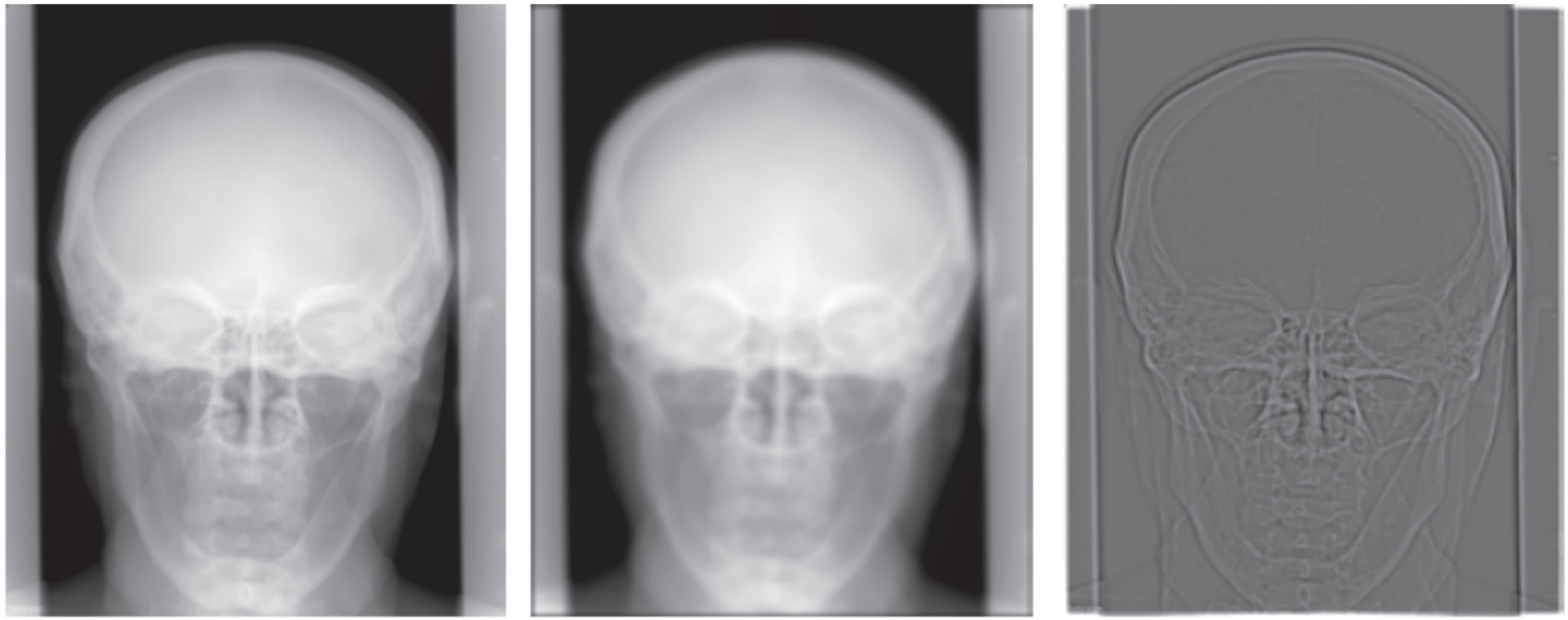
Medical Images - Pre-Processing

Lecture 7

Filtering X-ray



(a) (b) (c)

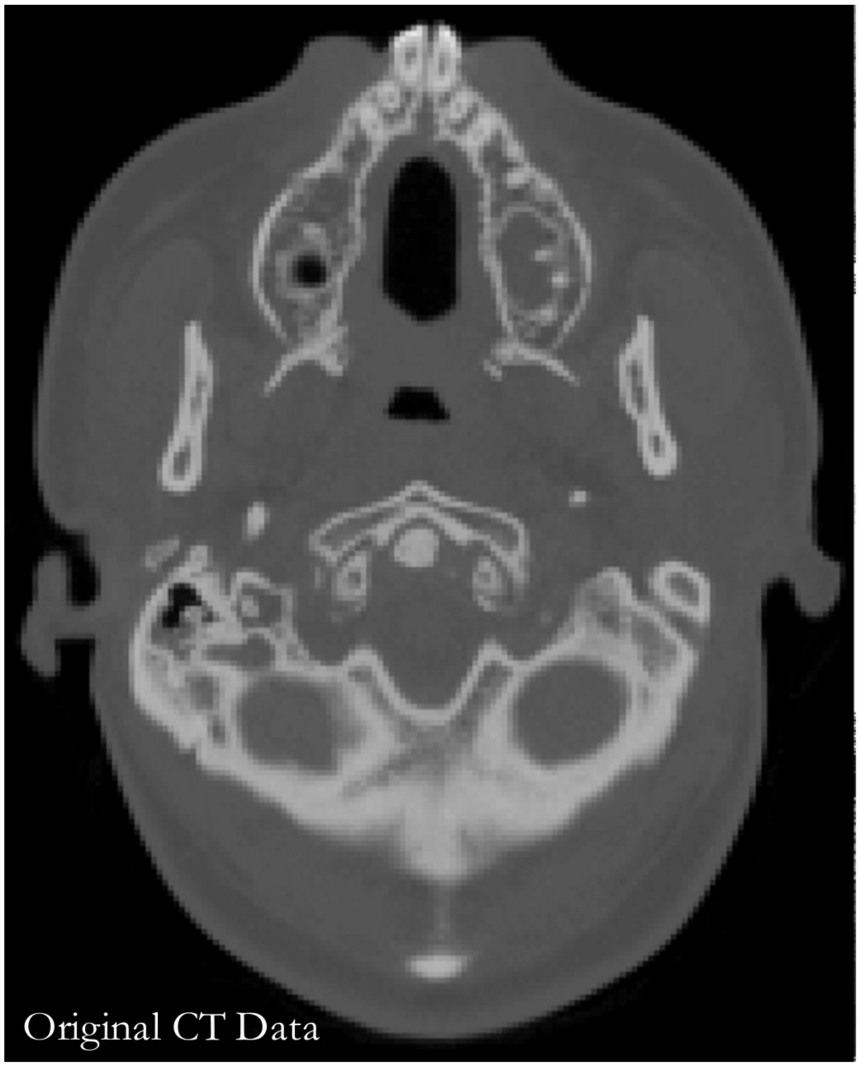
a. Radiography of the skull, b. low-pass filter with a Gaussian filter (std=15, 20 x 20), c. high-pass Filter obtained from subtracting b from a.

Hand X-ray Unsharp Masking (alpha=0.5)

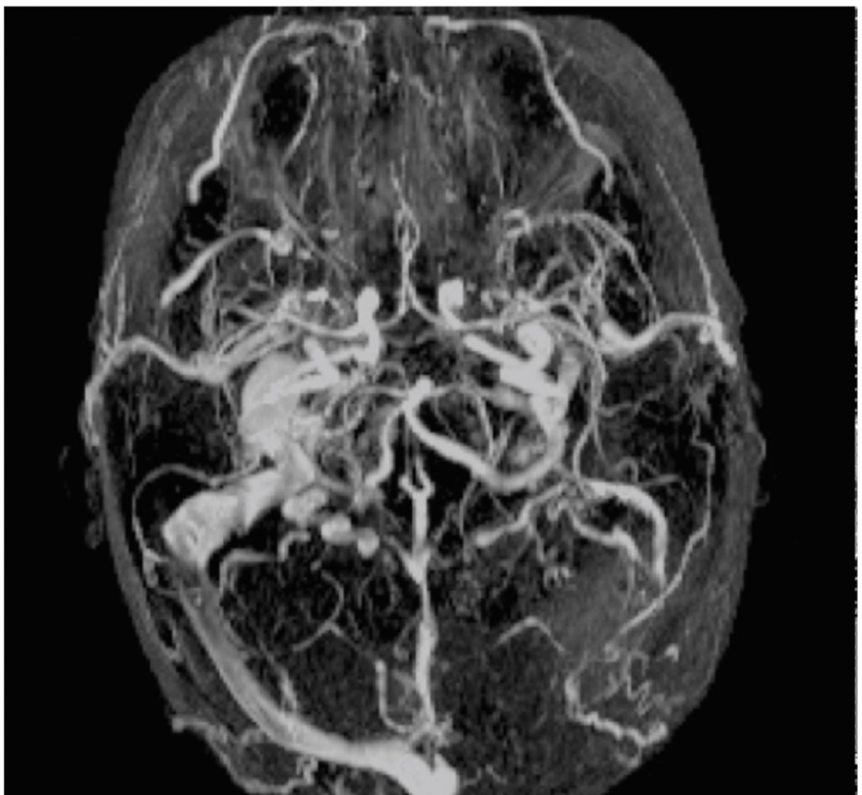
Original Image

Enhanced Image

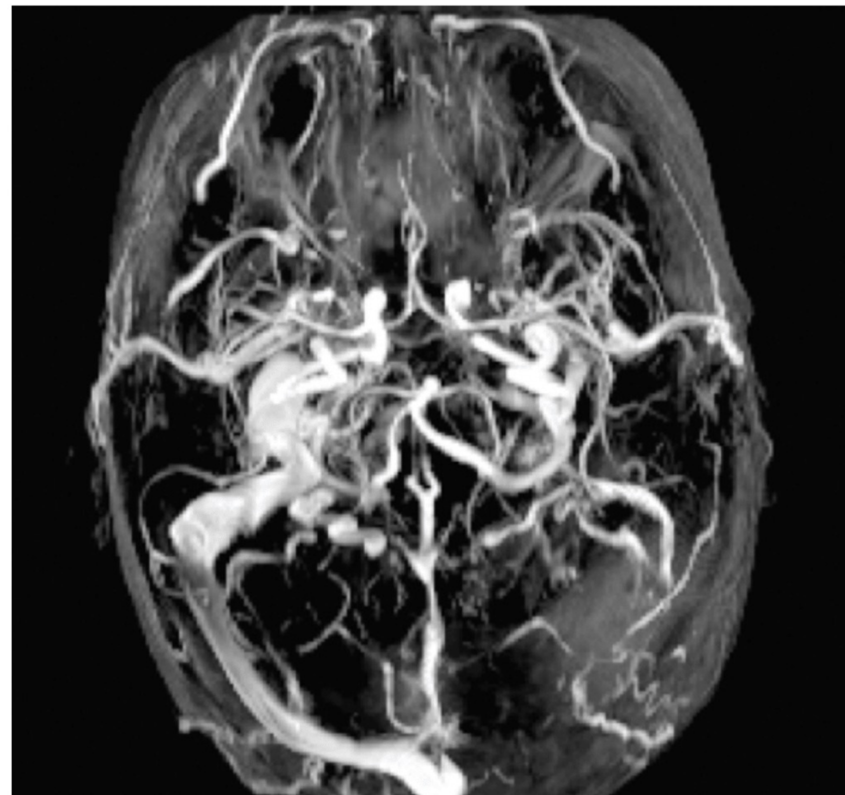
Unsharp Masking: Example CT (head, axial)



Adaptive Filtering: Example head MRA

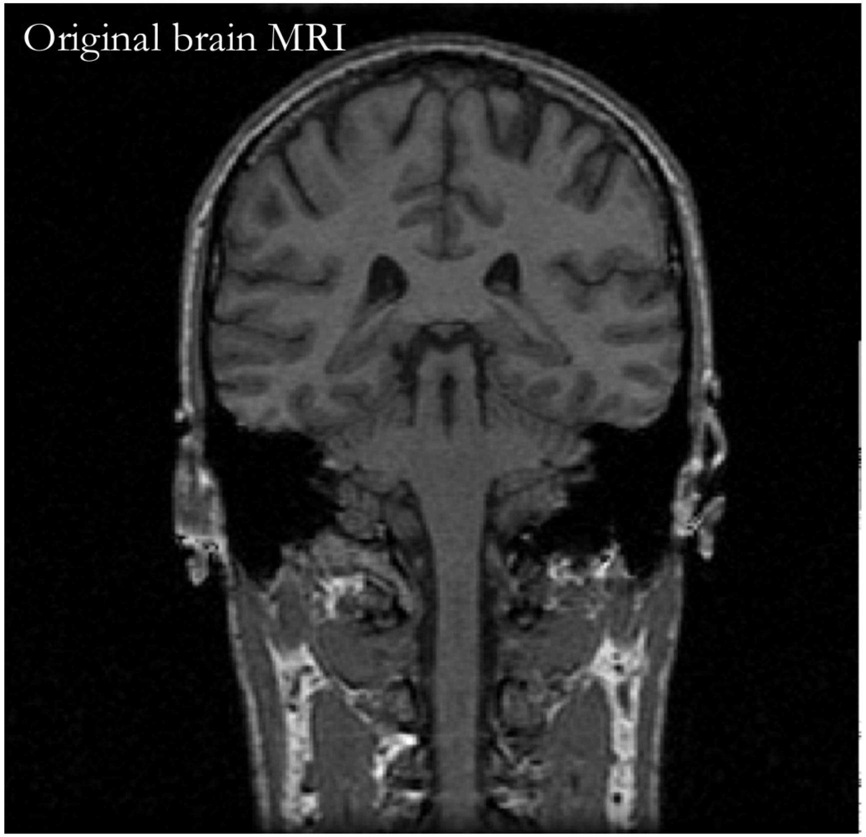


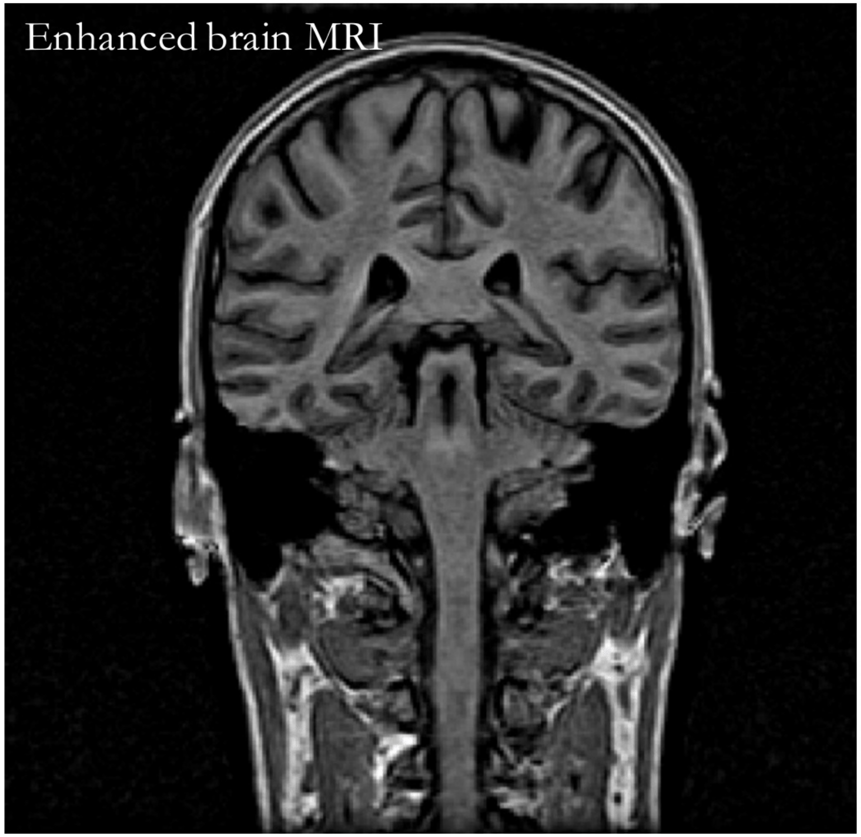
MIP of MRA data before filtering



MIP of MRA data after filtering

Adaptive Filtering: Example brain MRI





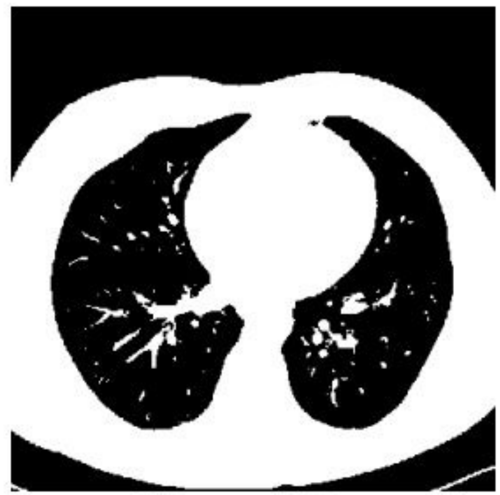
Note the improved contrast between brain and CSF (cerebrospinal fluid)

Brain MRI Image

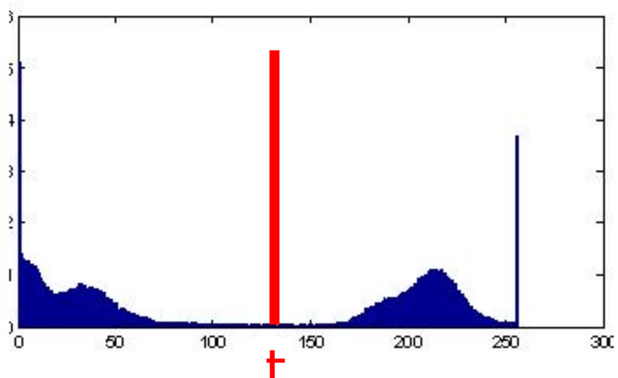
Edge

Otsu Thresholding

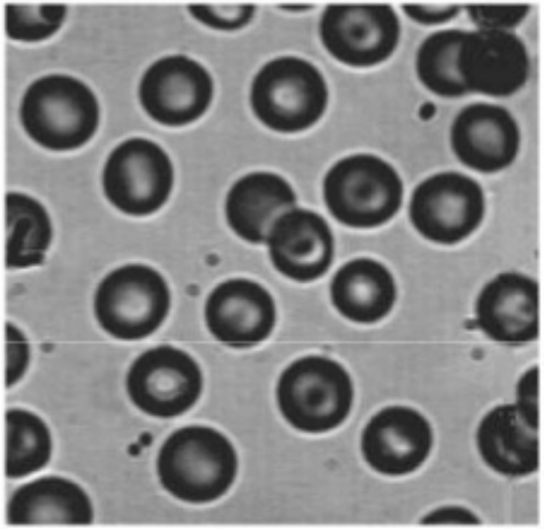
An image



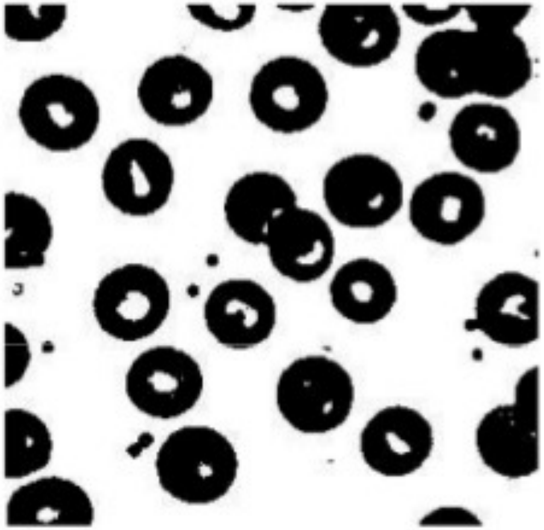
Binary image
by Otsu's method



Gray level histogram



Red Blood Cells Grayscale Image



Red Blood Cells Binary Image

How to improve (thresholded) Segmentation?

Mathematical Morphology

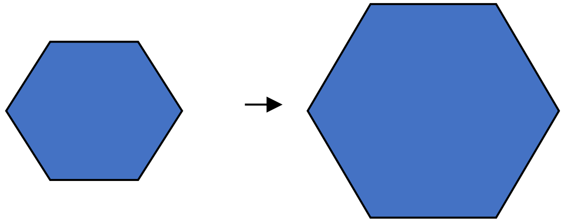
(Dilation, Erosion, Closing, Opening)

- Dilation

Dilation expands the connected sets of 1s of a binary image.

It can be used for

1. growing features



2. filling holes and gaps

Mathematical Morphology

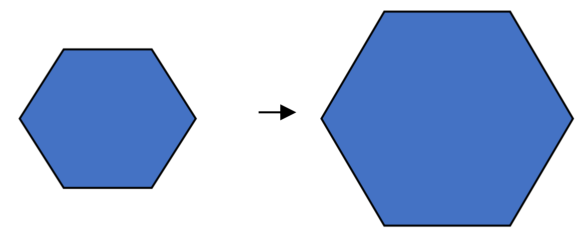
(Dilation, Erosion, Closing, Opening)

- Dilation

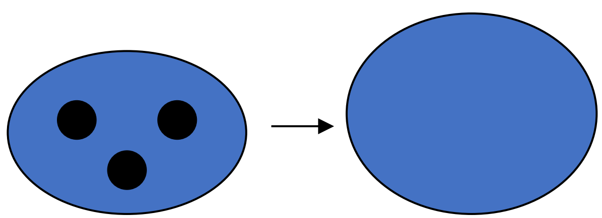
Dilation expands the connected sets of 1s of a binary image.

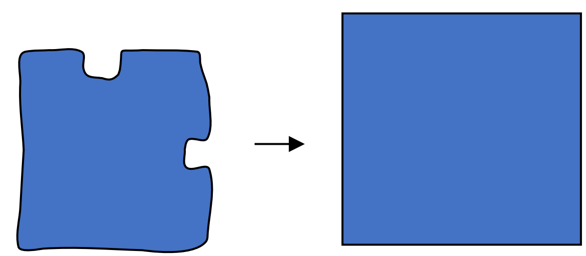
It can be used for

1. growing features



2. filling holes and gaps



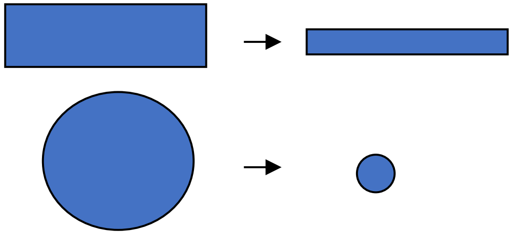


- Erosion

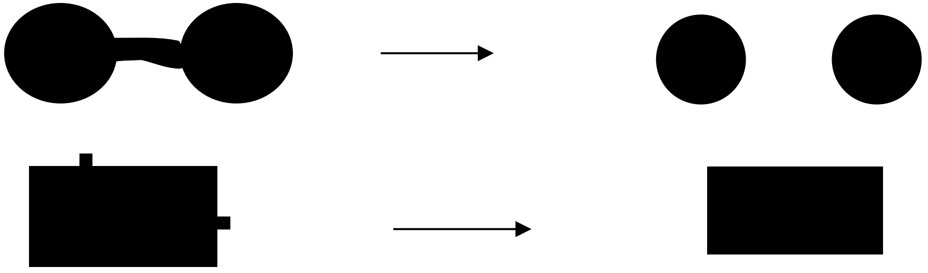
Erosion shrinks the connected sets of 1s of a binary image.

It can be used for

1. shrinking features



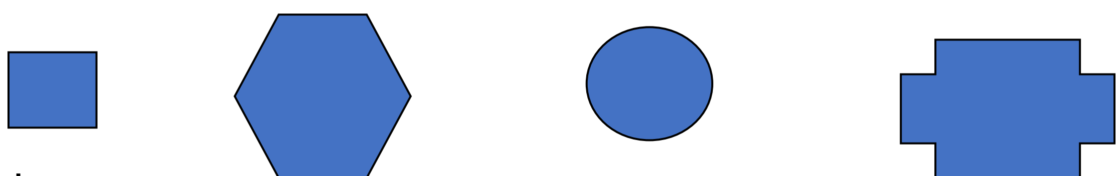
2. Removing bridges, branches and small protrusions



Structuring Elements

A structuring element is a shape mask used in the basic morphological operations.

They can be any shape and size that is digitally representable, and each has an origin.



box hexagon disk something

box(length,width) disk(diameter)

Dilation with Structuring Elements

The arguments to dilation and erosion are

1. **a binary image B**
2. **a structuring element S**

dilate(B,S) takes binary image B, places the origin of structuring element S over each 1-pixel, and ORs the structuring element S into the output image at the corresponding position.

$$\underset{B}{\boxed{\begin{matrix}0&0&0&0\\0&1&1&0\\0&0&0&0\end{matrix}}} \qquad \underset{S}{\boxed{\begin{matrix}1&\\1&1\end{matrix}}} \xrightarrow{\text{dilate}} \underset{B \oplus S}{\boxed{\begin{matrix}0&1&1&0\\0&1&1&1\\0&0&0&0\end{matrix}}}$$

origin

Erosion with Structuring Elements

erode(B,S) takes a binary image B, places the origin of structuring element S over every pixel position, and ORs a binary 1 into that position of the output image only if every position of S (with a 1) covers a 1 in B.

origin

$$\underbrace{\boxed{\begin{array}{ccccc}0&0&1&1&0\\0&0&1&1&0\\0&0&1&1&0\\1&1&1&1&1\end{array}}}_{B}\qquad \underbrace{\boxed{\begin{array}{c}1\\1\\1\end{array}}}_{S}\qquad \xrightarrow{\text{erode}}\qquad \underbrace{\boxed{\begin{array}{ccccc}0&0&0&0&0\\0&0&1&1&0\\0&0&1&1&0\\0&0&0&0&0\end{array}}}_{B \ominus S}$$

Opening and Closing

- Closing is the compound operation of dilation followed by erosion (with the same structuring element)
- Opening is the compound operation of erosion followed by dilation (with the same structuring element)

Original

After Opening

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				

a) Binary image **B**

1	1	1
1	**1**	1
1	1	1

b) Structuring Element **S**

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			

c) Dilation $B \oplus S$

				1	1		
				1	1		
				1	1		

d) Erosion $B \ominus S$

	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				

e) Closing $B \bullet S$

			1	1	1	1	
			1	1	1	1	
			1	1	1	1	
			1	1	1	1	
			1	1	1	1	

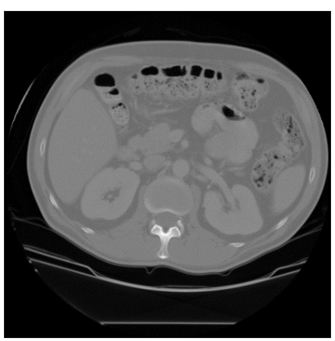
f) Opening $B \circ S$

Connected Components Labeling

Once you have a binary image, you can identify and then analyze each **connected set of pixels**.

The connected components operation takes in a binary image and produces a **labeled image** in which each pixel has the integer label of either the background (0) or a component.

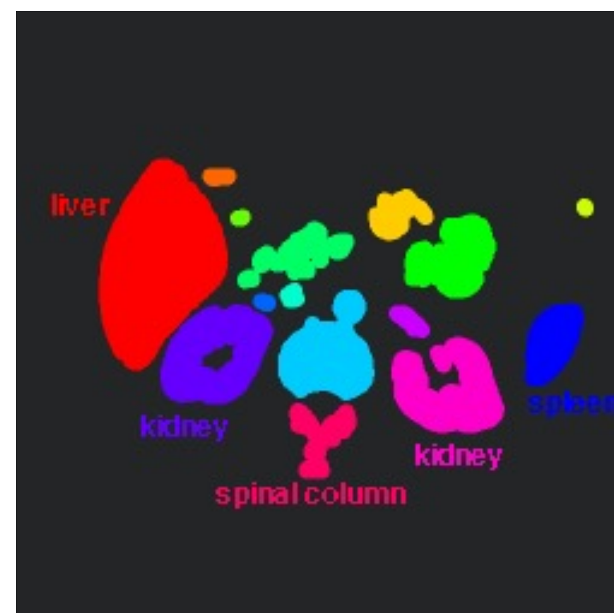
original



thresholded

opening + closing

connected components



Methods for CC Analysis

1. Recursive Tracking (almost never used)

2. Parallel Growing (needs parallel hardware)

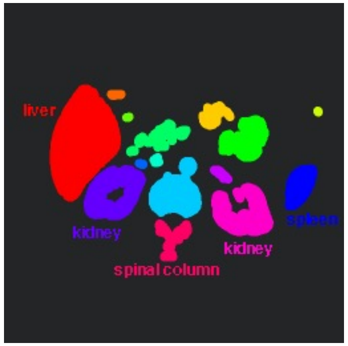
3. Row-by-Row (most common)

   a. propagate labels down to the bottom, recording equivalences

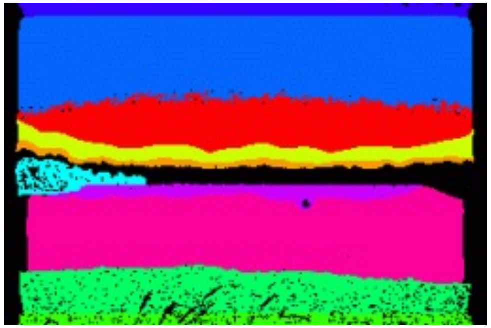
   b. Compute equivalence classes

   c. Replace each labeled pixel with the label of its equivalence class.

Labelings shown as Pseudo-Color



connected components of 1's from cleaned, thresholded image



connected components of cluster labels

Brain MRI Image

Edge

Image features

- Feature Detector
- Feature Descriptor
- Feature Classification

- Image Classification

- Object Classification

Object location is given
You just need to classify it

- Object Detection

You need to localize the candidate location
And then classify it

Feature Detector

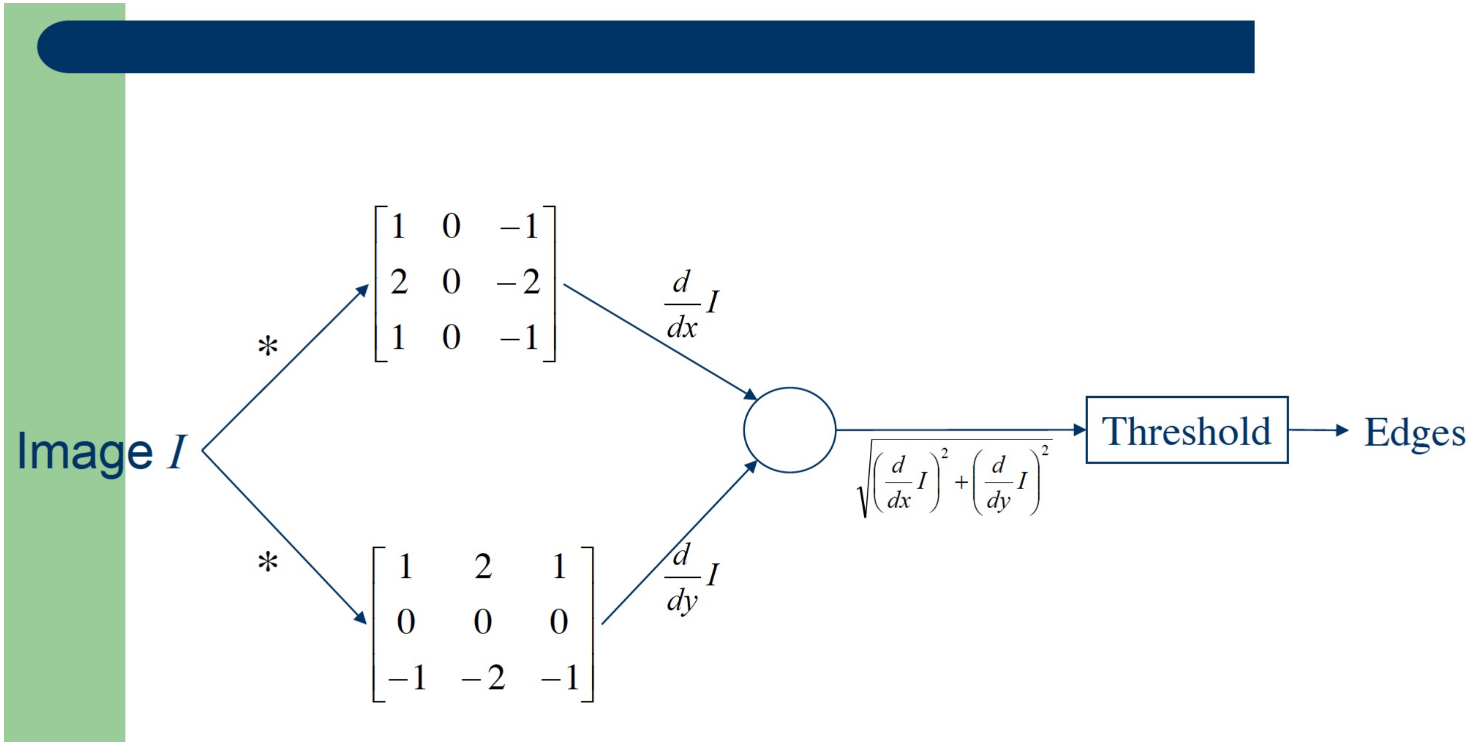
- Edges
- Corners
- Several Key points detector
  - SIFT (https://en.wikipedia.org/wiki/Scale-invariant_feature_transform)
  - SURF (https://en.wikipedia.org/wiki/Speeded_up_robust_features#:~:text=In%20computer%20vision%2C%20speeded%20up,%2C%20classification%2C%20or%203D%20reconstruction.&text=Its%20feature%20descriptor%20is%20based,around%20the%20point%20of%20interest.)

Feature Discriptors

- Histograms (Global or at interesting locations)
- Histogram of oriented gradients
- Local Binary Patterns

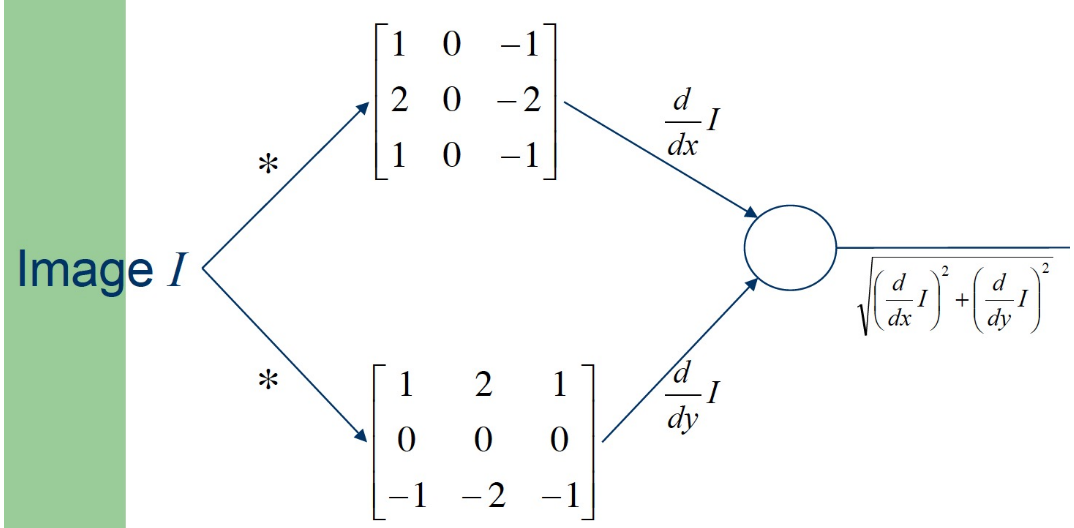
Feature Discriptors

- Histogram of oriented gradients



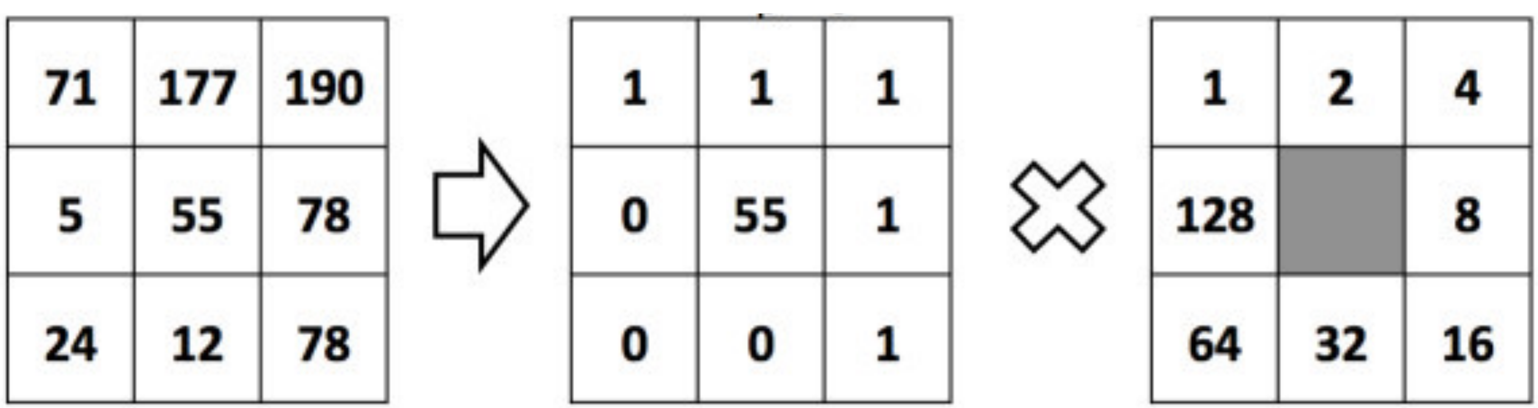
Feature Discriptors

- Histogram of oriented gradients



Feature Discriptors

- Local Binary Patterns



LBP=1 x 1 + 1 x 2 +1 x 4 + 1 x 8 + 1 x 16 + 0 x 32 + 0 x 64 + 0 x 128= 4 + 8 + 16 = 31

Feature Discriptors

- Local Binary Patterns

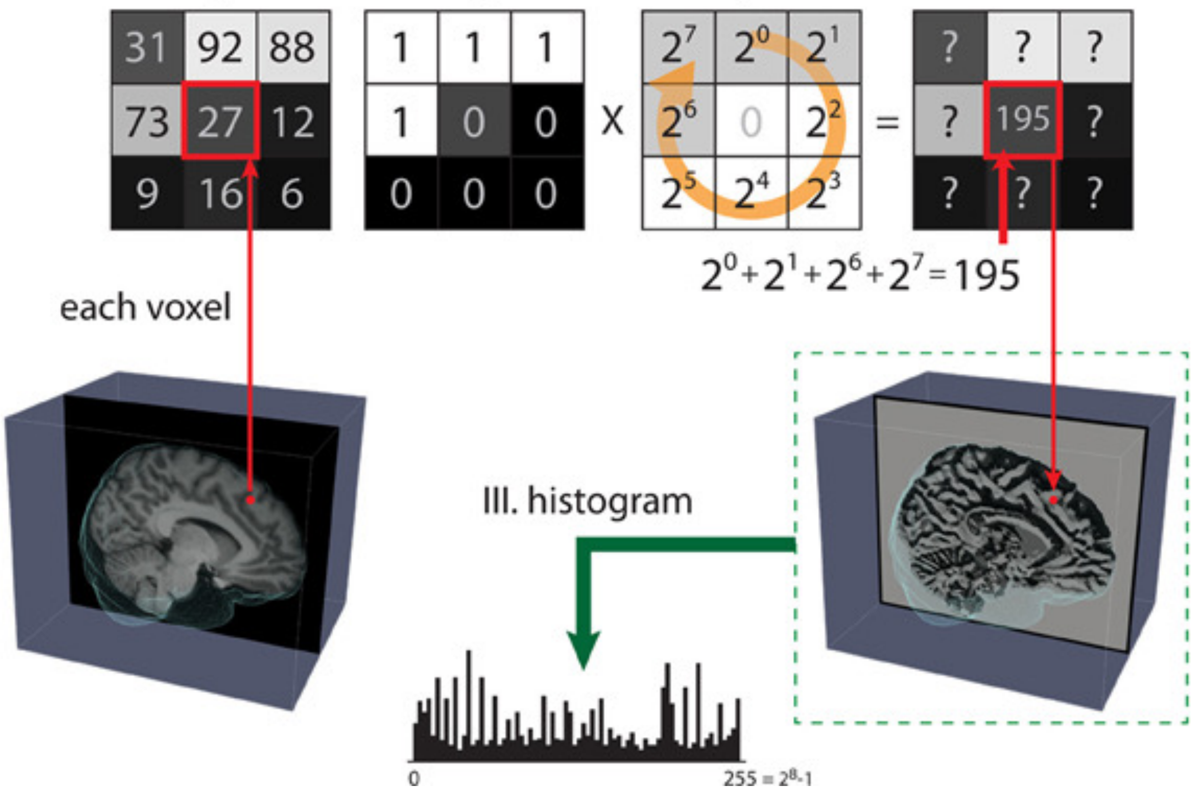


Image Segmentation

- Automatic Image Segmentation
  - Kmeans
  - Agglomerative
  - Meanshift
  - Superpixel Segmentation
  - Watershed Segmentation

- Interactive Image Segmentation
  - Grab Cut Segmentation
  - Active Contours

What is Clustering?

- Organizing data into classes such that:
  - High intra-class similarity
  - Low inter-class similarity

- Finding the class labels and the number of classes directly from the data (as opposed to *classification tasks*)

Image Segmentation

- Image segmentation- Process of partitioning a digital image into multiple homogeneous segments
- Image is divided into more meaningful and easier to analyse parts.

Why do we cluster?

- **Summarizing data**
  - Look at large amounts of data
  - Patch-based compression or denoising
  - Represent a large continuous vector with the cluster number

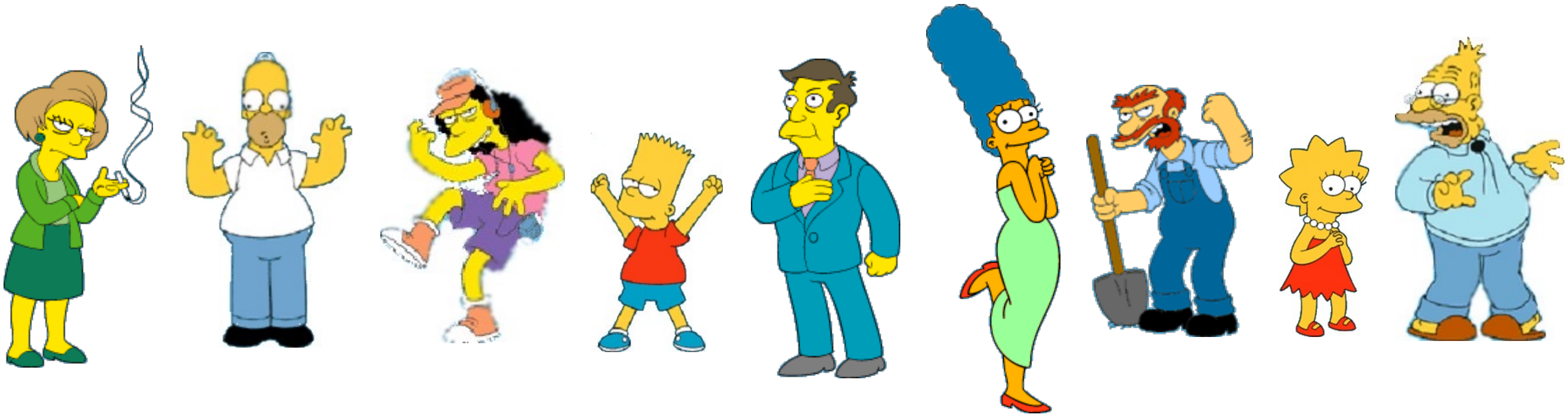
- **Counting**
  - Histograms of texture, color, SIFT vectors

- **Segmentation**
  - Separate the image into different regions

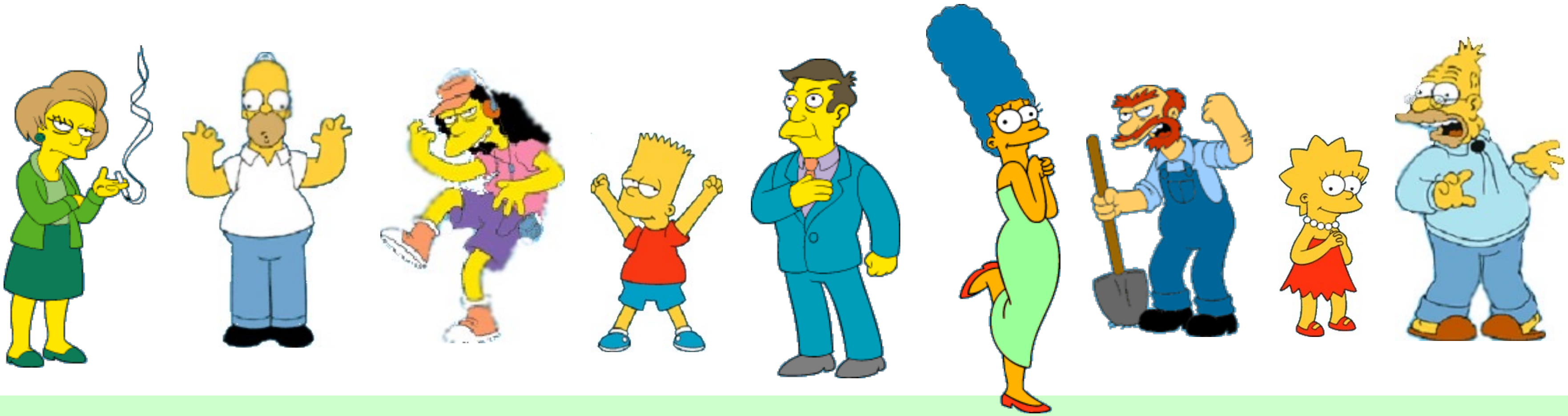
- **Prediction**
  - Images in the same cluster may have the same labels

Slide: Derek Hoiem

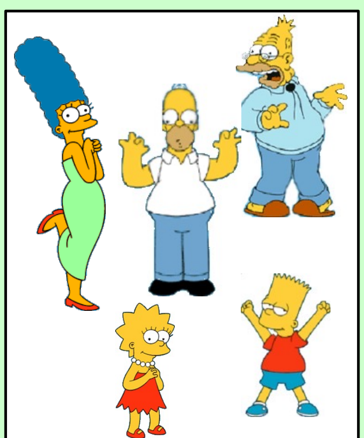
What is a natural grouping?



What is a natural grouping?

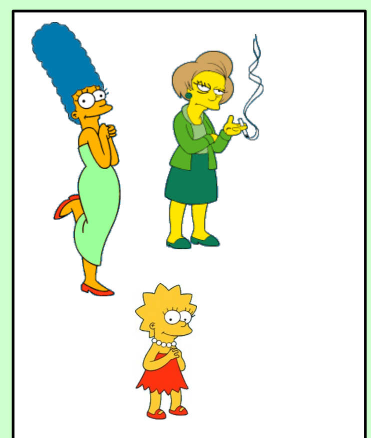


Clustering is subjective

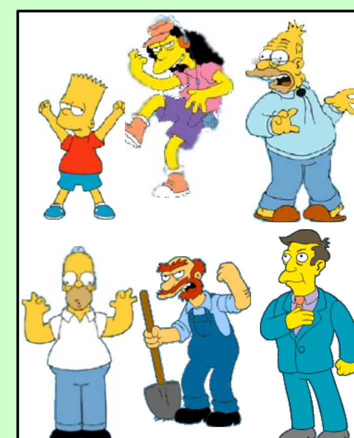


Simpson's Family

School Employees



Females



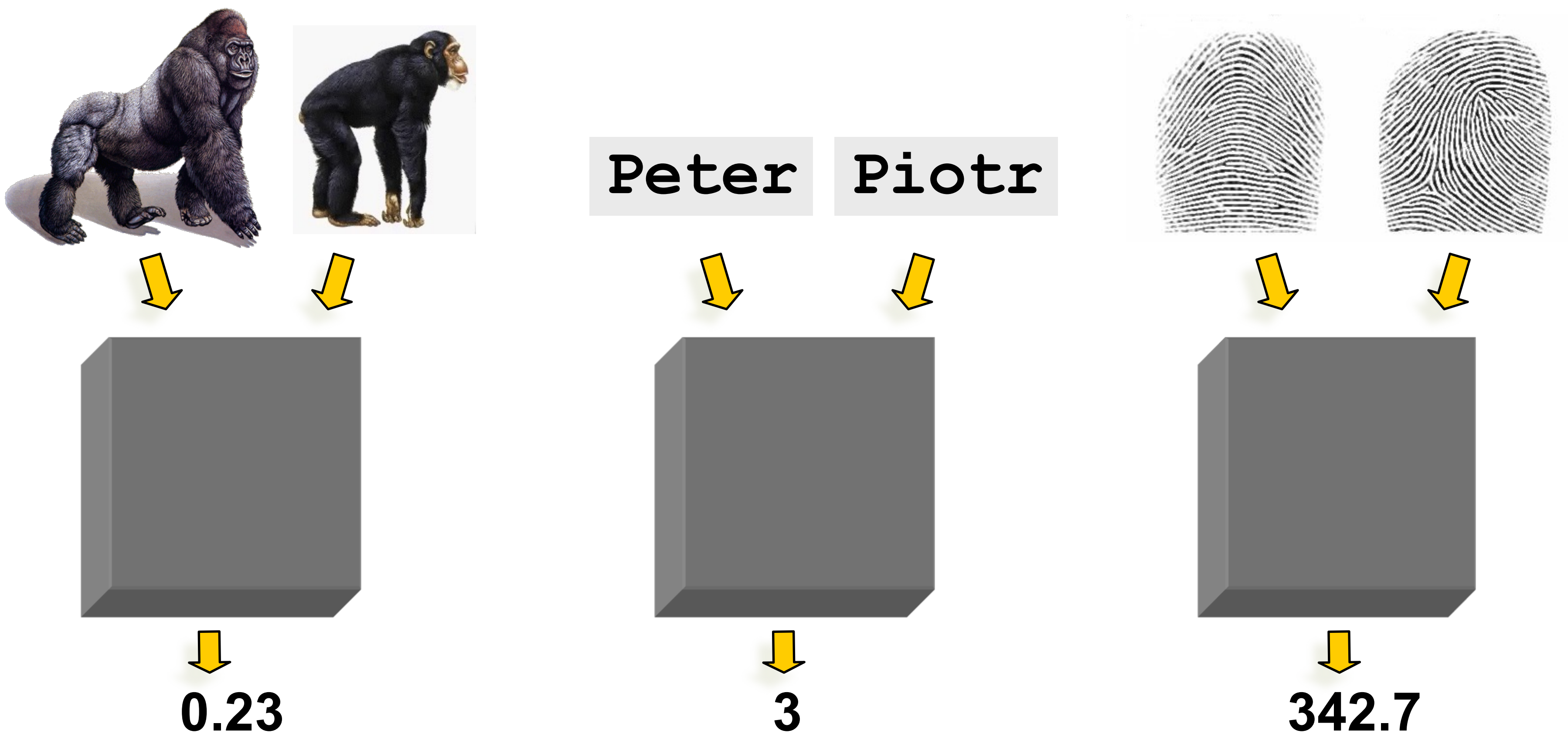
Males

What is similarity ?

<u>Cluster by features</u>

- **Color**
- **Intensity**
- **Location**
- **Texture**
- **….**

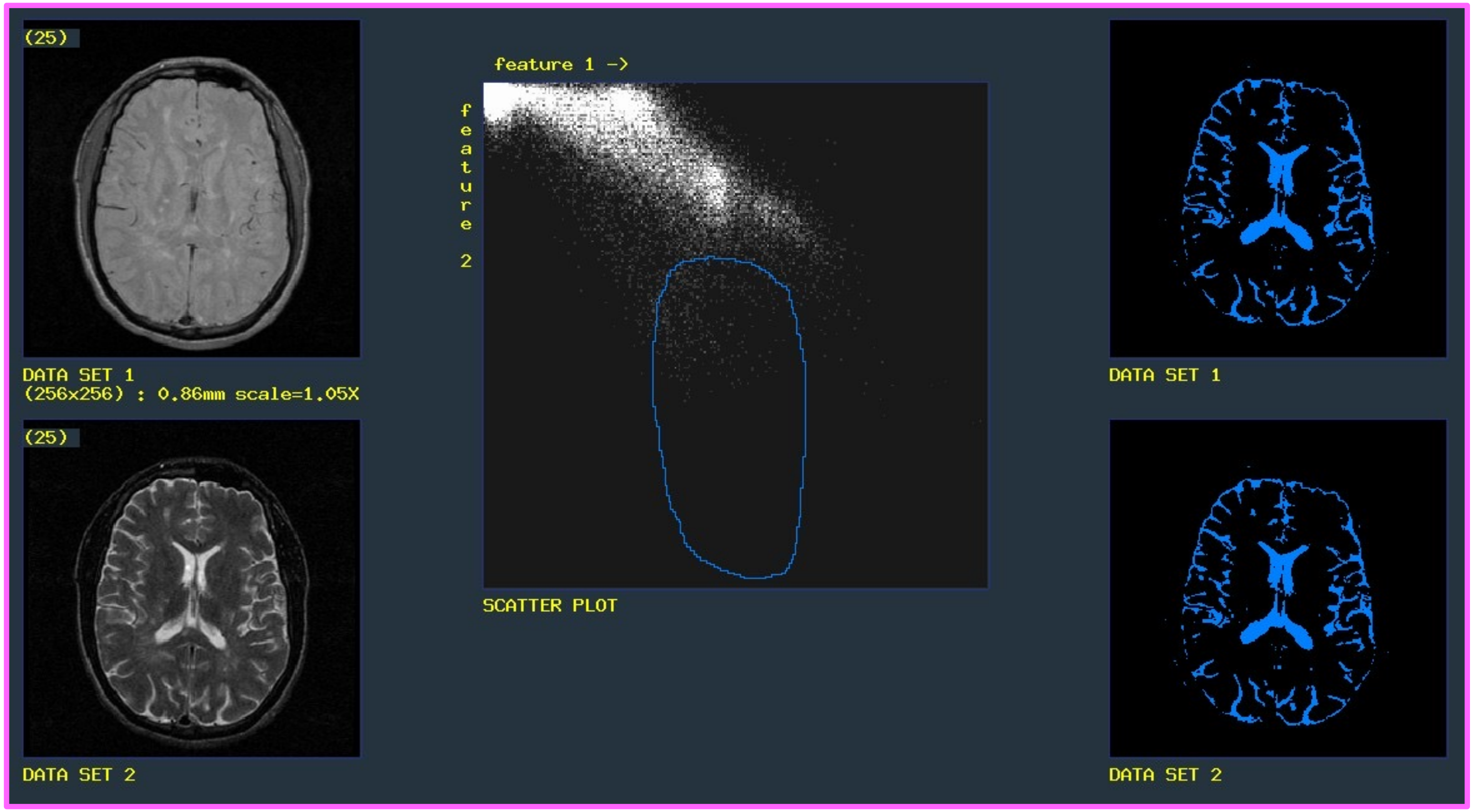
Distance metrics



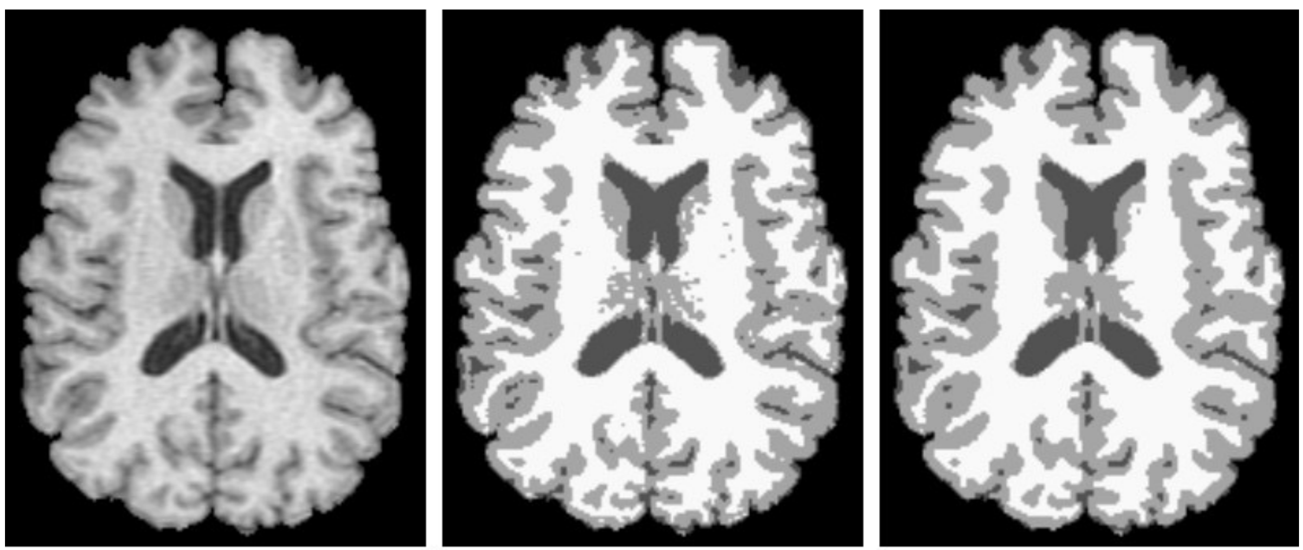
- **Local Distance**
- **Global Distance**

Motivation for Clustering in Medical Image Segmentation

- Assumption: The object of interest can be identified as a cluster in an appropriate feature space.



- **Clustering algorithms** essentially perform the same function as **classifier methods** without the use of training data.
- Thus, they are termed **unsupervised methods.**
- In order to compensate for the lack of training data, clustering methods iterate between segmenting the image and characterizing the properties of the each class.

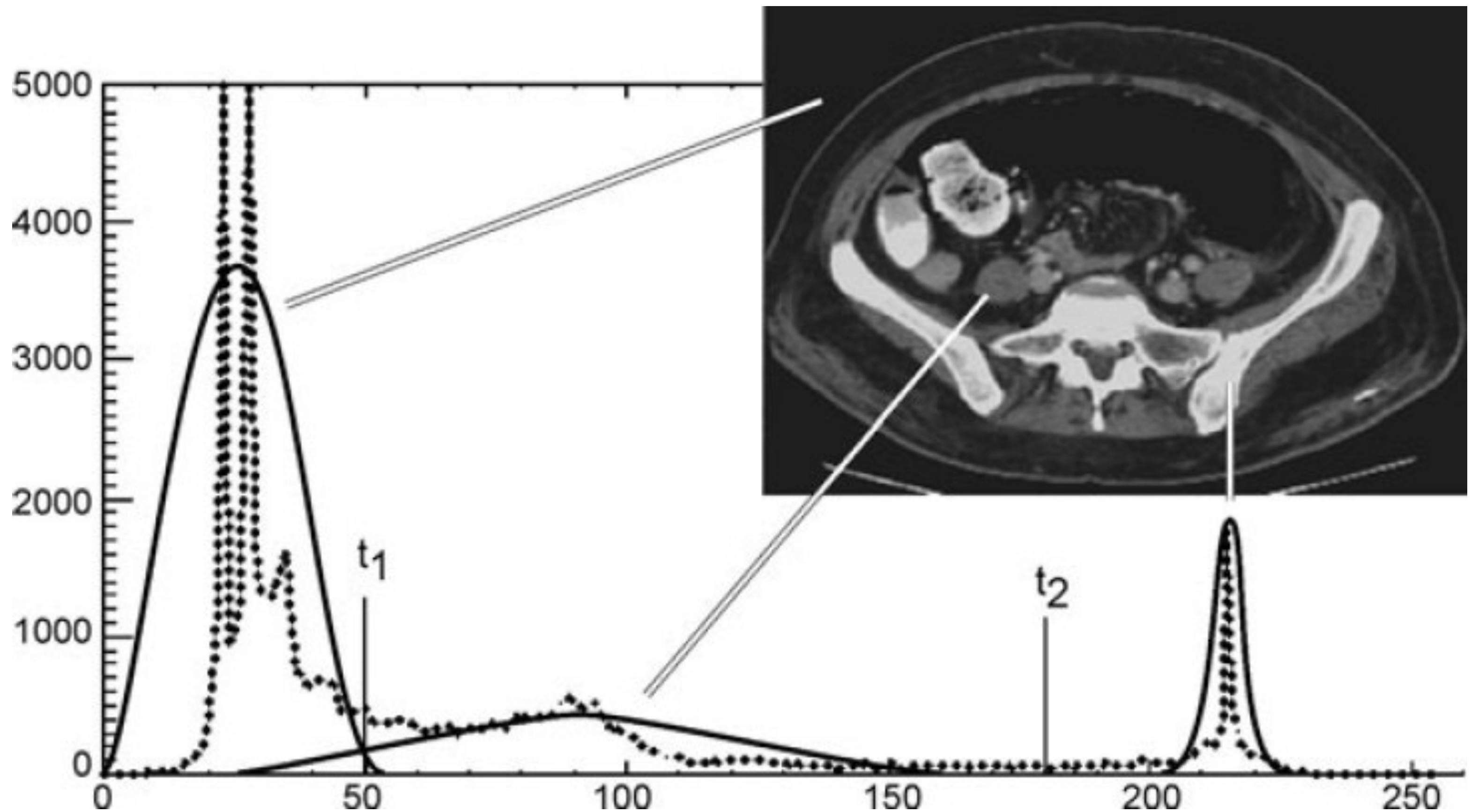


(a) (b) (c)

Fuzzy C-Means (FCM) FCM with Markov Prior

Pham et al

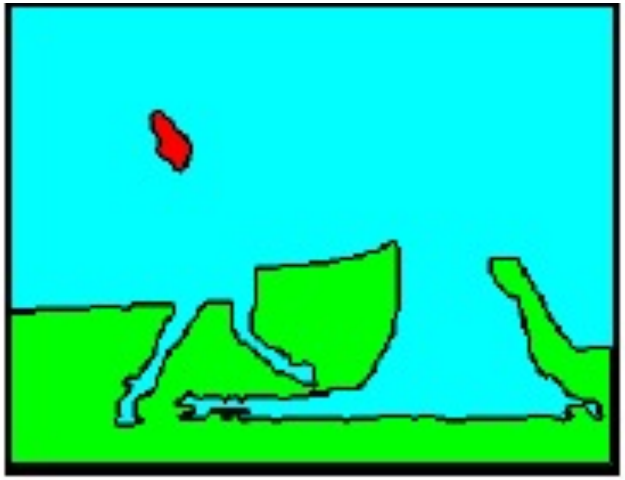
Motivation in Biomedical Image Segmentation



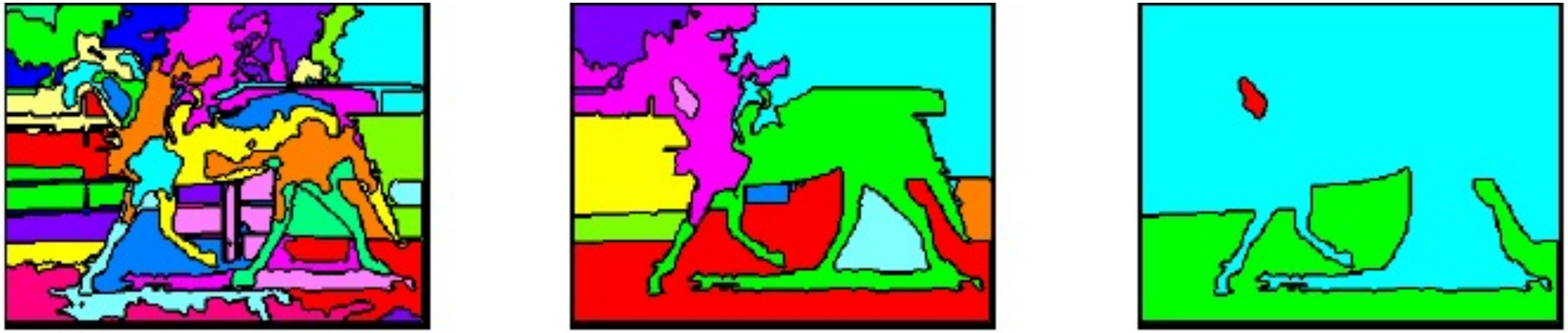
Segmenting the image based on threshold

Types of segmentations

Oversegmentation



Undersegmentation



Multiple Segmentations

How do we cluster?

- K-means
  - Iteratively re-assign points to the nearest cluster center
- Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- Mean-shift clustering
  - Estimate modes of probability density function
- Superpixel Segmentation

K-MEANS CLUSTERING

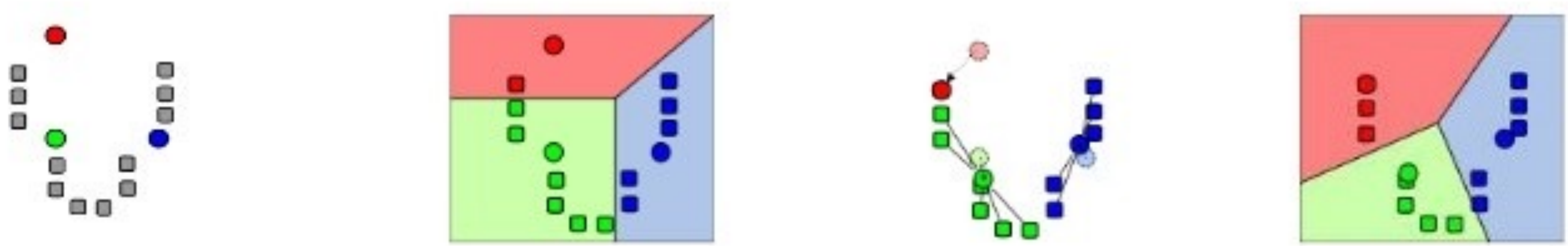
- Description

Given a set of observations $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$, where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets $(k \leq n)$ $\mathbf{S} = \{S_1, S_2, \ldots, S_k\}$ so as to minimize the within-cluster sum of squares (WCSS):

$$\underset{S}{\arg\min} \sum_{i=1}^{k} \sum_{x_j \in S_i} \left\| x_j - u_i \right\|^2$$

where $\boldsymbol{\mu}_i$ is the mean of points in S_i.

- Standard Algorithm



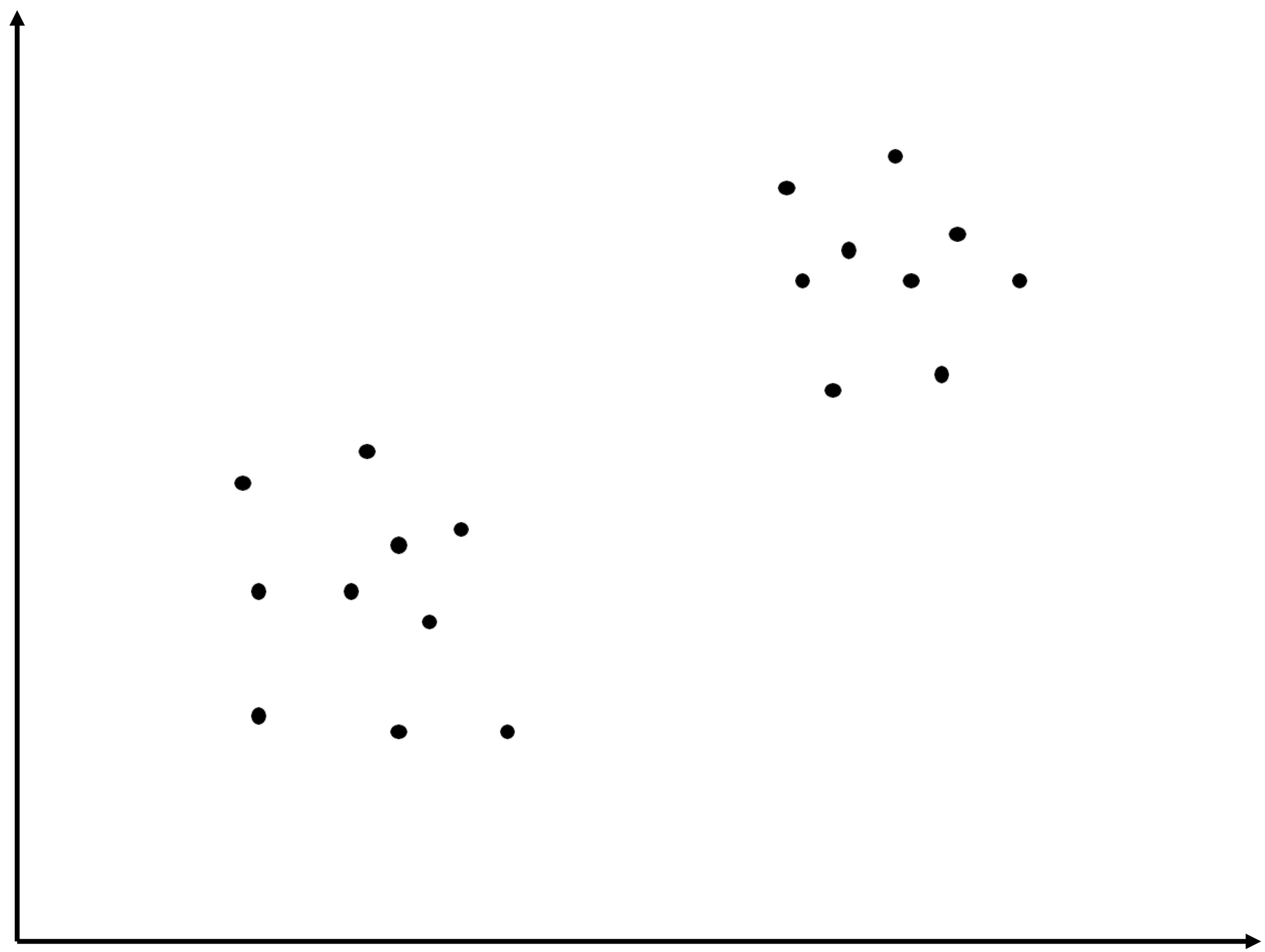
1) k initial "means" (in this case k=3) are randomly selected from the data set.

2) k clusters are created by associating every observation with the nearest mean.

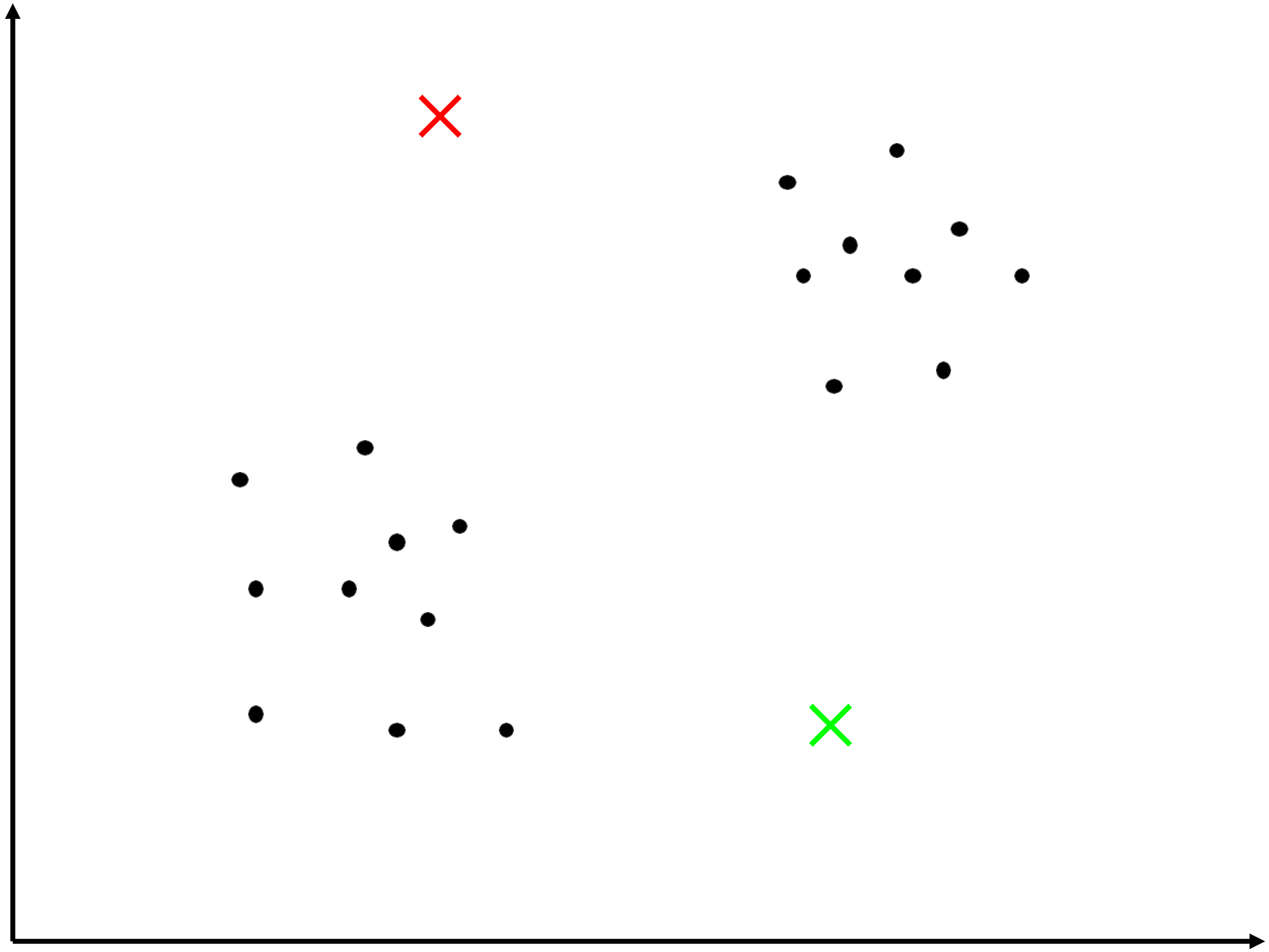
3) The centroid of each of the k clusters becomes the new means.

4) Steps 2 and 3 are repeated until convergence has been reached.

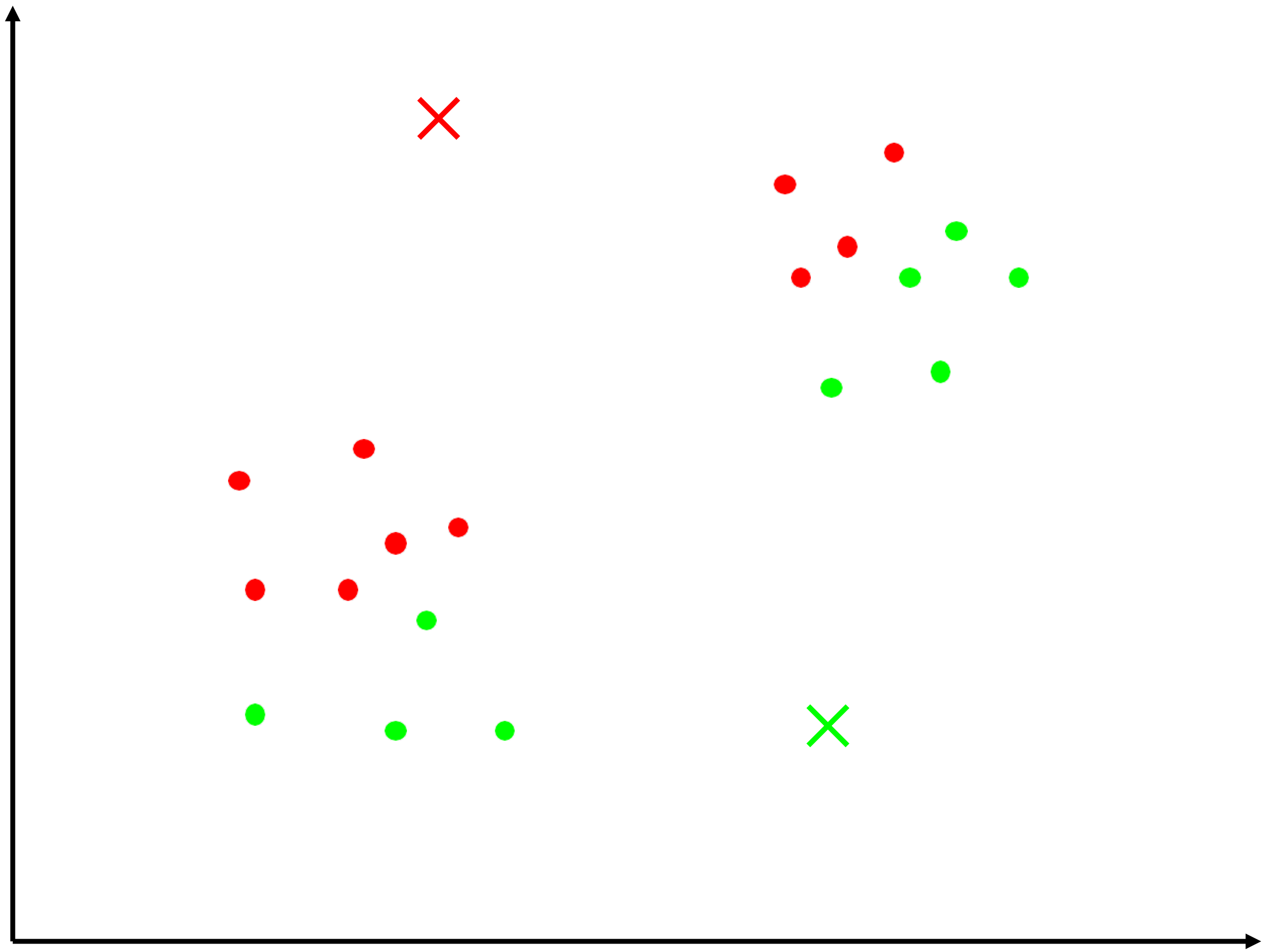
K-means Clustering



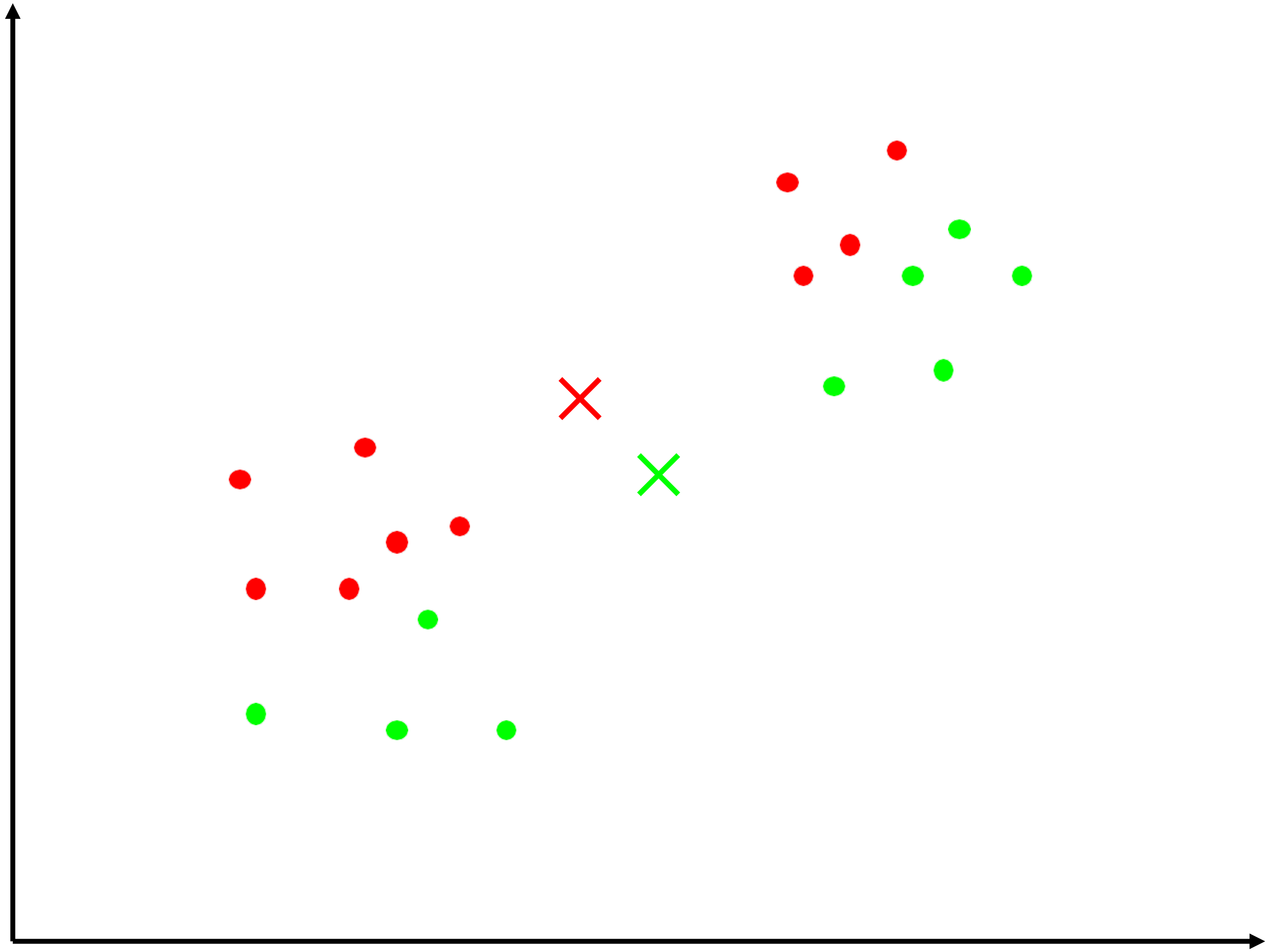
K-means Clustering



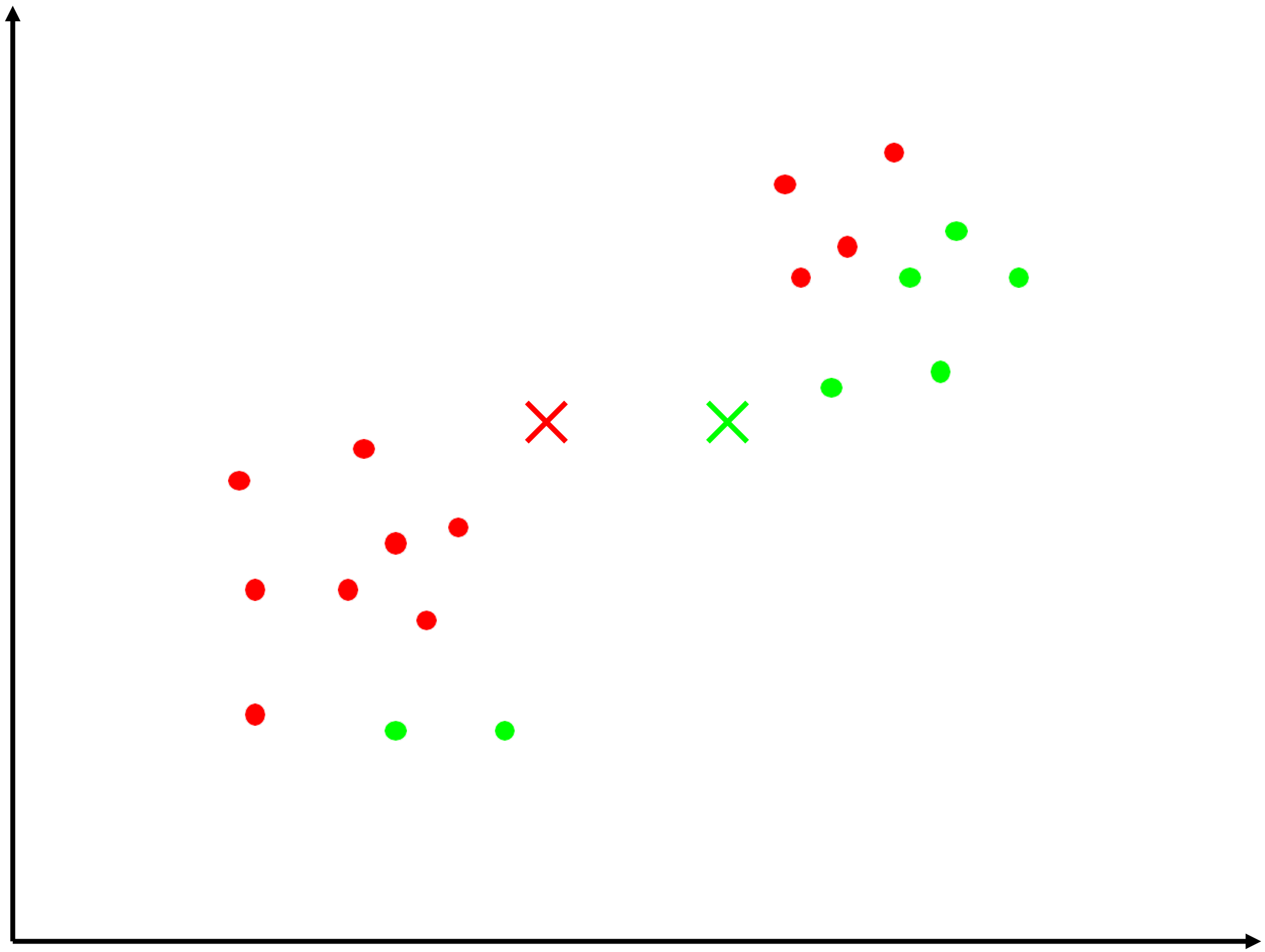
K-means Clustering



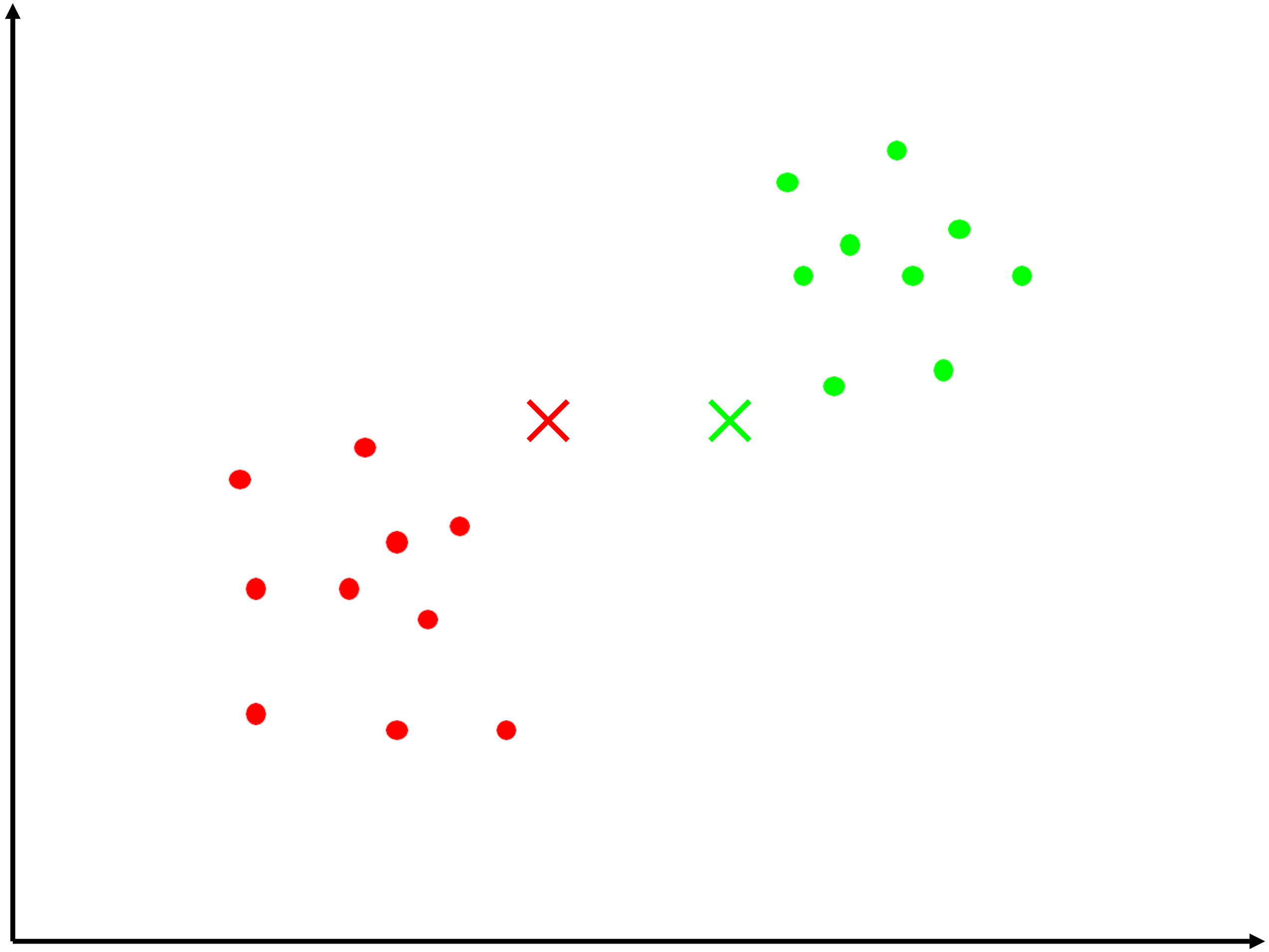
K-means Clustering



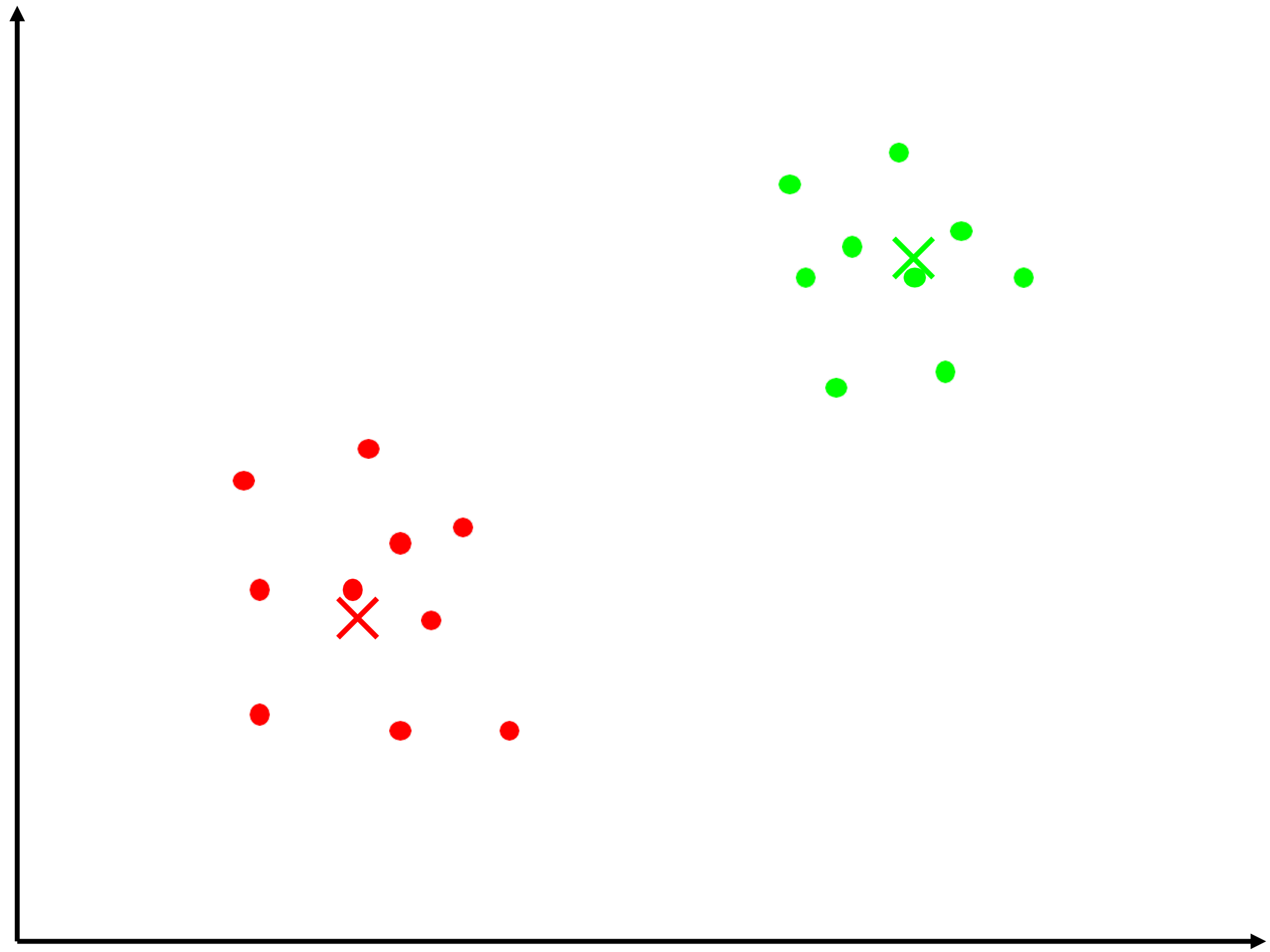
K-means Clustering



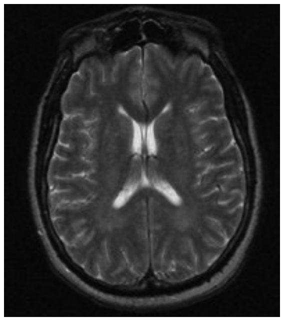
K-means Clustering

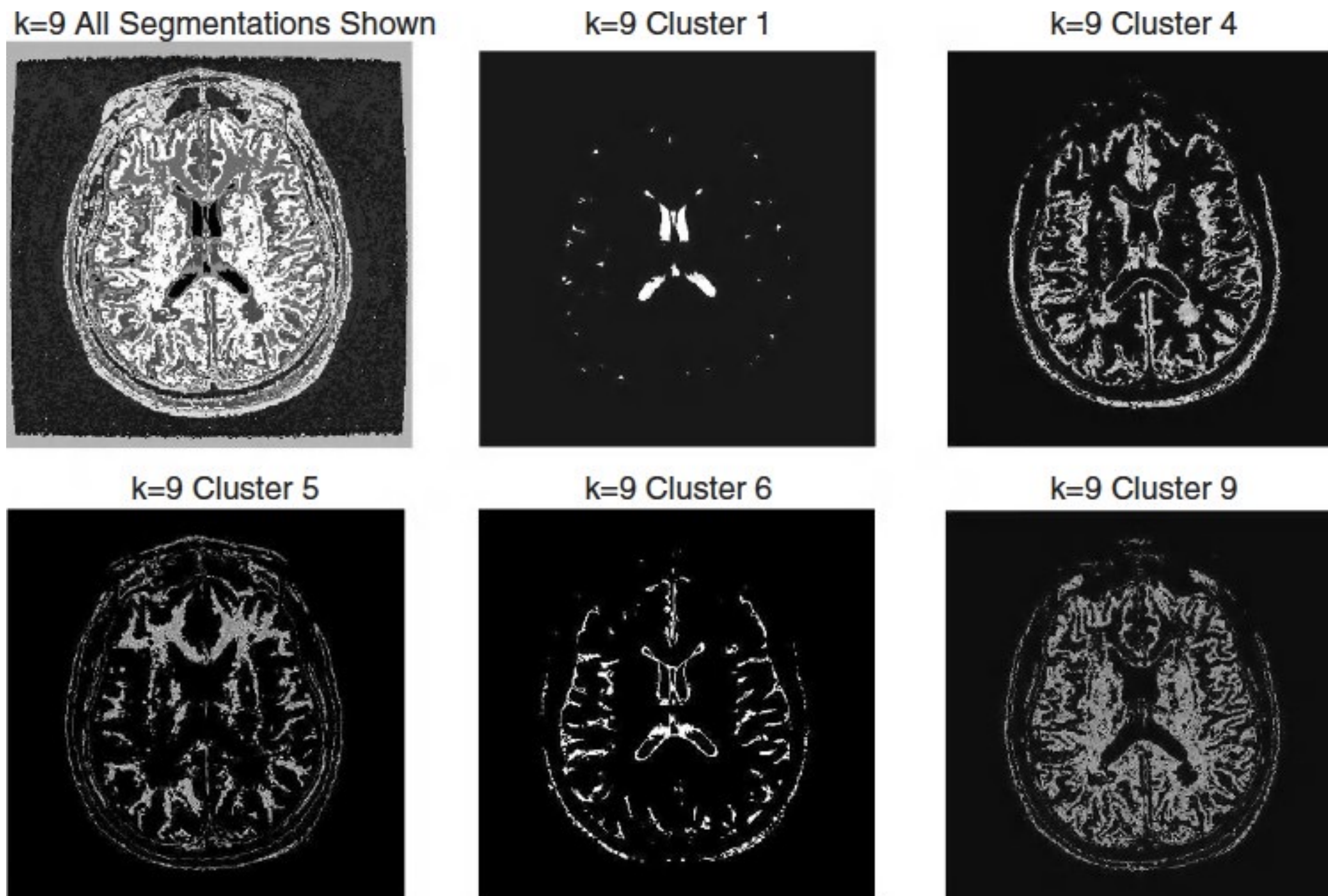


K-means Clustering



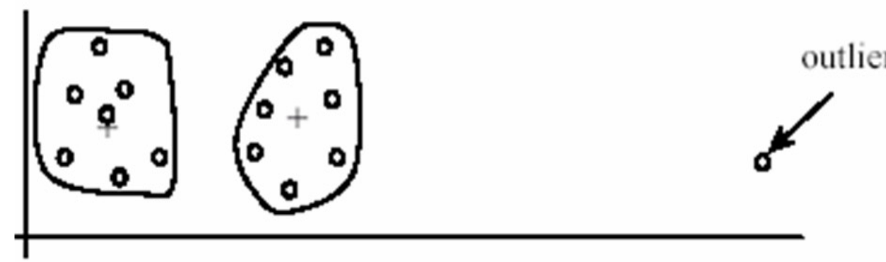
Applications in MRI Segmentation via K-means (K=9)



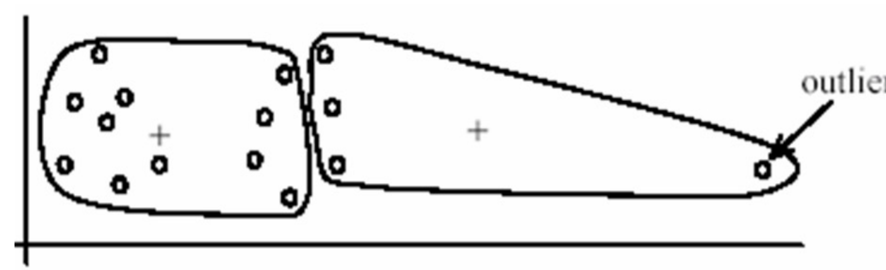


K-Means pros and cons

- Pros
  - Finds cluster centers that minimize conditional variance (good representation of data)
  - Simple and fast*
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers
  - Prone to local minima
  - All clusters have the same parameters (e.g., distance measure is non-adaptive)



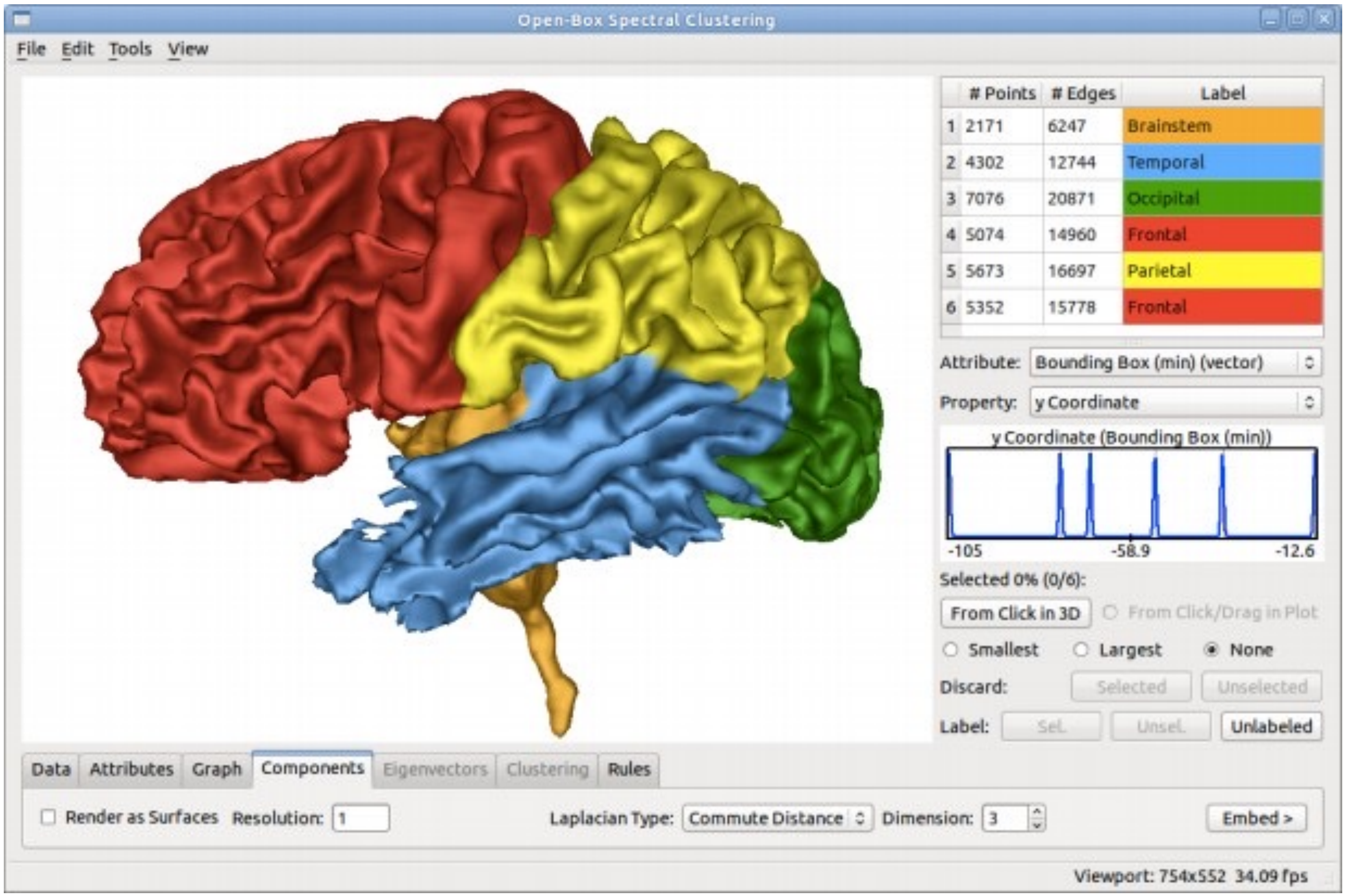
(B): Ideal clusters



- Usage
  - Rarely used for pixel segmentation

Clustering

- Similarity metric
- Distance metric



Open-box
Spectral clustering
Software for
Medical images

Schultz and Kindlmann 2013, IEEE TVCG

Common similarity/distance measures

- P-norms
  - City Block (L1)
  - Euclidean (L2)
  - L-infinity

$$\|\mathbf{x}\|_p := \left(\sum_{i=1}^{n} |x_i|^p \right)^{1/p}$$

$$\|\boldsymbol{x}\|_1 := \sum_{i=1}^{n} |x_i|$$

$$\|\boldsymbol{x}\| := \sqrt{x_1^2 + \cdots + x_n^2}$$

$$\|\mathbf{x}\|_\infty := \max\left(|x_1|, \ldots, |x_n|\right)$$

Here x_i is the distance between two points

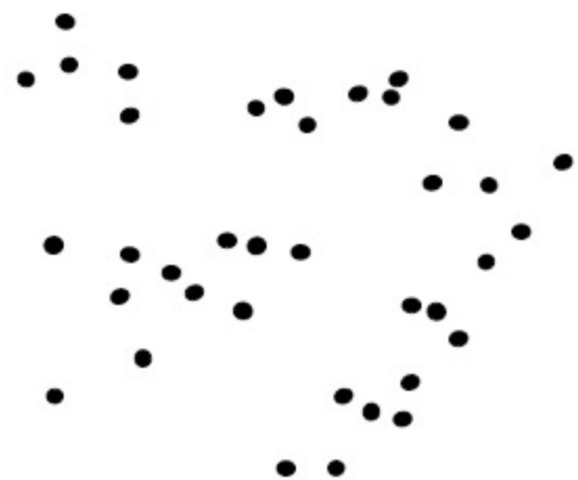
- Mahalanobis
  - Scaled Euclidean

$$d(\vec{x}, \vec{y}) = \sqrt{\sum_{i=1}^{N} \frac{(x_i - y_i)^2}{\sigma_i^2}}$$

- Cosine distance

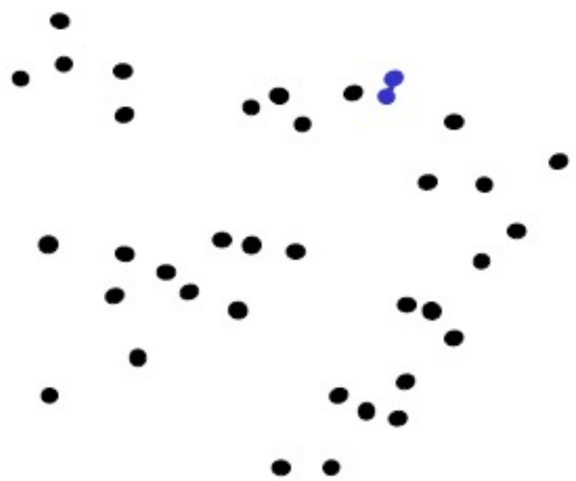
$$\text{similarity} = \cos(\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

Agglomerative clustering



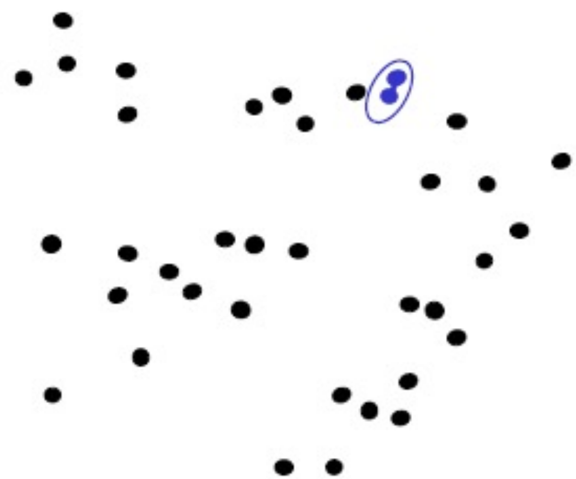
1. Say "Every point is its own cluster"

Agglomerative clustering



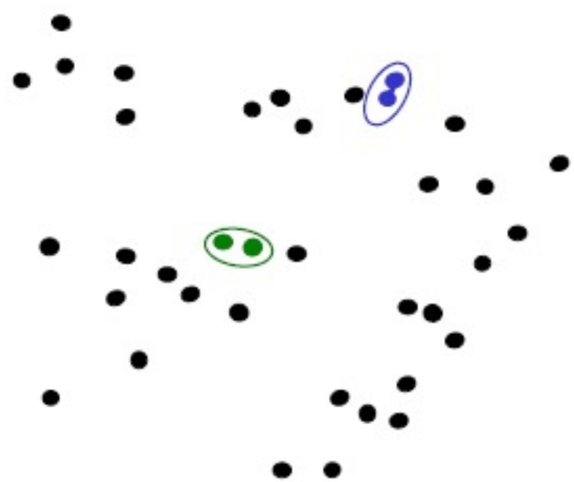
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters

Agglomerative clustering



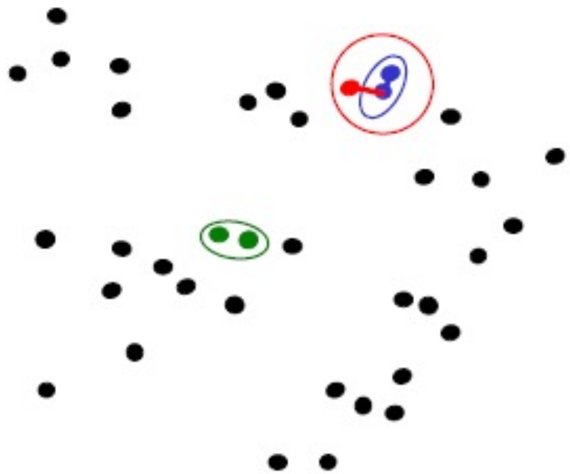
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster

Agglomerative clustering

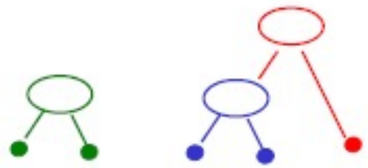


1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat

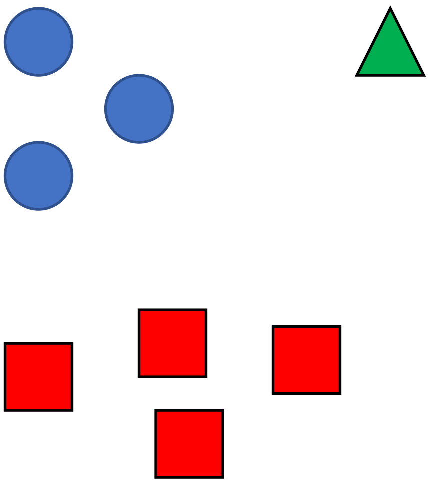
Agglomerative clustering



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat



Agglomerative clustering

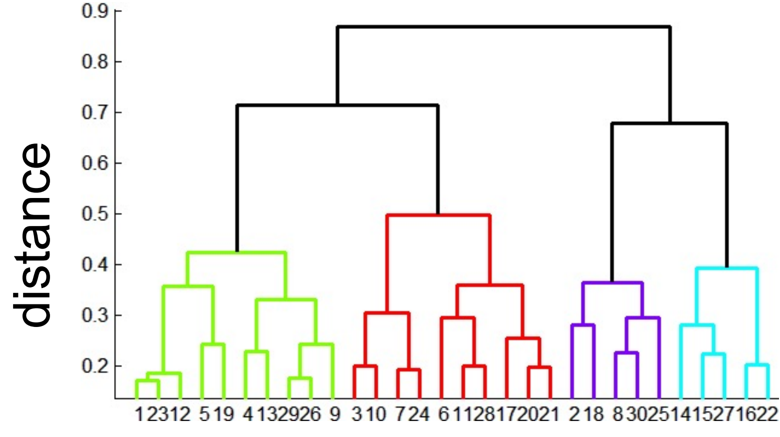


How to define cluster similarity?

- Average distance between points, maximum distance, minimum distance
- Distance between means or medoids

How many clusters?

- Clustering creates a dendrogram (a tree)
- Threshold based on max number of clusters or based on distance between merges



Conclusions: Agglomerative Clustering

Good

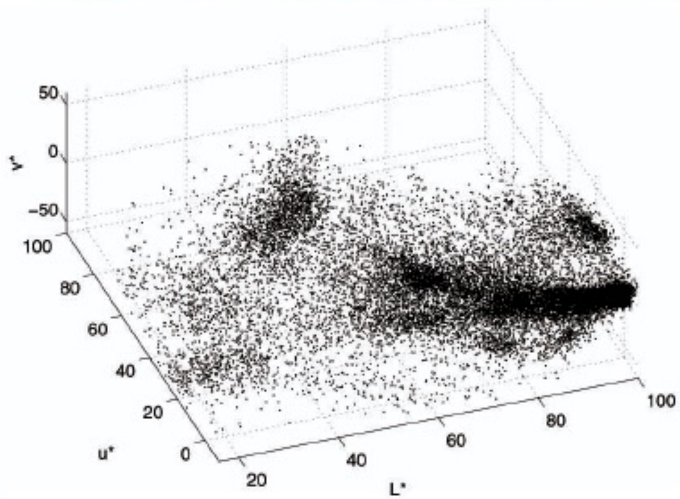
- Simple to implement, widespread application
- Clusters have adaptive shapes
- Provides a hierarchy of clusters

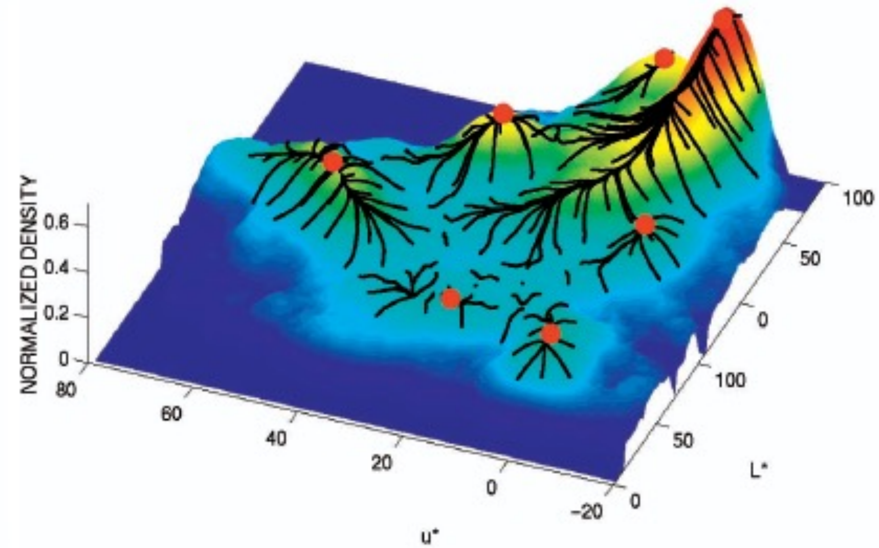
Bad

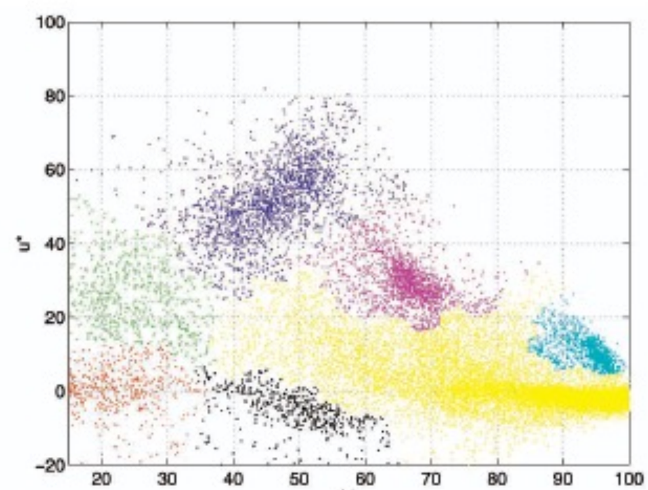
- May have imbalanced clusters
- Still have to choose number of clusters or threshold
- Sometimes not easy to get a meaningful hierarchy

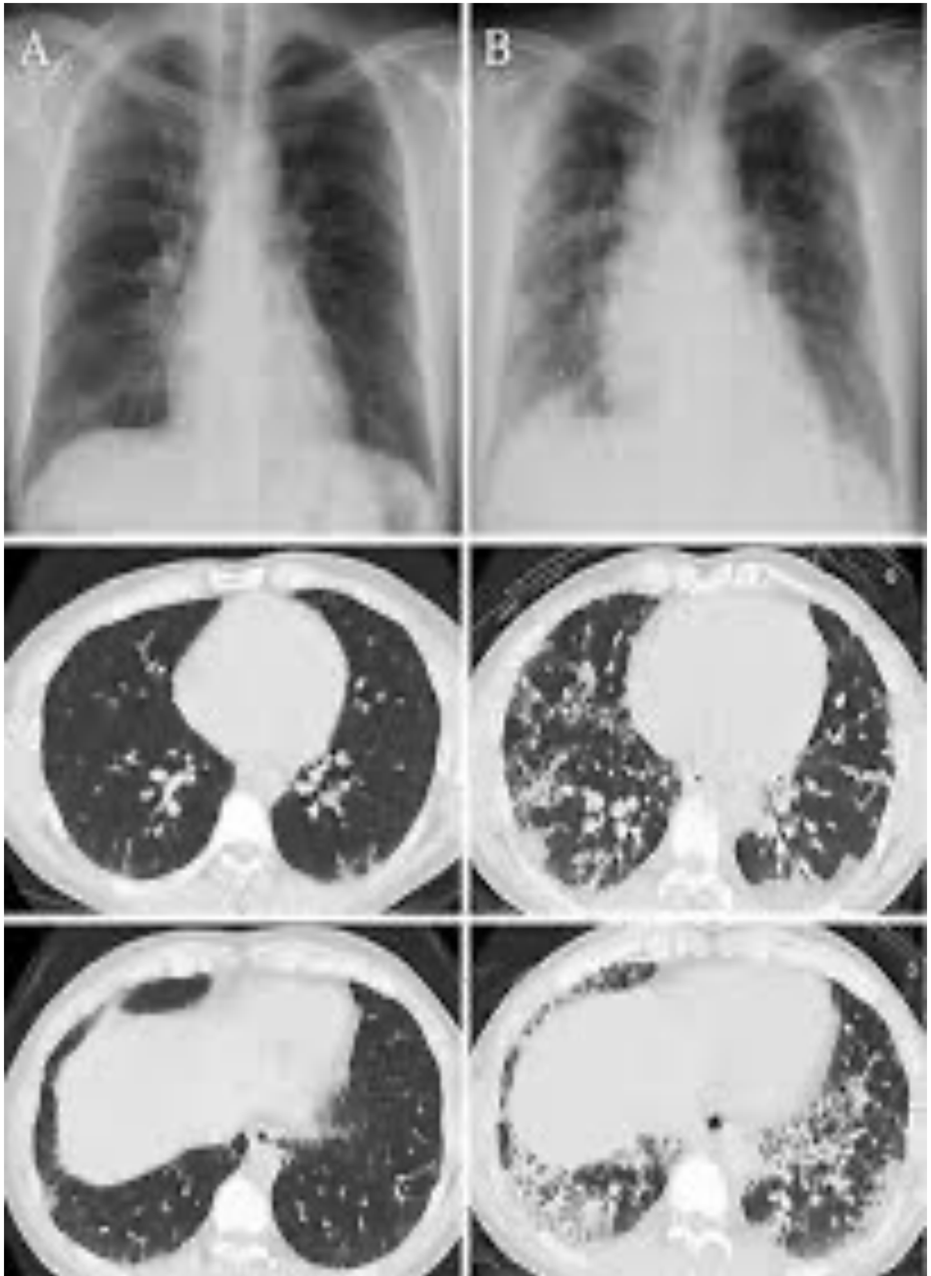
Mean shift algorithm

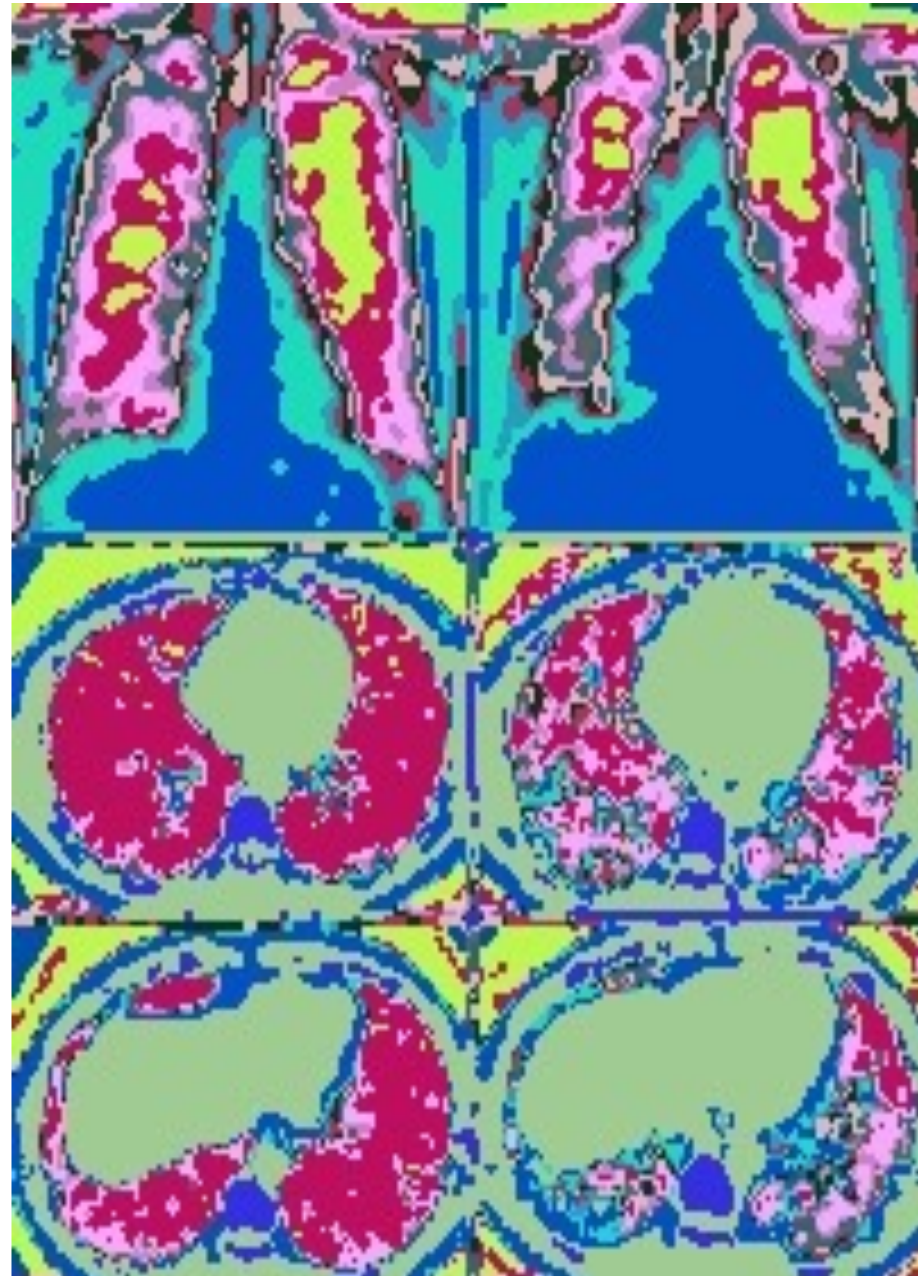
- Try to find *modes* of this non-parametric density



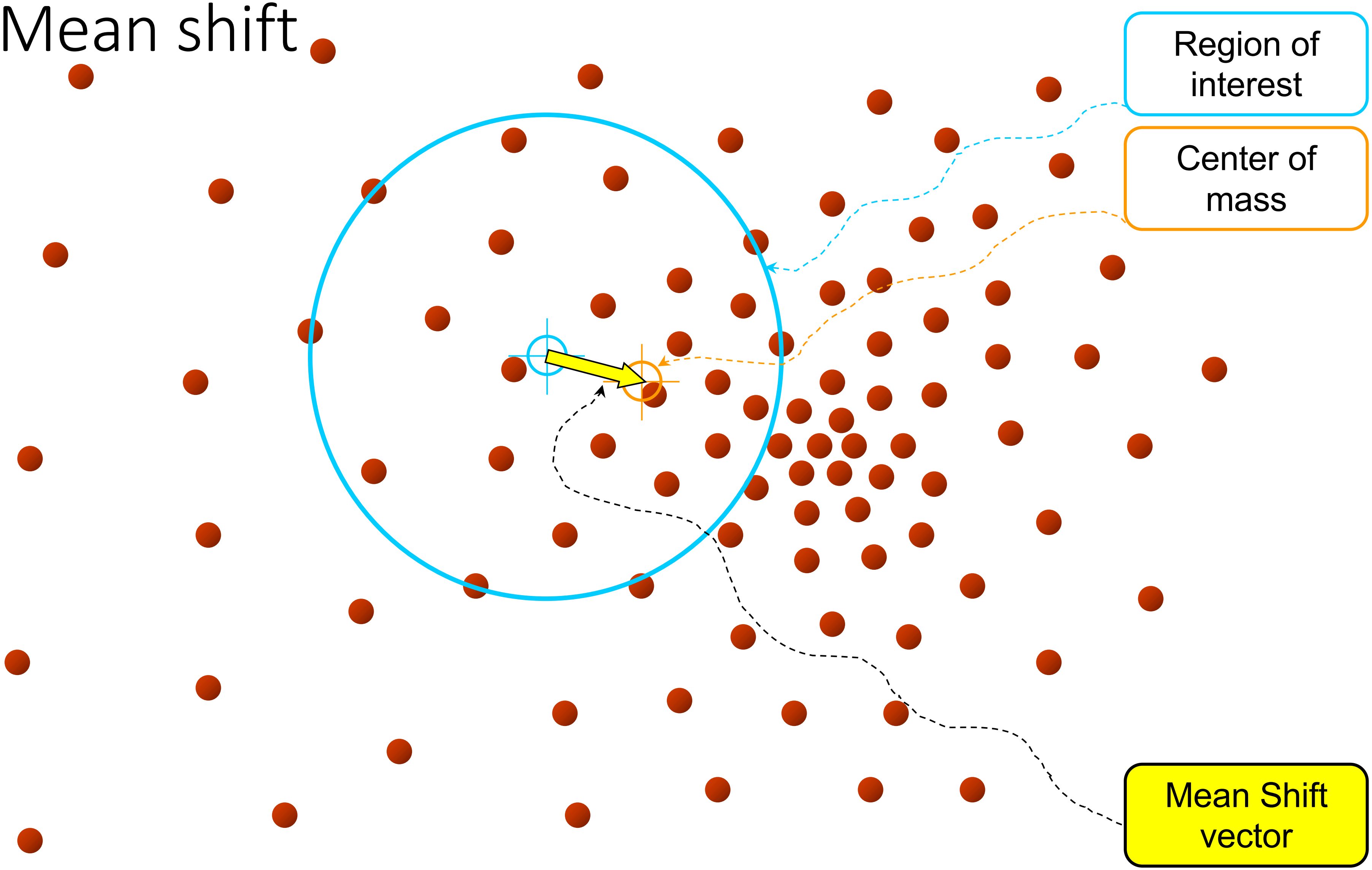





A
B

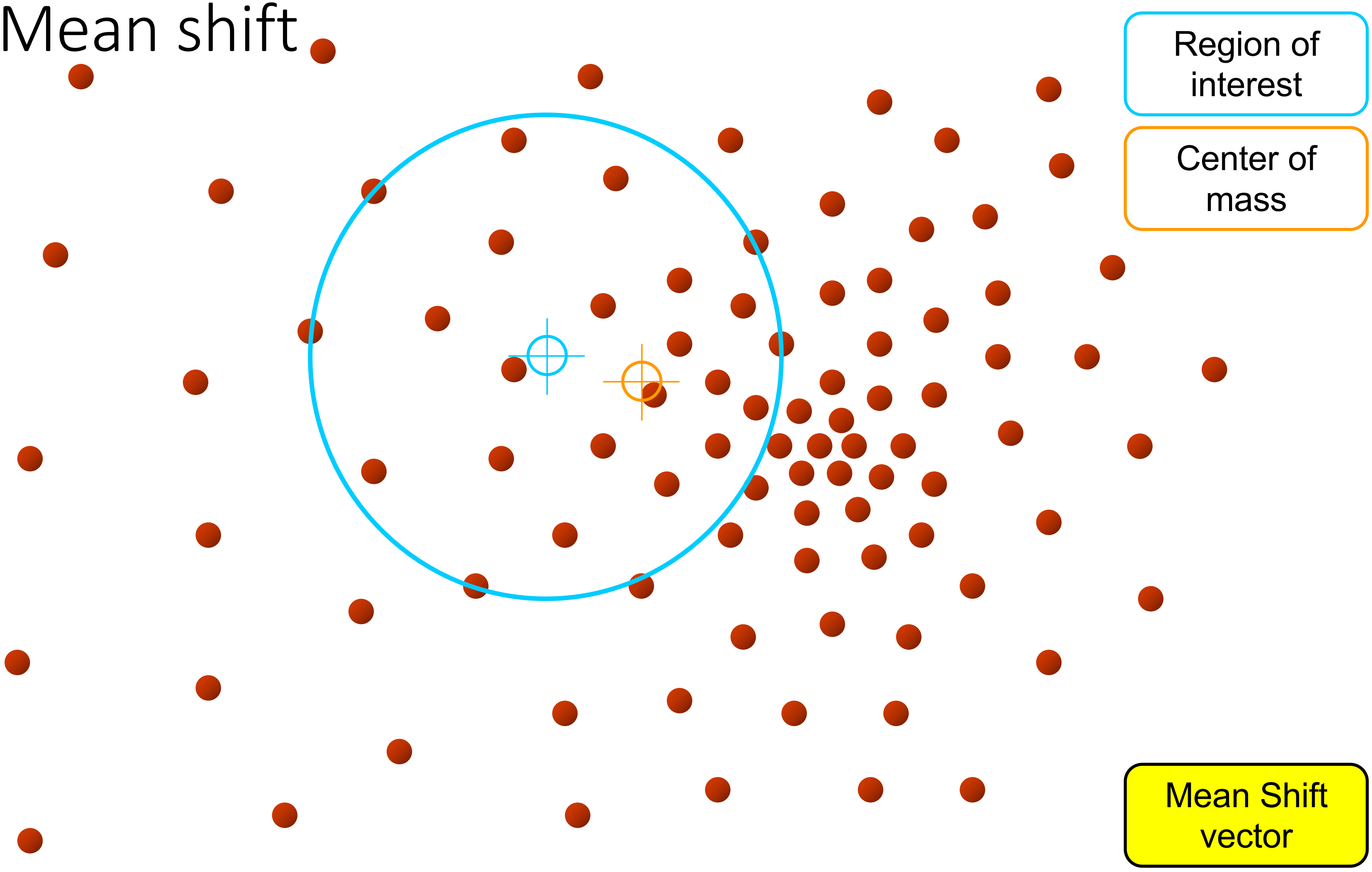


Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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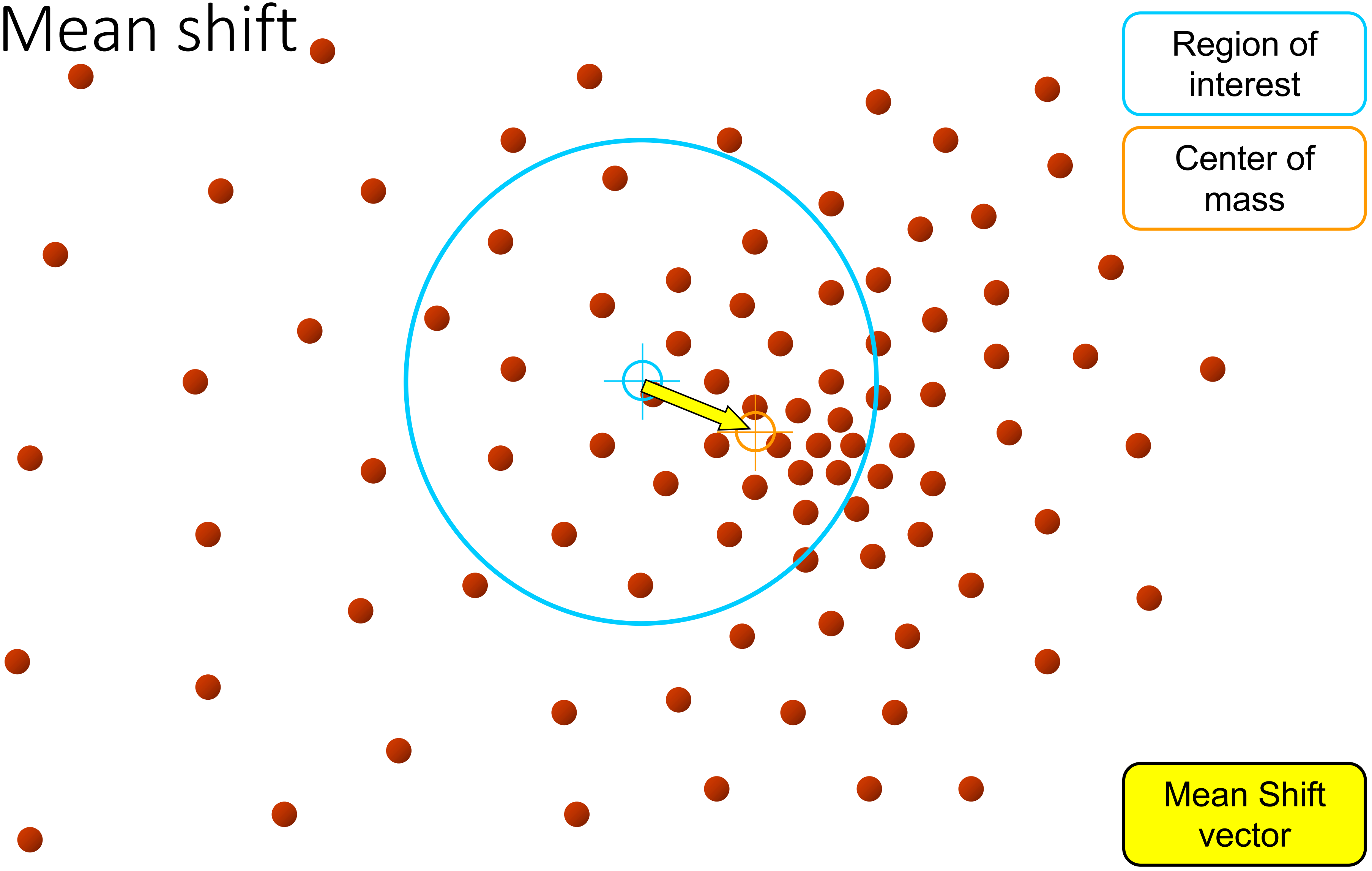
Mean shift



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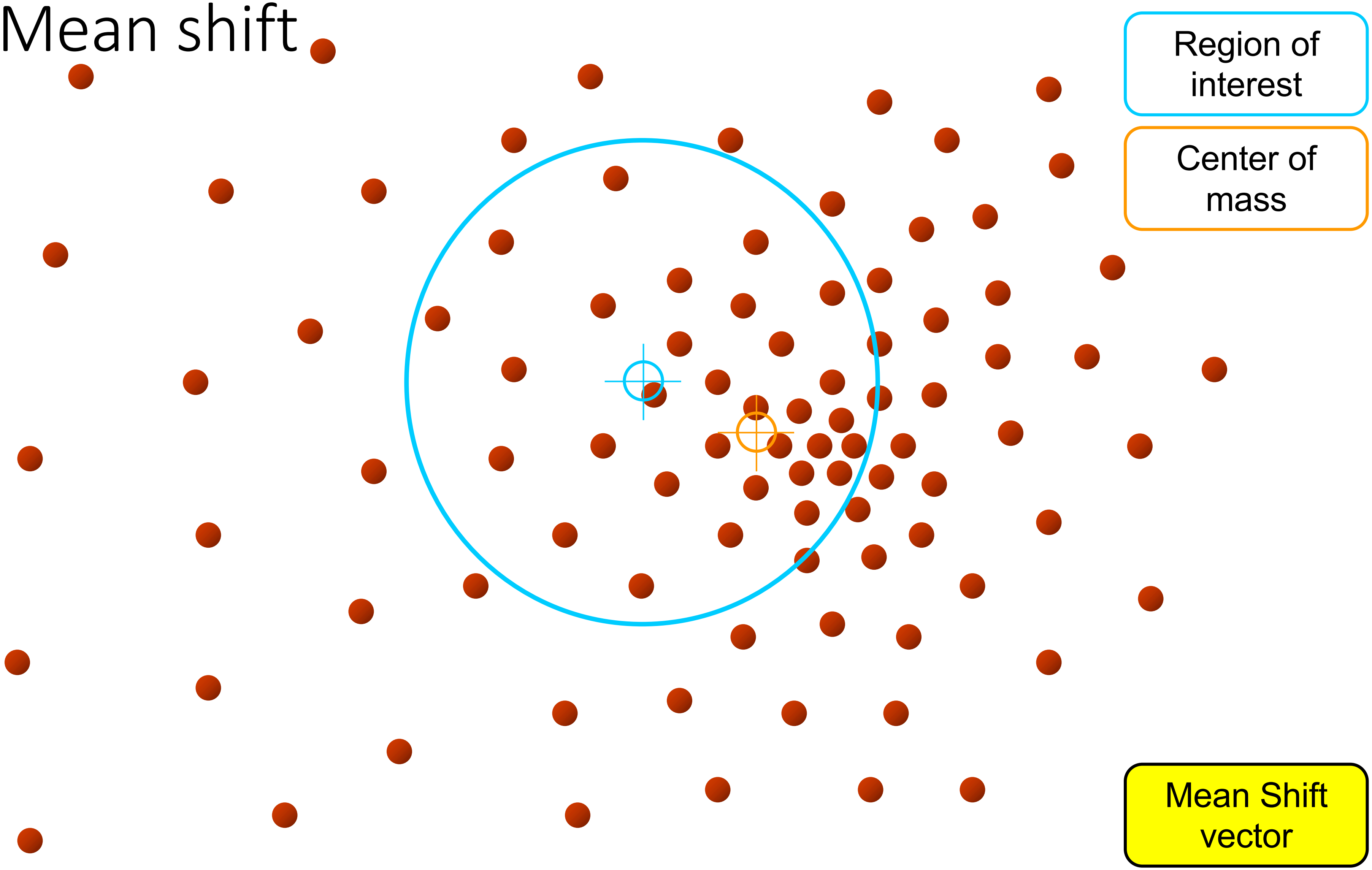
Mean shift



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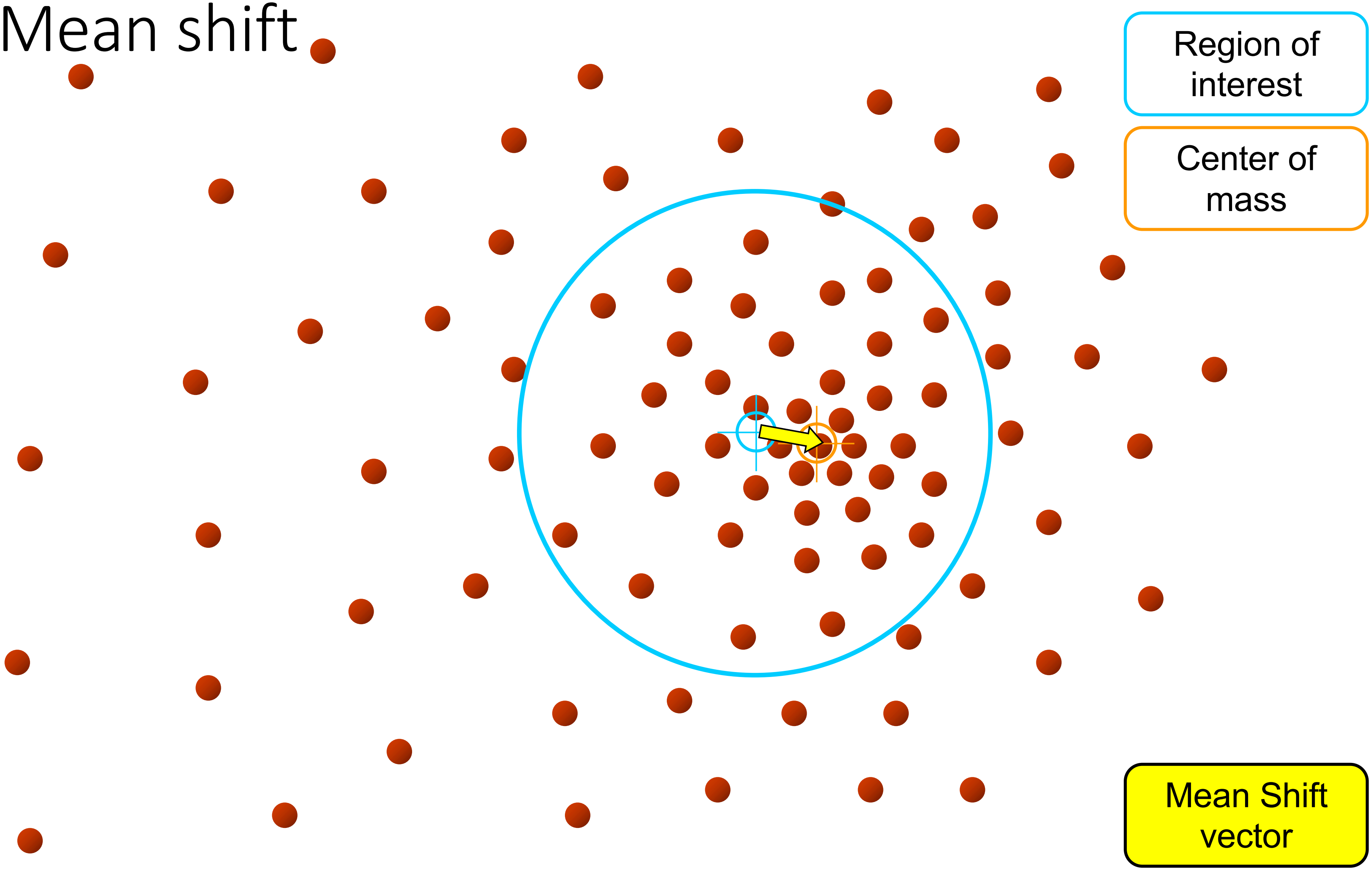
Mean shift



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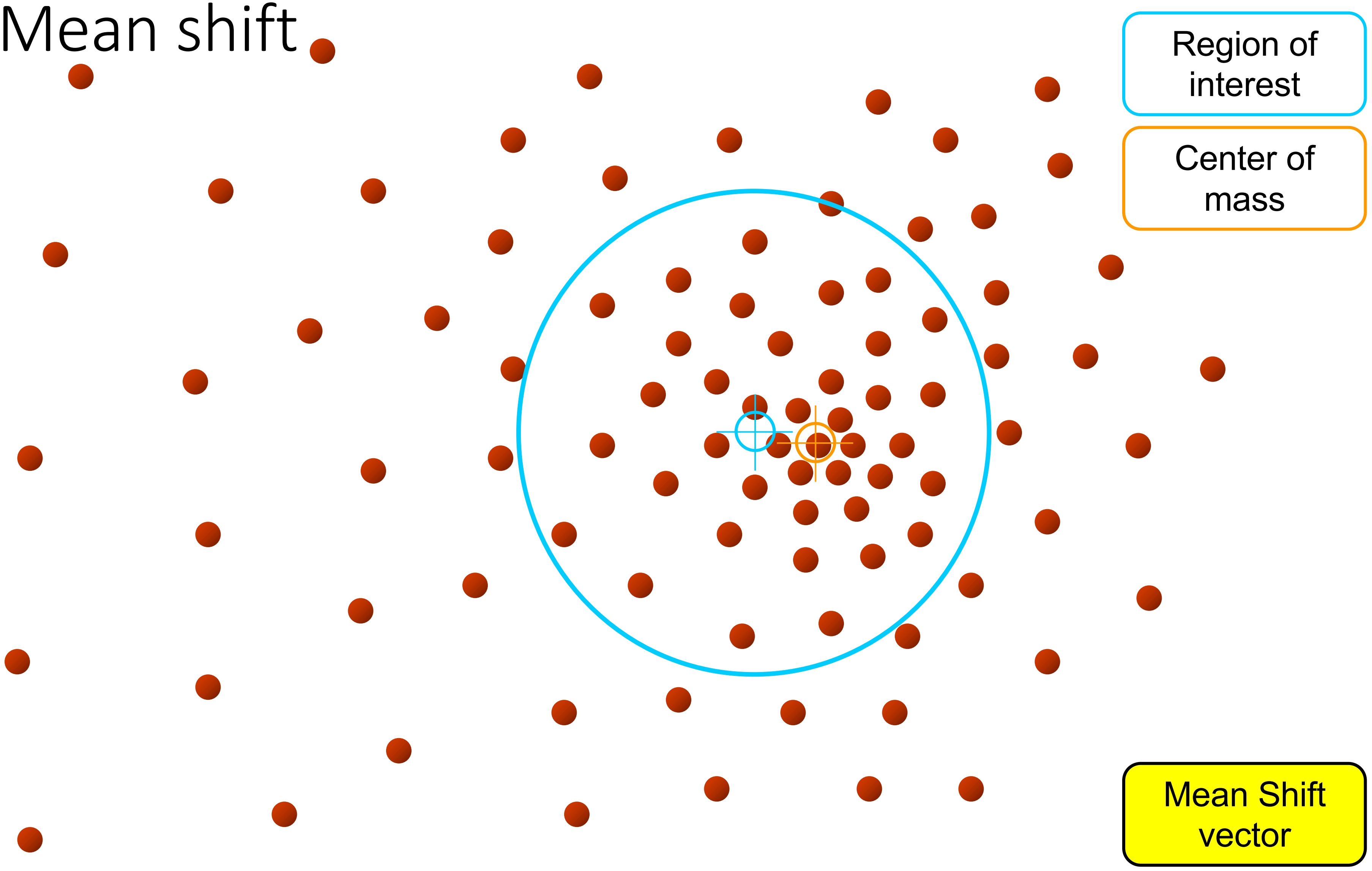
Mean shift



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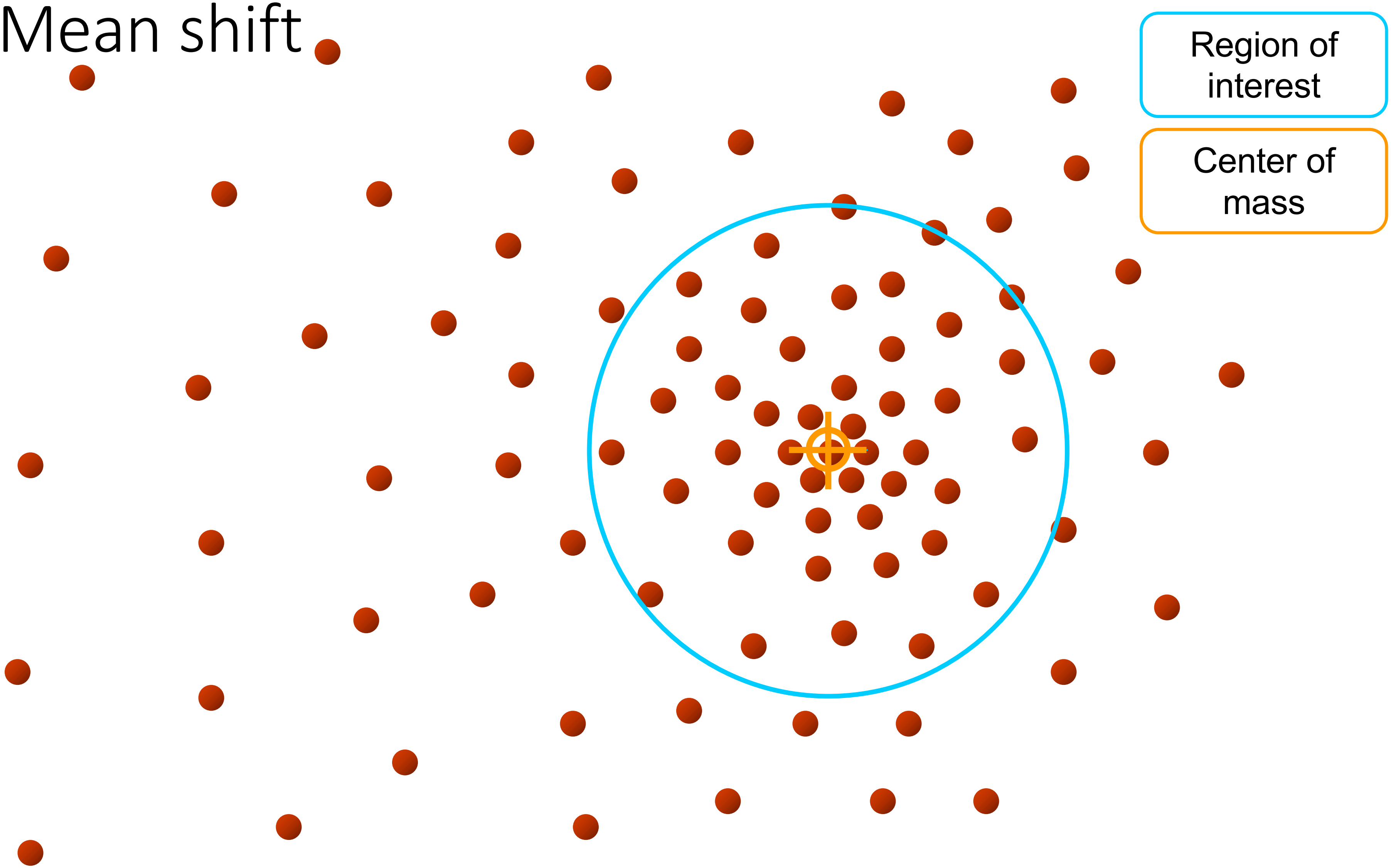
Mean shift



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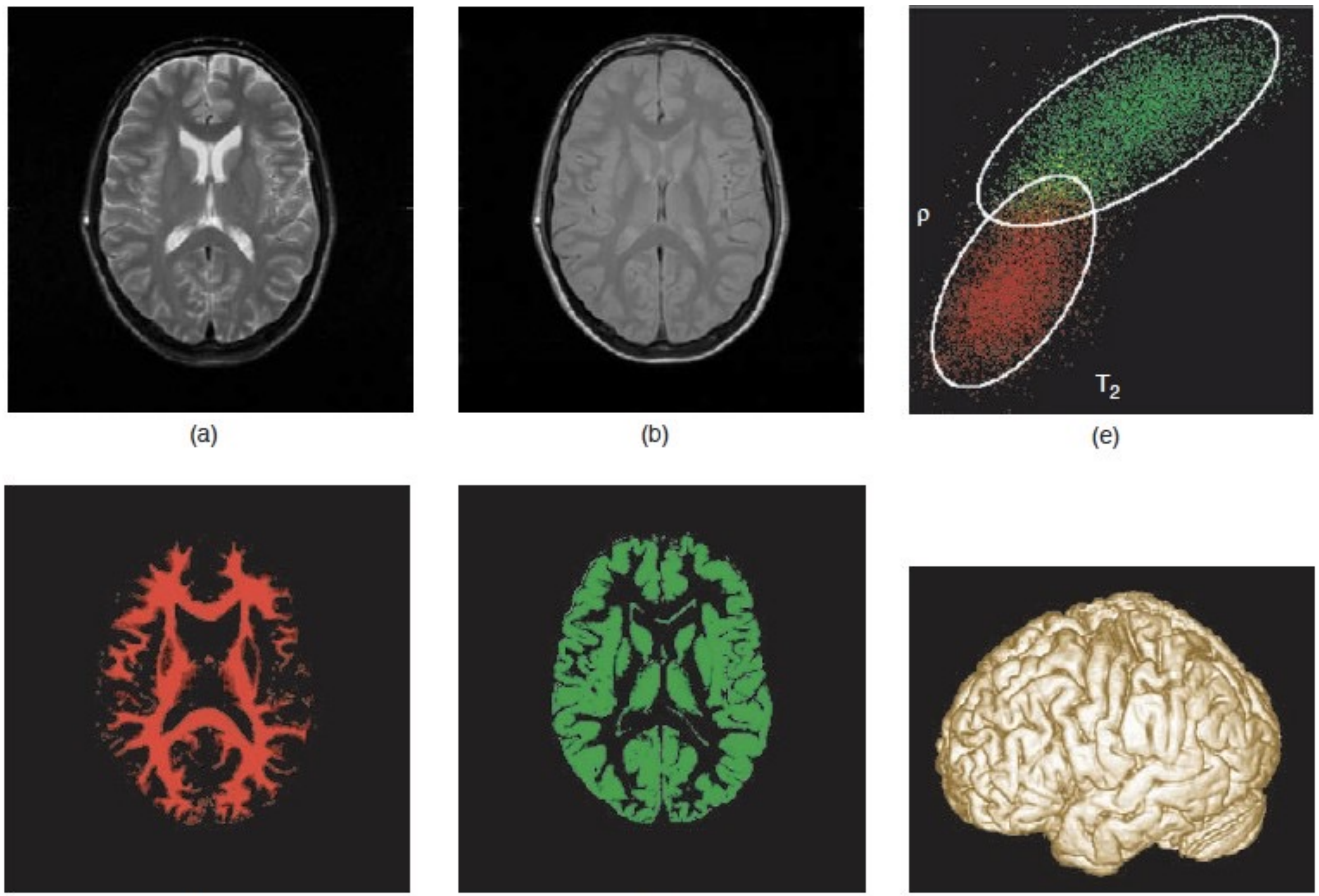
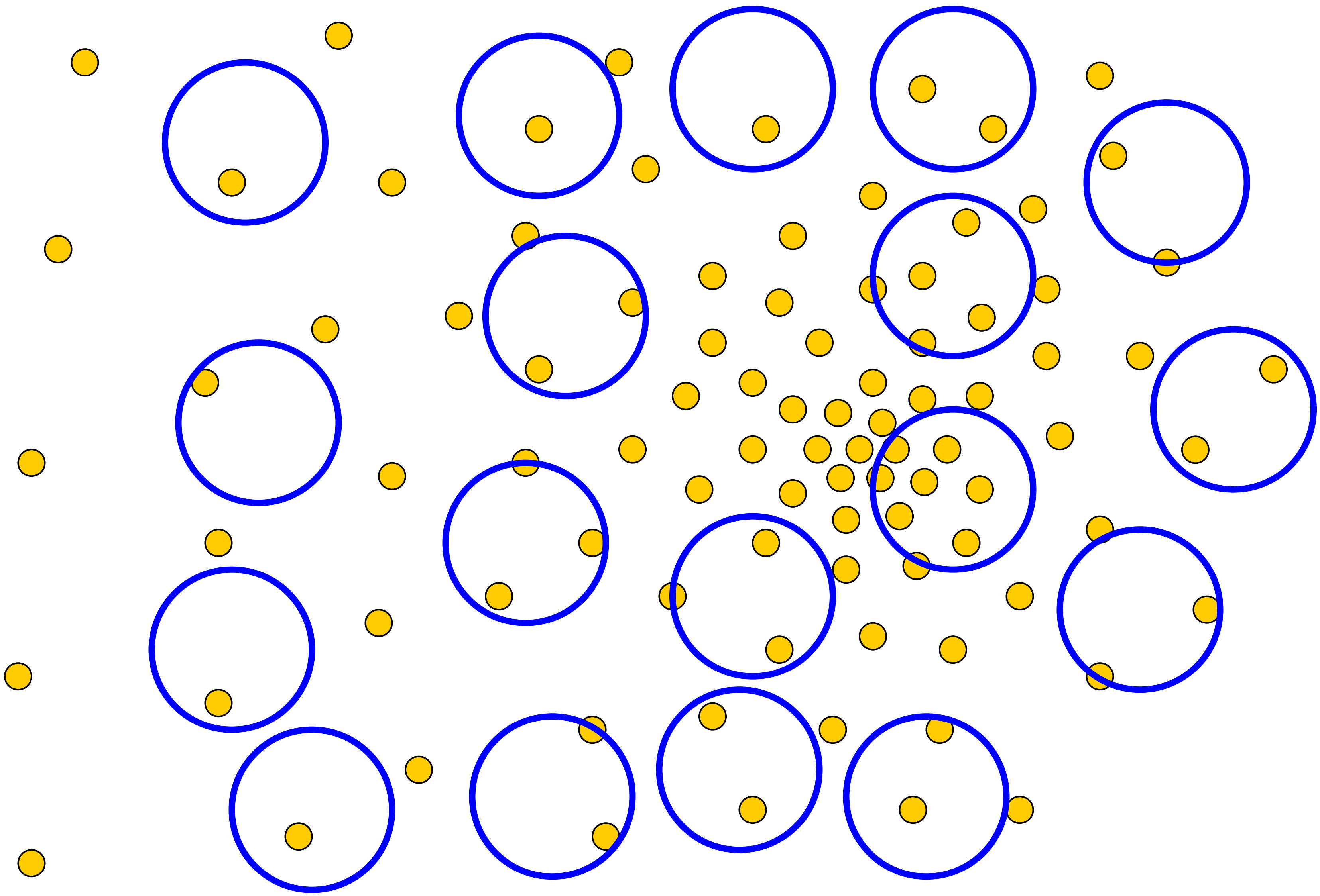
Applications in MR Brain Tissue Segmentation



(a) (b) (e)

(c) (d) (f)

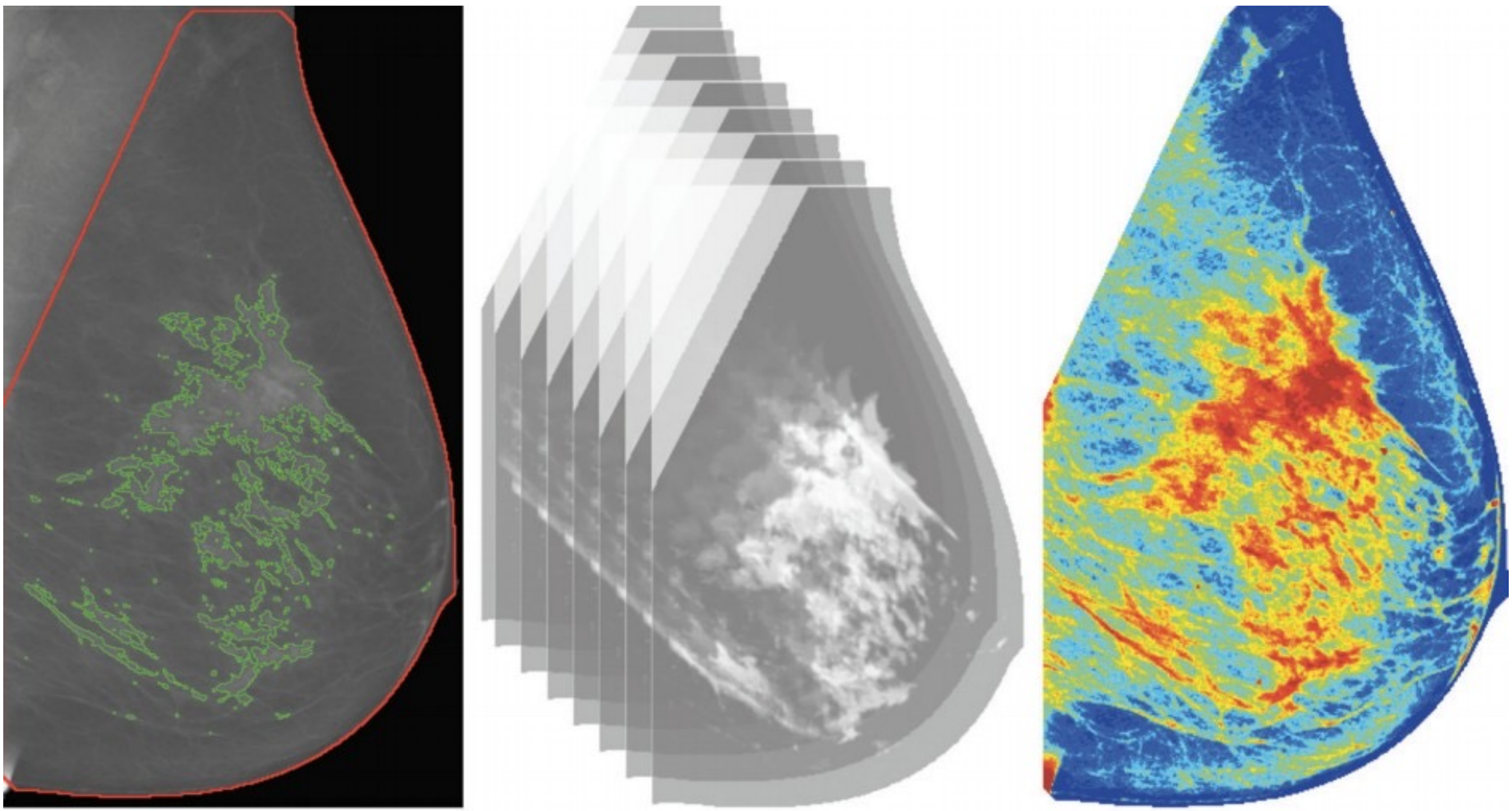
Real Modality Analysis



Multispectral/Multimodal Image Segmentation

- The segmentation techniques based on integration of information from several images are called multispectral or multimodal
- In multispectral images, each pixel is characterized by a set of features and the segmentation can be performed in multidimensional (multichannel) feature space using clustering algorithms

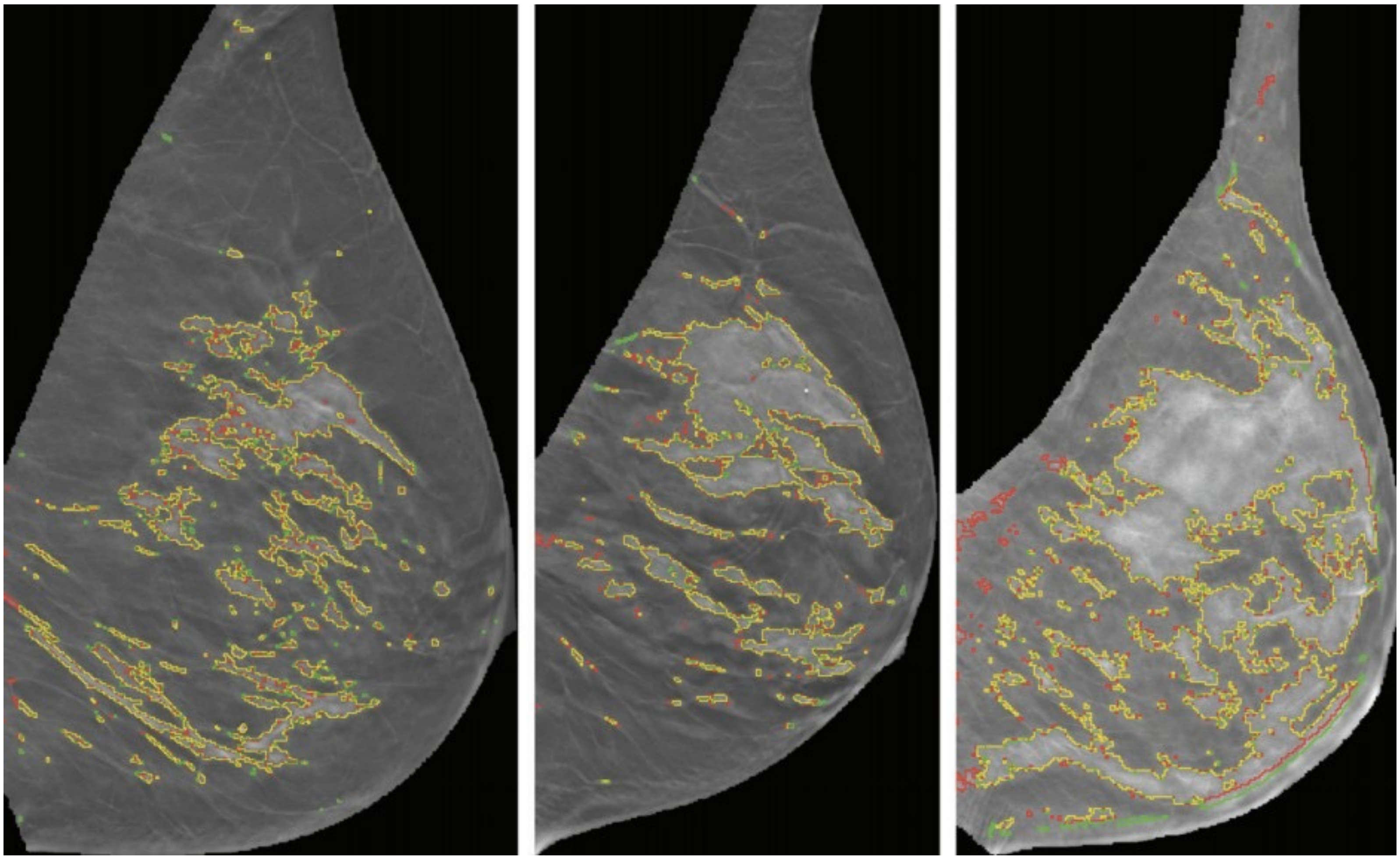
Quantitative Estimation of Volumetric Breast Tomosynthesis (3D Mammography) Images (Pertuz et al, Radiology 2015)



Quantitative Estimation of Volumetric Breast Tomosynthesis Images (Pertuz et al, Radiology 2015)

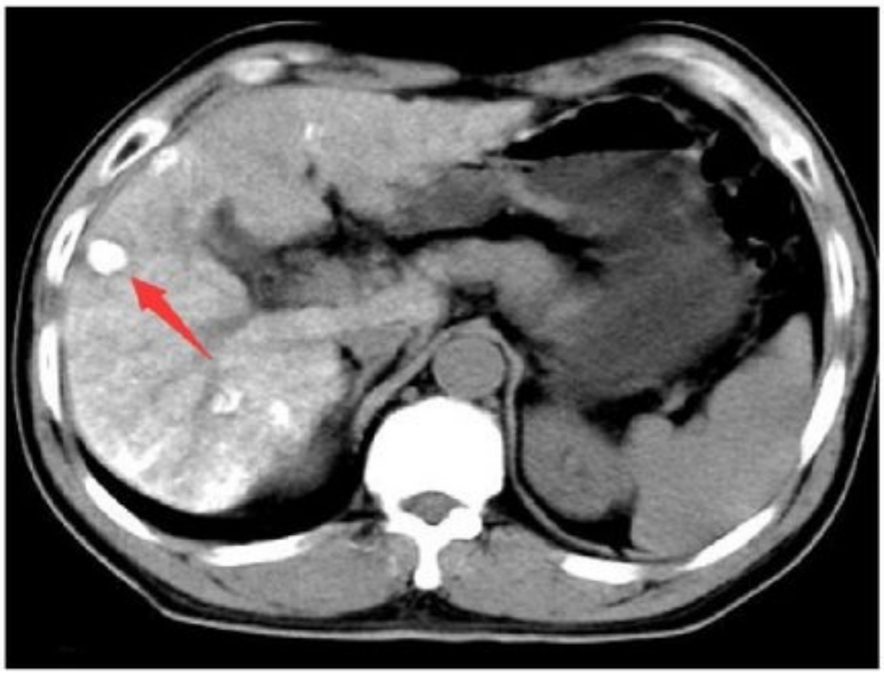
- Breast cancer is the most commonly diagnosed cancer in the United States and the second leading cause of death from cancer in women.
- Breast density is **an independent risk factor** for breast cancer
- Objective and accurate methods for the estimation of density are needed to ensure reliable estimation and, ultimately, yield quantitative reproducible measures that are clinically useful.
- Volume-based quantitative density methods, the aim is to better estimate the amount of fibroglandular (i.e., dense) tissue with respect to the total volume of the breast.

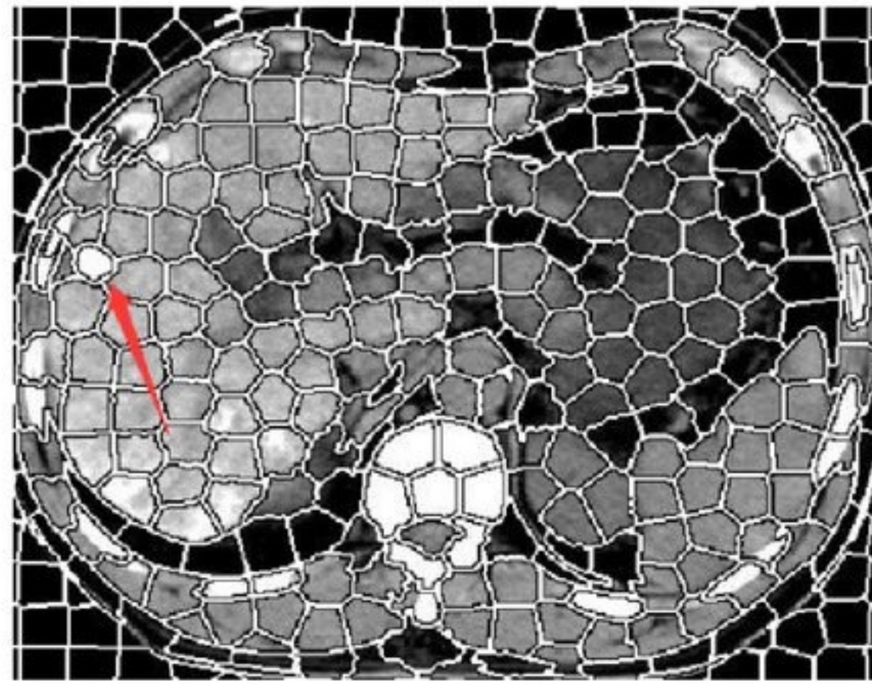
Quantitative Estimation of Volumetric Breast Tomosynthesis (3D Mammography) Images (Pertuz et al, Radiology 2015)

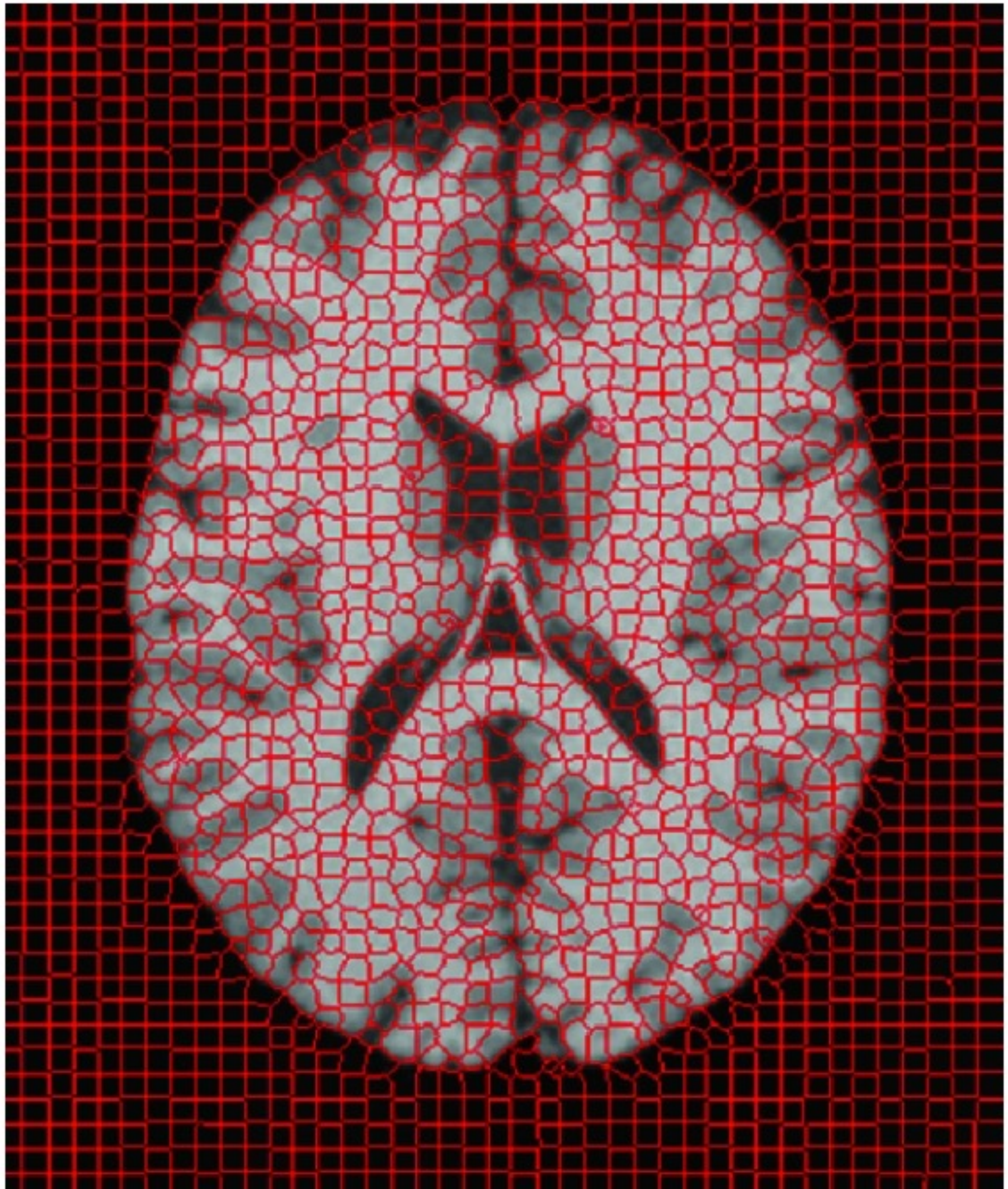


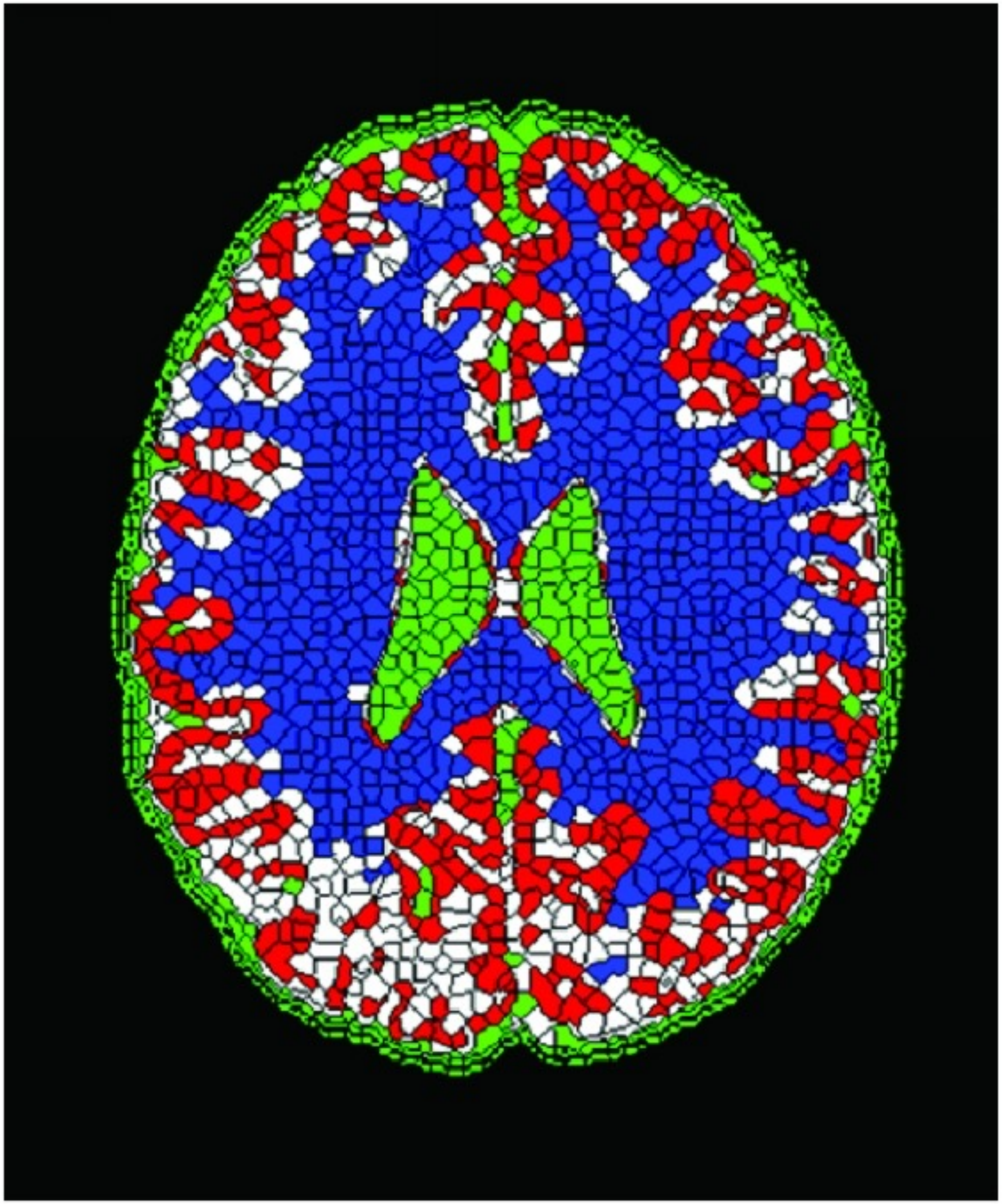
Red: human annotator, yellow: computer algorithm

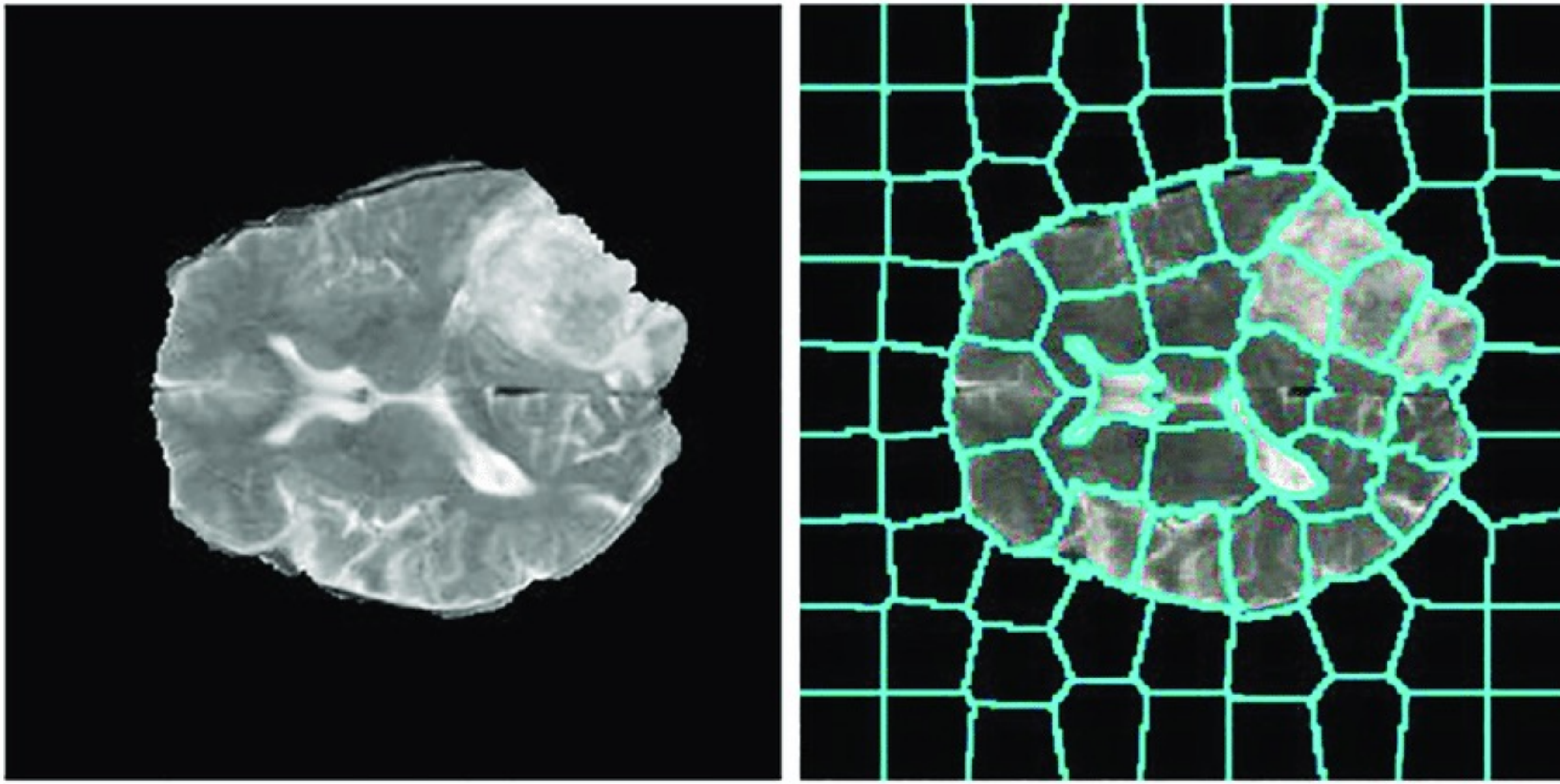
Superpixel Segmentation



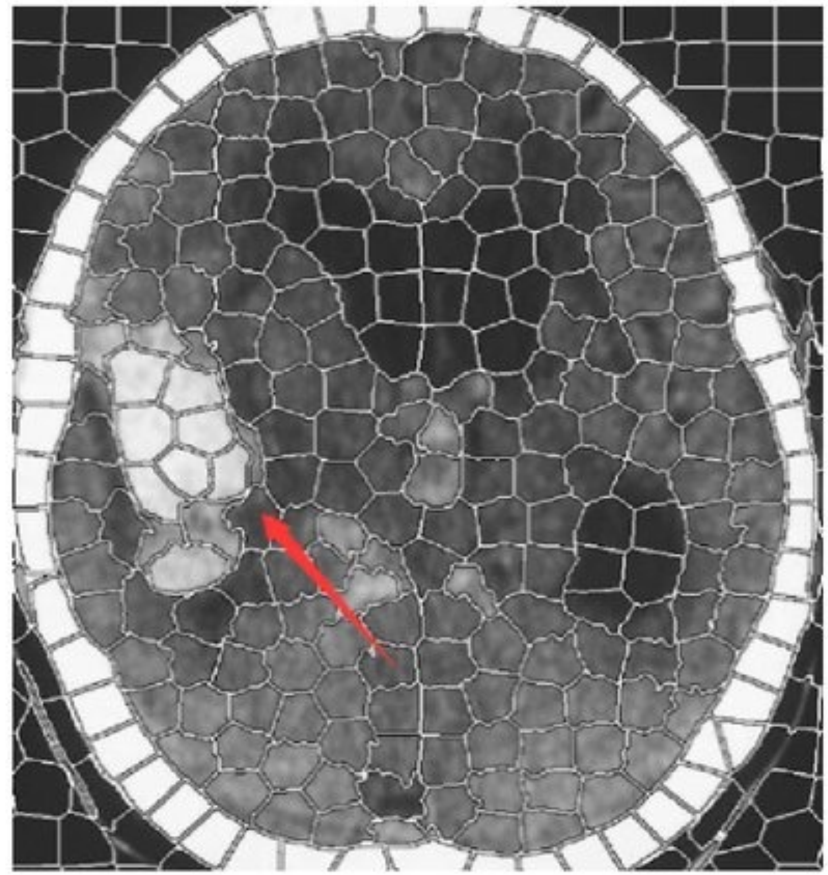




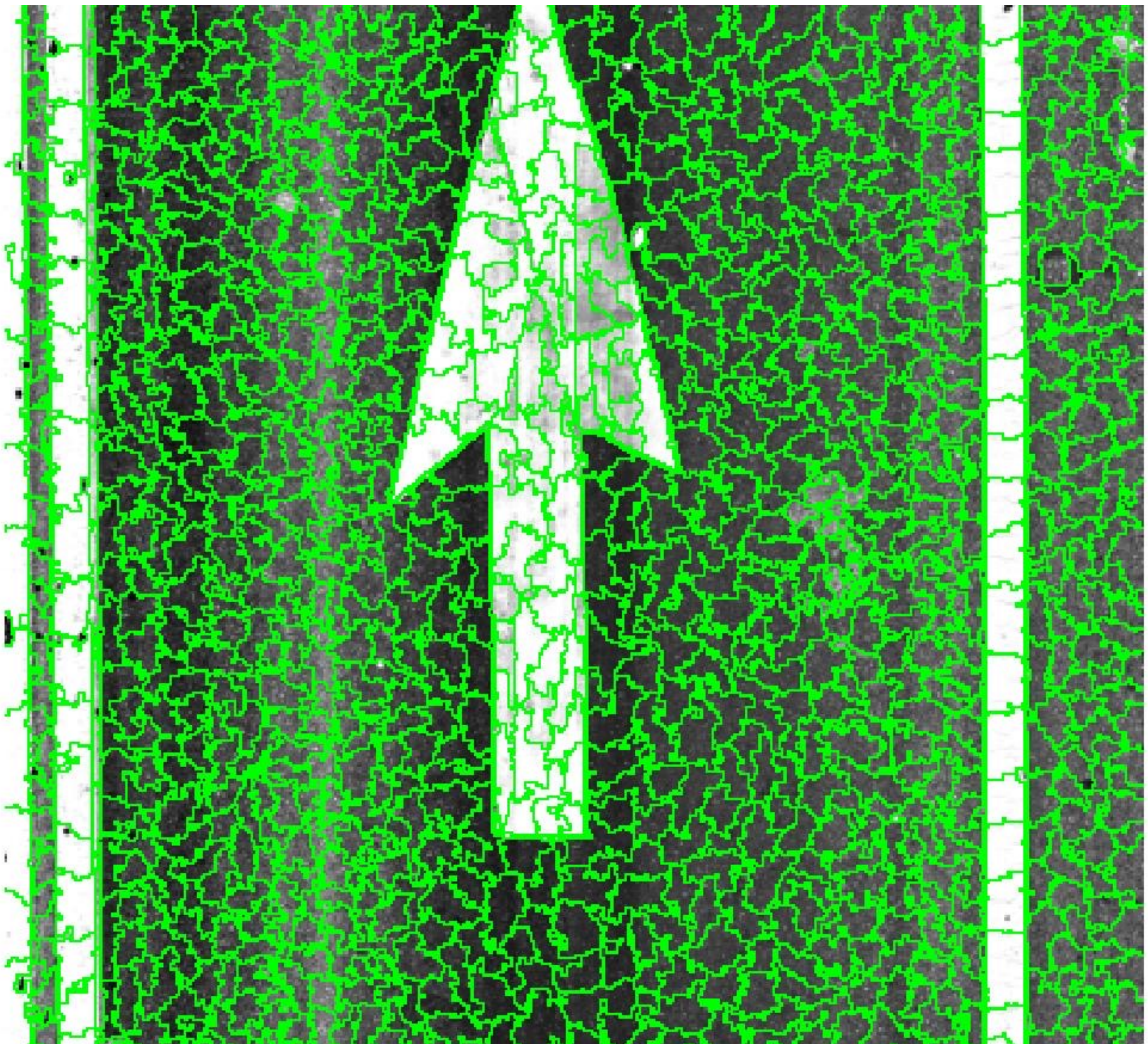


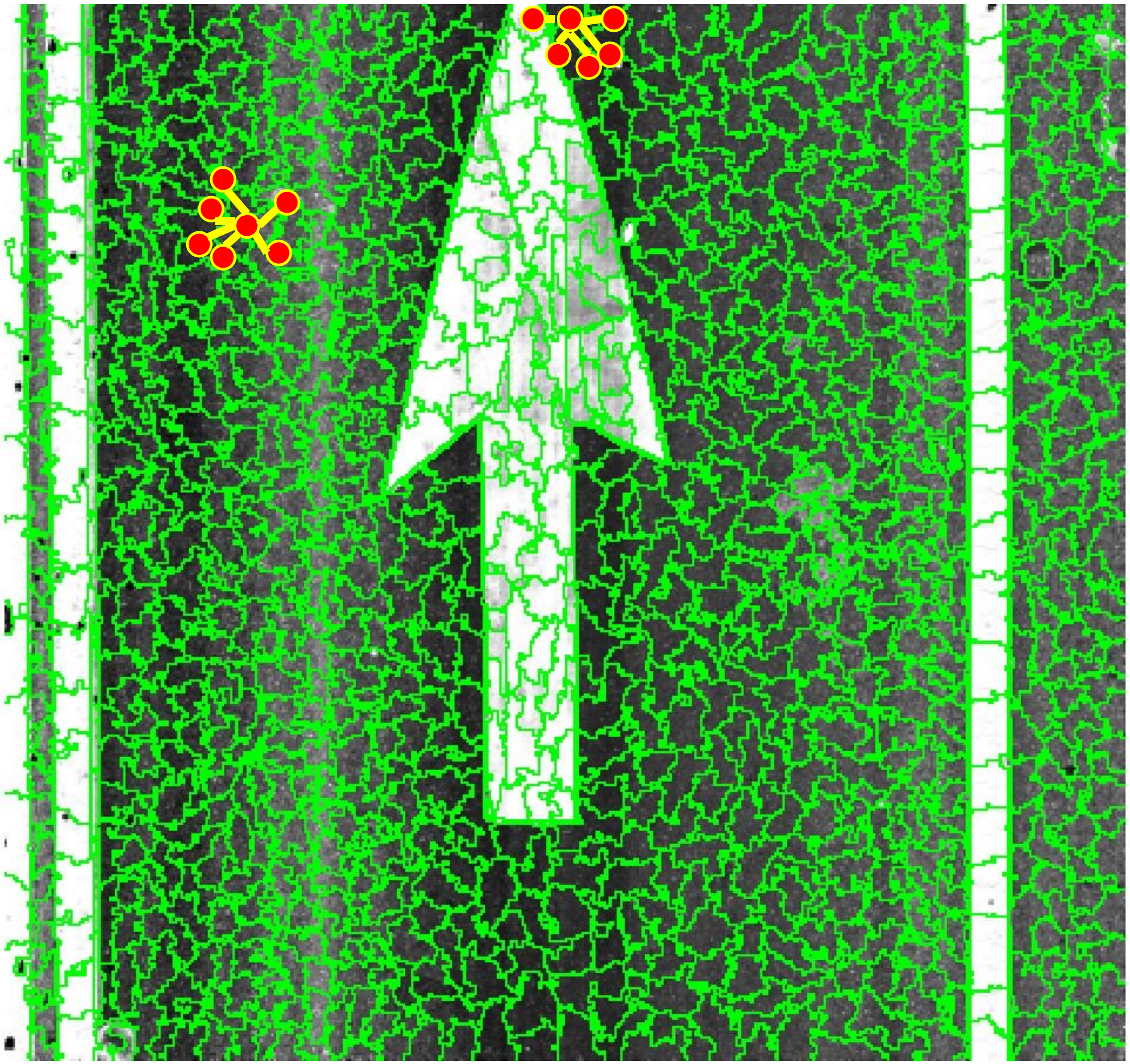


(a) (b)

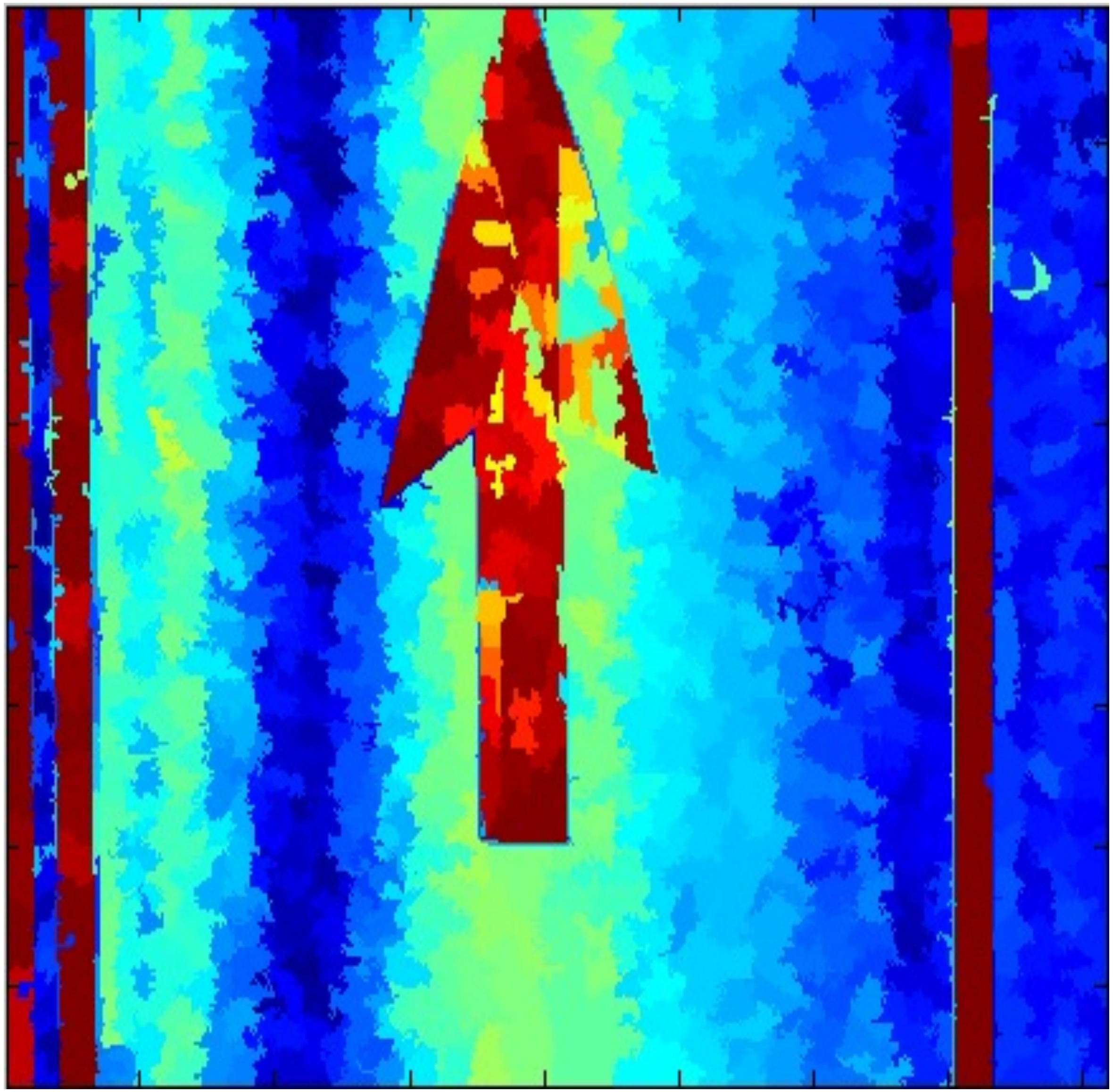


Graph-Cut Segmentation



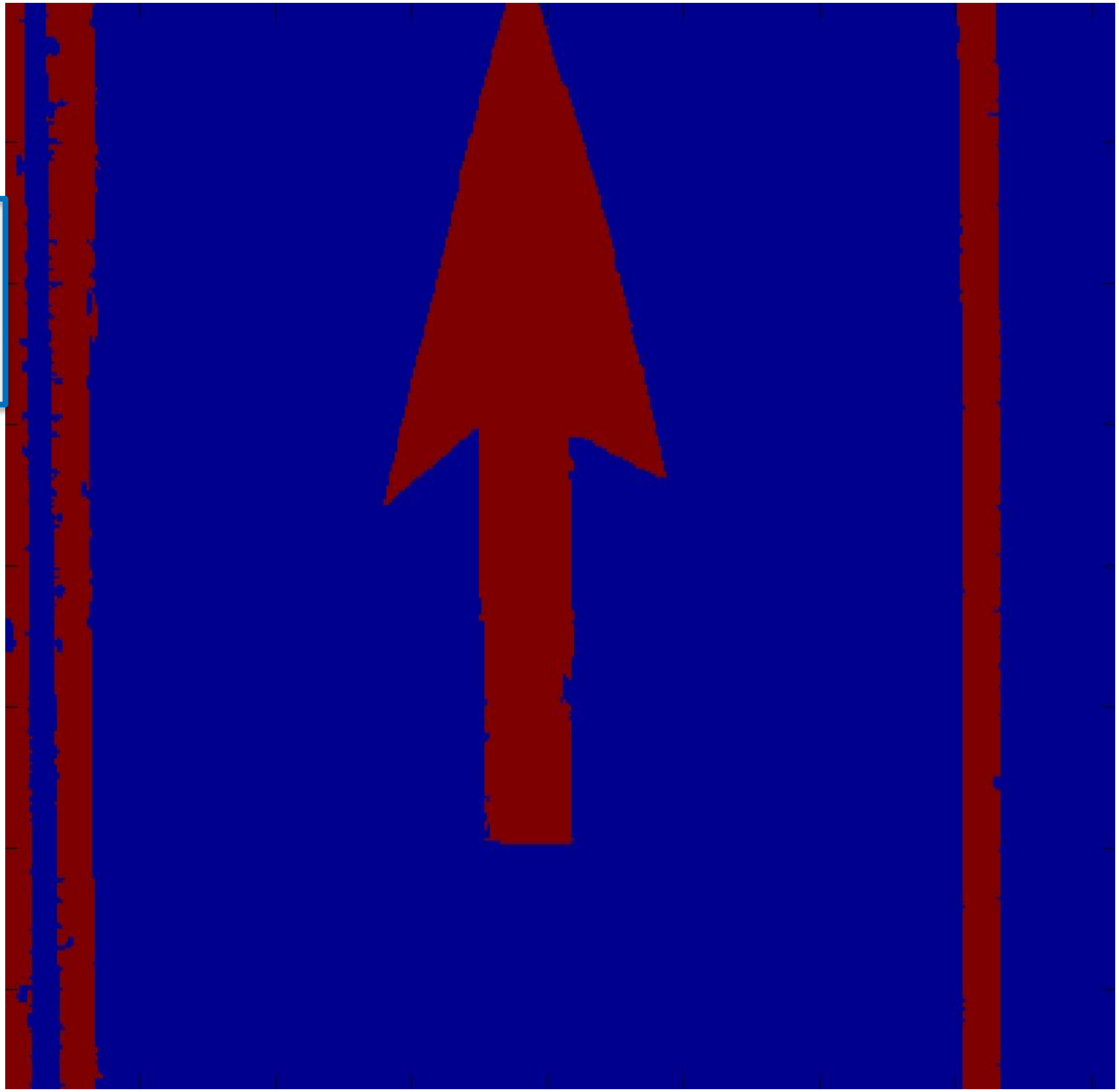


Superpixel
Object label



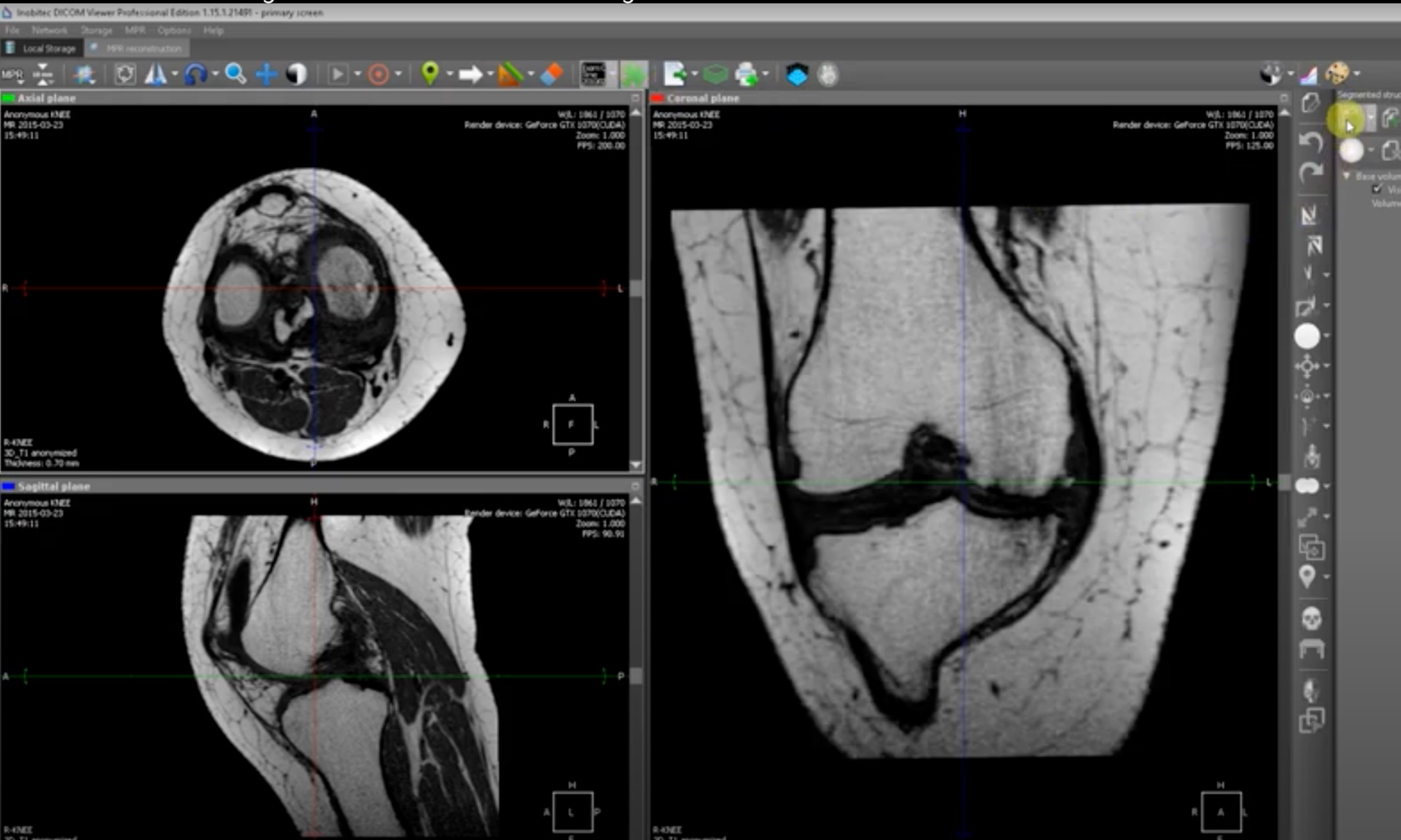
Superpixel
Object label

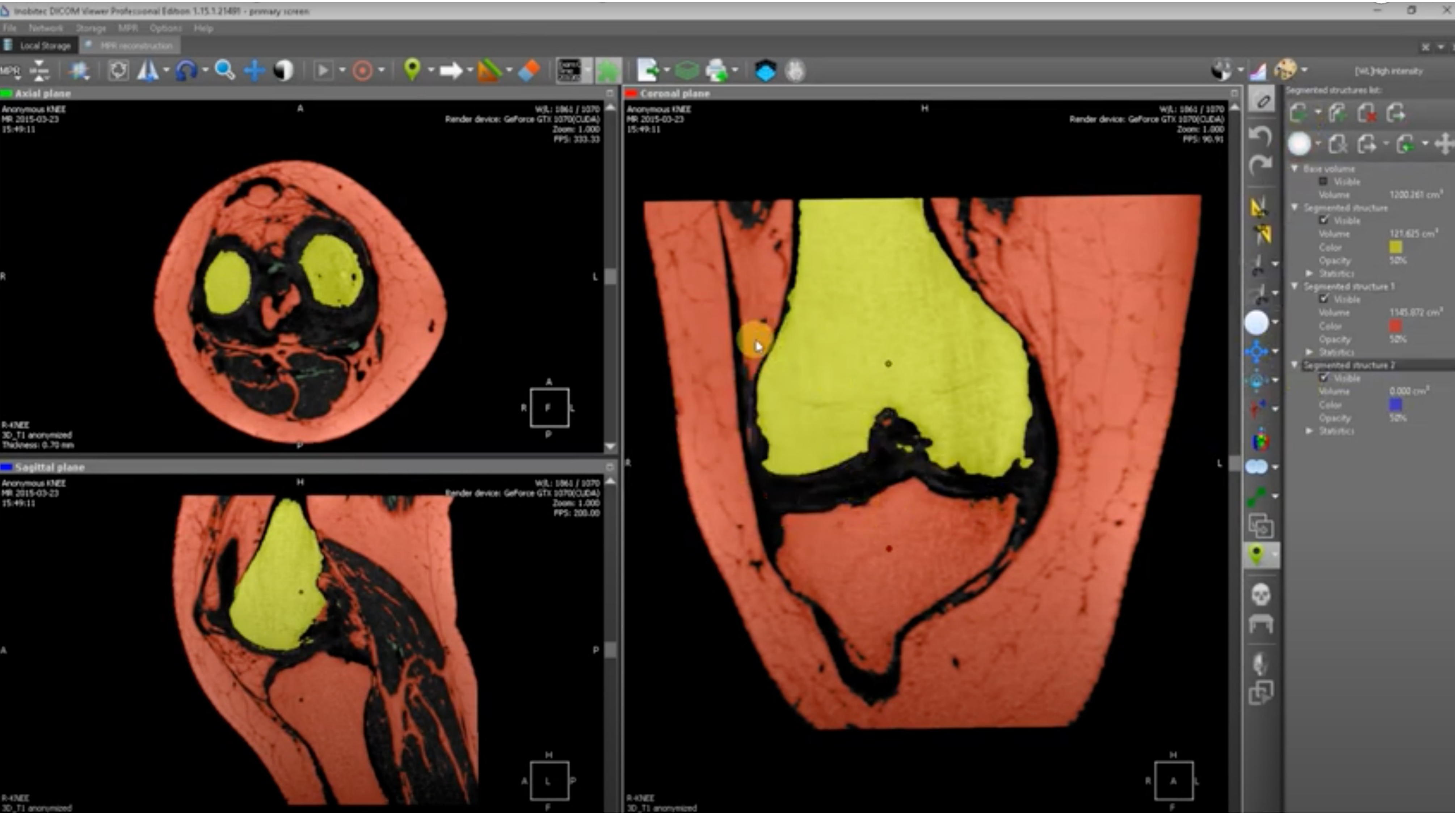
Incorporate
Neighborhood
Information

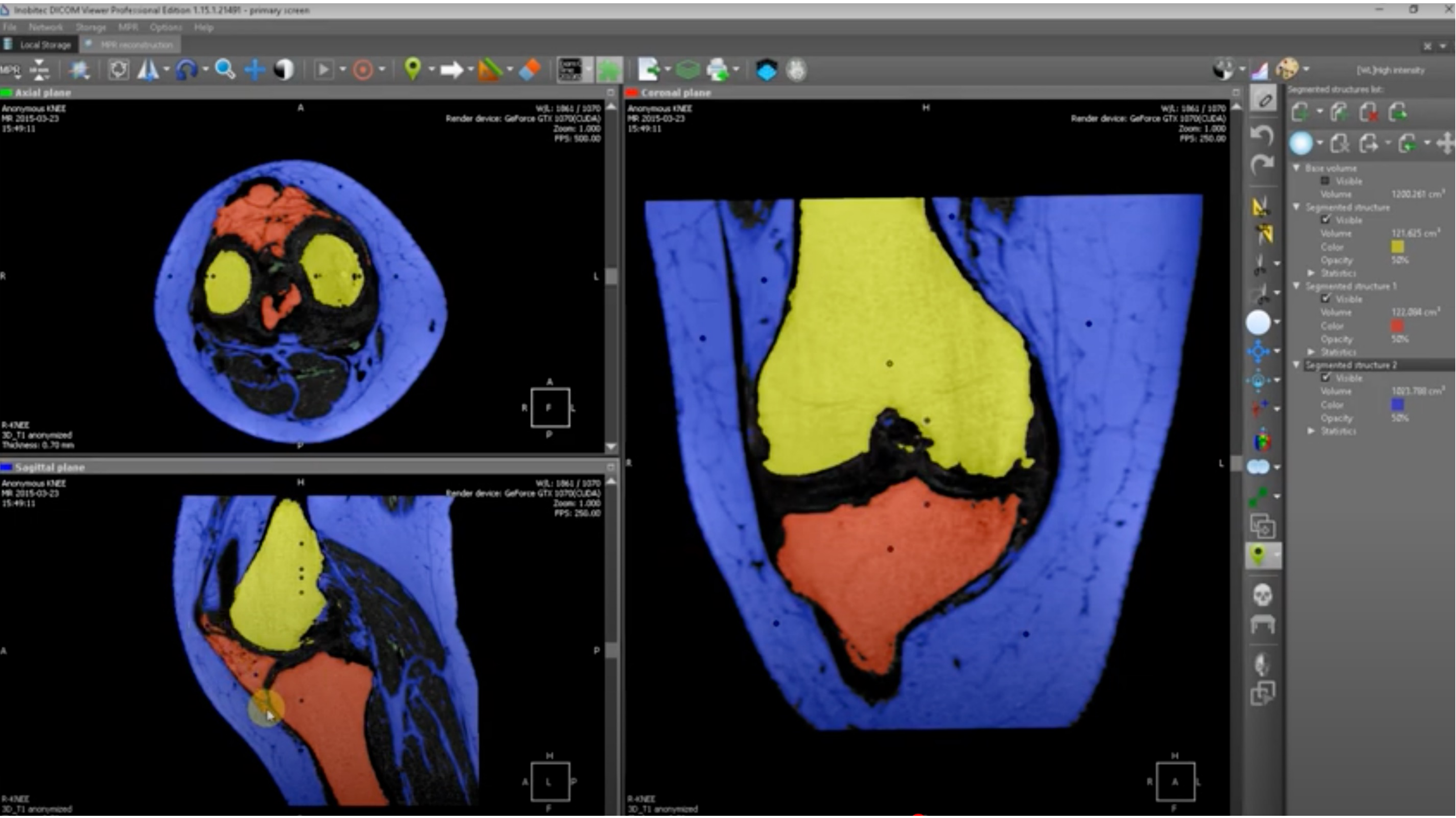


Interactive Segmentation

Marked watershed segmentation: MRI knee bones segmentation




Axial plane
Coronal plane
Sagittal plane
Anonymous KNEE
MR 2015-03-23
R-KNEE
3D_T1 anonymized
Segmented structures list:
Base volume
Segmented structure
Segmented structure 1
Segmented structure 2


Axial plane
Coronal plane
Sagittal plane
Anonymous KNEE
MR 2015-03-23
15:49:11
Render device: GeForce GTX 1070(CUDA)
R-KNEE
3D_T1 anonymized
Segmented structures list:
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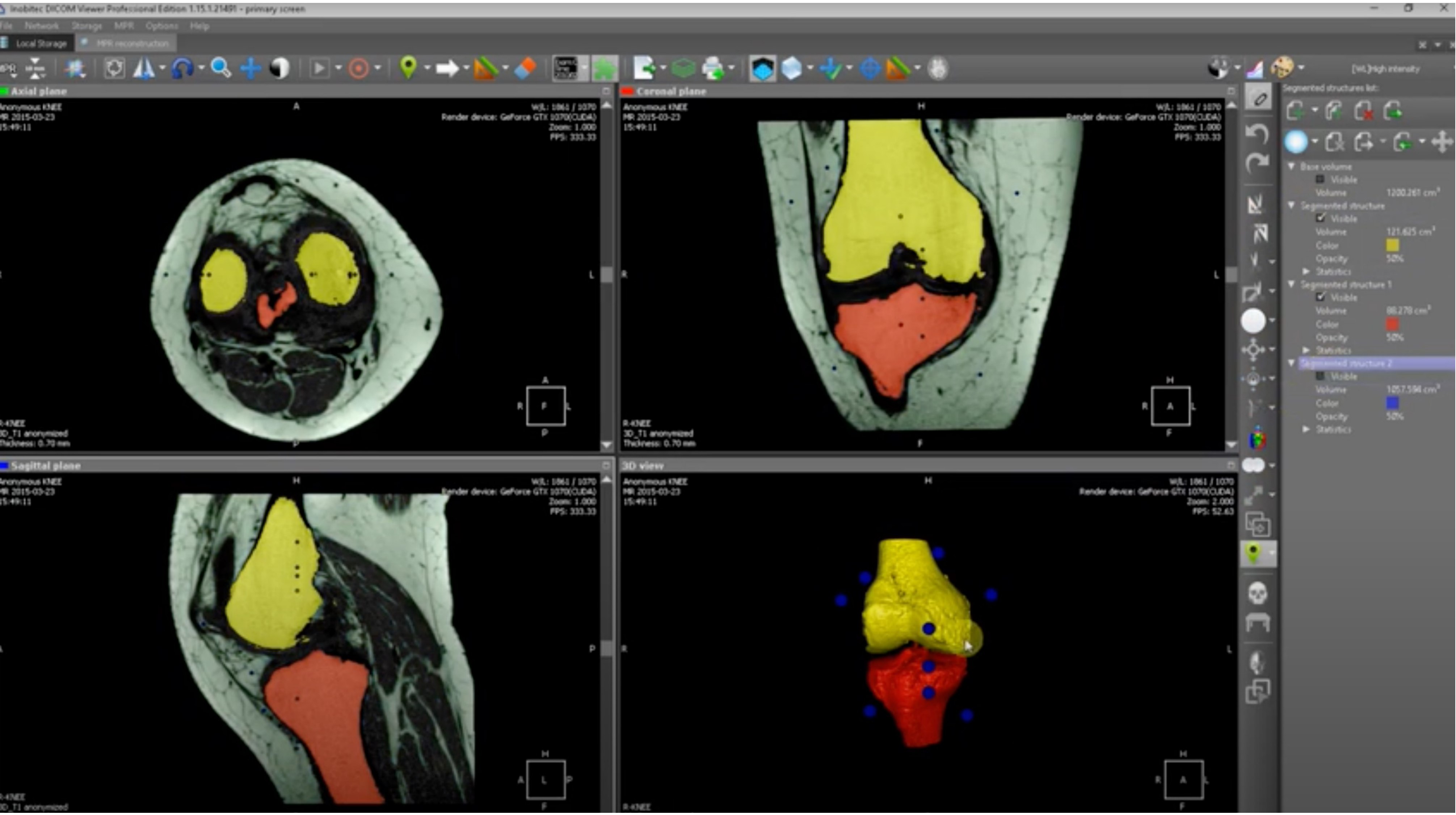
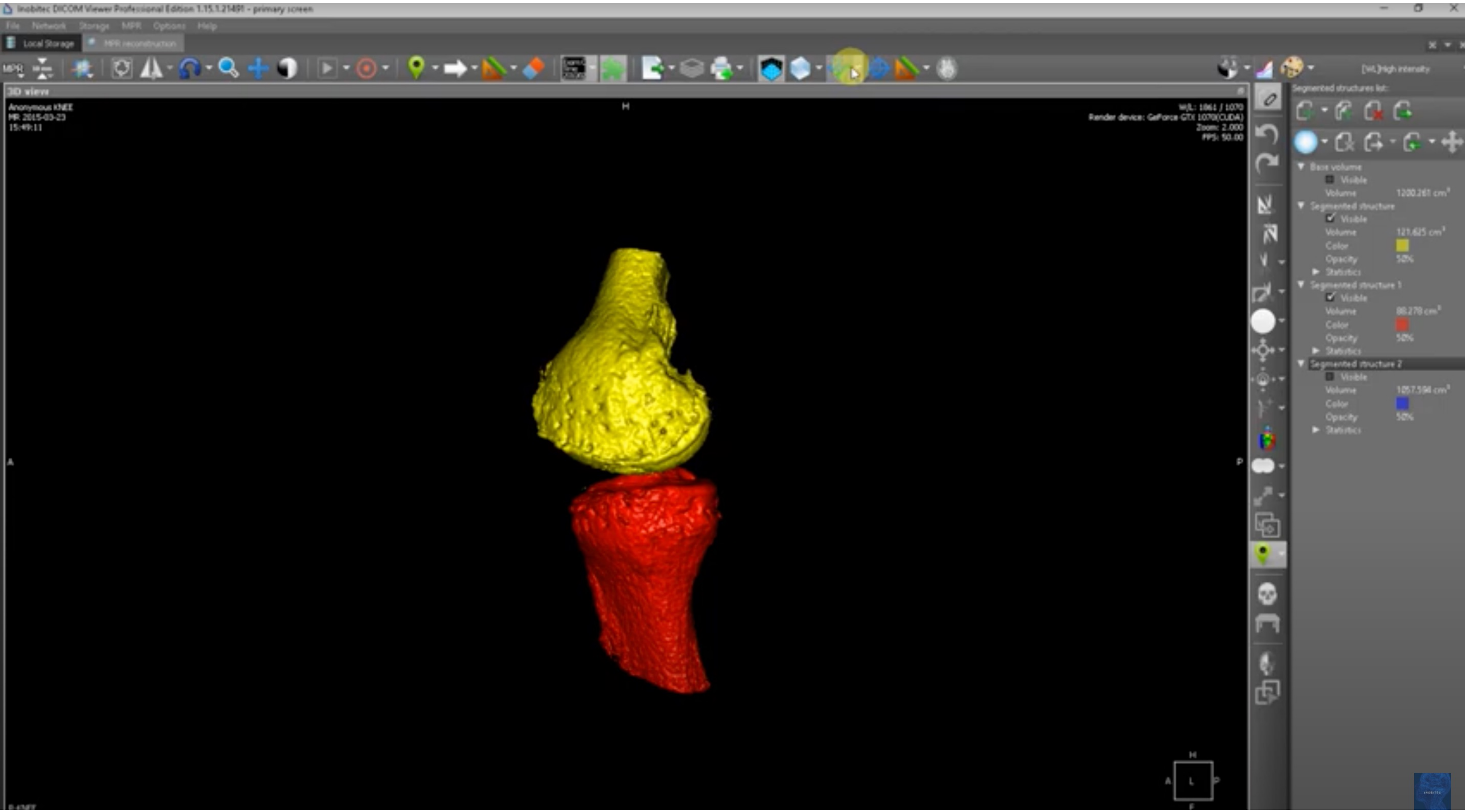
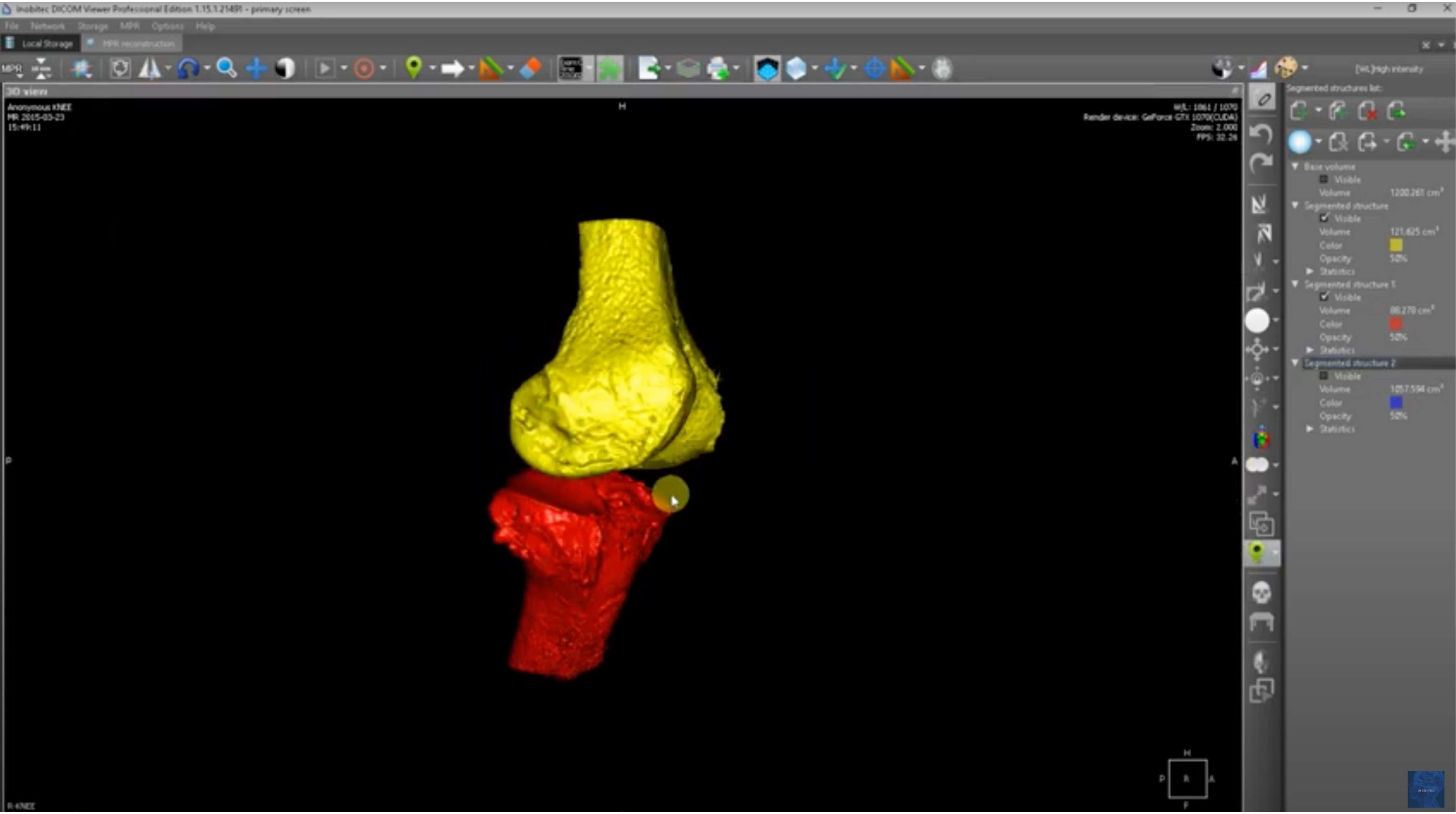
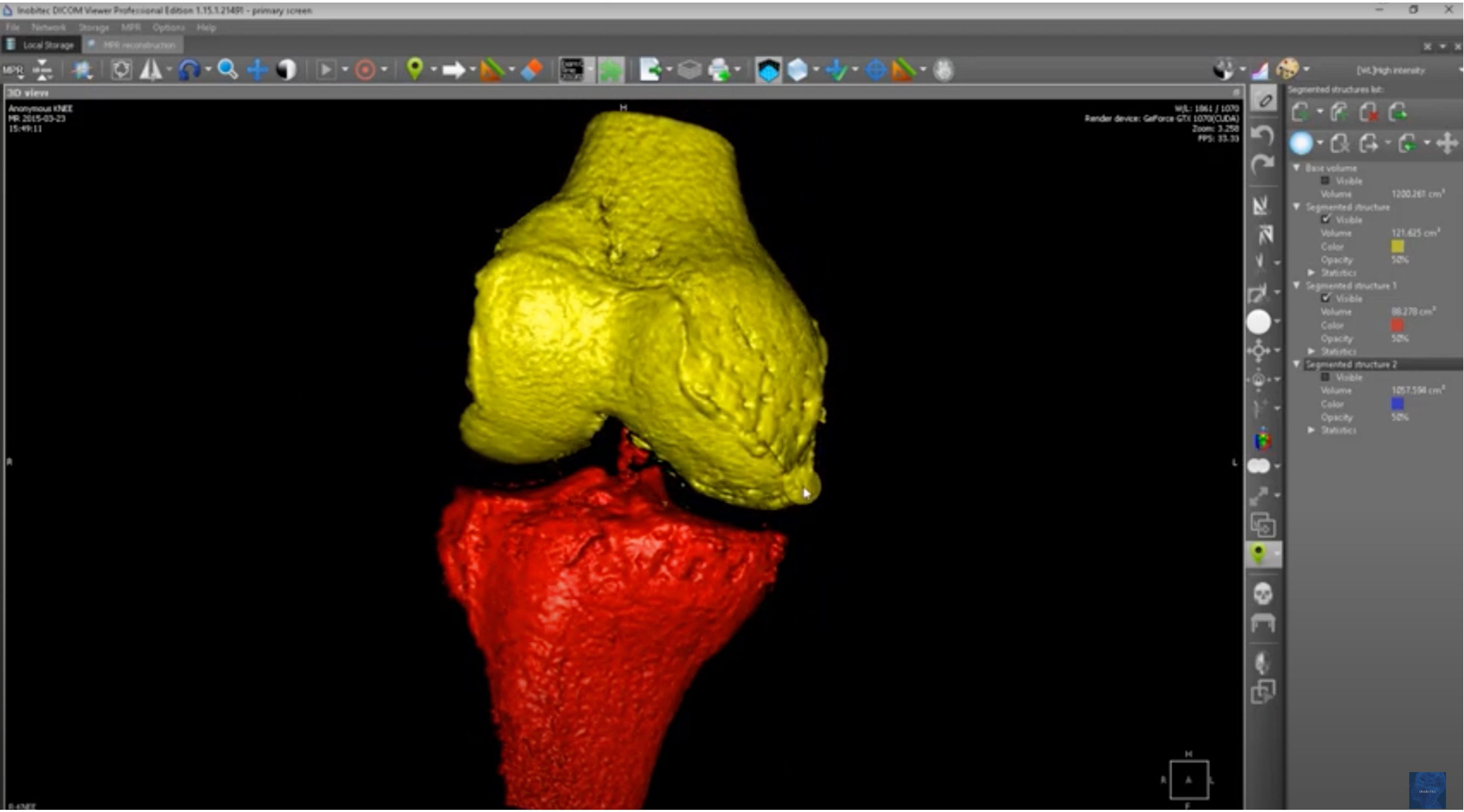
Segmented structure
Segmented structure 1
Segmented structure 2
Visible
Volume
Color
Opacity
Statistics

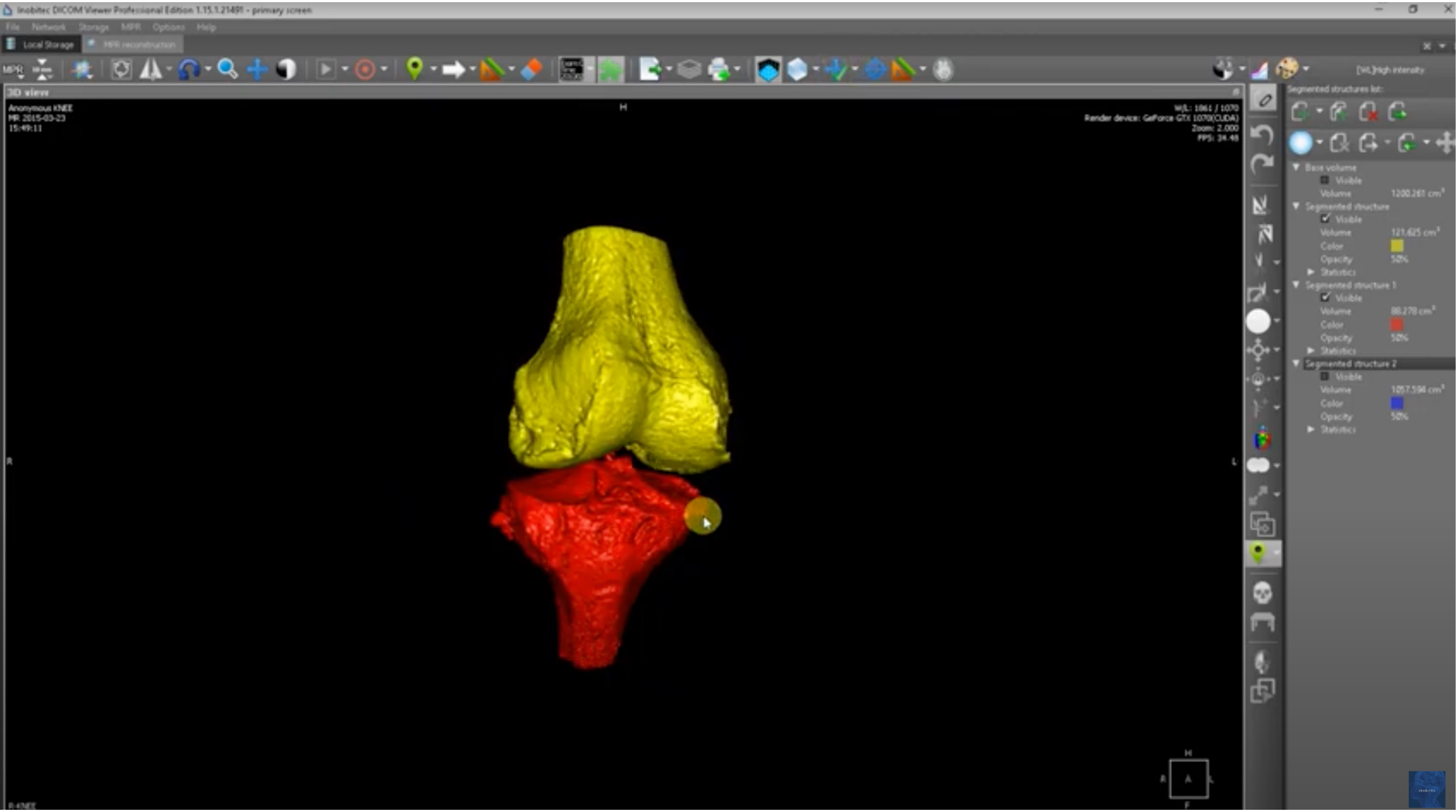

Axial plane
Coronal plane
Sagittal plane
3D view


Inobitec DICOM Viewer Professional Edition 1.15.1.21491 - primary screen
File
Network
Storage
MPR
Options
Help
Local Storage
MPR reconstruction
3D view
Anonymous KNEE
MR 2015-03-23
15:49:11
Segmented structures list:
Base volume
Visible
Volume 1200.261 cm³
Segmented structure
Visible
Volume 121.625 cm³
Color
Opacity 50%
Statistics
Segmented structure 1
Visible
Volume 88.278 cm³
Color
Opacity 50%
Statistics
Segmented structure 2
Visible
Volume 1057.598 cm³
Color
Opacity 50%
Statistics



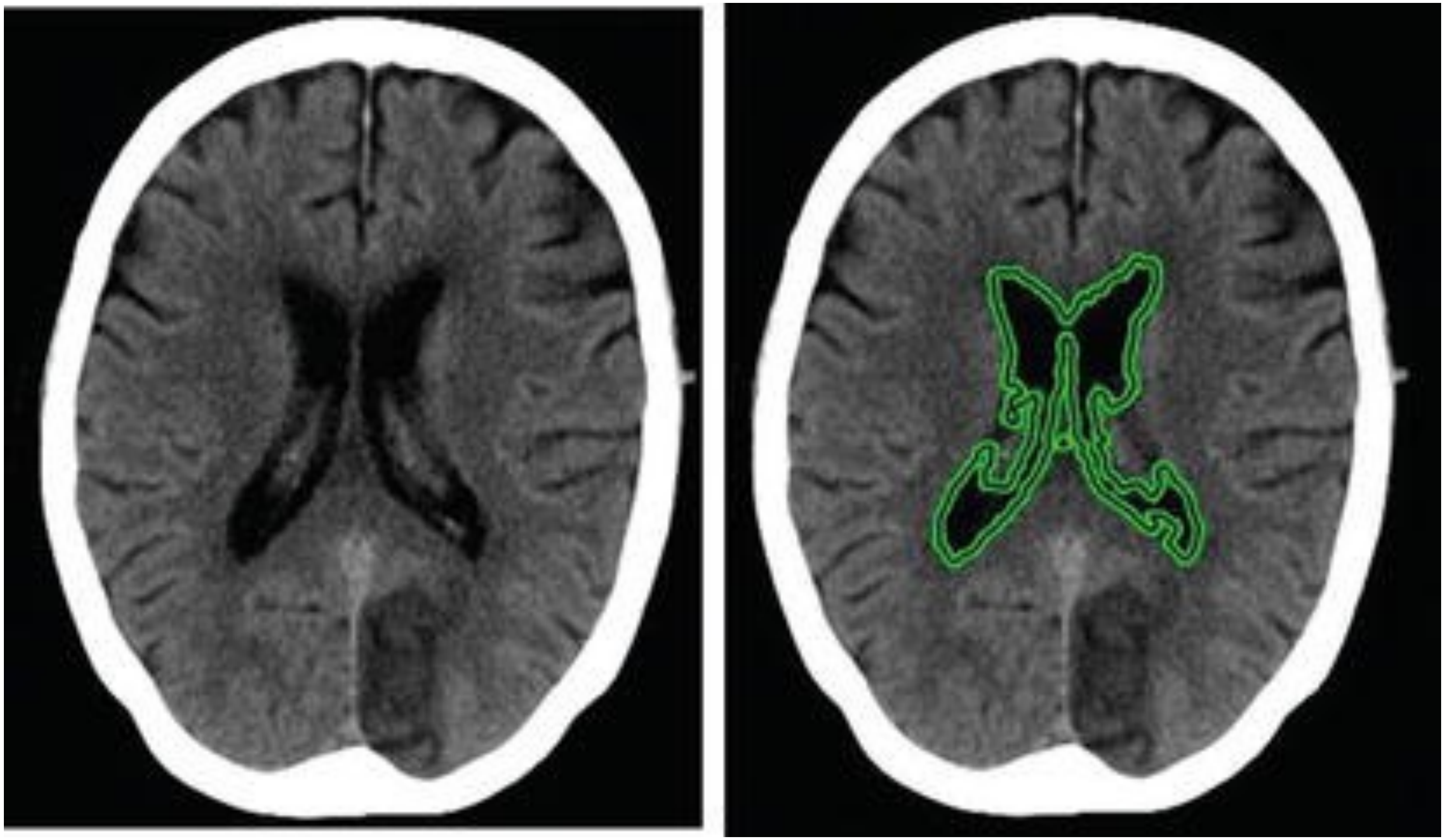
Inobitec DICOM Viewer Professional Edition 1.15.1.21491 - primary screen
File Network Storage MPR Options Help
Local Storage
MPR reconstruction
3D view
Anonymous KNEE
MR 2015-03-23
15:49:11
Segmented structures list:
Base volume
Visible
Volume
Segmented structure
Color
Opacity
Statistics
Segmented structure 1
Segmented structure 2


Inobitec DICOM Viewer Professional Edition 1.15.1.21491 - primary screen
File
Network
Storage
MPR
Options
Help
Local Storage
MPR reconstruction
3D view
Anonymous KNEE
MR 2015-03-23
15:49:11
W/L: 1861 / 1070
Render device: GeForce GTX 1070(CUDA)
Zoom: 3.250
FPS: 33.33
[WL]High intensity
Segmented structures list:
Base volume
Visible
Volume 1200.261 cm³
Segmented structure
Visible
Volume 121.625 cm³
Color
Opacity 50%
Statistics
Segmented structure 1
Visible
Color
Opacity 50%
Statistics
Segmented structure 2
Visible
Volume 1057.598 cm³
Color
Opacity 50%
Statistics


Inobitec DICOM Viewer Professional Edition 1.15.1.21491 - primary screen
File Network Storage MPR Options Help
Local Storage
MPR reconstruction
3D view
Anonymous KNEE
MR 2015-03-23
15:49:11
Render device: GeForce GTX 1070(CUDA)
Zoom: 2.000
Segmented structures list:
Base volume
Visible
Volume
Segmented structure
Visible
Volume
Color
Opacity
Statistics
Segmented structure 1
Visible
Volume
Color
Opacity
Statistics
Segmented structure 2
Visible
Volume
Color
Opacity
Statistics

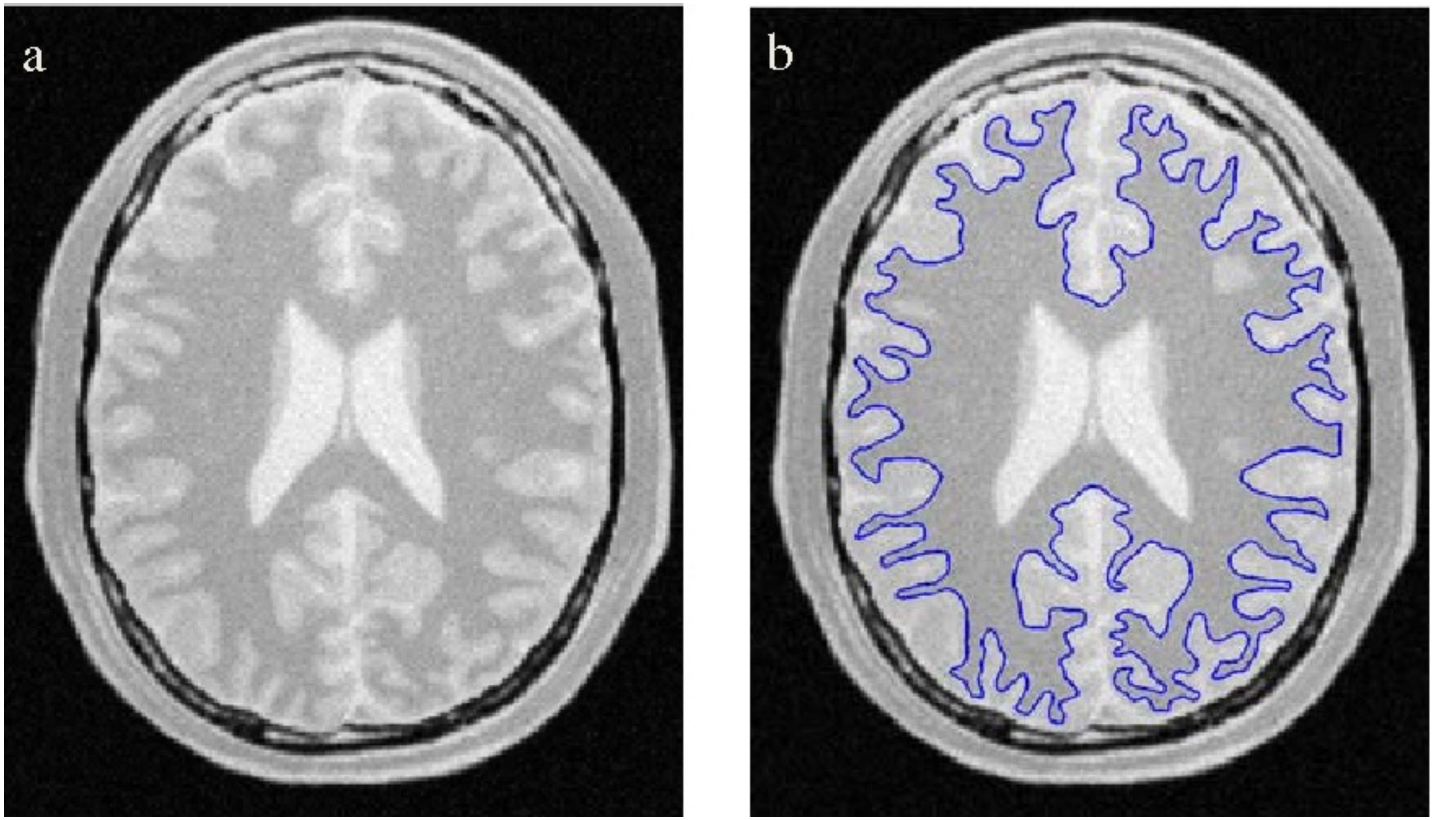
Interactive Segmentation

Active Contours



Interactive Segmentation

Active Contours

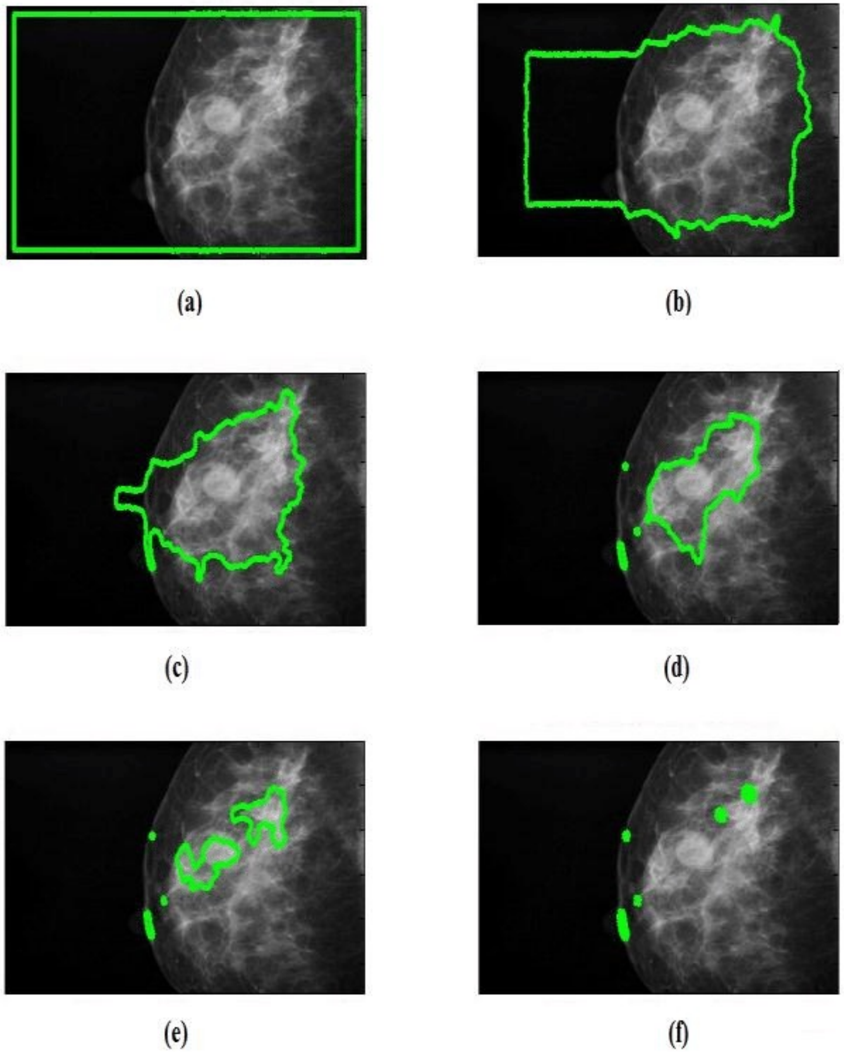


Interactive Segmentation

Active Contours

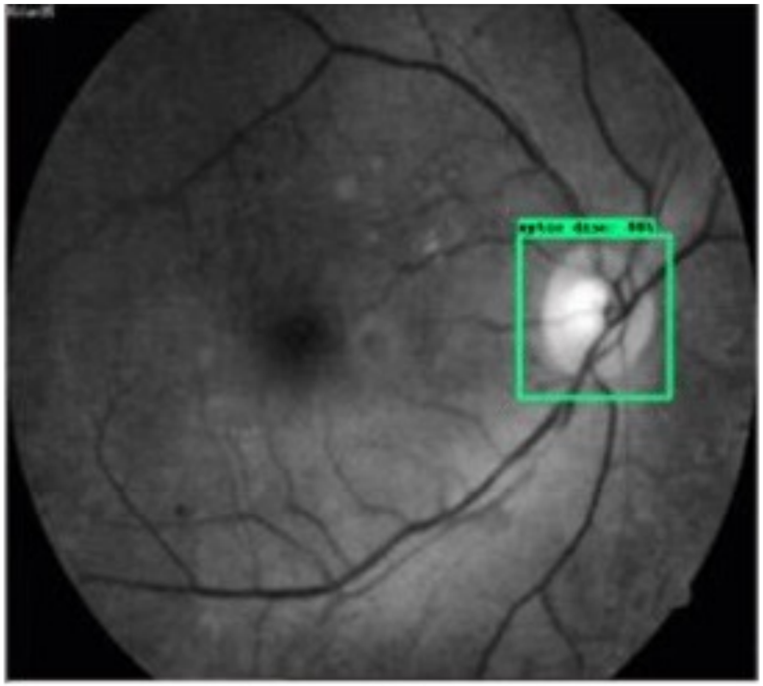
Interactive Segmentation

Active Contours (Failure case)



Interactive Segmentation

Grab Cut



GrabCut is an image segmentation method based on graph cuts.
Starting with a user-specified bounding box around the object to be segmented, the algorithm estimates the color distribution of the target object and that of the background using a Gaussian mixture model. This is used to construct a Markov random field over the pixel labels, with an energy function that prefers connected regions having the same label, and running a graph cut based optimization to infer their values.

References and Slide Credits

- Jayaram K. Udupa, MIPG of University of Pennsylvania, PA.
- P. Suetens, Fundamentals of Medical Imaging, Cambridge Univ. Press.
- N. Bryan, Intro. to the science of medical imaging, Cambridge Univ. Press.
- CAP 5415 Computer Vision (Fall 2016) Lecture Presentations
- Computer Vision (Lecture Presentations) by Dr. Mohsen Ali