



Computer Vision

Lecture 1: Introduction

23.10.2024

Manuel Heurich, Tim Landgraf



Meet the team

Manuel

Chief of
Assignments



Tim

Gives Lectures



<https://bioroboticslab.github.io/website/>



Assignments / Quizzes

- Assignments go deeper for selected key concepts in CV
 - Default: Jupyter notebooks, pull from git repo
 - Submission
 - in **groups** (max 2 students)
 - upload to Whiteboard as **PDF**
 - Collect **BONUS** points for quizzes
- 2 Quizzes instead of 1 Final
 - dates in KVV (don't forget to register!)
 - Approx. 45 min each
 - We'll grade **sum of points**, not average grades



List of Topics

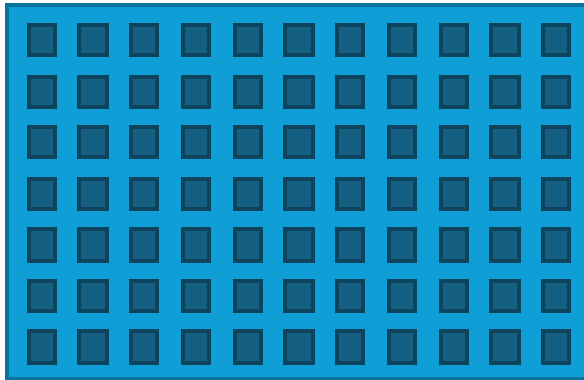
SUBJECT TO
CHANGE (Let
me know!)

1.	Introduction	Computer Vision Fundamentals
2.	Edge Detectors, Convolution	
3.	Color Histograms, HoG	
4.	Optic Flow	Conventional Computer Vision
5.	Hough Transform	
6.	SIFT / SURF	
7.	Introduction to Neural Information Processing	Deep Learning (Supervised)
8.	Convolutional Neural Networks	
9.	Image Classification, Object Detection	
10.	Vision Transformers, ConvMixer	
11.	Semantic Segmentation	
12.	Pose Estimation	
13.	Recurrent Neural Networks, Image Captioning	
14.	Contrastive Learning	Self-Supervised Learning
15.	BYOL, IJEPA, VICREG	

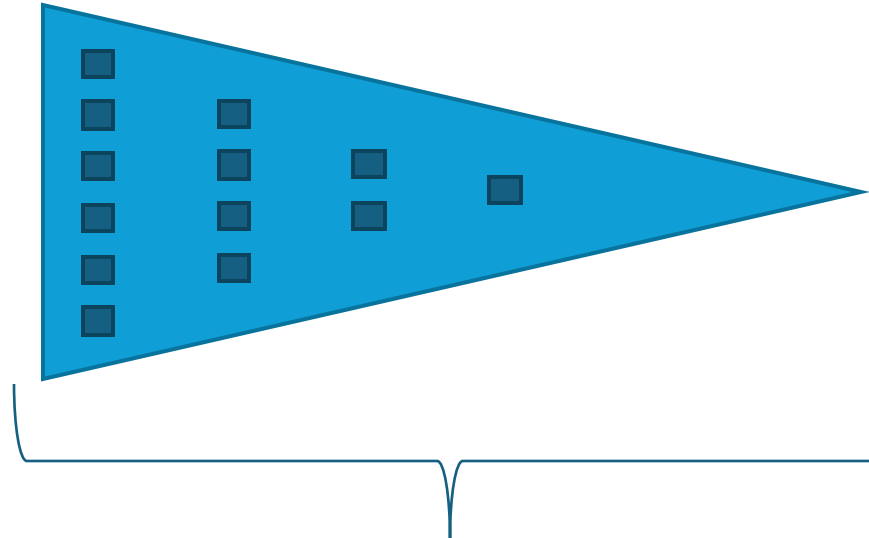


What is „Computer Vision“

High-dimensional,
raw pixel data



Relevant Features



Low-dimensional,
abstract information

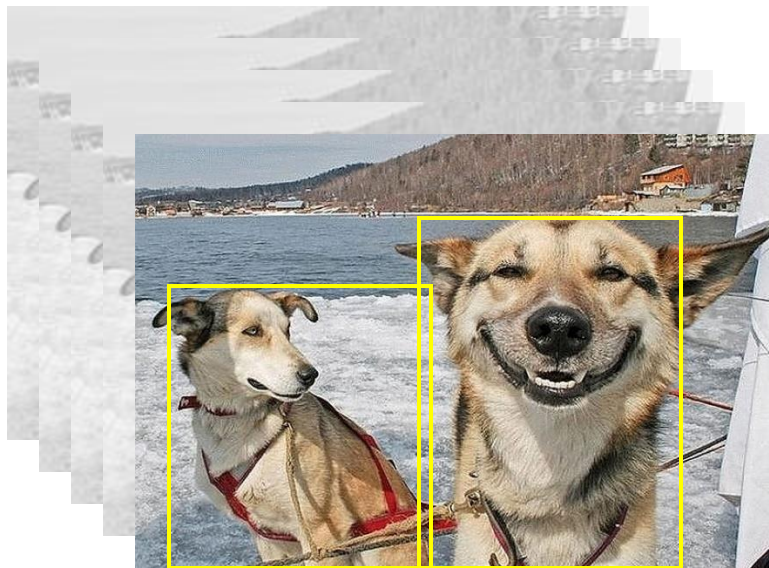


FEATURE EXTRACTION



What is „Computer Vision“

In



Out

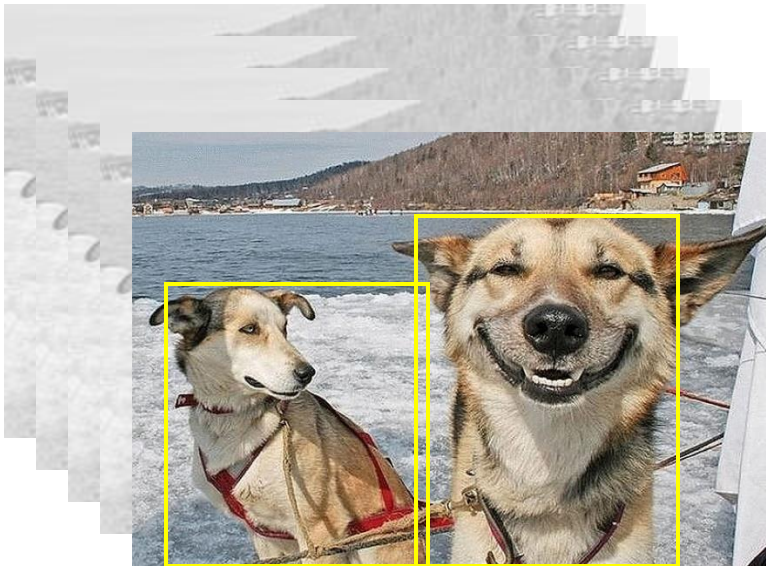
- dog is in / in not in image
- „dog“, „outside“, „smile“, „snow“
- bounding_box(400, 234, 200, 150)
- position(t)
- „two huskys on ice ...“

<https://blog.alldogboots.com/wp-content/uploads/2010/02/SmilingDog.gif>



What is „Computer Vision“

In



Out

- detection
- classification
- localisation
- tracking
- captioning
- segmentation

<https://blog.alldogboots.com/wp-content/uploads/2010/02/SmilingDog.gif>



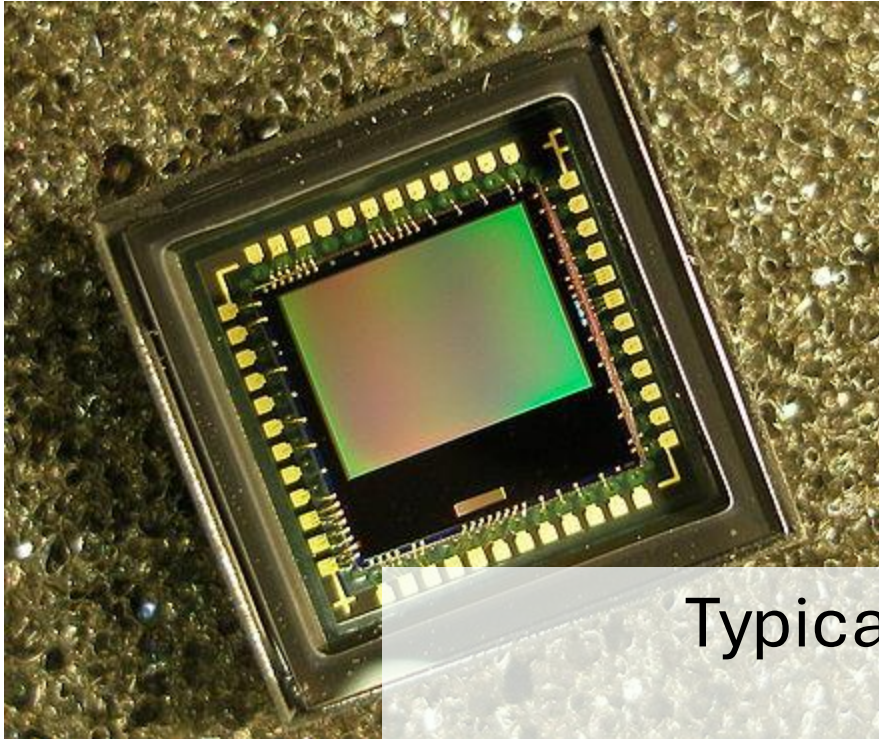
How do we represent digital images?



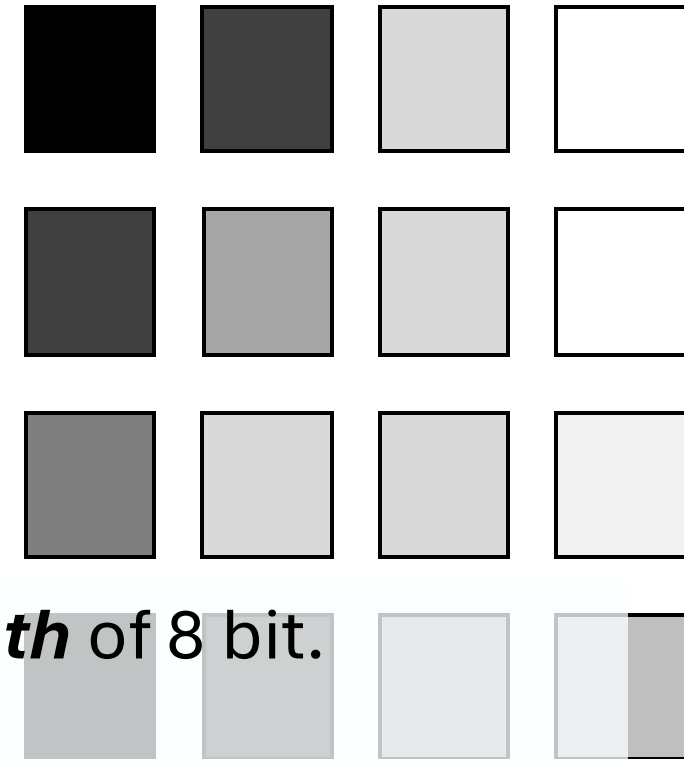
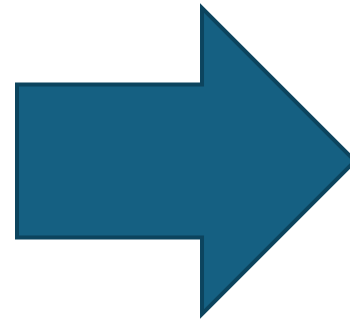


Grayscale Images

https://www.wikiwand.com/en/Active-pixel_sensor



CMOS sensor

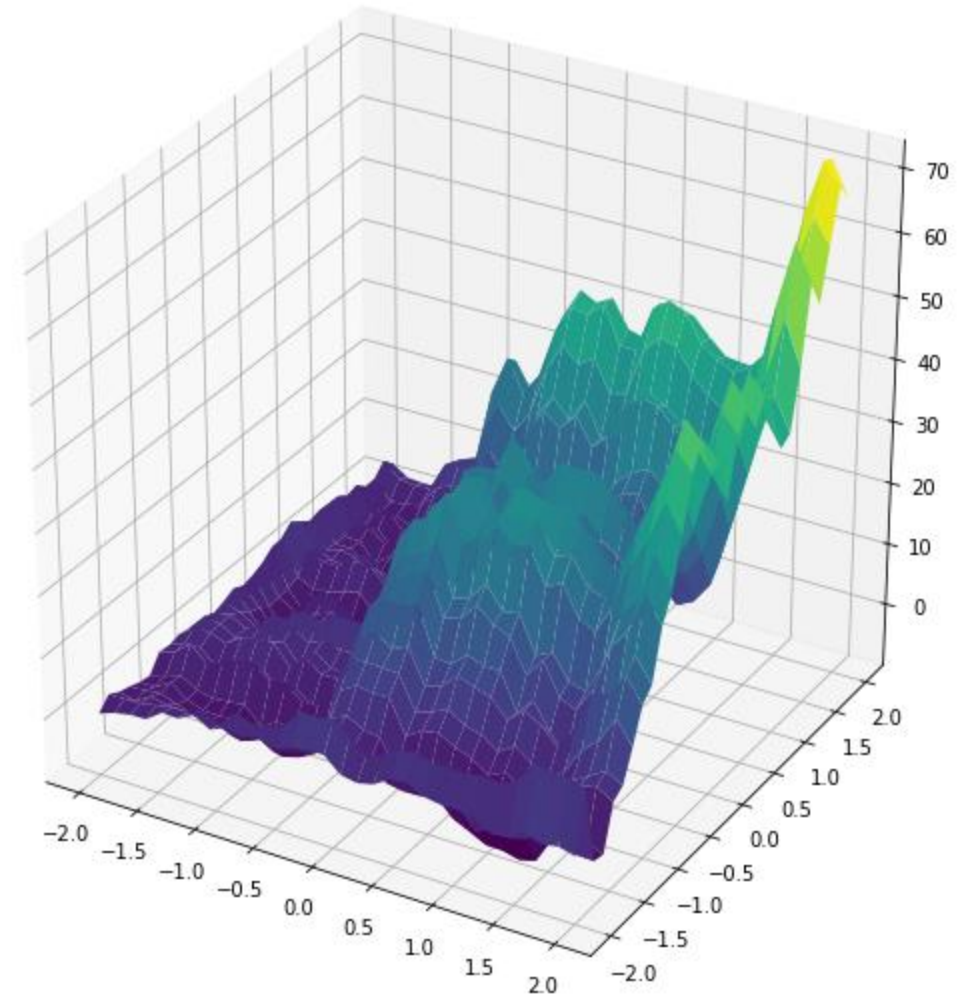
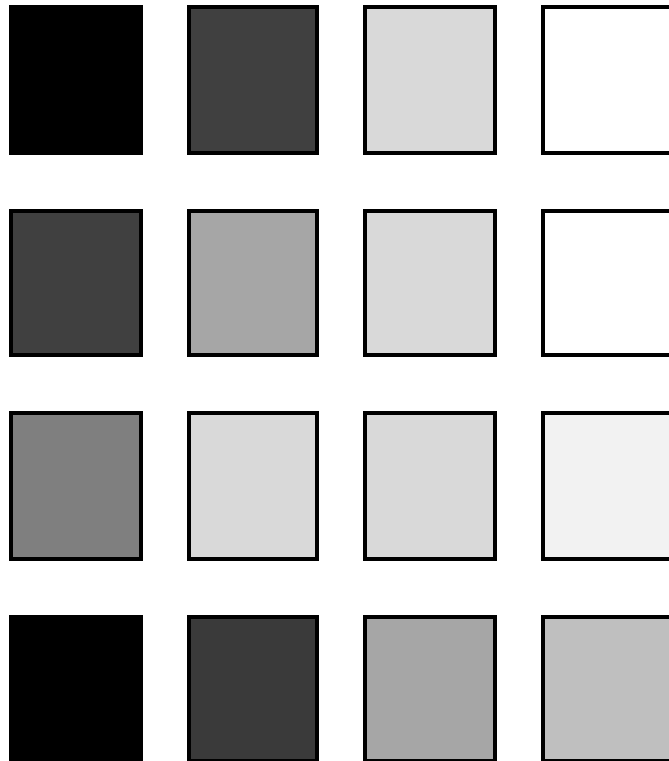


Typically, pixels have a **depth** of 8 bit.

This corresponds to **how many different gray values?**



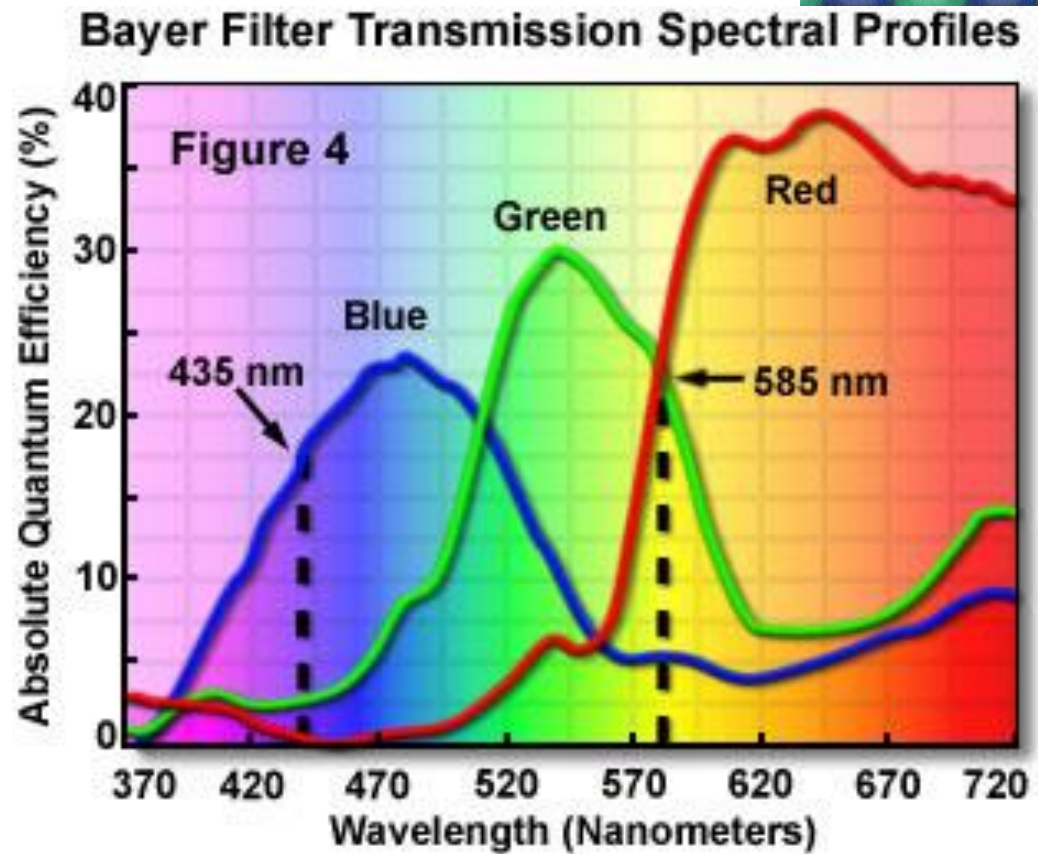
Grayscale Images





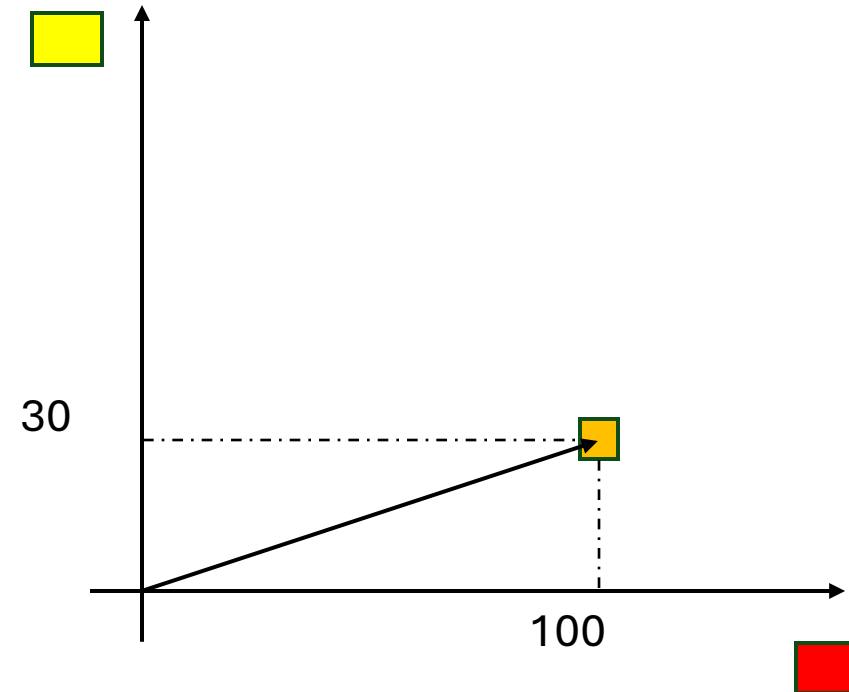
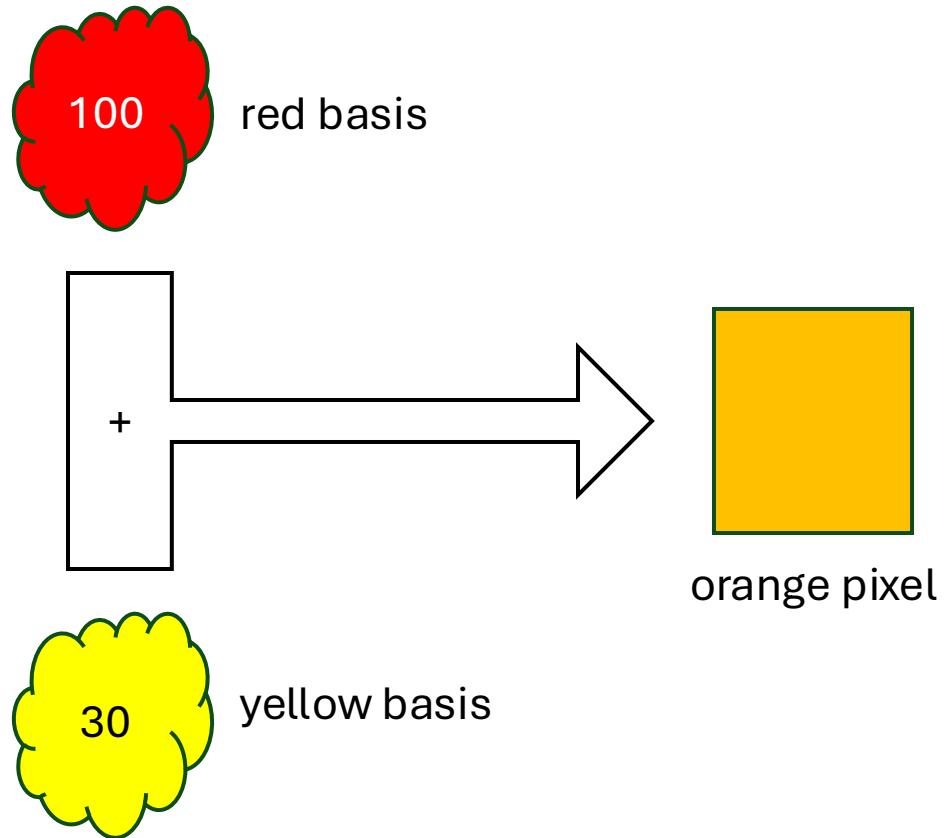
Color Images

TÄT



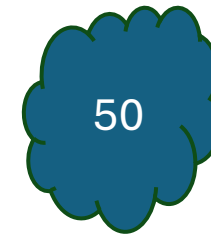
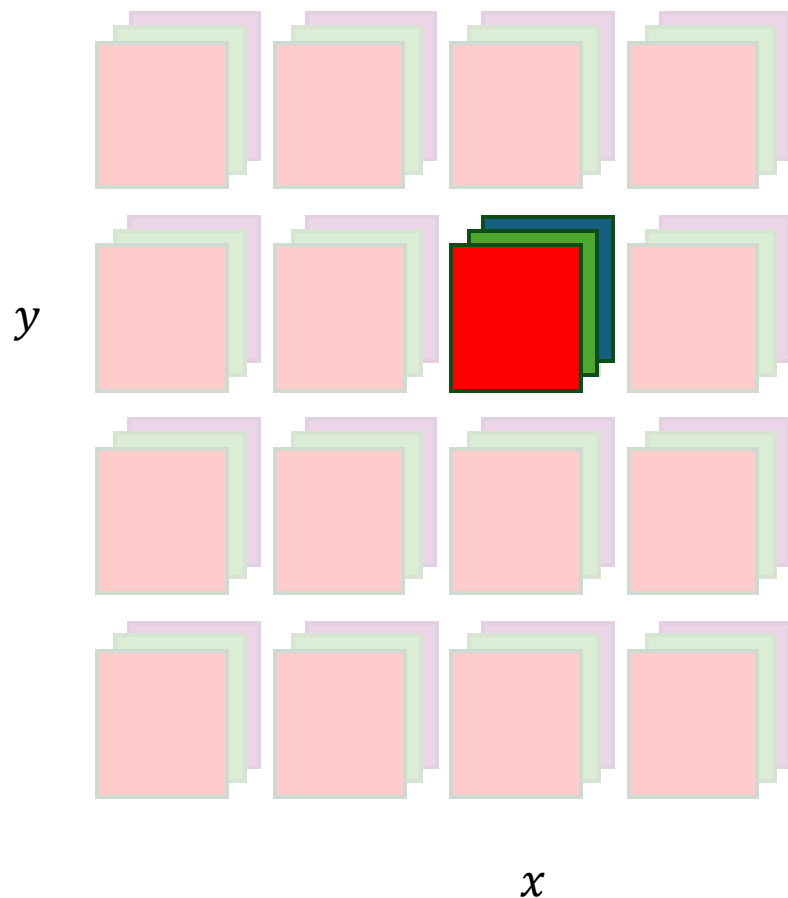


Color Images





Color Images: RGB color space

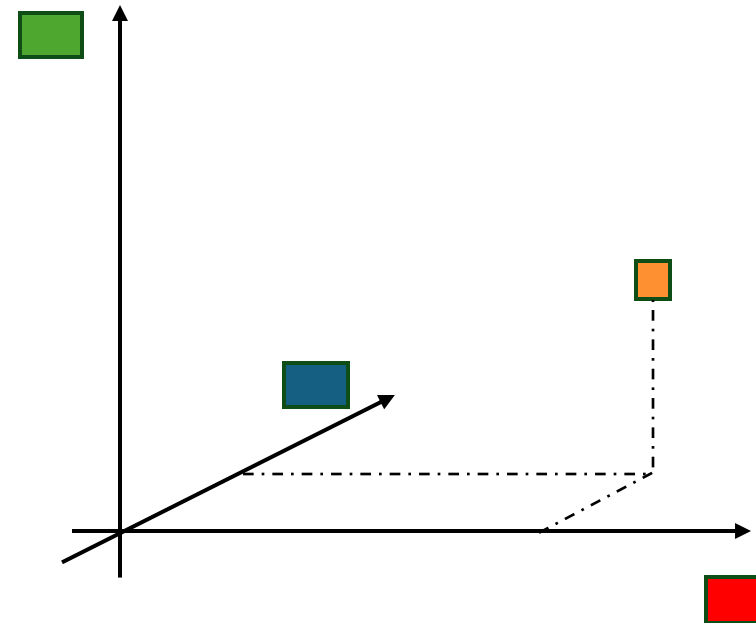
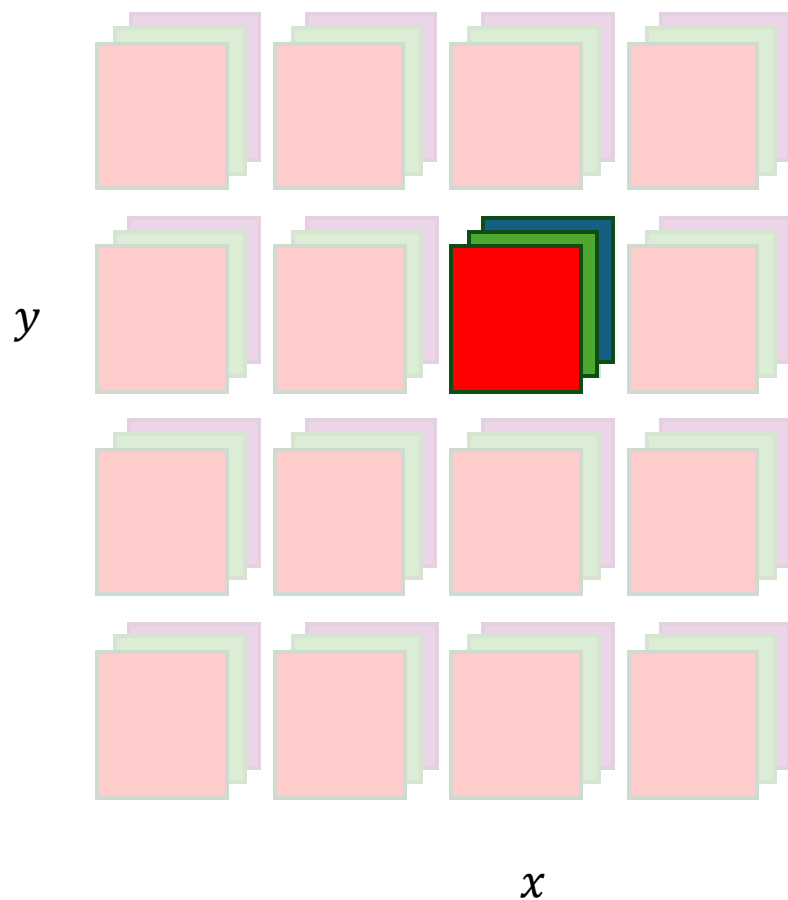


$$I(x, y) = \begin{pmatrix} 255 \\ 144 \\ 50 \end{pmatrix}$$





Color Images: RGB color space





- same-object variability
 - pose
 - shape
 - scale
 - motion
- intra-class variability
- between-class discriminability
- environmental variability
 - lighting
 - occlusion





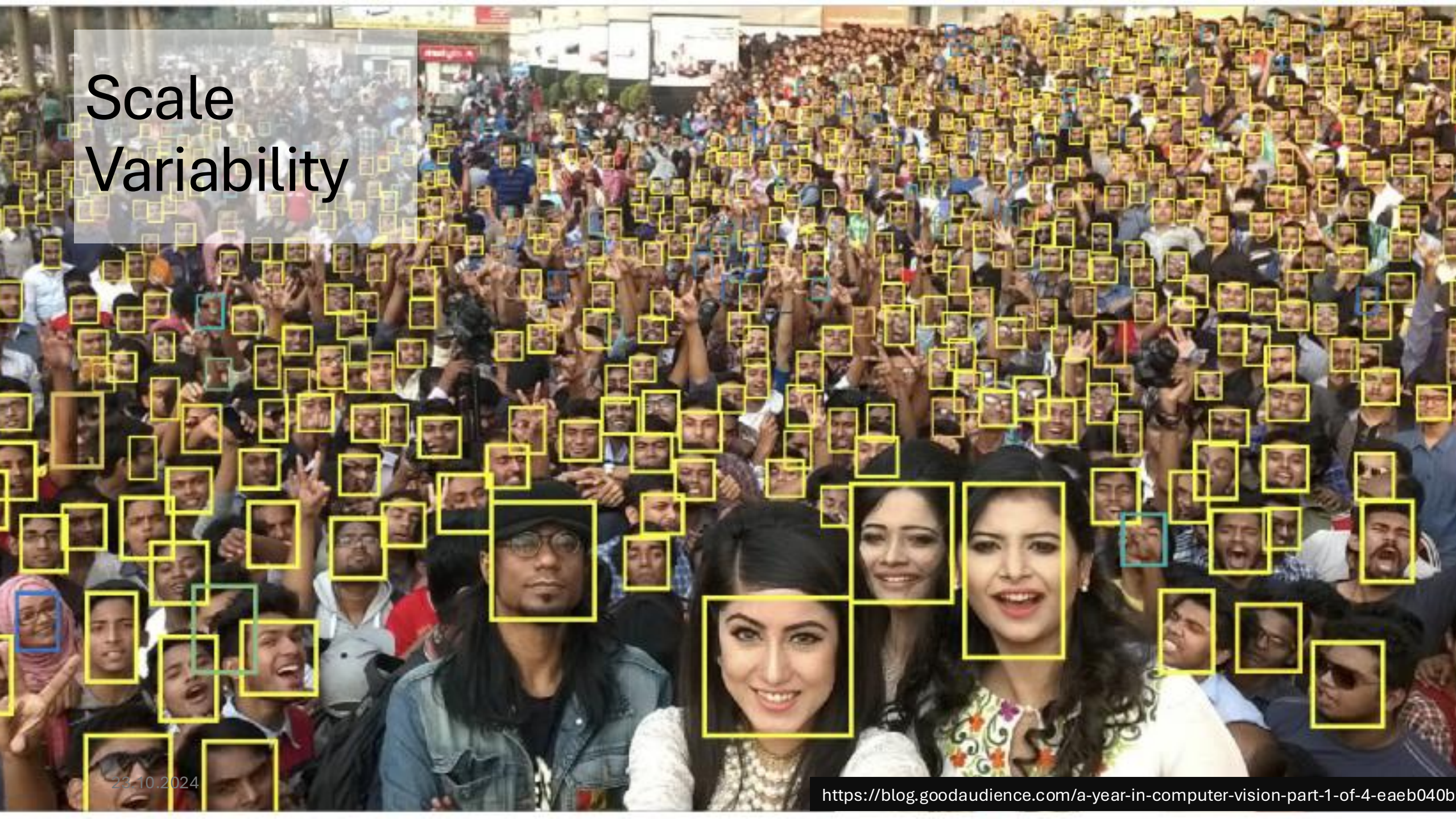
Between-class dicriminability



<https://www.pinterest.de/pin/5840674486958115/>



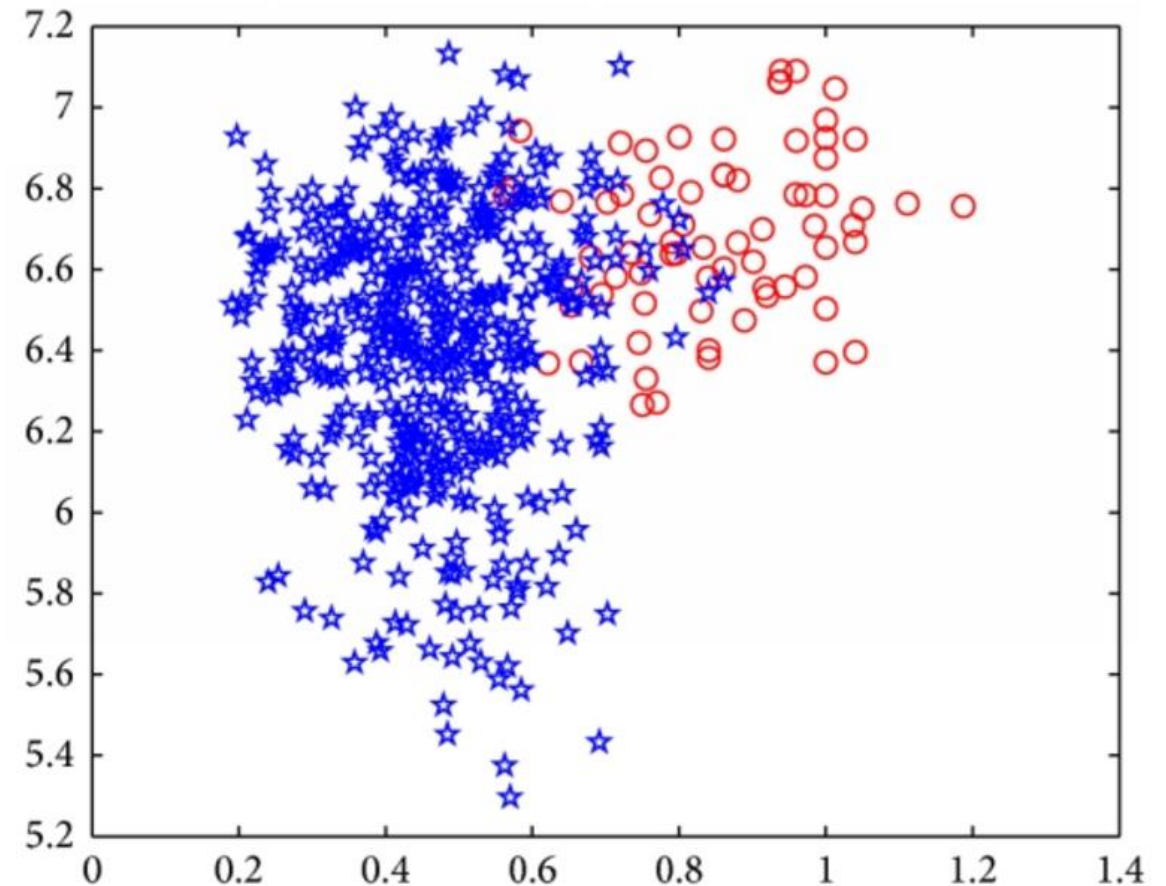
Scale Variability





Computer Vision: „what are **relevant** features?“

- comparing images on the level of pixel values?
- edges, color, motion, ...
- a huge part of „conventional“ computer vision was manually defining what *relevant* means
- since computer vision has become „deep“: features are *learned*



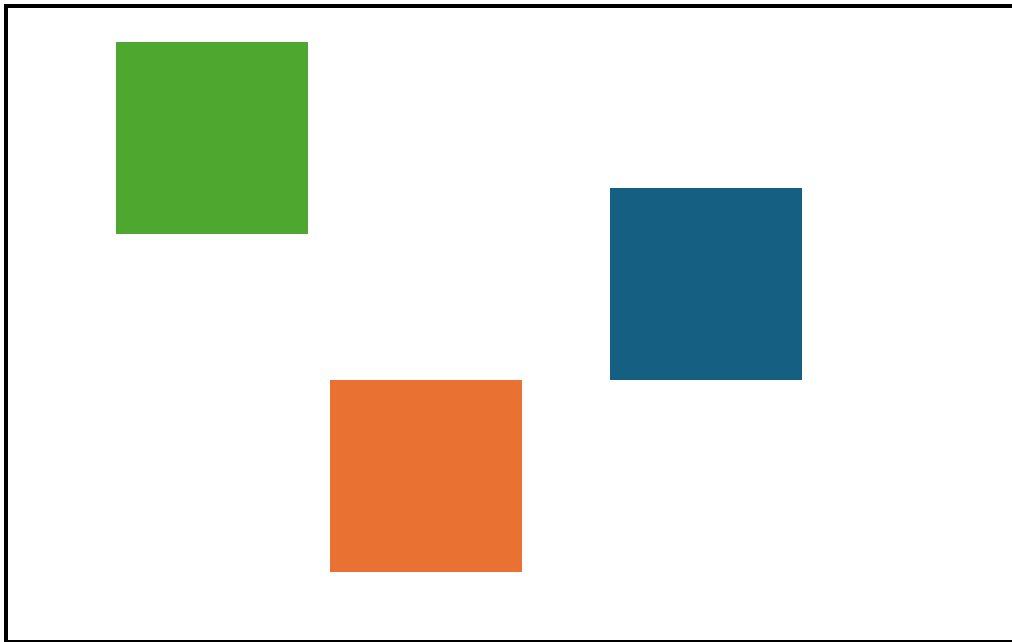
Color-based detection and tracking

- What is color?
- How can we use color to identify objects?
- How to represent foreground objects in color sub-spaces?
- What is the problem with color?

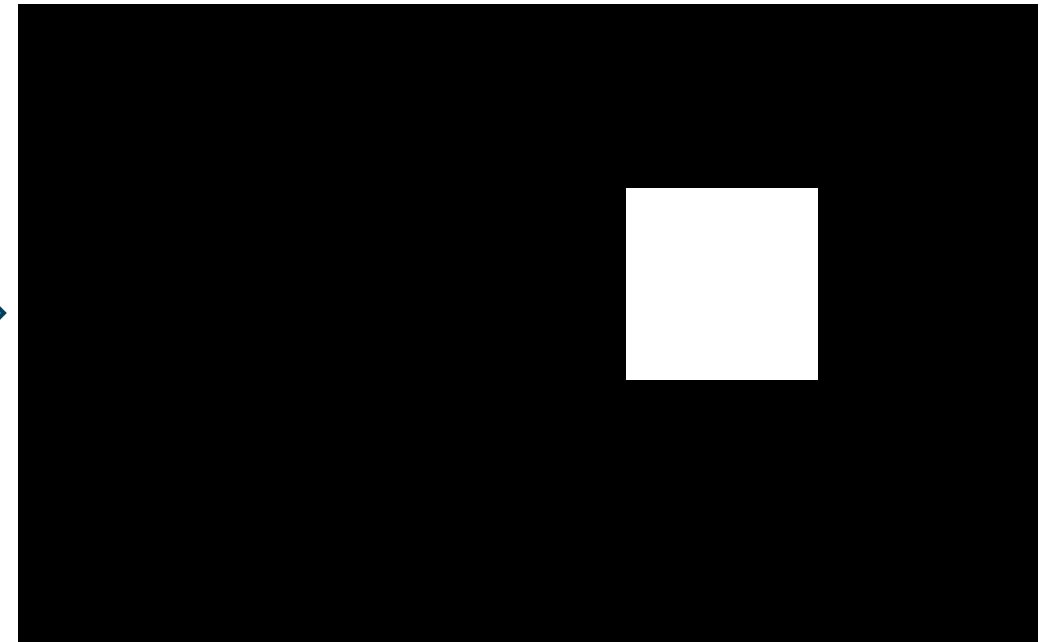
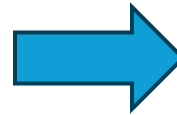


Detection via Binarization

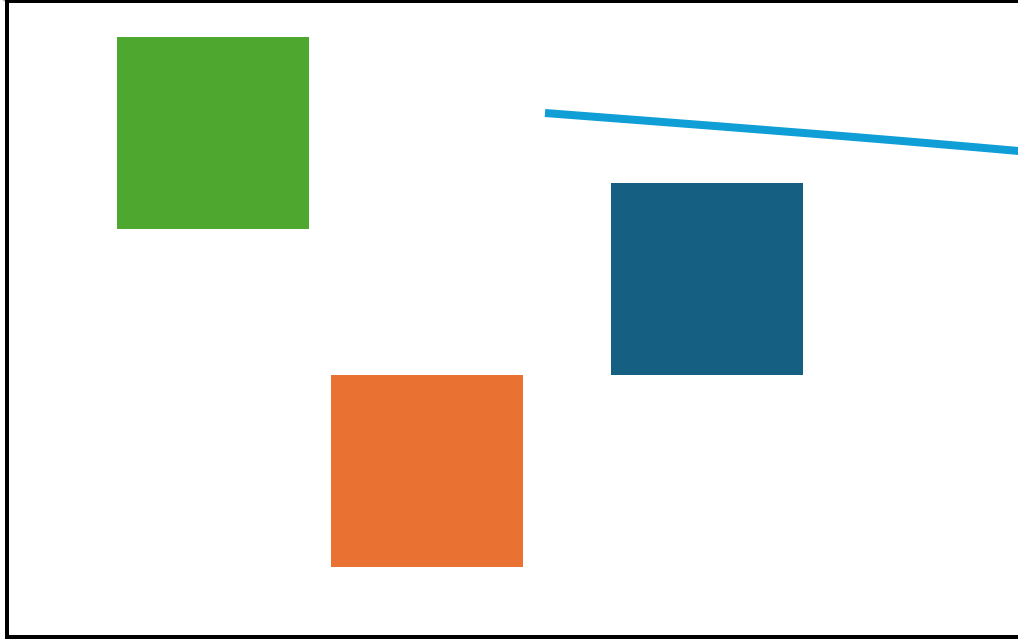
„look for blue objects“



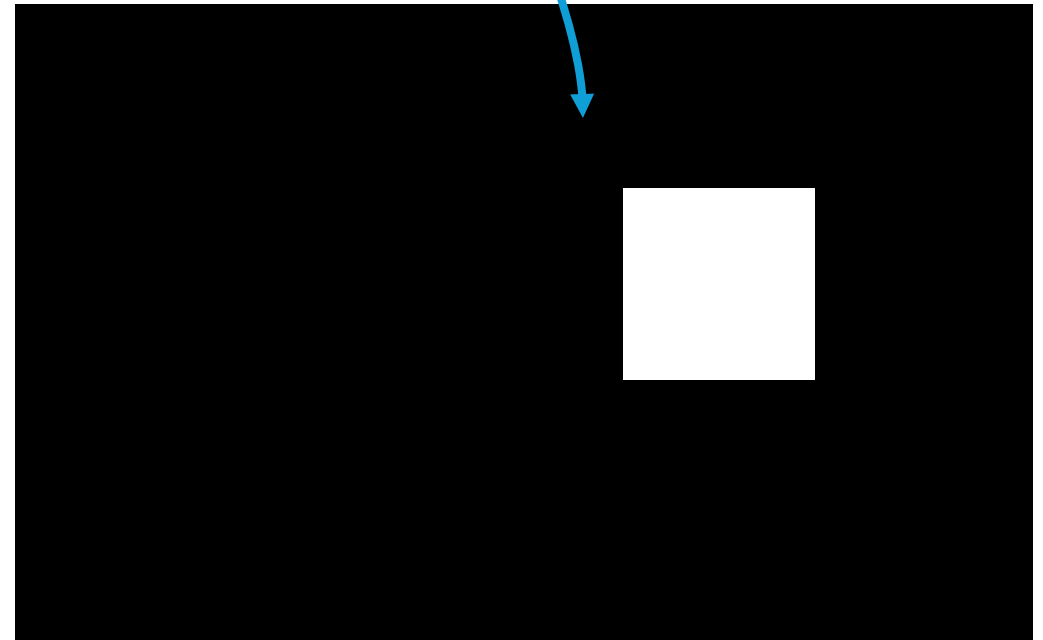
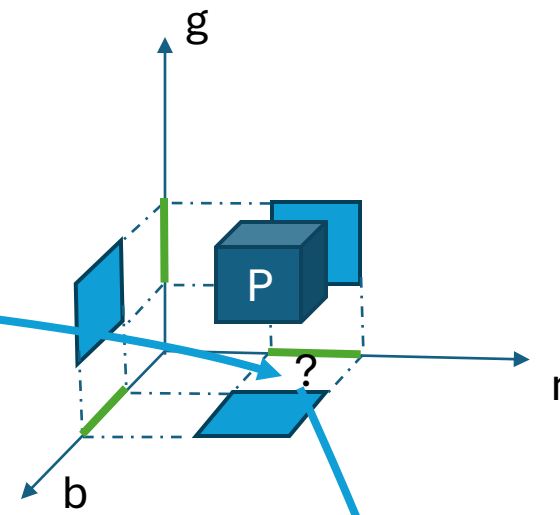
Colored objects in input image



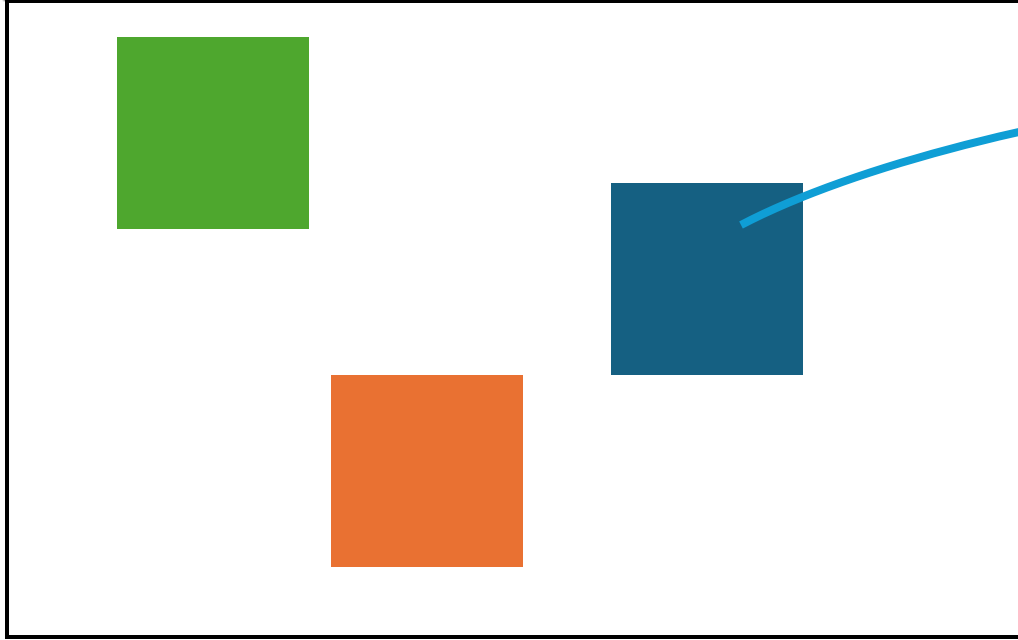
Binarization based on target color



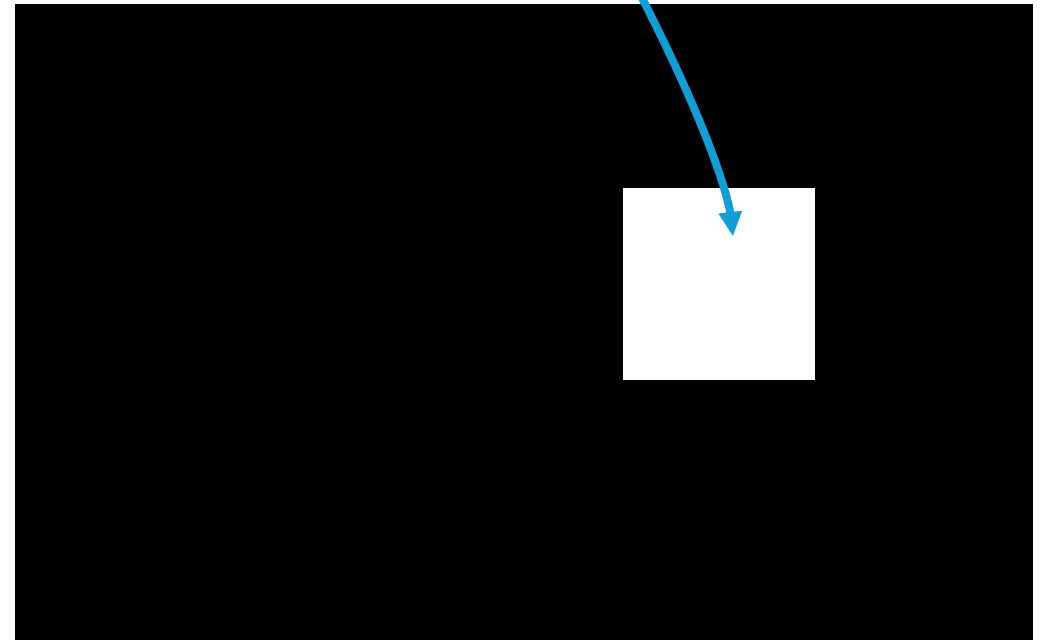
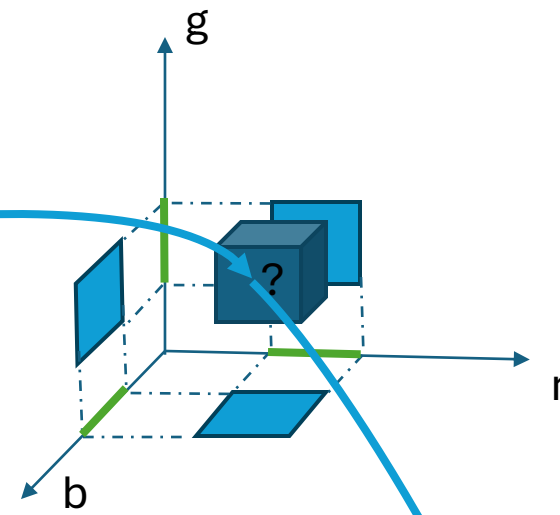
Colored objects in input image



Binarization based on target color



Colored objects in input image

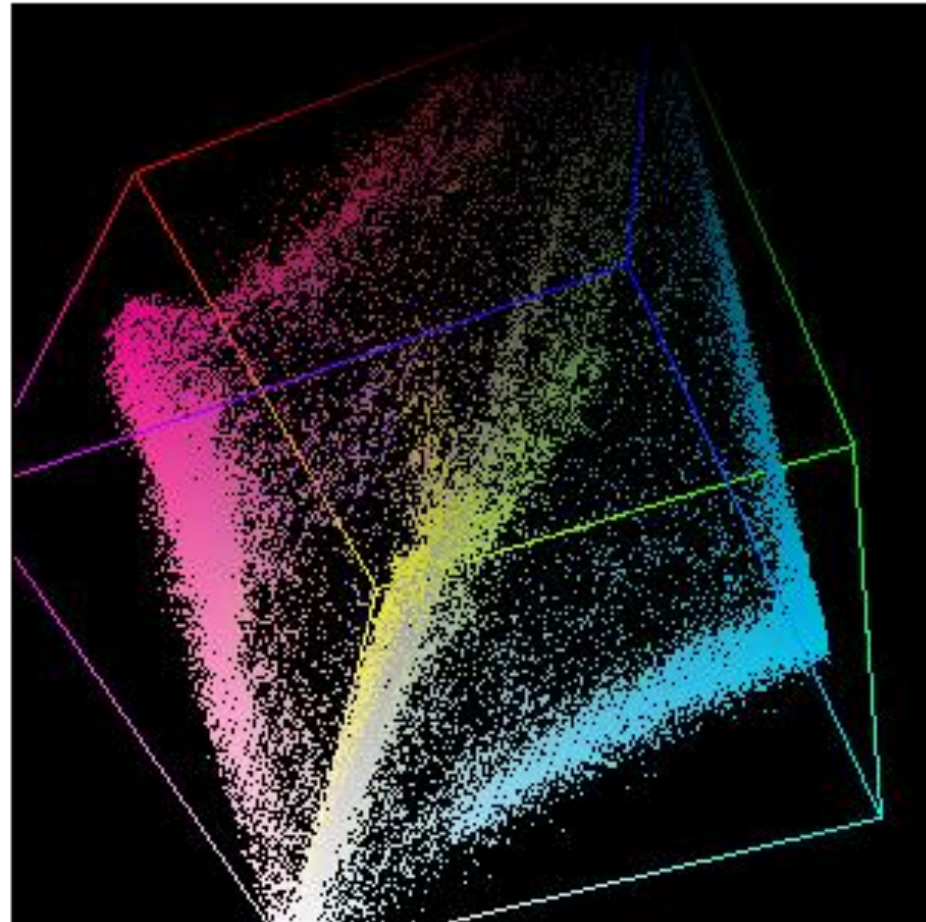


Binarization based on target color



Color-based detection and tracking

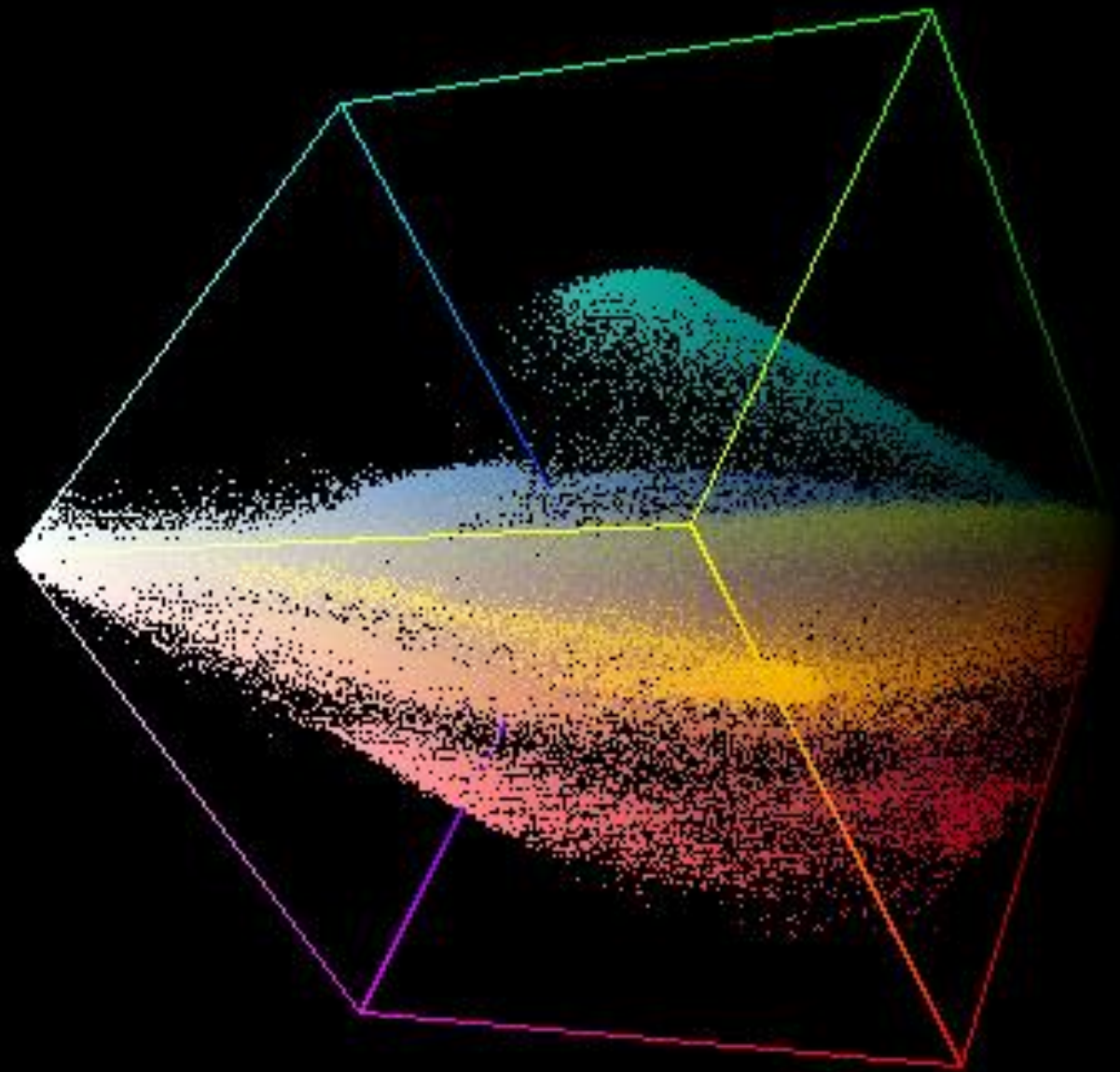
Are objects identifiable by color?

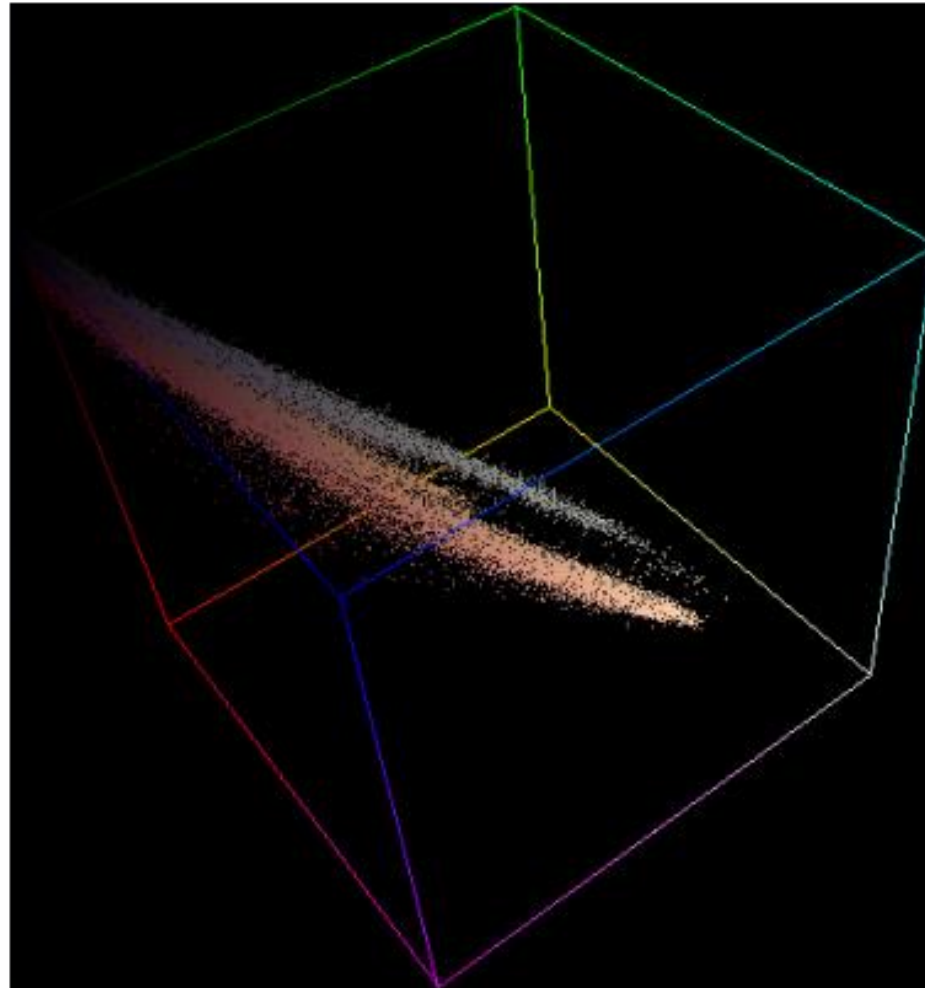




23.10.2024

<http://opensource.graphics/visualizing-the-3d-point-cloud-of-rgb-colo>







Ex. 1.1: detect colored objects in RGB

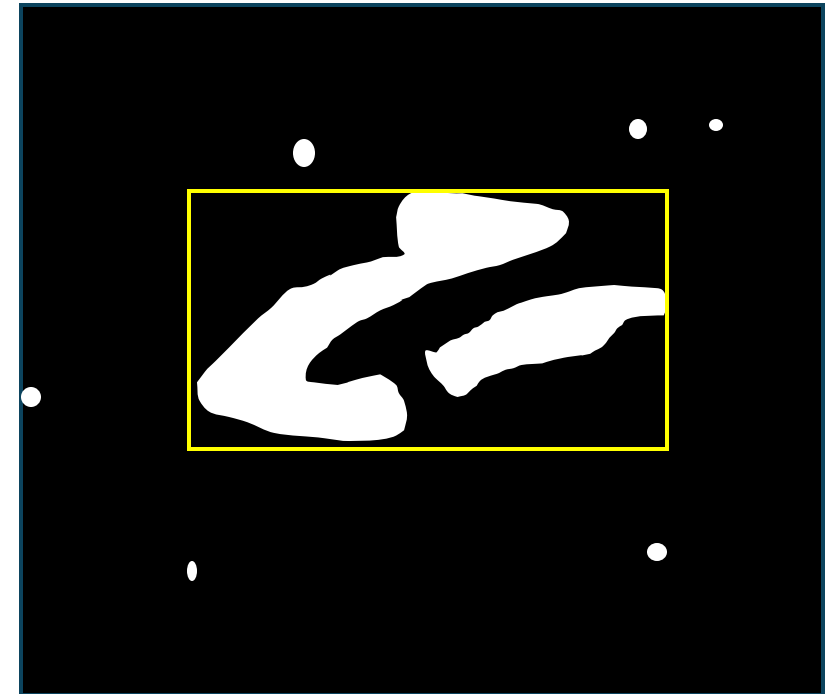
- define the „positive“ subspace P in the RGB cube
- iterate over all pixels in I and check if in P or $\sim P$
- write result to new image
- play around with size and shape of P and display binary image





Finding objects

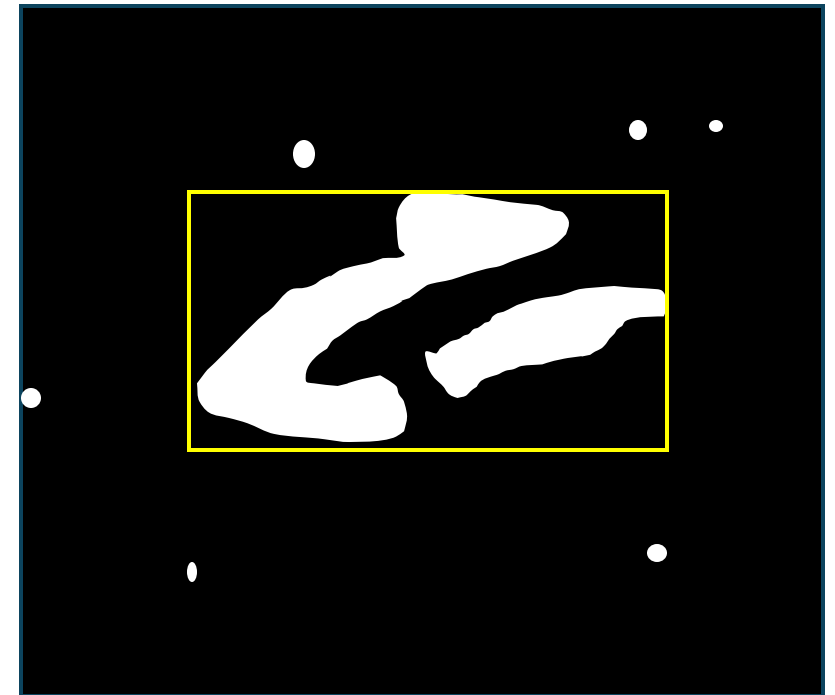
- Binary image still unhandy
- We need to extract the object's location
- How do we **represent** the object?
 - position
 - orientation
 - scale
 - spatial extent in image
 - ...





Finding objects

- Common recipe:
 1. apply **morphological operators**
 - remove noise
 - close gaps
 2. find **connected components**
 - iterate over all pixels
 - group pixels





Morphological operators

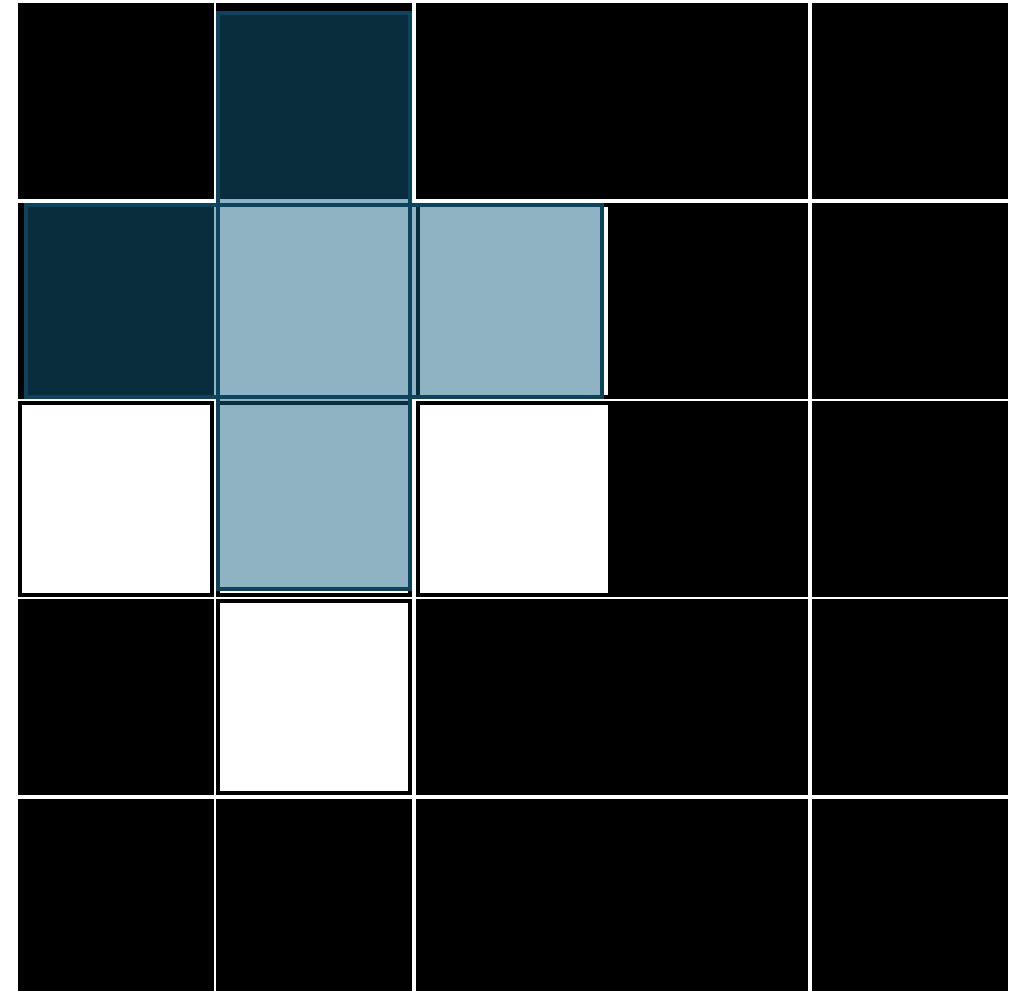
- **Structuring Element** defines neighborhood around input pixel
- Set output pixel to „1“ if
 - all neighborpixels are „1“ (**Erosion**)
 - at least one of them is „1“ (**Dilation**)





Morphological operators

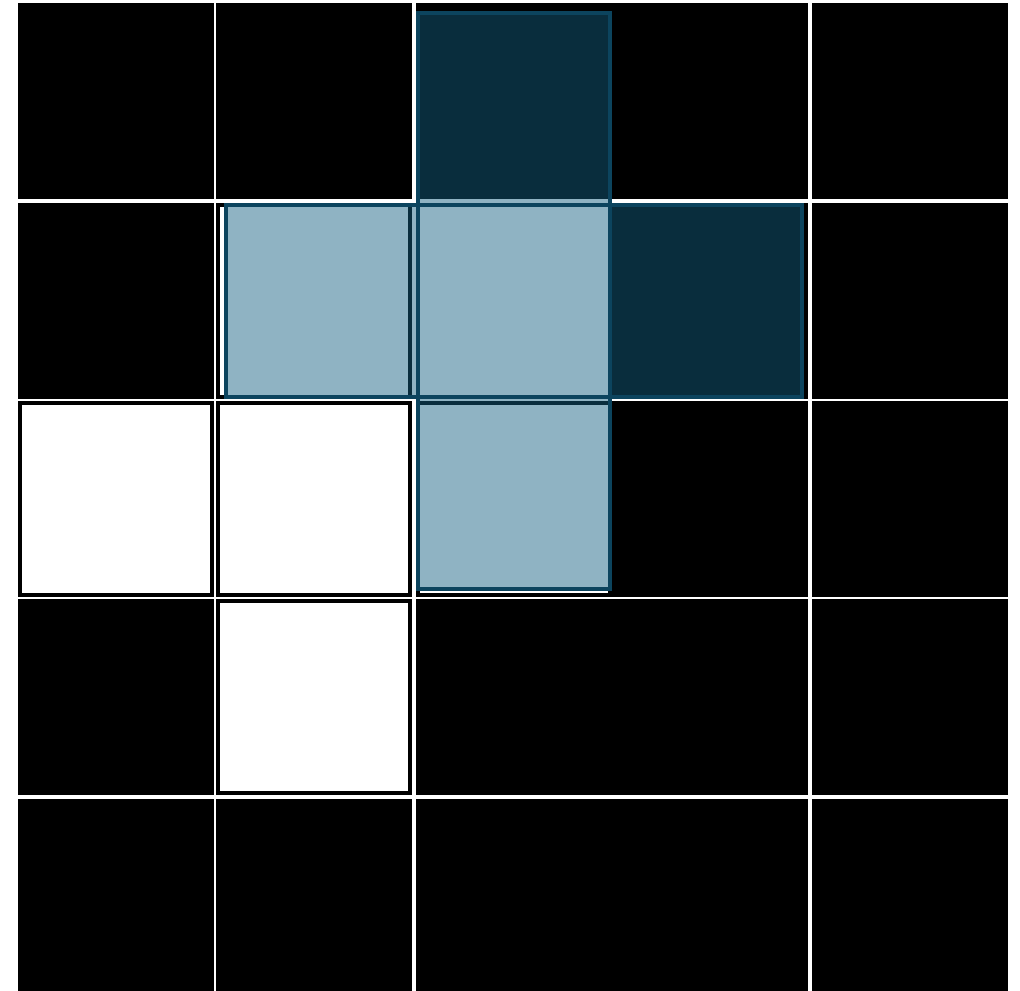
- **Structuring Element** defines neighborhood around input pixel
- Set output pixel to „1“ if
 - all neighborpixels are „1“ (**Erosion**)
 - at least one of them is „1“ (**Dilation**)





Morphological operators

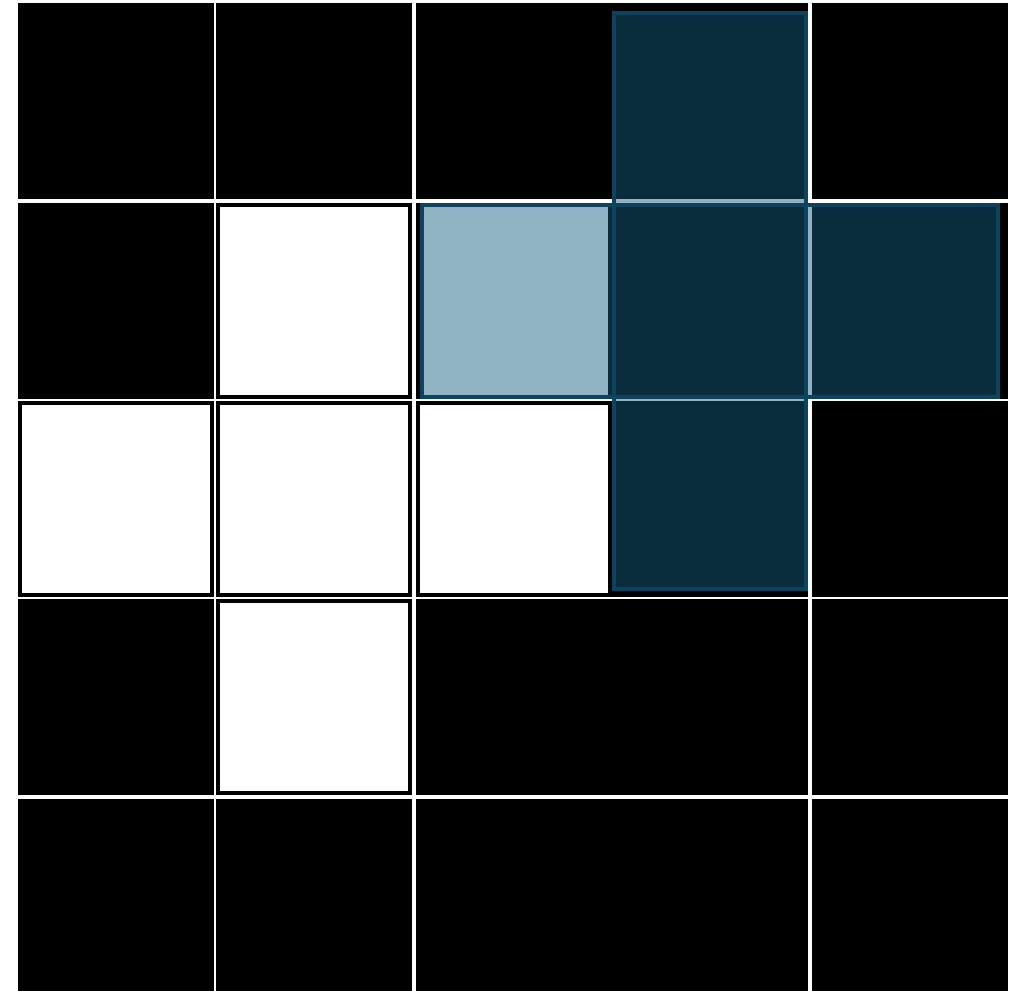
- **Structuring Element** defines neighborhood around input pixel
- Set output pixel to „1“ if
 - all neighborpixels are „1“ (**Erosion**)
 - at least one of them is „1“ (**Dilation**)





Morphological operators

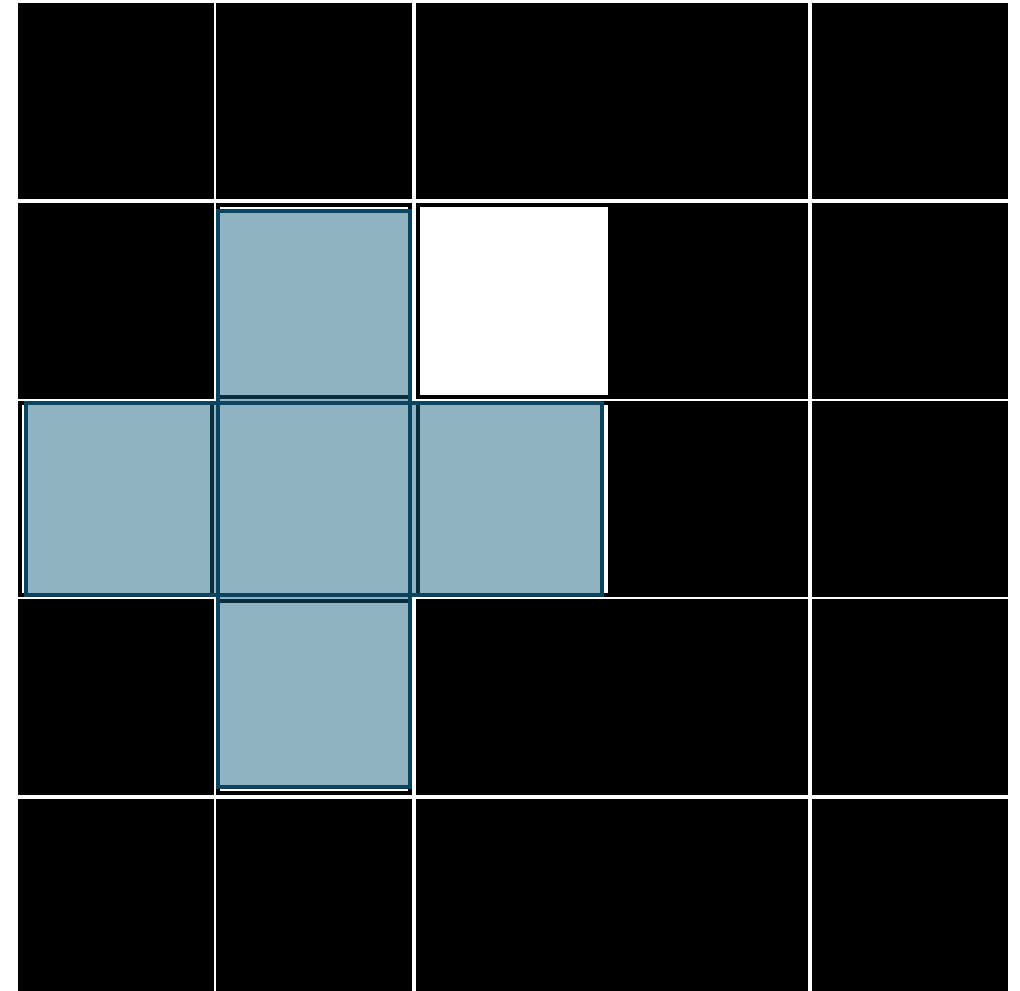
- **Structuring Element** defines neighborhood around input pixel
- Set output pixel to „1“ if
 - all neighborpixels are „1“ (**Erosion**)
 - at least one of them is „1“ (**Dilation**)





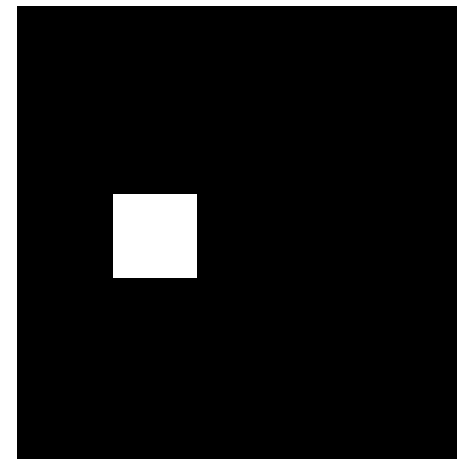
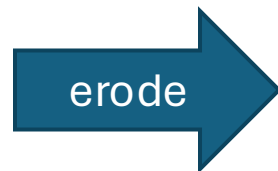
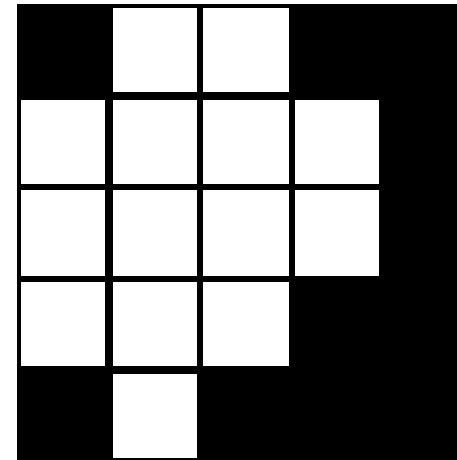
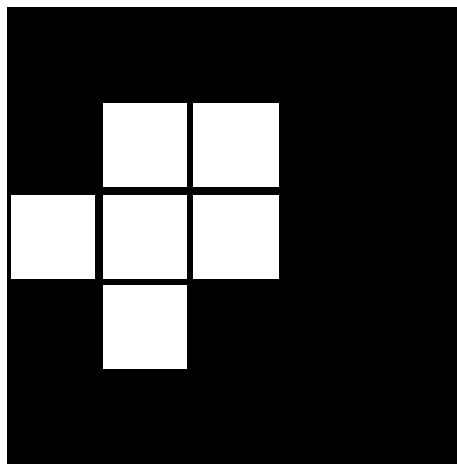
Morphological operators

- **Structuring Element** defines neighborhood around input pixel
- Set output pixel to „1“ if
 - all neighborpixels are „1“ (**Erosion**)
 - at least one of them is „1“ (**Dilation**)





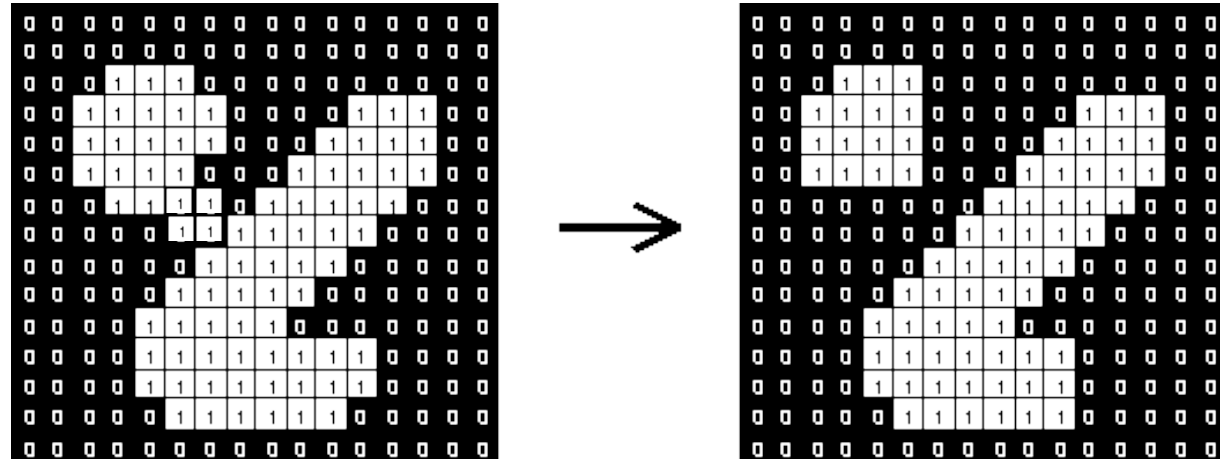
Morphological operators



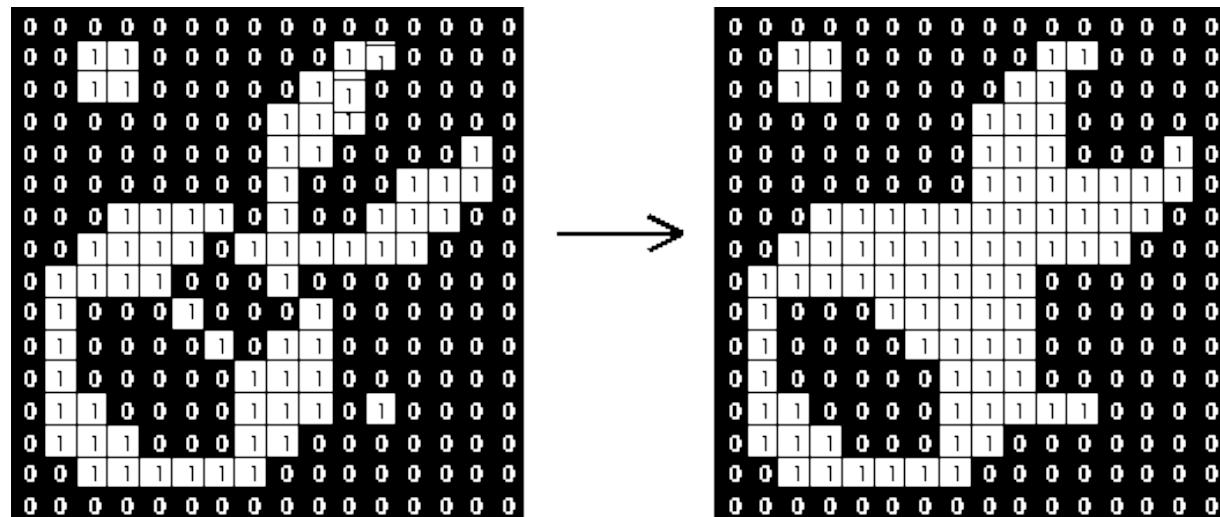


Morphological Operations

$$\text{Opening}(I) = \text{Dilate}(\text{Erode}(I))$$

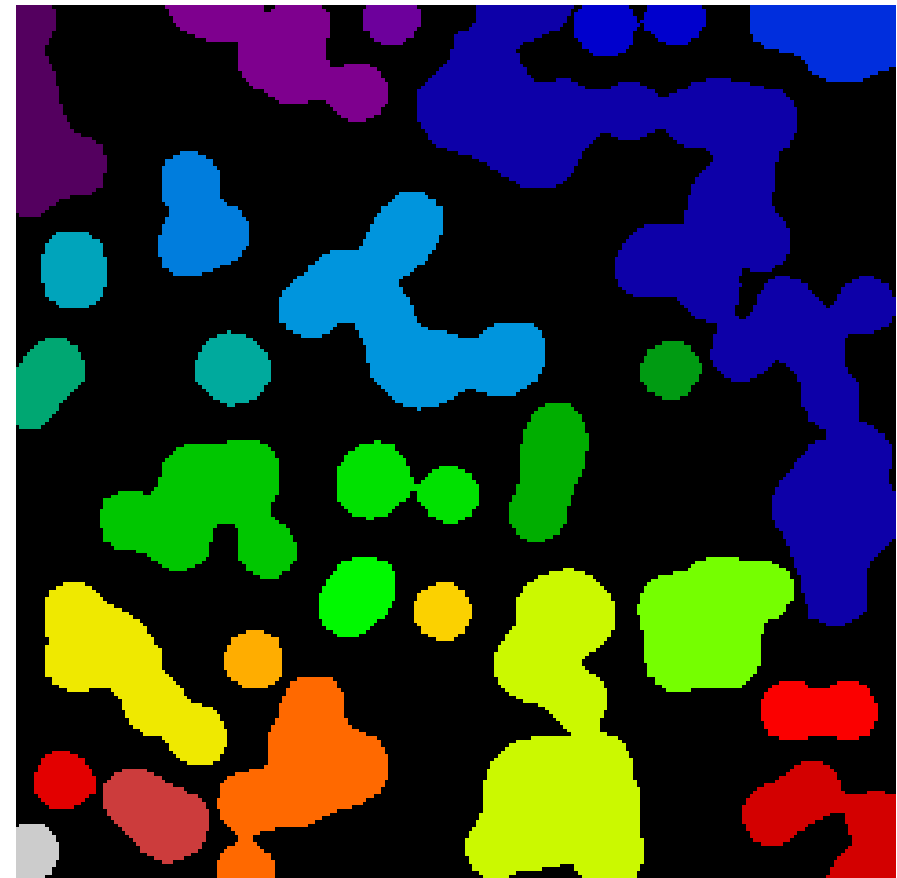
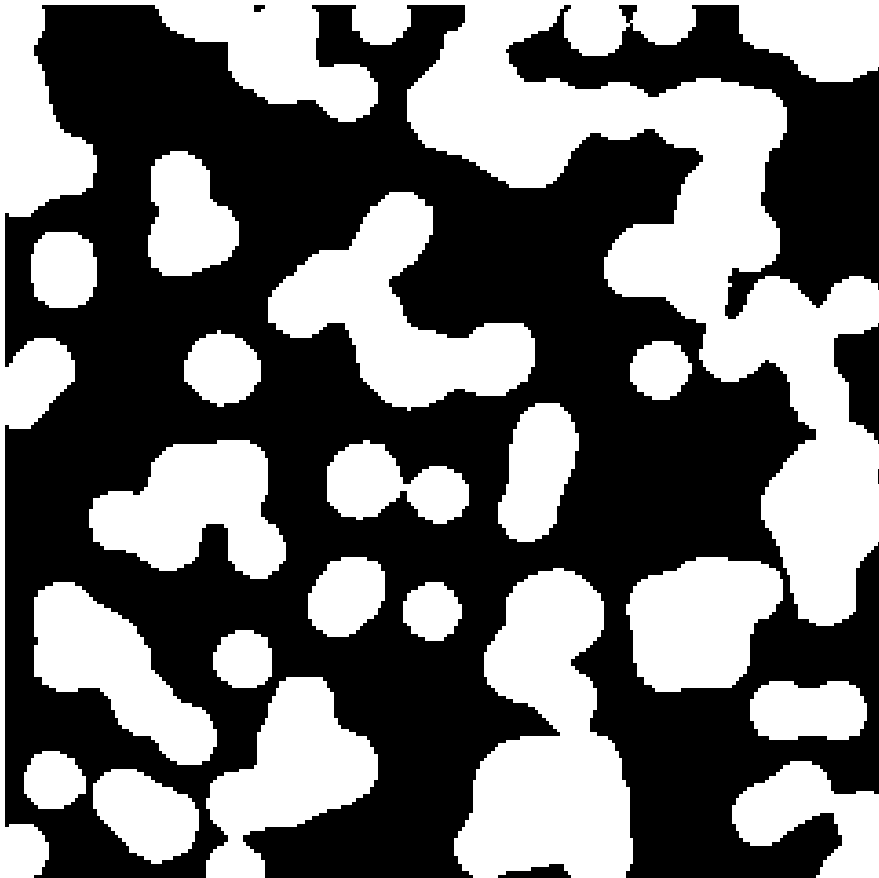


$$\text{Closing}(I) = \text{Erode}(\text{Dilate}(I))$$



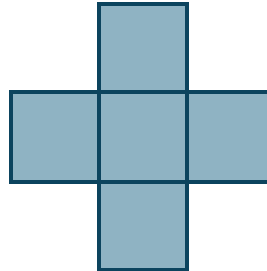
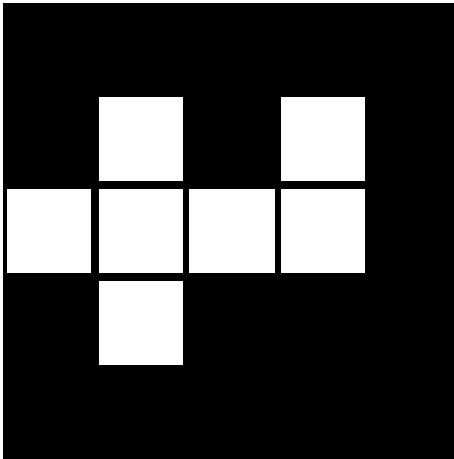


Find connected components

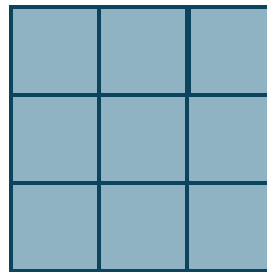




Find connected components



4-neighborhood

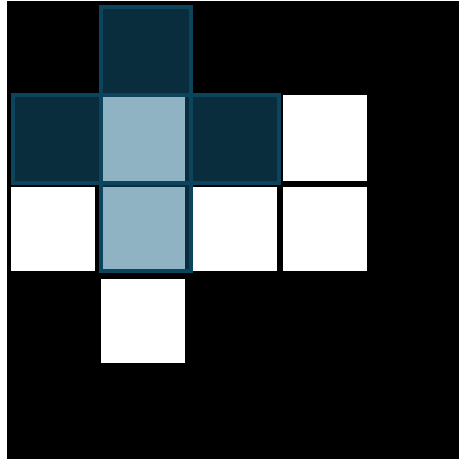


8-neighborhood

Today: The TWO-PASS Algorithm!

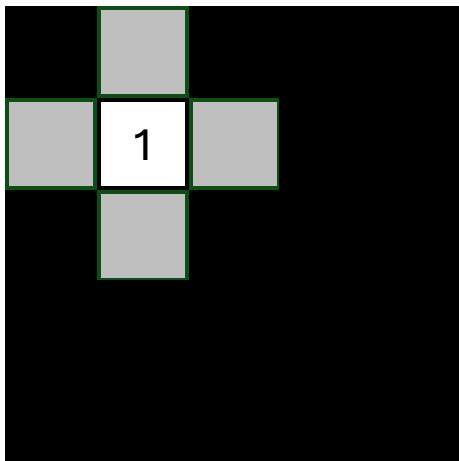


Find connected components



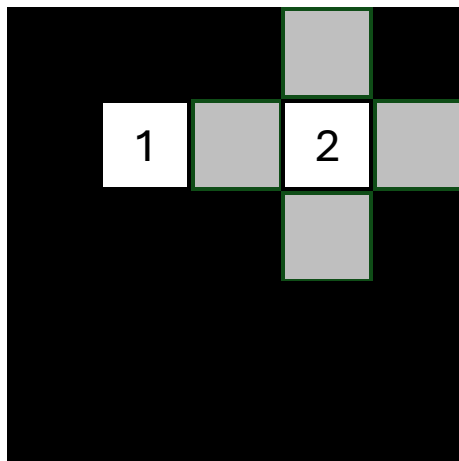
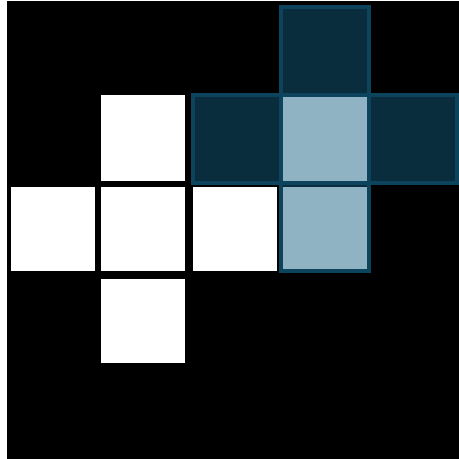
FIRST PASS!

- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If not: assign new label





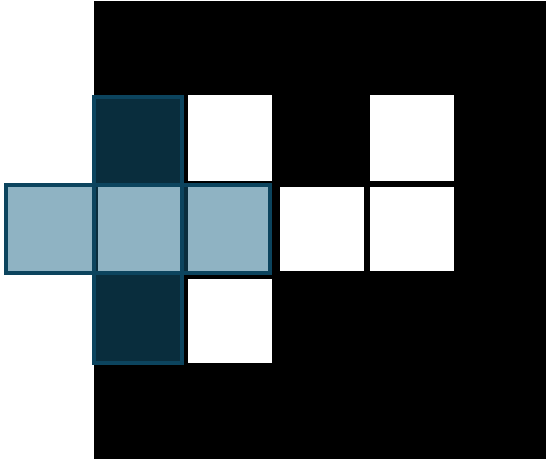
Find connected components



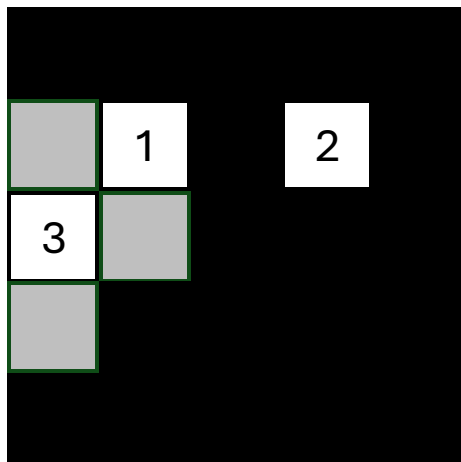
- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If not: assign new label



Find connected components

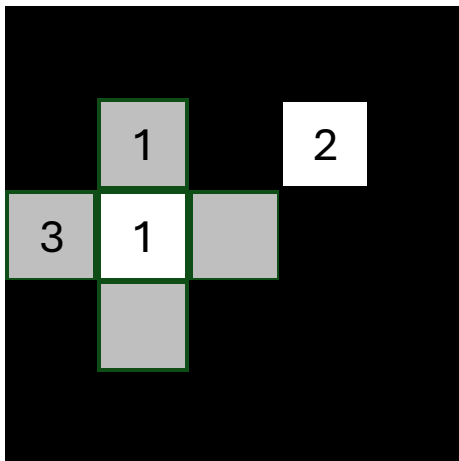
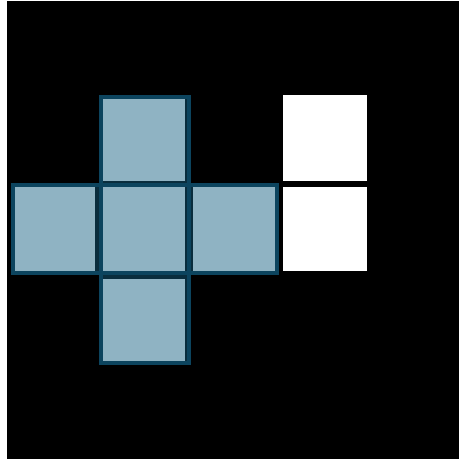


- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If not: assign new label





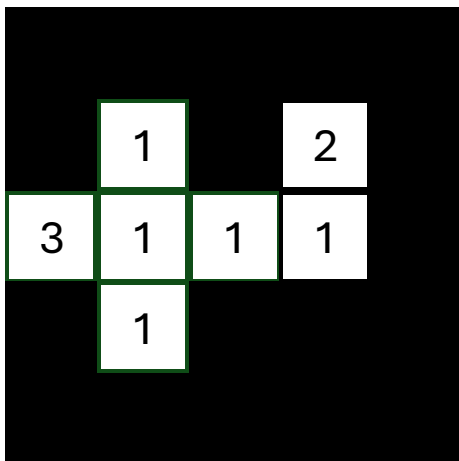
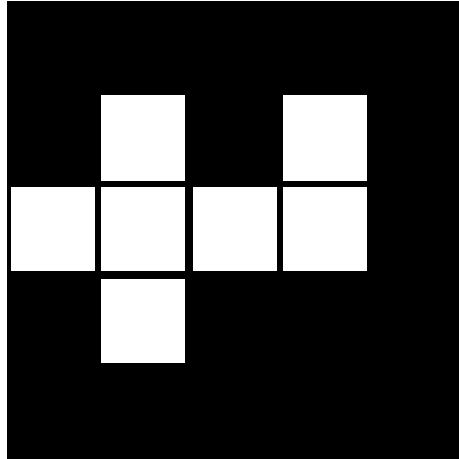
Find connected components



- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If not: assign new label
 - If yes: assign minimum



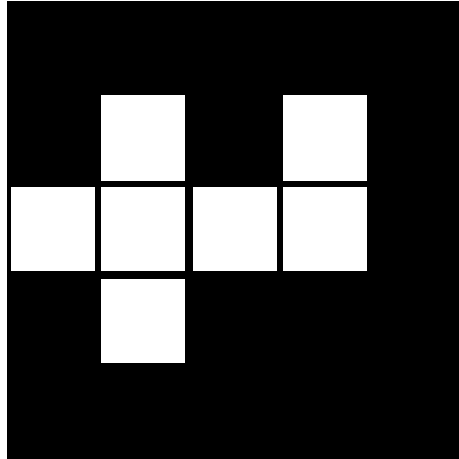
Find connected components



- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If not: assign new label
 - If yes: assign minimum

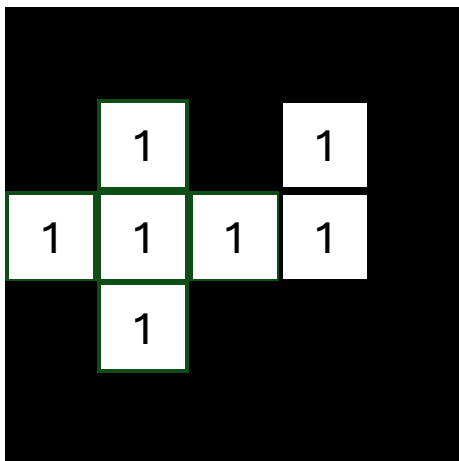


Find connected components



SECOND PASS!

- Scan the input image, pixel by pixel
- If the center pixel is 1
 - check if neighbors have been labeled
 - If yes: assign minimum





Ex. 1.2: connected components in color detections

- starting from the binary color detection image
- erase noise with an erosion operation
- dilate once to get original size of object
- find connected components with two-pass algorithm
- challenge 1: can you do it with one pass?
- challenge 2: extract bounding box „on-the-fly“
 - draw bounding box on original image





Another popular feature: brightness differences to background

- Static scene with (more/less) static background?
- Objects discriminable from background?
- use “Background Subtraction”!





Background Subtraction

- estimate a **background model** (sometimes „**background hypothesis**“)
- the simplest variant is integrating all frames into one background image:

$$B_t = \alpha B_{t-1} + (1 - \alpha)I_t$$
$$0 < \alpha < 1$$

- This is called an **exponential average**: the influence of an image exponentially decays over time





Background Subtraction

- Difference to background model: $D_t = |B_t - I_t|$
- Difference larger than threshold? $D_t > \theta ? 1:0$
- Post-process binary image with
 - Erosion / Dilation
 - Connected components analysis

