

# Visual Computing

## 2024/2025

Class 11

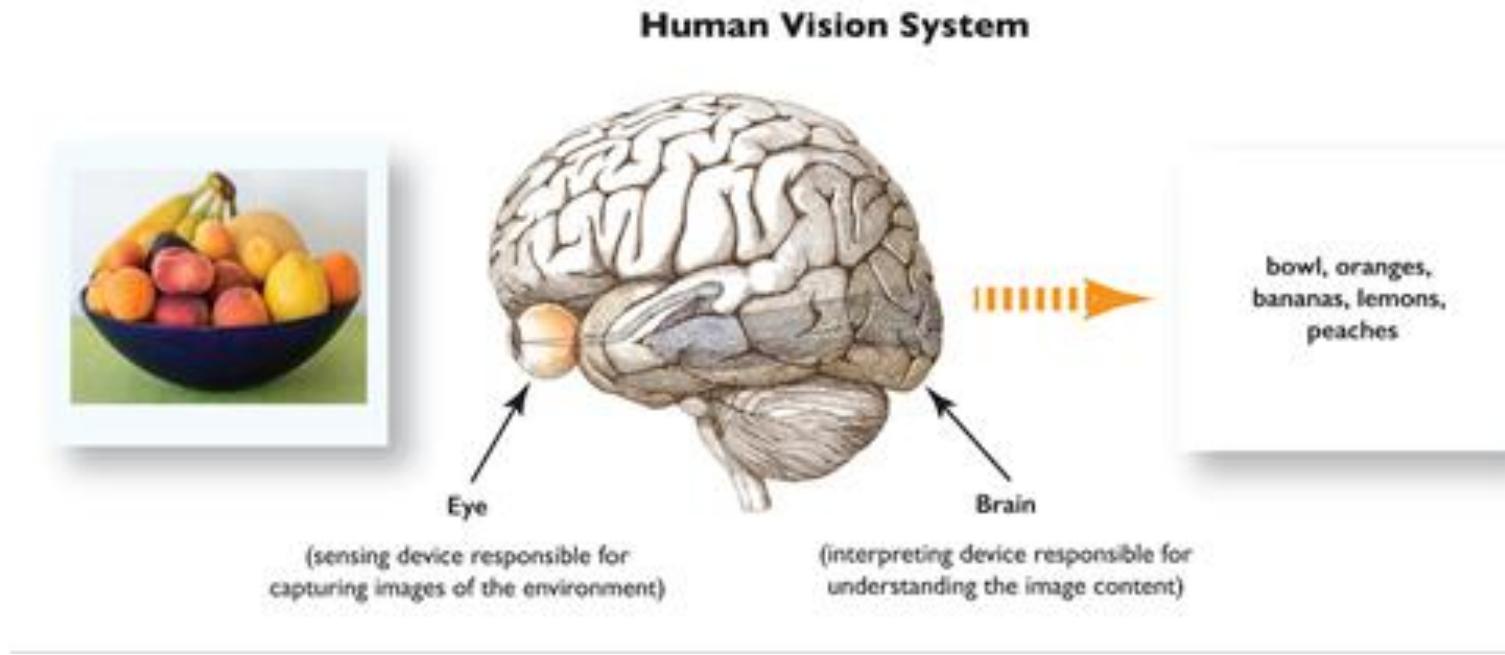
Introduction to Computer Vision

# Agenda

- ▶ What is Computer Vision
- ▶ Image Features
- ▶ Basics of object detection
- ▶ Approaches to Computer Vision
- ▶ Applications
- ▶ Off-the-shelf Tools

# Human Vision

## Making sense of what we see



# Human Vision

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# Human Vision

## Making sense of what we see



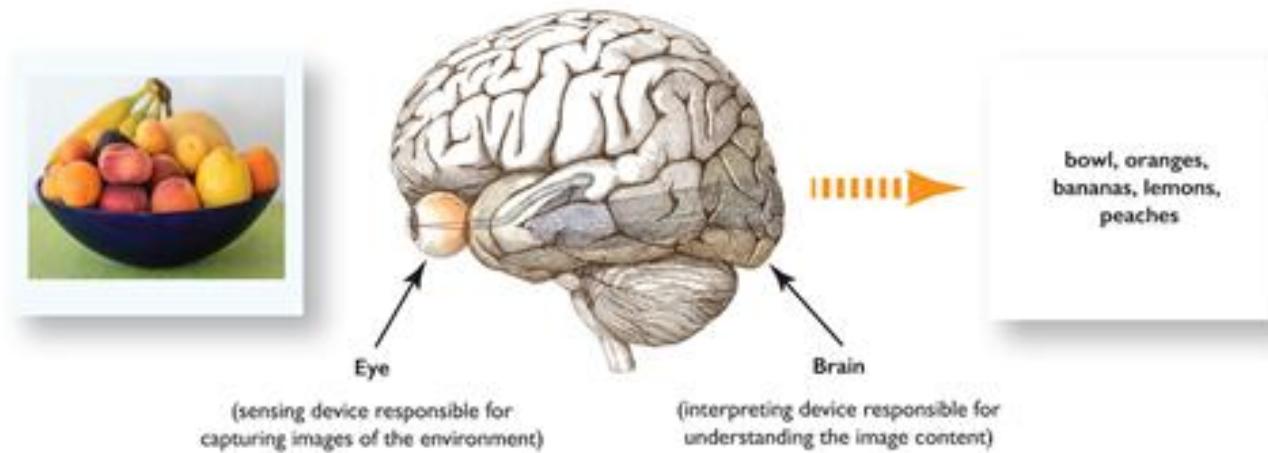
# Human Vision

## Making sense of what we see

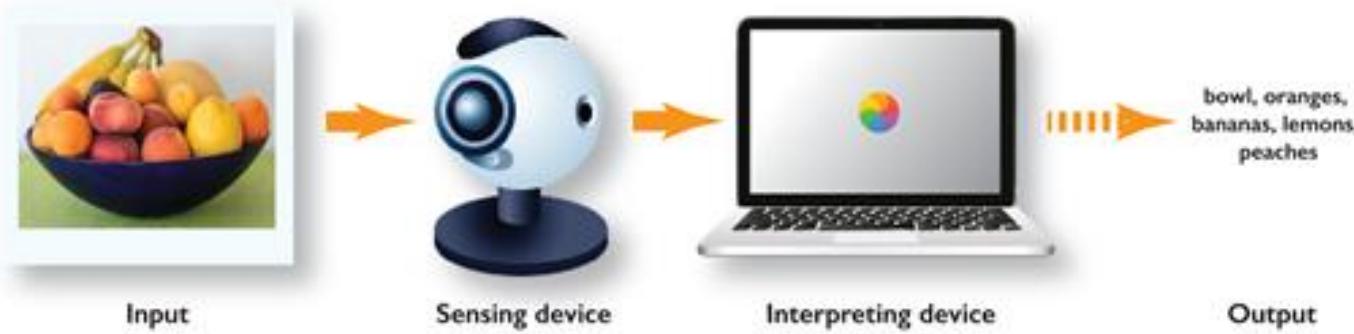


# Rise of Computer Vision

**Human Vision System**



**Computer Vision System**



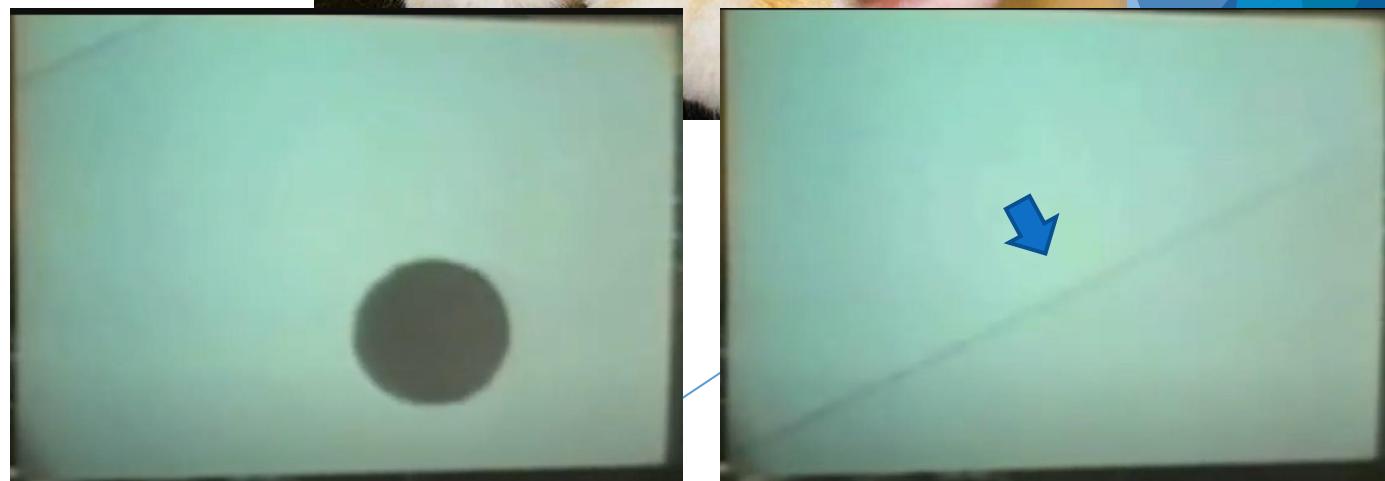
# Computer Vision

Computer vision is the field of computer science that works on enabling computers to **identify and process objects in the same way that humans do.**

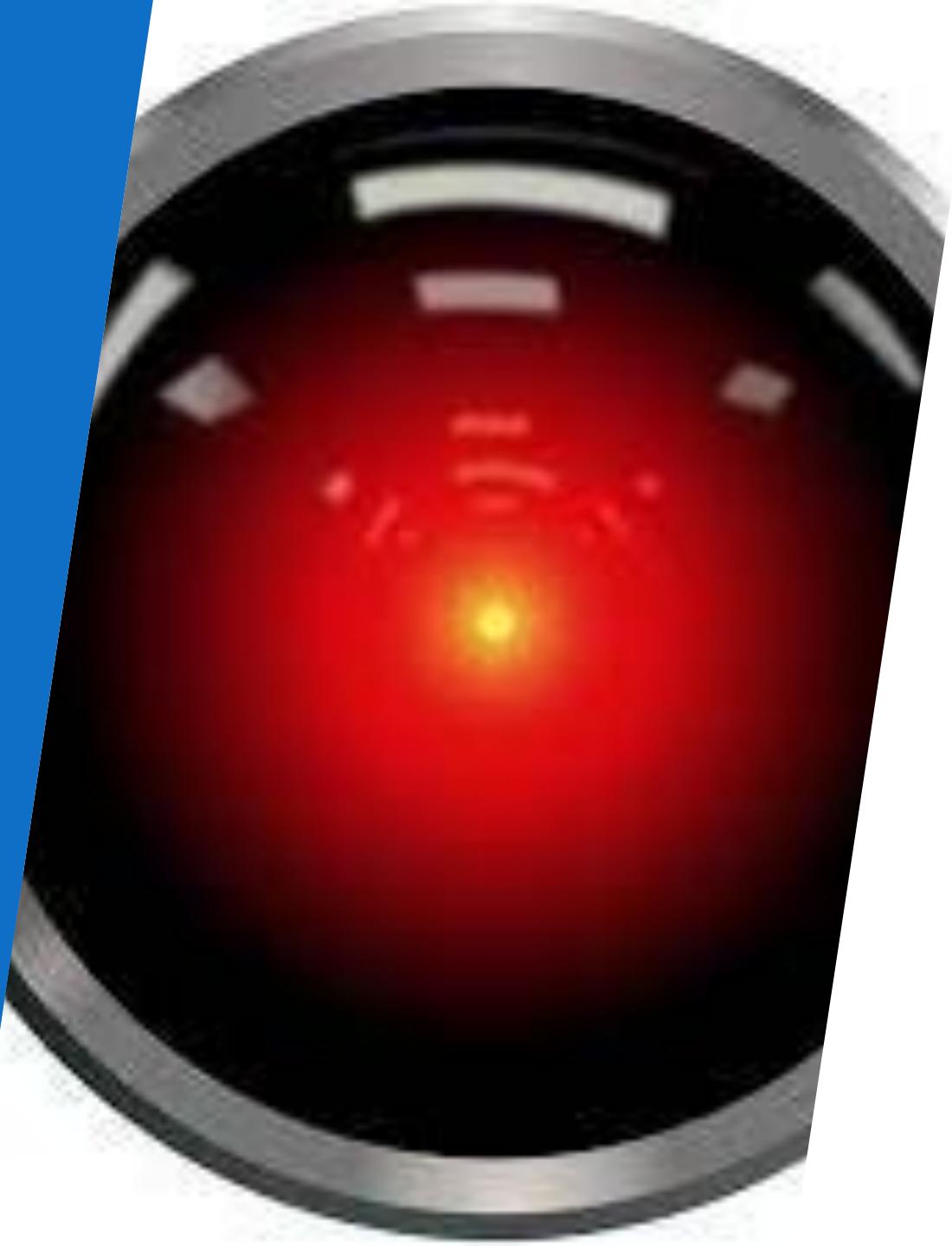
i.e., **make sense** of images and videos beyond a set of pixels or simple regions providing a **meaningful interpretation**

# Some History

- ▶ The foundations of Computer Vision date back to the 1950s and 1960s
- ▶ Experiments with cats studying how neurons react to various stimuli
- ▶ Human vision discovered to be hierarchical
  - ▶ Edges, shapes, objects,...



<https://www.youtube.com/watch?v=lOHayh06LJ4>



# Some History

- ▶ The field of artificial intelligence is founded in Dartmouth College in 1956
- ▶ **Machines as intelligent as human beings predicted in a generation time**
- ▶ In **1966** Sussman and Minsky work on linking a camera to a computer and **having the computer describe what it saw**... something **ongoing, nowadays**...

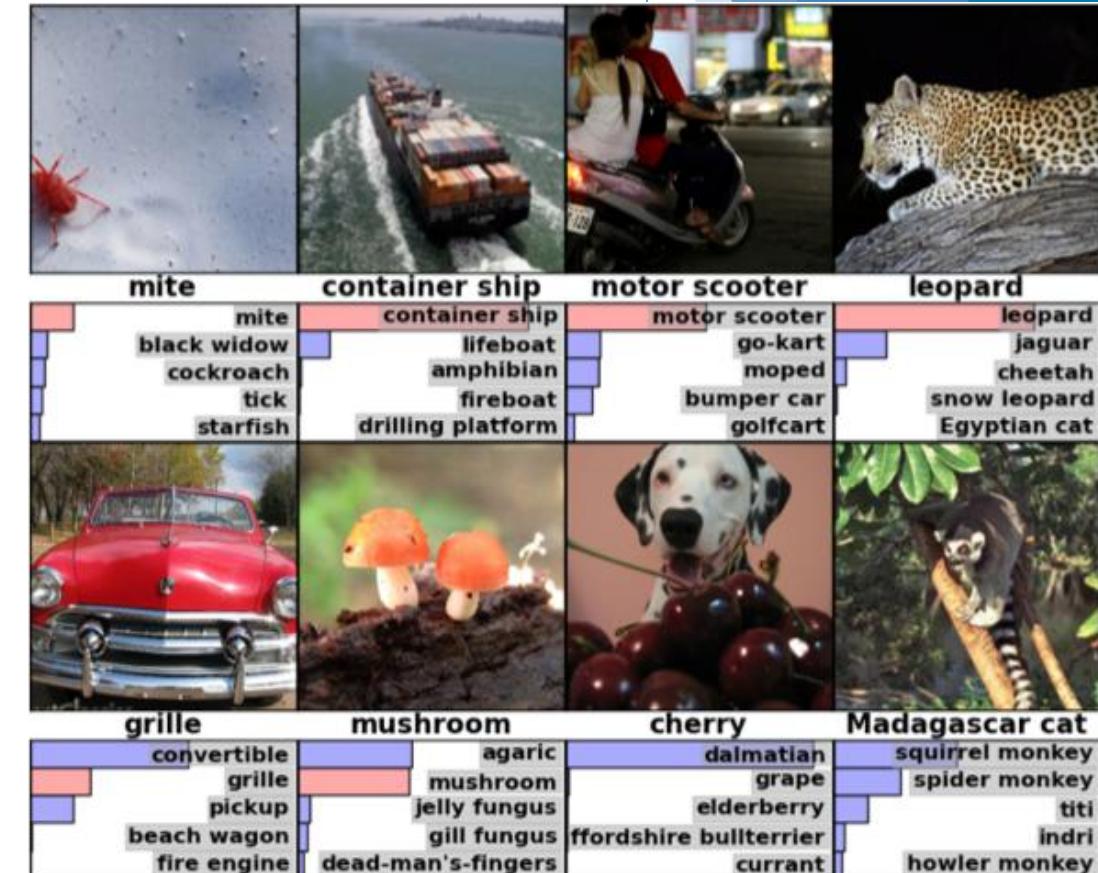
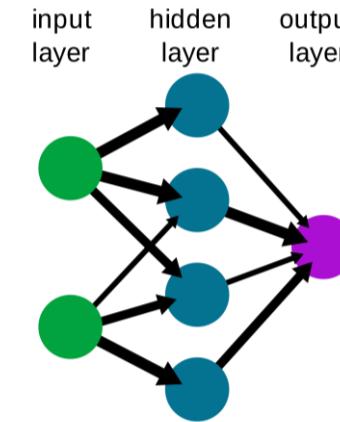
# Some History

Neural Networks gain momentum in the 1980s

Cornerstone at ImageNet Large Scale Recognition Challenge (ILSVRC) 2012 with the introduction of a deep neural network: **AlexNet** (error rate: 15.3%; second place was 26.2%)

**AlexNet** considered 1.2 million images to train

Since then, error rates fell to **just a few percent**

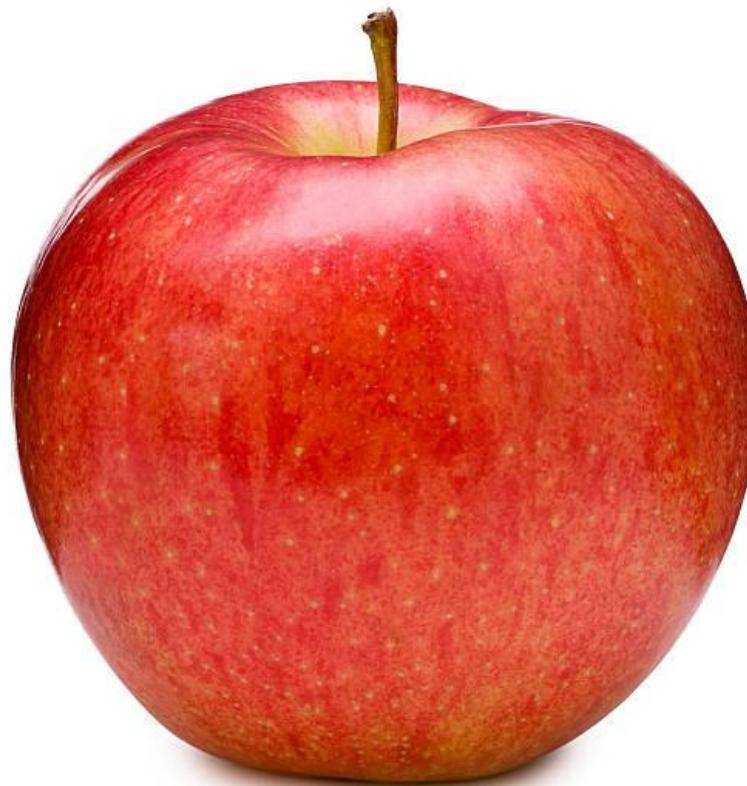


A close-up photograph of a lion's head and upper body. The lion has a light brown coat and is looking slightly to the left. In its mouth, it holds a black Canon EOS 7D camera body with a large lens attached. The lens is positioned in front of the lion's eye, creating a visual metaphor where the lion appears to be "looking" through the camera.

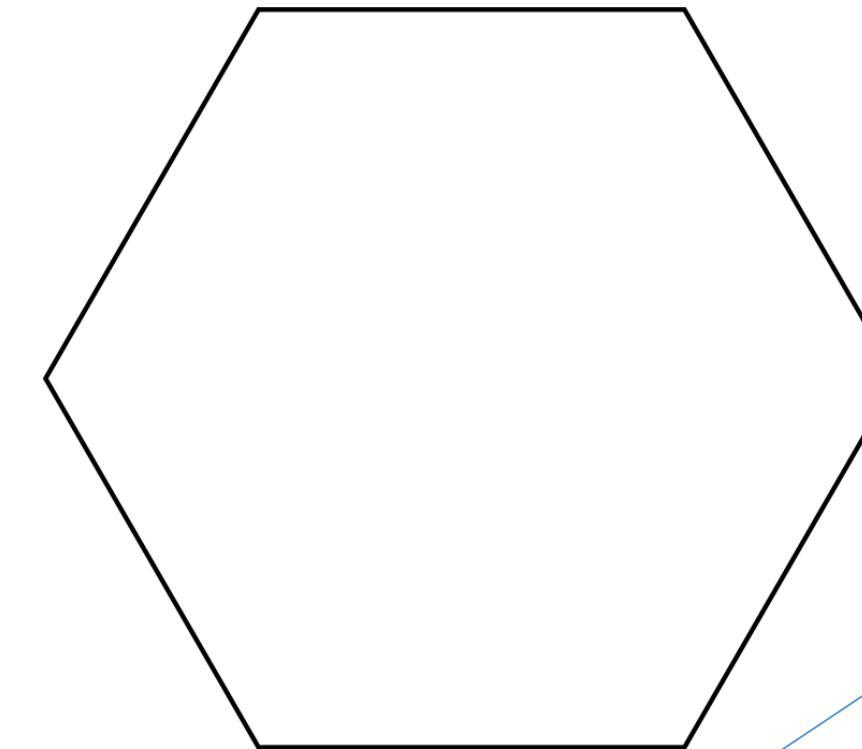
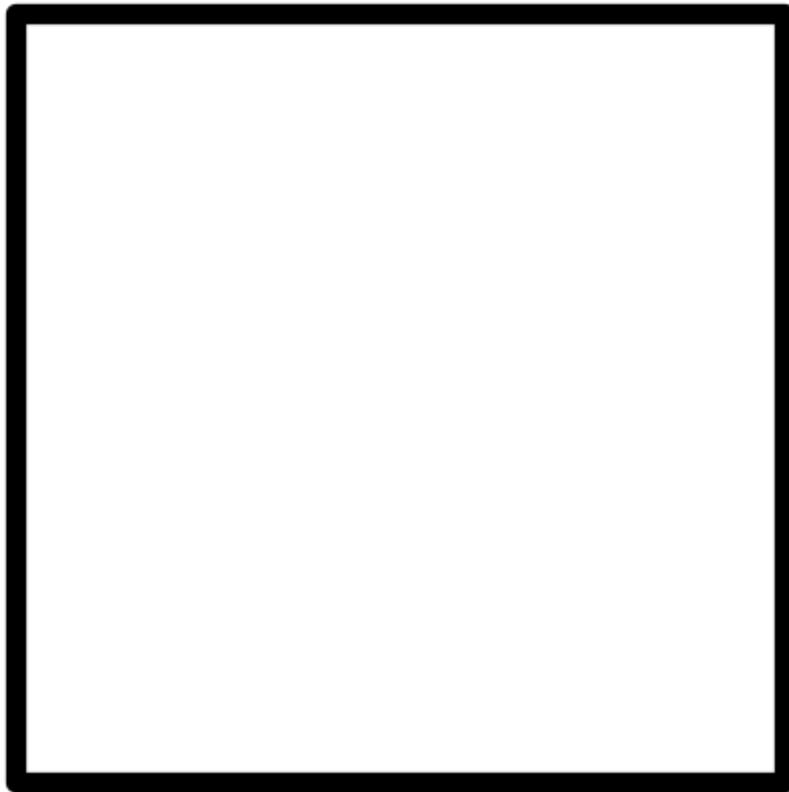
How do humans  
recognize objects?

# How do we make the distinction?

Without going into visual perception...



# How do we make the distinction?



A close-up, side-profile photograph of two male soccer players facing each other against a dark background. The player on the left has dark hair and a full, reddish-brown beard; he is wearing a dark blue jersey with red accents and the word "PARIS" visible. The player on the right has dark hair and is wearing a dark blue jersey with yellow stripes on the shoulders. They appear to be in a serious conversation.

How do we make the distinction?

# We Recognize Patterns

So, we – more or less – easily **find patterns** that help us identify different objects at different semantic levels (primate, person, old man, Samuel)

For computer vision, **how can we approach the problem in a similar fashion?**

# Image Features

Features are a form of representing **object characteristics** and patterns that may allow identifying it

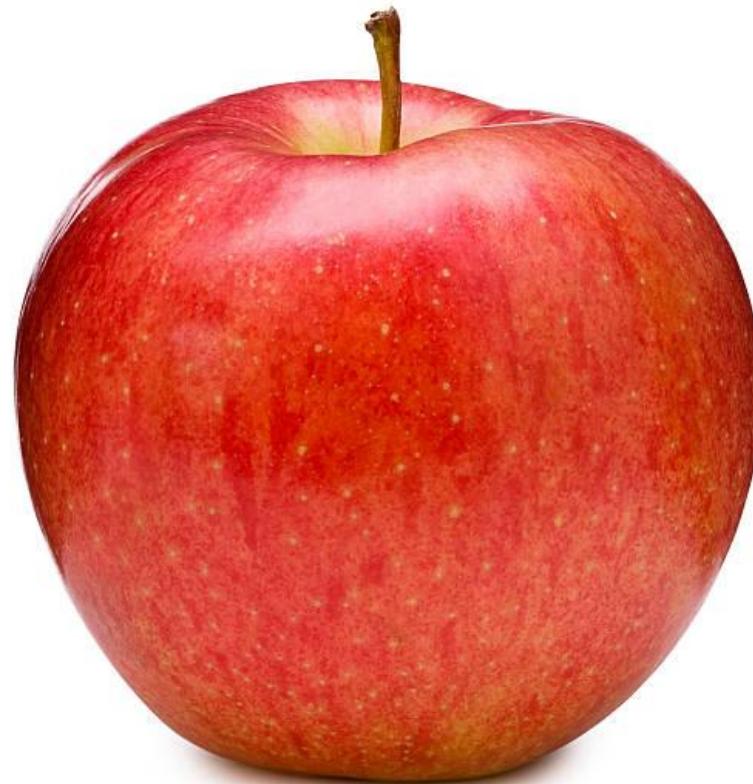
They can be local or global

Color, edges, corners, luminance, gradient,...

Often considered in sets (e.g., **feature vectors**)

# How do we make the distinction?

{color = red}



{color = orange}



# How do we make the distinction?

{color = red, +??}



{color = orange, +??}



**More than one feature** may be required to distinguish between objects

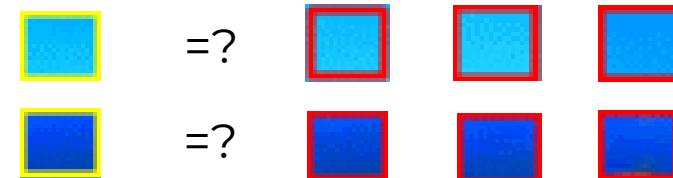
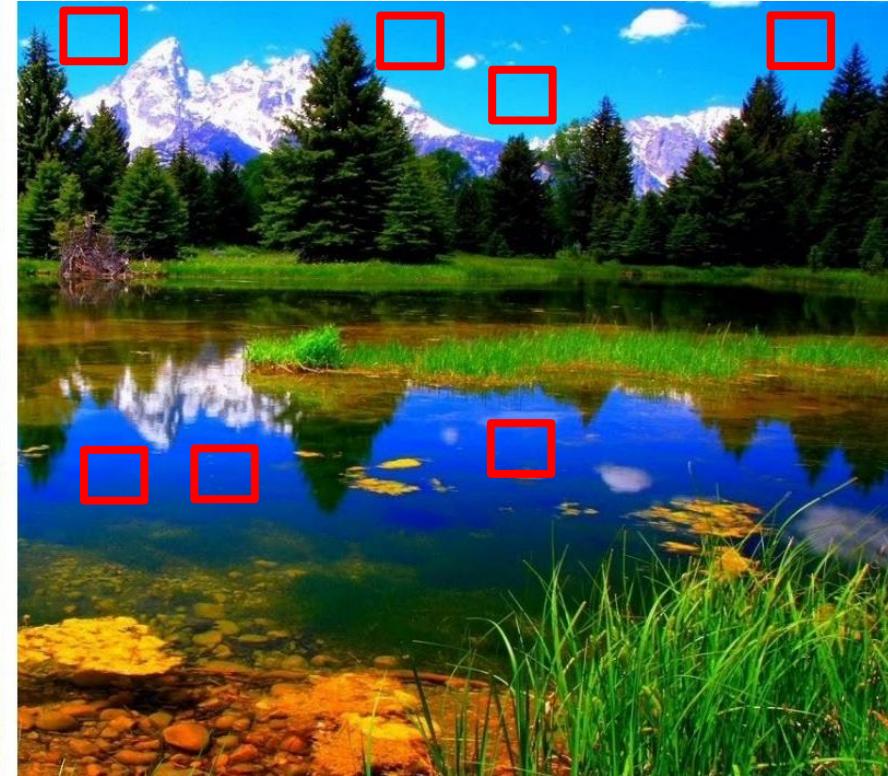
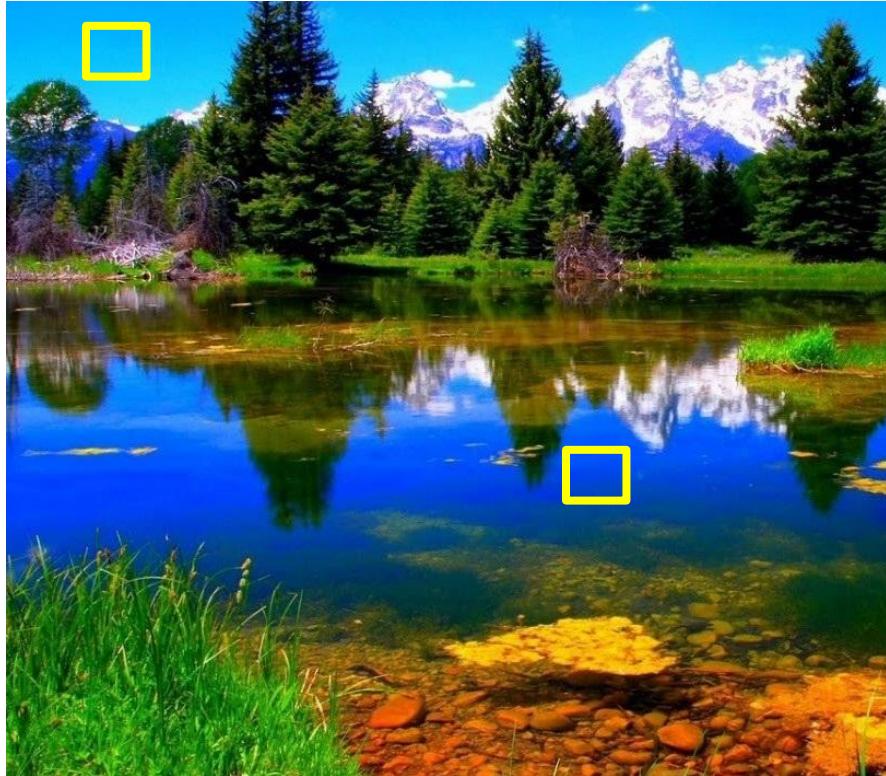
# Matching Problem

# Matching Problem

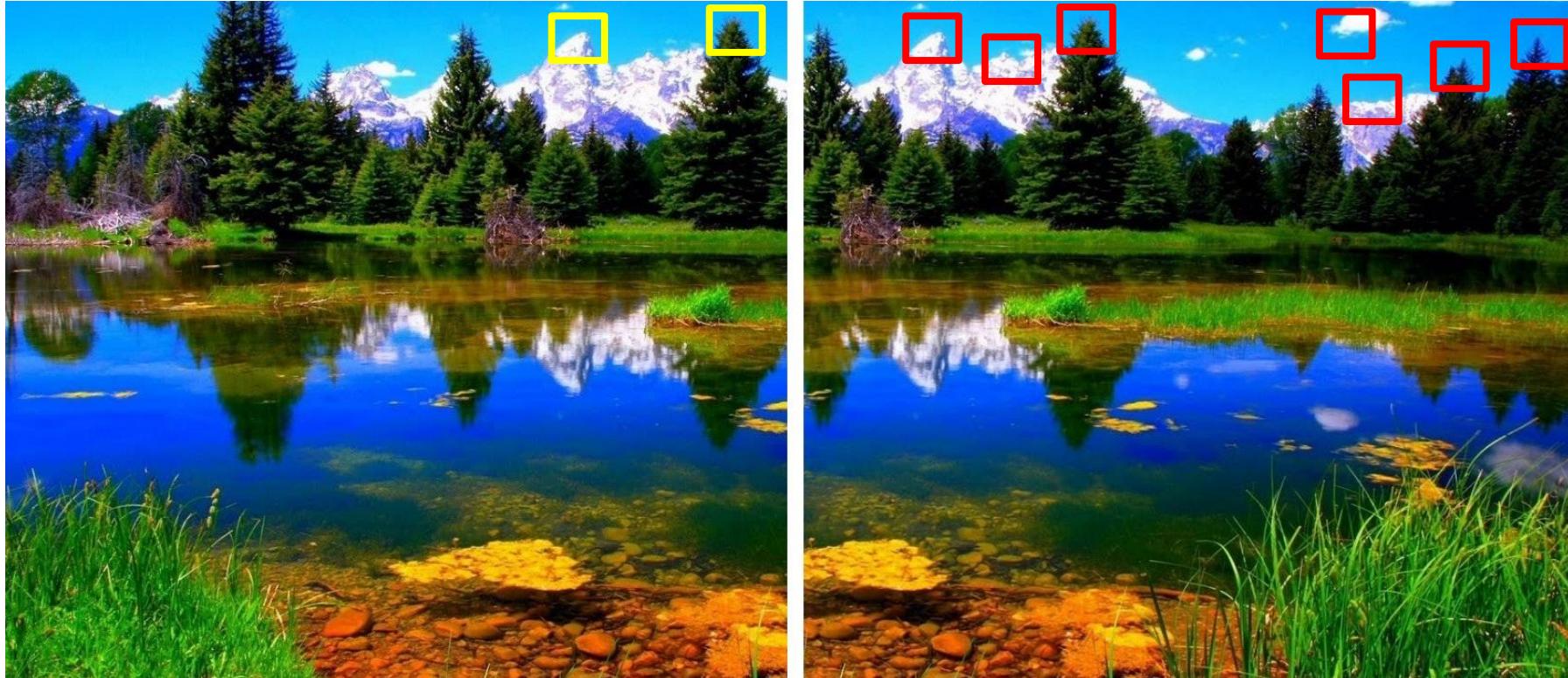


How do we align the images to obtain the larger panorama?

# Matching Problem



# Matching Problem



Are these any  
better?

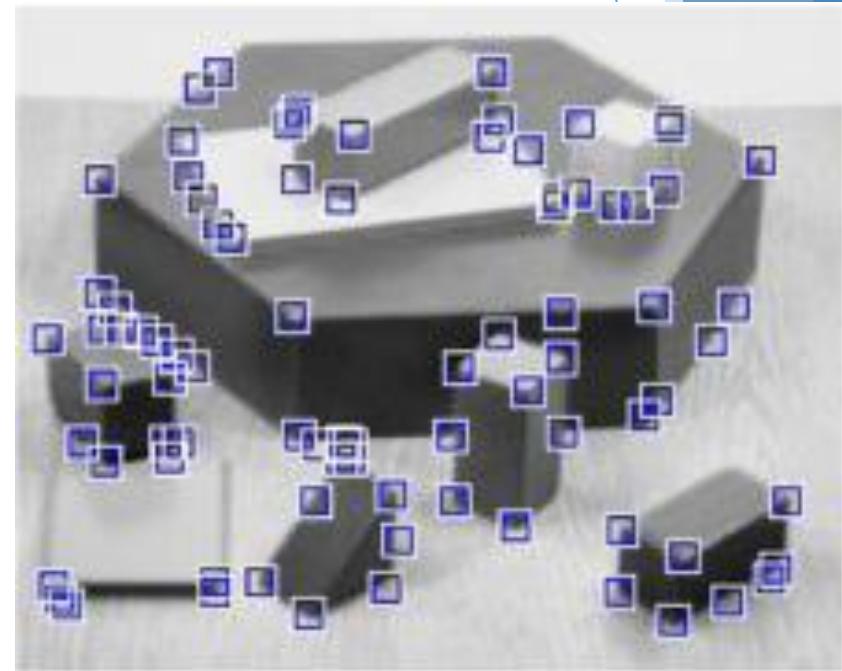


# Corners

**Junctions** of contours

Generally, **less variable with changes of viewpoint**

Characterized by **large variations in the neighbourhood** around it



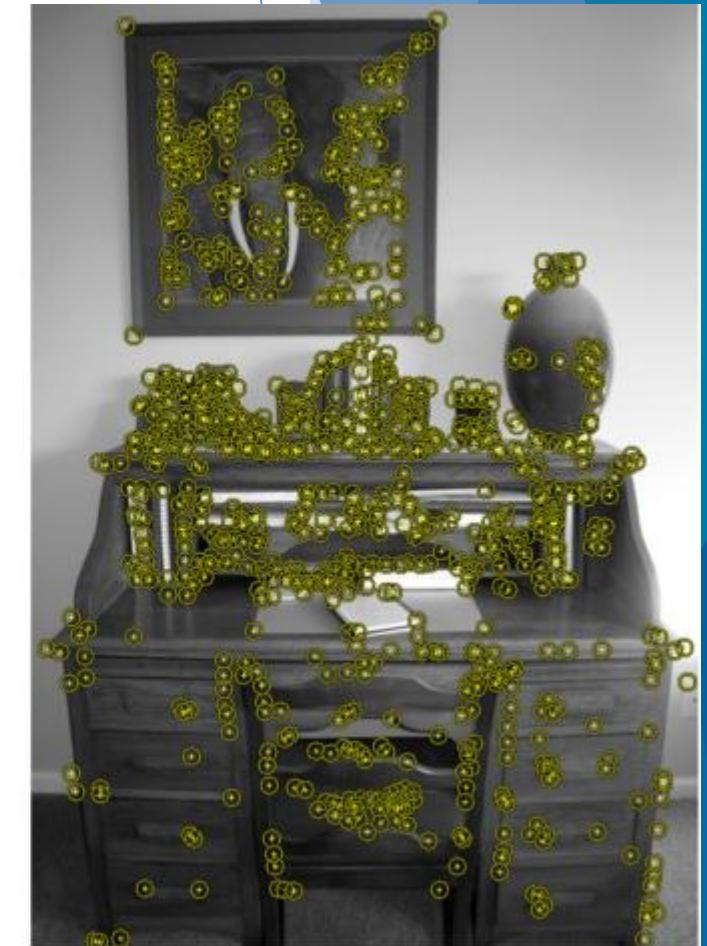
# Feature Examples

## Corners

**Harris Corner Detection**  
(or Shi-Tomasi Corner Detector)

What happens to the results if we rotate the image?

What happens if we scale the image?





# Feature Examples

## Scale-Invariance

### Scale-Invariant Feature Transform (SIFT)

- ▶ Checks different image scales using gaussian filtering to determine **keypoints**

### Speed-up Robust Features (SURF)

- ▶ Faster version of SIFT

Overall idea is to determine **keypoints** and compute a **descriptor** at each keypoint considering the neighbourhood

# Feature Examples

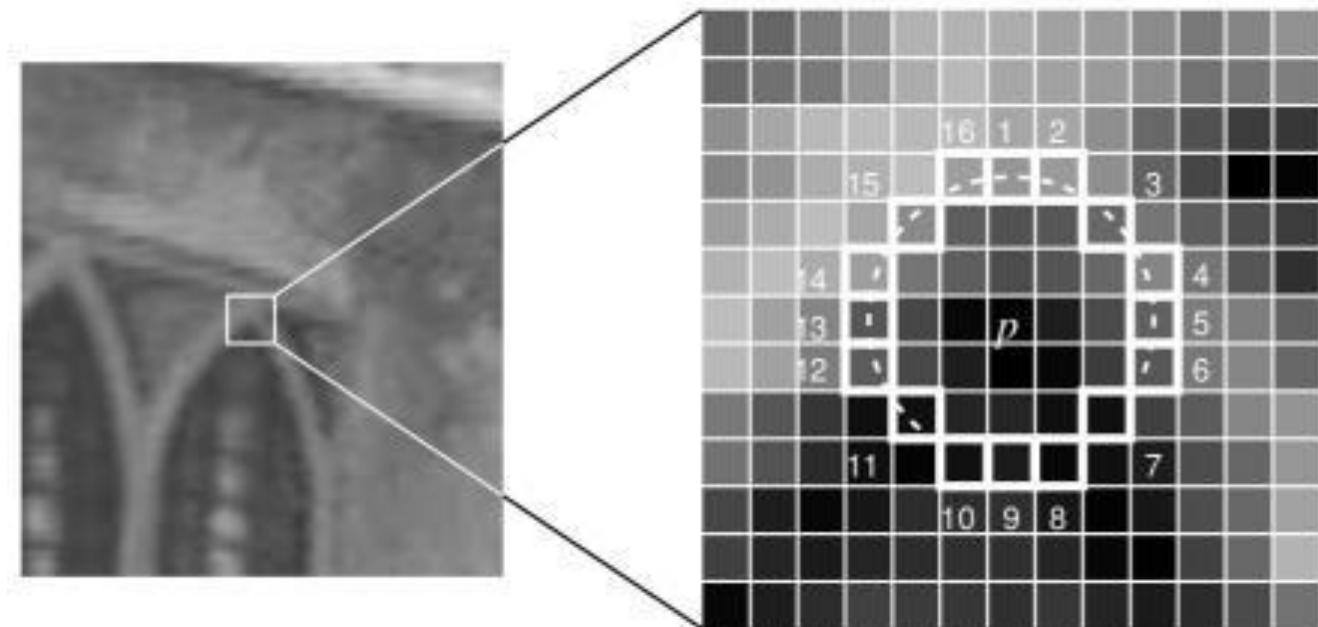
## Faster approaches

Features from Accelerated Segment Test (**FAST**)

Binary Robust Independent Elementary Features (**BRIEF**)

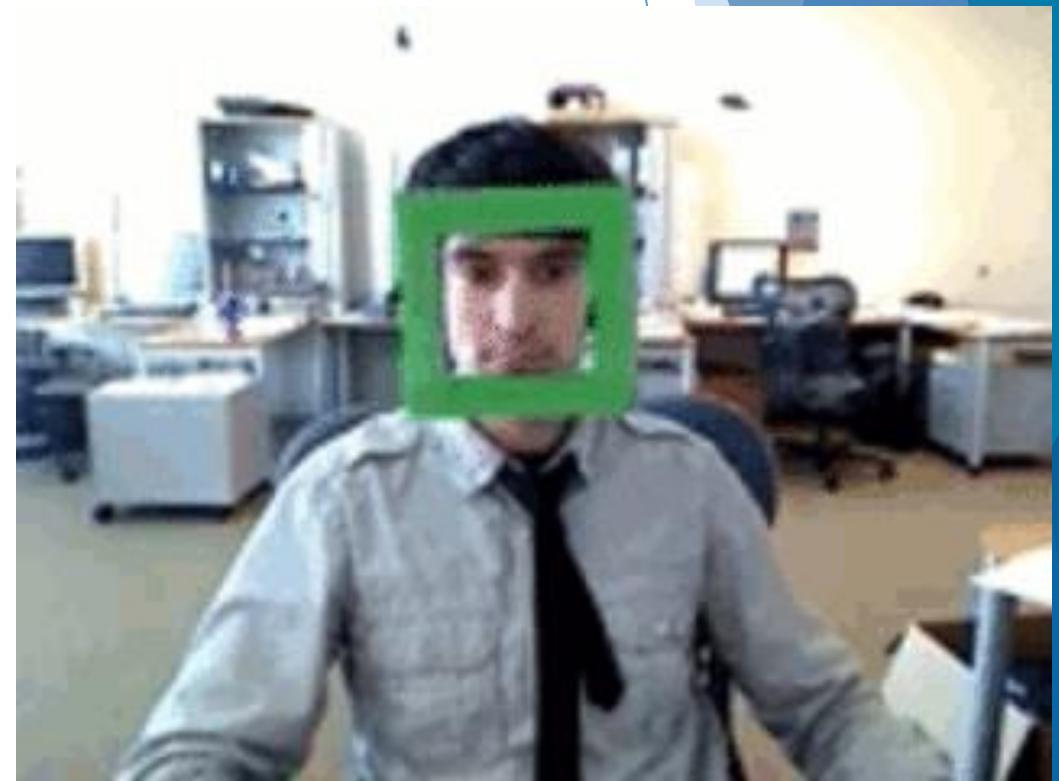
Oriented FAST and Rotated BRIEF (**ORB**)

Overall idea is to determine **keypoints** and compute a **descriptor** at each keypoint considering the neighbourhood

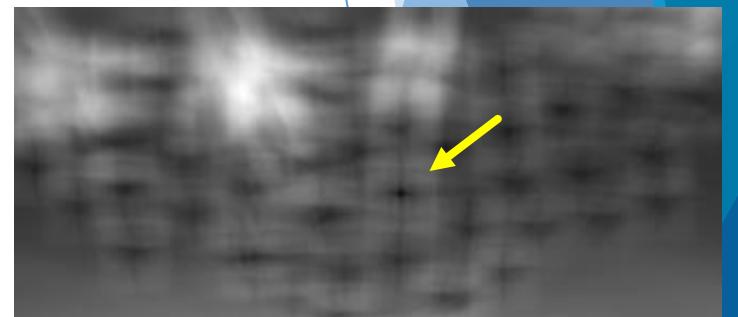


# Object tracking

How do we follow an object in a video?



# Object tracking template matching



Slide template over image  
and compute distance

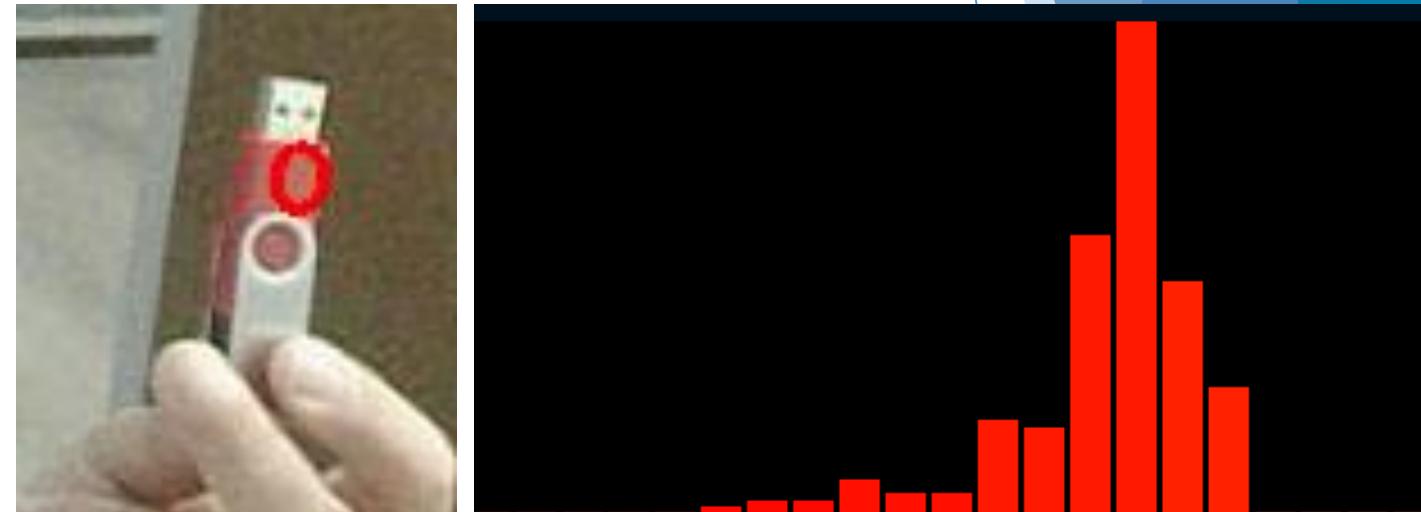
Find point (s) of least  
distance

# Object tracking histogram matching

Instead of using the pixels as template, one can use the histogram

- ▶ Slightly more immune to large scale changes or some rotations

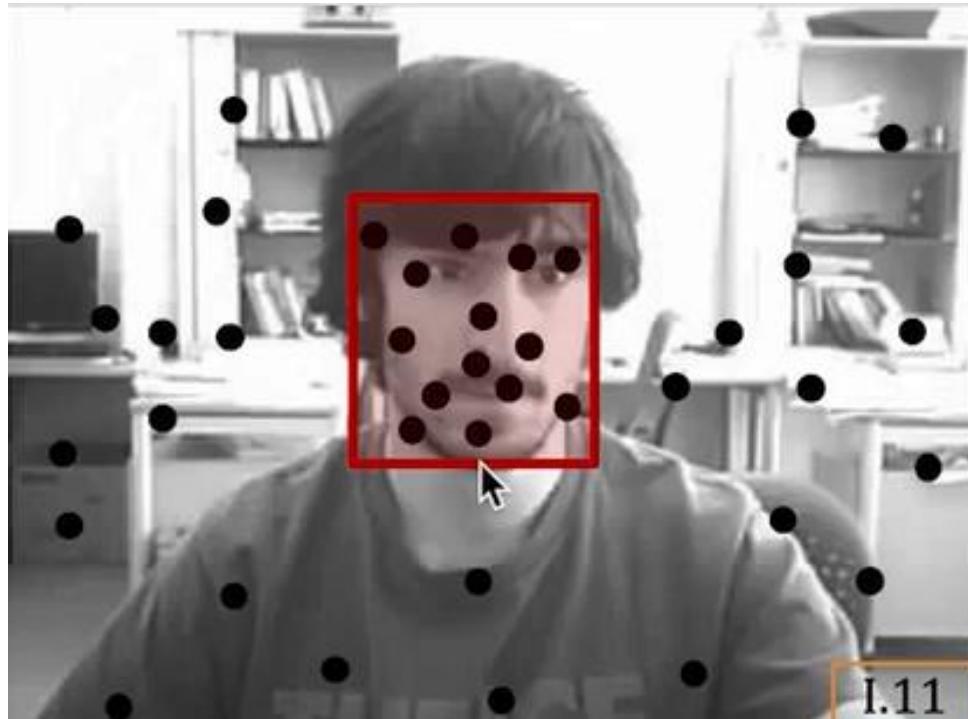
Sliding window over image computing histograms and their distance to template



If there are similar objects/background (i.e., with similar histogram) matching will be tricky or varying

# Object tracking

## Feature detection

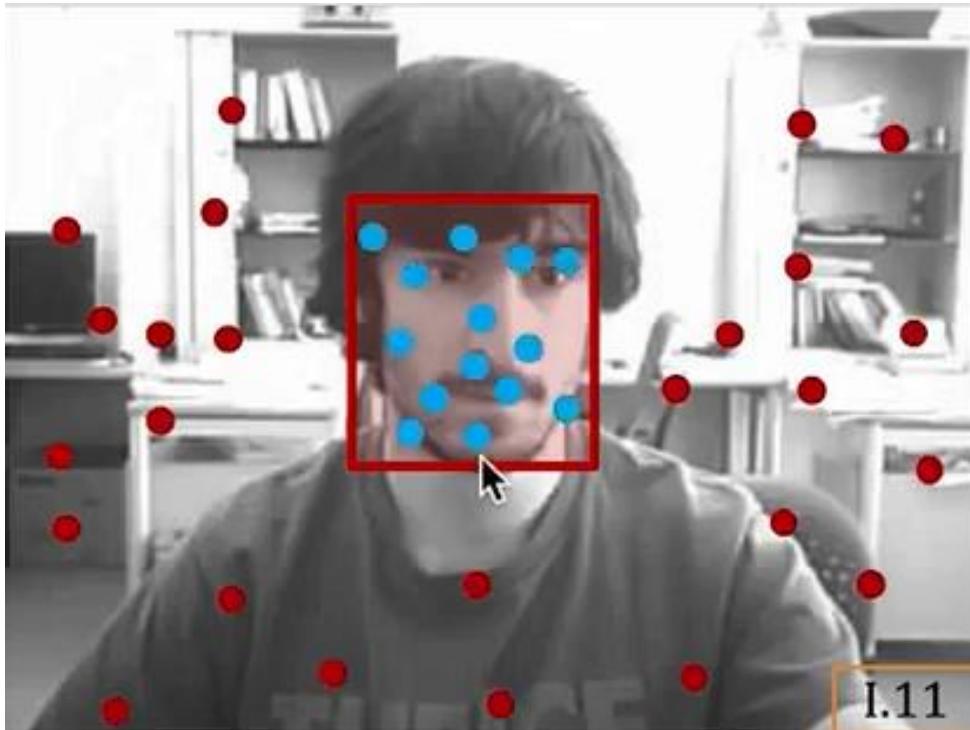


Select object (e.g., manually, or face detection)

Compute features (e.g., SIFT or ORB)

# Object tracking

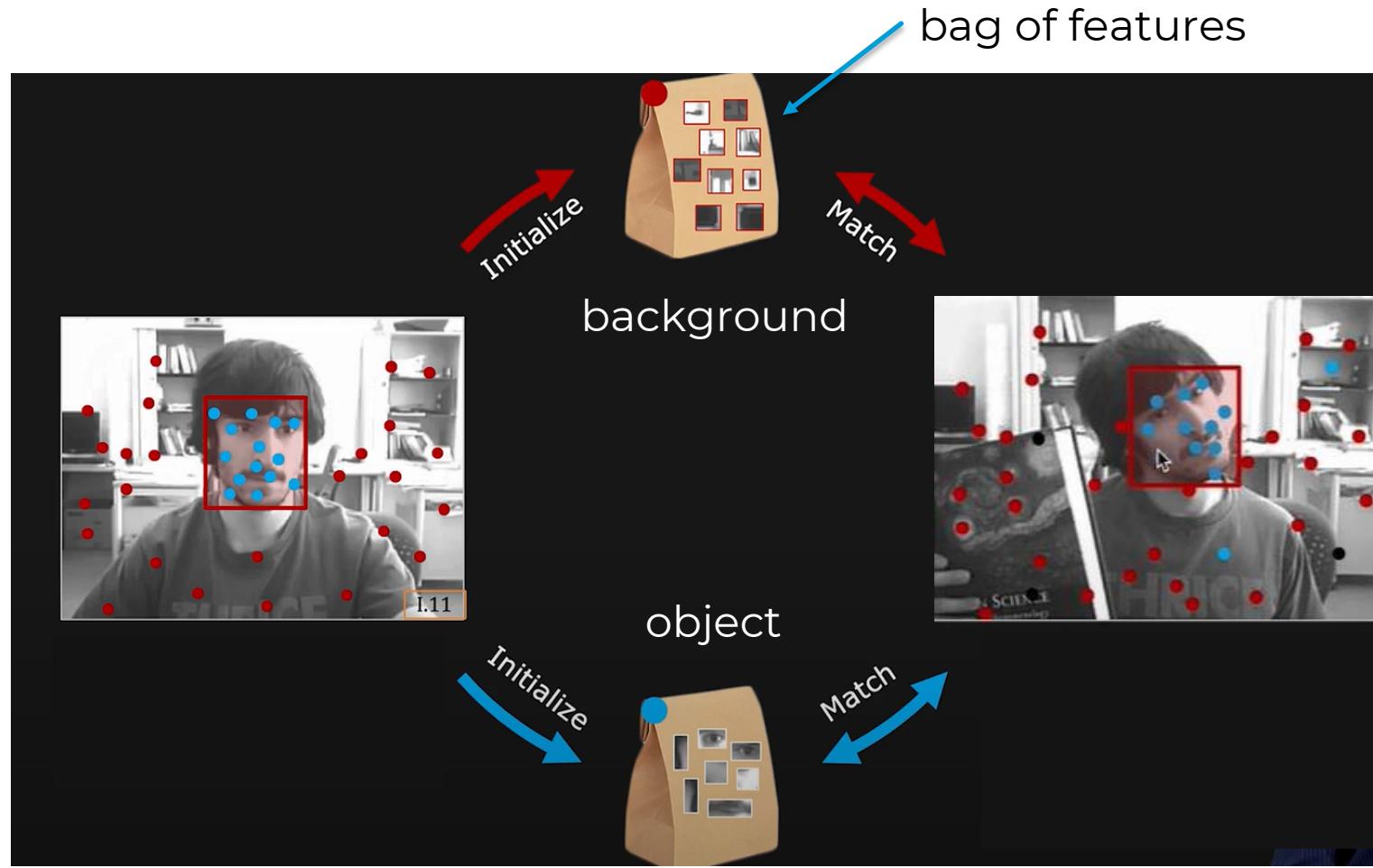
## Feature detection



Find all features for  
object and for  
background

# Object tracking

## Feature detection



Features selected as  
**background** and **object**

Features computed for  
new frame

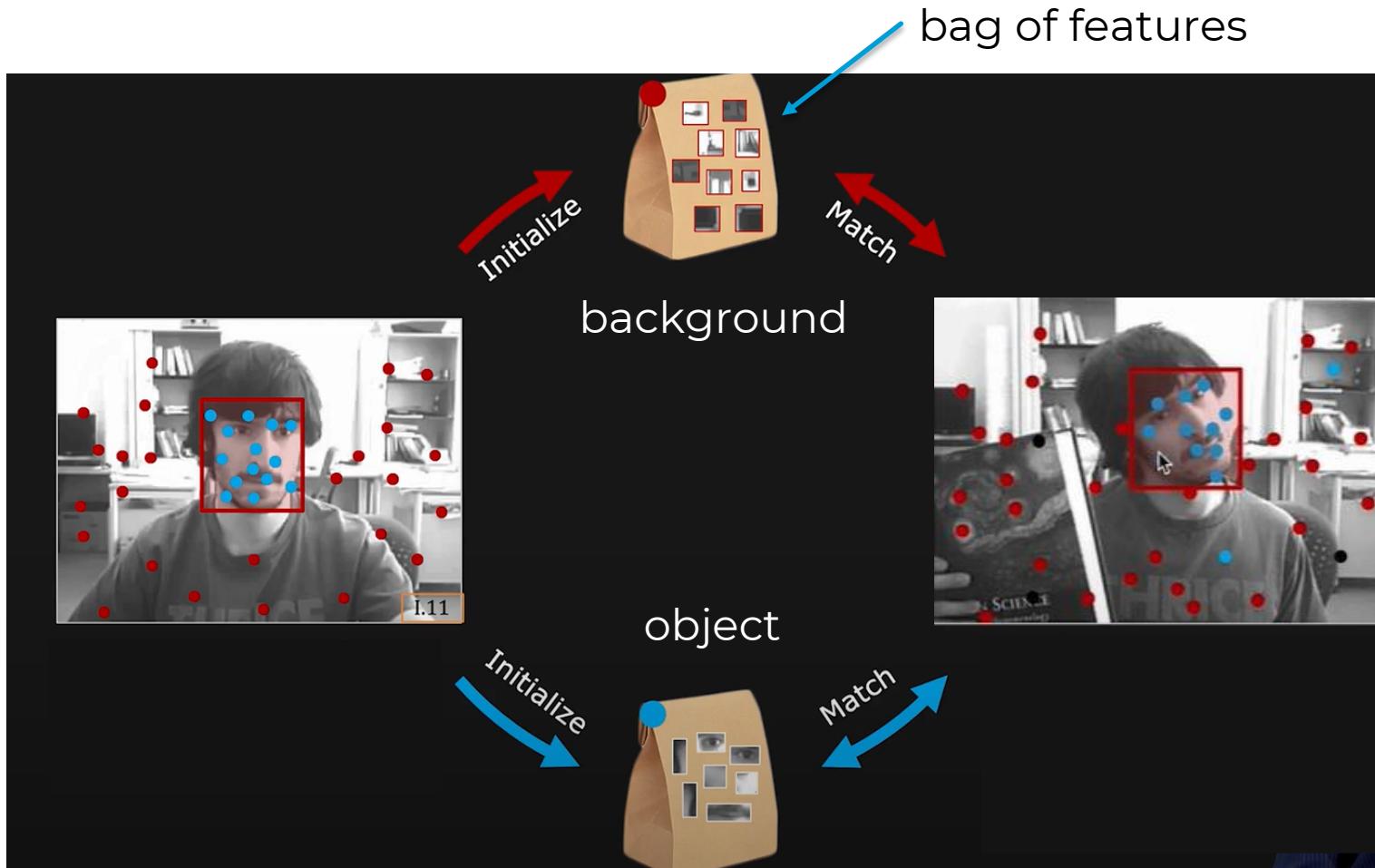
New features compared  
with bags

“Closest bag” sets type of  
feature

Object window  
encompassing the **most**  
**object features and less**  
**background**

# Object tracking

## Feature detection



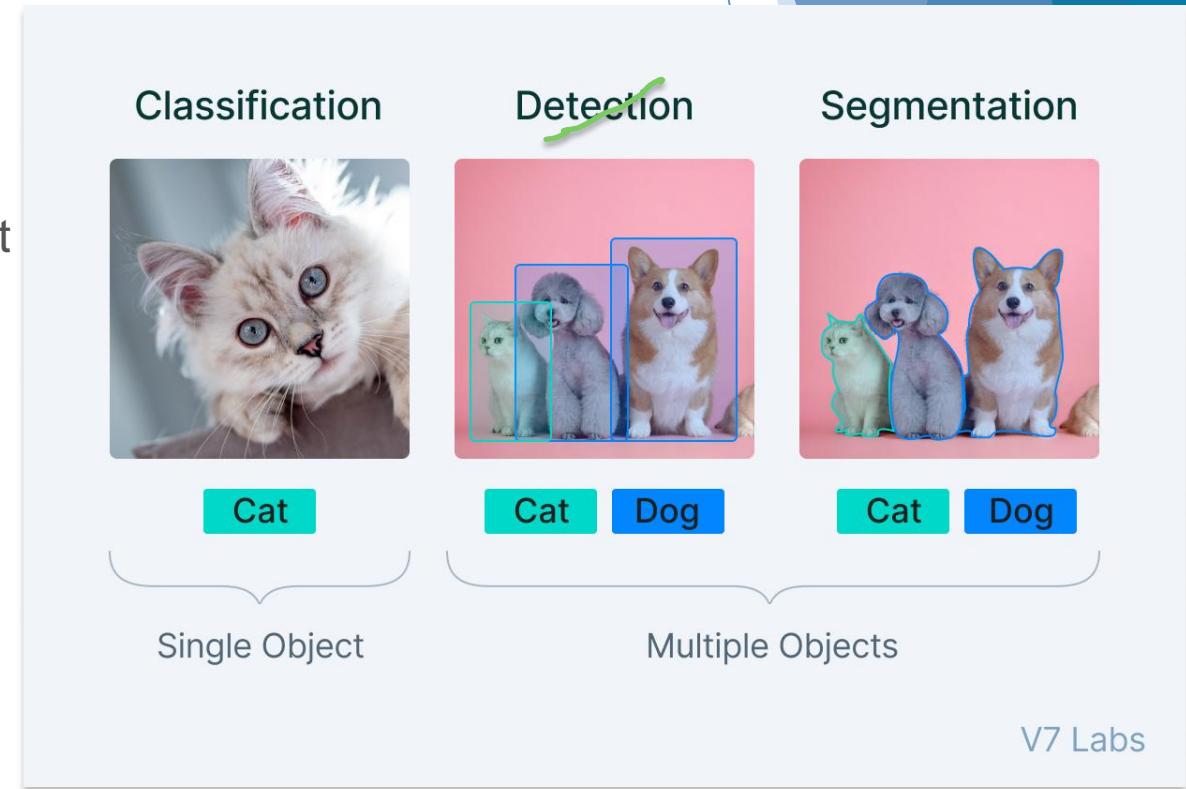
Since object changed position and orientation,  
**refresh object and background bags of features** for next frame

# **Approaches to Computer Vision Implementation**

Early days, machine learning, deep learning

# Common Computer Vision Tasks

- **Object Classification:** What broad category of object is in this photograph?
- **Object Identification:** Which type of a given object is in this photograph?
- **Object Detection:** Where are the objects in the photograph?
- **Object Segmentation:** What pixels belong to the object in the image?
- **Object Recognition:** What objects are in this photograph and where are they?
- .....



# Early days

Database of **labelled objects** to detect

**Annotate** the **database** with features judged relevant

Get a new image and **compute the same features**

**Define criteria** (algorithm) to check if it matches existing image (e.g., distance between features)

**Most aspects manually defined** by developer and the computer is just a way to apply it

# Machine Learning

A **database** is created and **labelled**

A **set of features** are defined

**Method learns** from the examples **what features work best** to distinguish between the classes

In this approach, **decision criteria (model) is optimized by the method**

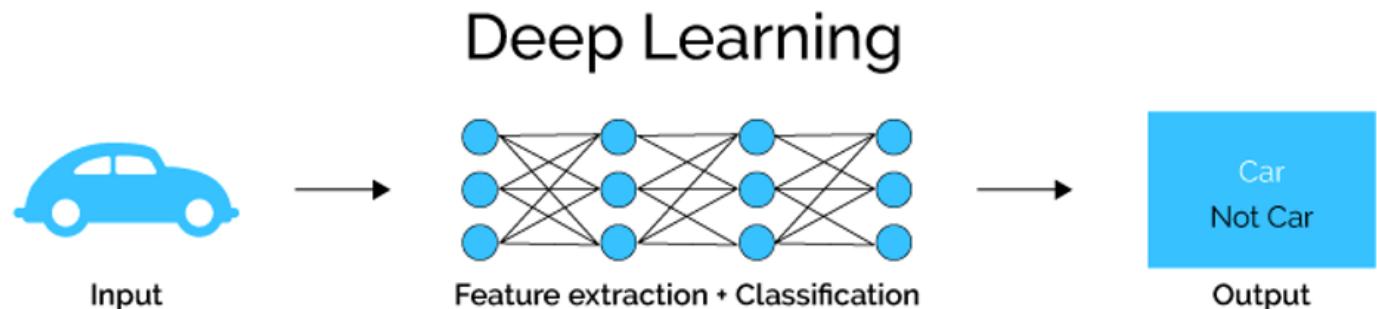
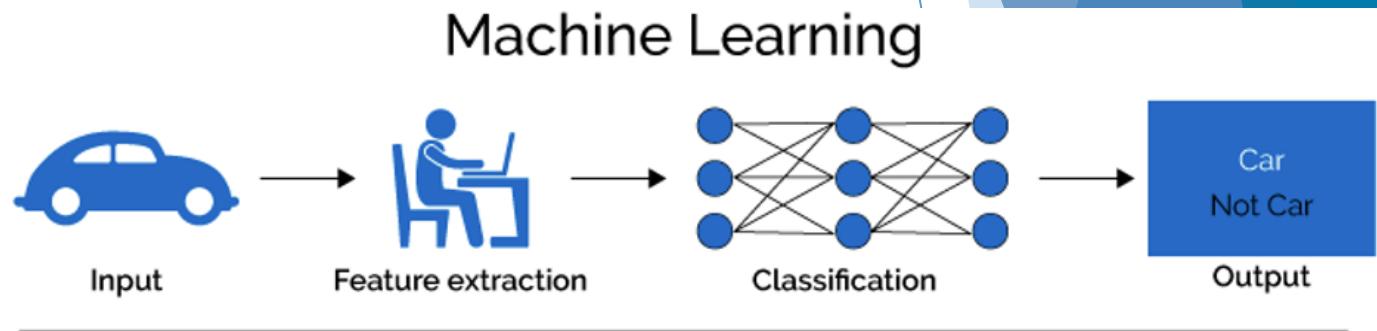
# Deep Learning

Relies on neural networks

Solves a problem by going through a **large** set of labelled data

It finds patterns that allow distinguishing between the classes

Does not require defining the features or rules



A photograph of a metal pegboard used for organizing tools. Various hand tools are hanging from the pegs, including hammers, wrenches, screwdrivers, pliers, and a power drill. A red pipe wrench is prominently featured in the foreground, leaning against the board.

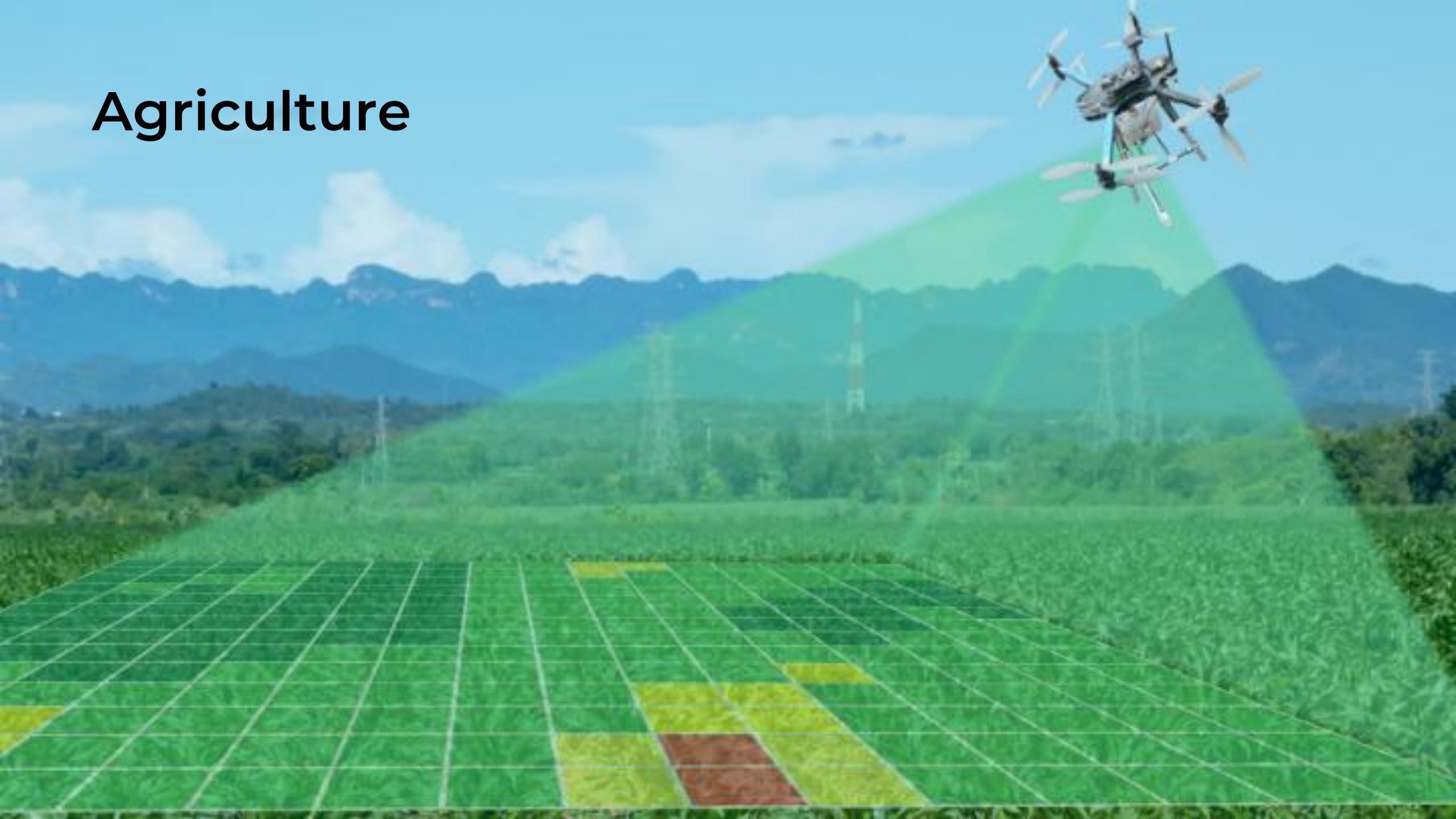
# Applications of Computer Vision



# Facial Recognition

mobidev

# Agriculture



# Autonomous Driving



# Augmented Reality



# Health



# Human Pose Tracking



# Smart Cities





Off-the-Shelf Solutions

# Off-the-Shelf Solutions

There are **several pre-trained models** for several types of objects

These can be applied directly to new images or video streams for object detection, identification, etc.

Remember: **pre-trained models detect a set of objects, not everything that we want...**



# OpenCV cascade classifiers



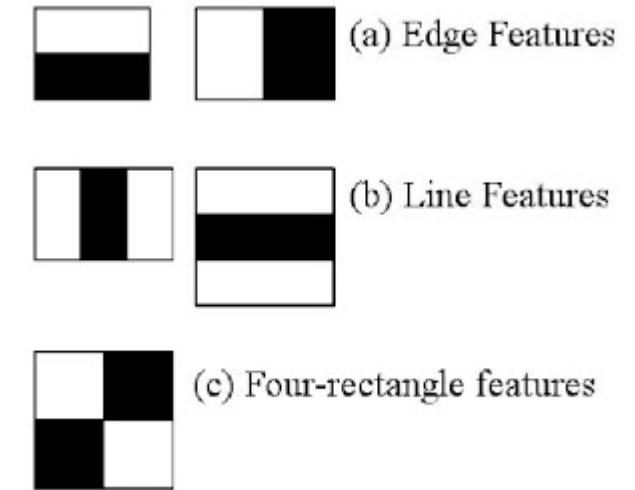
Features are like kernels applied to the hole image in all sizes and locations (24x24 image = 160000 features!)

During training this is reduced to around 6000 features

These are applied in cascade to classify image (e.g., if one fails, the image is discarded, and the process stops)

Several pre-trained classifiers (e.g., body, face, eyes)

Very fast!



Viola & Jones (2002)

# Cascade Classifiers

## Haar filters



Easy to compute, since it is just adding values

But it can be improved...

$$V_A[i,j] = \sum (\text{pixel intensities in white area}) - \sum (\text{pixels intensities in black area})$$

# Computing Filter Response

## Integral Image

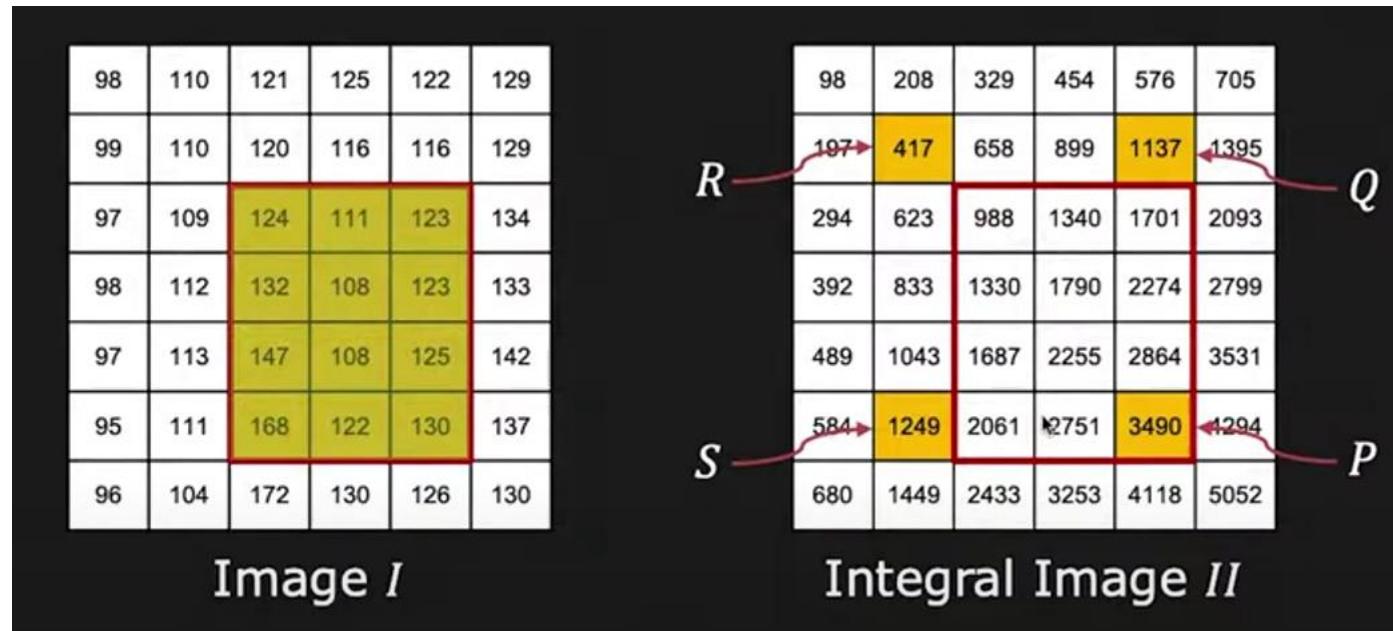
Each position stores the sum of the image square with the right lower corner in that pixel

98	110	121	125	122	129
99	110	120	116	116	129
97	109	124	111	123	134
98	112	132	108	123	133
97	113	147	108	125	142
95	111	168	122	130	137
96	104	172	130	126	130

98	208	329	454	576	705
197	417	658	899	1137	1395
294	623	988	1340	1701	2093
392	833	1330	1790	2274	2799
489	1043	1687	2255	2864	3531
584	1249	2061	2751	3490	4294
680	1449	2433	3253	4118	5052

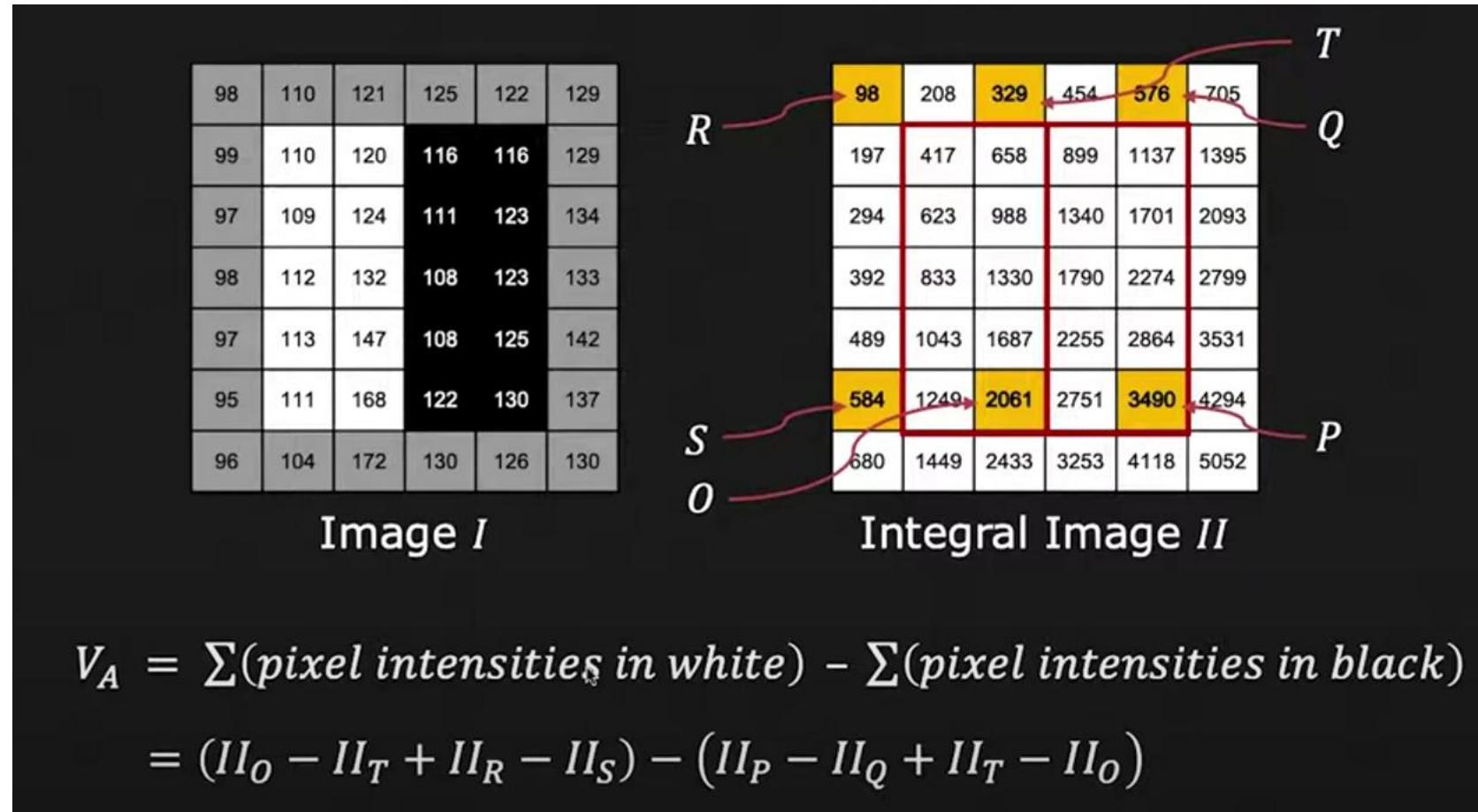
# Computing Filter Response

## Integral Image



$$\begin{aligned}
 \text{Sum} &= II_P - II_Q - II_S + II_R \\
 &= 3490 - 1137 - 1249 + 417 = 1521
 \end{aligned}$$

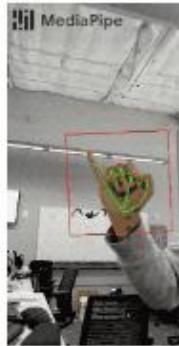
# Computing Filter Response

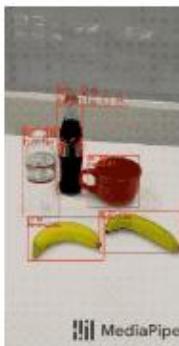


# You Only Look Once (YOLO)



# MediaPipe

Face Detection	Face Mesh	Iris	Hands	Pose	Holistic
					

Hair Segmentation	Object Detection	Box Tracking	Instant Motion Tracking	Objectron	KNIFT
					

# Bibliography

- ▶ Learning OpenCV 4 Computer Vision with Python 3
- ▶ Abhinav Dadhich, “Practical Computer Vision”, Packt Publishing, 2018



**Hands On!**