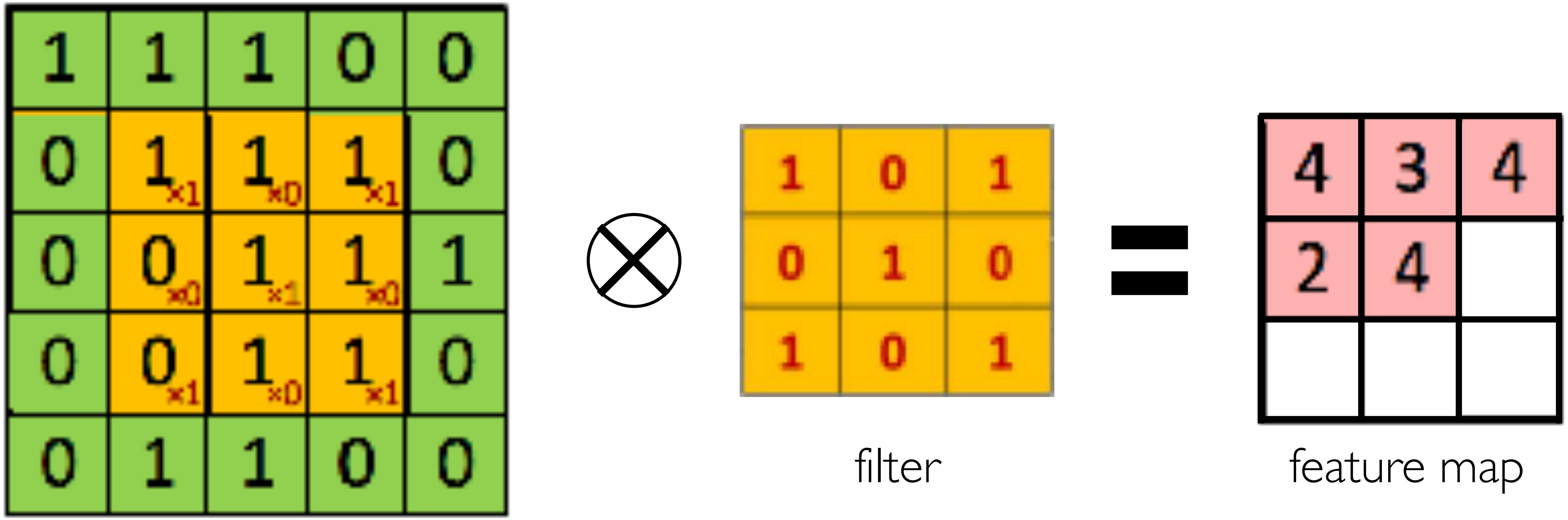
# The Convolution Operation

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



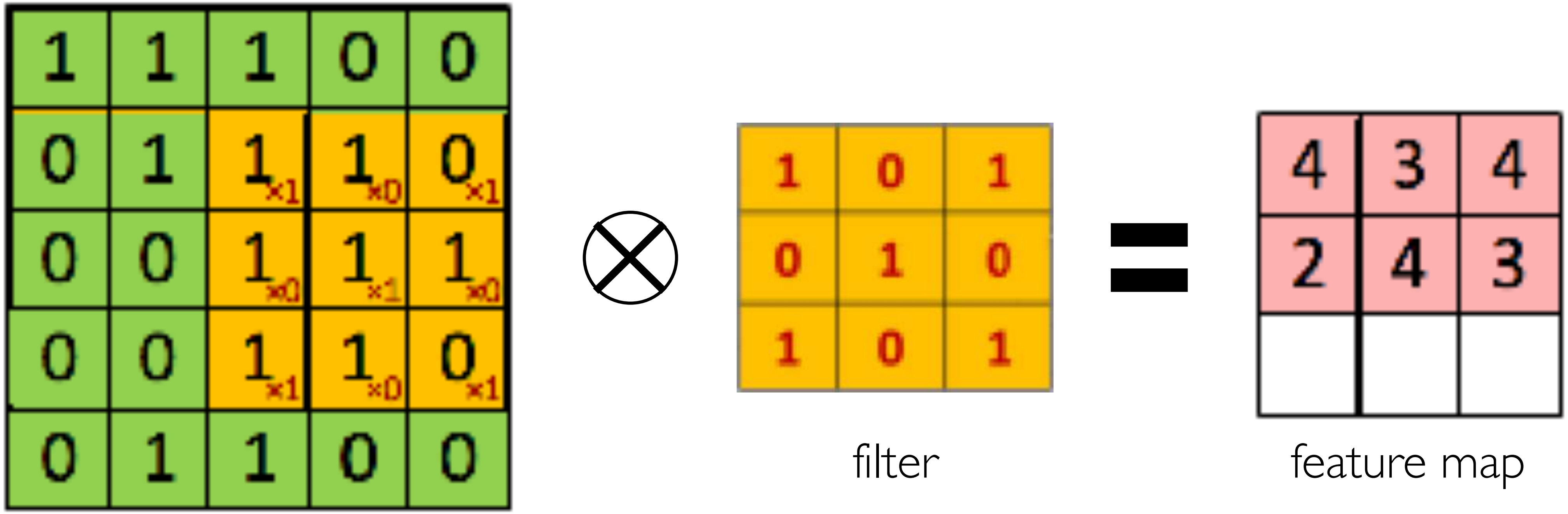
# The Convolution Operation

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:

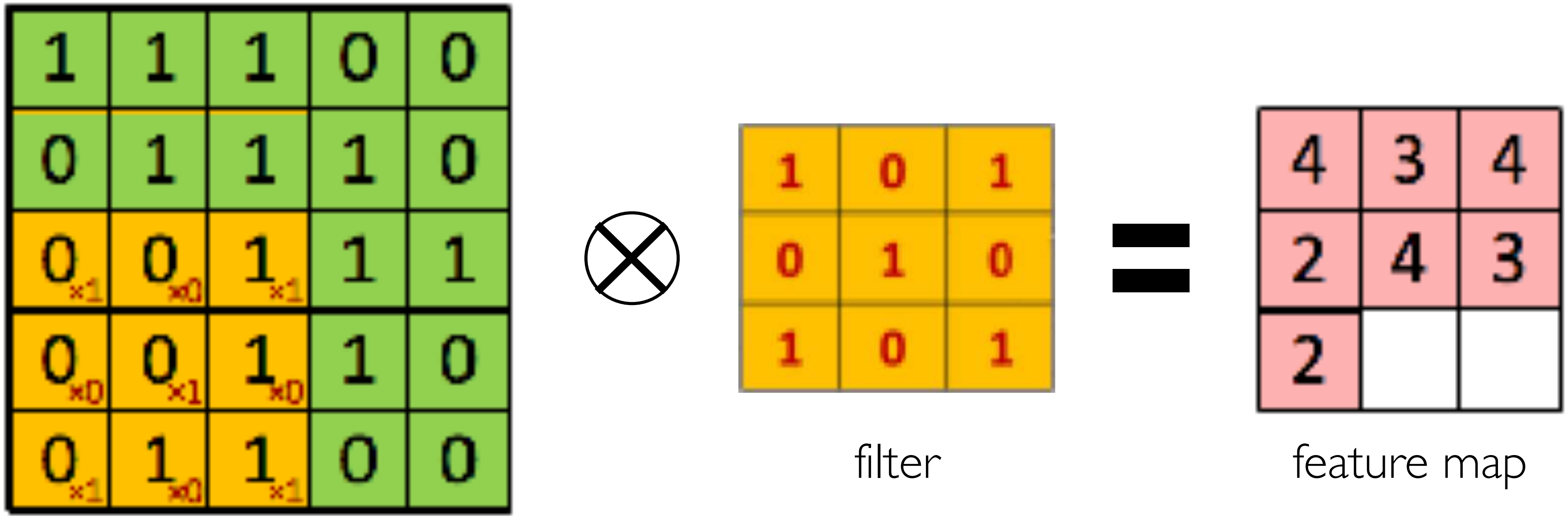



filter

feature map

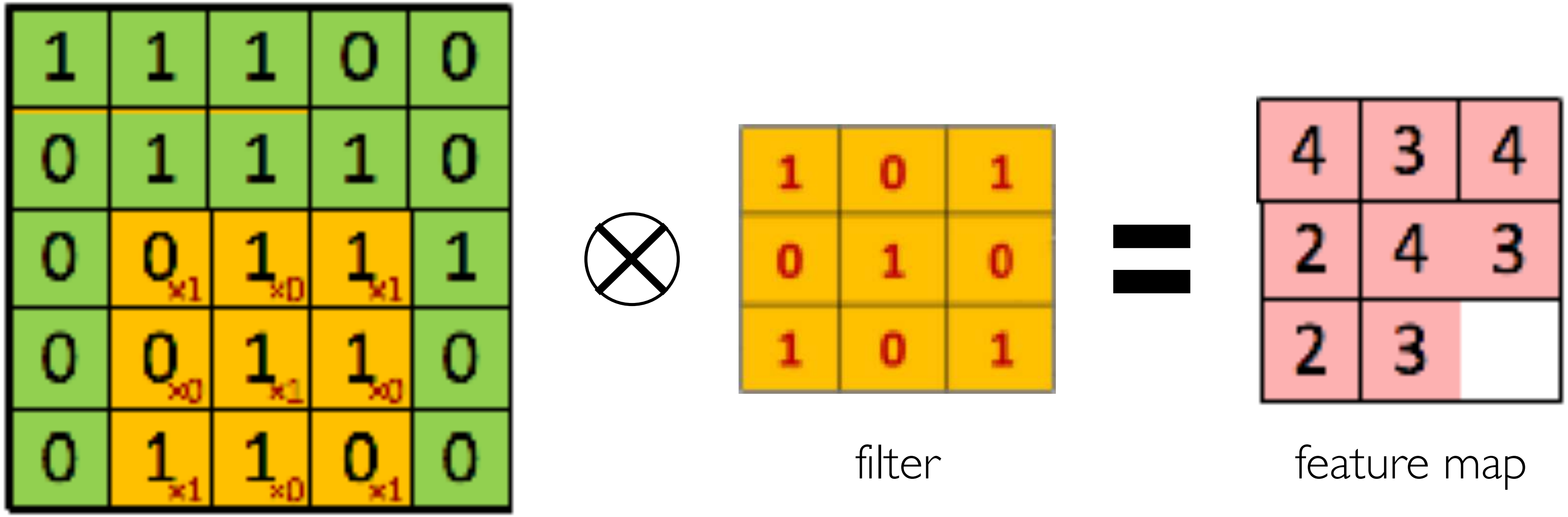
# The Convolution Operation

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



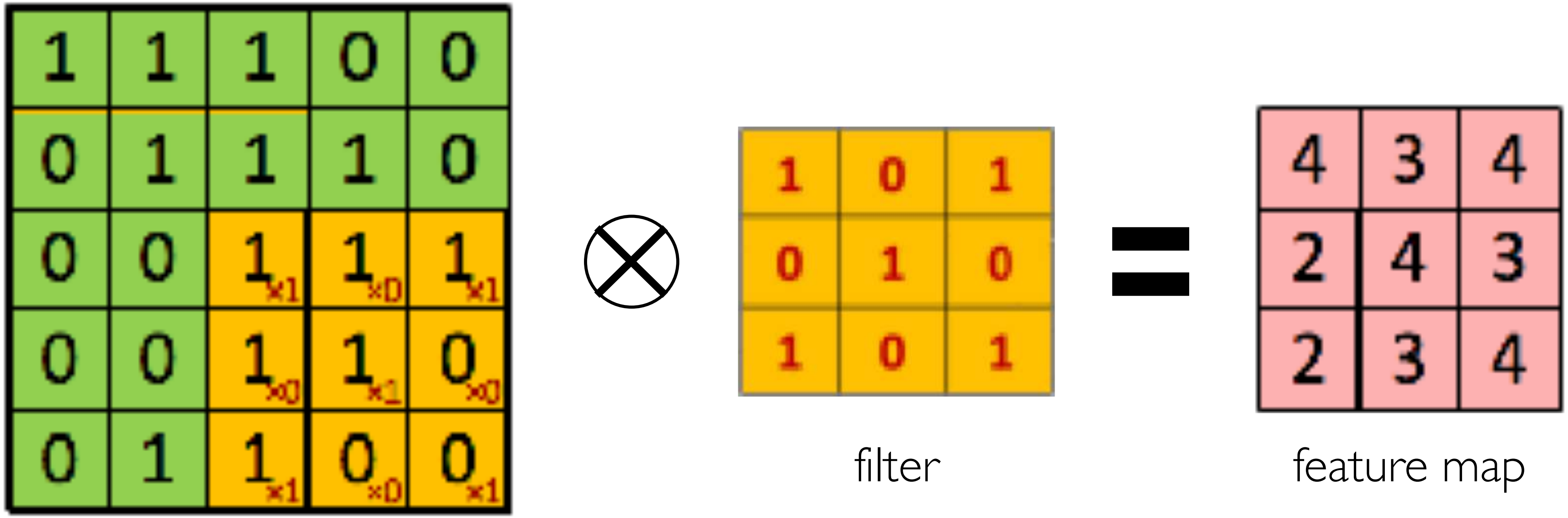
# The Convolution Operation

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

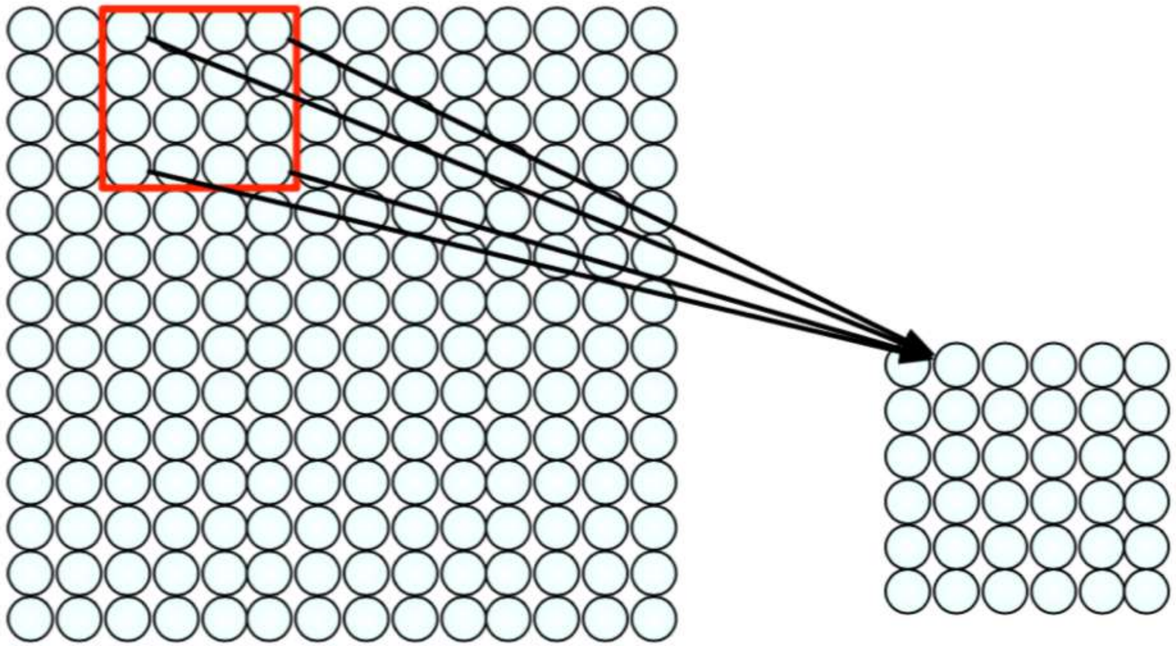
Original


Sharpen


Edge Detect


"Strong" Edge Detect

# Feature Extraction with Convolution



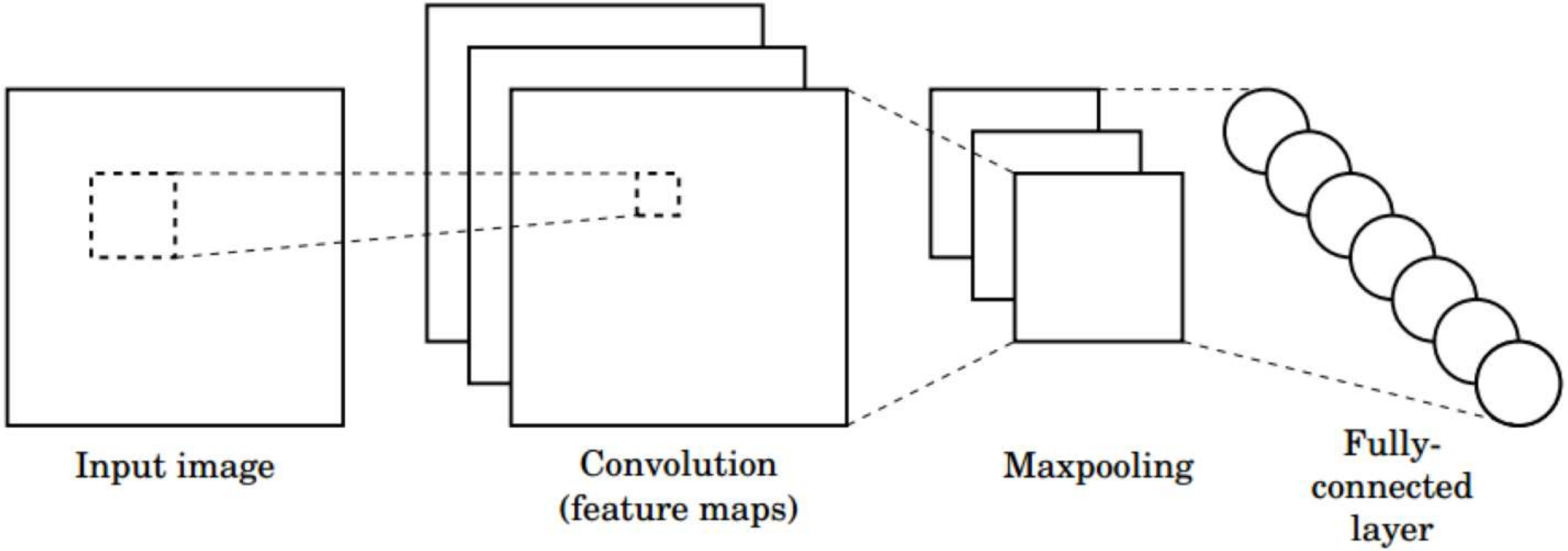
1) Apply a set of weights – a filter – to extract **local features**

2) Use **multiple filters** to extract different features

3) **Spatially share** parameters of each filter

# Convolutional Neural Networks (CNNs)

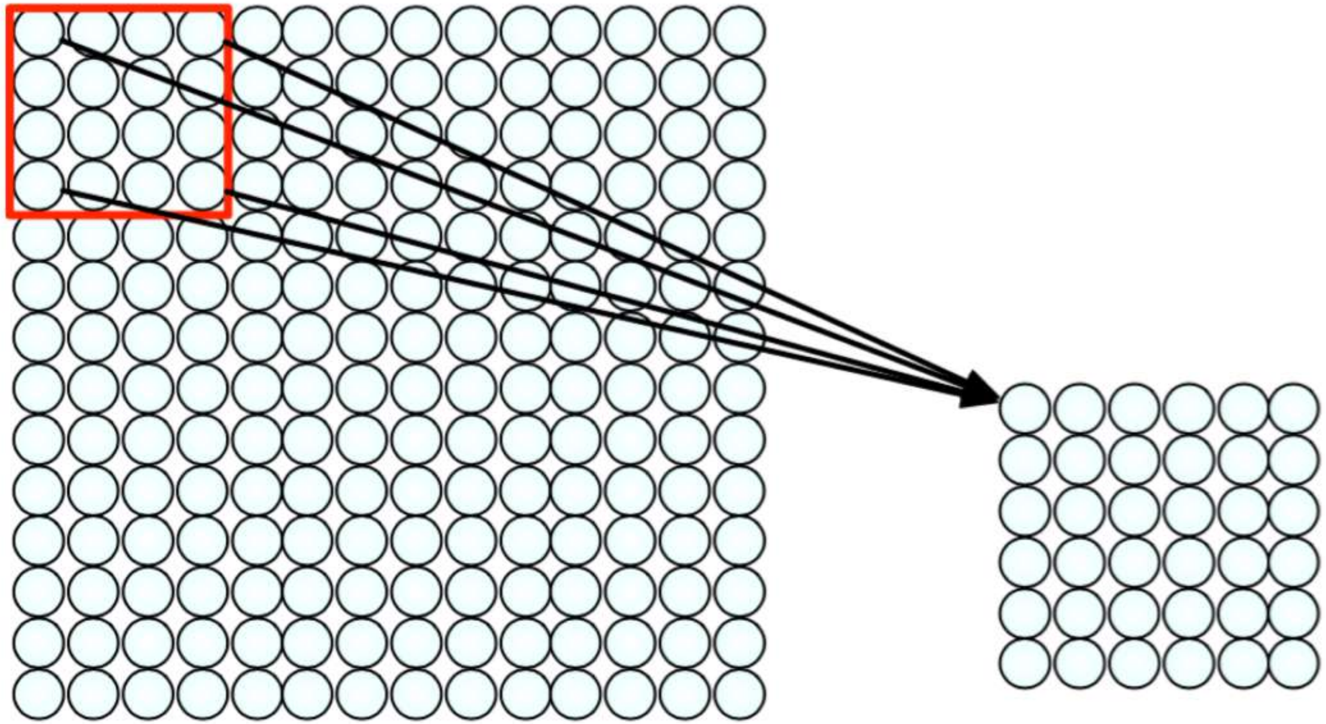
# CNNs for Classification




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.**

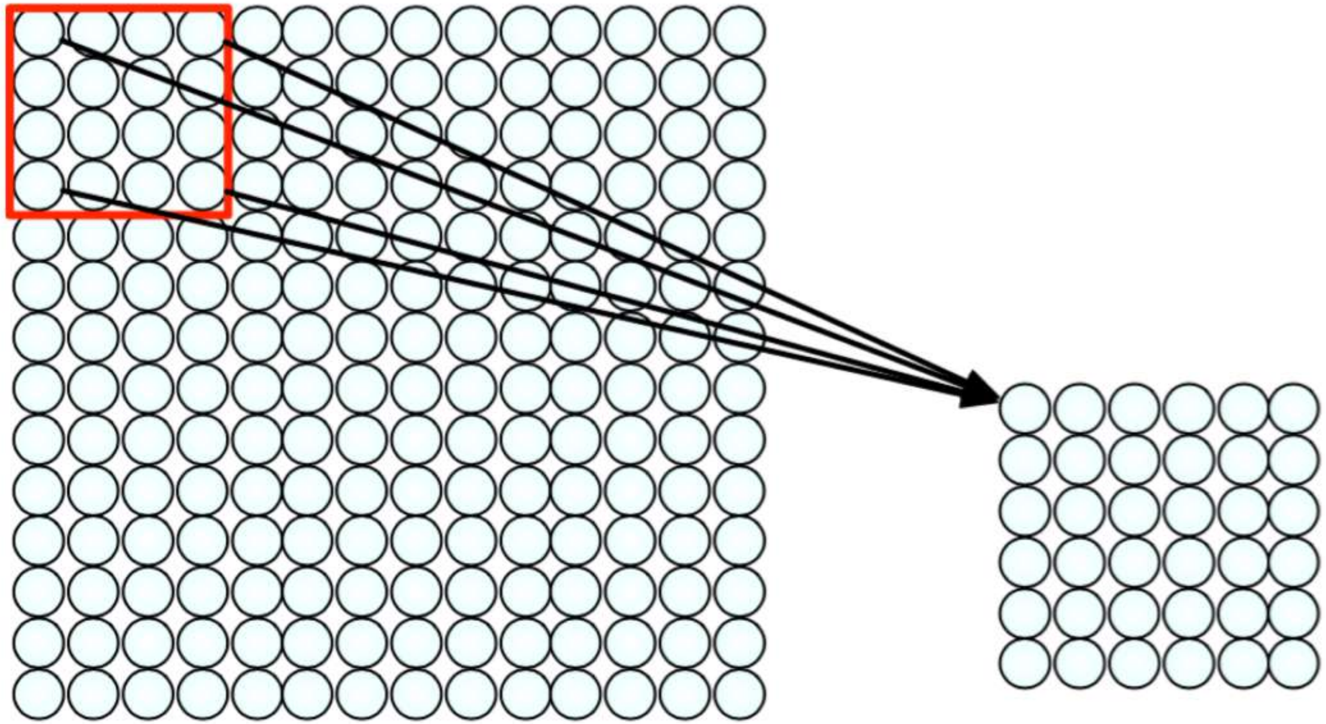
# Convolutional Layers: Local Connectivity



**For a neuron in hidden layer:**

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

# Convolutional Layers: Local Connectivity



**For a neuron in hidden layer:**

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

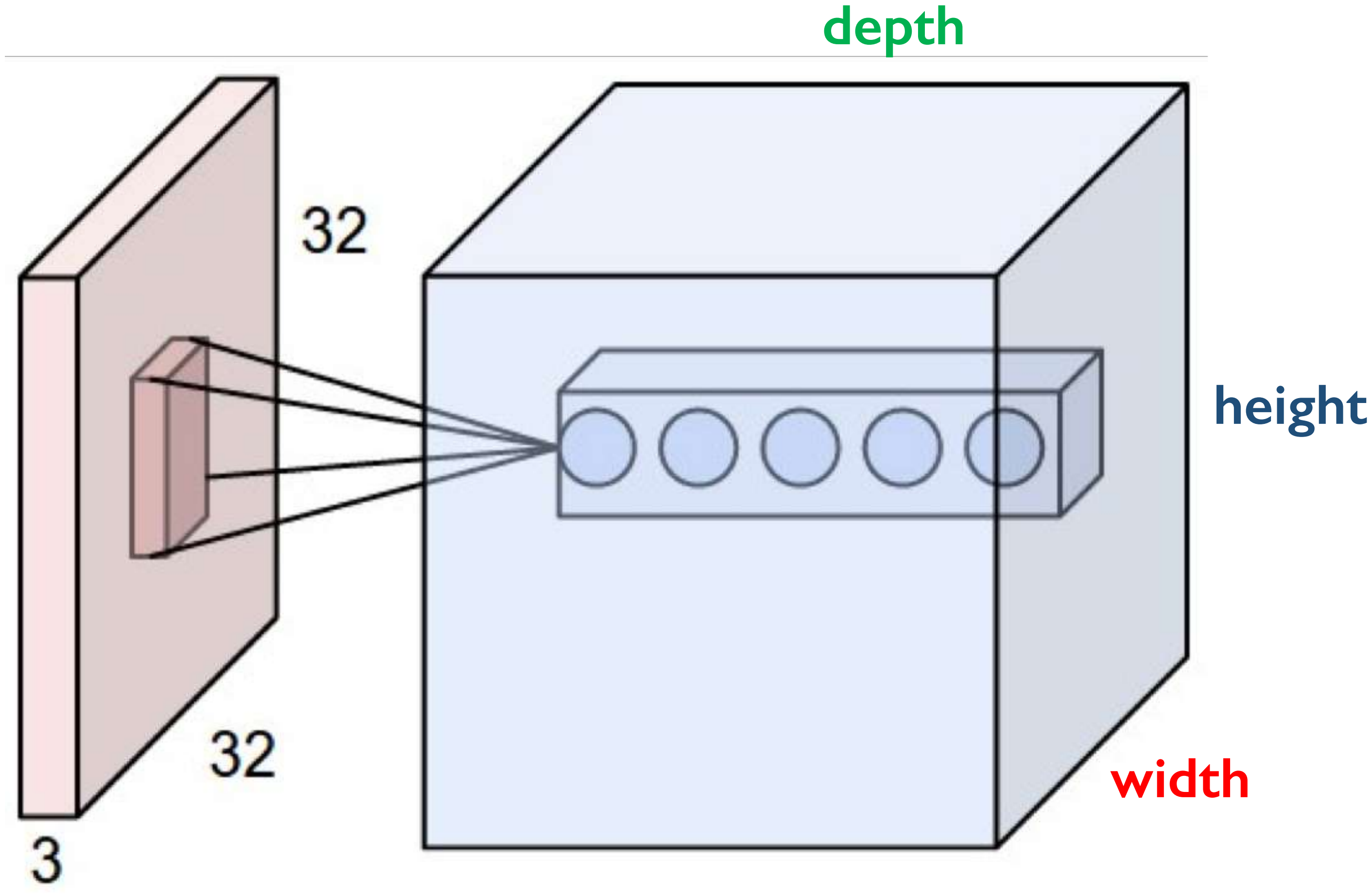
4x4 filter: matrix of weights $w_{ij}$

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

for neuron (p,q) in hidden layer

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

# CNNs: Spatial Arrangement of Output Volume




**Layer Dimensions:**

$h \; x \; w \; x \; d$

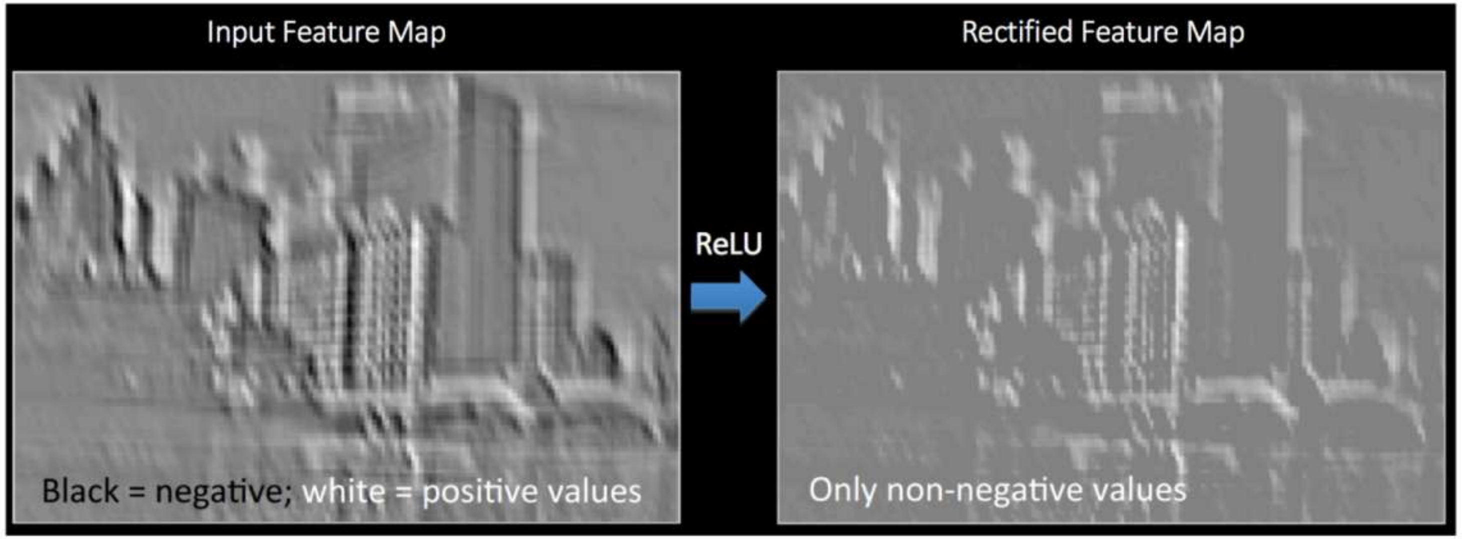
where h and w are spatial dimensions
d (depth) = number of filters

**Stride:**
Filter step size

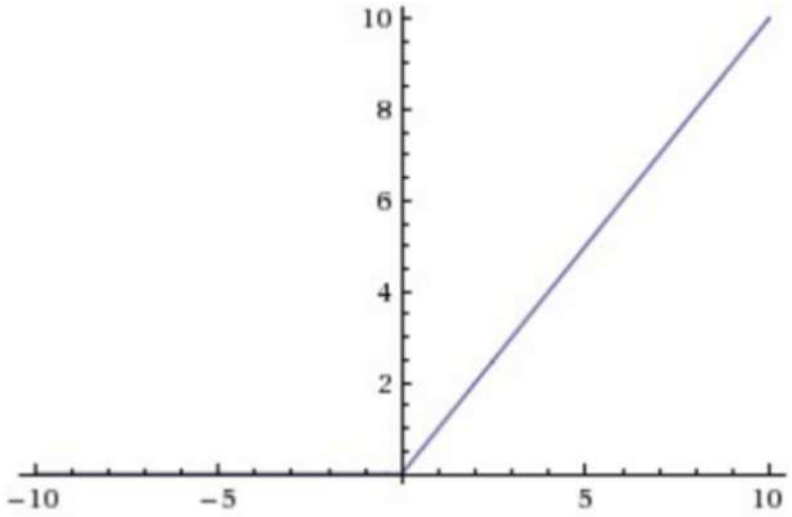
**Receptive Field:**
Locations in input image that
a node is path connected to

# 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!**

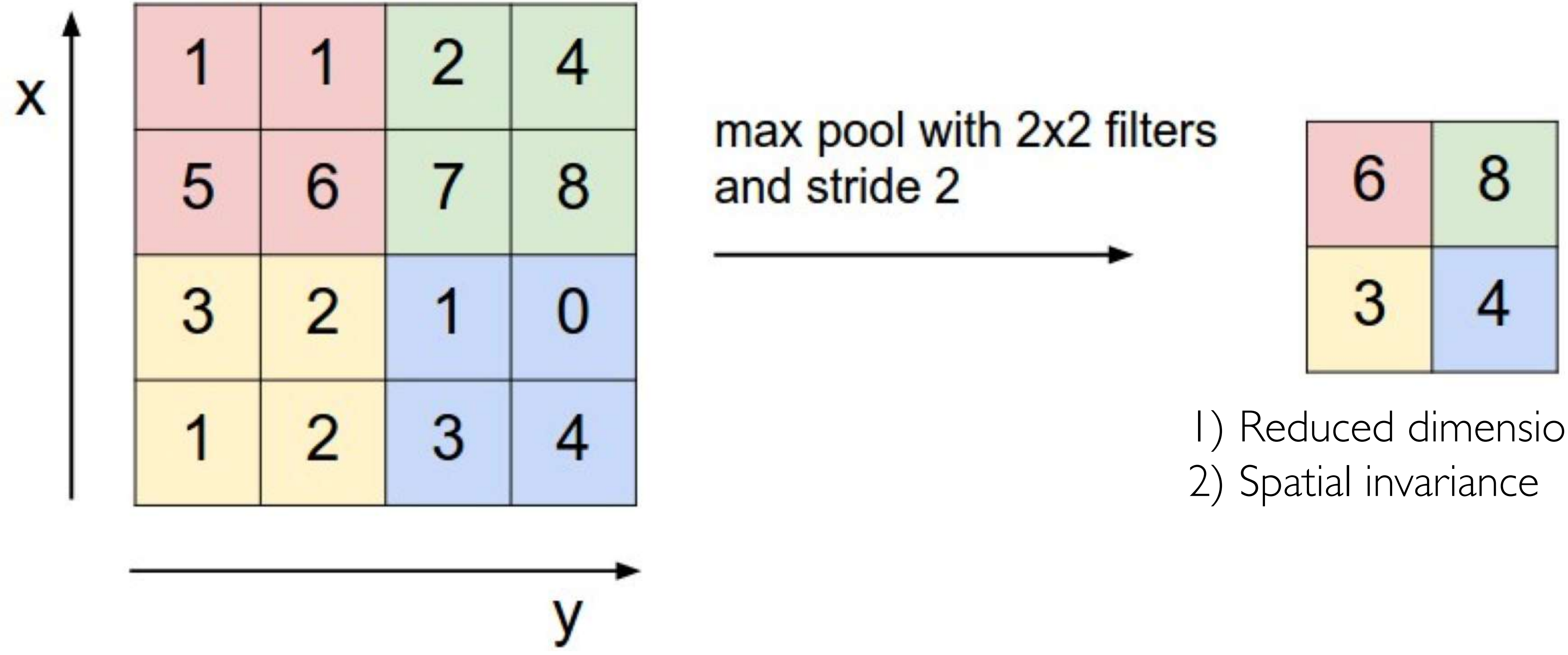



**Rectified Linear Unit (ReLU)**




$$g(z) = \max(0, z)$$

# Pooling

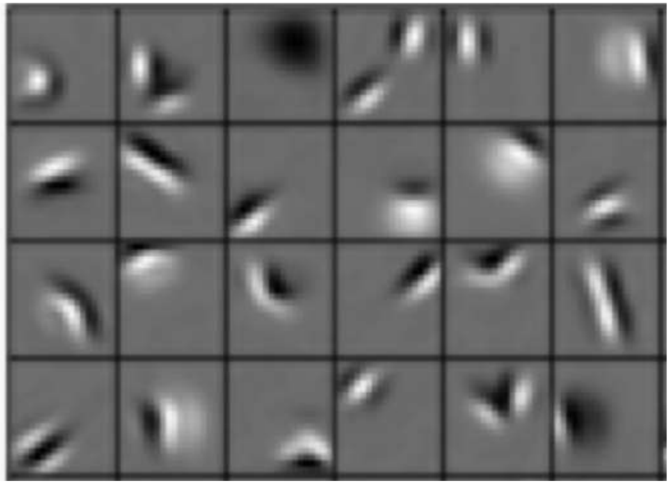



1) Reduced dimensionality
2) Spatial invariance

How else can we downsample and preserve spatial invariance?

# Representation Learning in Deep CNNs

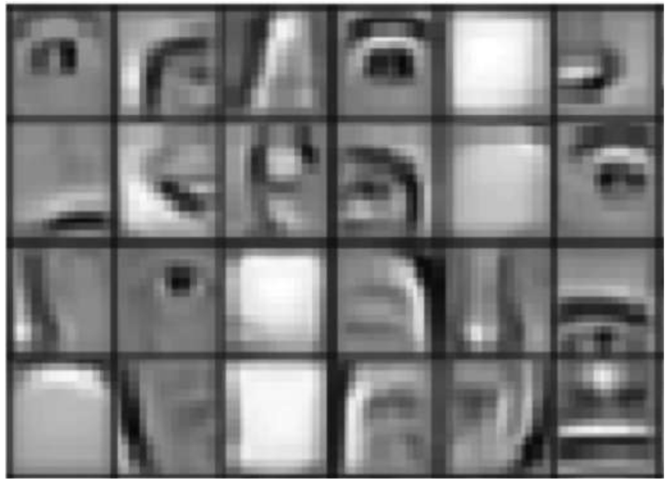
Low level features



Edges, dark spots

Conv Layer 1

Mid level features



Eyes, ears, nose

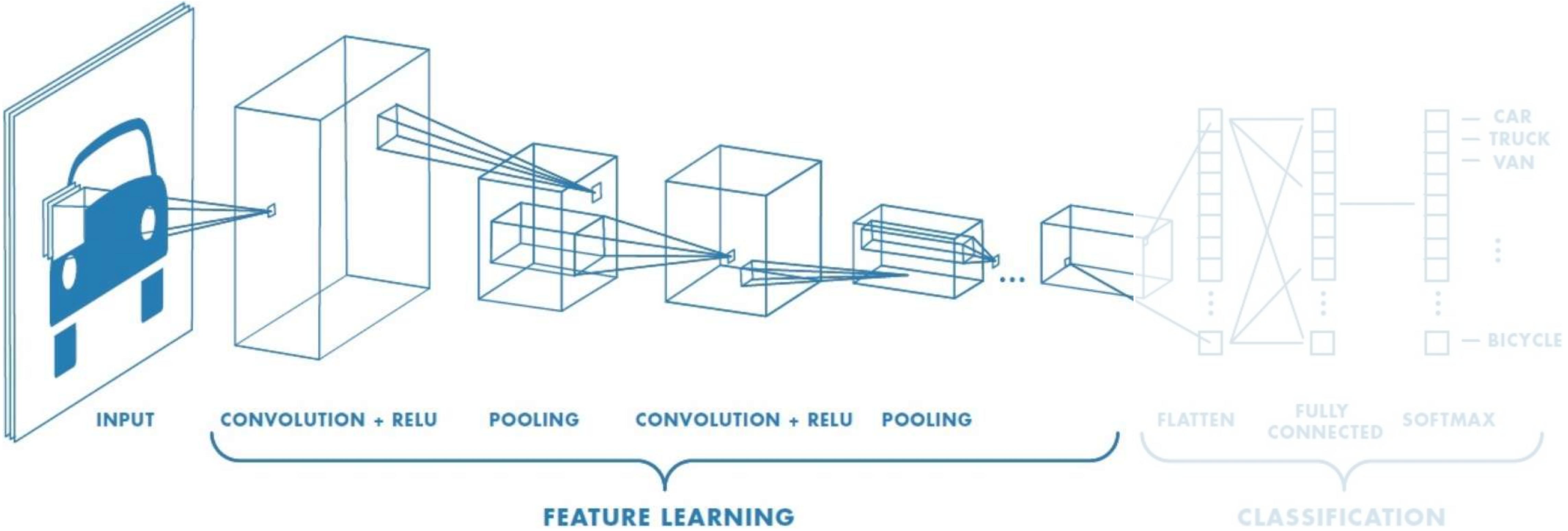
Conv Layer 2

High level features

Facial structure

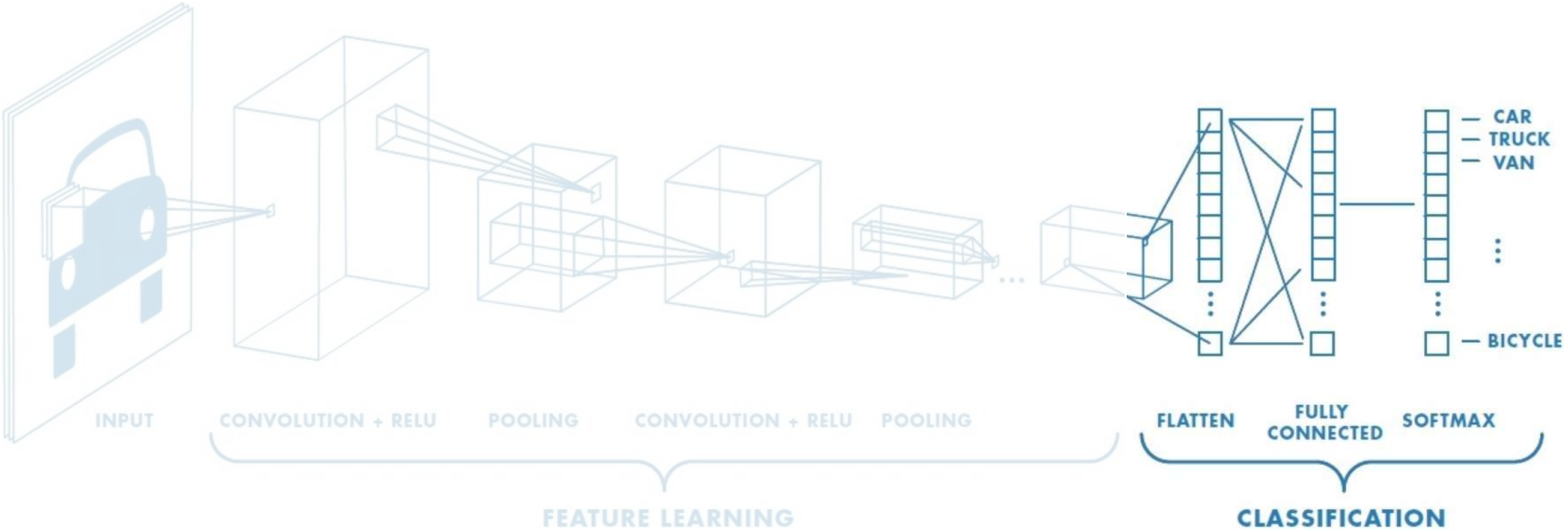
Conv Layer 3

# 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**

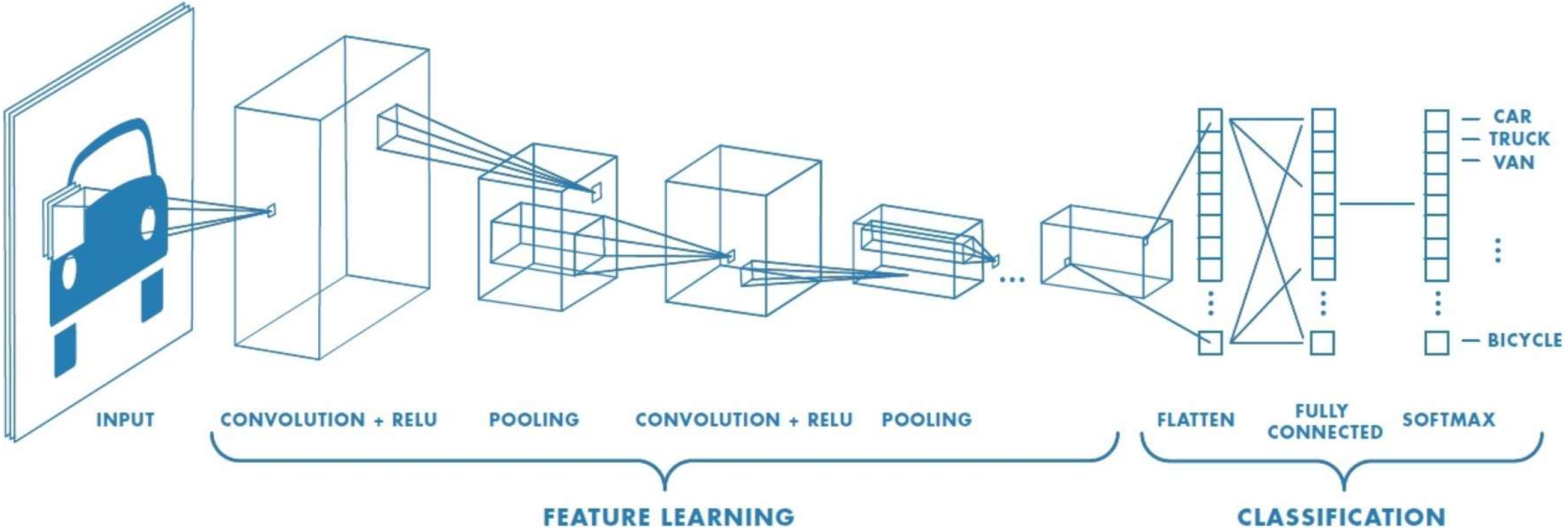
# CNNs for Classification: Class Probabilities




- 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

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

# 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"*

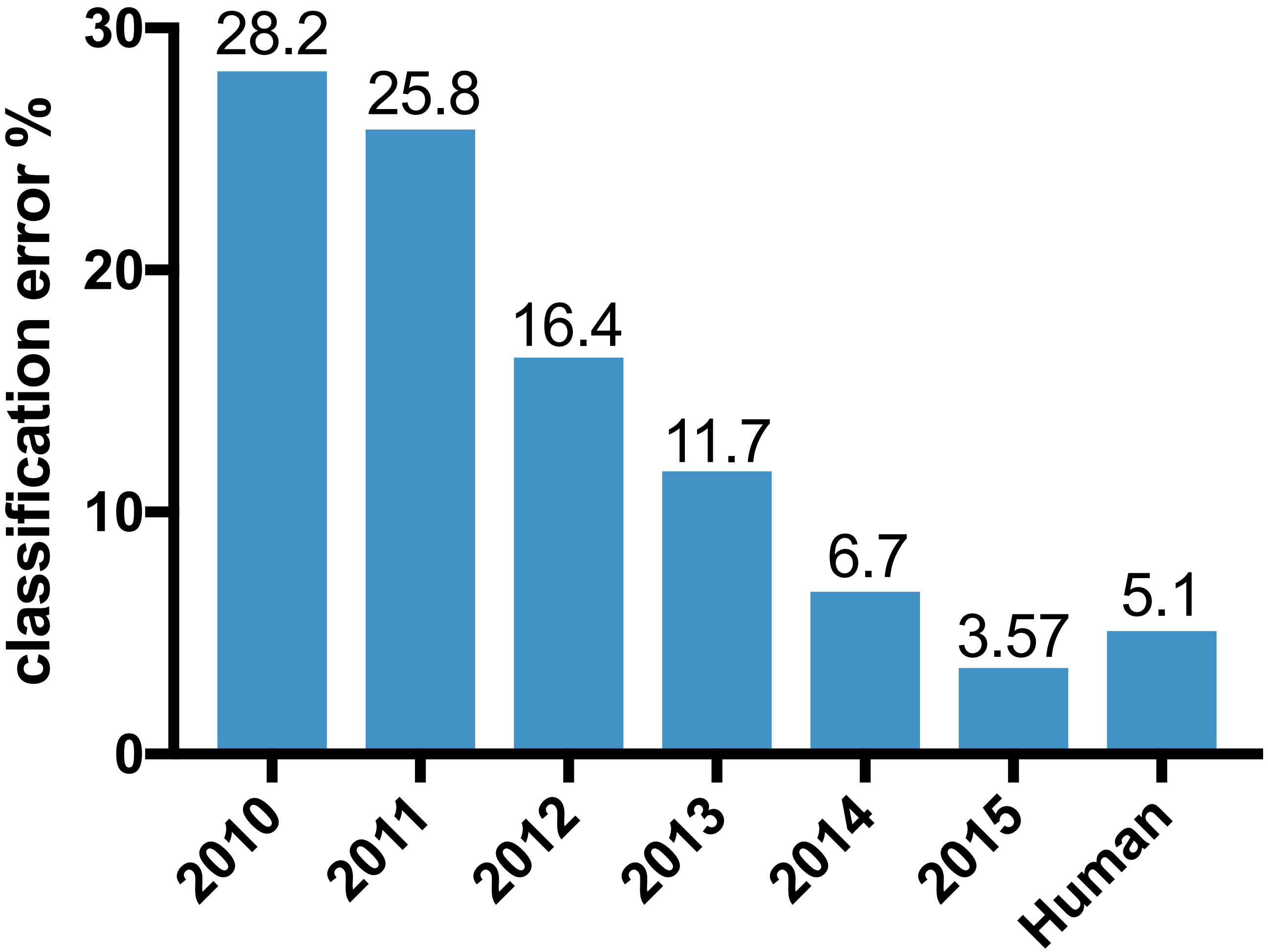
1409 pictures of bananas.

# ImageNet Challenge


**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

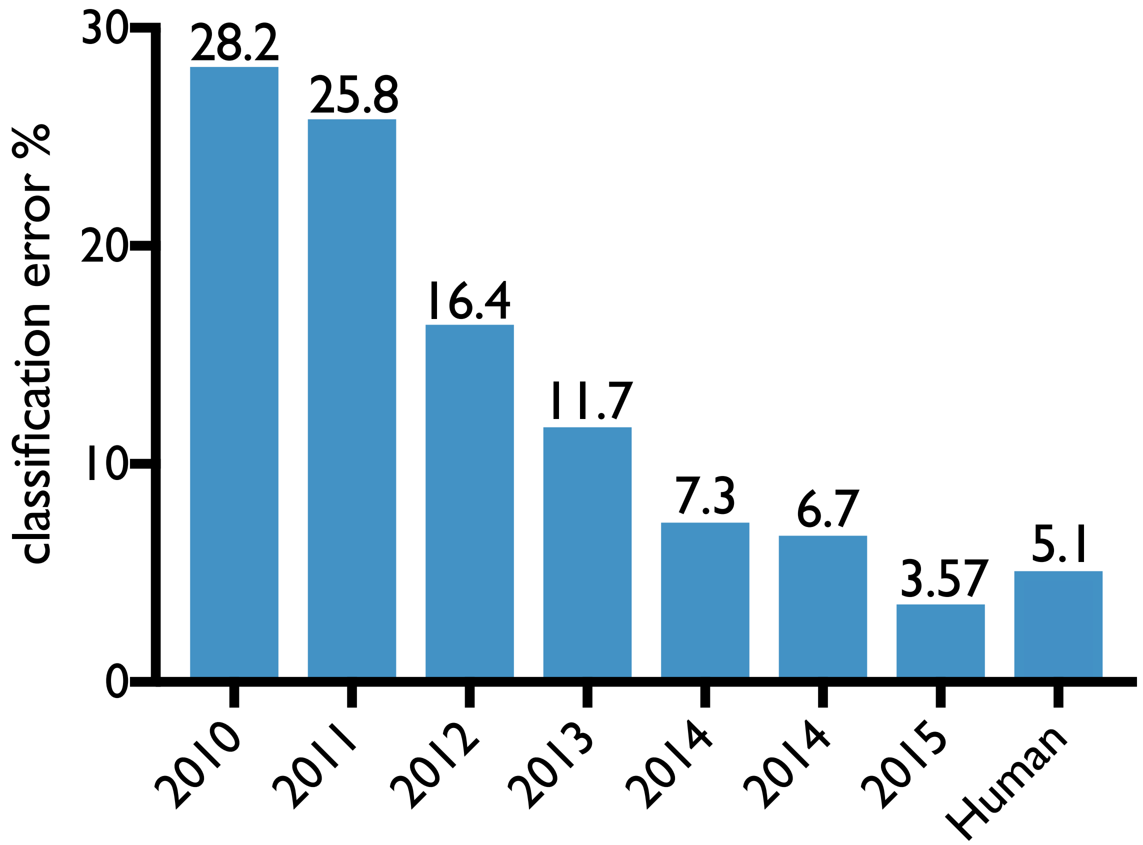
**2013: ZFNet**
- 8 layers, more filters

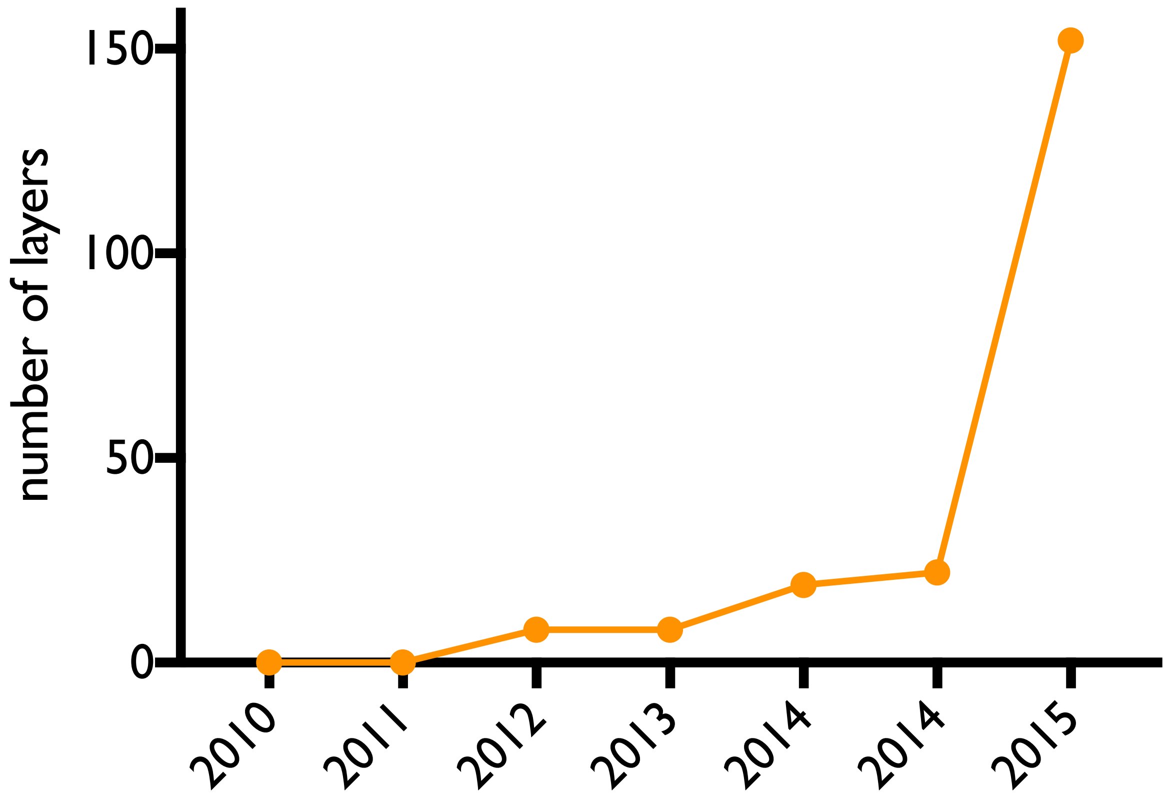
**2014: VGG**
- 19 layers

**2014: GoogLeNet**
- "Inception" modules
- 22 layers, 5million parameters

**2015: ResNet**
- 152 layers

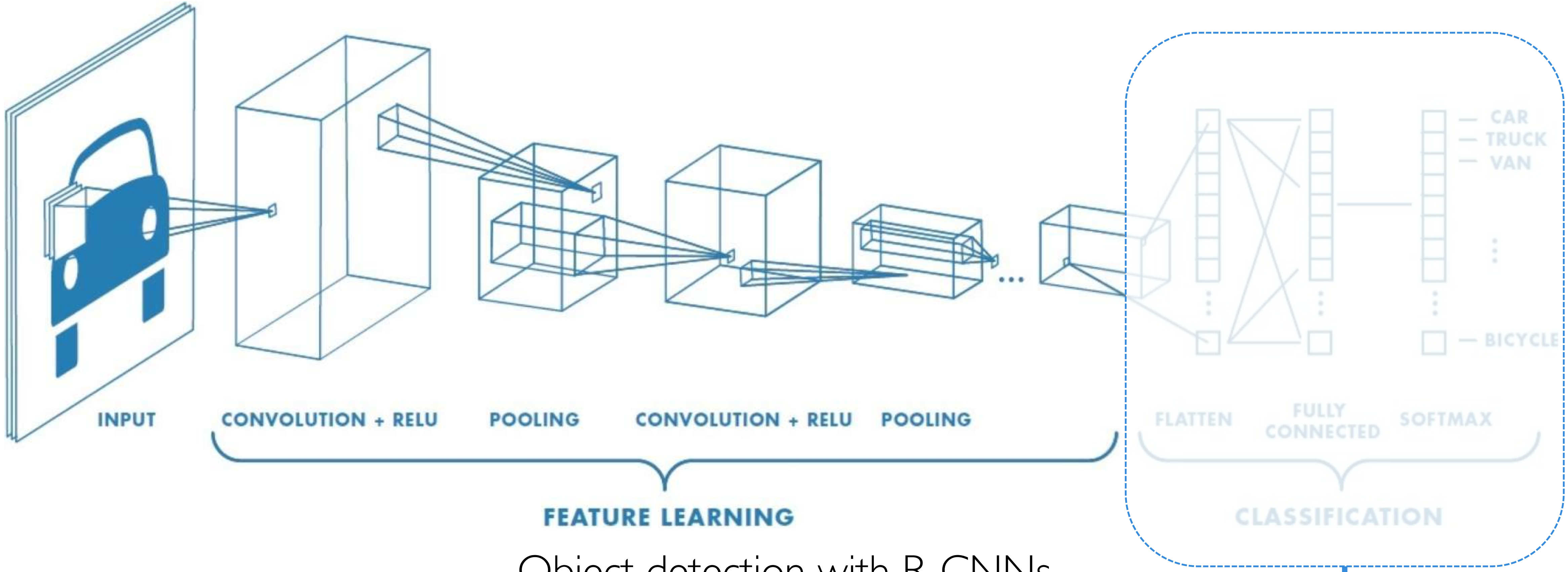
# ImageNet Challenge: Classification Task



# An Architecture for Many Applications

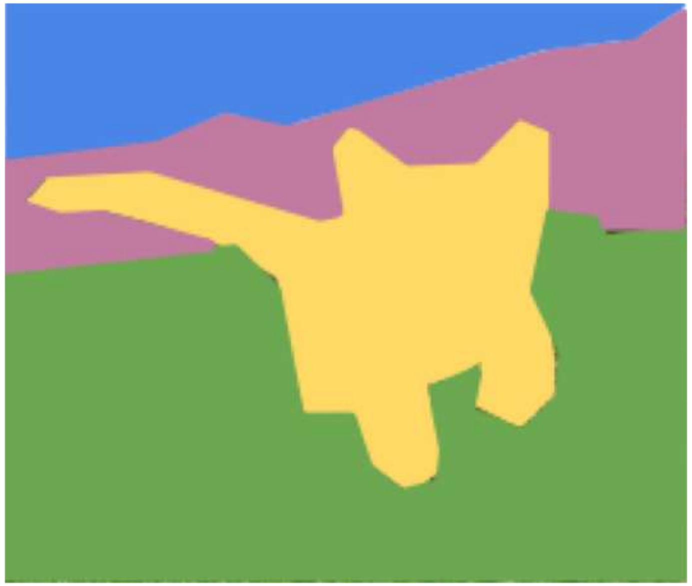
# An Architecture for Many Applications




Object detection with R-CNNs
Segmentation with fully convolutional networks
Image captioning with RNNs

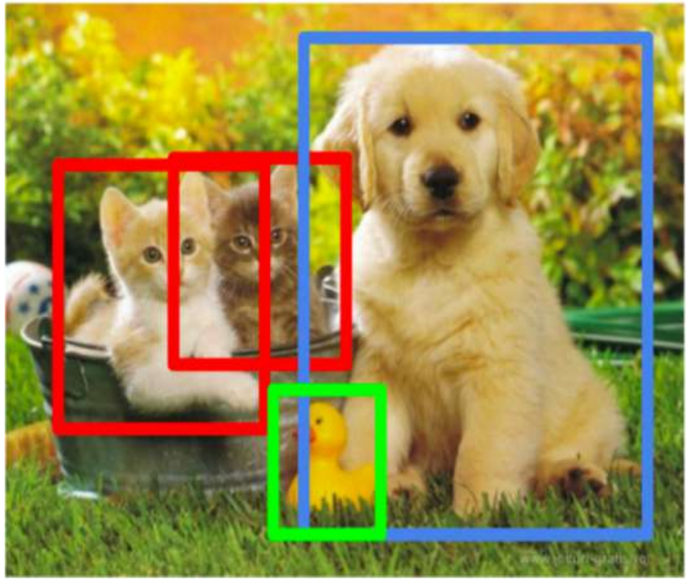
# Beyond Classification

## Semantic Segmentation



CAT

## Object Detection



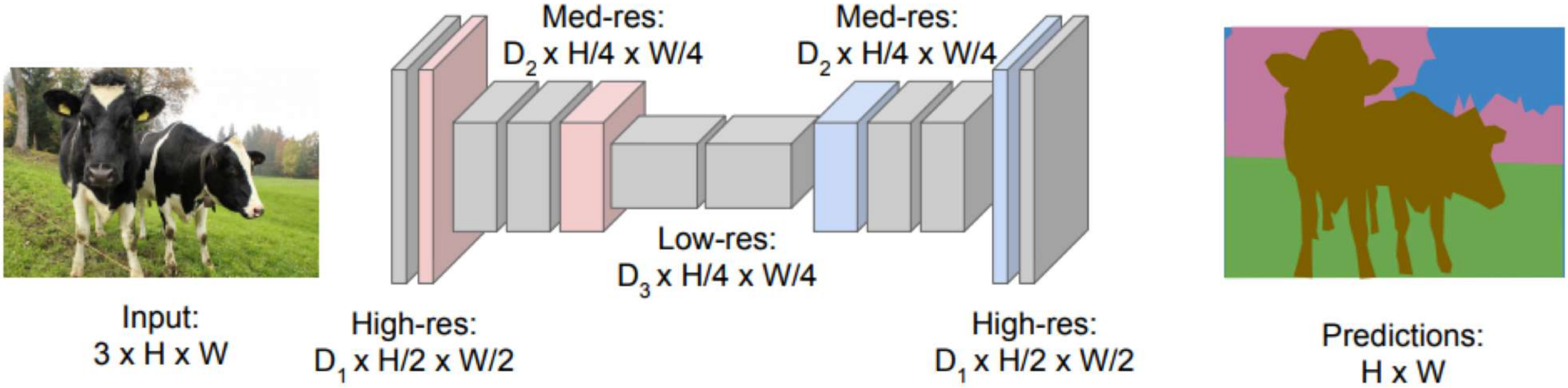
CAT, DOG, DUCK

## Image Captioning

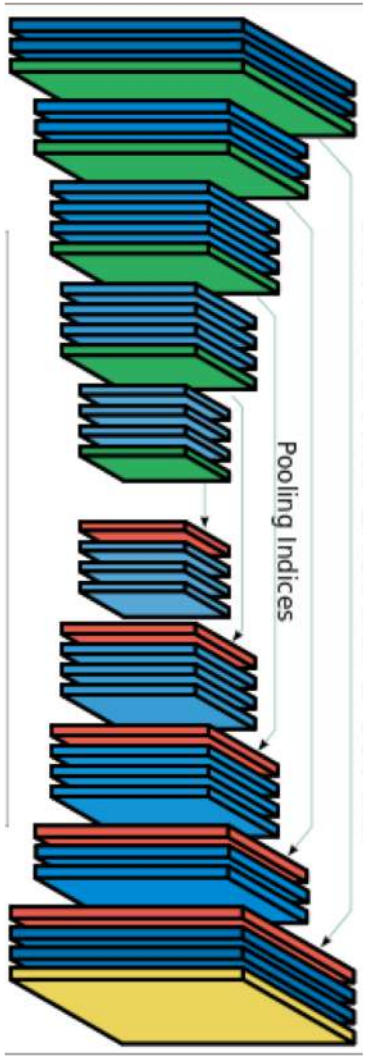
The cat is in the grass.

# Semantic Segmentation: FCNs

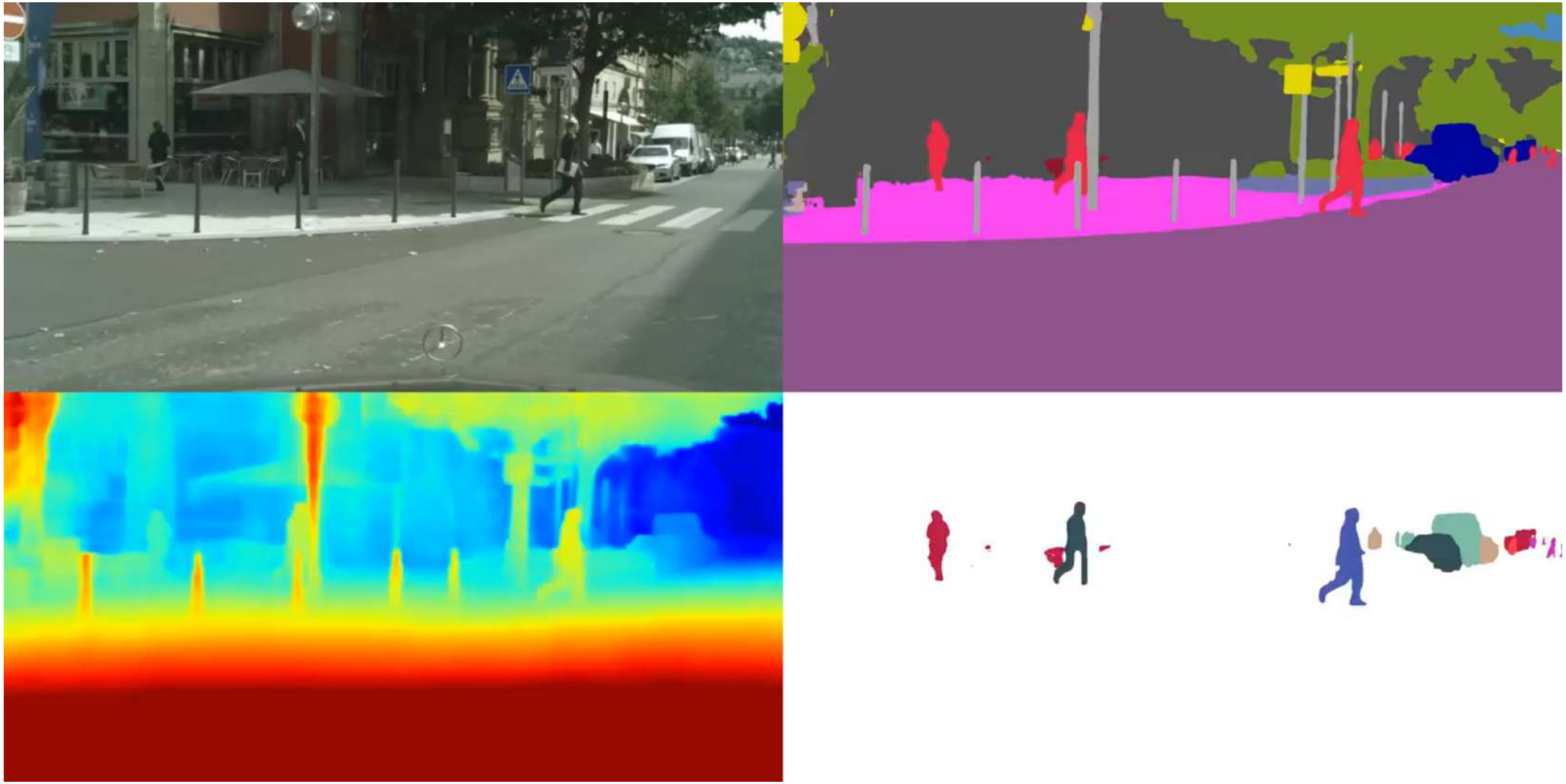
FCN: Fully Convolutional Network.
Network designed with all convolutional layers,
with **downsampling** and **upsampling** operations



# Driving Scene Segmentation

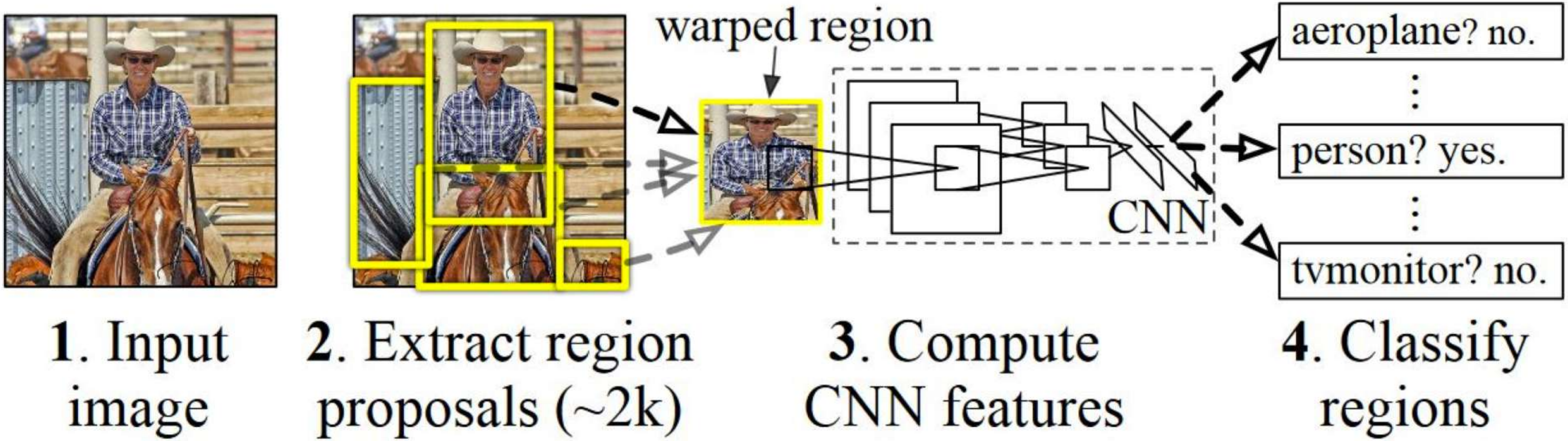



# Driving Scene Segmentation

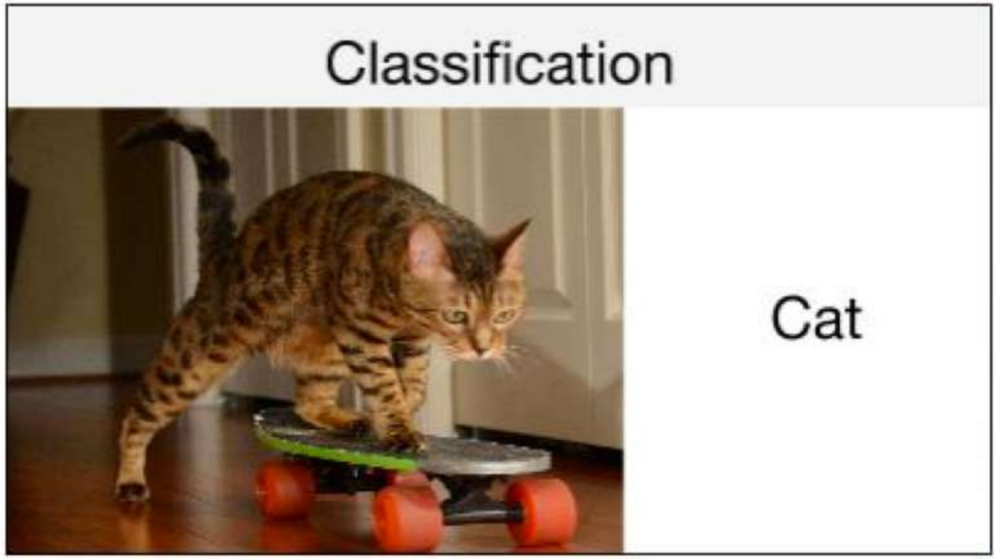


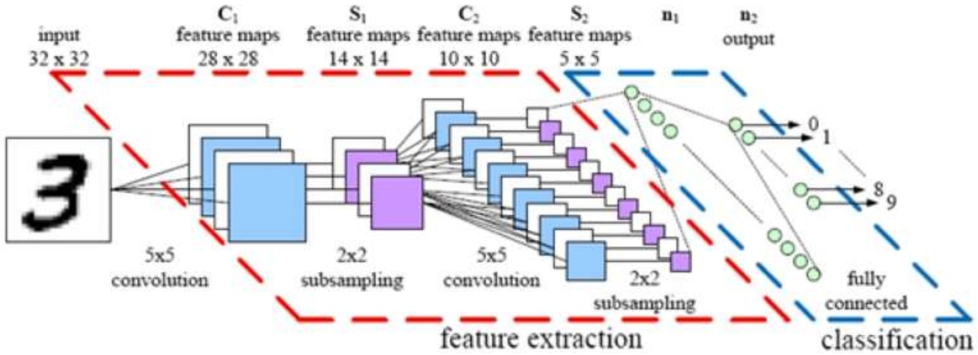
# Object Detection with R-CNNs

R-CNN: Find regions that we think have objects. Use CNN to classify.



# Image Captioning using RNNs



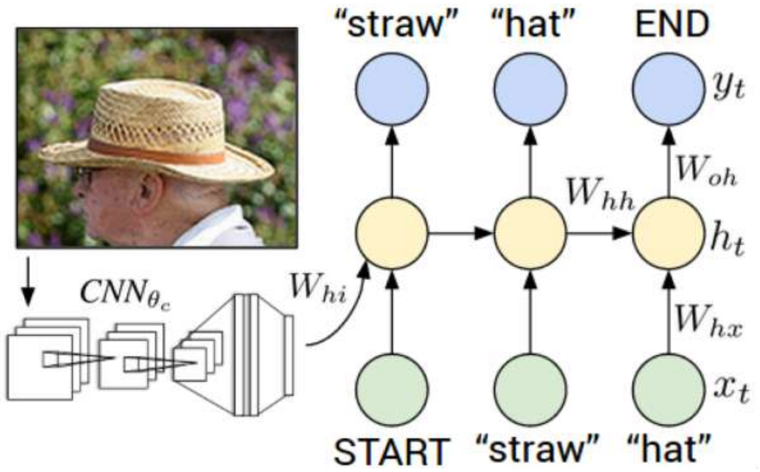



# Image Captioning using RNNs







# Deep Learning for Computer Vision: Impact and Summary

# Data, Data, Data

ImageNet:
22K categories. 14M images.

Airplane

Automobile

Bird

Cat

Deer

Dog

Frog

Horse

Ship

Truck

CIFAR-10

MNIST: handwritten digits

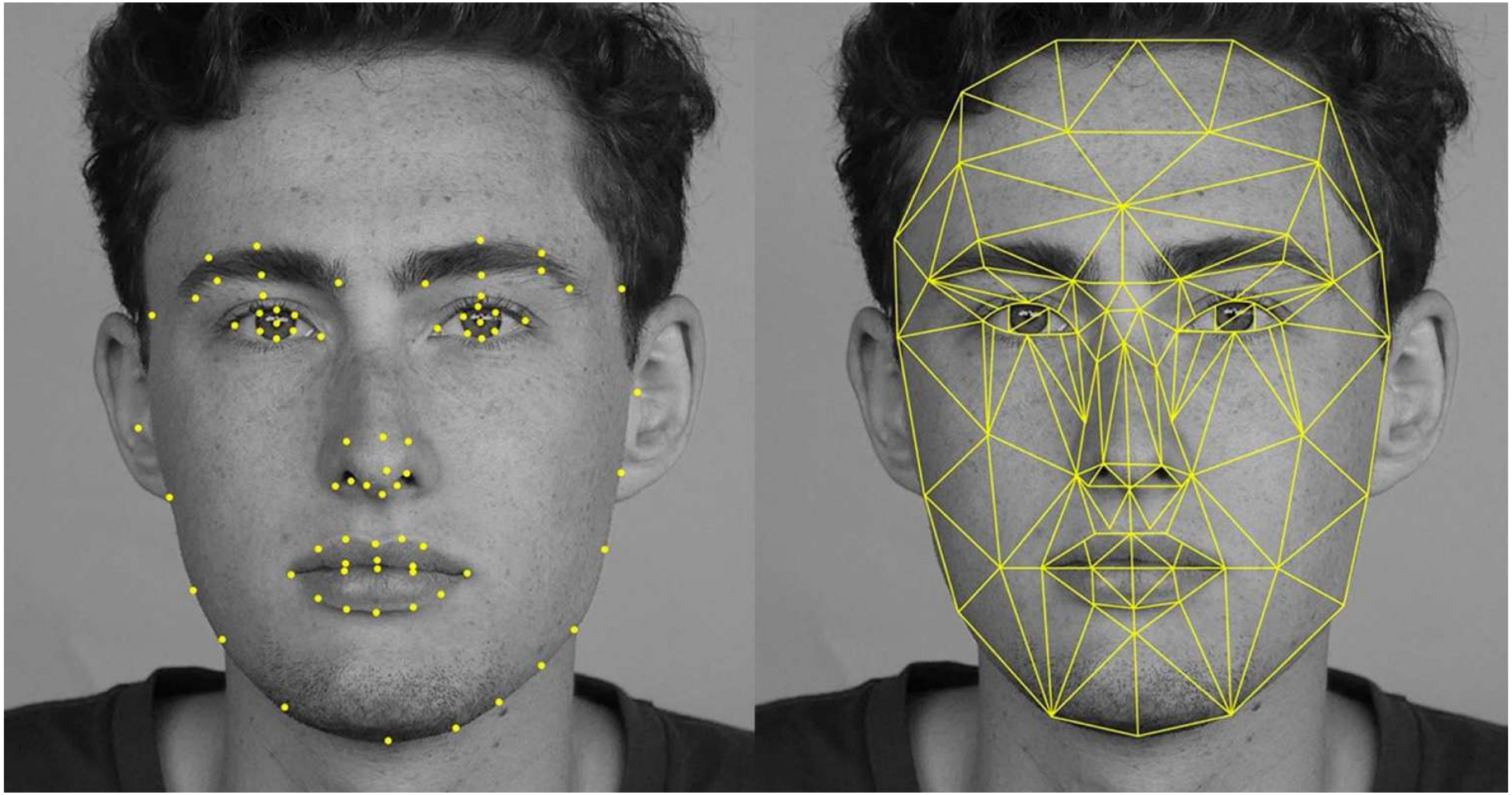
places
THE SCENE RECOGNITION DATABASE

places: natural scenes

# Deep Learning for Computer Vision: Impact

# Impact: Face Detection

6.S191 Lab!

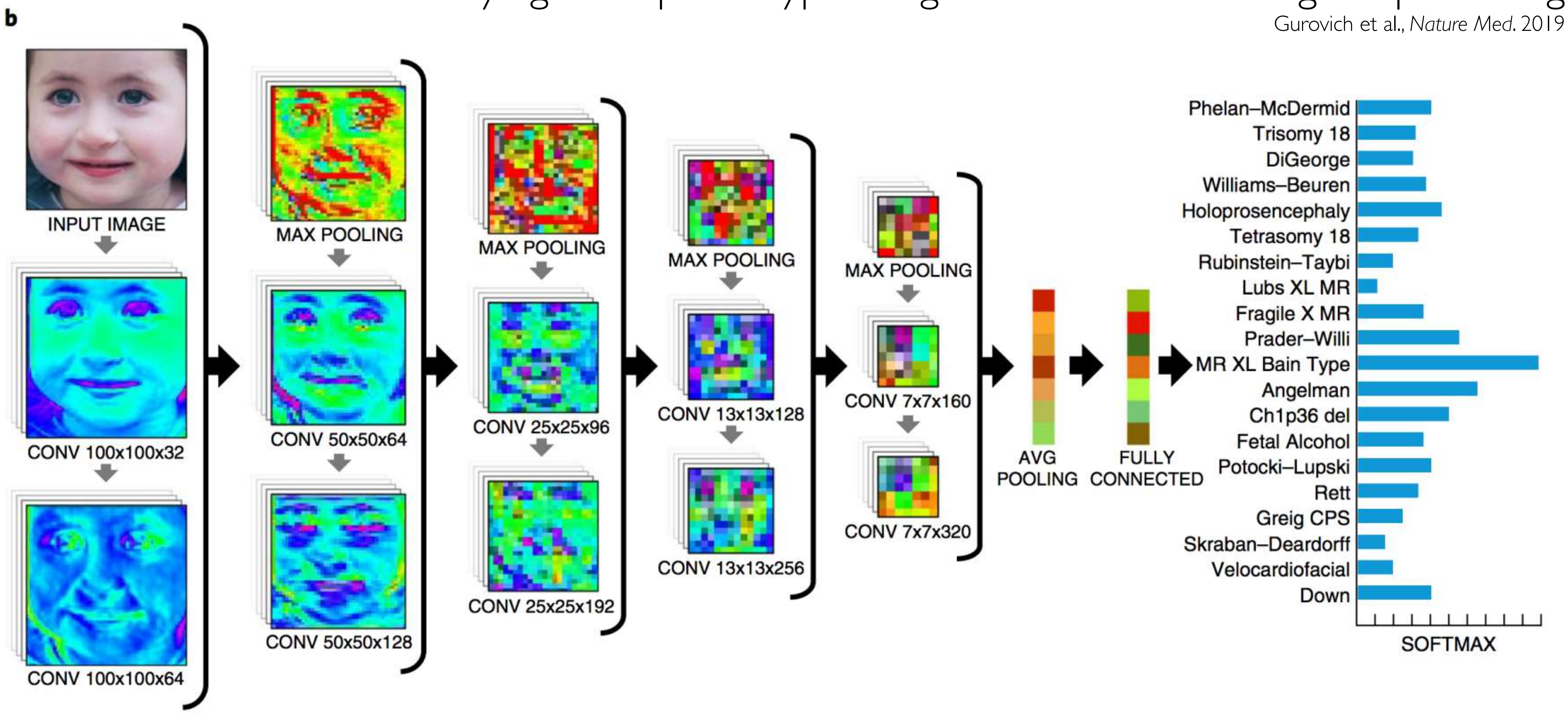


# Impact: Self-Driving Cars

# Impact: Healthcare

Identifying facial phenotypes of genetic disorders using deep learning

Gurovich et al., *Nature Med.* 2019



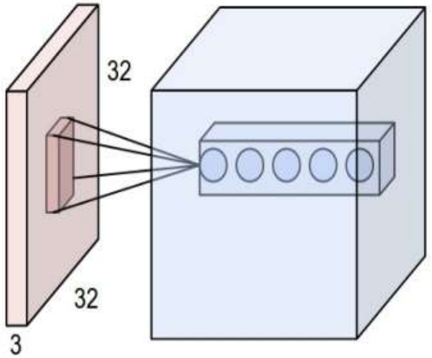
# Deep Learning for Computer Vision: Summary

## Foundations

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

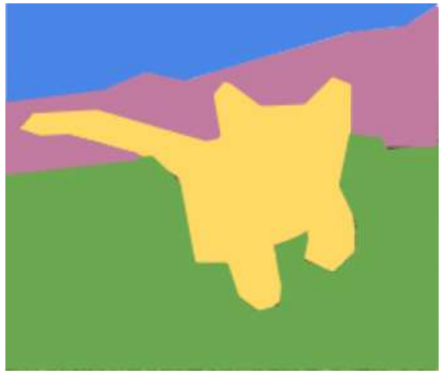

## CNNs

- CNN architecture
- Application to classification
- ImageNet




## Applications

- Segmentation, object detection, image captioning
- Visualization



# References

goo.gl/hbLkF6

End of Slides