Deep Learning for Computer Vision
MIT 6.S191

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Vision: Evolutionary Origins

Vision: 540 million years of data

vs.

Bipedal movement: 230+ million years of data

Human language: ~100 thousand years of data

Opabinia, 540 mil. years ago

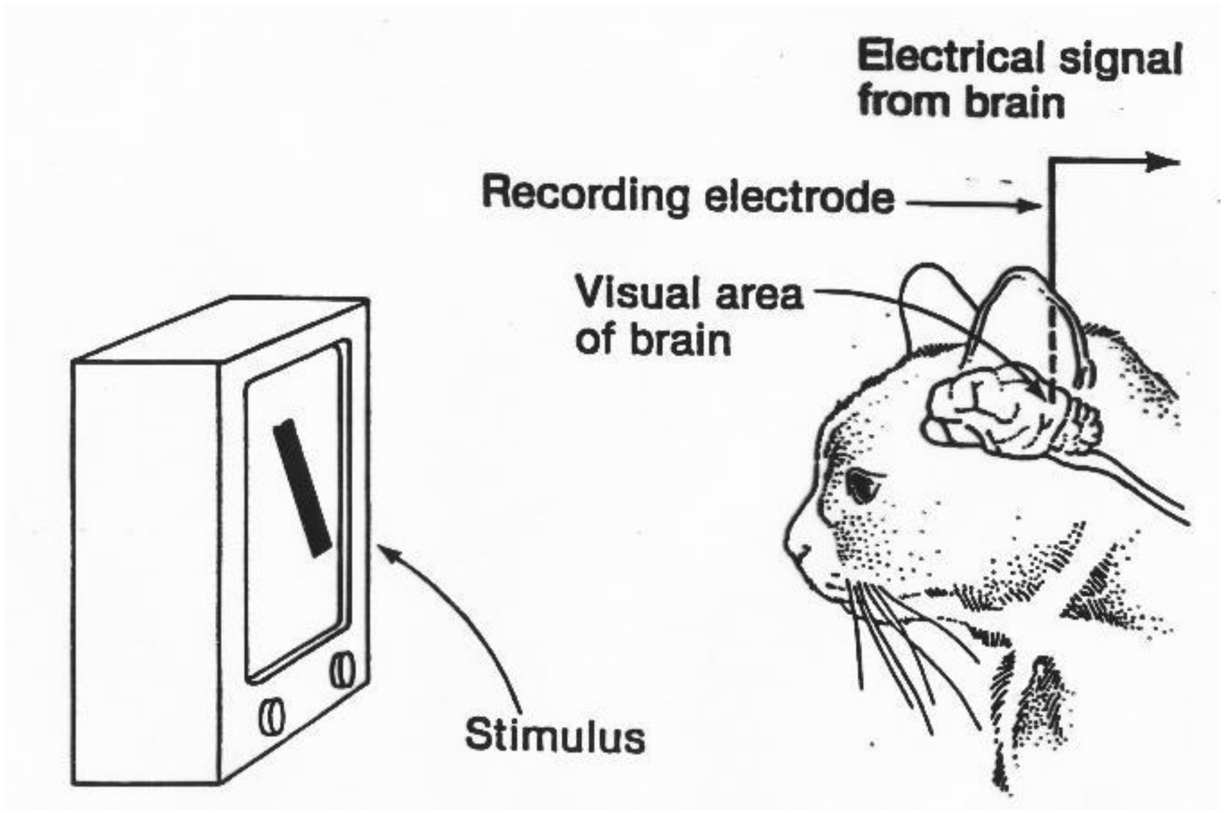
Can we understand neural basis of vision?

How is visual information processed?

Can we use that structure to inform computer vision?

Hubel & Wiesel, Harvard. 1960s

The Visual Cortex

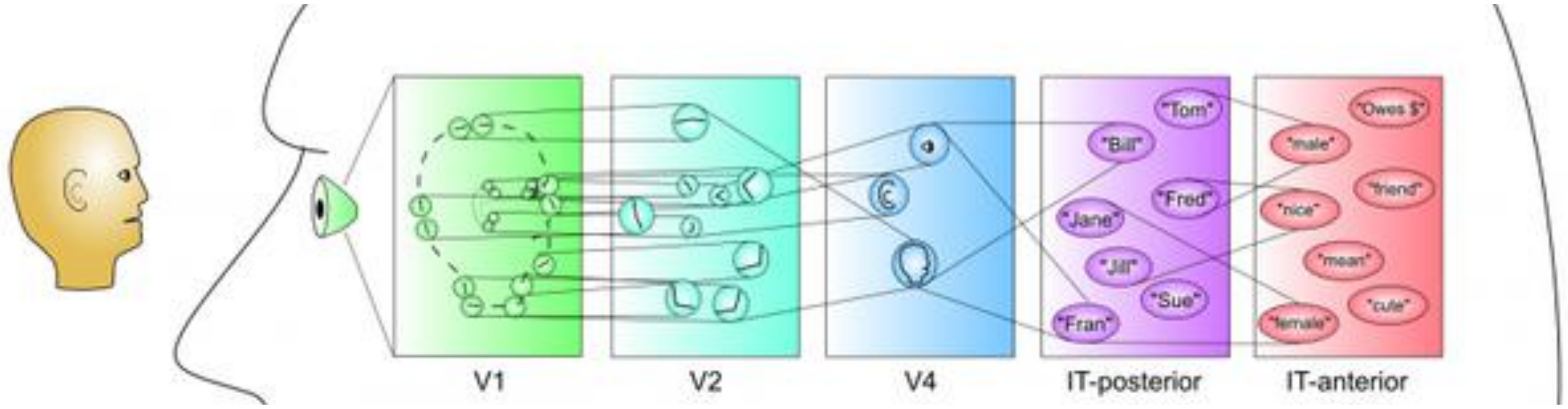


1) Spatial Invariance

2) Receptive Field

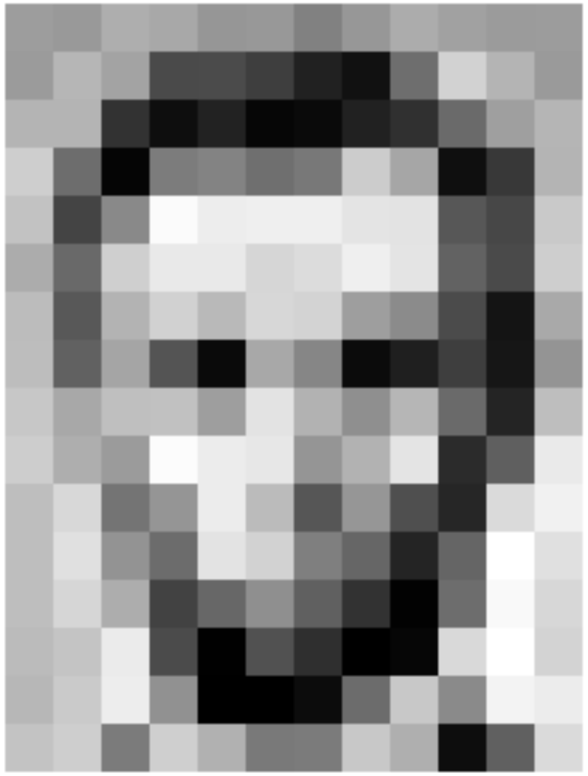
3) Hierarchy

The Visual Cortex

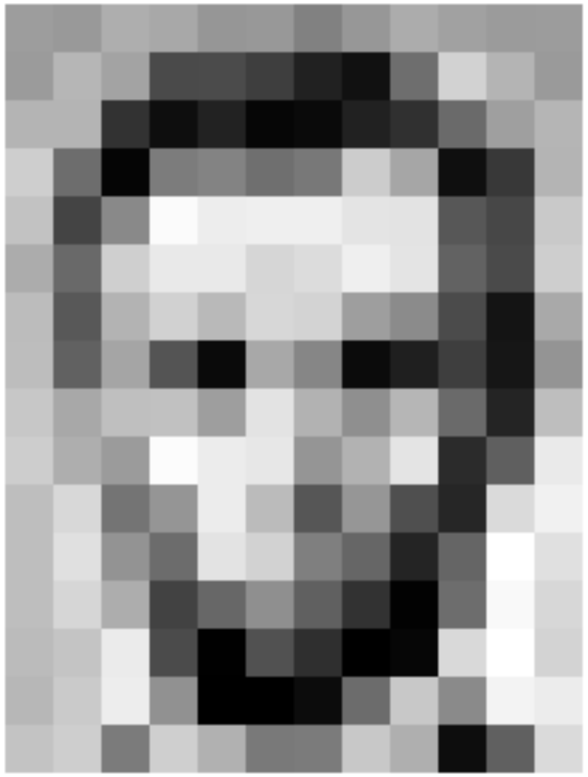


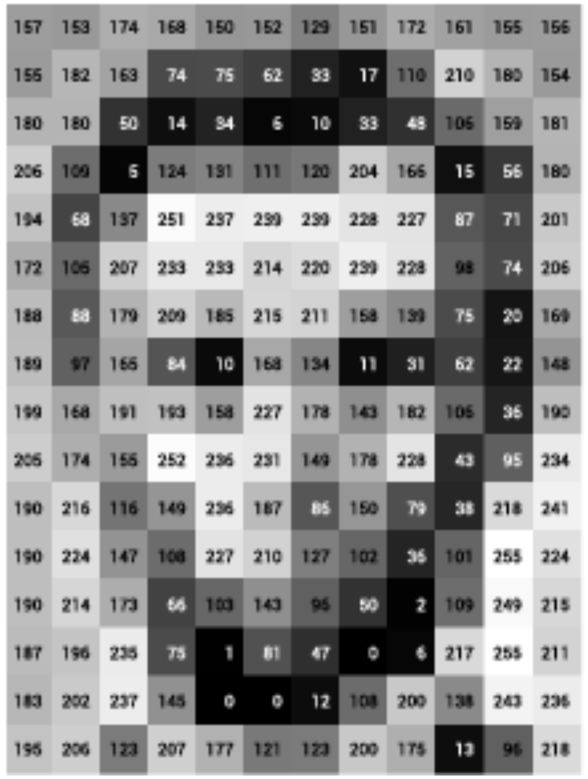
What Computers “See”

Images Are Numbers



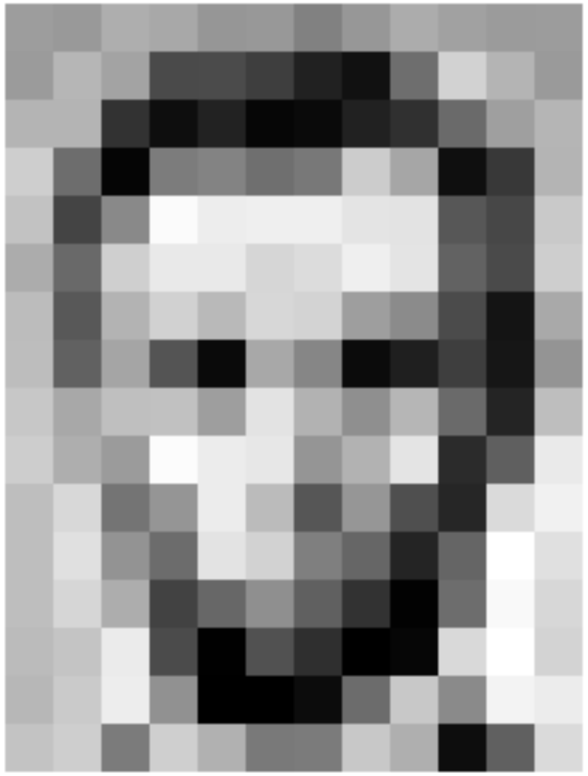
Images Are Numbers

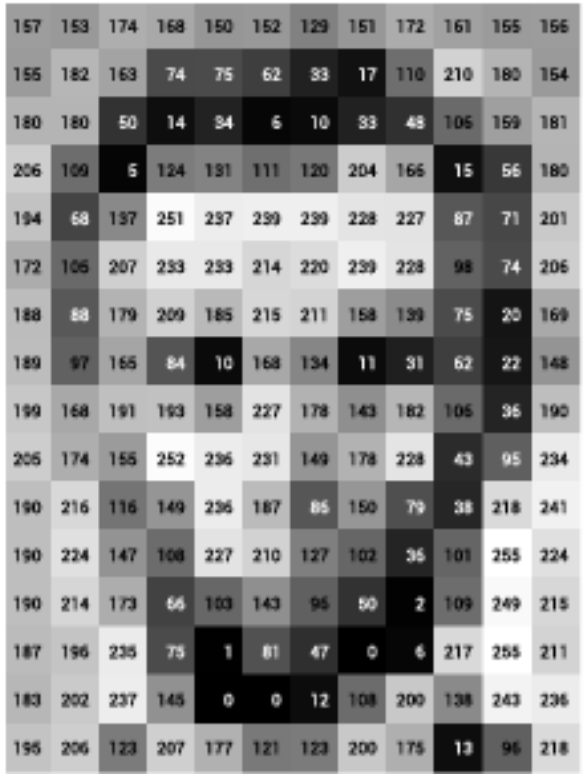




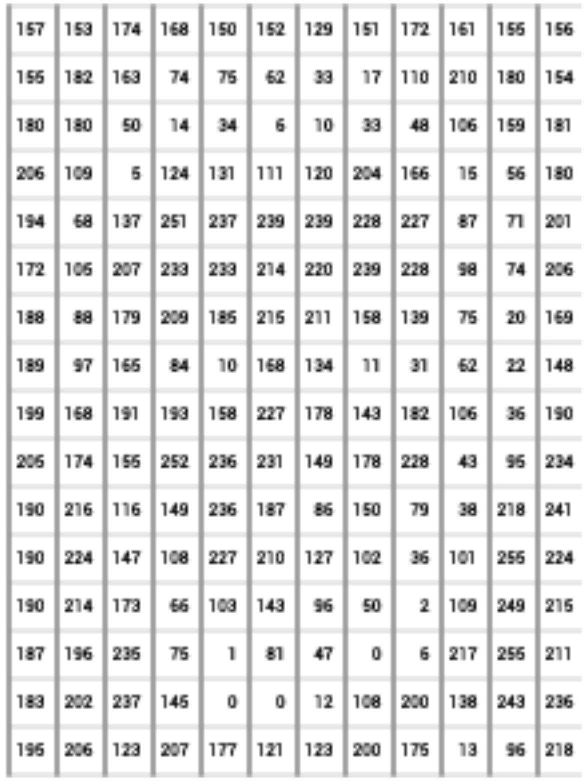
157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	33	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	109	5	124	131	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	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





What the computer sees



157	153	174	168	150	152	129	151	172	161	155	156
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190	224	147	108	227	210	127	102	36	101	255	224
190	214	173	66	103	143	96	50	2	109	249	215
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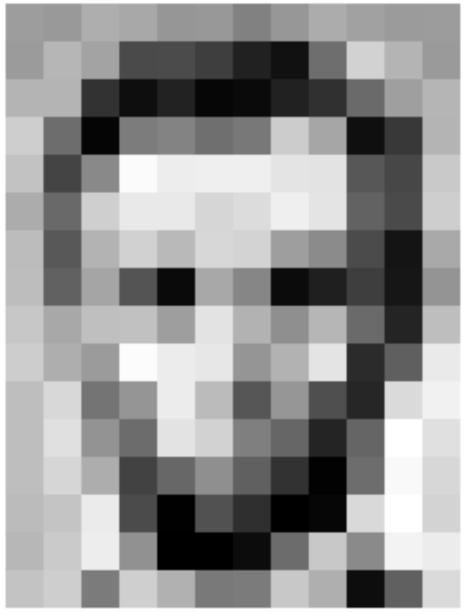
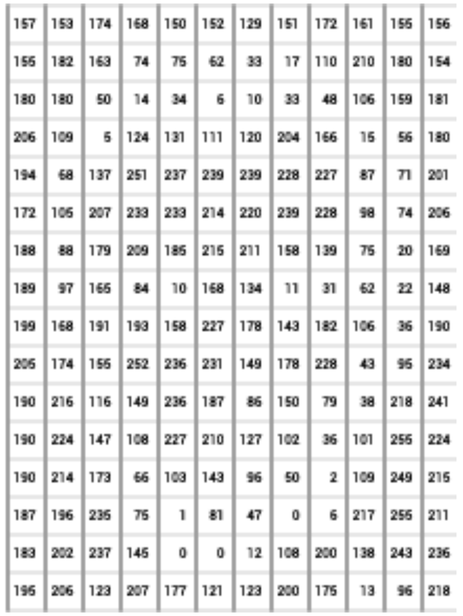
An image is just a matrix of numbers [0,255]!
i.e., 1080x1080x3 for an RGB image

Tasks in Computer Vision



Input Image



157	153	174	168	150	152	129	151	172	161	155	156
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Pixel Representation

$\xrightarrow{\qquad}$ $\xrightarrow[\text{classification}]{\qquad}$

Lincoln	0.8
Washington	0.1
Jefferson	0.05
Obama	0.05

- **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

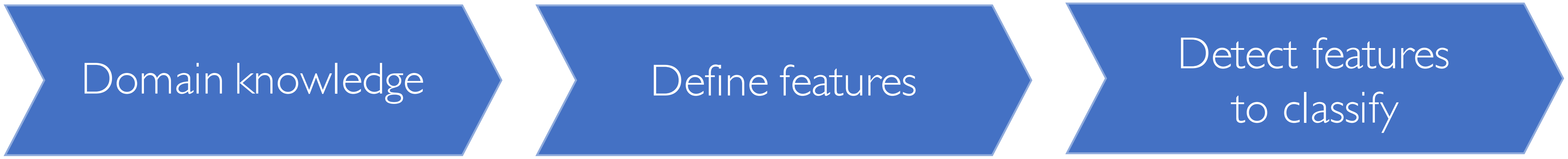
Let's identify key features in each image category

Nose,
Eyes,
Mouth

Wheels,
License Plate,
Headlights

Door,
Windows,
Steps

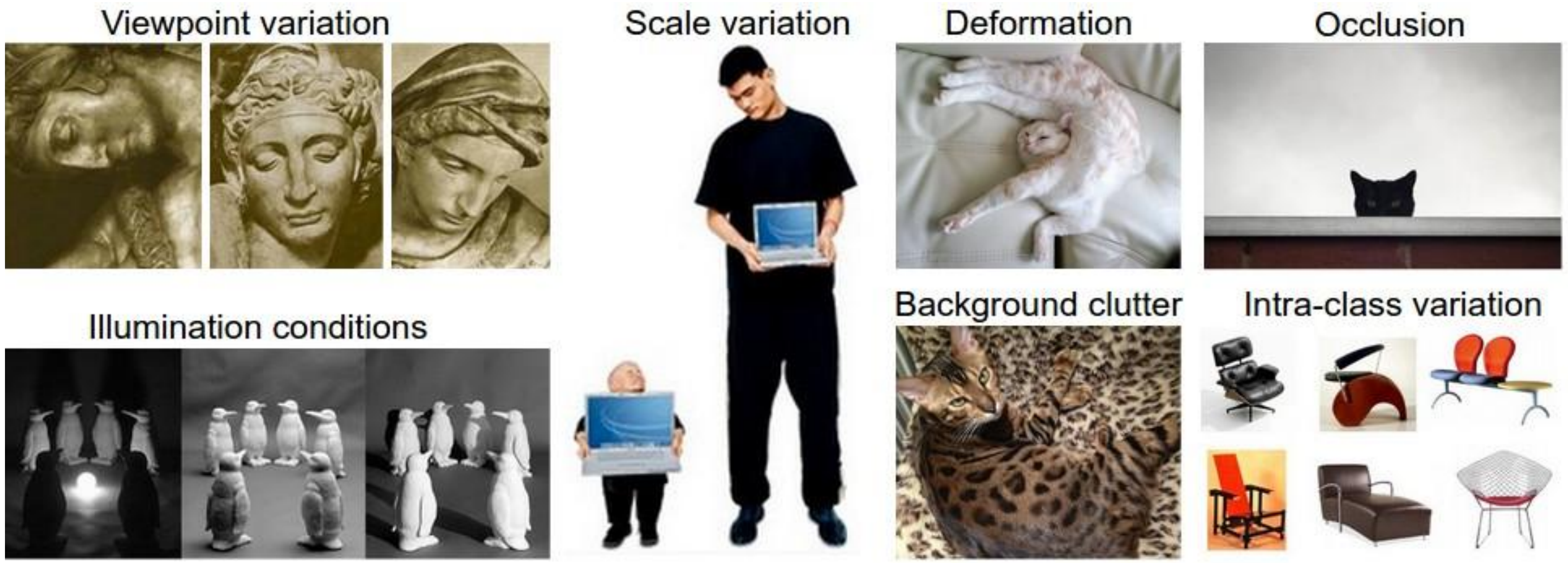
Manual Feature Extraction



Problems?

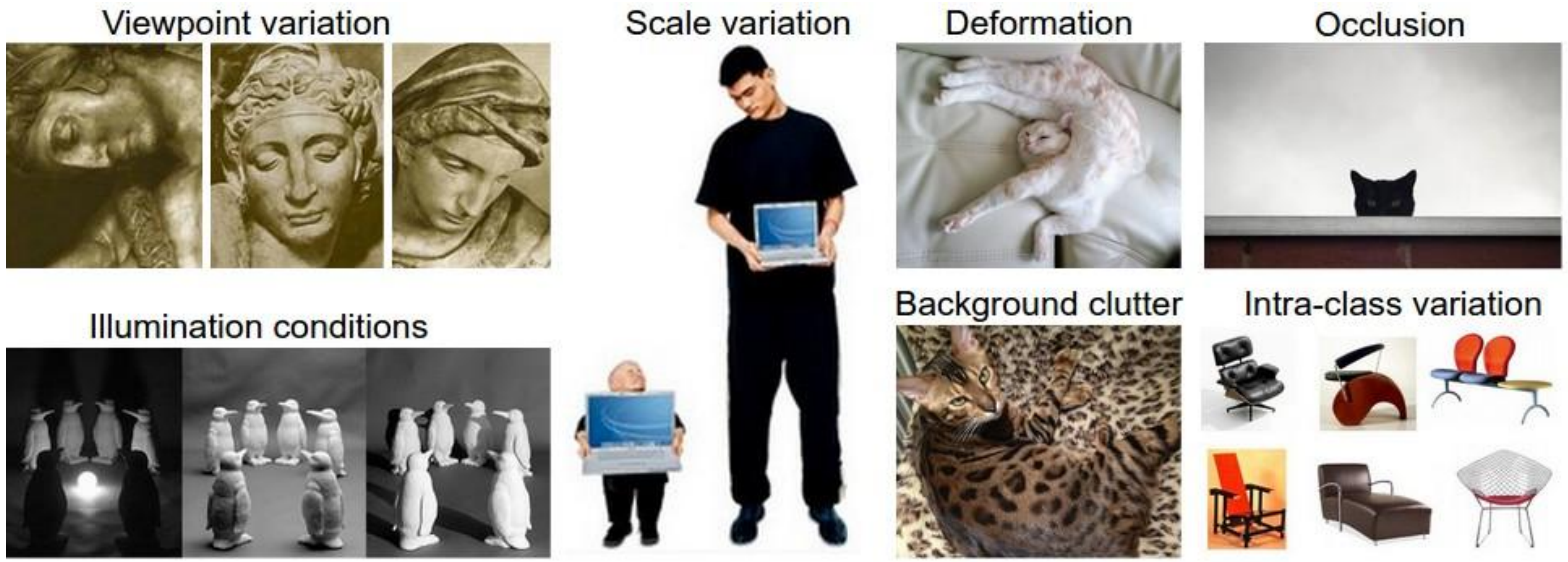
Manual Feature Extraction

Domain knowledge → Define features → Detect features to classify



Manual Feature Extraction

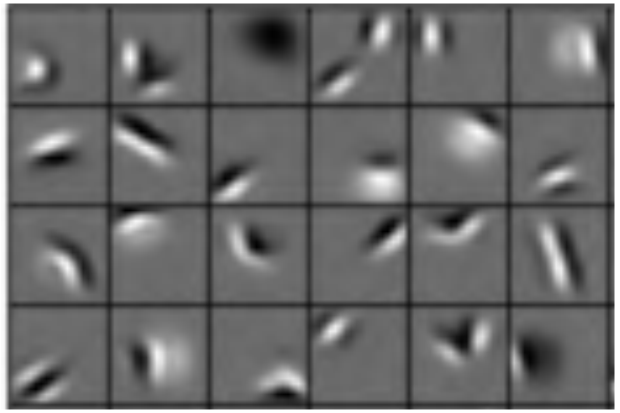
Domain knowledge → Define features → **Detect features to classify**



Learning Feature Representations

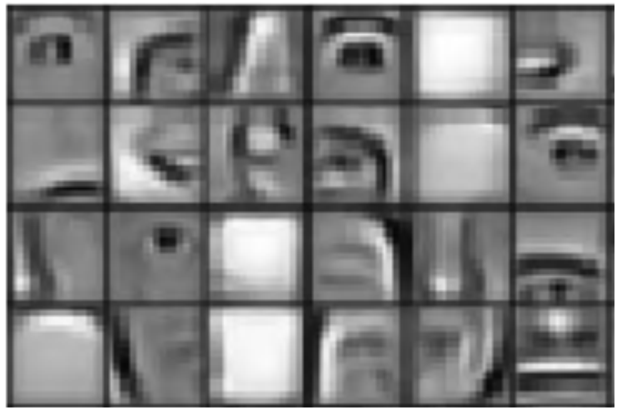
Can we **learn hierarchy of features** directly from the data instead of hand engineering?

Low level features



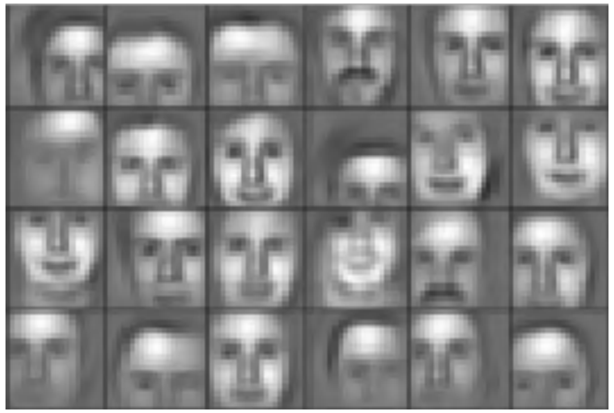
Edges, dark spots

Mid level features



Eyes, ears, nose

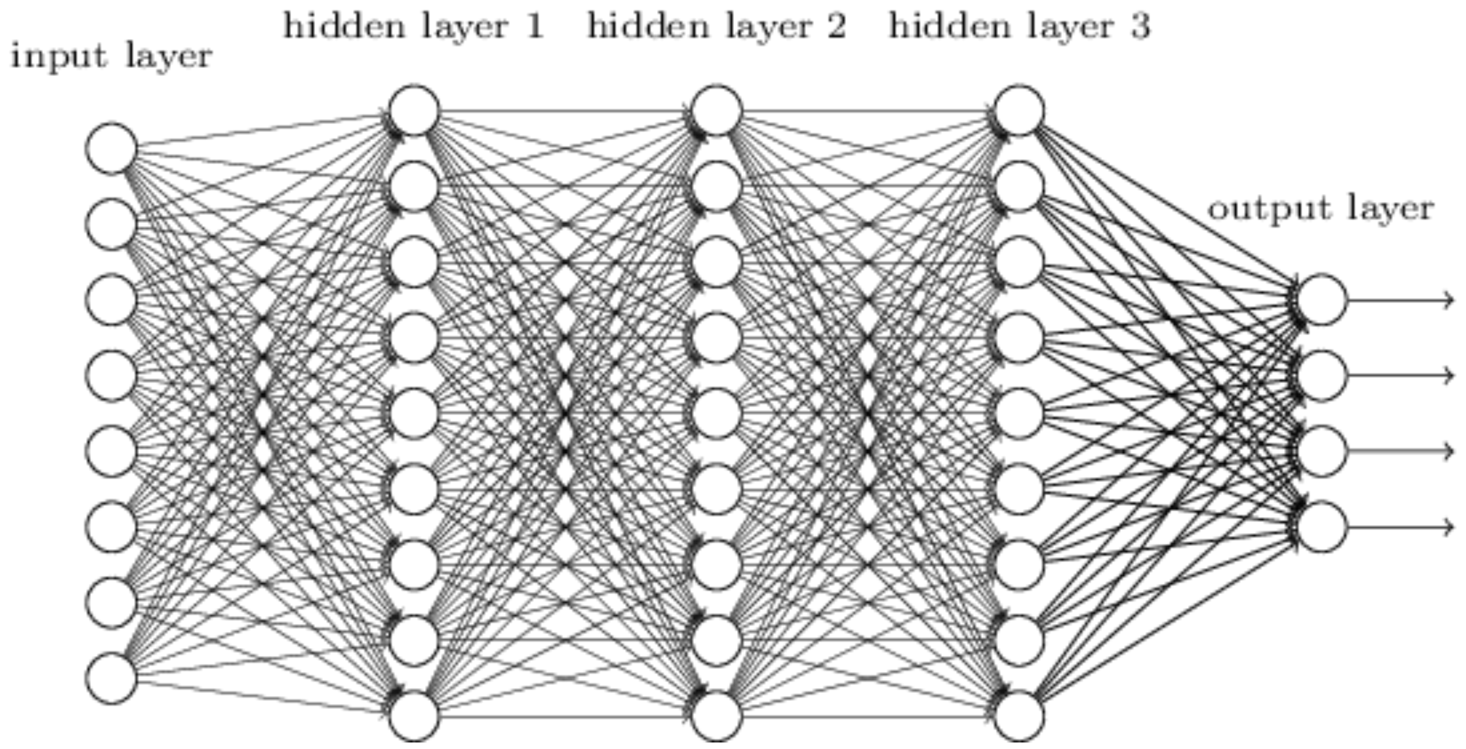
High level features



Facial structure

Learning Visual Features

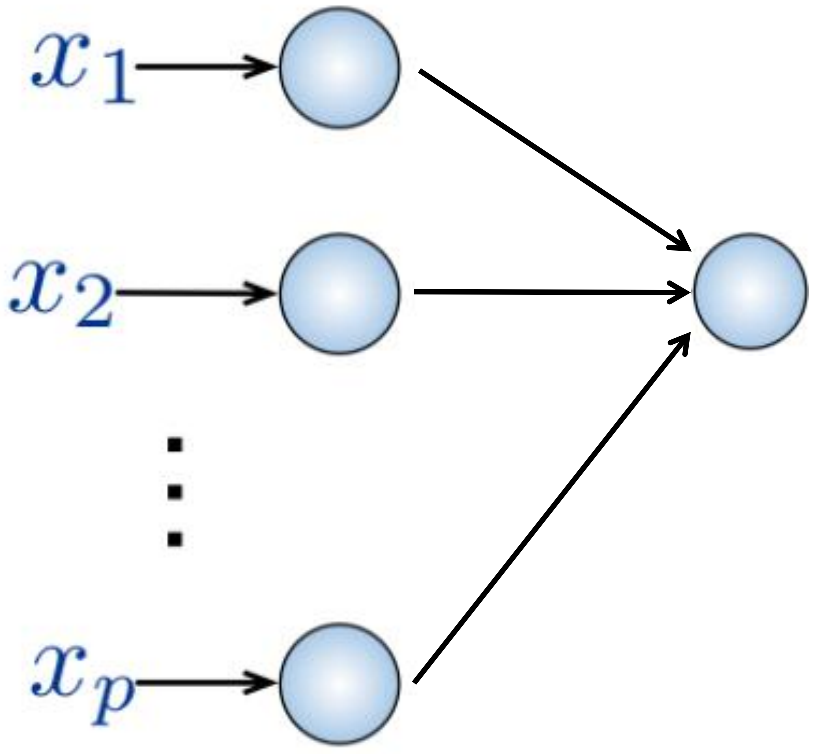
Fully Connected Neural Network



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

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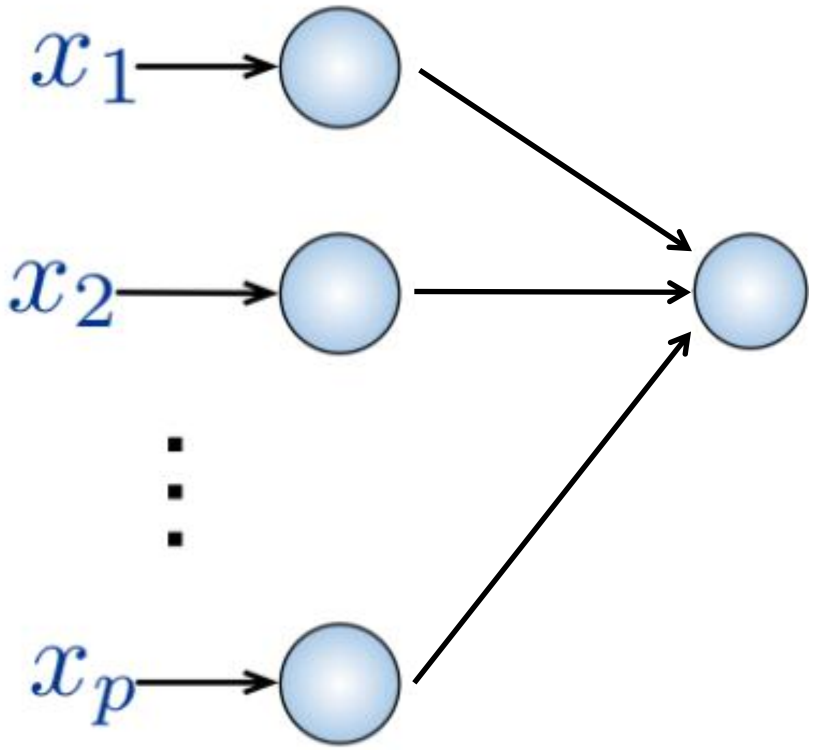
- 2D image
- Vector of pixel values



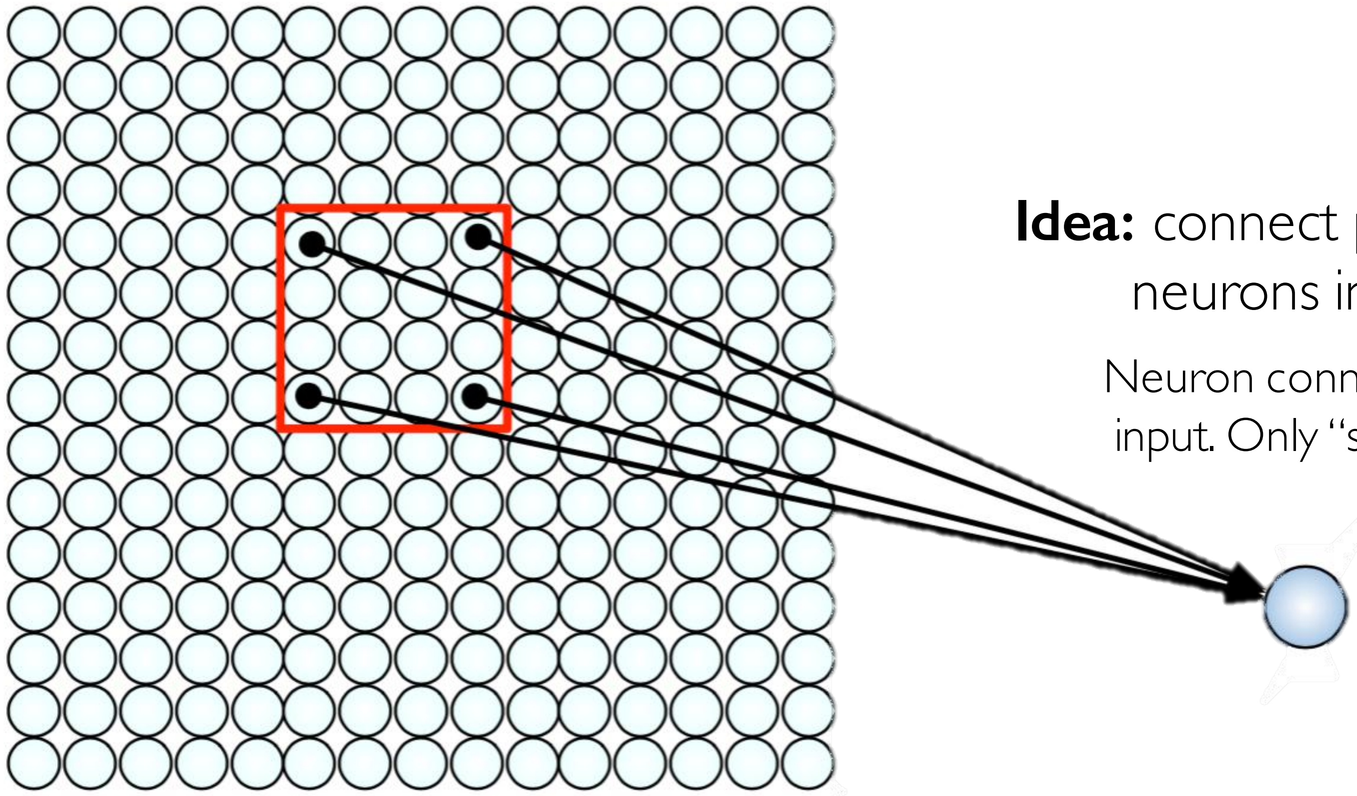
Fully connected:

- 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

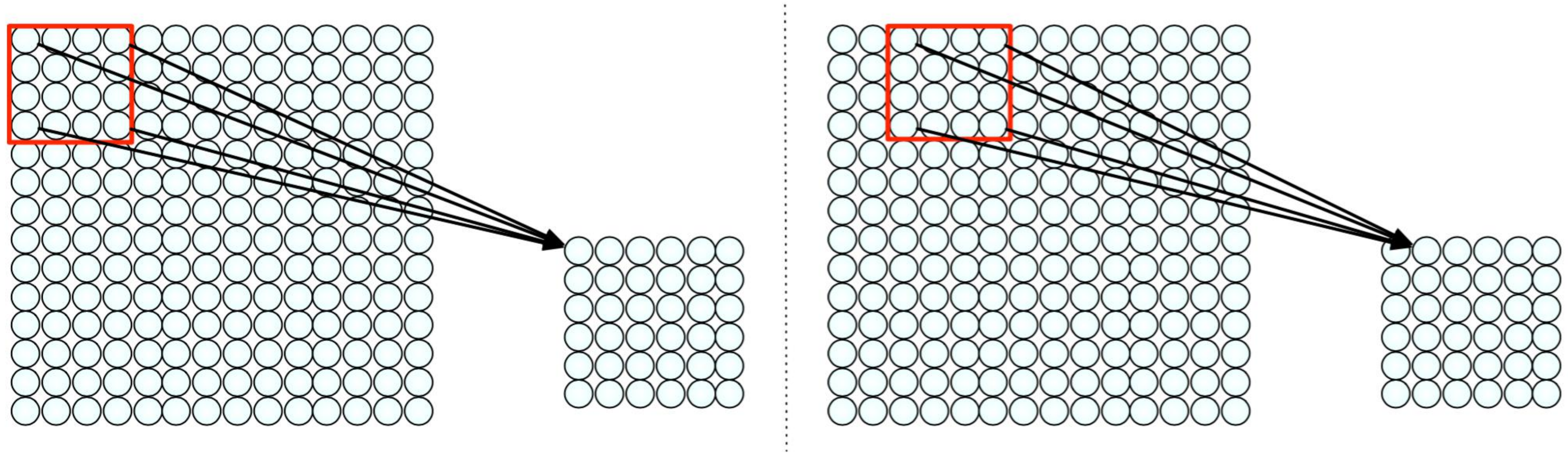
Input: 2D image.
Array of pixel values



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**

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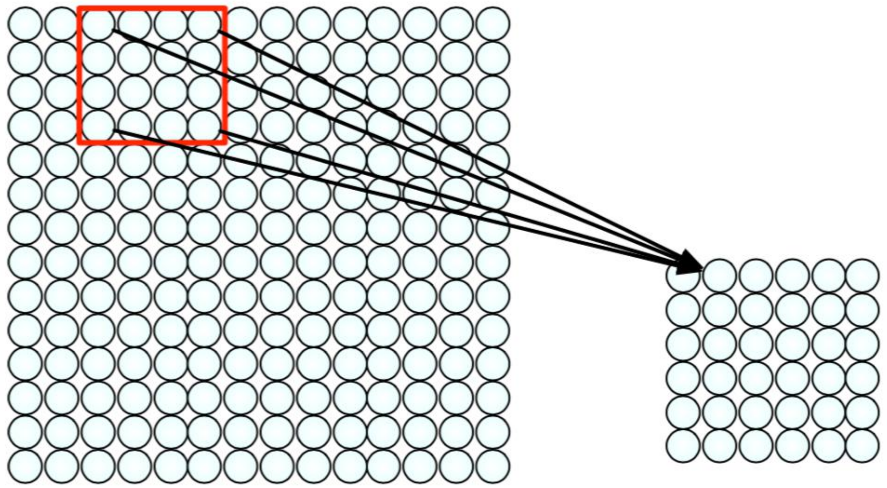
1) Apply a set of weights – a filter – to extract **local features**

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**

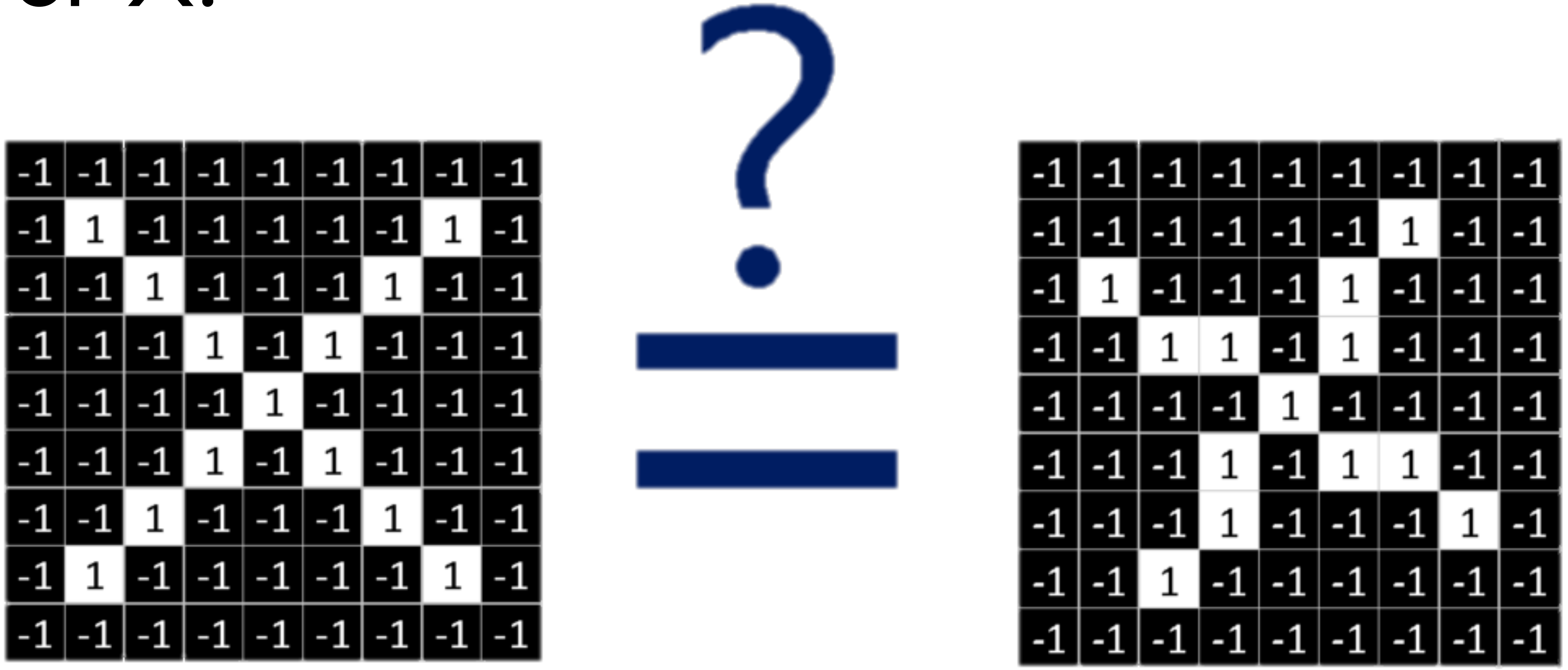
2) Use **multiple filters** to extract different features

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

Feature Extraction and Convolution

A Case Study

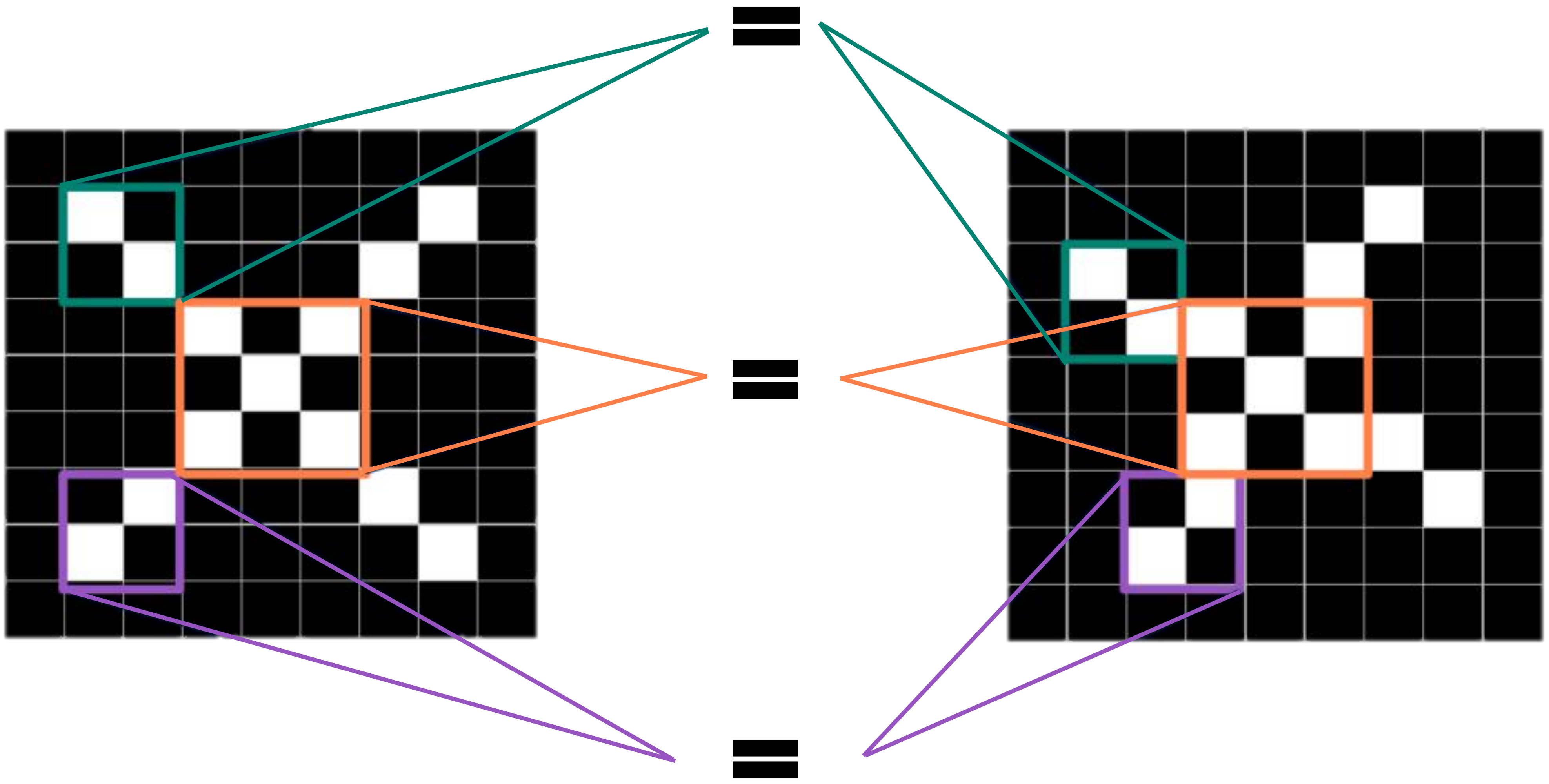
X or X?



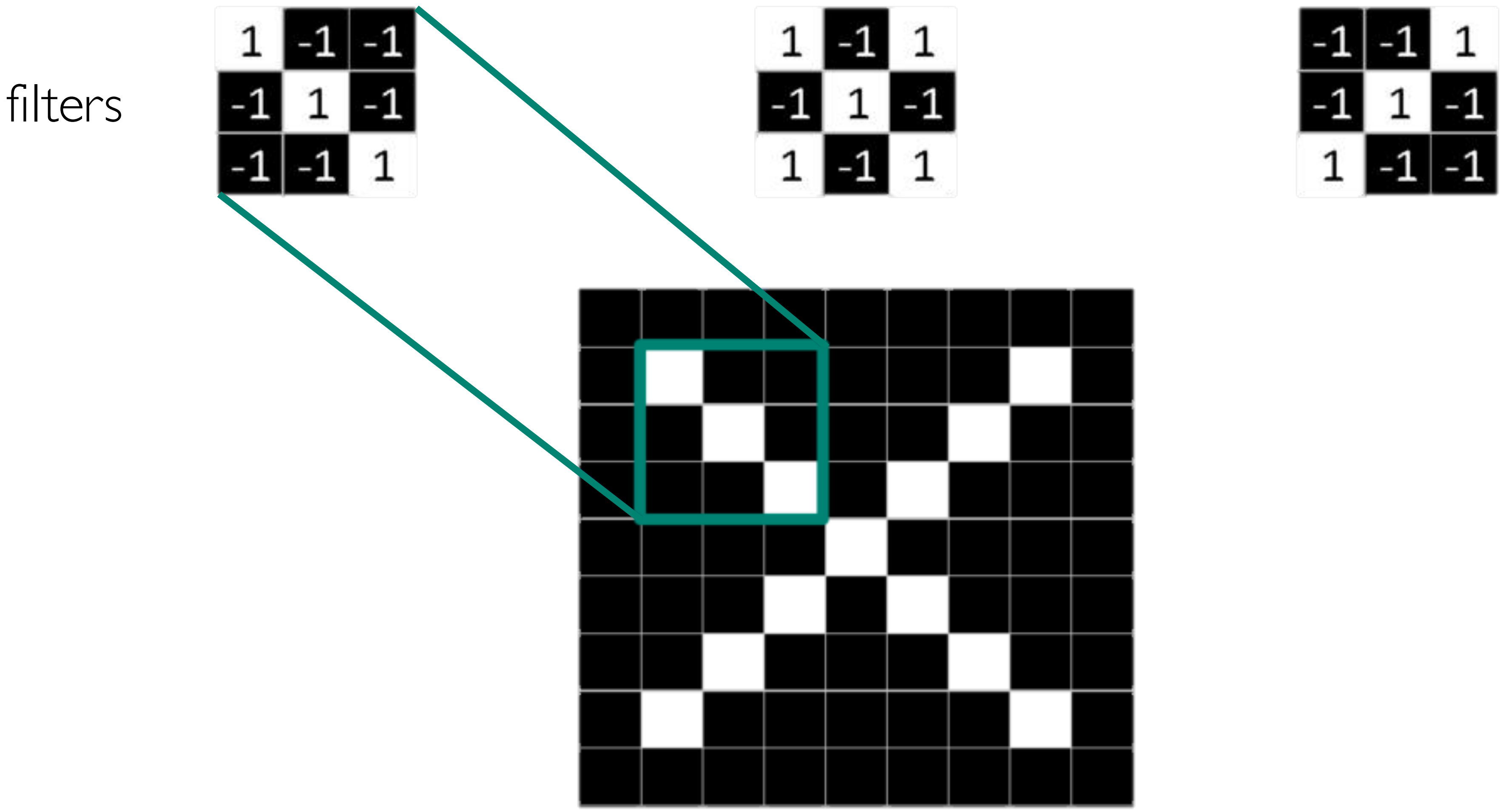
$$\begin{bmatrix} -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix} \overset{?}{=} \begin{bmatrix} -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & 1 & -1 & -1 \\ -1 & 1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & 1 & 1 & -1 & 1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & 1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & 1 & 1 & -1 & -1 \\ -1 & -1 & -1 & 1 & -1 & -1 & -1 & 1 & -1 \\ -1 & -1 & 1 & -1 & -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 & -1 \end{bmatrix}$$

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.

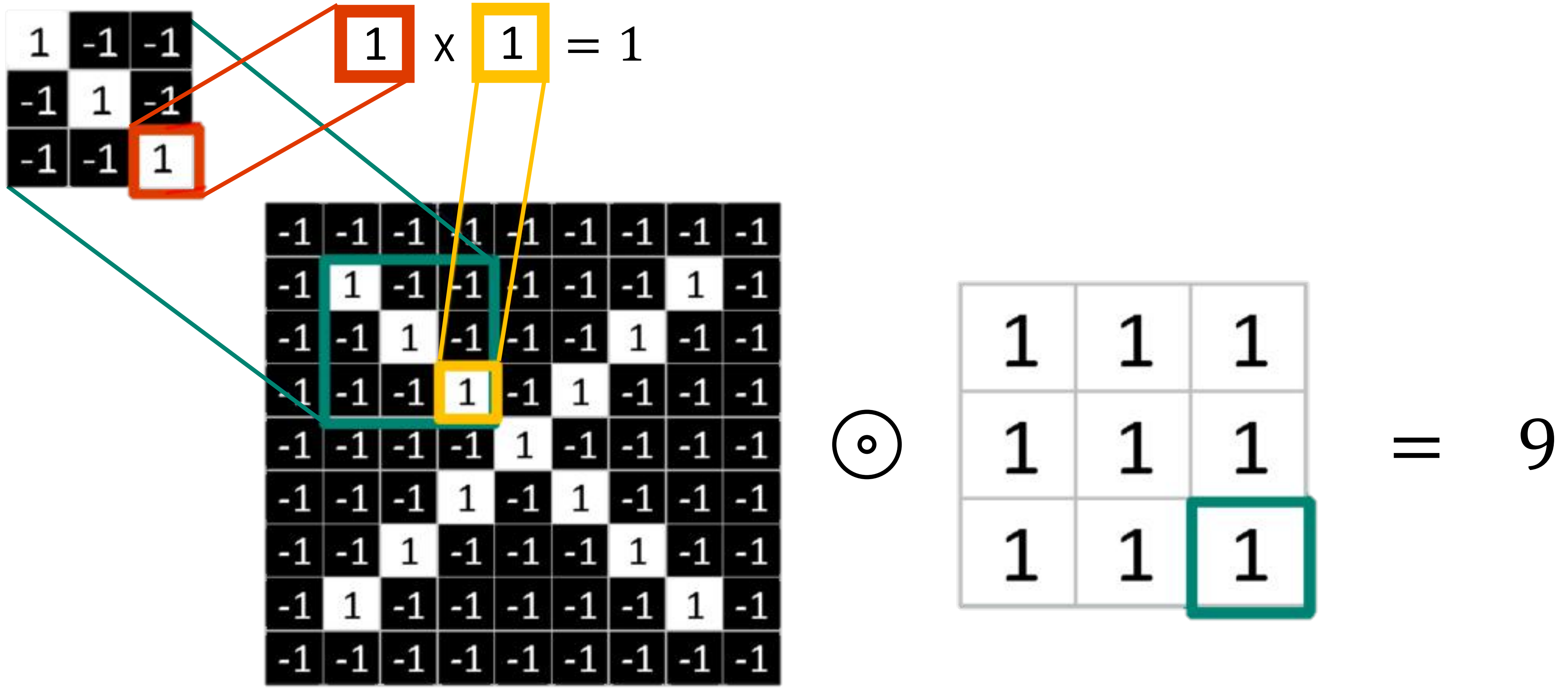
Features of X



Filters to Detect X Features



The Convolution Operation

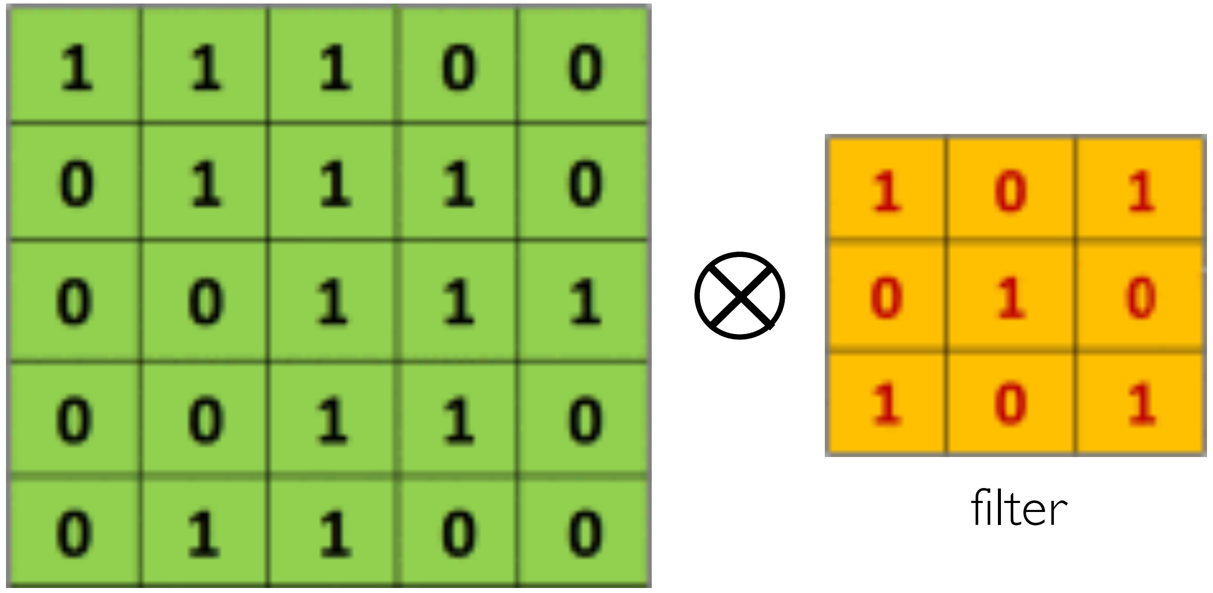


Element wise multiply

Add outputs

The Convolution Operation

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



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

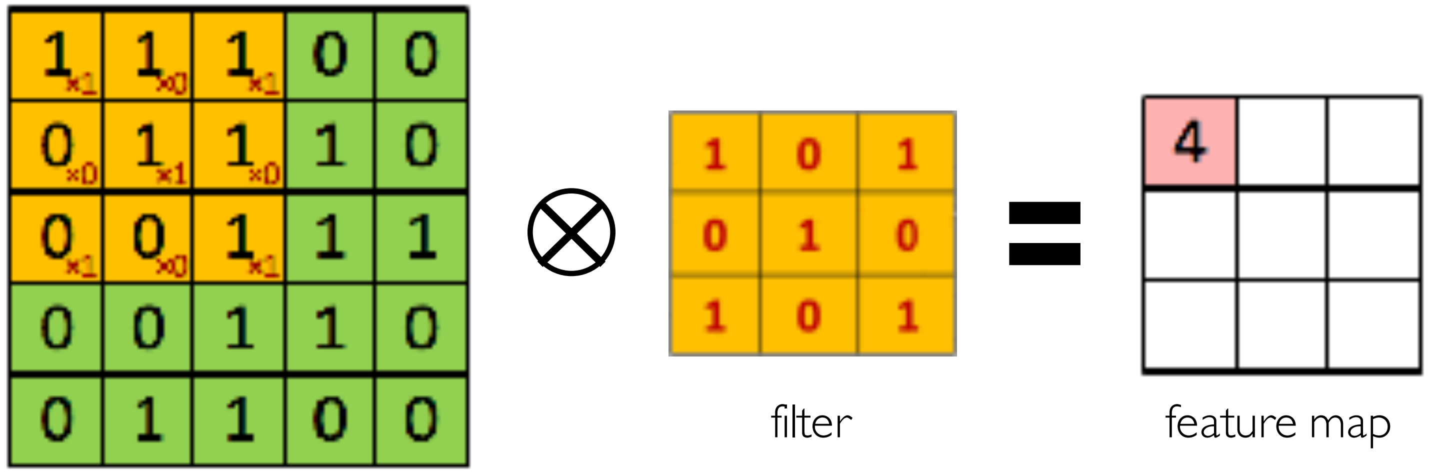
filter

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:

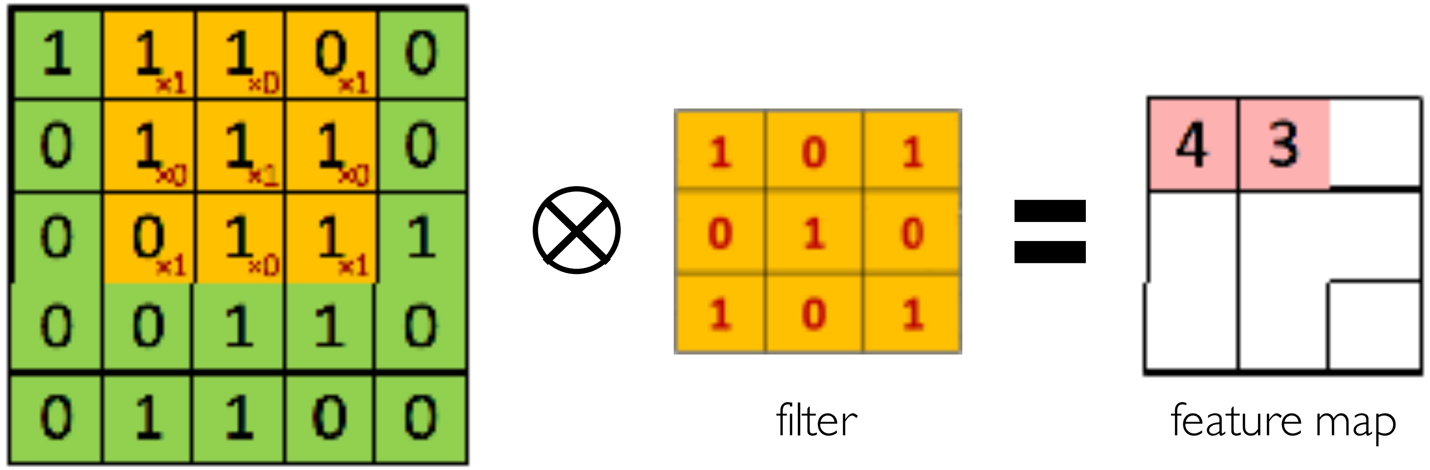


filter

feature map

The Convolution Operation

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



filter

feature map

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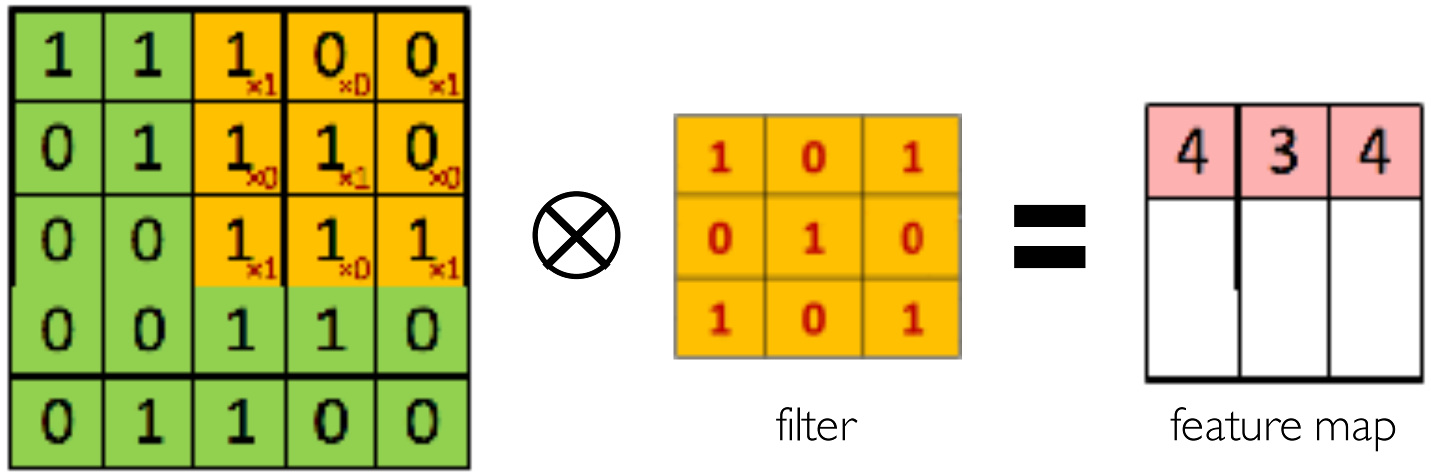

filter

feature map

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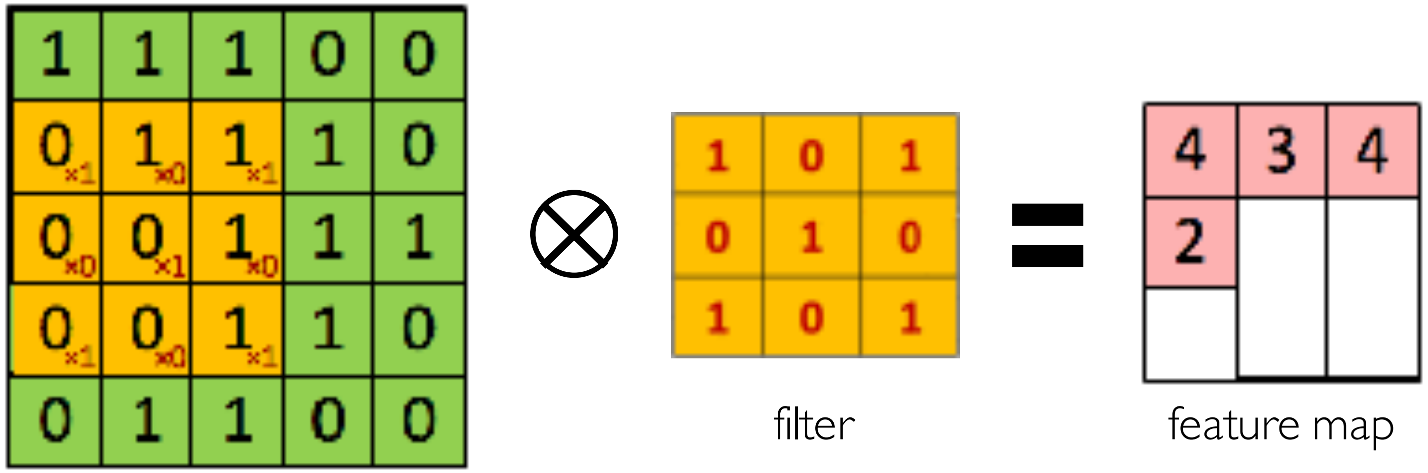

filter

feature map

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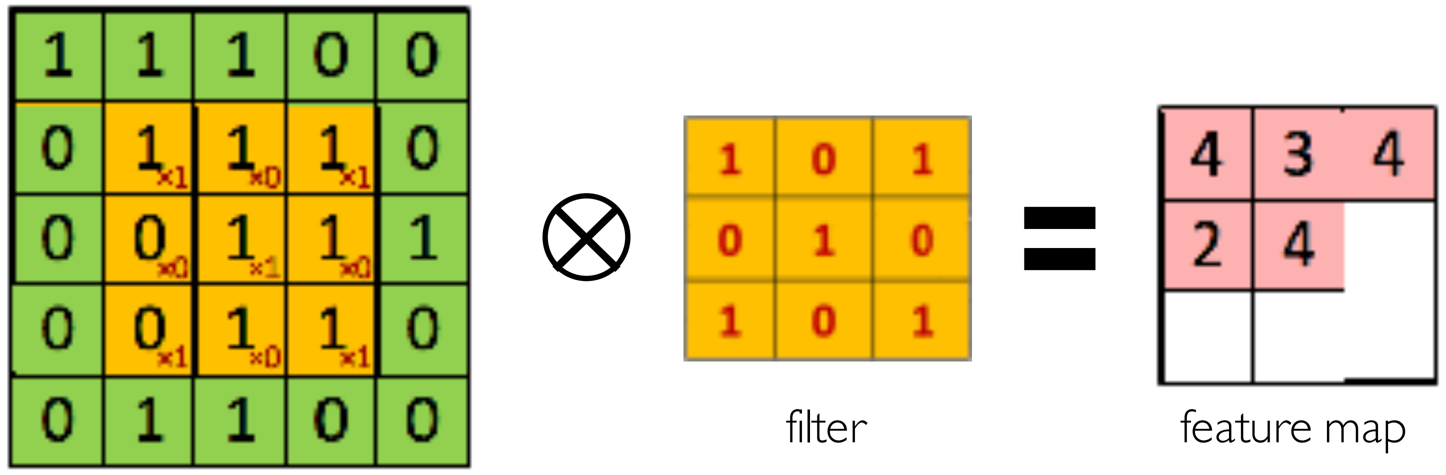

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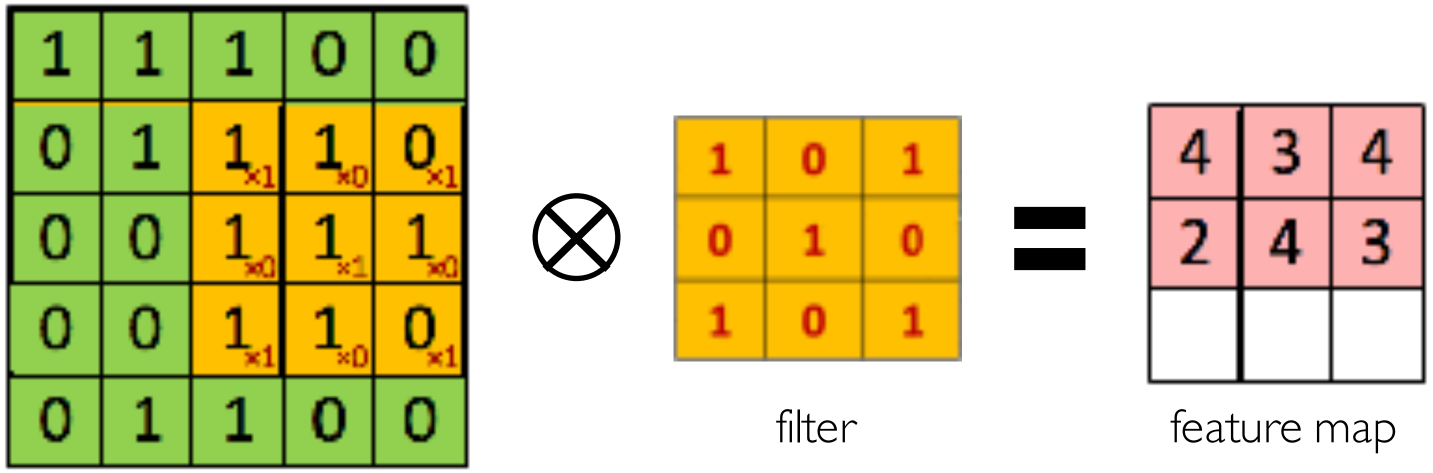

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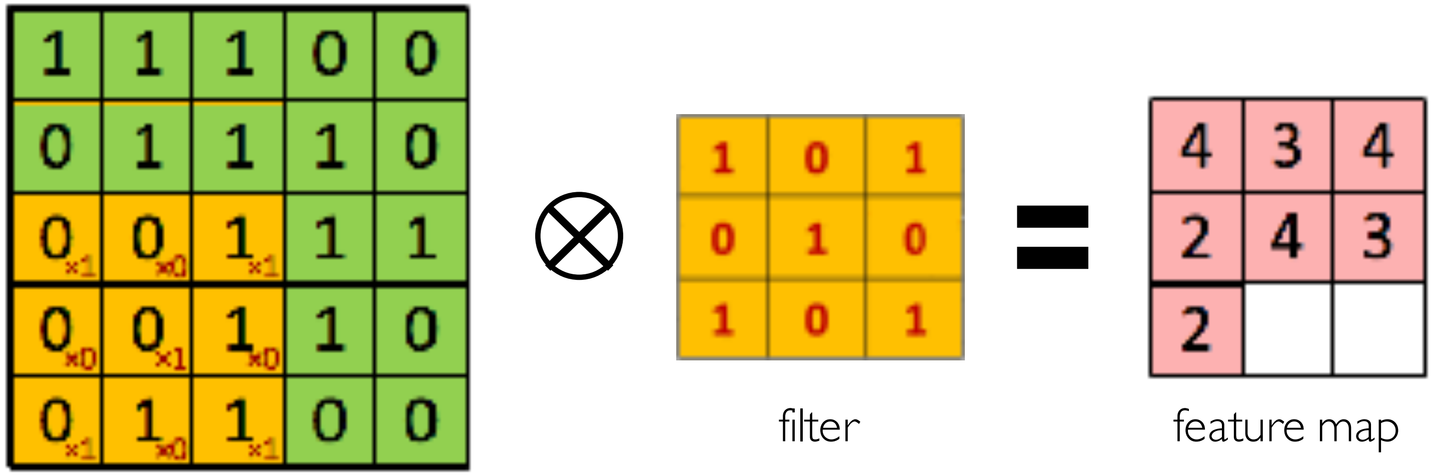

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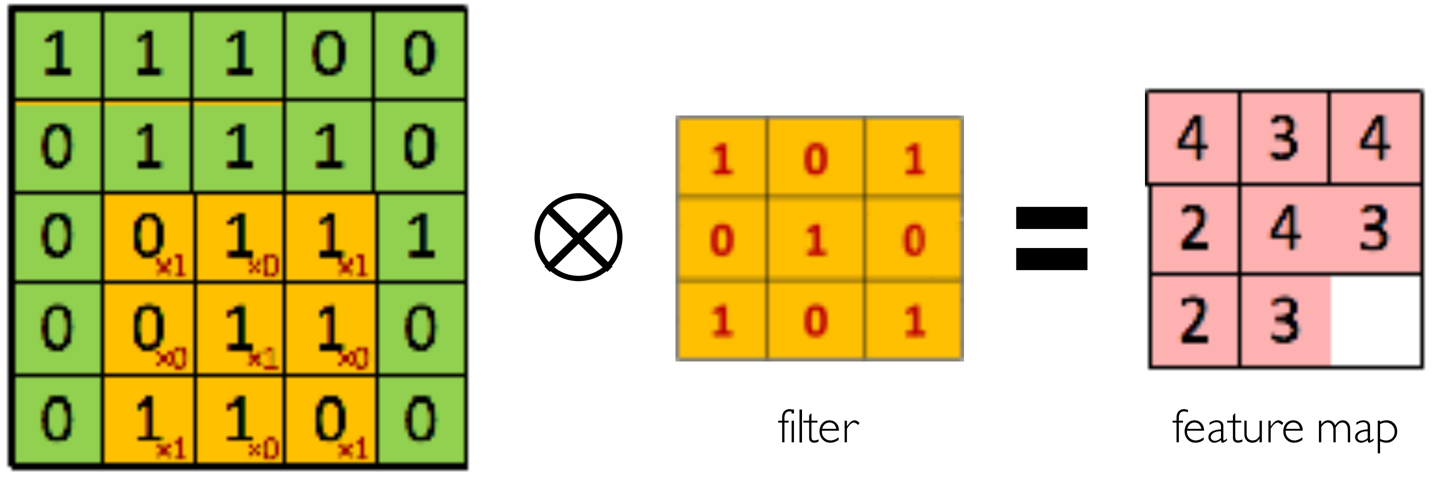

filter

feature map

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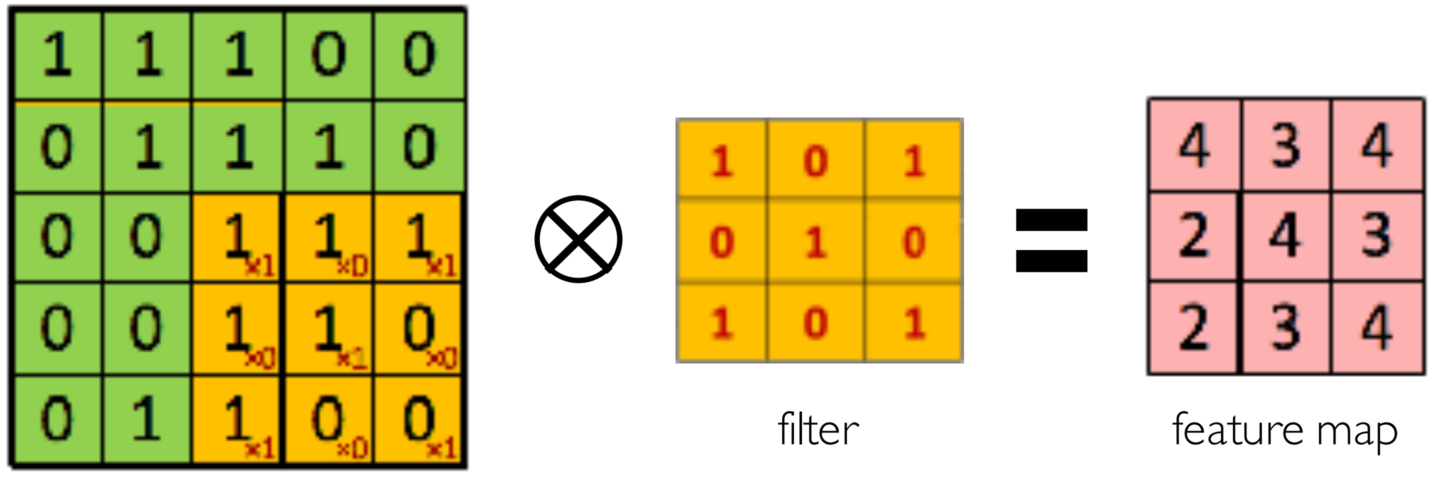
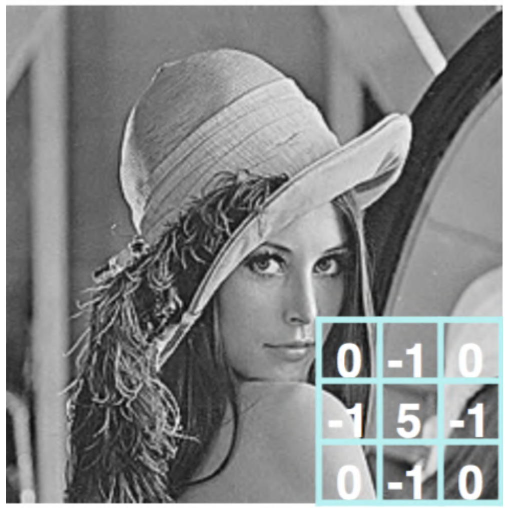


filter

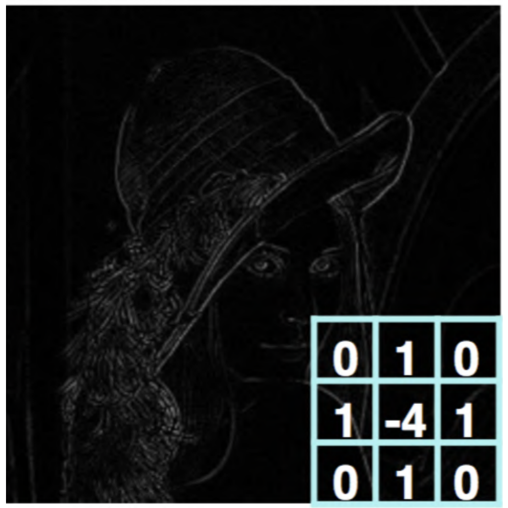
feature map

Producing Feature Maps

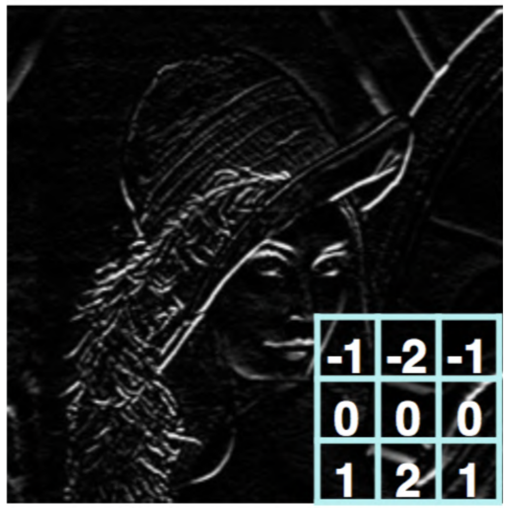
Original



Sharpen

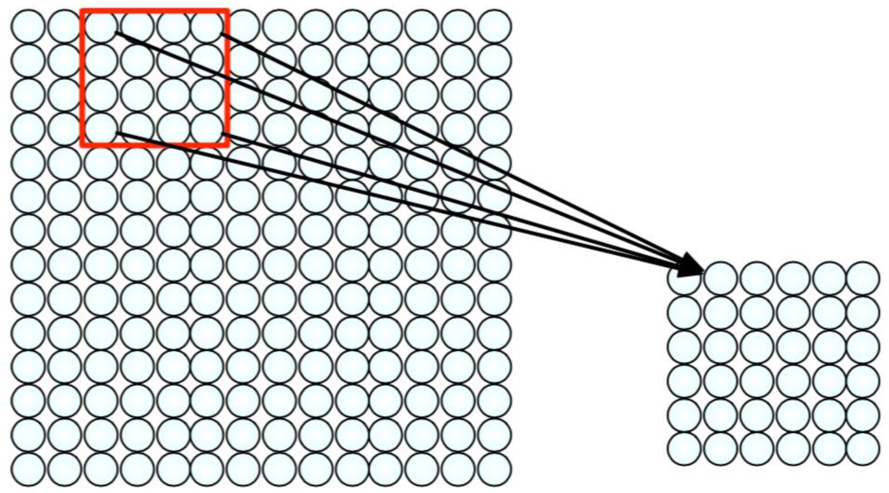


Edge Detect



"Strong" Edge Detect

Feature Extraction with Convolution



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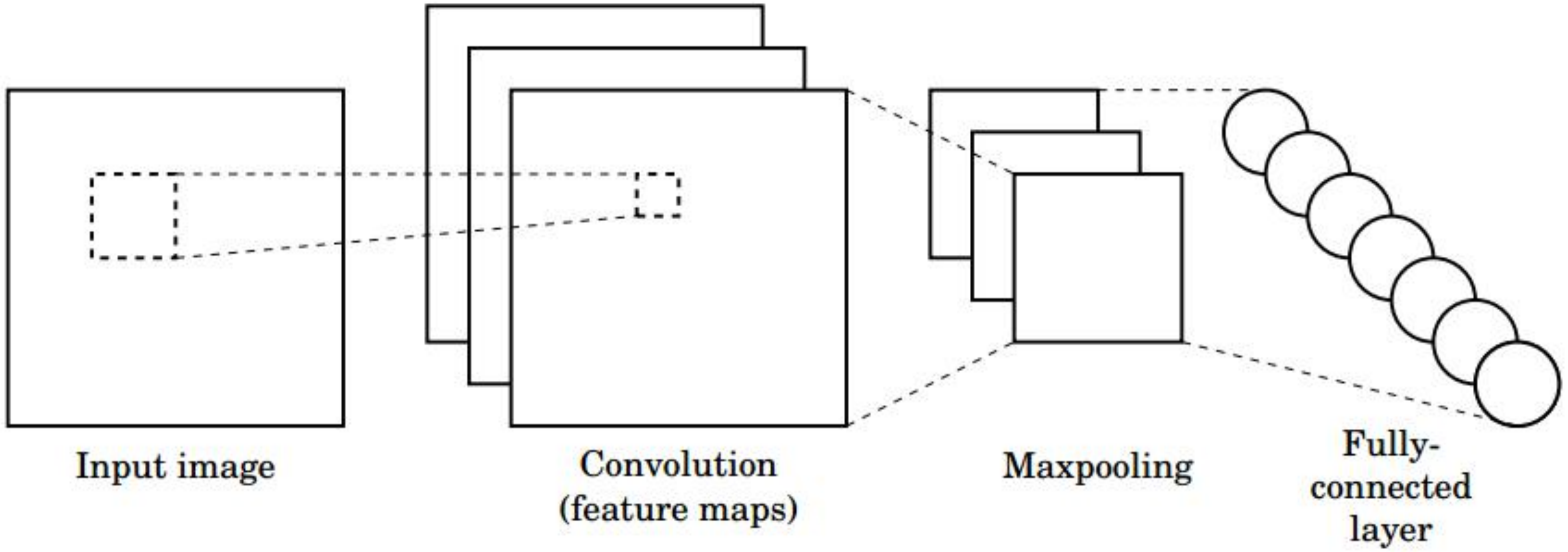
Convolutional Neural Networks (CNNs)

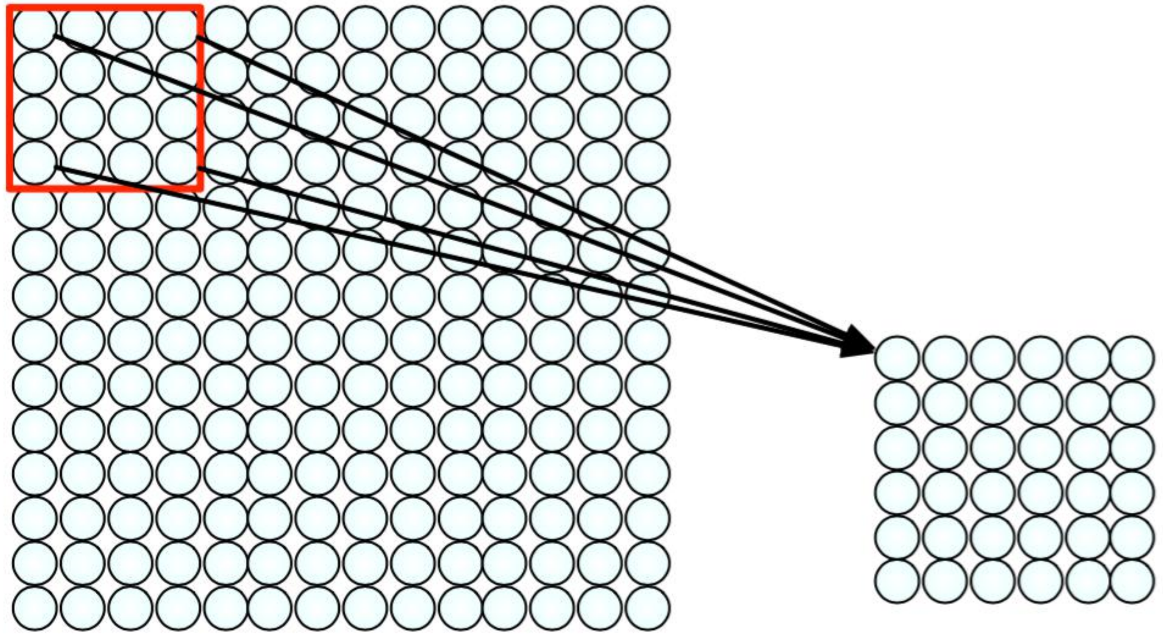
CNNs for Classification



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.

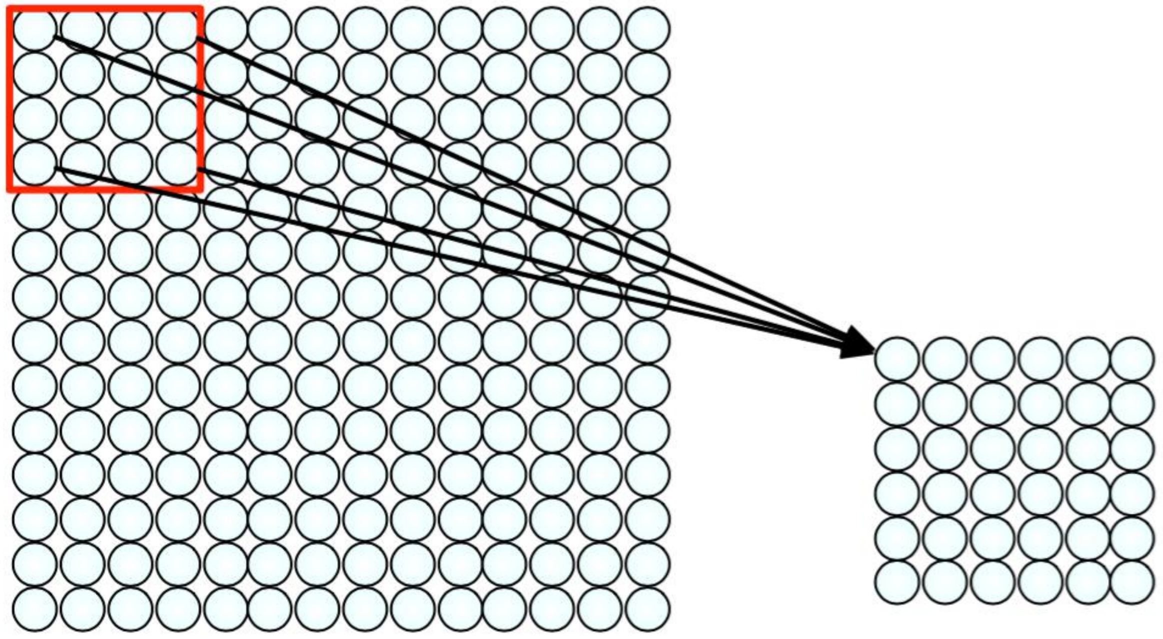
Convolutional Layers: Local Connectivity



For a neuron in hidden layer:

- Take inputs from patch the neuron "sees"
- Compute weighted sum
- Apply bias

Convolutional Layers: Local Connectivity



For a neuron in hidden layer:

- Take inputs from patch the neuron "sees"
- Compute weighted sum
- Apply bias

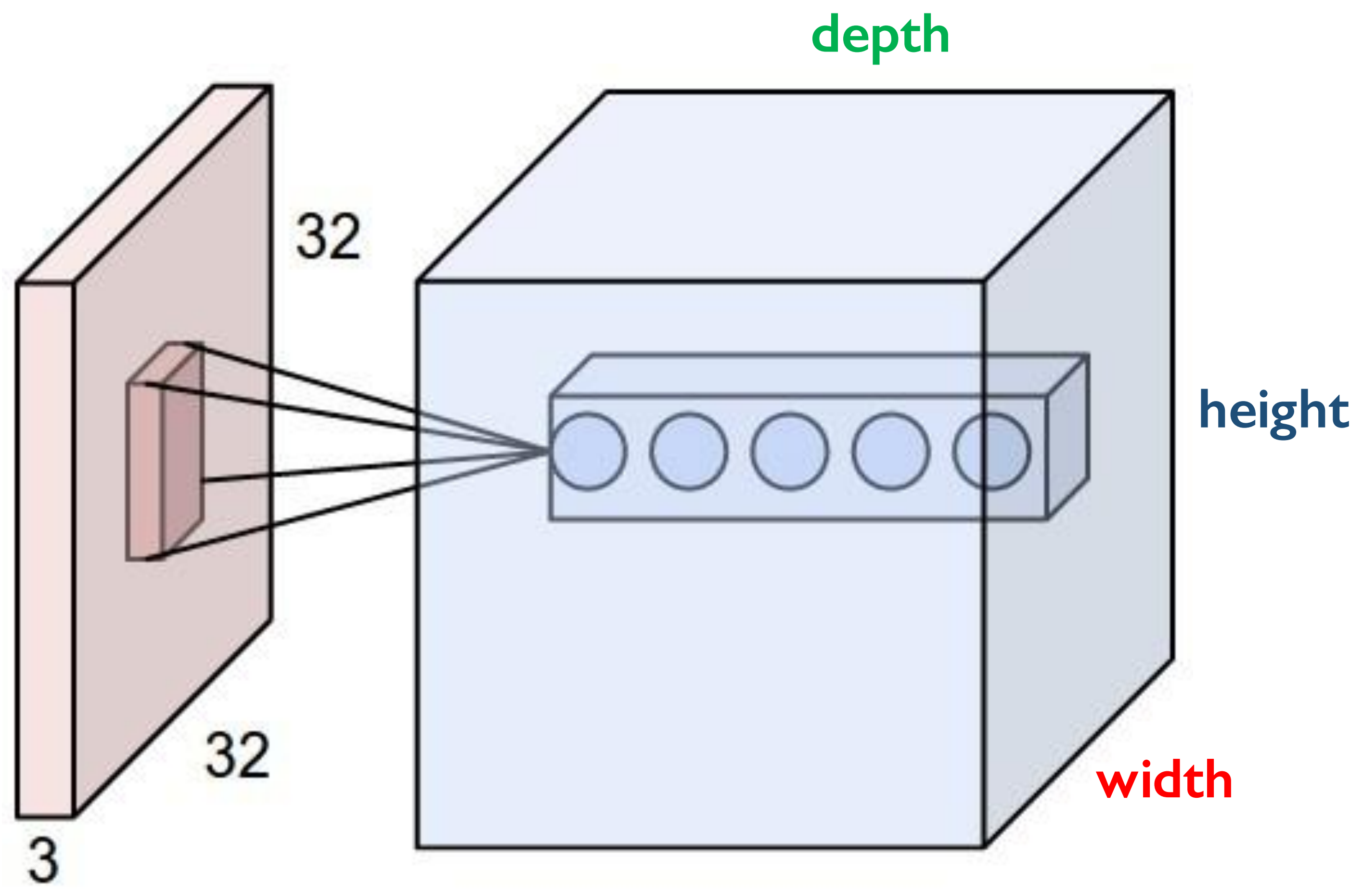
4x4 filter: matrix of weights θ_{ij}

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

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:

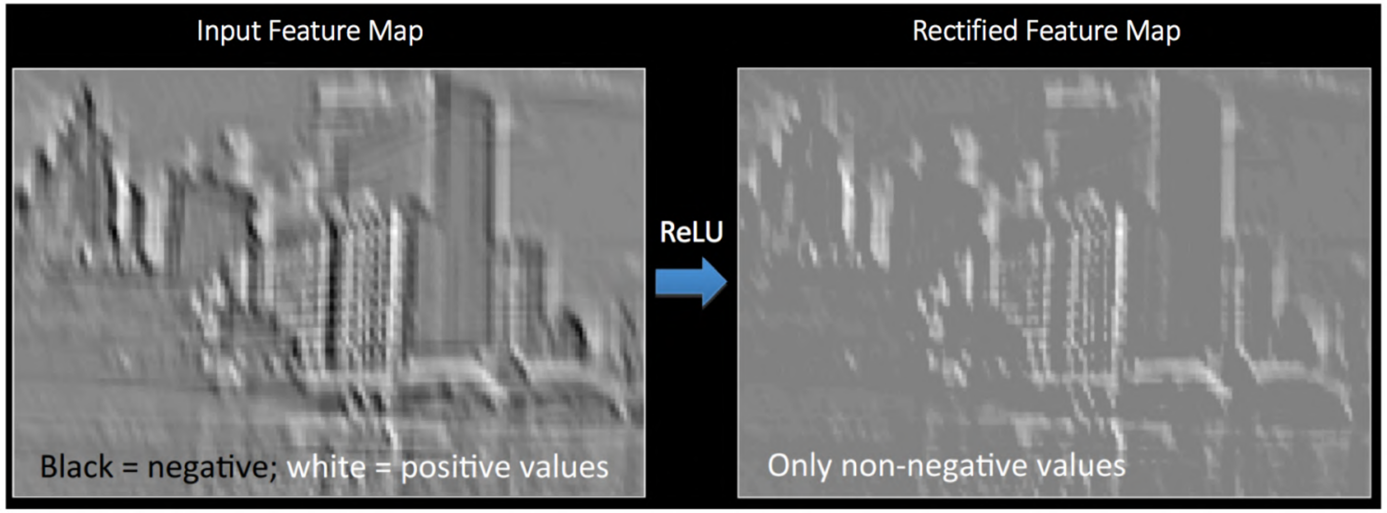
Filter step size

Receptive Field:

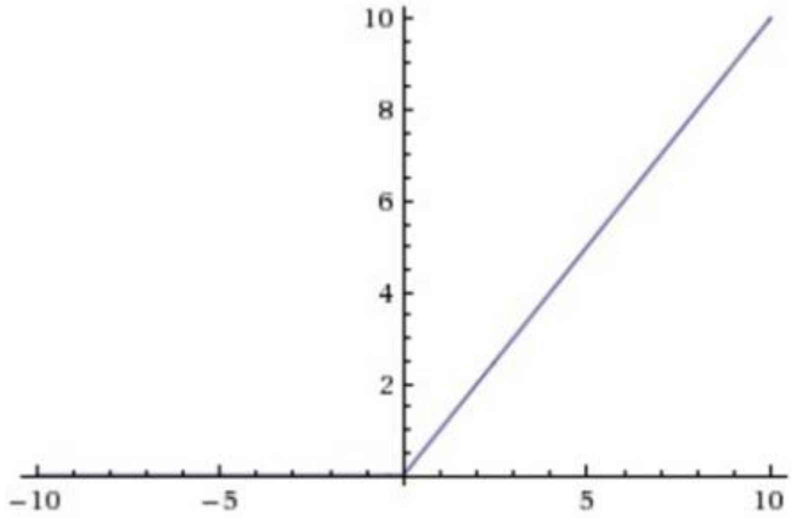
Locations in input image that
a node is path connected to

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**

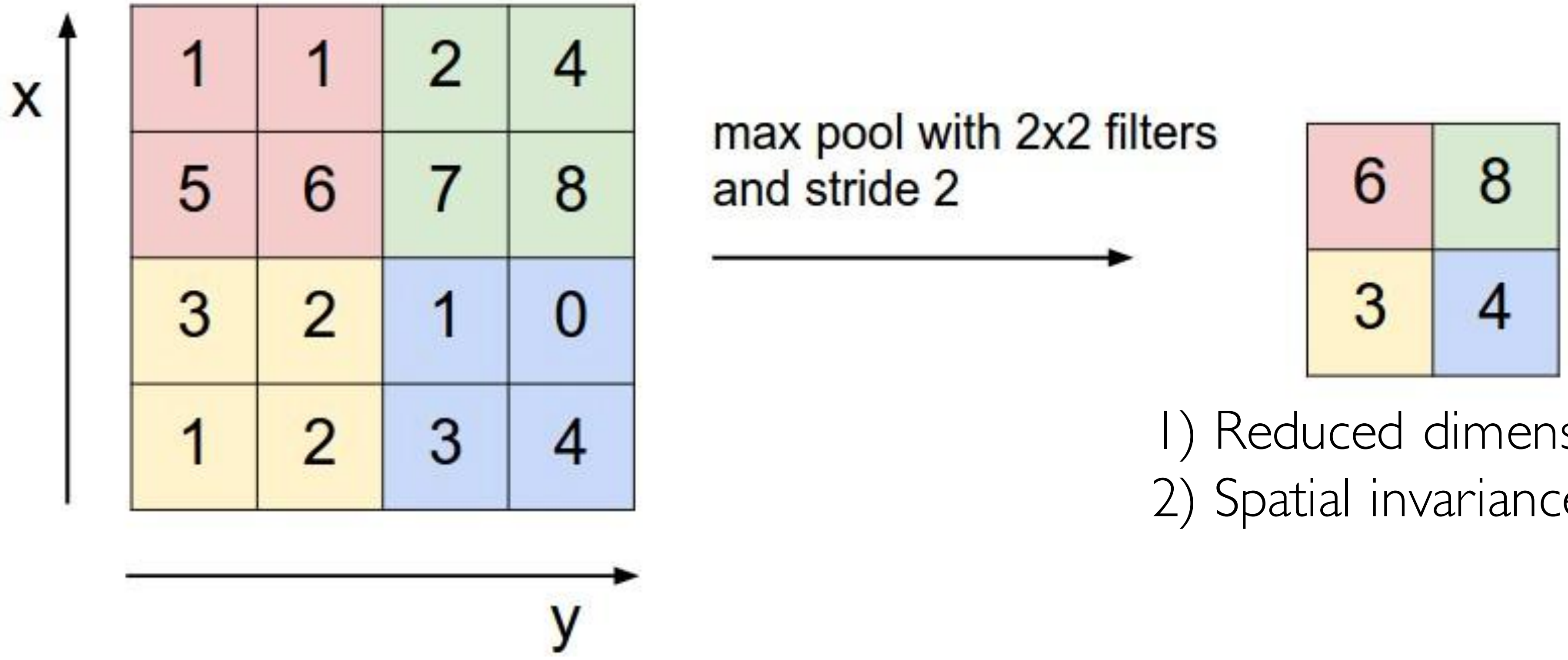


Rectified Linear Unit (ReLU)



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

Pooling

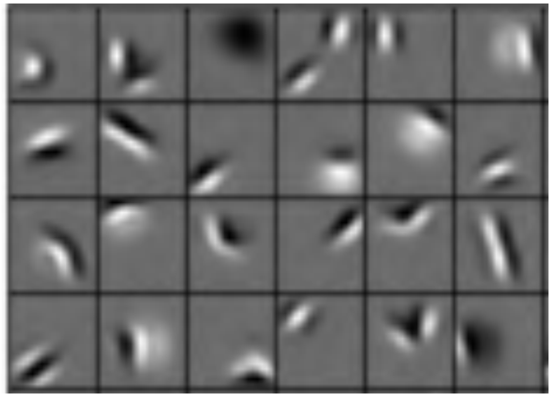


1) Reduced dimensionality
2) Spatial invariance

How else can we downsample and preserve spatial invariance?

Representation Learning in Deep CNNs

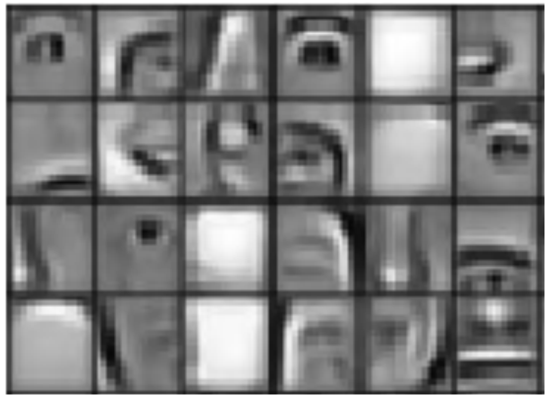
Low level features



Edges, dark spots

Conv Layer 1

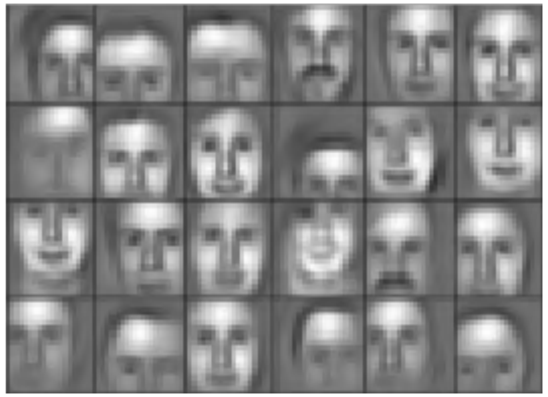
Mid level features



Eyes, ears, nose

Conv Layer 2

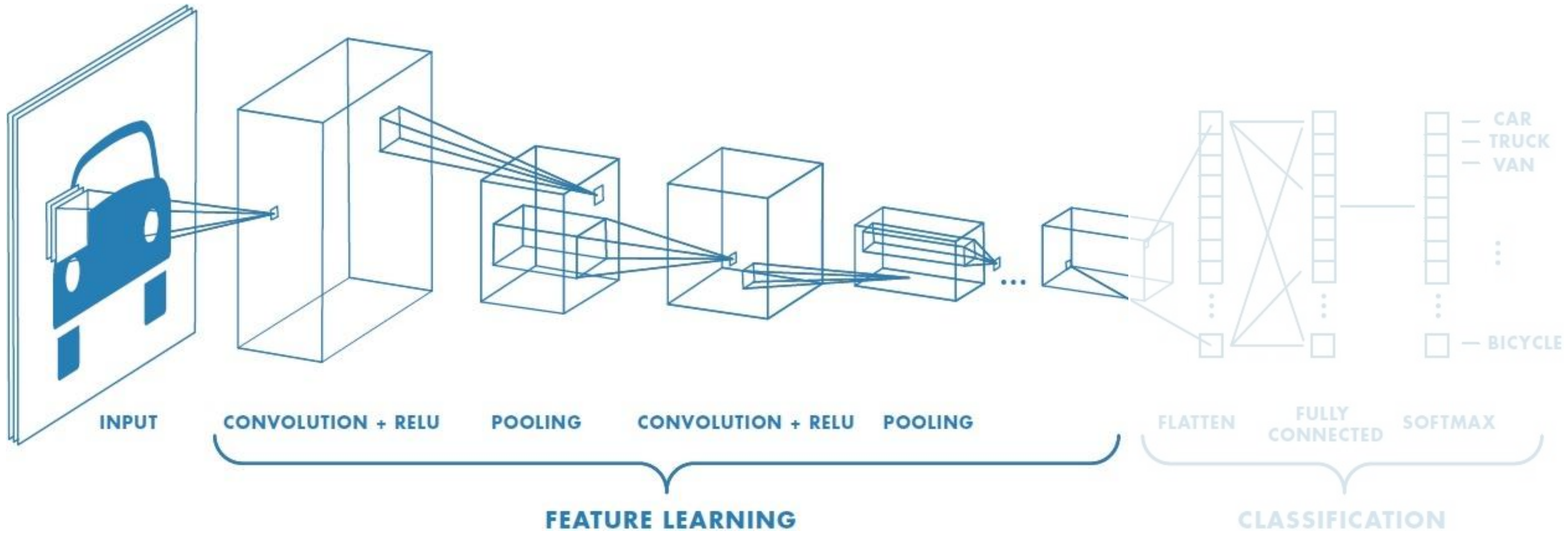
High level features



Facial structure

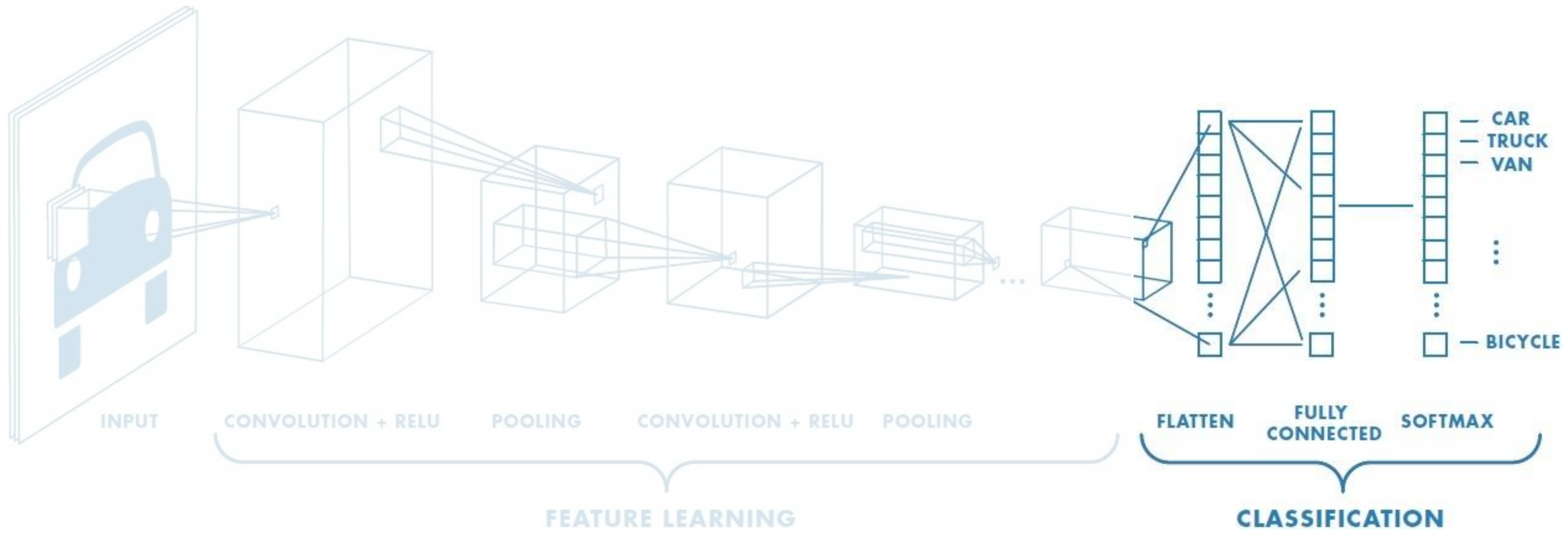
Conv Layer 3

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**

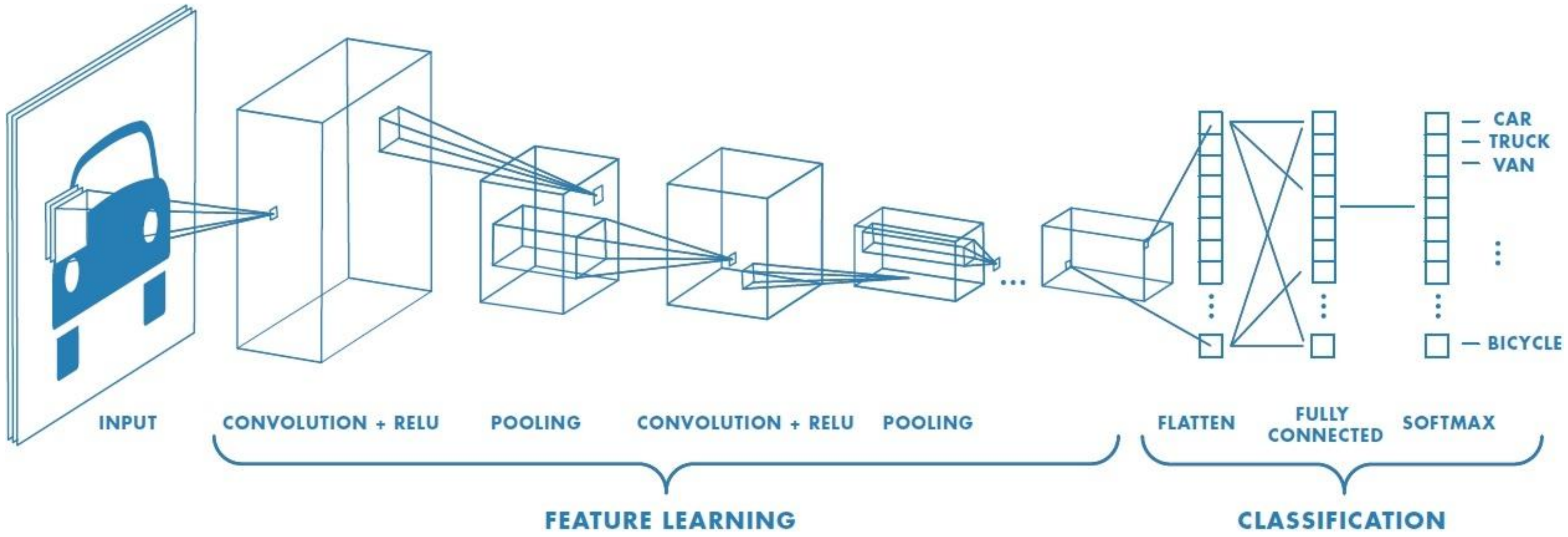
CNNs for Classification: Class Probabilities



- 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

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

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"

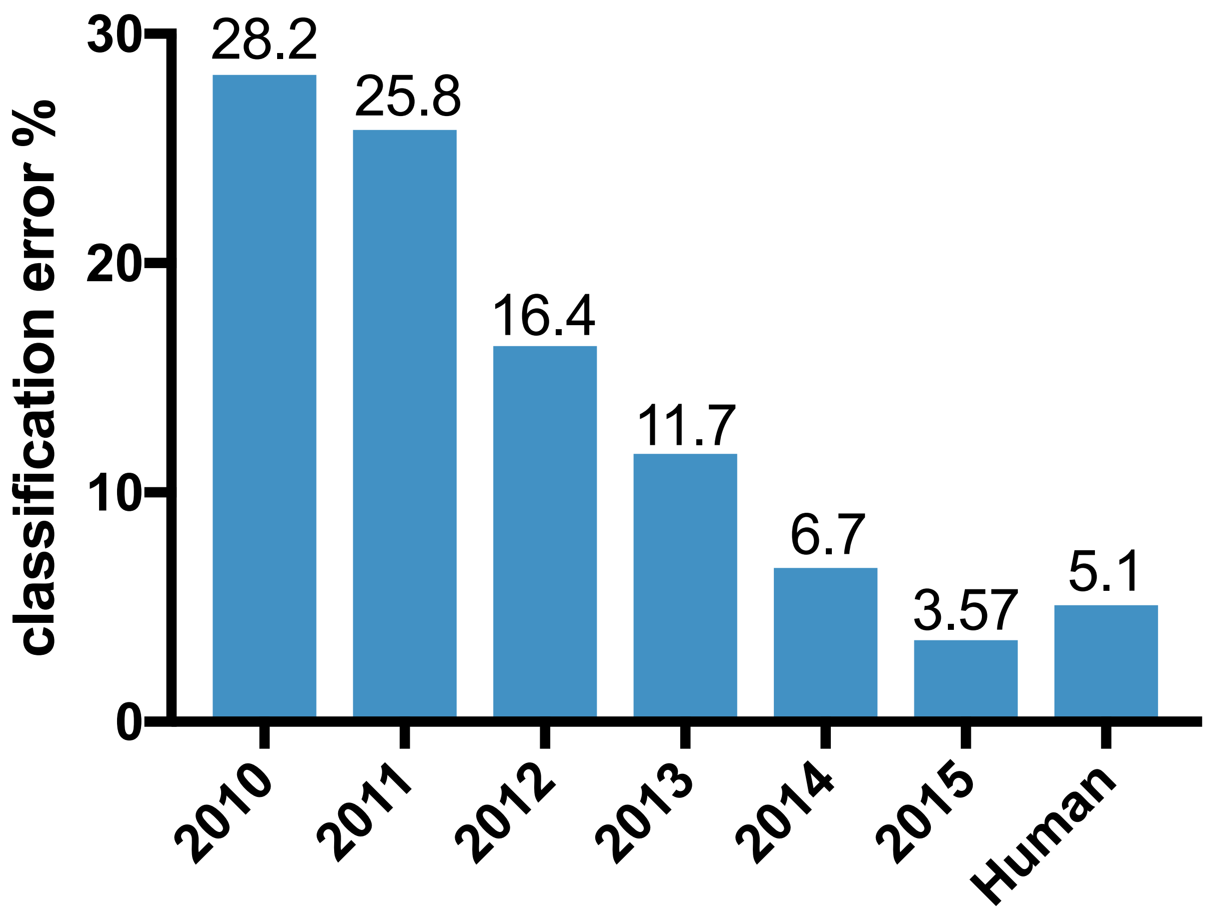
1409 pictures of bananas.

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

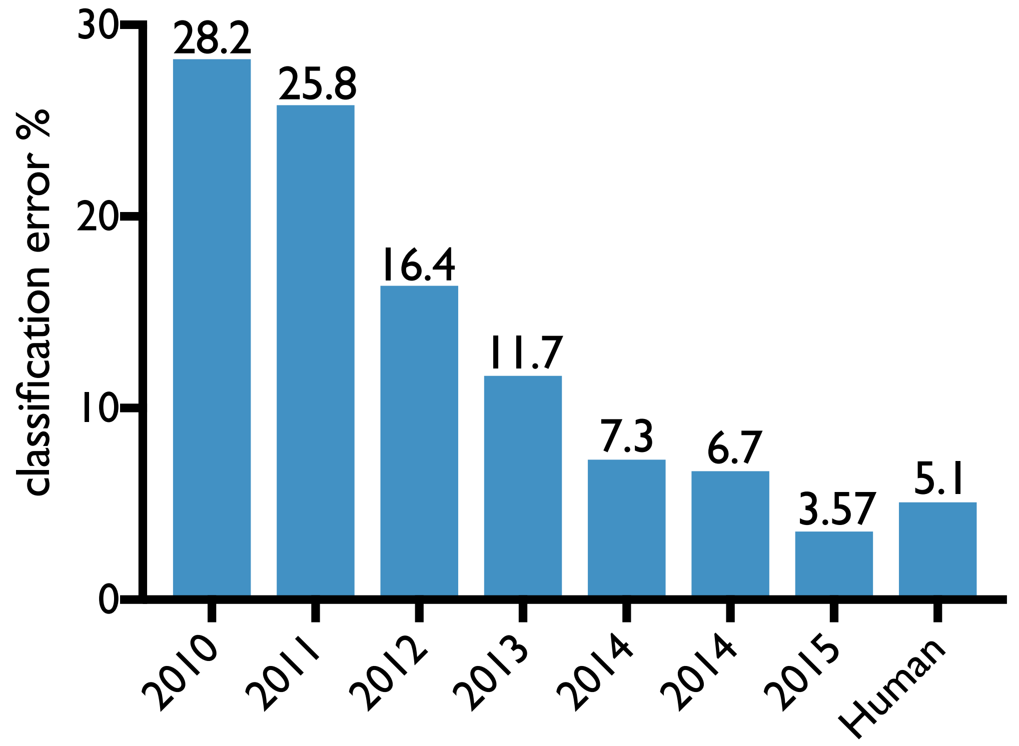
2013: ZFNet
- 8 layers, more filters

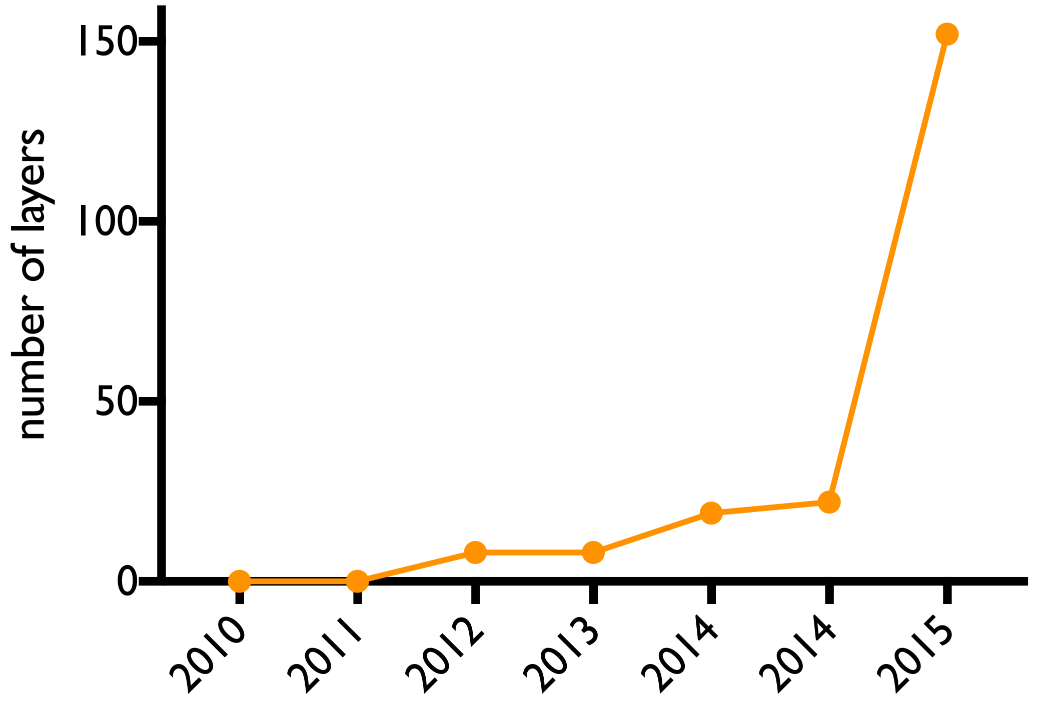
2014: VGG
- 19 layers

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

2015: ResNet
- 152 layers

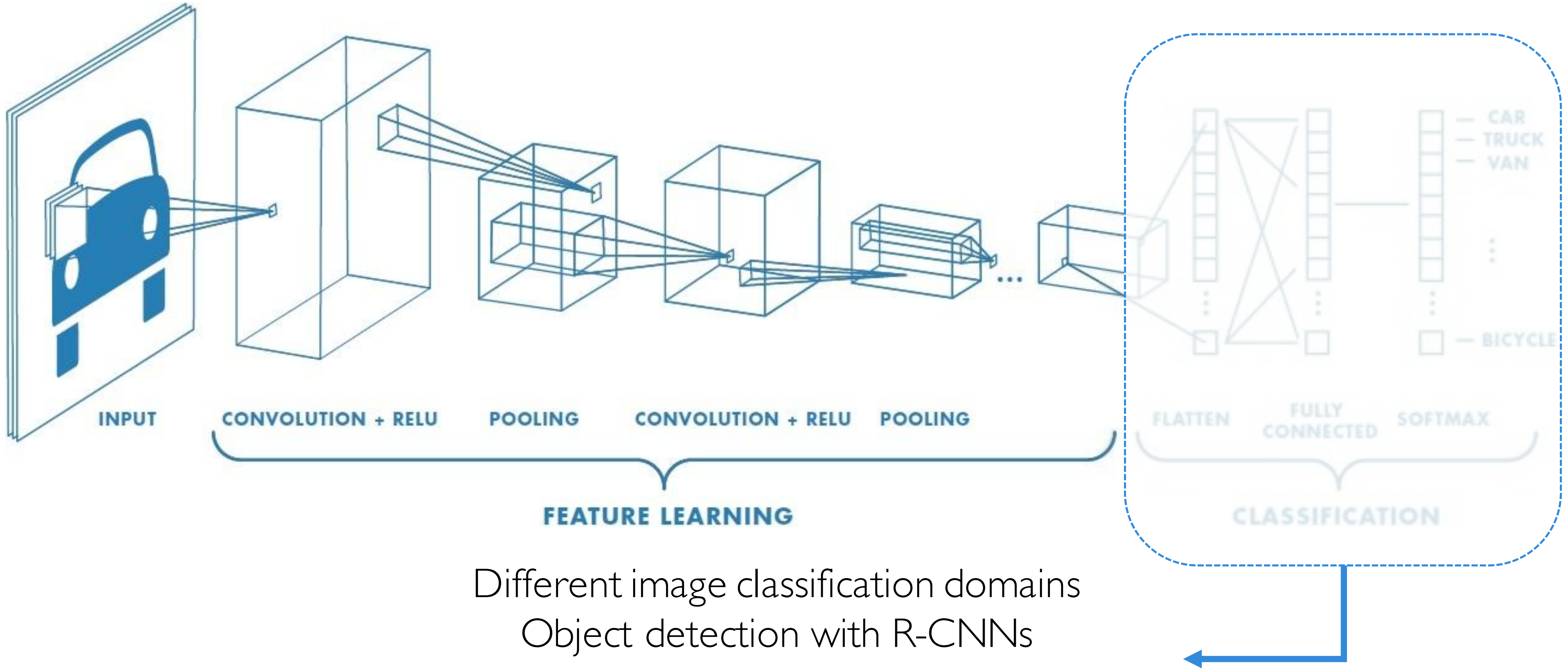
ImageNet Challenge: Classification Task





An Architecture for Many Applications

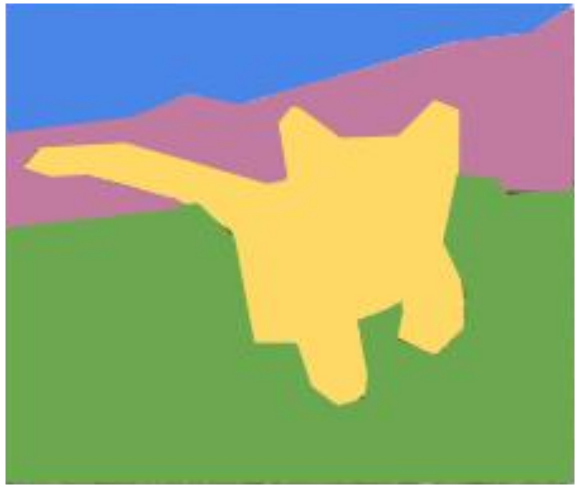
An Architecture for Many Applications



Different image classification domains
Object detection with R-CNNs
Segmentation with fully convolutional networks
Image captioning with RNNs

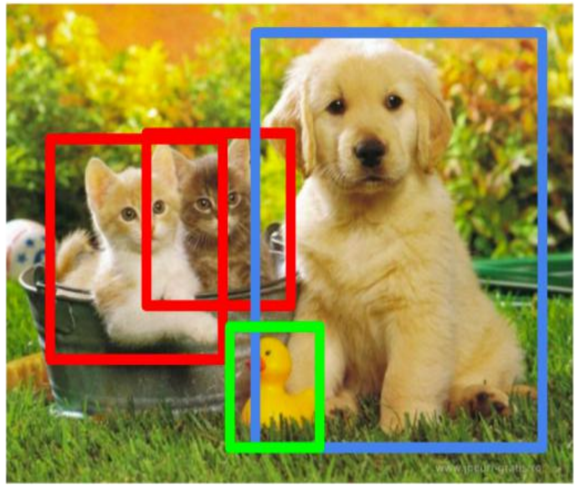
Beyond Classification

Semantic Segmentation



CAT

Object Detection



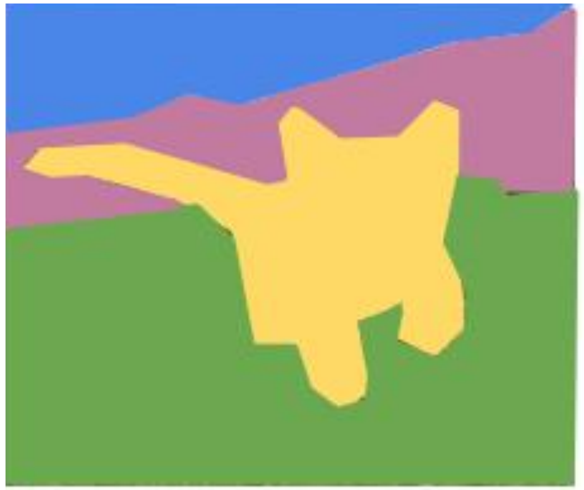
CAT, DOG, DUCK

Image Captioning

The cat is in the grass.

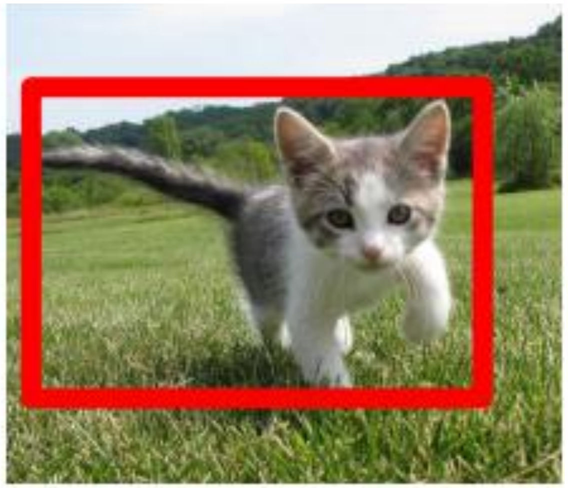
Beyond Classification

Semantic Segmentation



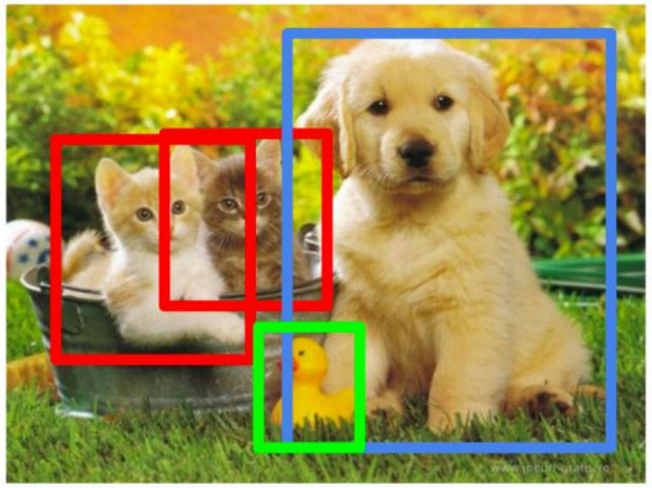
CAT

Classification + Localization



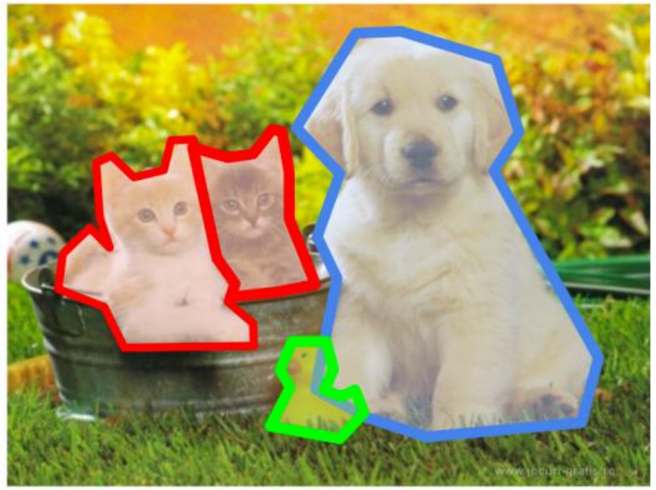
CAT

Object Detection



CAT, DOG, DUCK

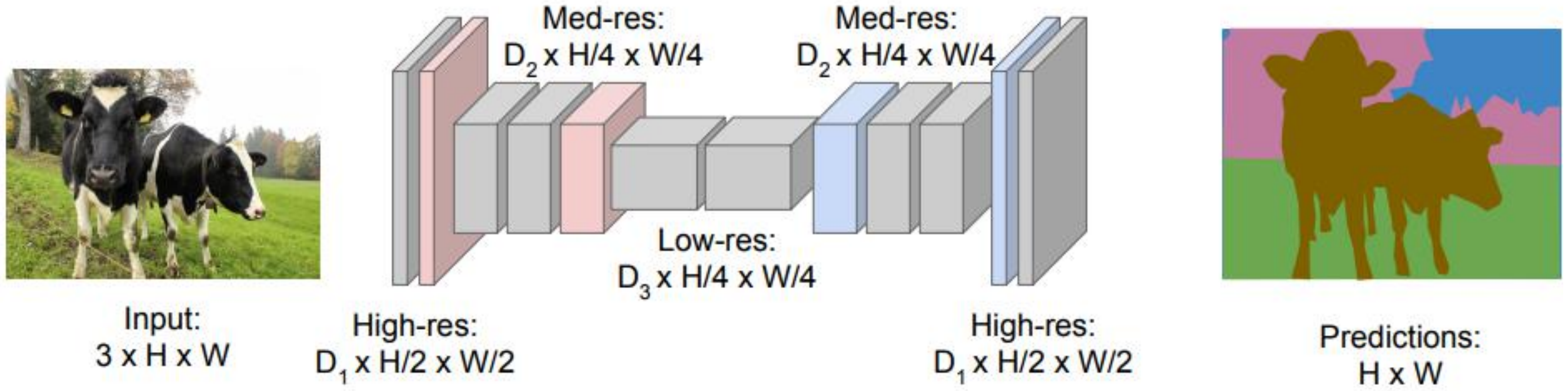
Instance Segmentation



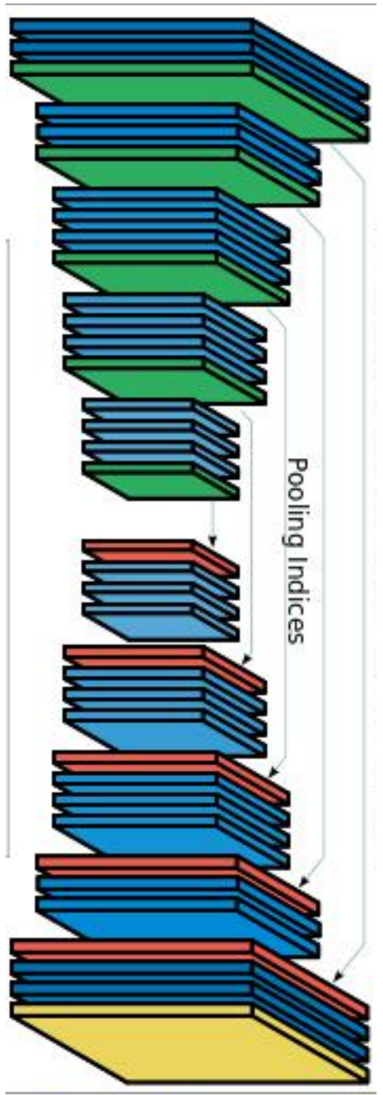
CAT, DOG, DUCK

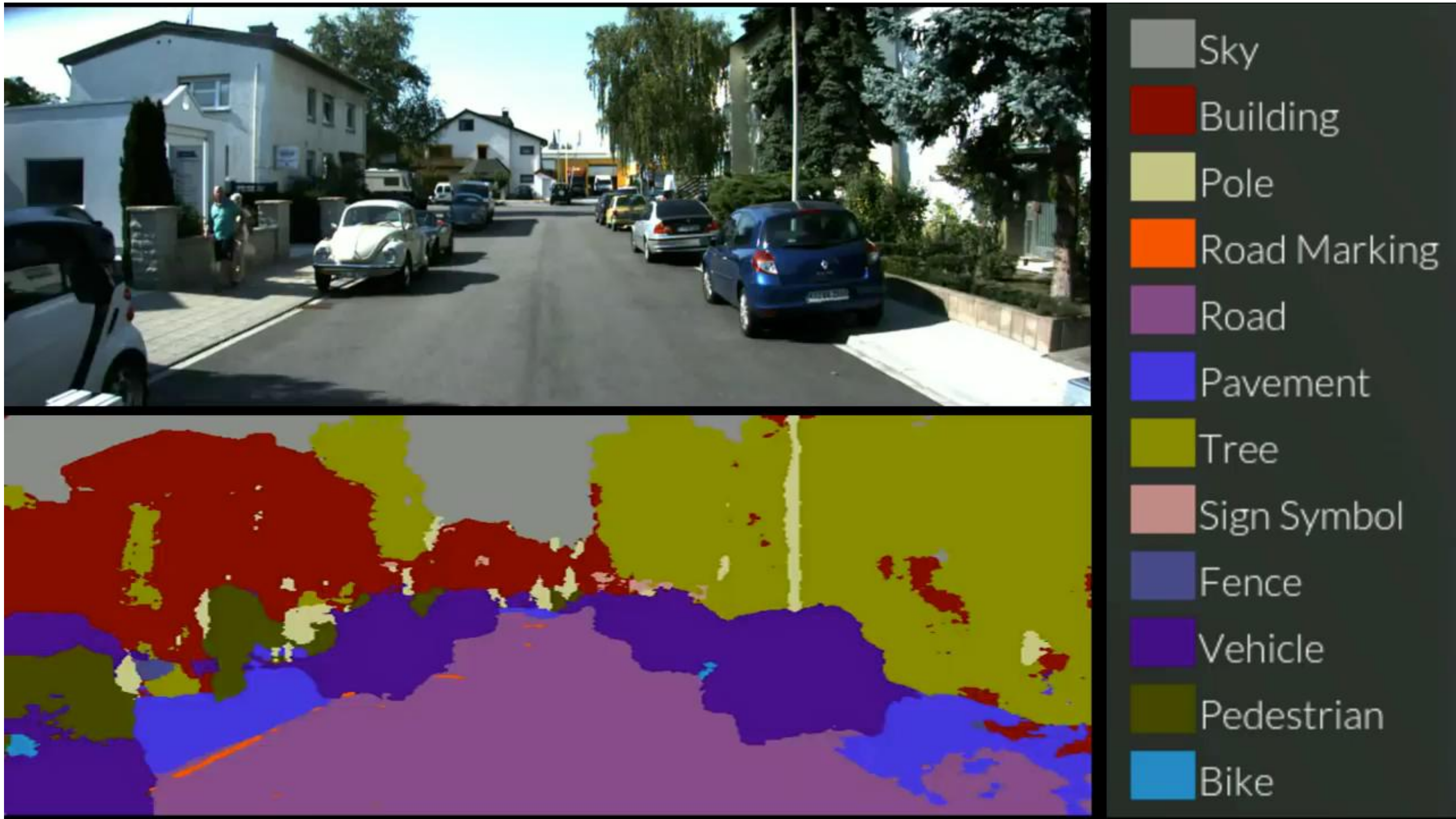
Semantic Segmentation: FCNs

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



Driving Scene Segmentation





Object Detection with R-CNNs

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

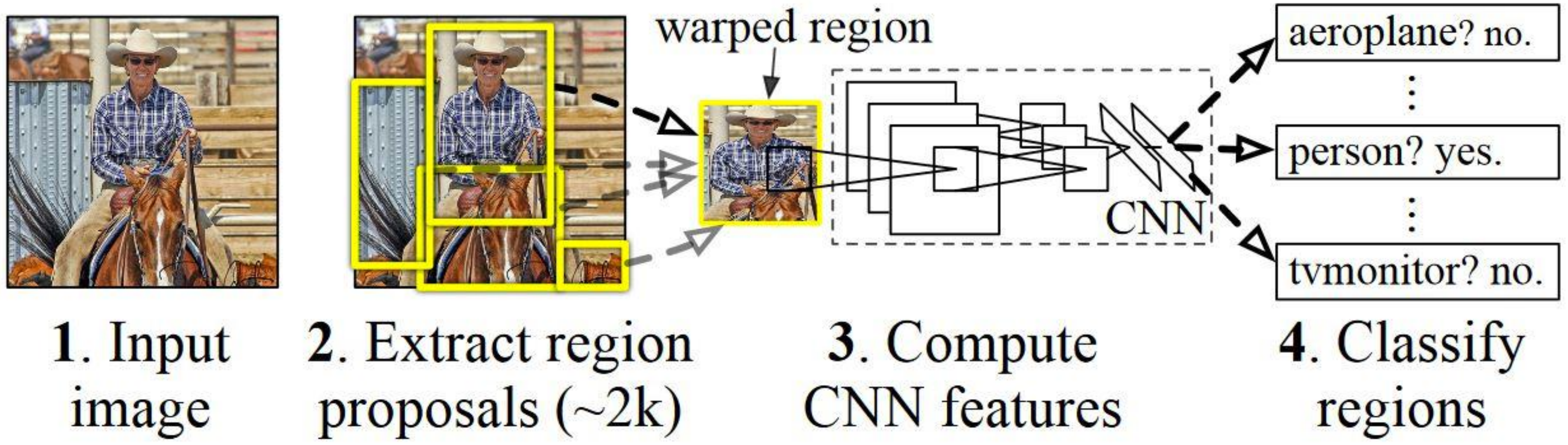
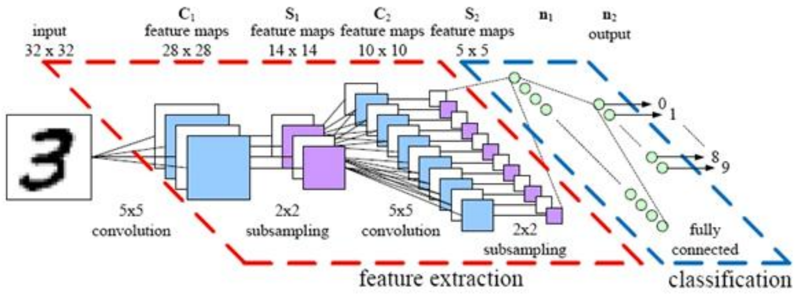
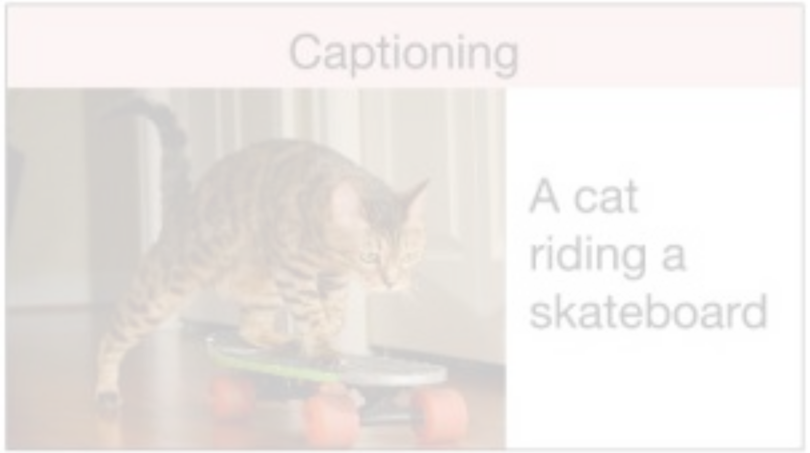


Image Captioning using RNNs





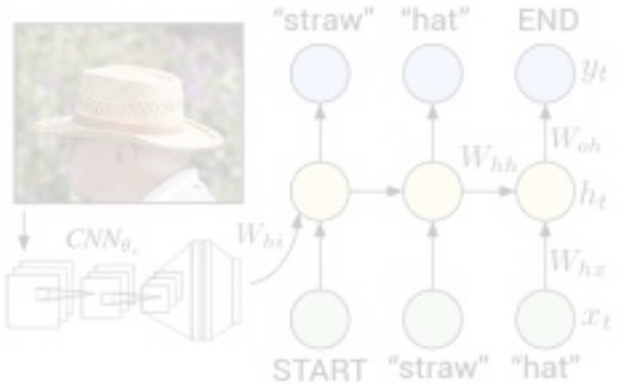
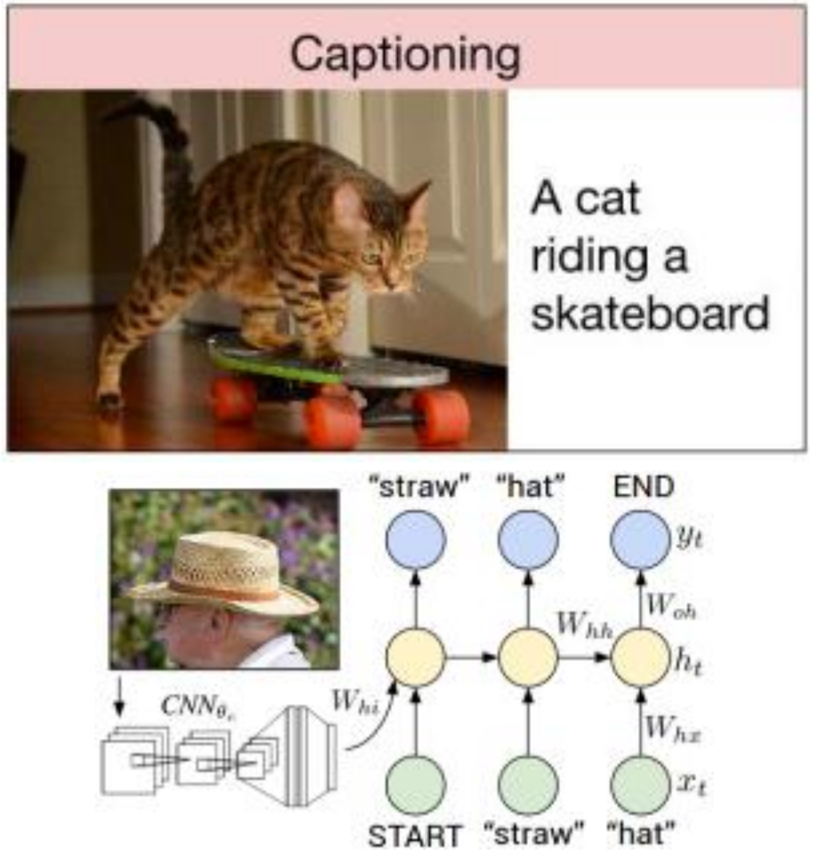


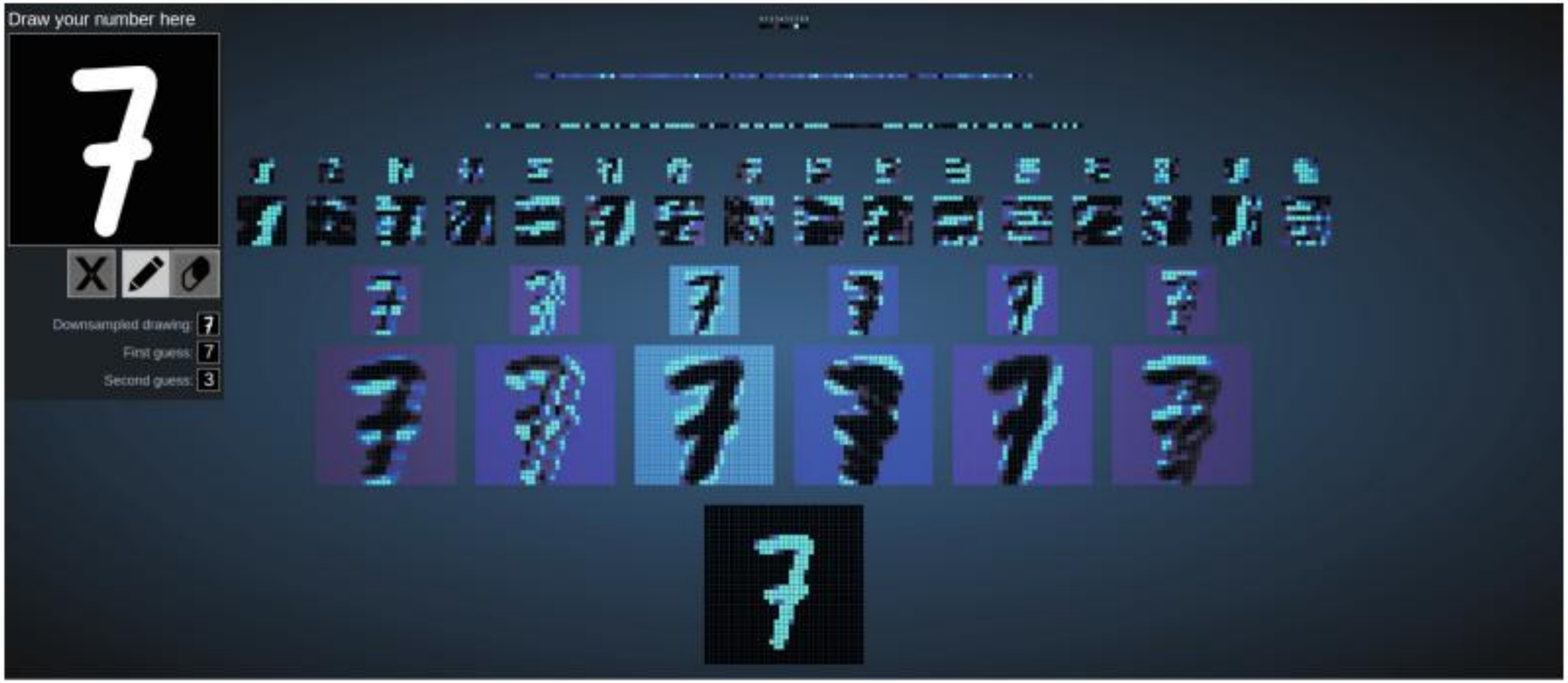
Image Captioning using RNNs

Classification
Cat
feature extraction
classification



Visualizing Convolutional Neural Networks

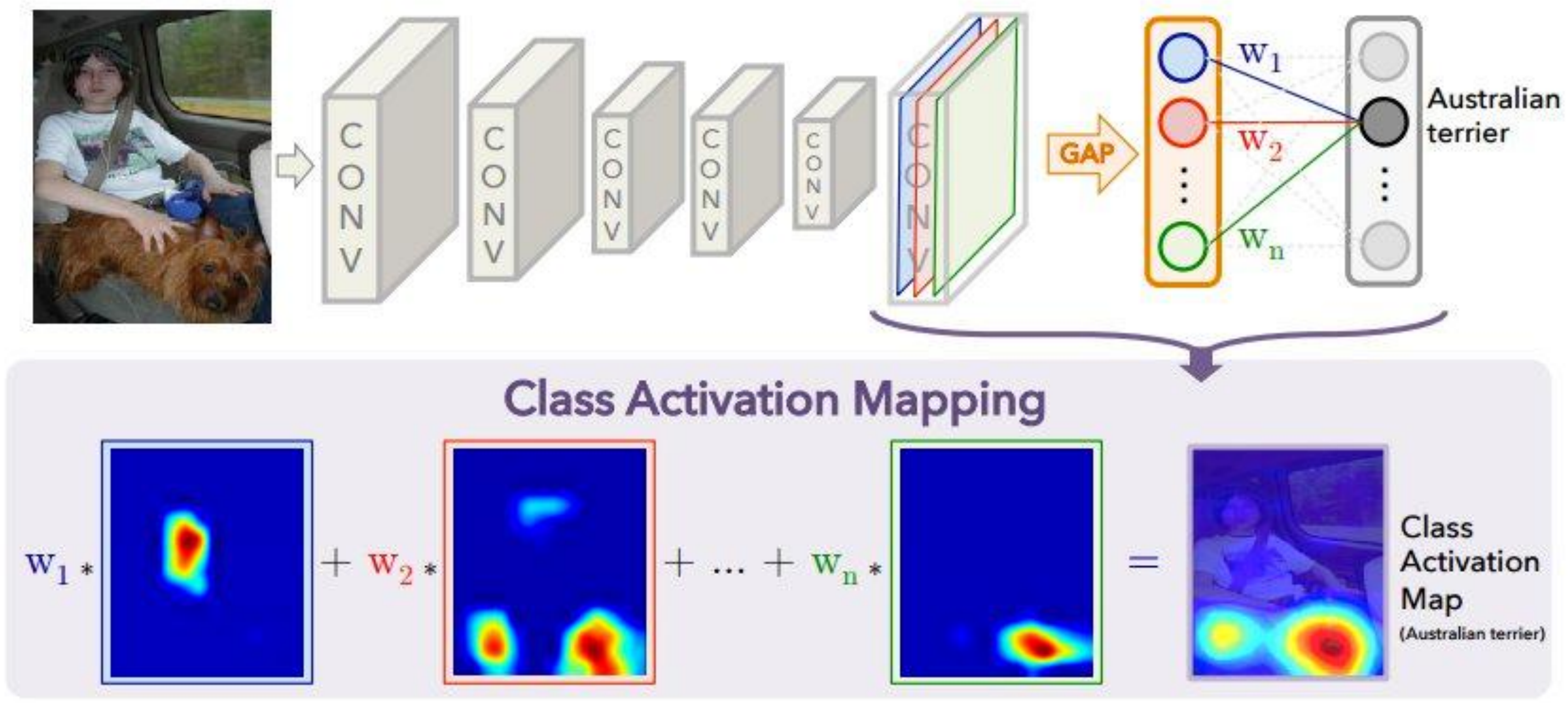
Peering Inside CNNs



Class Activation Maps (CAMs)

6.S191 Lab!

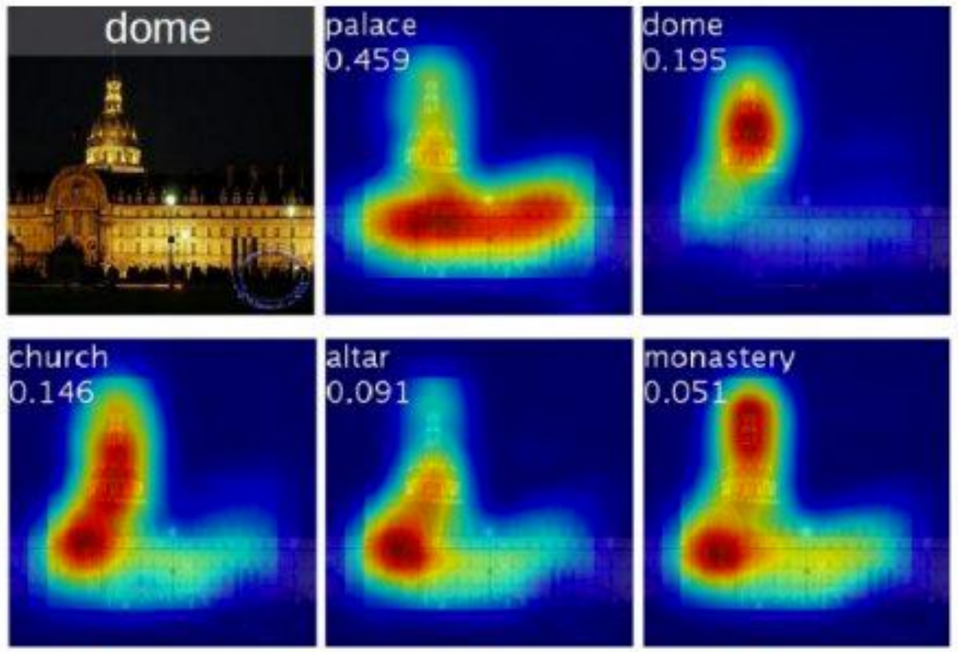
A **class activation map (CAM)** for a given class
highlights the image regions used by the CNN to identify that class



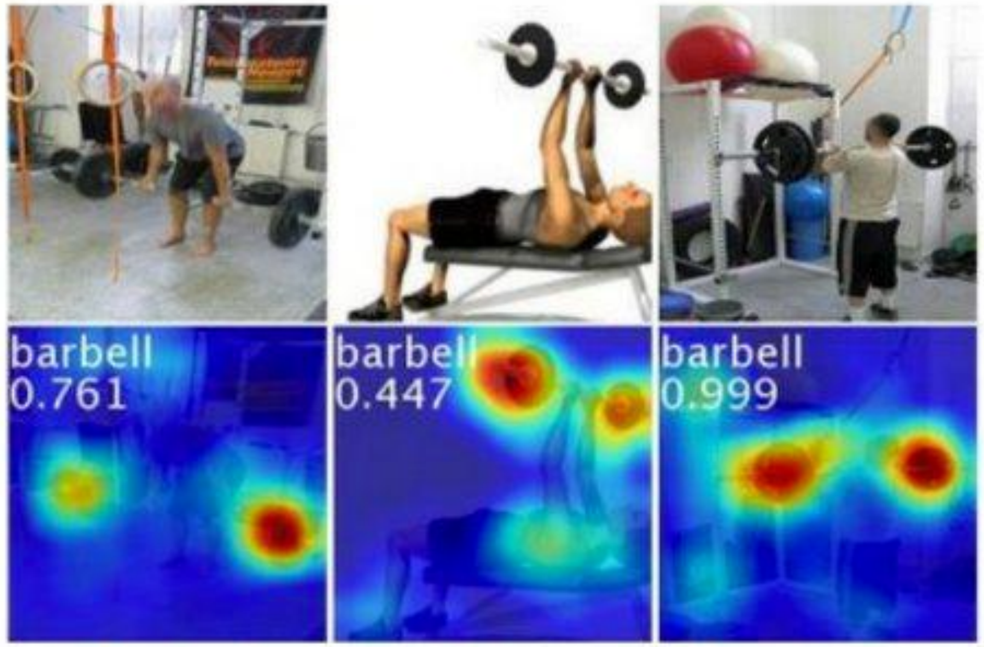
Class Activation Maps (CAMs)

6.S191 Lab!

A **class activation map (CAM)** for a given class
highlights the image regions used by the CNN to identify that class



Class activation maps of top 5 predictions



Class activation maps for one object class

Deep Learning for Computer Vision: Impact and Summary

Data, Data, Data

ImageNet:
22K categories. 14M images.

MNIST: handwritten digits

places

THE SCENE RECOGNITION DATABASE

places: natural scenes

Airplane

Automobile

Bird

Cat

Deer

Dog

Frog

Horse

Ship

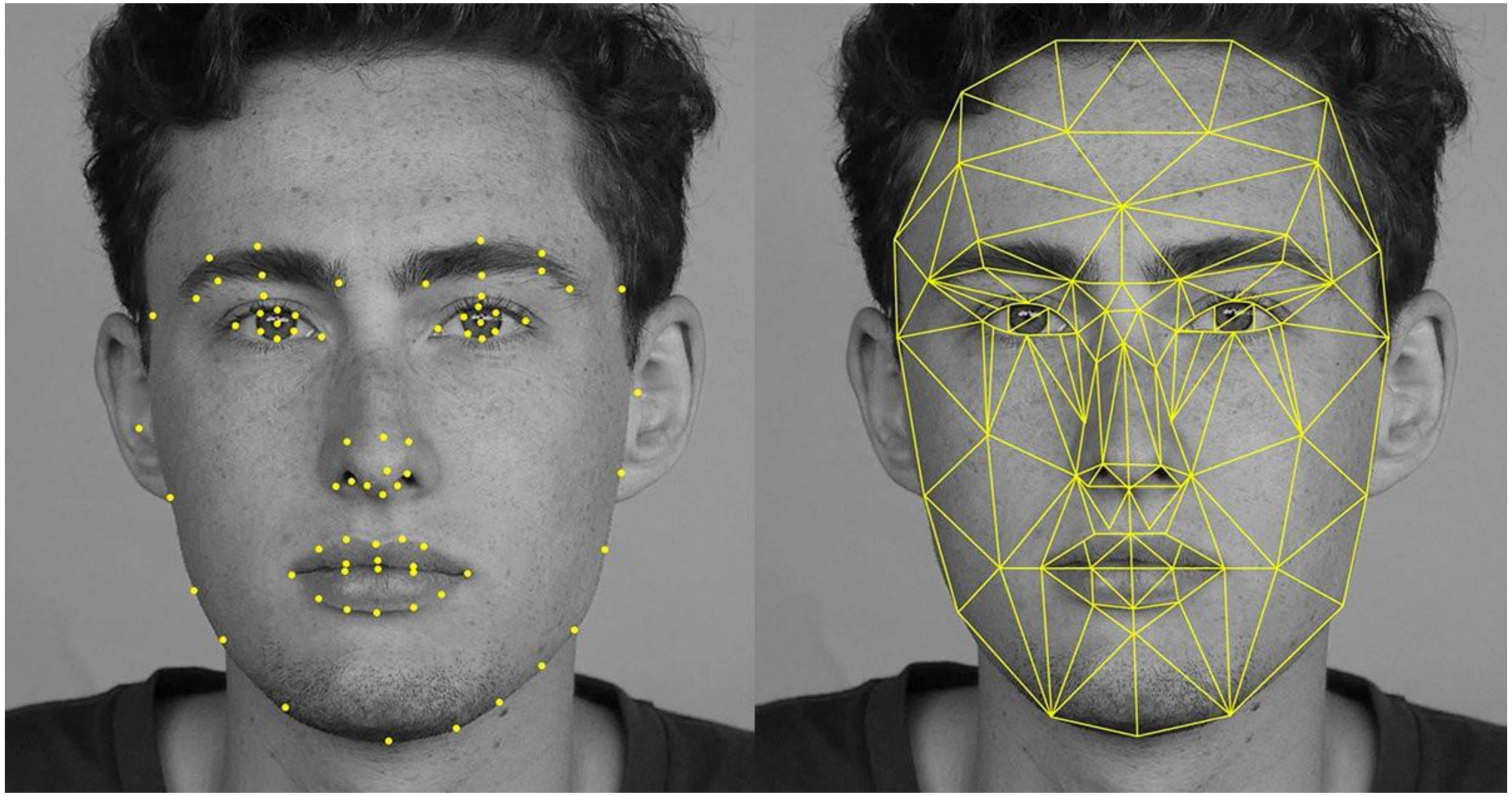
Truck

CIFAR-10

Deep Learning for Computer Vision: Impact

nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
LESIONS LEARNT
Artificial intelligence powers detection of skin cancer from images PAGES 30 & 115
person
person
person
skateboard
dog

Impact: Face Recognition



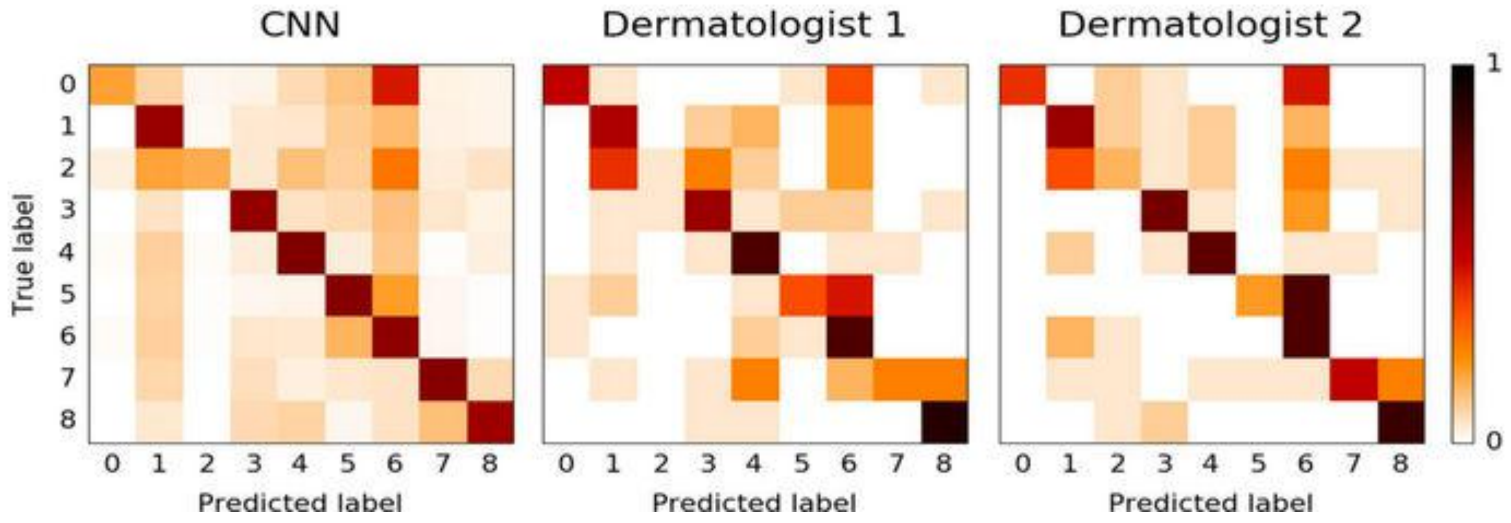
Impact: Self-Driving Cars

[18]

Impact: Medicine

nature
THE INTERNATIONAL WEEKLY JOURNAL OF SCIENCE
LESIONS LEARNT
Artificial intelligence powers detection of skin cancer from images PAGES 36 & 115
NATURE.COM/NATURE

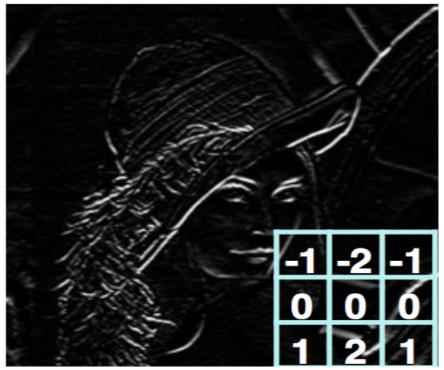
Dermatologist-level classification of skin cancer with deep neural networks



Deep Learning for Computer Vision: Review

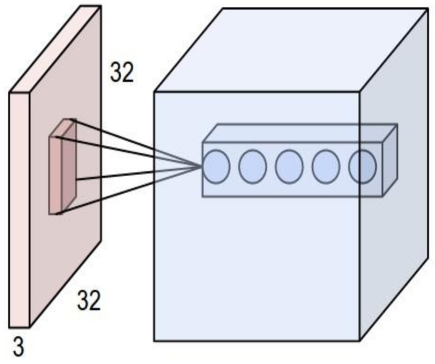
Foundations

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



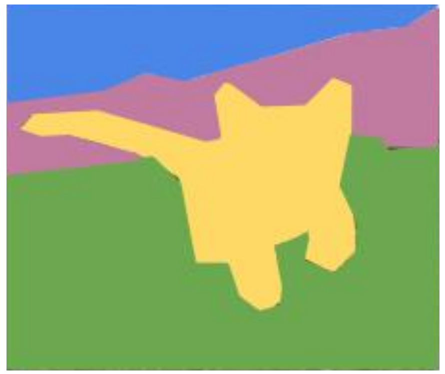
CNNs

- CNN architecture
- Application to classification: ImageNet



Applications

- Segmentation, object detection, image captioning
- Visualization



References:

https://goo.gl/ZuBkGx