AI Summer School 2024

Medical Imaging Informatics

University of Pittsburgh

Image Filtering, Morphology, Shape Analysis

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Pitt SHRS
School of Health and Rehabilitation Sciences

Computational Pathology & AI Center of Excellence

IEEE COMPUTER SOCIETY

Learning Objectives

After completing this lecture, you should be able to:

- Understand image filtering and demonstrate what can be achieved by image filtering
- Understand the convolution operation
- Learn how image derivatives work
- Learn image semantic could be embedded in edges
- Understand edge detection metrics
- What does object segmentation mean and why we are doing it
- How do segmentation algorithms work
- How does the Watershed algorithm work in the context of object segmentation

Outline

- Image Histogram
- Image Filtering
- Image Derivative
- Edge Detection
- Object Segmentation
- Watershed Algorithm

Recall from the previous lectures

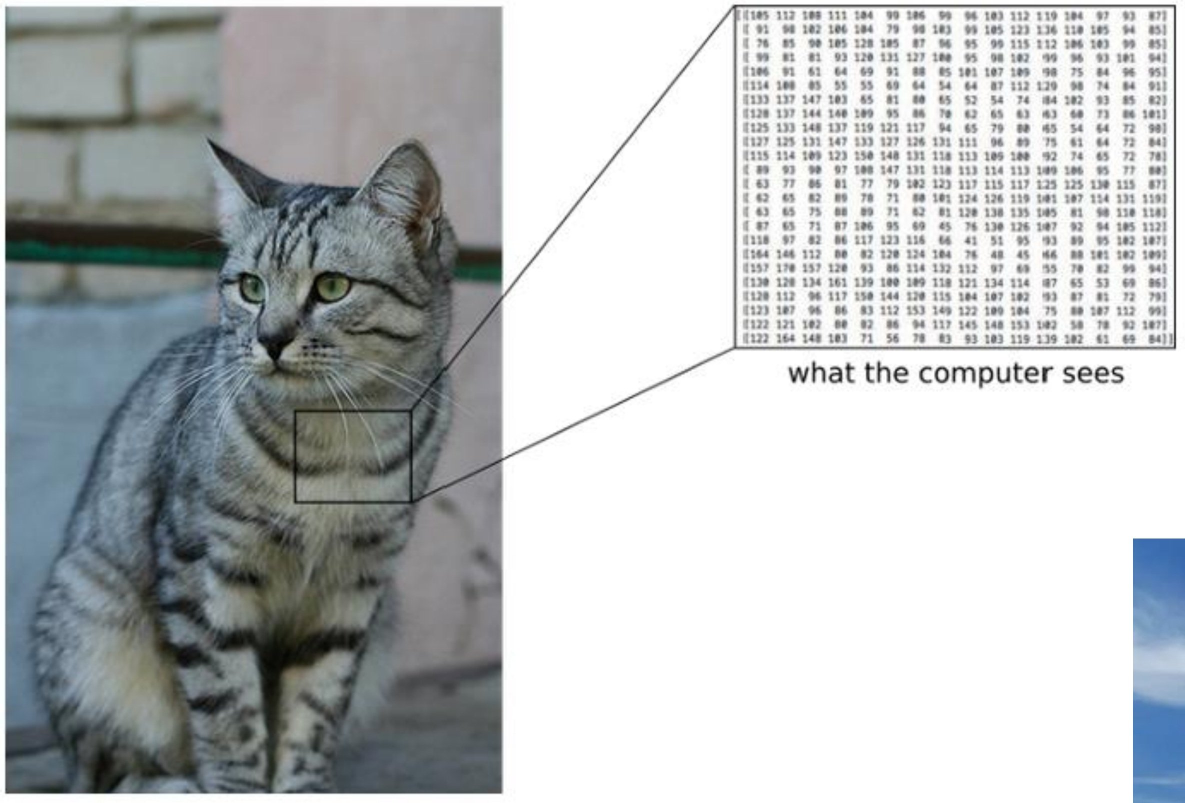


Image from: https://bam098.medium.com/image-classification-c8bcb1d7811e

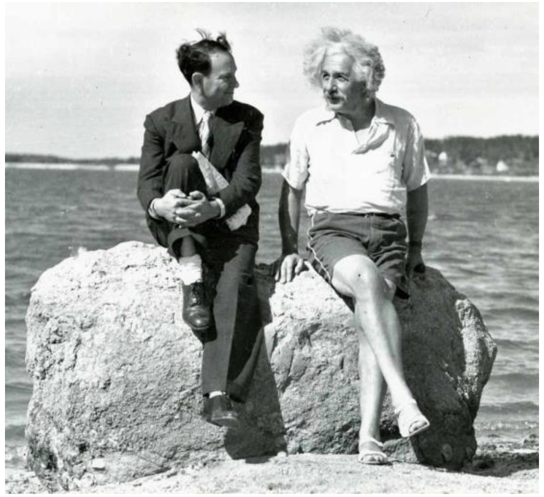


Image Filtering

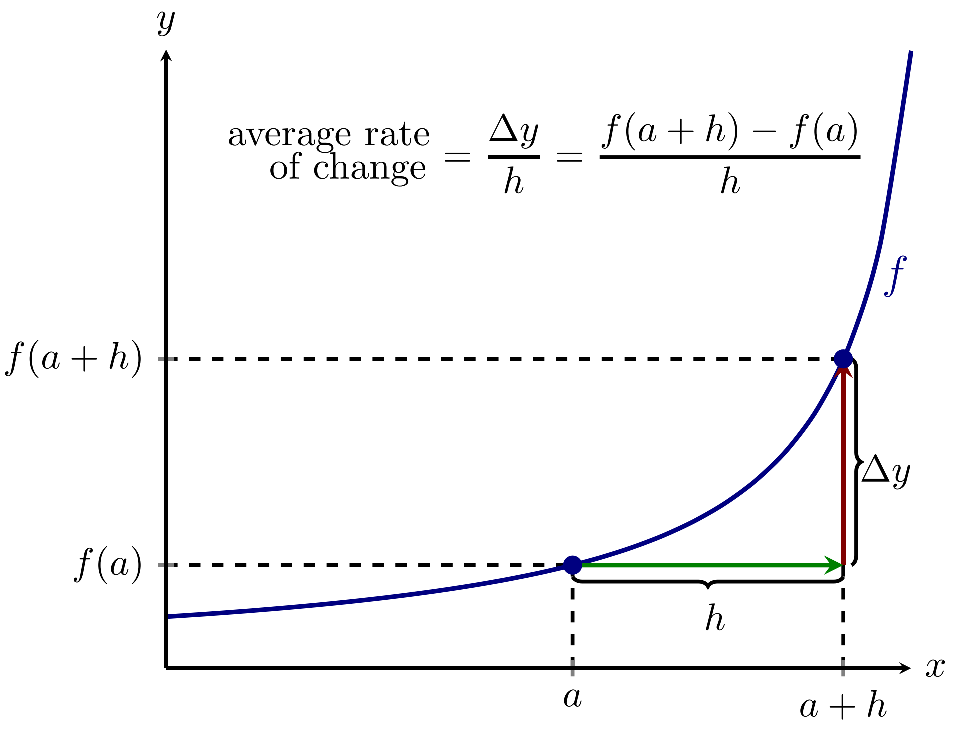
Applications:

- **Image quality enhancement:** denoising, contrast enhancement.
- **Information extraction from images:** edges, distinctive points, texture.
- **Pattern detection and recognition:** image matching

Derivative

Derivative: Rate of Change!!!

$$\frac{df}{dx} = \lim_{\Delta x \to 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x) = f_x$$



$$a = \frac{dv}{dt} \text{ acceleration}$$

Derivative of Functions and Discrete Derivative

$$y = x^4$$

$$\frac{df}{dx} = \lim_{\Delta x \to 0} \frac{f(x) - f(x - \Delta x)}{\Delta x} = f'(x)$$

$$\frac{dy}{dx} = 4\,x^3$$

$$\frac{df}{dx} = \frac{f(x) - f(x-1)}{1} = f'(x)$$

$$\frac{df}{dx} = f(x) - f(x-1) = f'(x)$$

$$\frac{df}{dx} = f(x) - f(x-1) = f'(x)$$

Backward Difference

$$\frac{df}{dx} = f(x) - f(x+1) = f'(x)$$

Forward Difference

Discrete Derivative; an example

$$f(x) = 11 \quad 15 \quad 12 \quad 10 \quad 14 \quad 25 \quad 19$$

$$f'^{(x)} = 0 \quad 4 \quad -3 \quad -2 \quad 4 \quad 11 \quad -6$$

Derivative Filter | Derivative Mask: [-1   1]

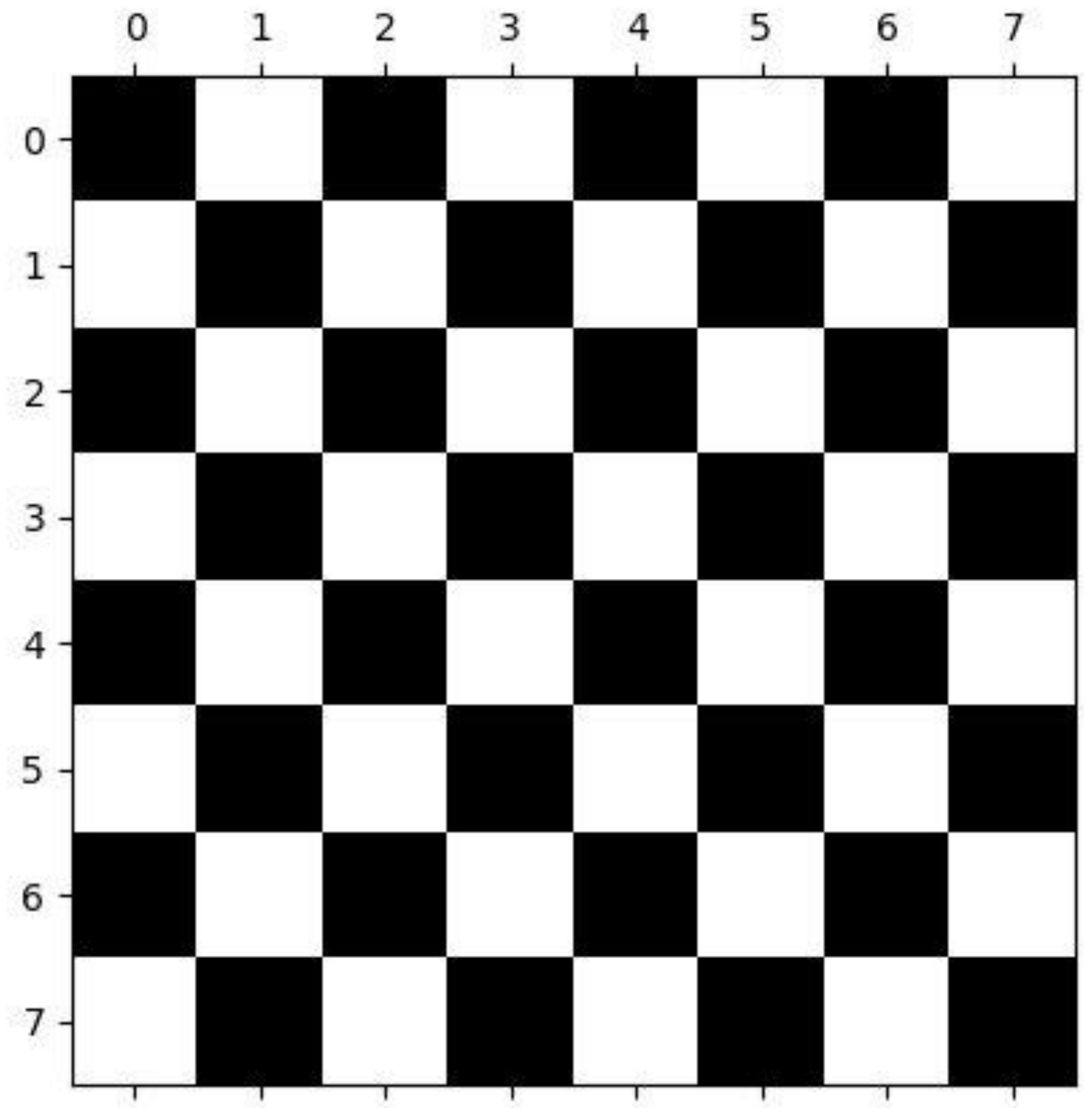
Discrete Derivative; Image is 2D

$f(x,y)$

$$\nabla f(x,y) = \begin{bmatrix} \dfrac{\partial f(x,y)}{\partial x} \\ \dfrac{\partial f(x,y)}{\partial y} \end{bmatrix} = \begin{bmatrix} f_x \\ f_y \end{bmatrix}$$

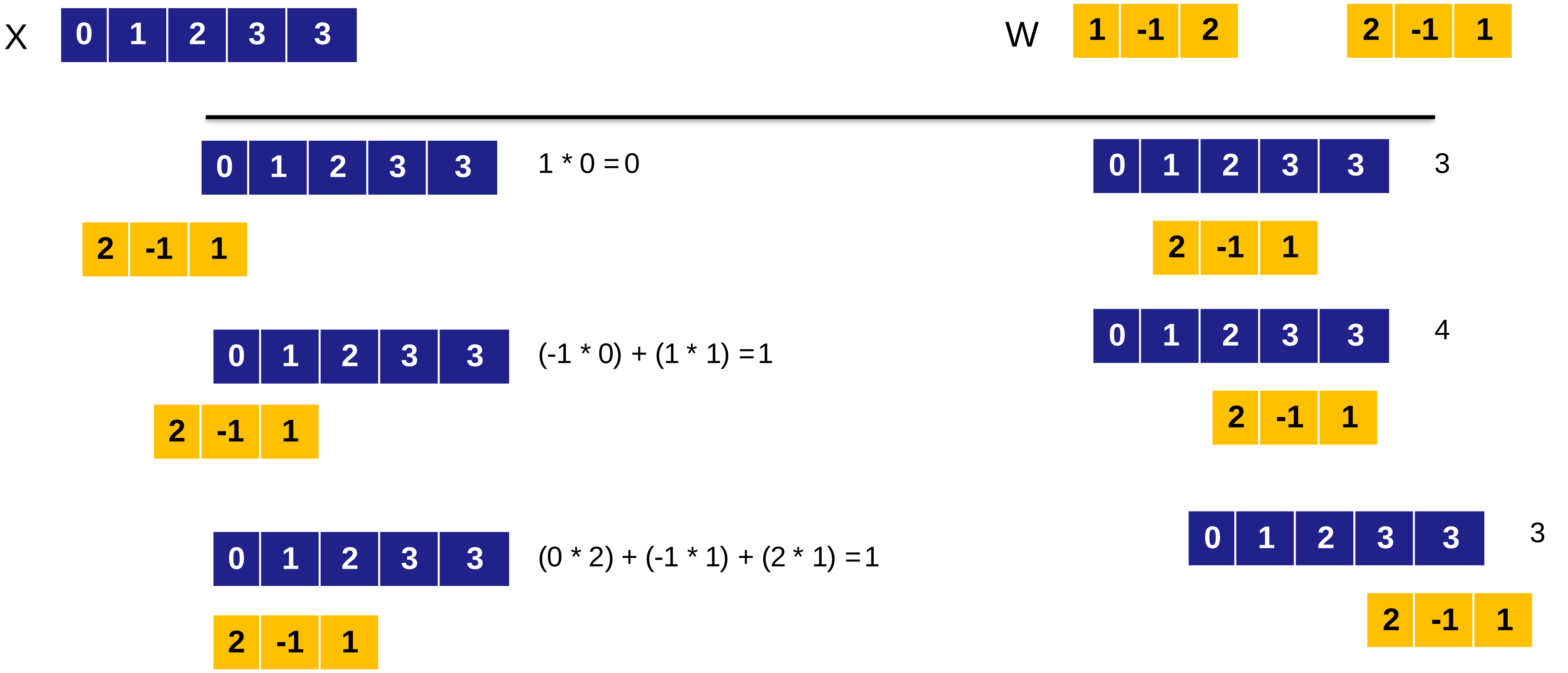
Derivative masks $f_x \Rightarrow \frac{1}{3}\begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$ $f_y \Rightarrow \frac{1}{3}\begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$

Discrete Derivative



Convolution

In mathematics, Convolution is an operation which does the integral of the product of 2 functions (e.g., 2 signals), with one of the signals flipped.



Convolution

0	1	2	3	3	6

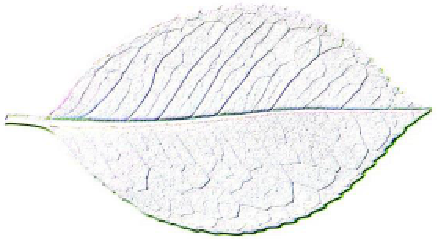
2	-1	1

Output: X

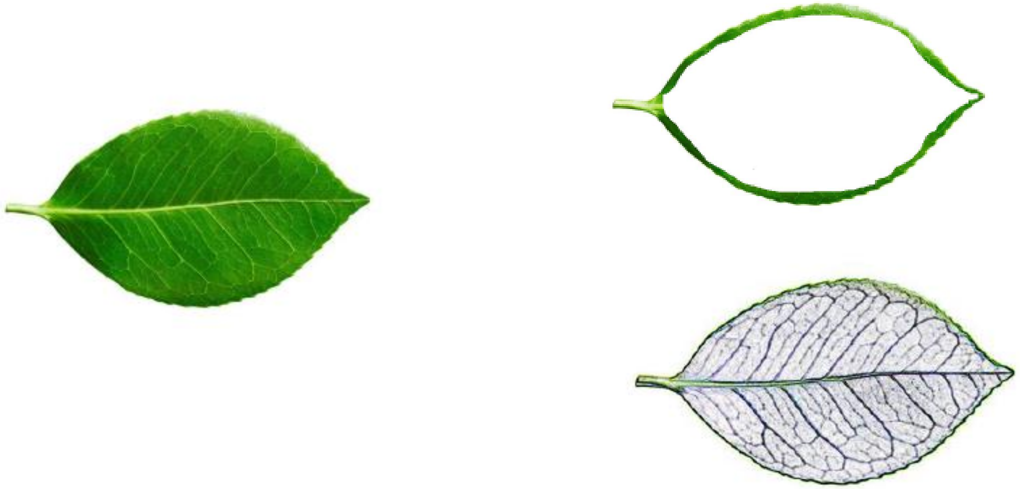
0	1	1	3	4	3	6

Convolution

-1	-1	-1
-1	8	-1
-1	-1	-1



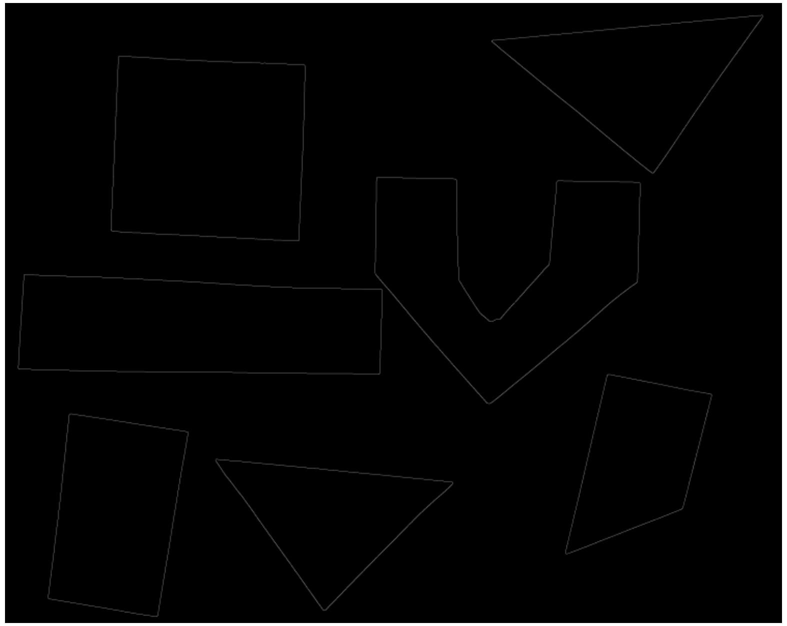
Convolution of an image (left) with an edge detector convolution kernel (middle). Right is the output.



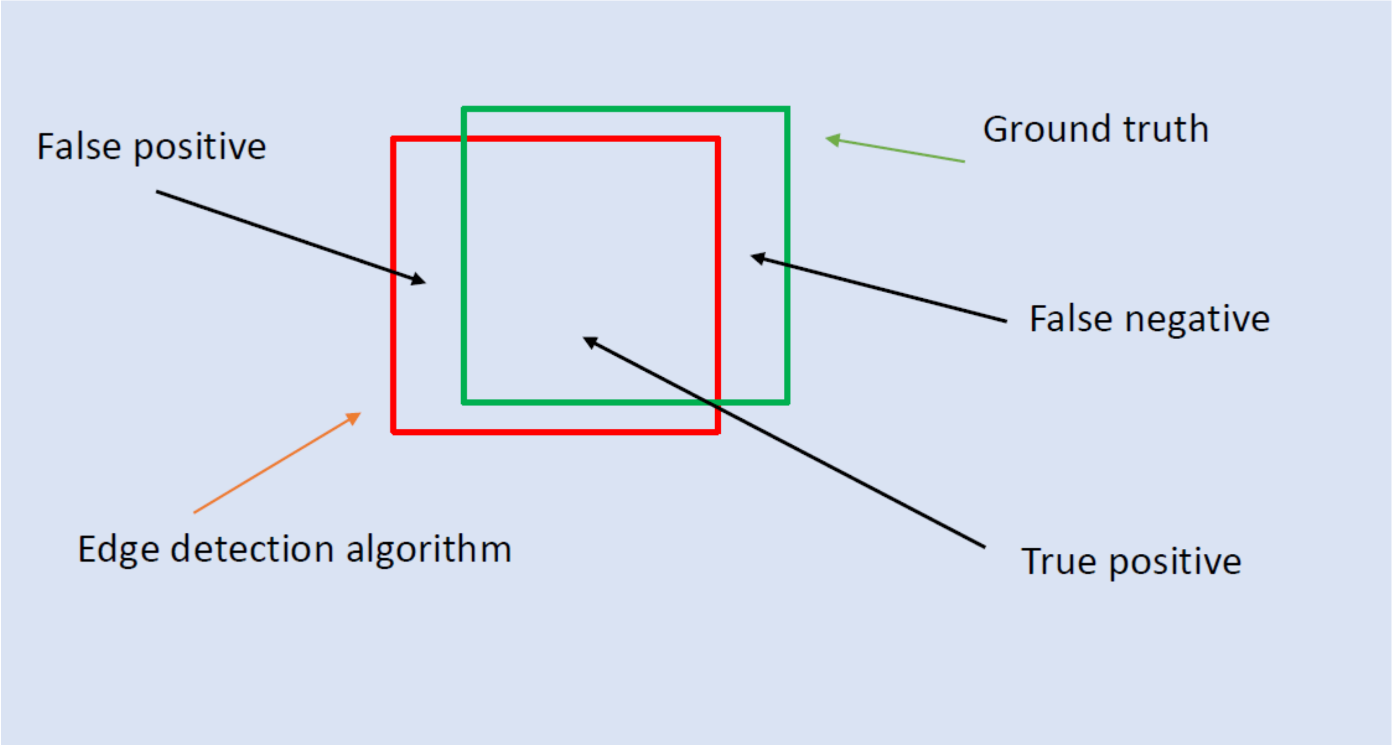
2-minutes break

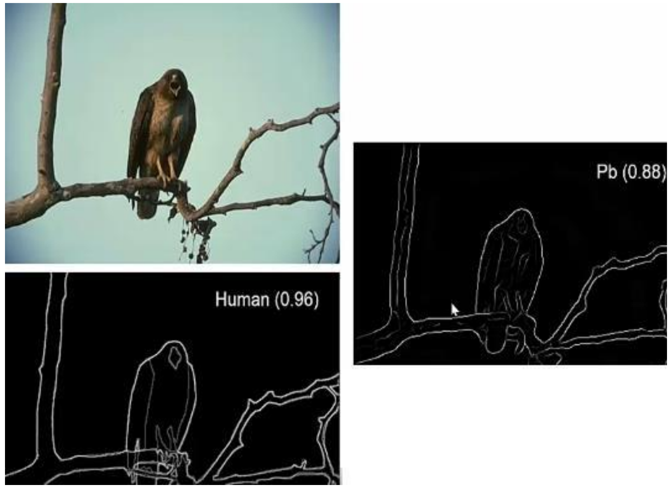
Edge Detection: What?

Sudden changes in color or intensity.



Edge Detection: Metrics





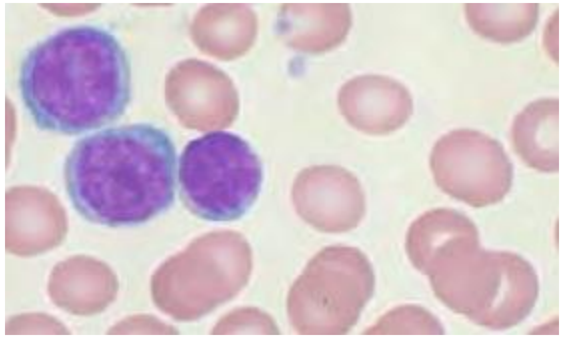
Slide Credit: James Hays

Object Segmentation

Object segmentation is the process of partitioning/dividing an image into multiple regions of interest (objects).

Some Applications:

- Counting objects in images
- Medical diagnosis
- Face recognition



Citation: Nelikanti A. Segmentation and Analysis of Cancer Cells in Blood Samples. Indian Journal of Computer Science and Engineering (IJCSE).. 2015.

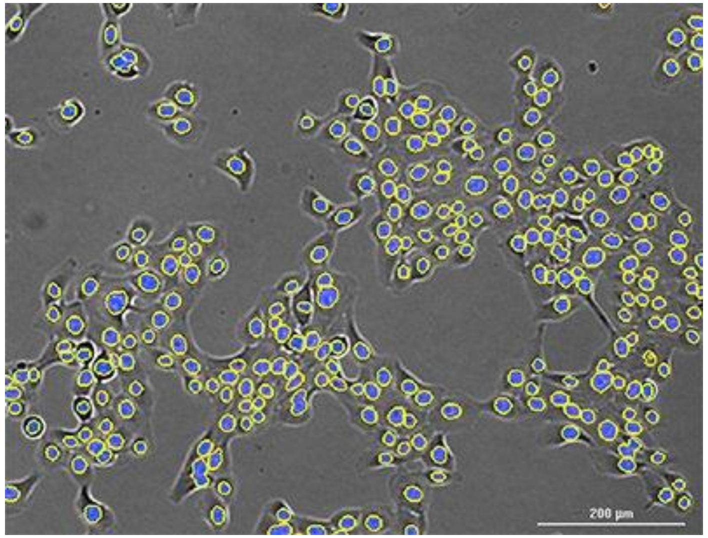
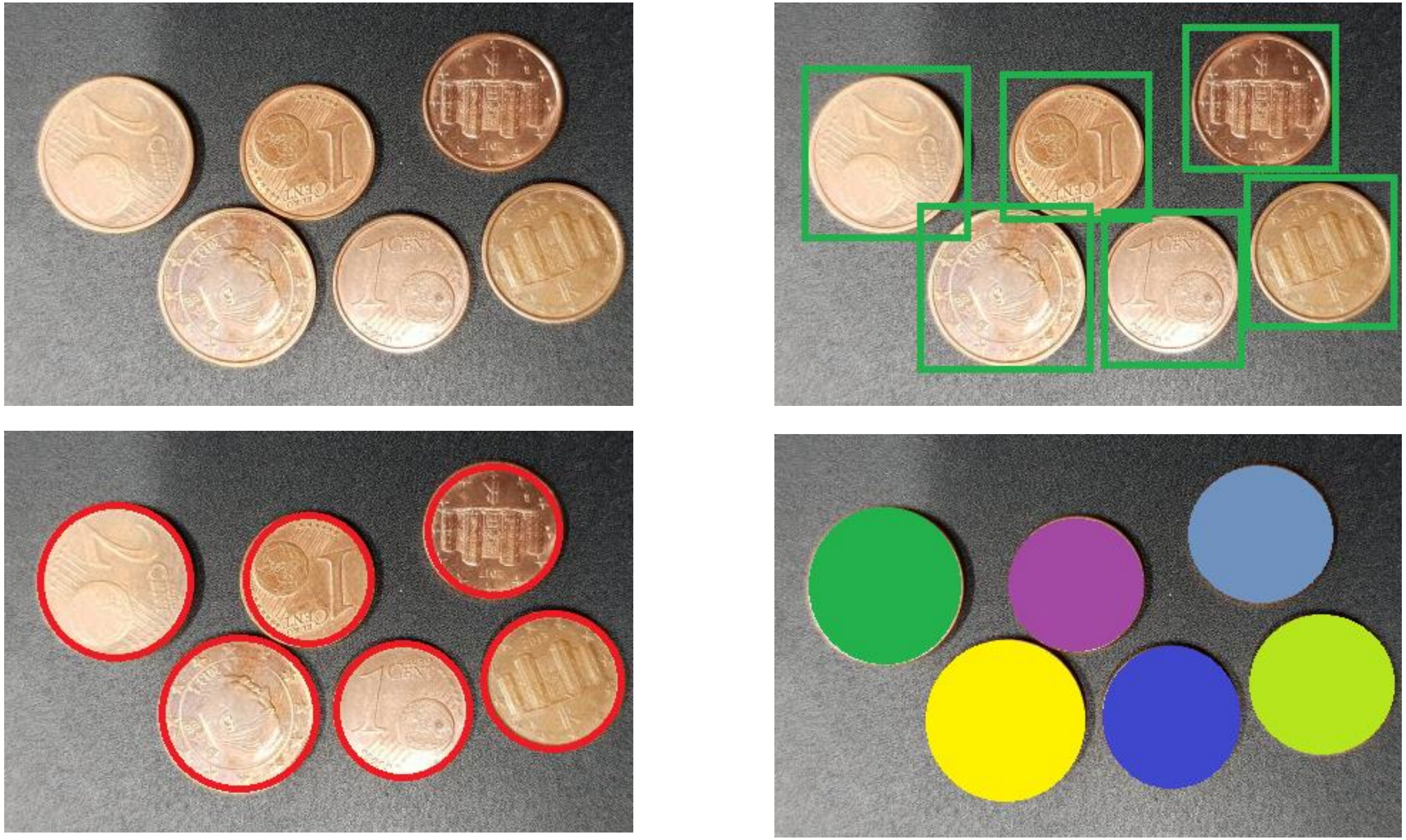


Image from: https://www.biotek.com/applications/cell-counting.html

Citation: Khan K, Mauro M, Leonardi R. Multi-class semantic segmentation of faces. In2015 IEEE International Conference on Image Processing (ICIP) 2015 Sep 27 (pp. 827-831). IEEE.

Object Segmentation



Object Segmentation: Watershed Algorithm

Image from: https://science.howstuffworks.com/environmental

Object Segmentation: Watershed Algorithm

This is the strategy: We must think of a grayscale image as a topographic surface.

- high-intensity pixel values represent peaks (white areas)
- low-intensity values represent valleys or local minima (black areas)

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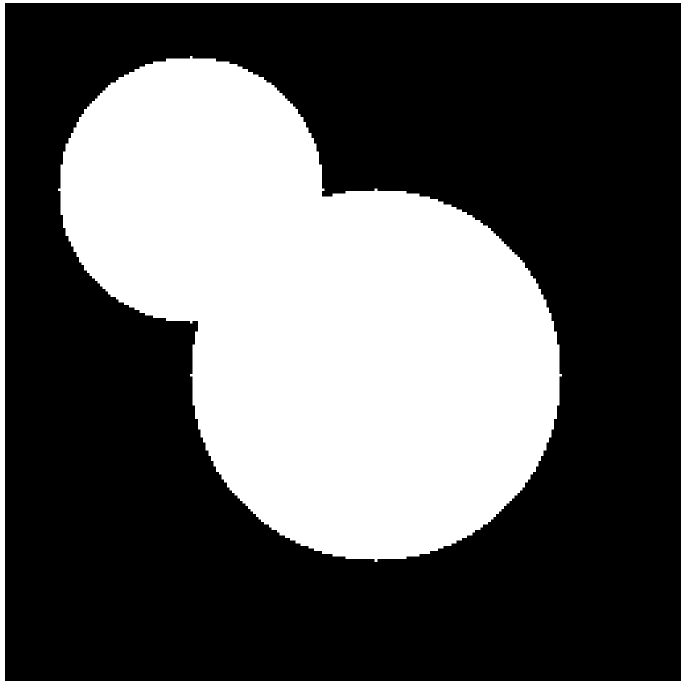

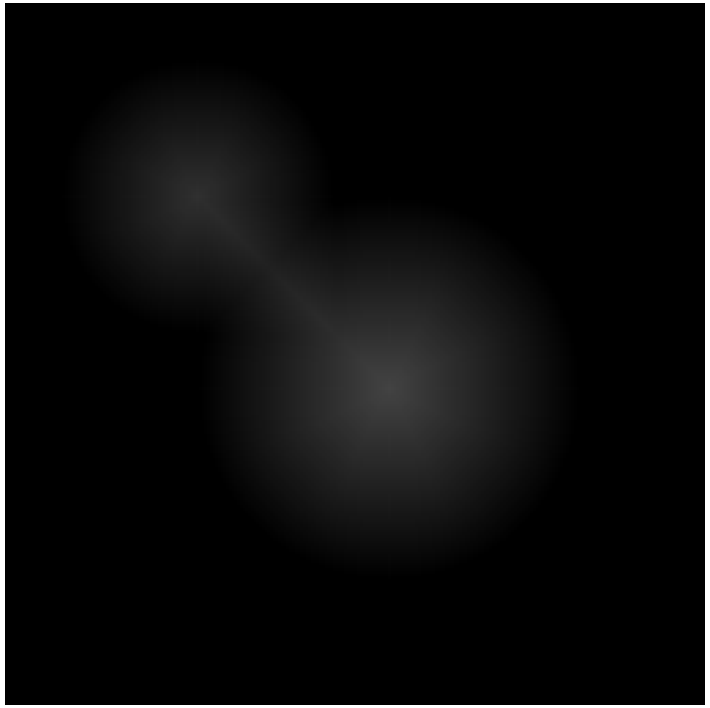

Object Segmentation: Watershed Algorithm

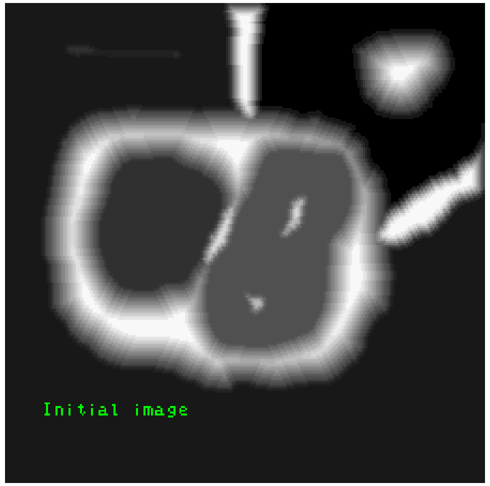

Image from: http://datahacker.rs

- Start with all pixels with the lowest possible value.
  - These form the basis for initial watersheds
- For each intensity level **<u>k</u>**:
  - For each group of pixels of intensity **<u>k</u>:**

    \- **If** adjacent to exactly one existing region, add these pixels to that region

    \- **Else if** adjacent to more than one existing regions, mark as boundary

    \- **Else** start a new region

Thank you!

Questions!