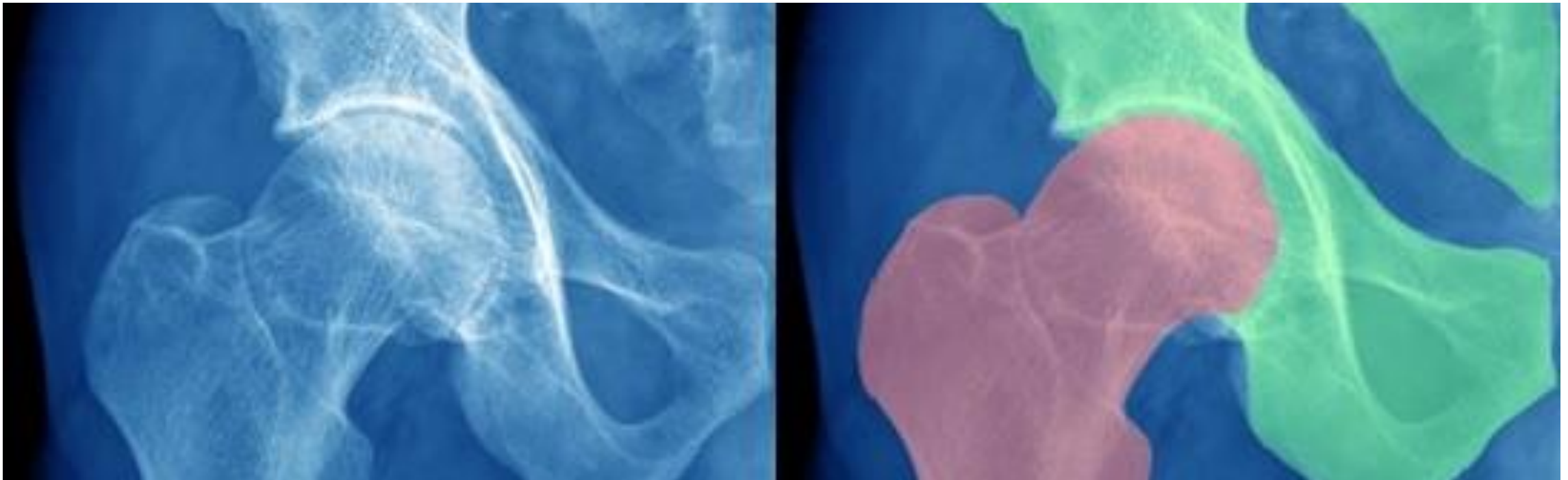


# Image Segmentation

From top-down to bottom-up



# Agenda

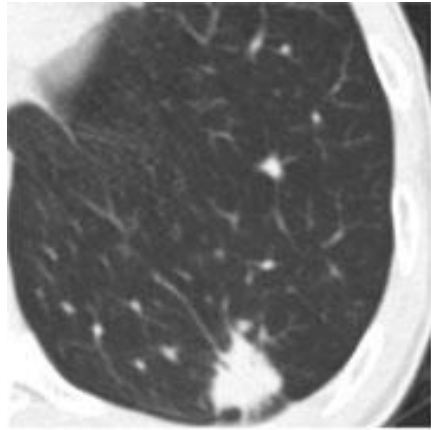
- Recap
- Image segmentation (focus on classical methods):
  - Gray-level Thresholding
  - Kernel & Filtering
  - Region Growing
  - Level set
  - Edge Detection
  - Active contours
- Segmentation Evaluation:
  - DICE Coefficient
  - JACCARD Index

# RECAP



# Recall: ML Imaging Tasks

## Classification



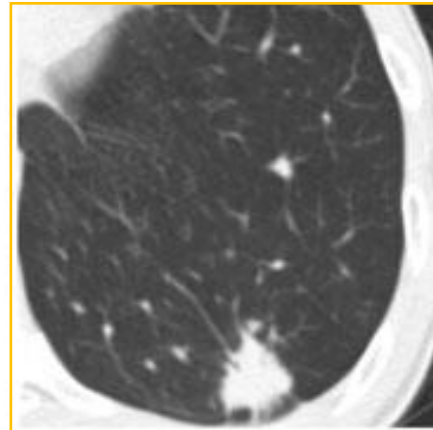
### **Adenocarcinoma**

Adenoma

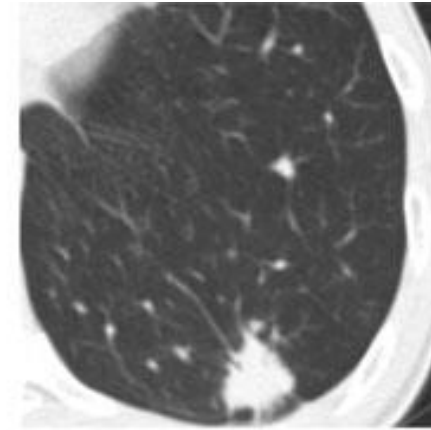
Mesothelioma

...

## Detection



## Segmentation



# Recall: ML Imaging Tasks

Output  
Space &  
Size?

## Classification

Multiclass: # of Classes  
Multilabel:  $2^n$

### Adenocarcinoma

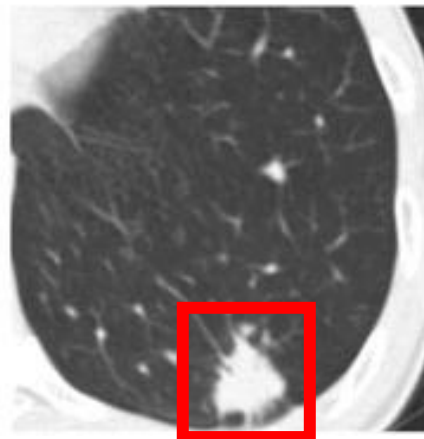
Adenoma

Mesothelioma

...

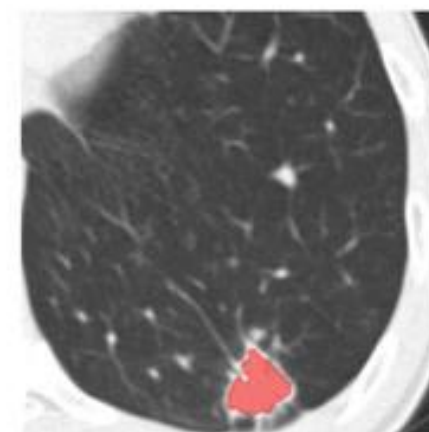
## Detection

4 numbers:  
 $(x_1, y_1), (x_2, y_2)$   
 $\mathbb{R}$



## Segmentation

$n^{w*h}$



# General Recipe for ML Modeling



Define of the problem

Collect (Historical) data

(**Always!**) Look at the data (e.g., *analyze statistics*)

Decide on an evaluation metric(s)

Define Features

Split the dataset

Train and compare Models

Hyperparameter tuning

Select a model and apply (inference / predictions)

# General Recipe for ML Modeling



Define of the problem

Collect (Historical) data

(**Always!**) Look at the data (e.g., *analyze statistics*)

Decide on an evaluation metric(s)

Define Features

Split the dataset

Train and compare Models

Hyperparameter tuning

Select a model and apply (inference / predictions)



Decide on an evaluation metric(s)



What metrics do you know?





Decide on an evaluation metric(s)

What would you use for:

Classification?

Regression?

Clustering?

Detection?

Segmentation?



What would you use for:

# Classification?

Precision  
Recall  
F1-Score  
Mathew's Correlation Coefficient (MCC)  
ROC  
AUC  
Confusion Matrix



What would you use for:

# Classification?

Precision  
Recall  
F1-Score  
Mathew's Correlation Coefficient (MCC)  
ROC  
AUC  
Confusion Matrix

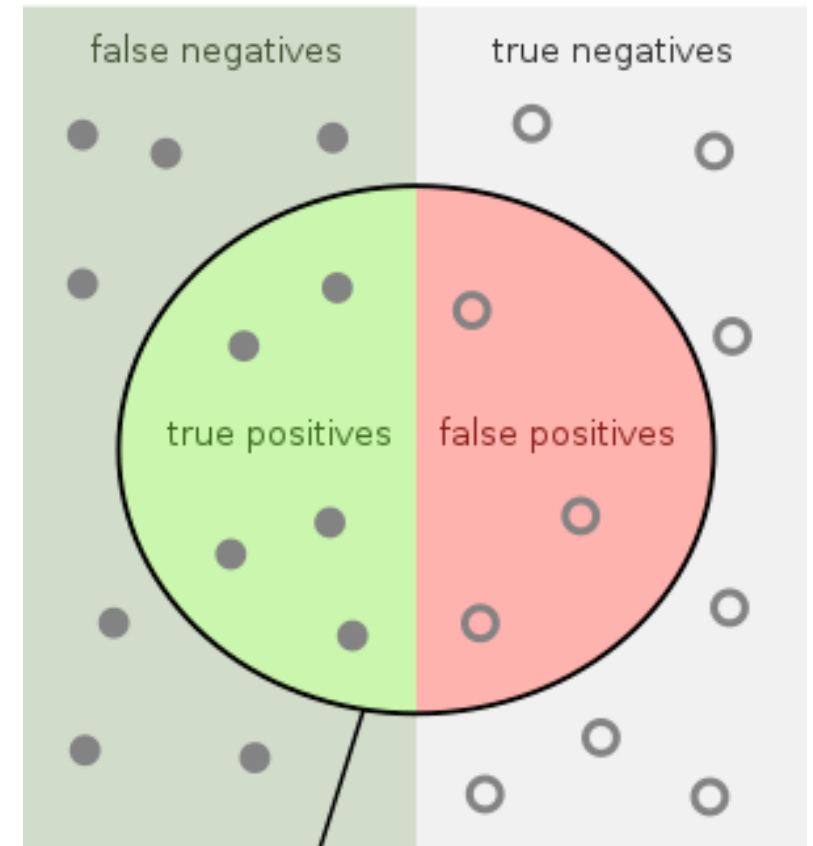
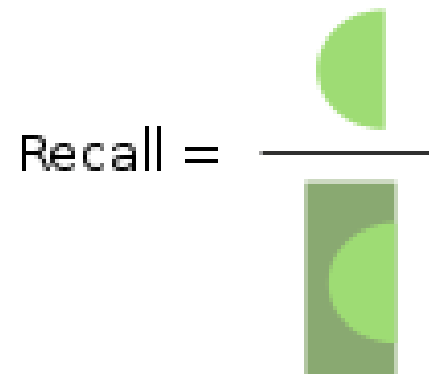
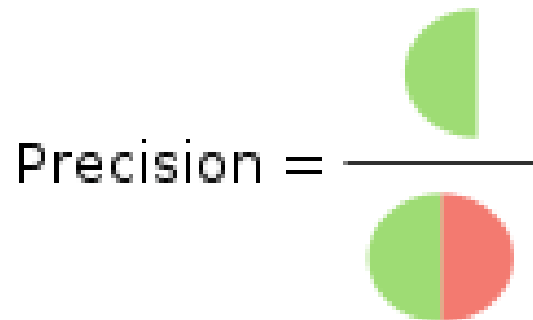
What would you use for:

# Classification

	P	N
P	TP	FP
N	FN	TN

$$\text{Precision: } \frac{TP}{TP + FP}$$

$$\text{Recall: } \frac{TP}{TP + FN}$$



What would you use for:

# Classification

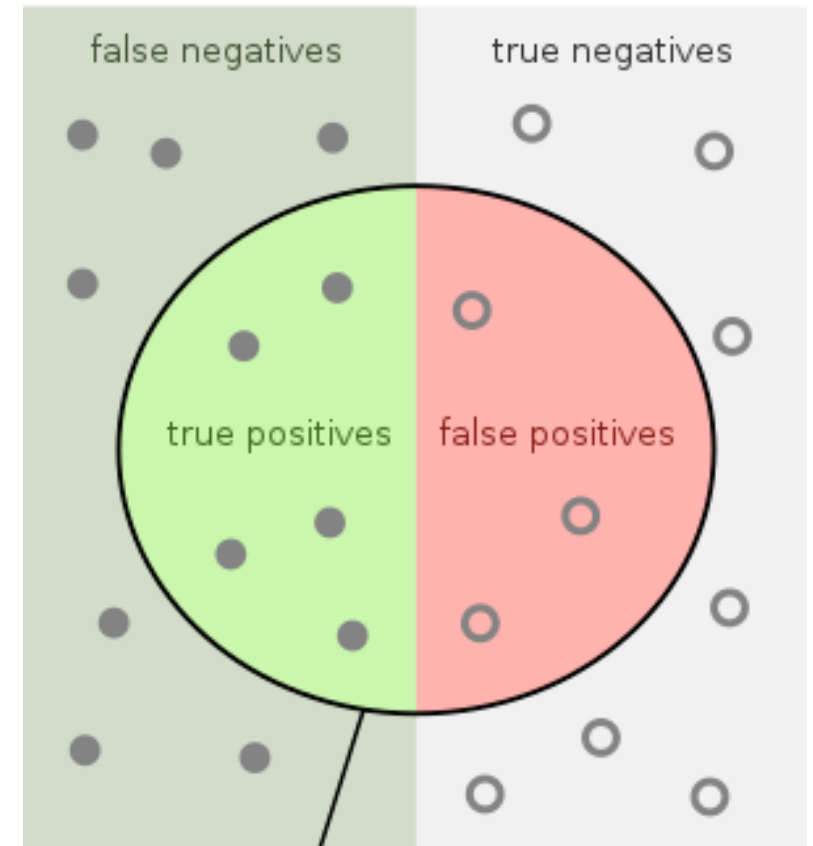
	P	N
P	TP	FP
T	FN	TN

$F1$ :

$$2 \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}}$$

$$\frac{2 \times TP}{2 \times TP + FP + FN}$$

What is missing?



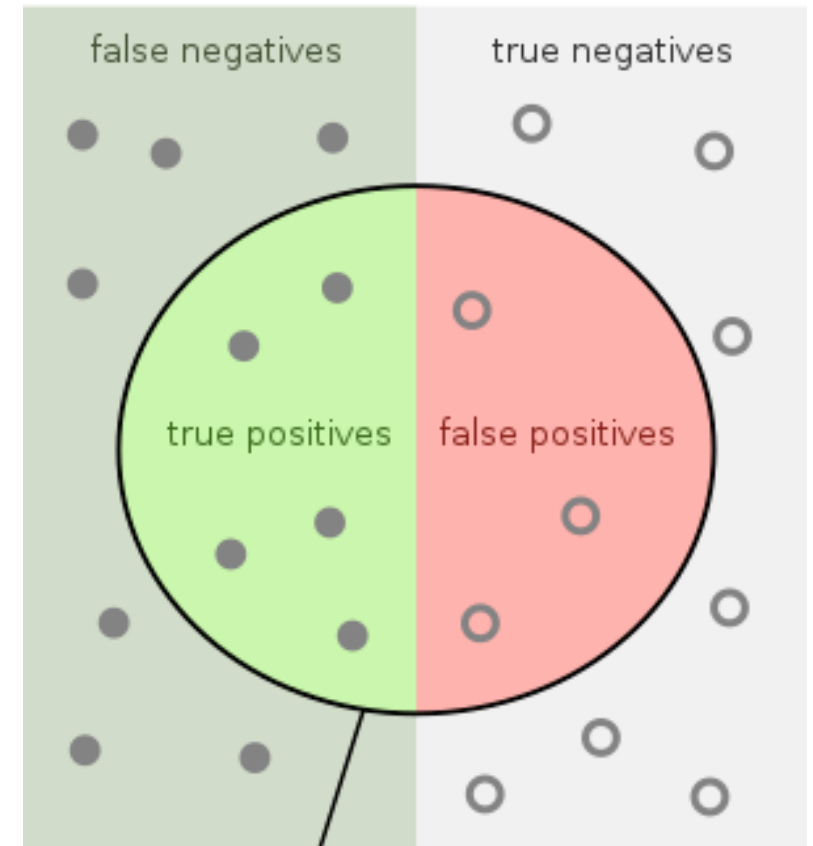
What would you use for:

# Classification

	P	N
P	TP	FP
T	FN	TN

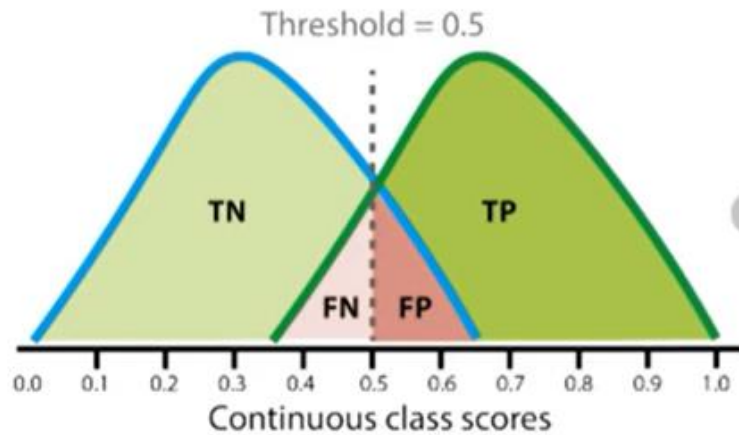
*MCC:*

$$\frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

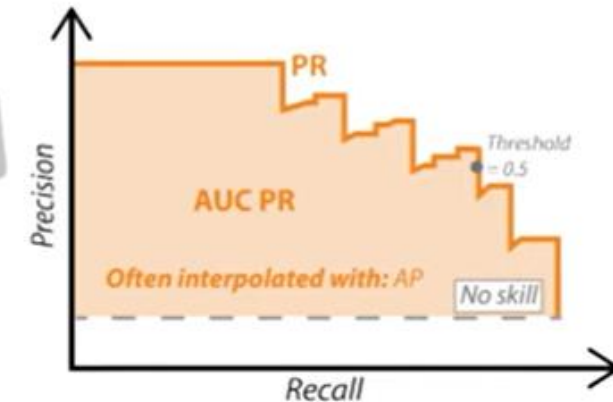
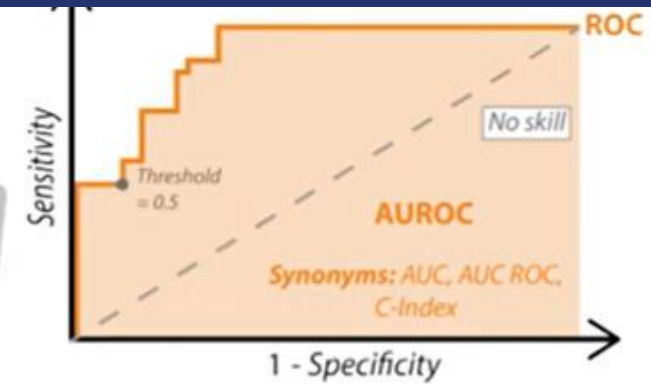


What would you use for:

# Classification



Scan over thresholds





Decide on an evaluation metric(s)

What would you use for:

Classification?

Regression?

Clustering?

Detection?

Segmentation?



What would you use for:

# Regression

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y})^2$$

$$RMSE = \sqrt{MSE}$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}|$$



Decide on an evaluation metric(s)

What would you use for:

Classification?

Regression?

Clustering?

Detection?

Segmentation?

What works?

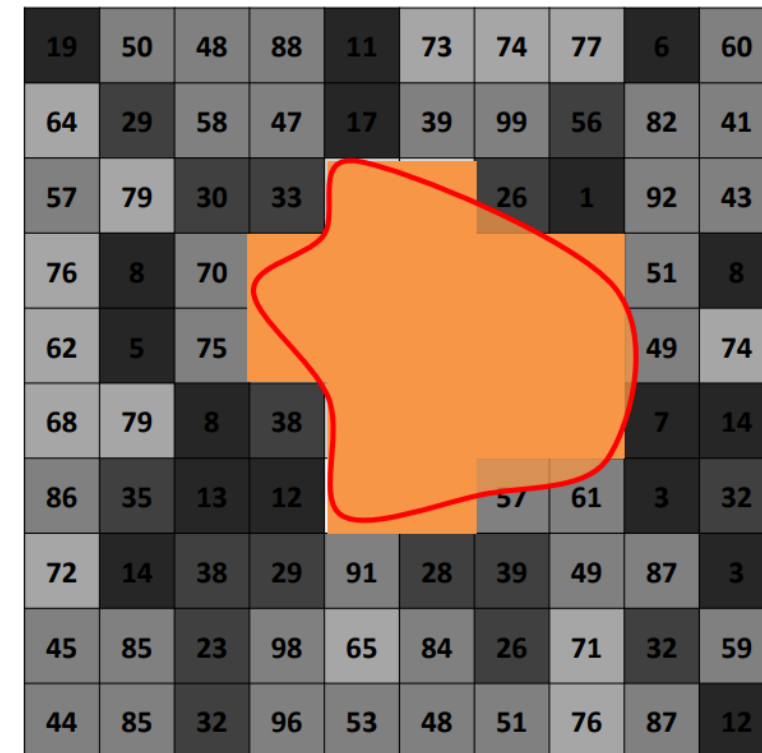
## Segmentation

Keep in mind:

- Images are 2D, 3D, 4D...
- Most medical images are 16-bit

Definition: Clustering image elements as “**belong together**”

- Partitioning
  - Divide into regions/sequences with coherent internal properties
- Grouping
  - Identify sets of coherent tokens in image



65535

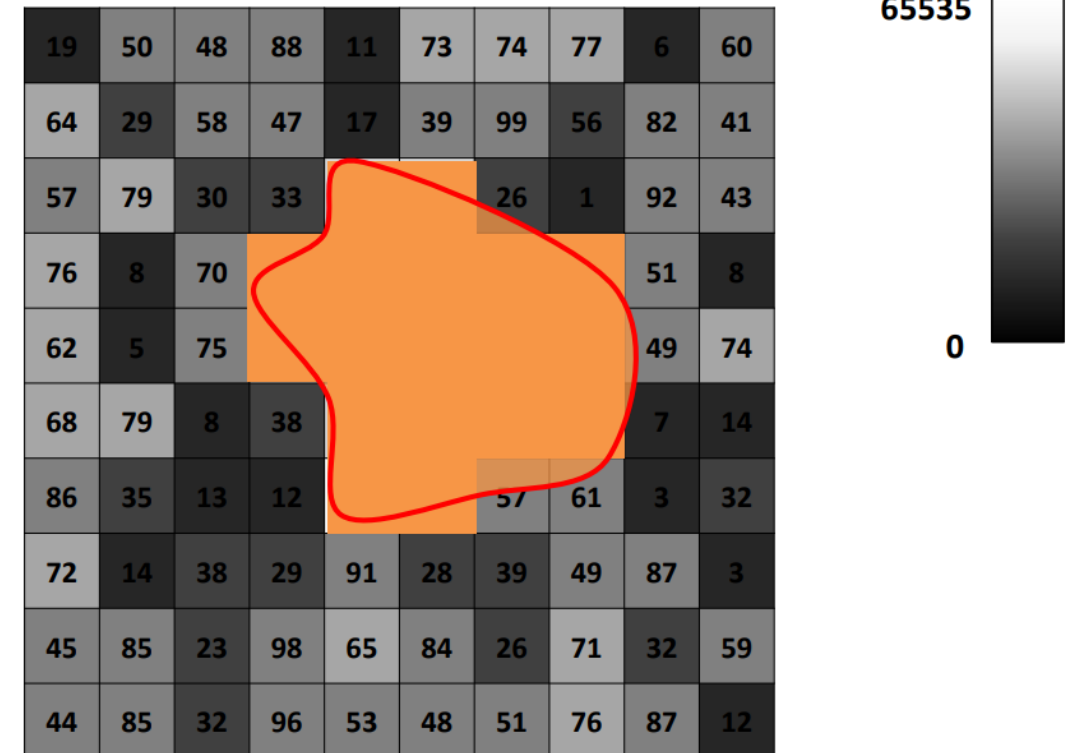
0

What would you use for:

# Segmentation

Definition: Clustering image elements as “**belong together**”

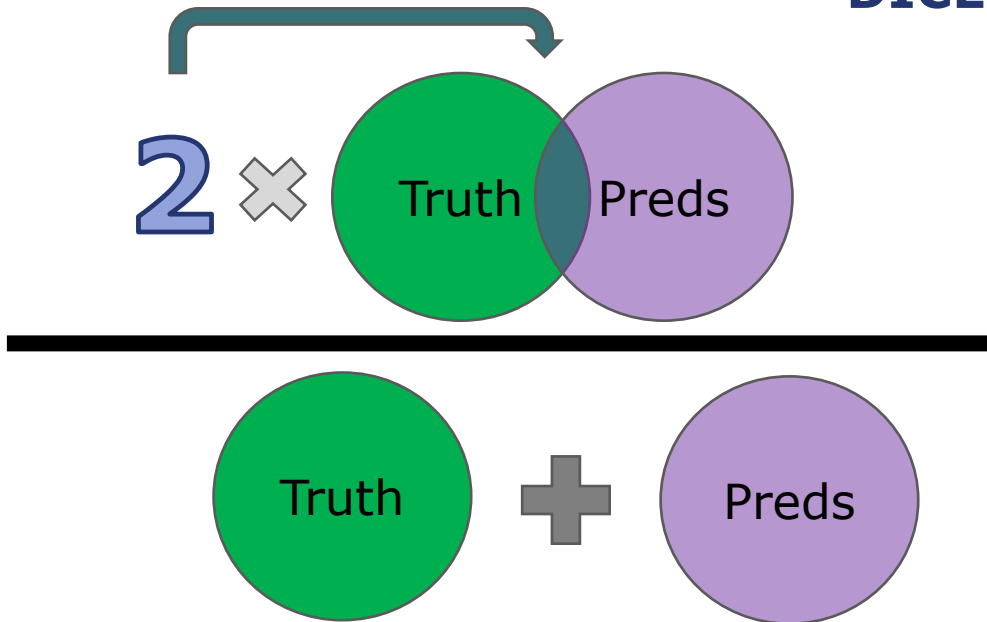
- Two approaches:
  - Pixel-wise categorical labels
  - Implicit Representations



What would you use for:

# Segmentation

## DICE Coefficient (F1-Score)



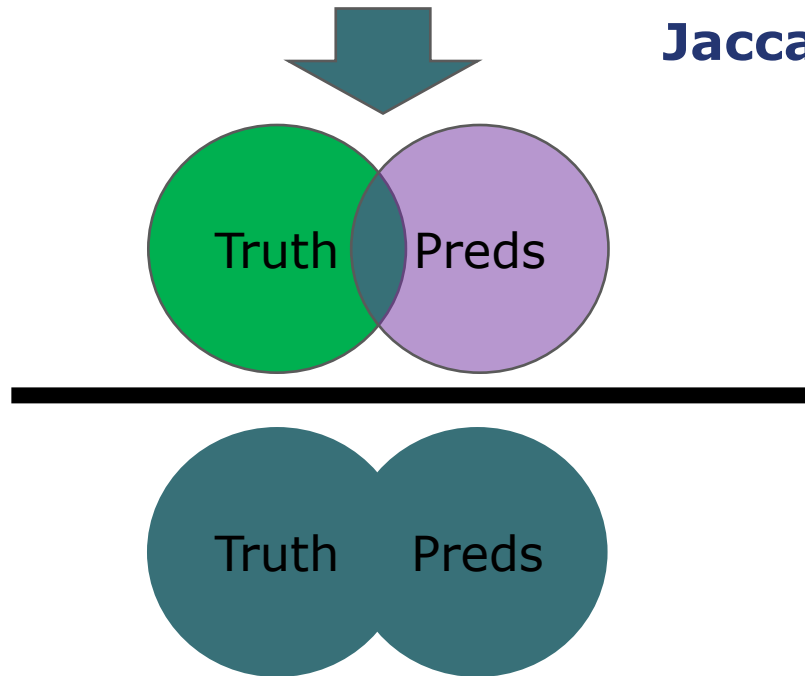
$$\frac{2 * \text{Overlap Area}}{\text{Total Pixel Combined}}$$

Division for  
normalization  
(to be between 0-1)

What would you use for:

# Segmentation

**Jaccard Index (AUC)**

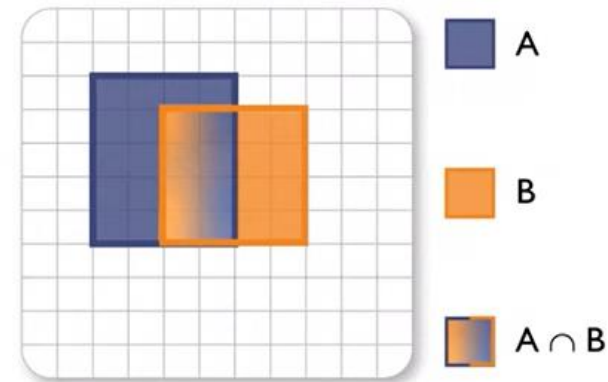
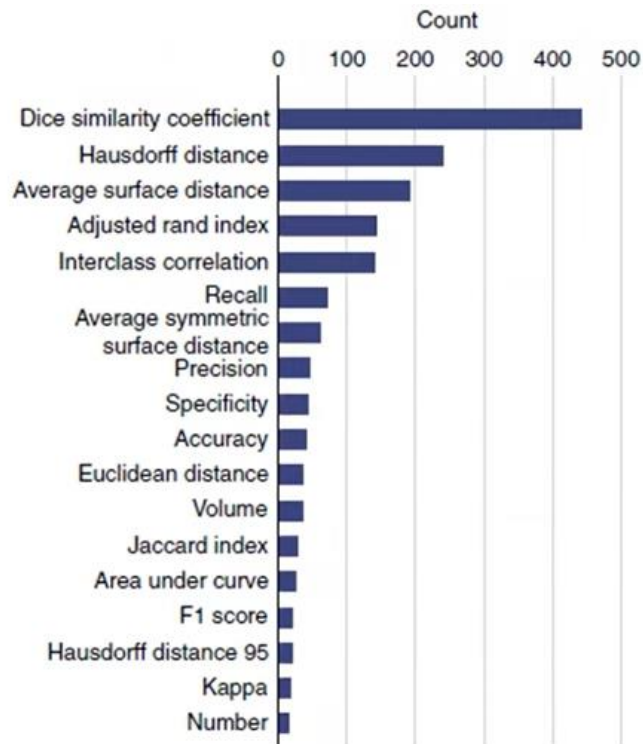


$$IOU = \frac{\text{Overlap Area}}{\text{Area of Union}}$$

Division for  
normalization  
(to be between 0-1)

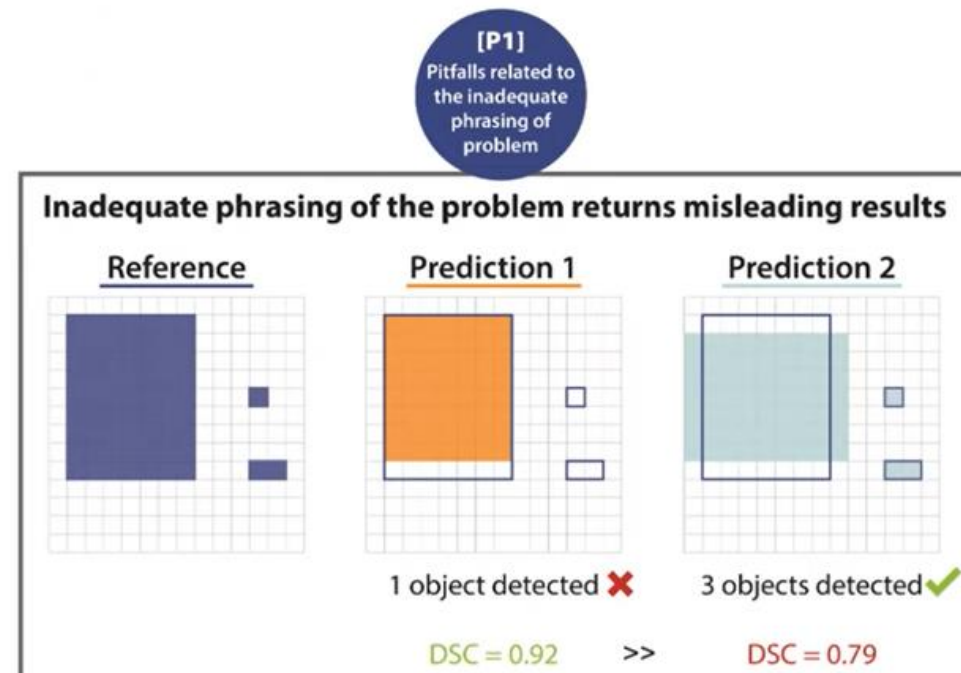
# Dice Similarity Coefficient

Most widely used metric



# Dice Similarity Coefficient

Pitfalls: Object Detection vs. Segmentation



[2206.01653] Metrics reloaded: Recommendations for image analysis validation ([arxiv.org](https://arxiv.org/abs/2206.01653))



# Motivation

- Organ detection
  - Heart, liver, lungs in MRI / CT Scans
- Brain segmentation
  - Thalamus, hippocampus
- Quantitative Measurements
  - Ultrasound
- Image-guided surgery

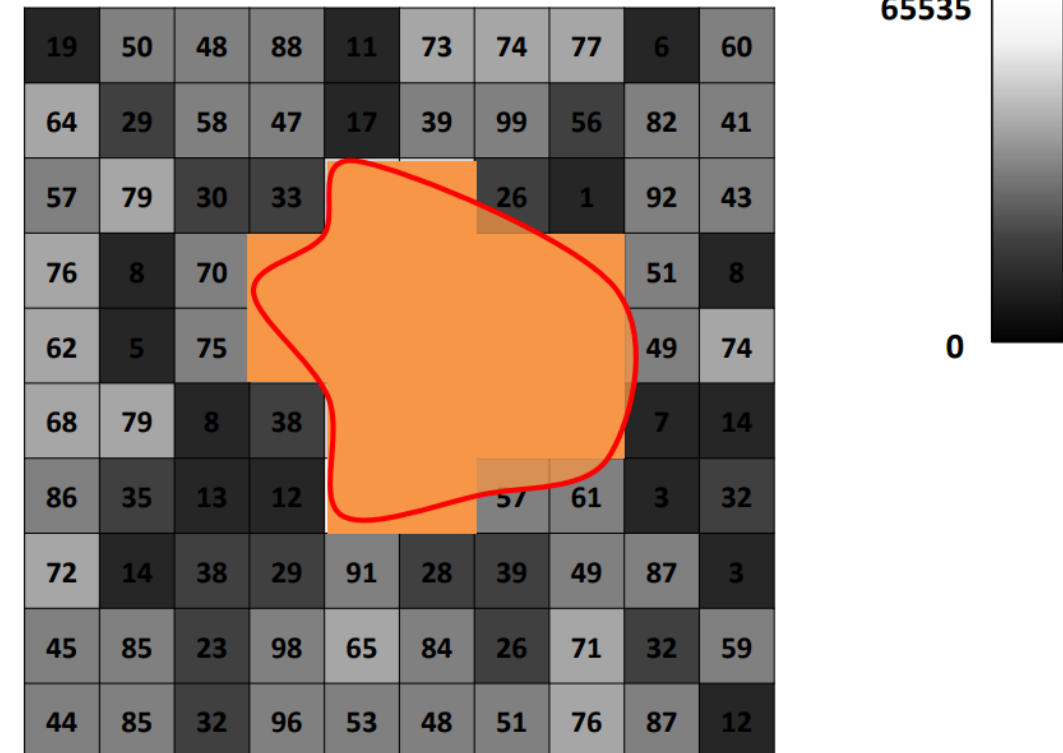


What would you use for:

# Segmentation

Definition: Clustering image elements as “**belong together**”

- Two approaches:
  - Pixel-wise categorical labels
  - Implicit Representations

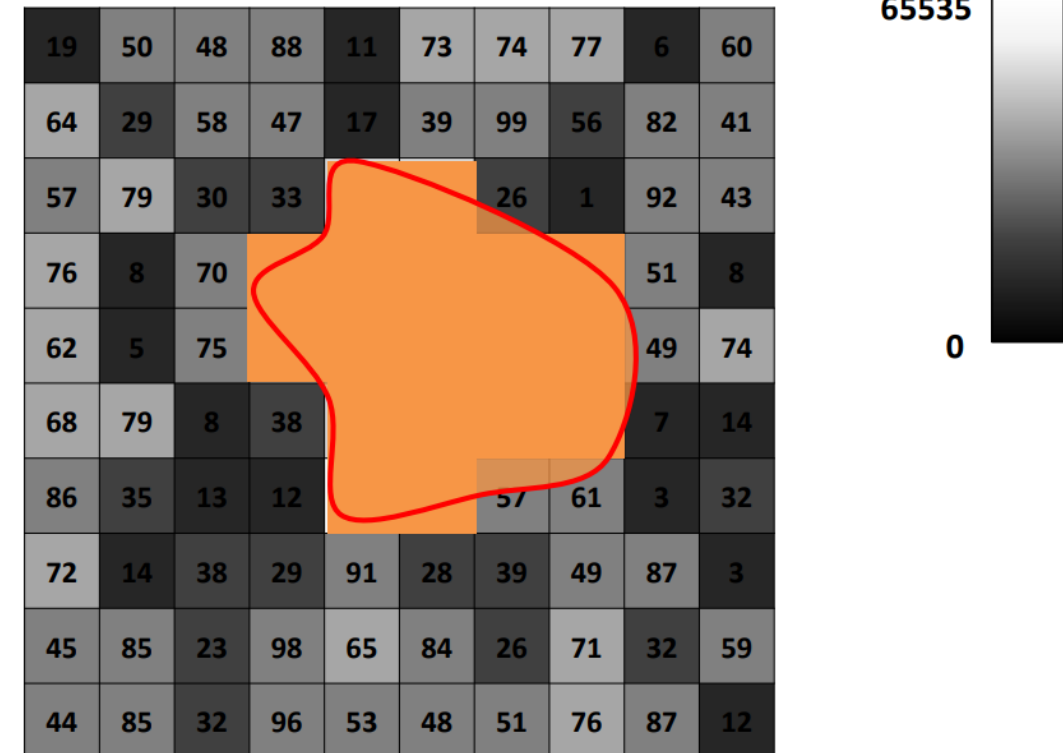


What would you use for:

# Segmentation

Definition: Clustering image elements as “**belong together**”

- Two approaches:
  - **Pixel-wise categorical labels**
  - Implicit Representations





# Pixel-wise Image Segmentation

Pixel-wise labeling is the most common representation.

Categorical labels can range from 0–N.

19	50	48	88	11	73	74	77	6	60
64	29	58	47	17	39	99	56	82	41
57	79	30	33	134	145	26	1	92	43
76	8	70	100	184	173	156	176	51	8
62	5	75	118	176	189	189	163	49	74
68	79	8	38	103	127	110	164	7	14
86	35	13	12	198	108	57	61	3	32
72	14	38	29	91	28	39	49	87	3
45	85	23	98	65	84	26	71	32	59
44	85	32	96	53	48	51	76	87	12

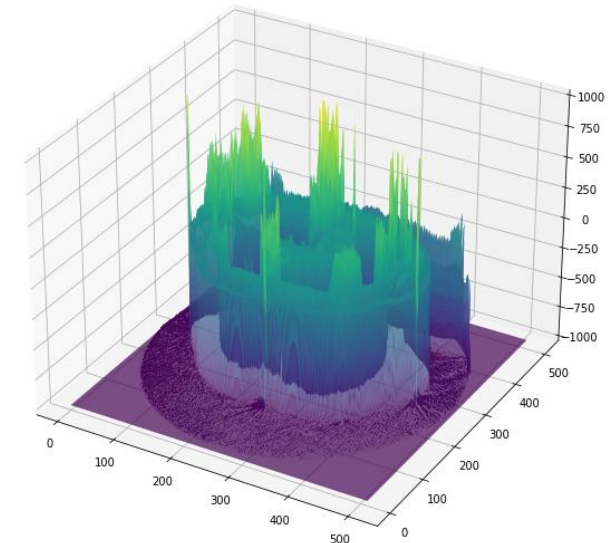
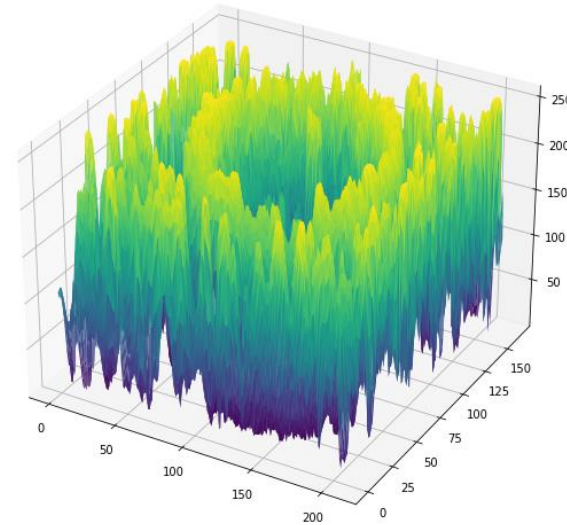
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	1	1	0	0	0	0
0	0	0	1	1	1	1	1	0	0
0	0	0	1	1	1	1	1	0	0
0	0	0	0	1	1	1	1	0	0
0	0	0	0	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

 Foreground  
 Background

# Segmentation Methods

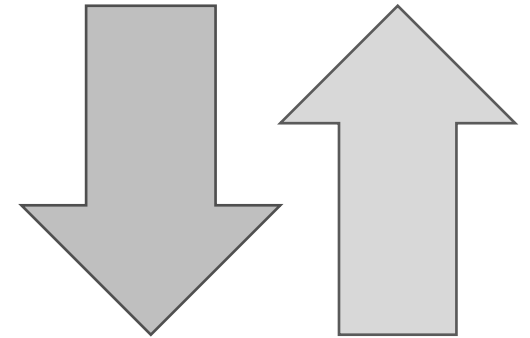
## Random Taxonomy

- Based on global knowledge:
  - Histogram-Based Thresholding
- Edge-based
  - Filters
- Region-Based
  - KNN/GMM
- A combination the two
  - Edge-based and Region-Based are duals for each other.



# Clustering in Vision: Grouping Pixels

Top down vs. bottom-up segmentation

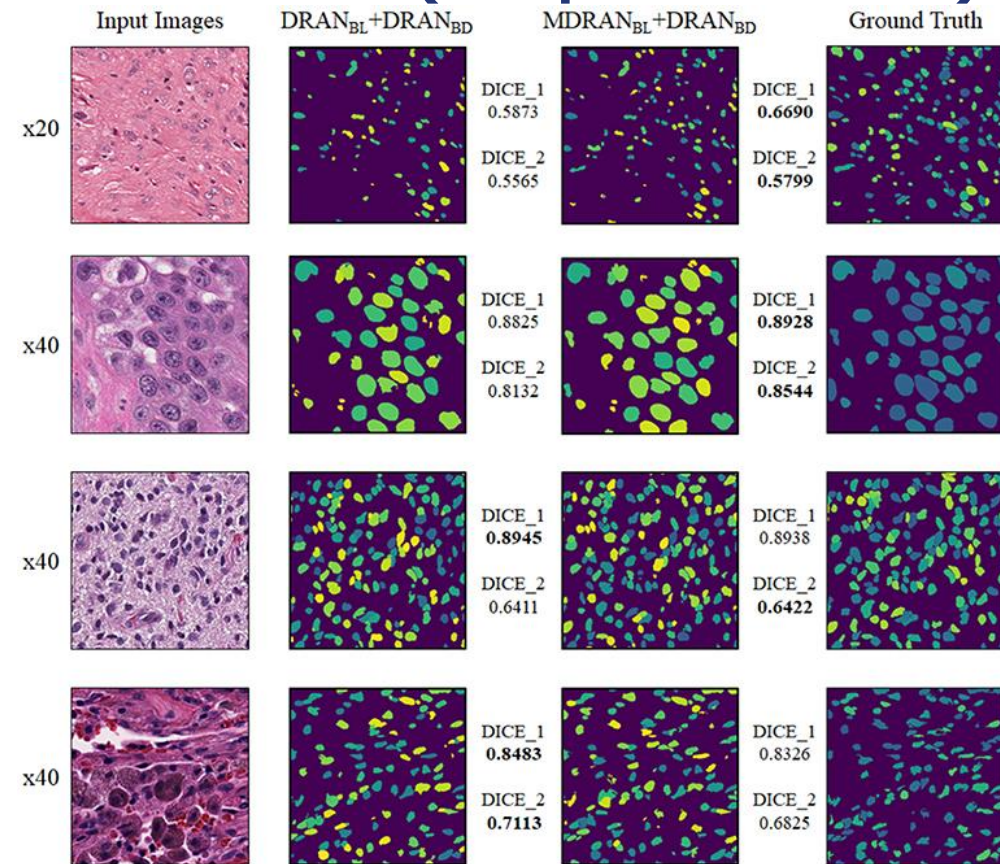


- Top down: pixels belong together because they are from the same object
- Bottom up: pixels belong together because they look similar
- Hard to measure success:
  - Evaluation metrics depend on the application – each measure a different aspect
  - [\(55\) Lena Maier-Hein @ ICBINB Seminar Series – YouTube](#)  
Shows examples where the metrics are high, but the models still miss



# Segmentation via Classification (supervised)

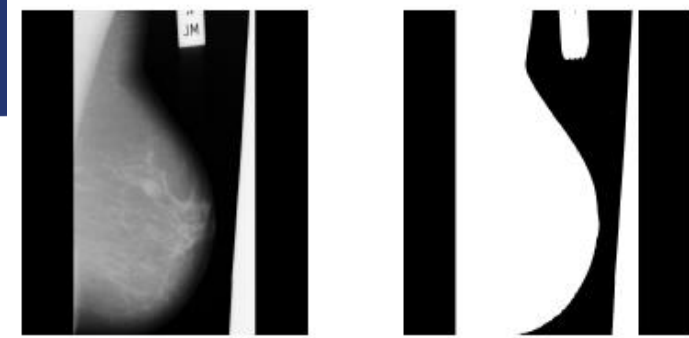
- **Classifier:**  
KNN, Support Vector Machine (SVM), NN, etc.
- **Features:**
  - Voxel value
  - Voxel position
  - Gradient magnitude
  - Neighboring values
- **Labels:**
  - Foreground/Background (binary) or Class IDs (multiclass)
- **Requires Labeled Training Data**



# Segmentation via Clustering (Unsupervised)

## K-Means

- **Algorithm:**
- Pick **K** feature space cluster centers at random
- While not converged
  - Assign each pixel to the nearest cluster
  - Recalculate cluster centers as the centroid of pixels in that cluster

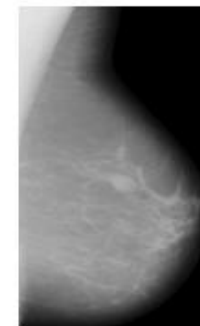


(b)

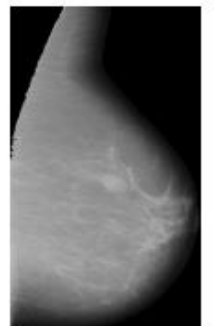


(c)

(d)



(e)



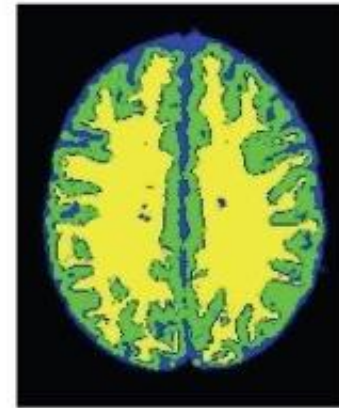
(f)



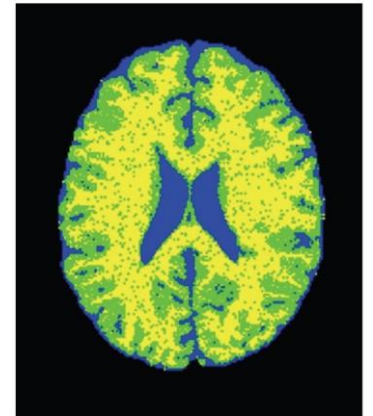
# Segmentation via Clustering (Unsupervised)

## Gaussian Mixture Models (GMM)

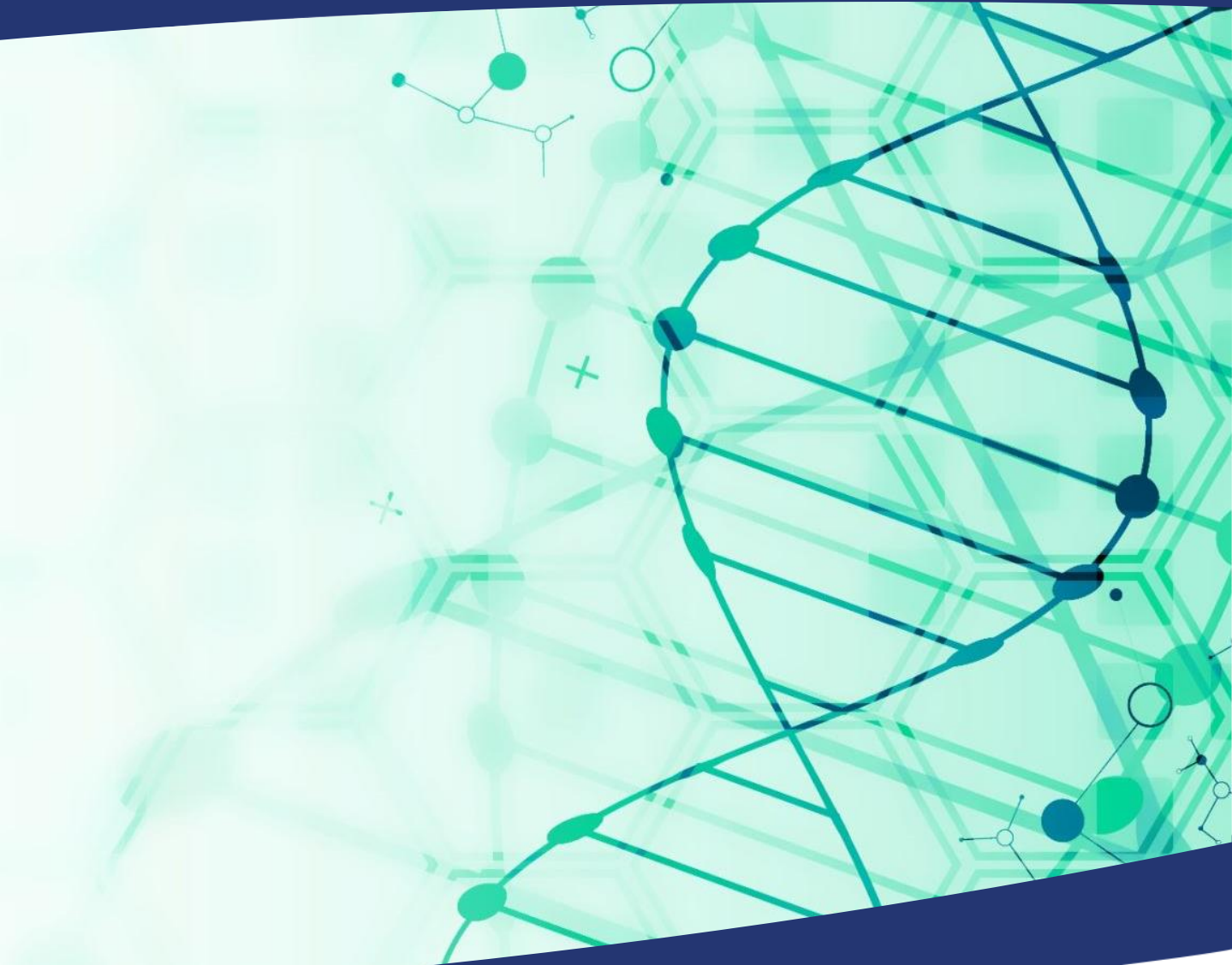
- **Algorithm:**
- Pick **K** feature space cluster centers using K-Means
- Initialize Gaussians (random mean & co-variance)
- While not converged
  - Calculate the probabilities for each pixel to each Gaussian
  - Recalculate the mean and the co-variance of each Gaussian



(c)



# THRESHOLDING

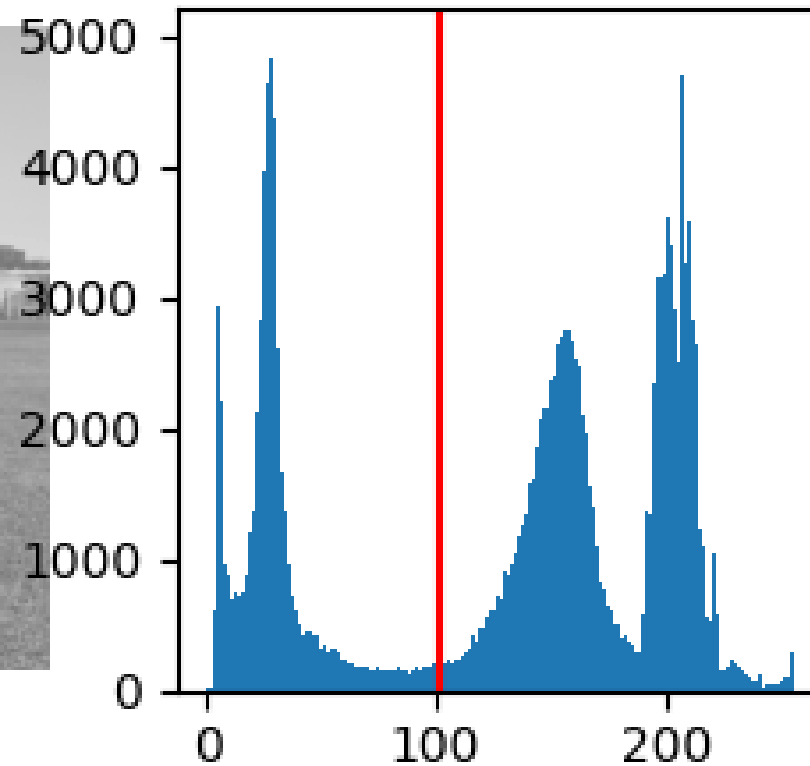


# Thresholding

Original



Histogram

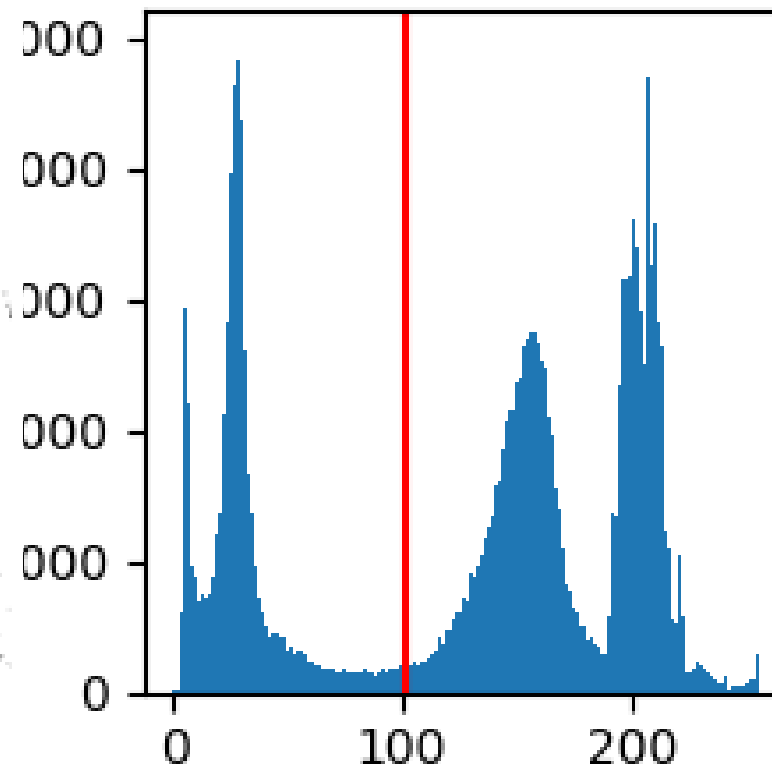


# Thresholding

Thresholded



Histogram

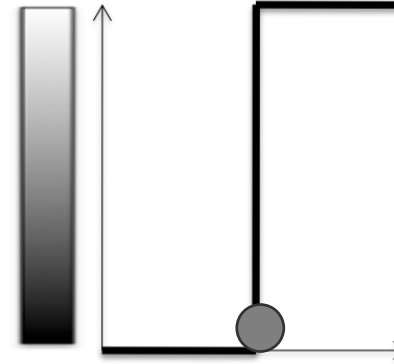


# Intensity Thresholding

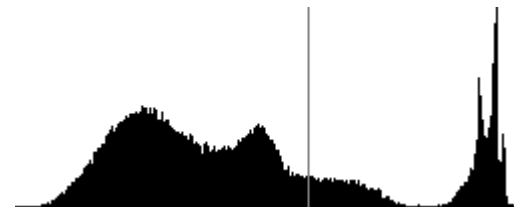
- Input: **Gray-level** images
- Output: **binary Image**
- Works best on high-contrast images

Algorithm:

- Choose a threshold pixel value  $T$
- For every pixel
  - if pixel  $\geq T$ , label as *foreground*
  - Else: label as *background*



But how to  
choose  $T$ ?



# Choosing a Threshold Value

Example: Otsu's Method

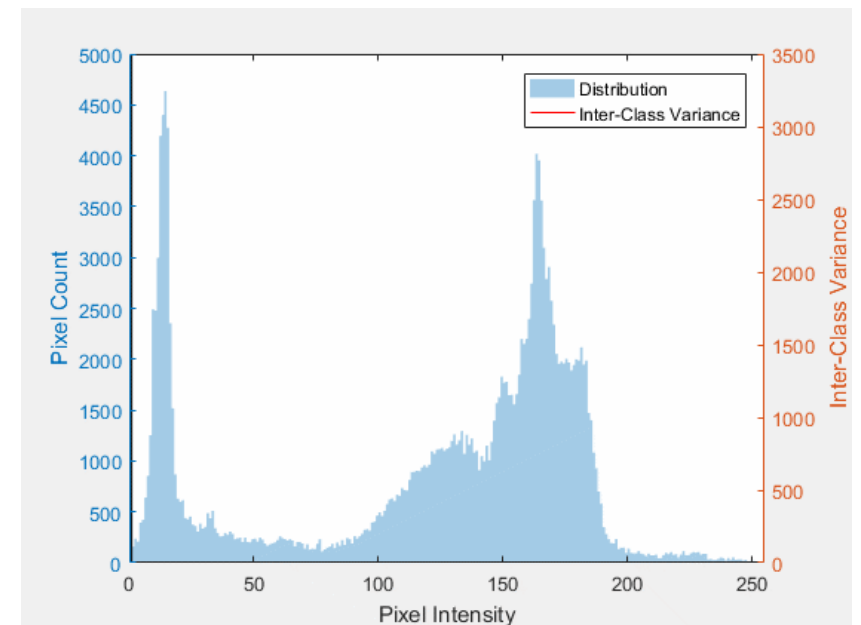
Searches the point  $t$  that minimizes the *variance* of foreground and background pixel values, weighted by class probabilities\*.

$$\sigma_{\omega}^2(t) = P_a(t) \sigma_a^2(t) + P_b(t) \sigma_b^2(t)$$

Works well for bi-modal histograms.

\* **Probabilities:** count how many pixels with those colors belong to the foreground, and how many to the background

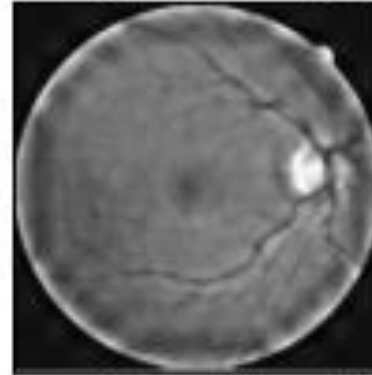
[Otsu Thresholding - The Lab Book Pages](#)



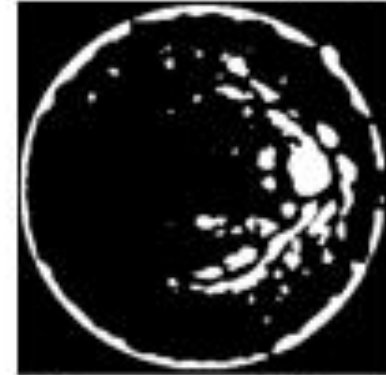
# Adaptive Thresholding

- Global Thresholding:
  - operates on the whole image
- Adaptive Thresholding:
  - Using a running-window
  - Every patch is handled on its own

Original Image



Global Thresholding ( $v = 127$ )



# Choosing a Threshold Value

- Many algorithms exist:
  - Maximum Entropy
  - Niblack
  - Li's
  - Kapur
  - Sauvola
  - Wolf ...
- Often, task-dependent
  - no single perfect threshold value exists.
- Thresholding leads to multiple disconnected components (i.e., "islands")

[manuelaguadomtz/pythreshold](#): PyThreshold is a python package featuring Numpy/Scipy implementations of state-of-the-art image thresholding algorithms. (github.com)



# Thresholding



- What are your Take-Aways

# Thresholding

## Take-Aways

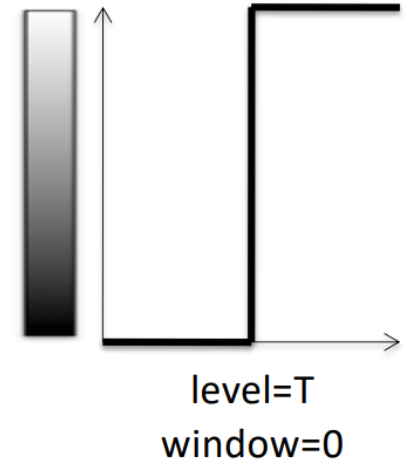
- A method to detect a middle point through the image histogram
- Clusters the image to foreground/background
- Operates either globally or on a running-window

# REGION-GROWING

# Thresholding

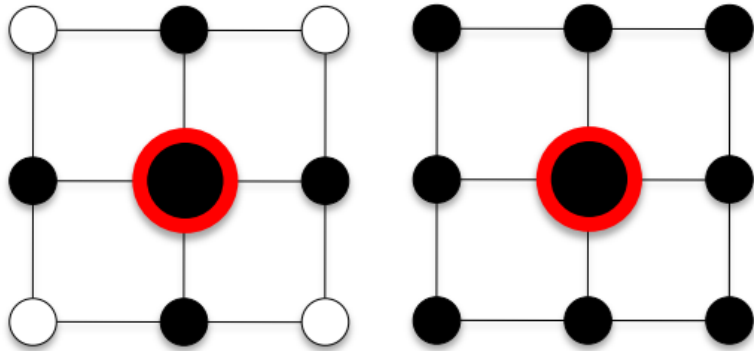
## Recap

- Given a threshold level  $T$ , for every pixel:
  - If  $\text{pixel} \geq T$ , label as *foreground*, else as *background*
- Otsu's Method
  - minimize variance of foreground and background pixel values weighted by class probabilities
- Maximum entropy
  - Maximize sum of each class's entropy:  $H(t) = -\sum_i p(a_i) \log p(a_i) - \sum_i p(b_i) \log p(b_i)$
- Adaptive/local Threshold
  - Running window (same as filters)
  - Local mean, local median, Sauvola, Perwit, ...



# Connectivity

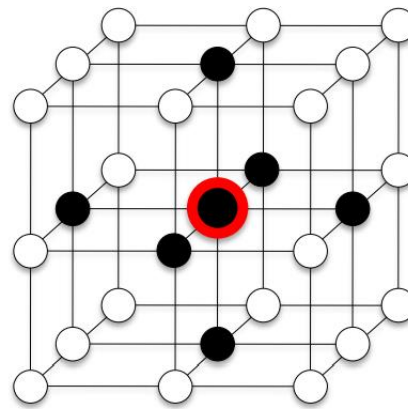
Defining Anatomic Regions Based on Contiguity



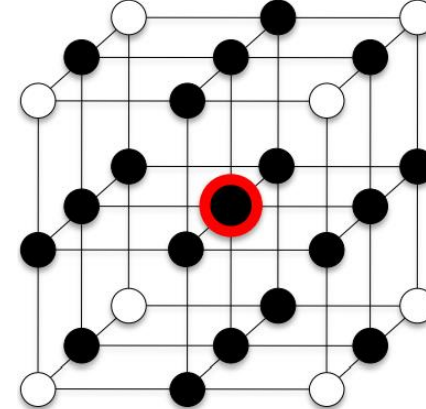
4-neighbor

8-neighbor

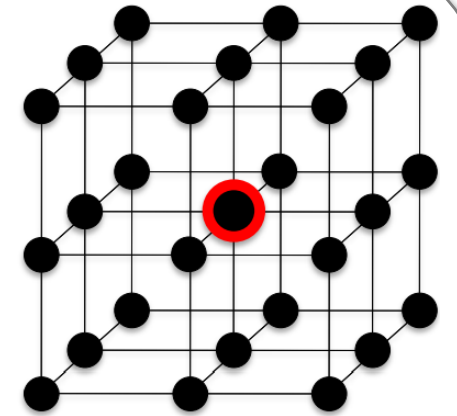
2D



6-neighbor  
(share face)



18-neighbor  
(share edge)



26-neighbor  
(share vertex)

3D

# Region-Growing

Group pixels with similar properties – finding continuous regions

## Algorithm:

- Select “seed” pixels according to some criteria
  - Add to a region and push to the back of the queue
- While the queue is not empty
  - For each neighbor of the front of the queue:
    - If the neighbor meets the criteria and isn’t in the region
      - add to the region and push to the back of the queue
  - Pop head of the queue

## Example Implementation

## Notes:

Criteria can be anything (e.g., global threshold)

\* If you are familiar with Graph Theory: This is a breadth-first search

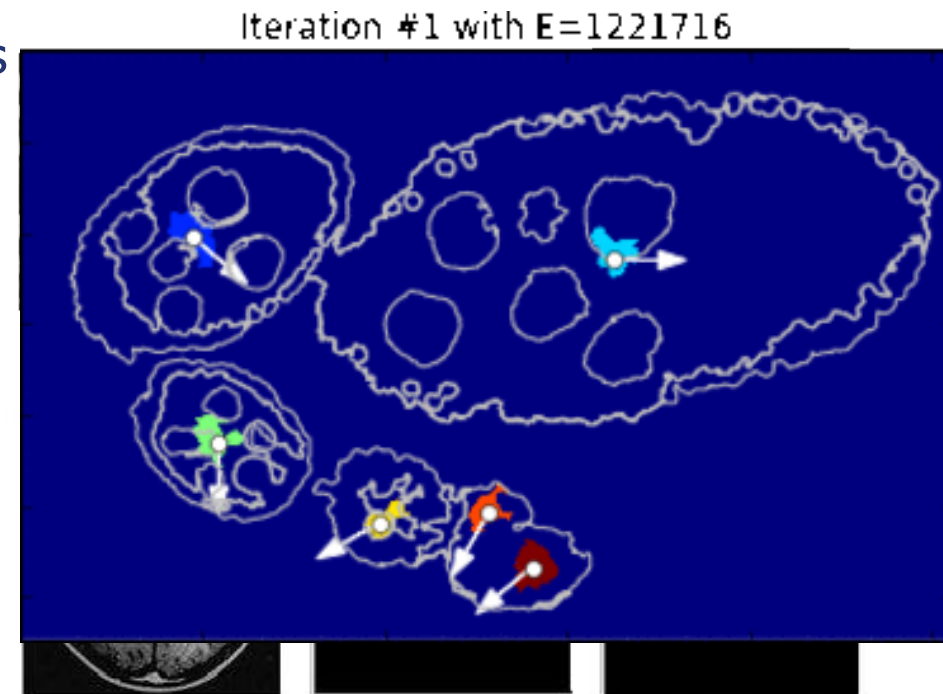


Figure 5(a). Original Image

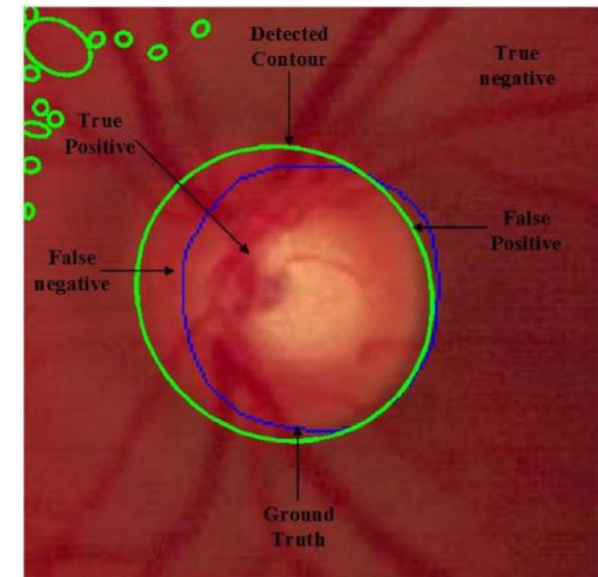
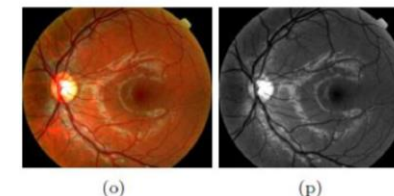
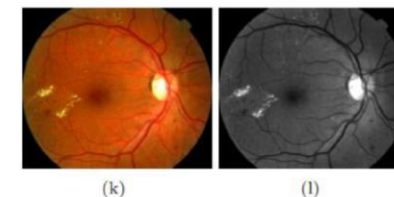
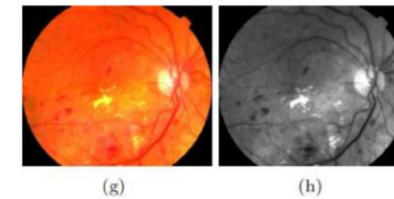
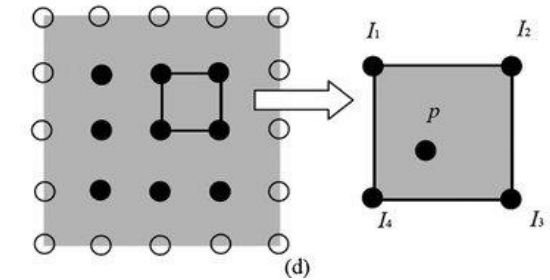
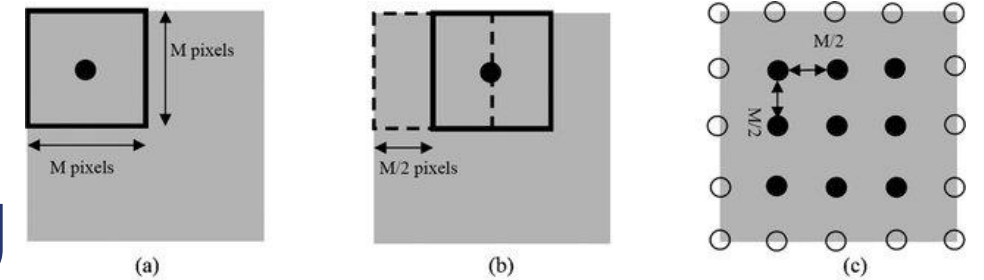
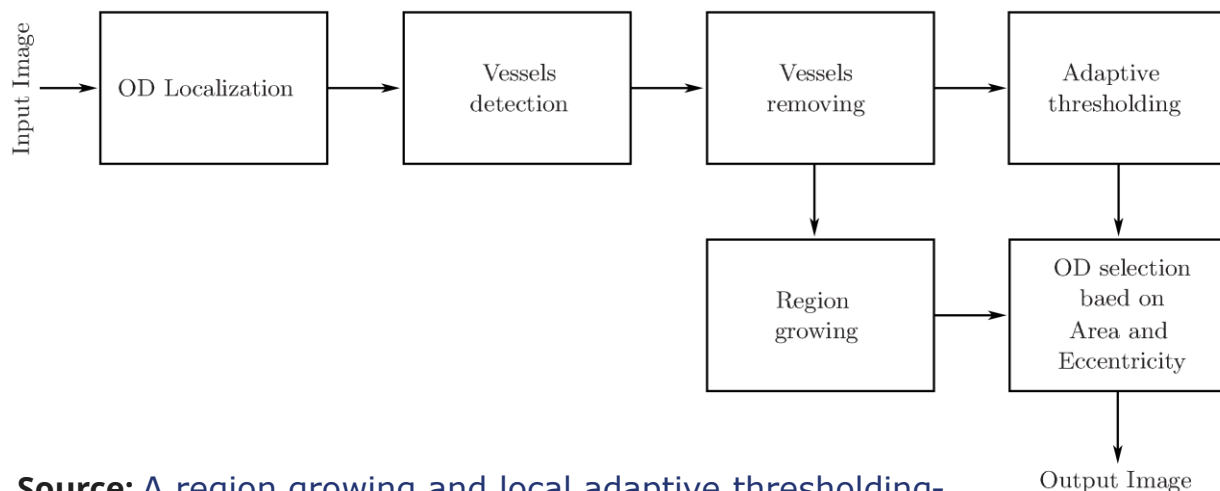
Figure 5(b). Seed points

Figure 5(c). Result of Region growing

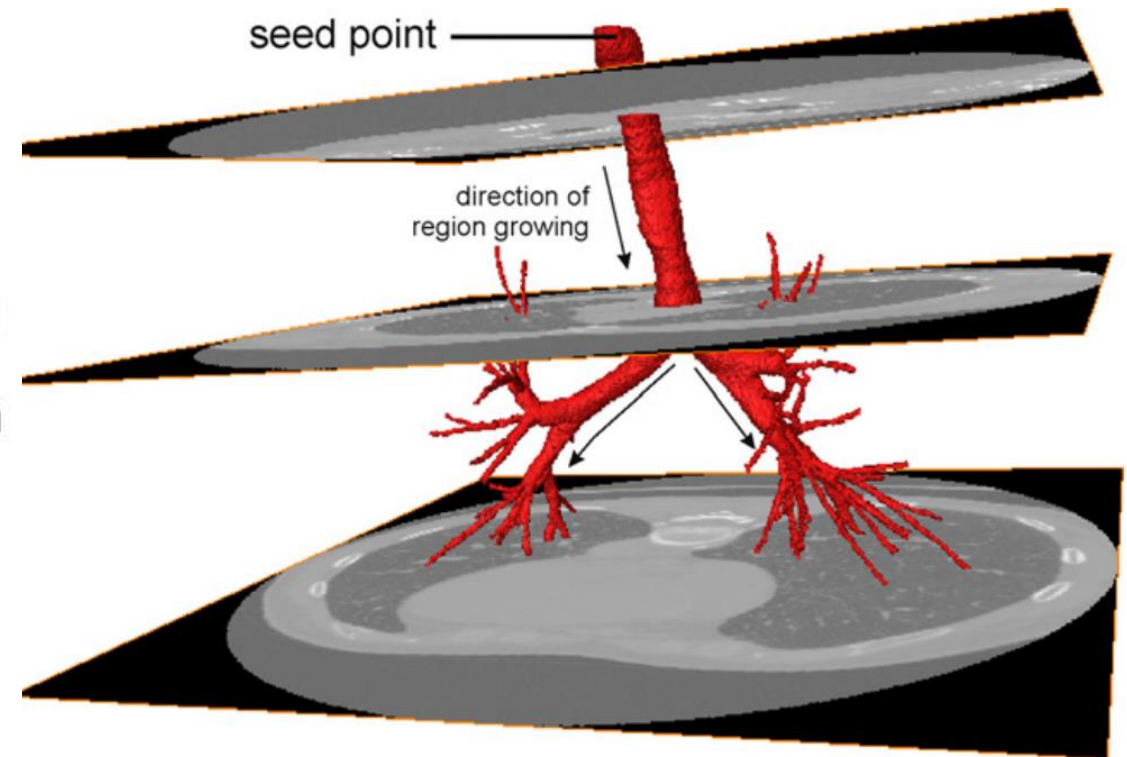
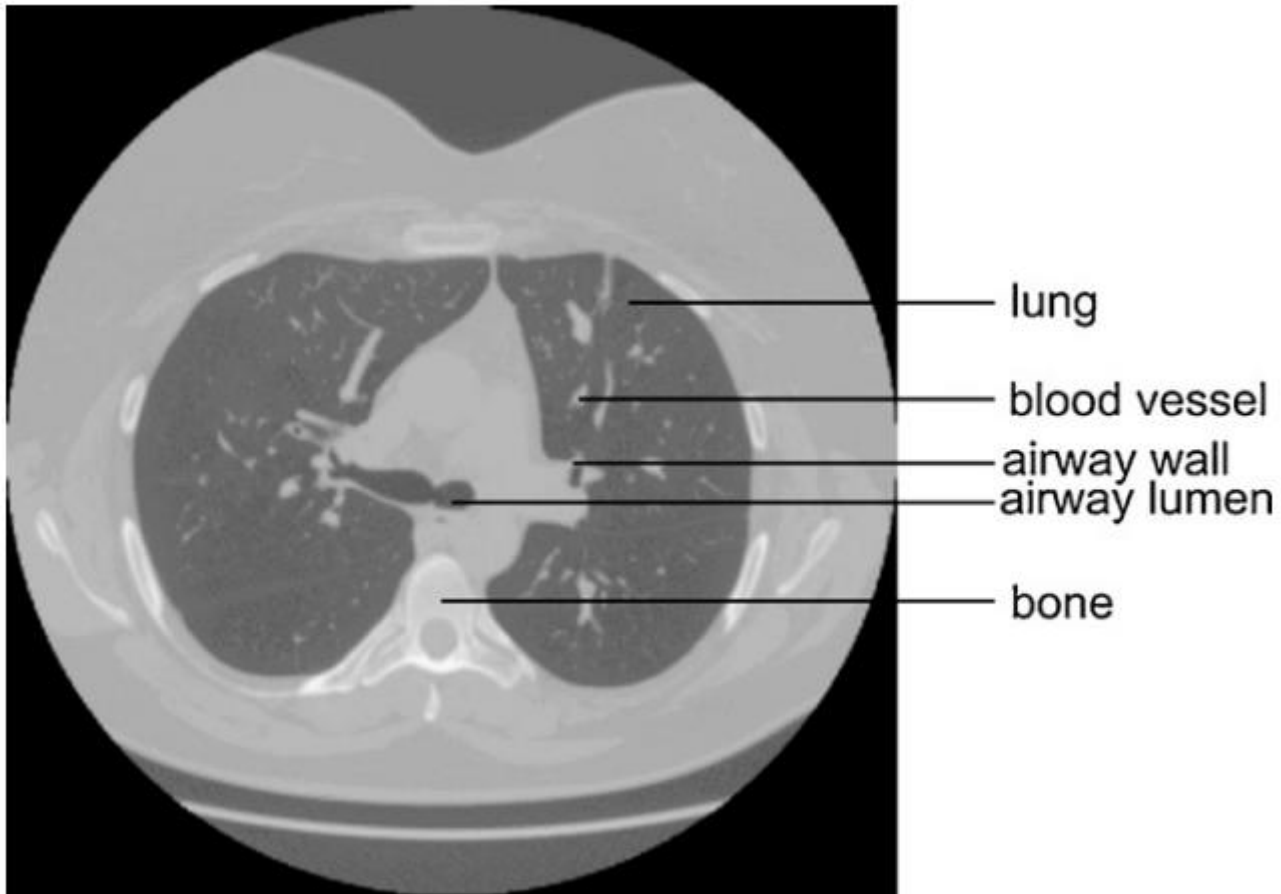
Figure 5. segmentation by Region Growing<sup>22</sup>

# Local Adaptive Thresholding

- Calculating the thresholds separately on different regions of the image.
- Note: Regions can be chosen 'smartly'



# Region Growing – Best for a Continuous Region

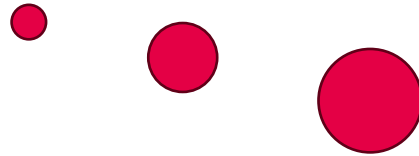




# KERNELS & FILTERS



# Kernels & Filters



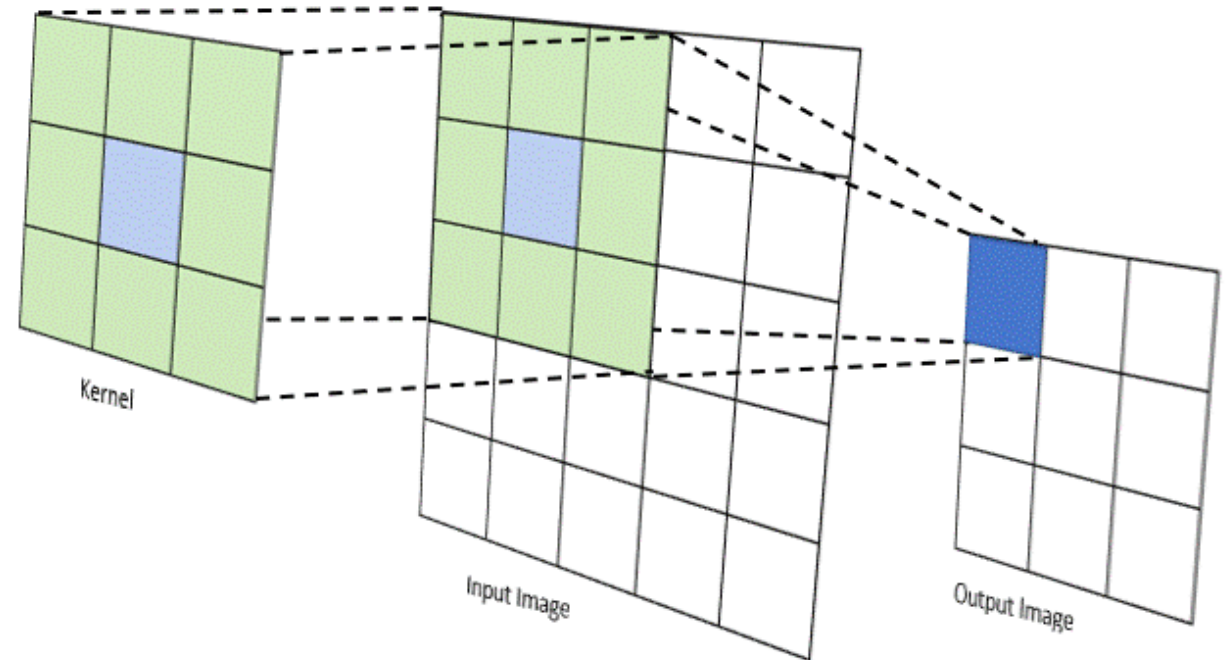
Kernel – a 2 parameters function:  $f(x_1, x_2)$

These parameters can be scalars or matrices

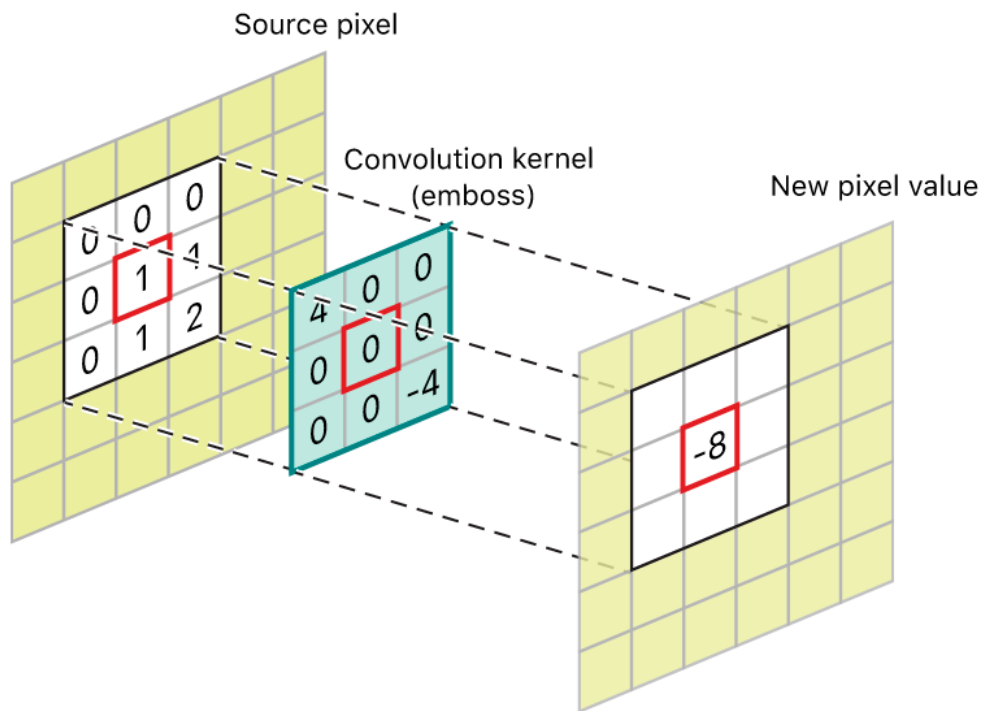
Q: Where have we met  
(and used) **Kernels**  
before in ML?

# Image Kernels (Filters)

- Kernel: a fixed matrix of numbers
- Calculates an average on the image, using a *sliding window*



# Image Kernels (Filters)



- Different Kernels exist.
  - Used for: **blur**, **sharpen**, **shift**
- It can also detect **edges**, and more.
- Try it yourself:  
<https://setosa.io/ev/image-kernels/>

Input      Kernel      Output

0	1	2
3	4	5
6	7	8

 $*$ 

0	1
2	3

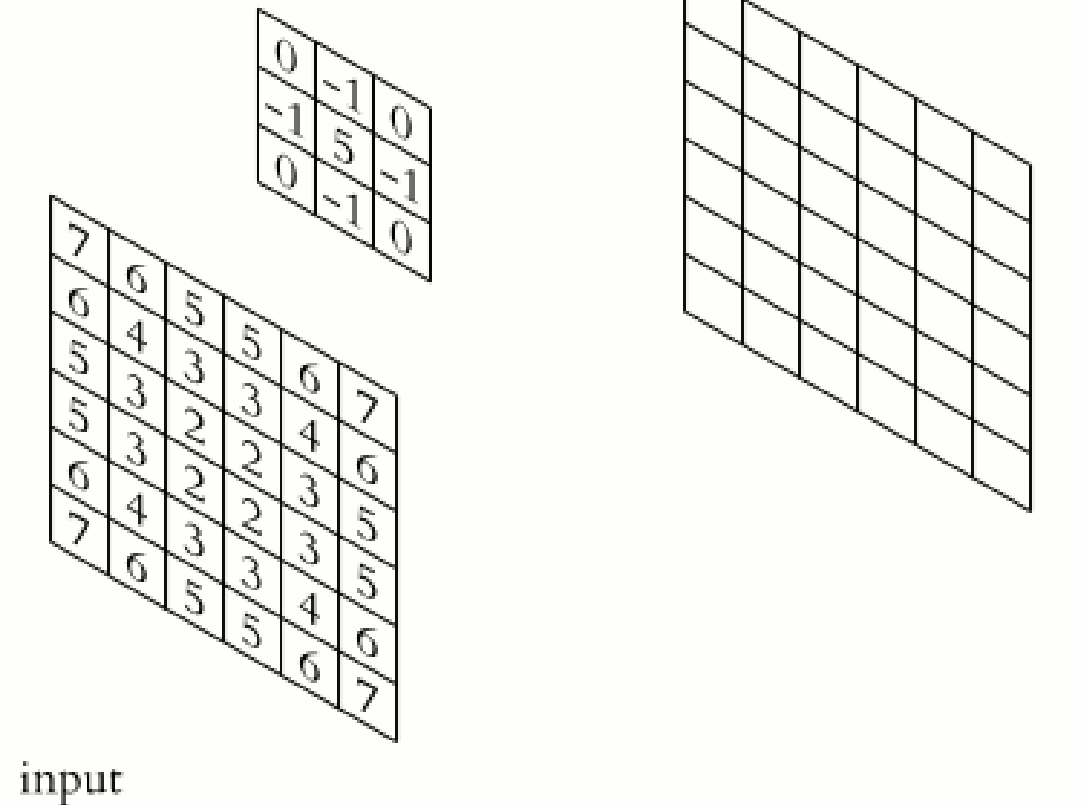
 $=$ 

19	25
37	43

[Image Kernels explained visually \(setosa.io\)](https://setosa.io/ev/image-kernels/)

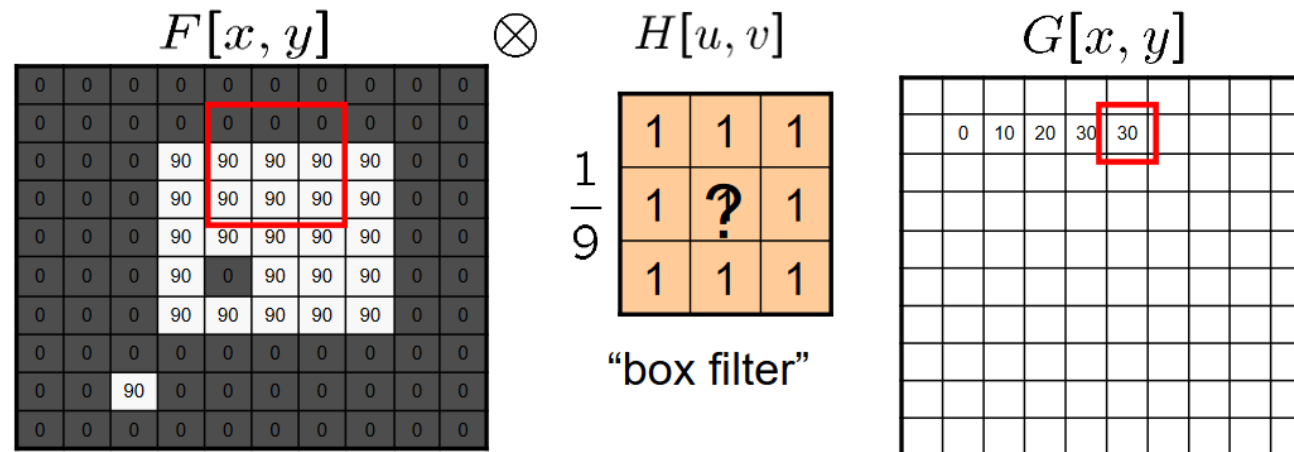
# Aka “Convolution”

(we’ll meet it again in  
neural networks)



# Averaging Filter

- What values belong in the kernel H for the moving average example?



$$G = H \otimes F$$



Removes high-frequency components from the image ("low-pass filter").

# Gaussian Filters

- What if we want nearest neighboring pixels to have the most influence on the output?

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$

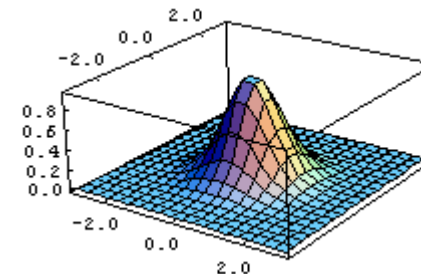
$\frac{1}{16}$

1	2	1
2	4	2
1	2	1

$H[u, v]$

This kernel approximates a 2d Gaussian function:

$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$

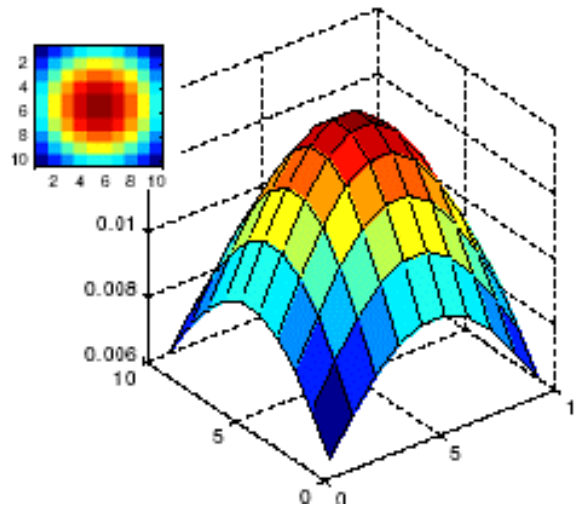


# Gaussian Filters

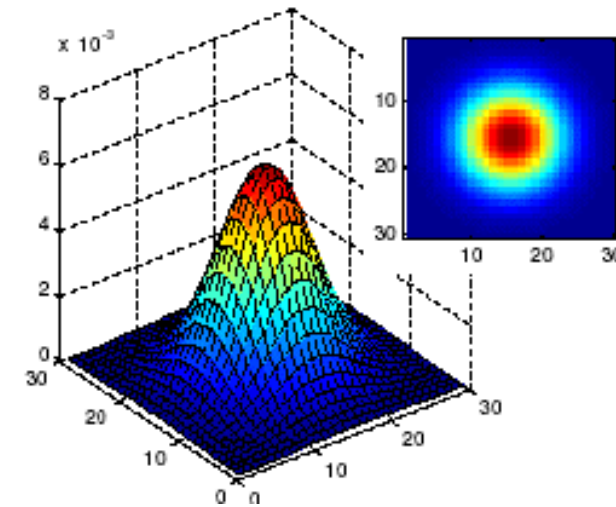
Hyperparameters affect the result: **Kernel Size**

**Kernel Size** - determines the range the smoothing takes into account

**Note:** Gaussian function has infinite support, but discrete filters use *finite* kernels



$\sigma = 5$  with  
10 x 10  
kernel



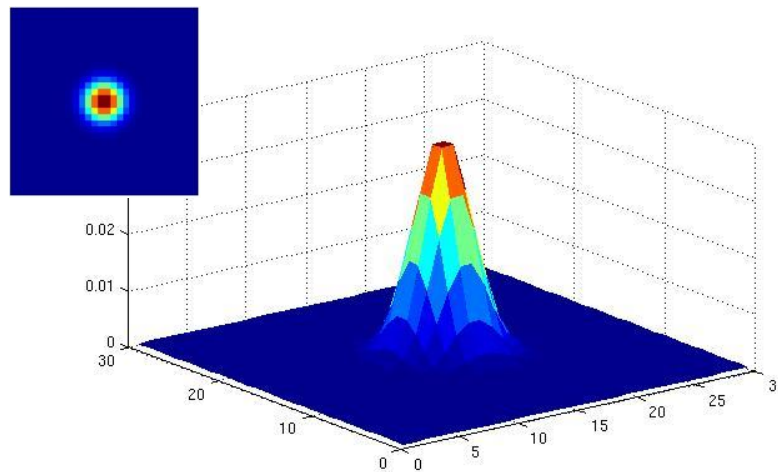
$\sigma = 5$  with  
30 x 30  
kernel



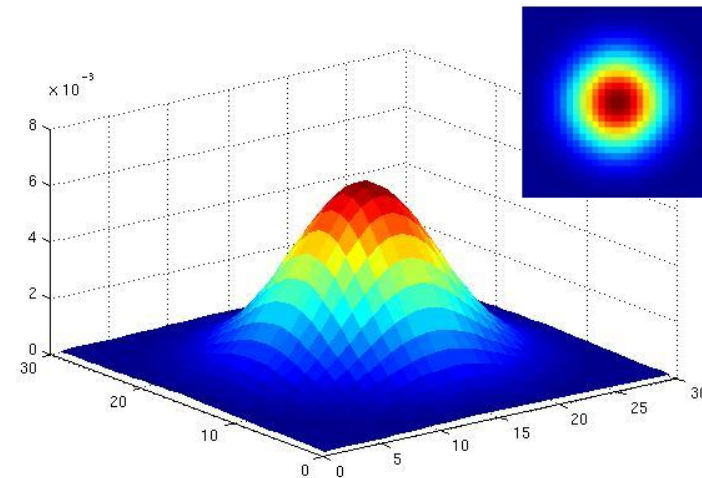
**Variance** of Gaussian -  
determines extent of  
smoothing

# Gaussian Filters

Hyperparameters affect the result: Gaussian **Variance**



$\sigma = 2$  with  
 $30 \times 30$   
kernel



$\sigma = 5$  with  
 $30 \times 30$   
kernel

