Computer Vision

CSC-455

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Image Segmentation Algorithms (Techniques)

- Thresholding: Global vs Adaptive.
- Region Growing
- Region Splitting and Merging
- Cluster Analysis:

  k-Mean Clustering
  k-Mode Clustering
  Hierarchical Clustering
  Fuzzy C-Mean Clustering
  Mean Shift Segmentation

Image Segmentation

- Group similar components (such as, pixels in an image, image frames in a video)
- Applications: Finding tumors, veins, etc. in medical images, finding targets in satellite/aerial images, finding people in surveillance images, summarizing video, etc.

Image Segmentation

- **Segmentation algorithms are based on one of two basic properties of gray-scale values:**
  - **Discontinuity**
    - **Partition an image based on abrupt changes in gray-scale levels.**
    - **Detection of isolated points, lines, and edges in an image.**
  - **Similarity**
    - **Thresholding, region growing, and region splitting/merging.**

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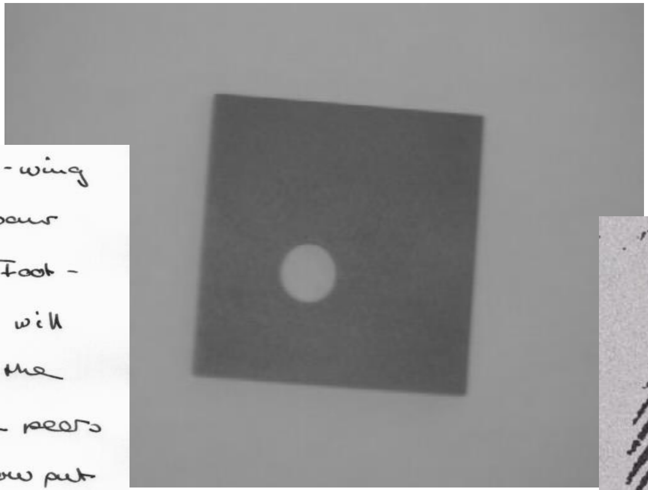
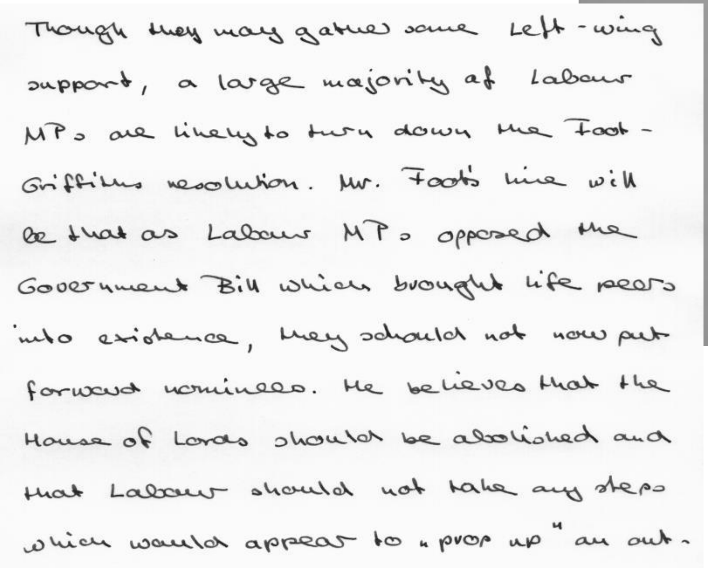
Thresholding

- Segmentation into two classes/groups
  - Foreground (Objects)
  - Background





Though they may gather some Left-wing
support, a large majority of Labour
MPs are likely to turn down the Foot-
Griffiths resolution. Mr. Foot's line will
be that as Labour MPs opposed the
Government Bill which brought life peers
into existence, they should not now put
forward nominees. He believes that the
House of Lords should be abolished and
that Labour should not take any steps
which would appear to "prop up" an out-

Thresholding

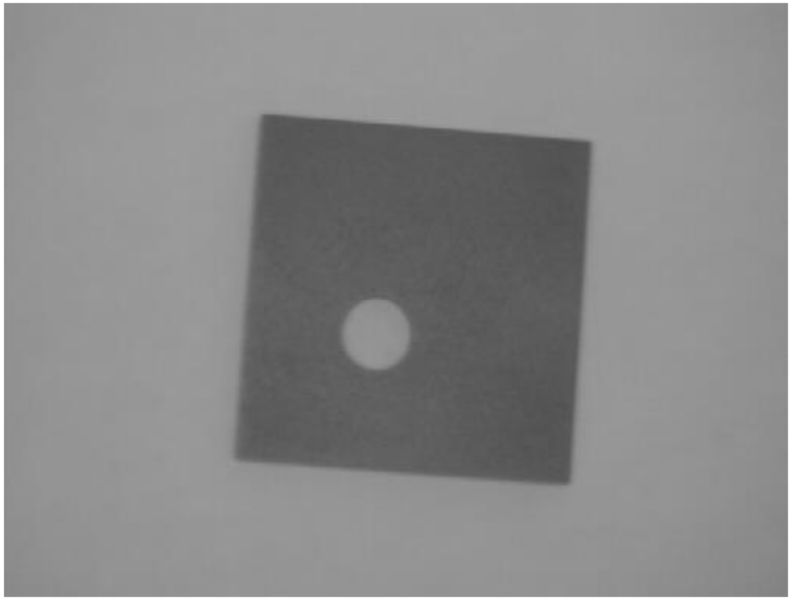
$$g(x, y) = \begin{cases} 1 & \text{if} \;\; f(x, y) > T \\ 0 & \text{if} \;\; f(x, y) \leq T \end{cases}$$

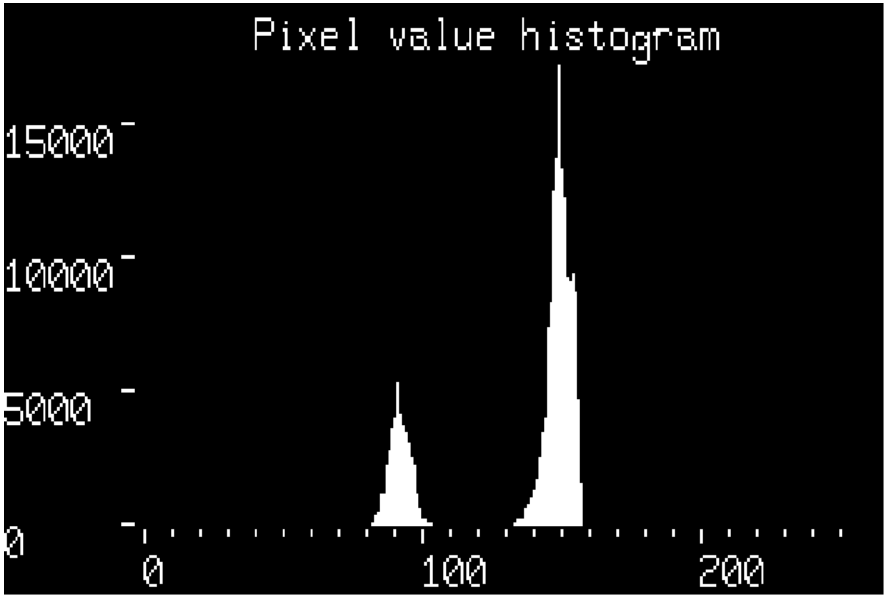
Objects & Background

- Global Thresholding
- Local/Adaptive Thresholding

Global Thresholding

- Single threshold value for entire image
- Fixed ?
- Automatic
  - Intensity histogram





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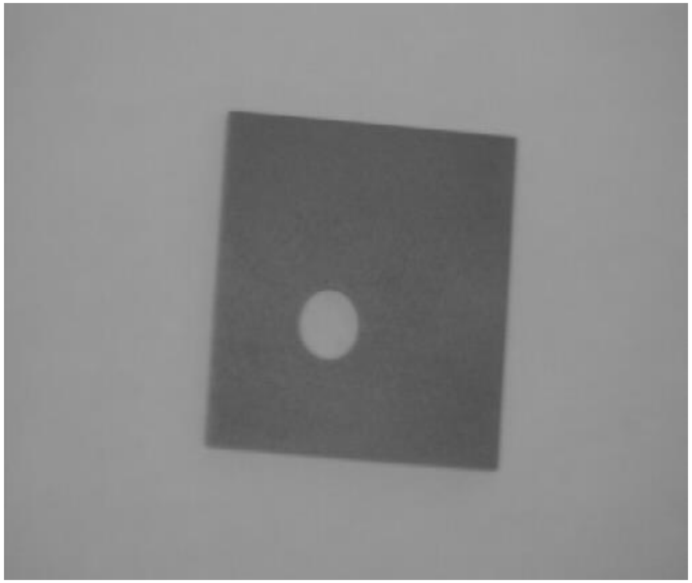
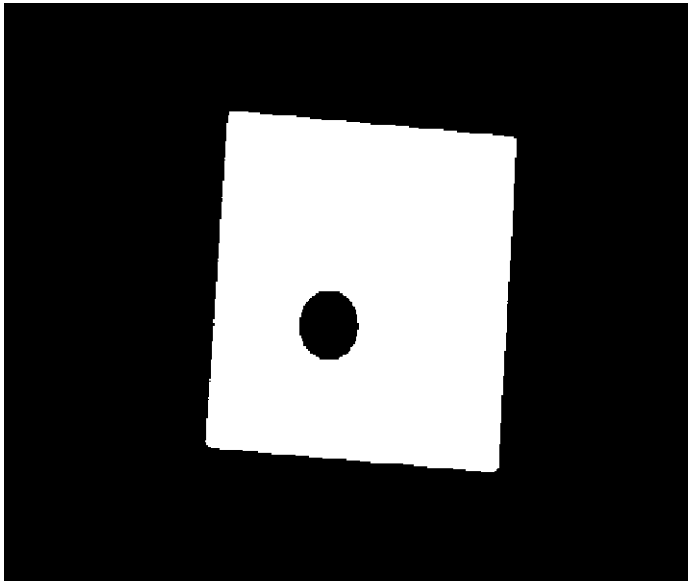
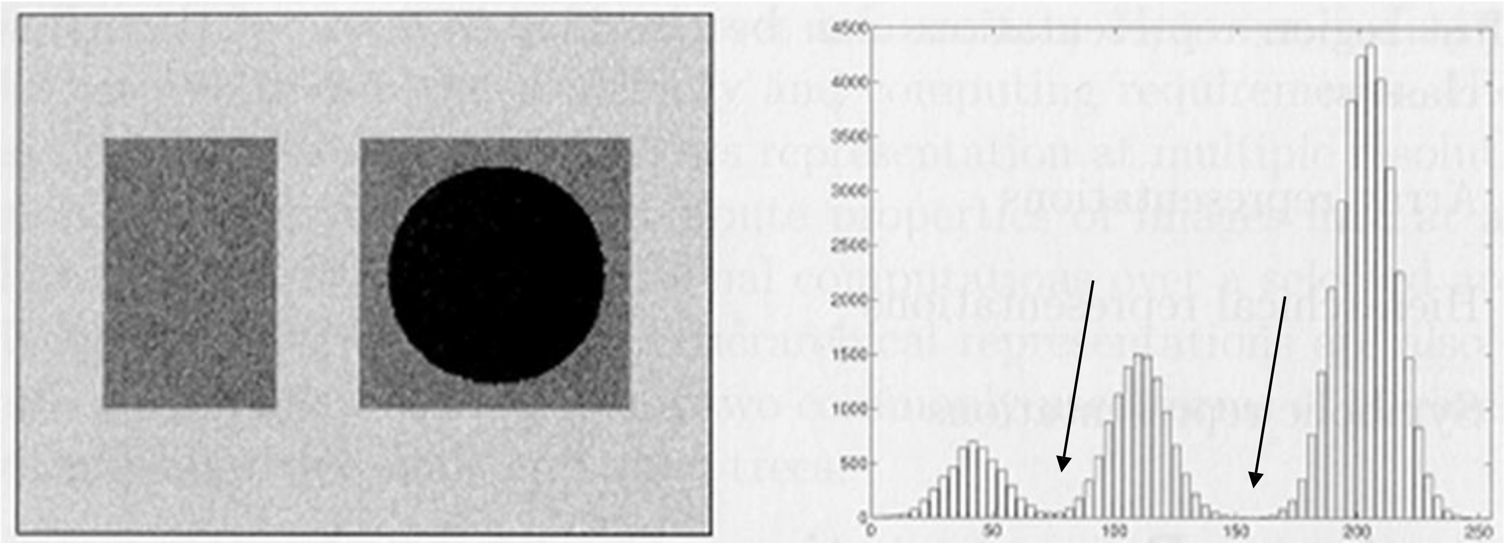




Global Thresholding

- Estimate an initial T
- Segment Image using T: Two groups of pixels G1 and G2
- Compute average gray values m1 and m2 of two groups
- Compute new threshold value T=1/2(m1+m2)
- Repeat steps 2 to 4 until: abs(T_i – T_{i-1})<epsilon

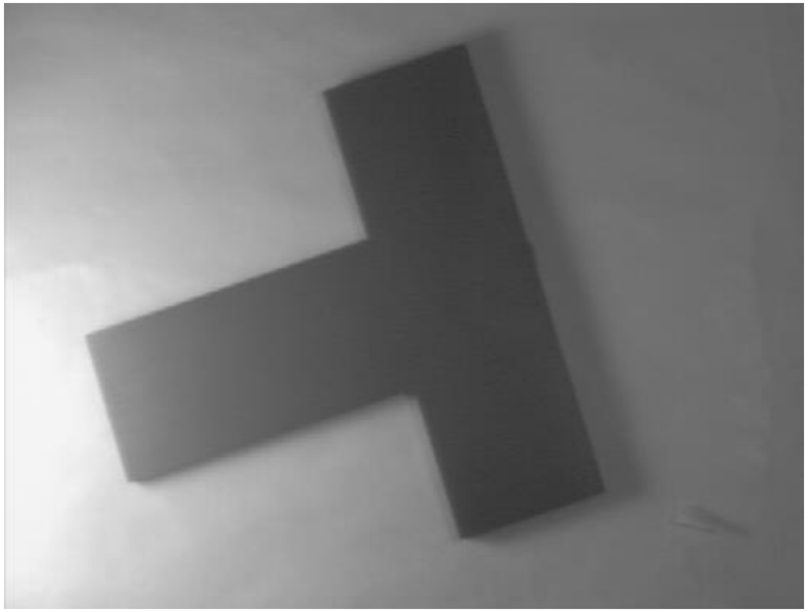
Global Thresholding

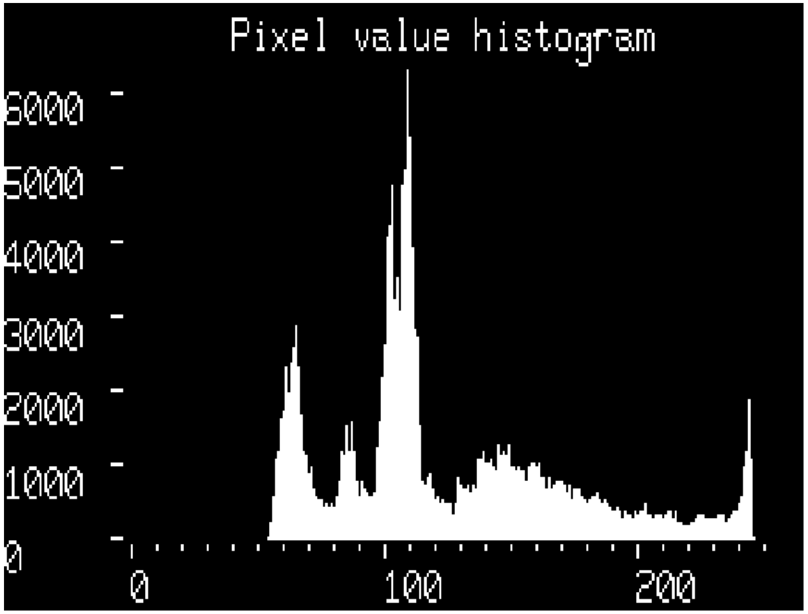


Multilevel thresholding

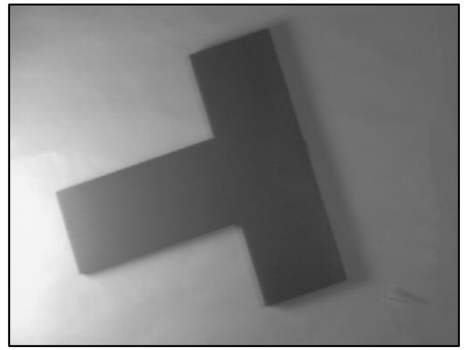
Thresholding

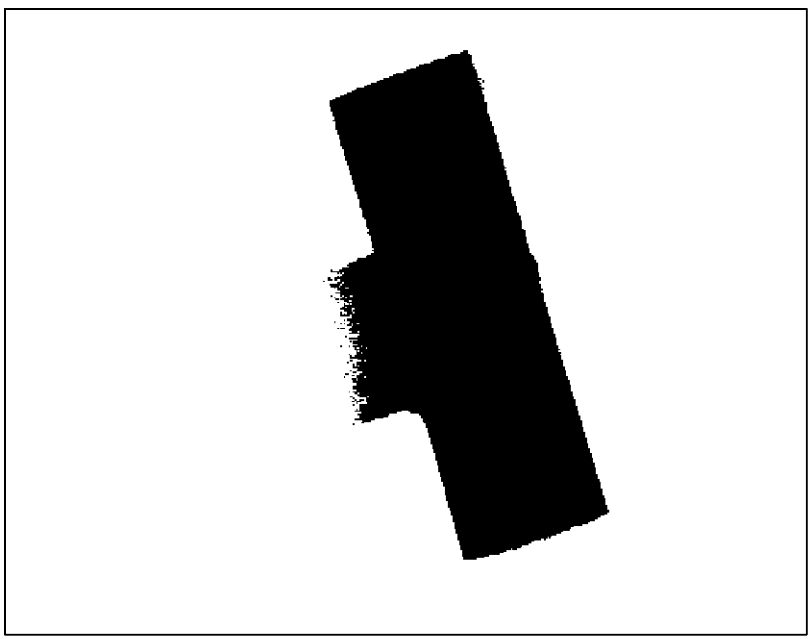
- Non-uniform illumination:

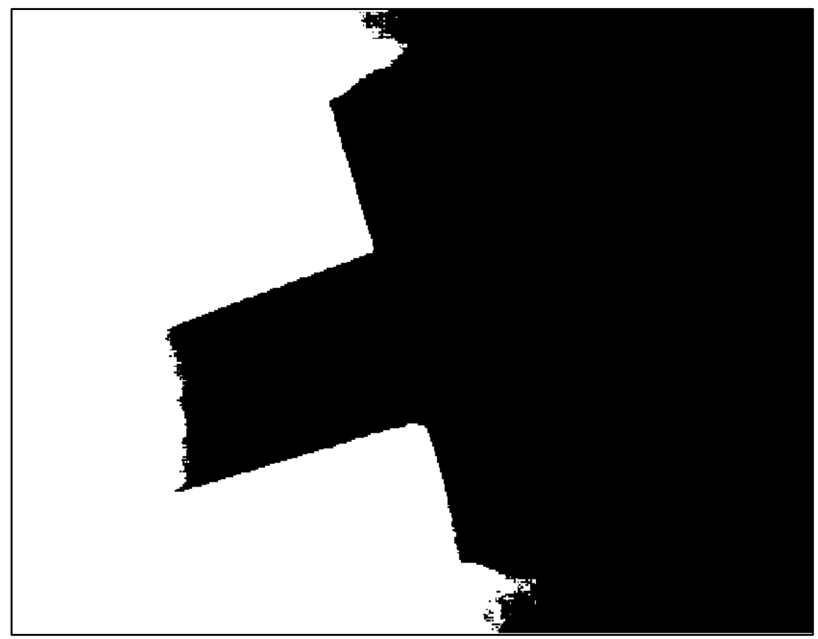




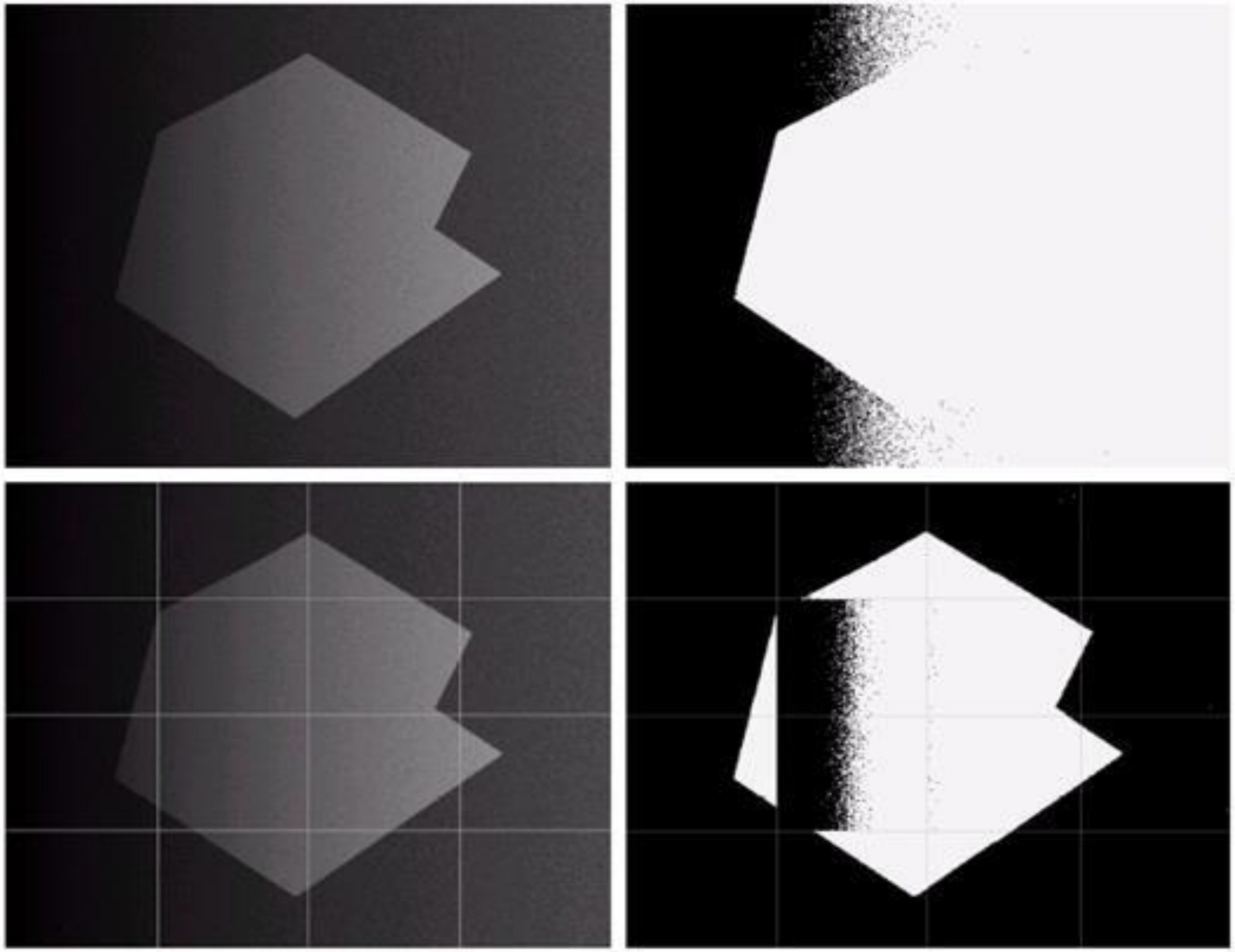
Global Thresholding







Adaptive Thresholding



Adaptive Thresholding

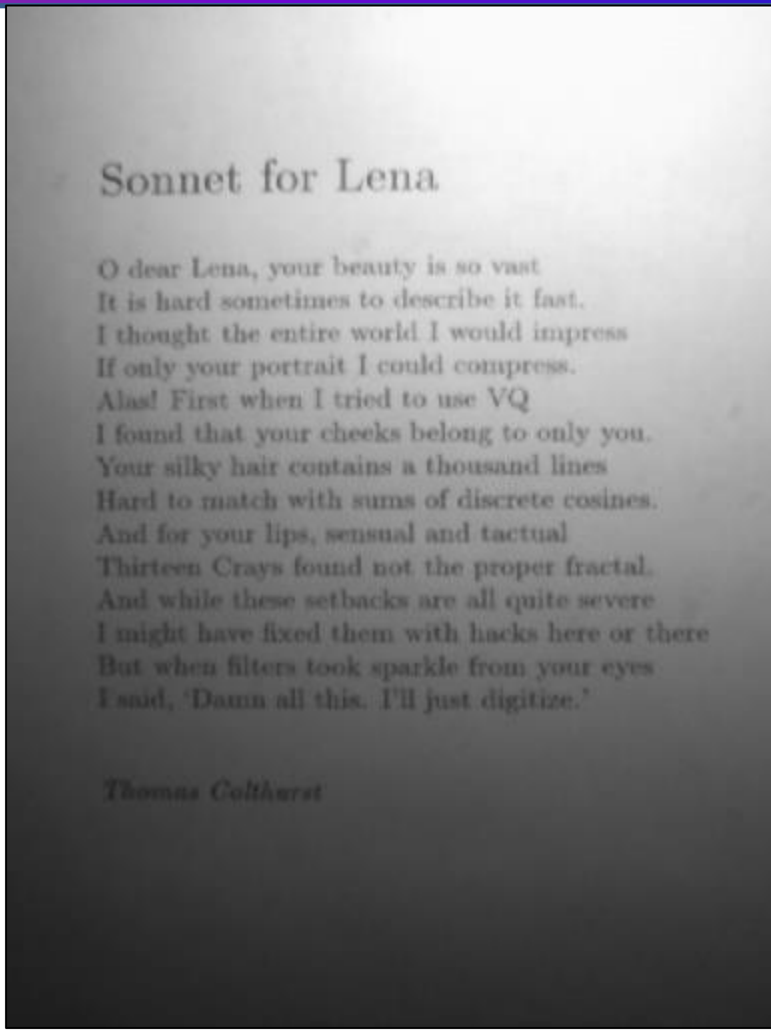
- Threshold: function of neighboring pixels

$$T = mean\ T$$

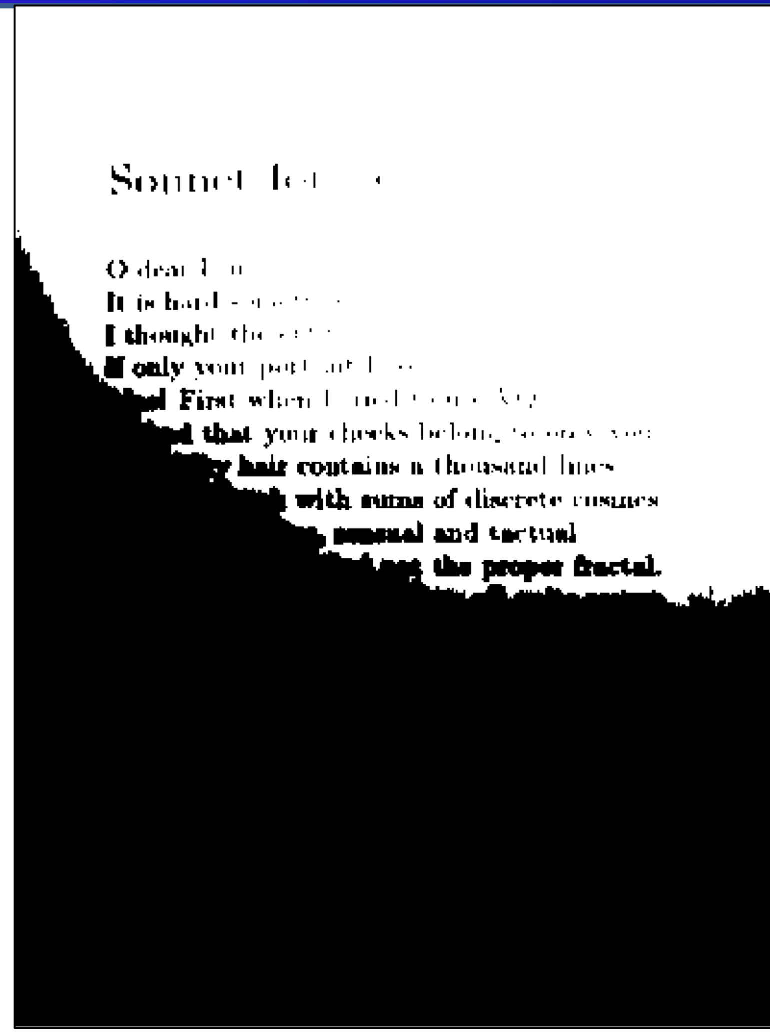
$$= median$$

$$T = \frac{\max + \min}{2}$$

Adaptive Thresholding

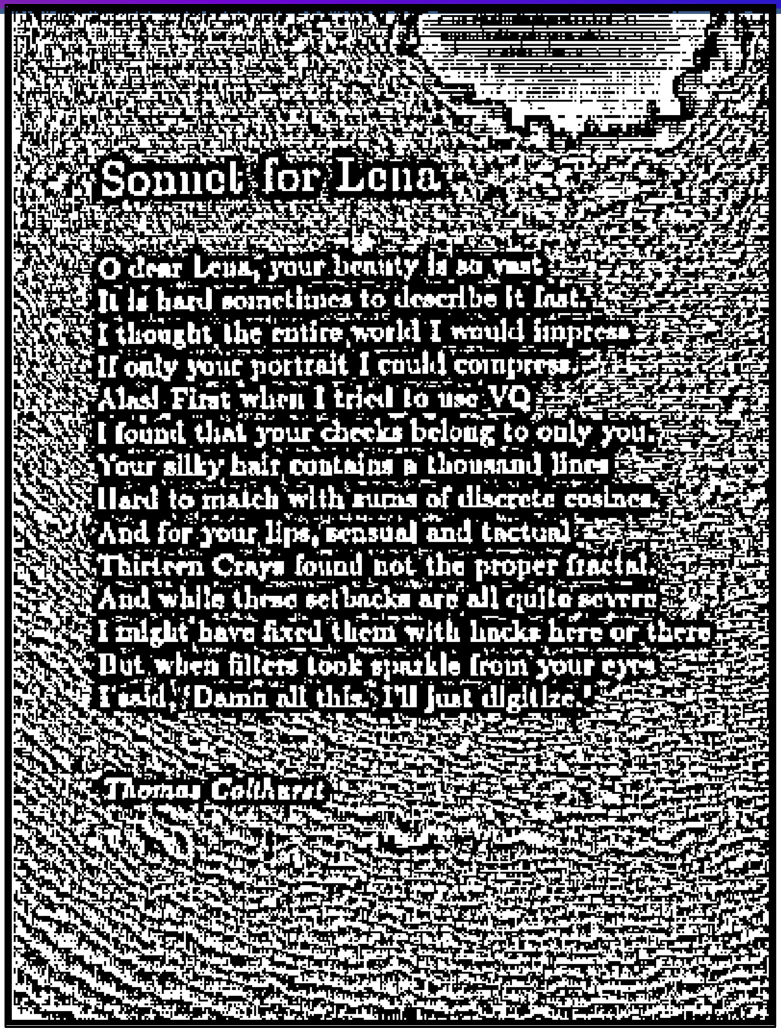


Original Image



Global Thresholding

Adaptive Thresholding

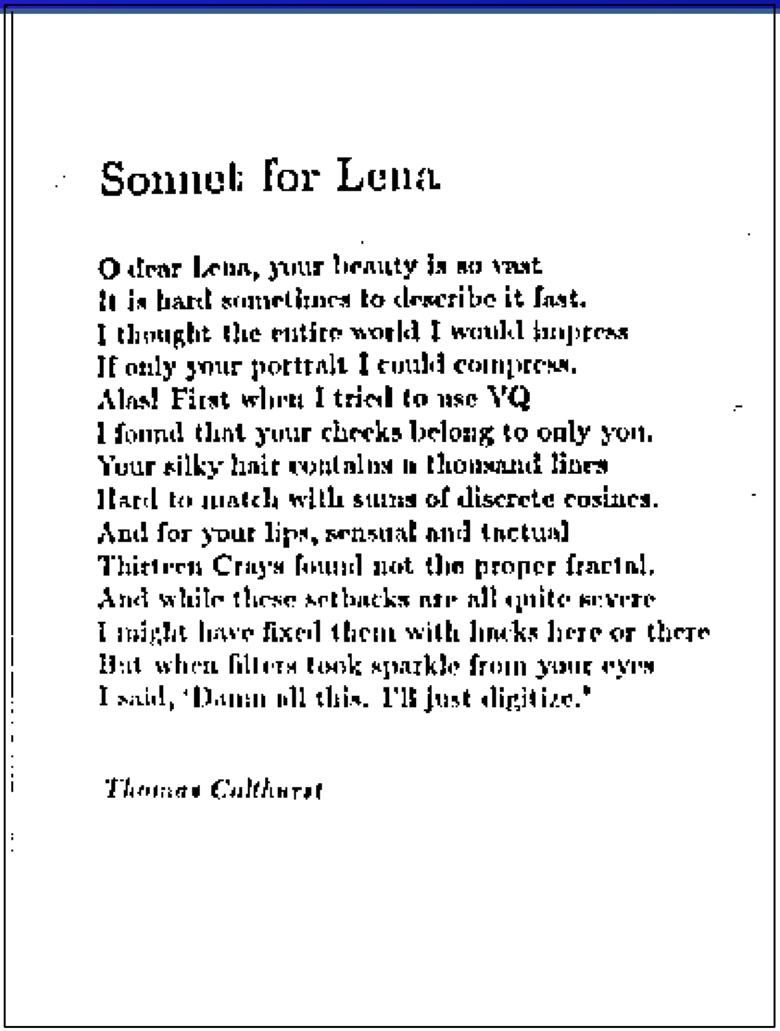


Sonnet for Lena

O dear Lena, your beauty is so vast
It is hard sometimes to describe it fast.
I thought the entire world I would impress
If only your portrait I could compress.
Alas! First when I tried to use VQ
I found that your cheeks belong to only you.
Your silky hair contains a thousand lines
Hard to match with sums of discrete cosines.
And for your lips, sensual and tactual
Thirteen Crays found not the proper fractal.
And while these setbacks are all quite severe
I might have fixed them with hacks here or there
But when filters took sparkle from your eyes
I said, 'Damn all this. I'll just digitize.'

Thomas Colthurst

T=mean, neighborhood=7x7



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T=mean-Const., neighborhood=7x7

Adaptive Thresholding

- Niblack Algorithm

$$T = m + k \times s$$

$$m = \text{mean}$$

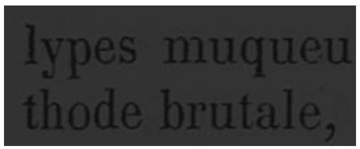
$$s = \text{standard deviations}$$

$$k = \text{ Niblack constant}$$

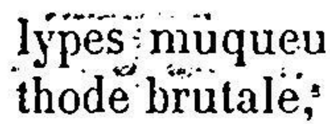
- Neighborhood size???

Document Binarization

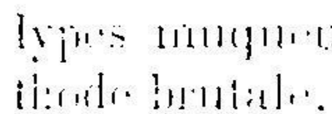
- Local Thresholding – Examples



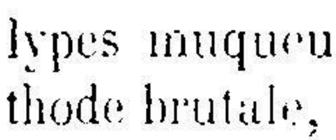
Original



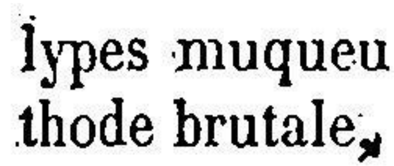
Niblack



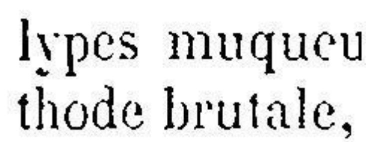
Sauvola



Wolf



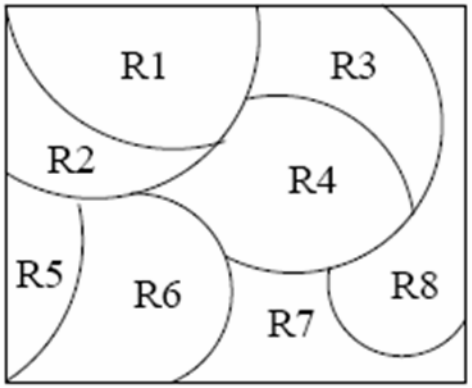
Feng



NICK

Region-Based Segmentation

- Divide the image into regions
  - $R_1, R_2, \ldots, R_N$
- Following properties must hold:



(1) $R_1 \cup R_2 \cup \cdots \cup R_n = R$

(2) R_i is connected

(3) $R_i \cap R_j = empty$

(4) $P(R_i) = \text{True}$

(5) $P(R_i \cup R_j) = \text{False}$ (For adjacent regions)

Image Segmentation Algorithms (Techniques)

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Region-Based Segmentation

- Region Growing
  - Region growing: groups pixels or subregions into larger regions.
  - *Pixel aggregation:* starts with a set of "seed" points and from these grows regions by appending to each seed points those neighboring pixels that have similar properties (such as gray level).

1. Choose the seed pixel(s).
2. Check the neighboring pixels and add them to the region if they are similar to the seed
3. Repeat step 2 for each of the newly added pixels; stop if no more pixels can be added

Predicate: for example abs(z_j - seed) < Epsilon

Region-Based Segmentation

- Example

10	10	10	10	10	10	10
10	10	10	69	70	10	10
59	10	60	64	59	56	60
10	59	10	<u>60</u>	70	10	62
10	60	59	65	67	10	65
10	10	10	10	10	10	10
10	10	10	10	10	10	10

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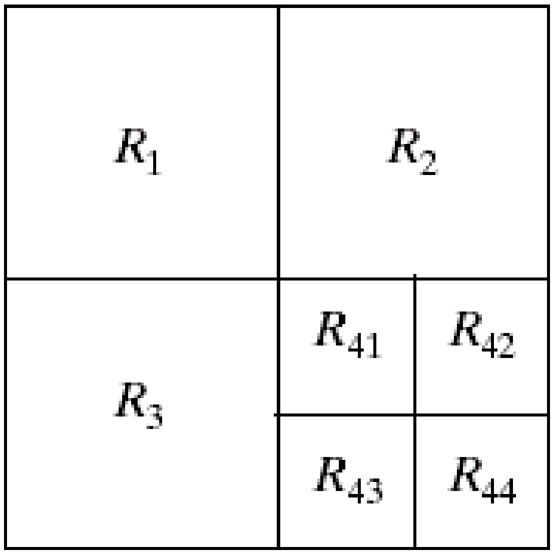
Region-Based Segmentation

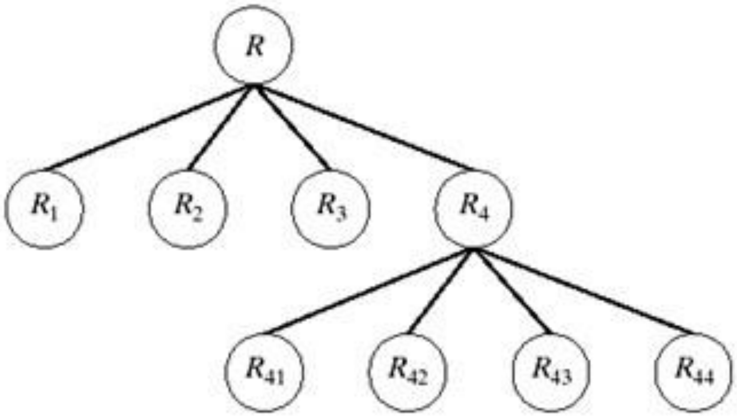
- Region Splitting
  - Region Growing: Starts from a set of seed points.
  - Region Splitting: Starts with the whole image as a single region and subdivide the regions that do not satisfy a condition.
  - Image = One Region R
  - Select a predicate P (gray values etc.)
  - Successively divide each region into smaller and smaller quadrant regions so that:

$$P(R_i) = true$$

Region-Based Segmentation

- Region Splitting





Problem? Adjacent regions could be same

Solution? Allow Merge

Region-Based Segmentation

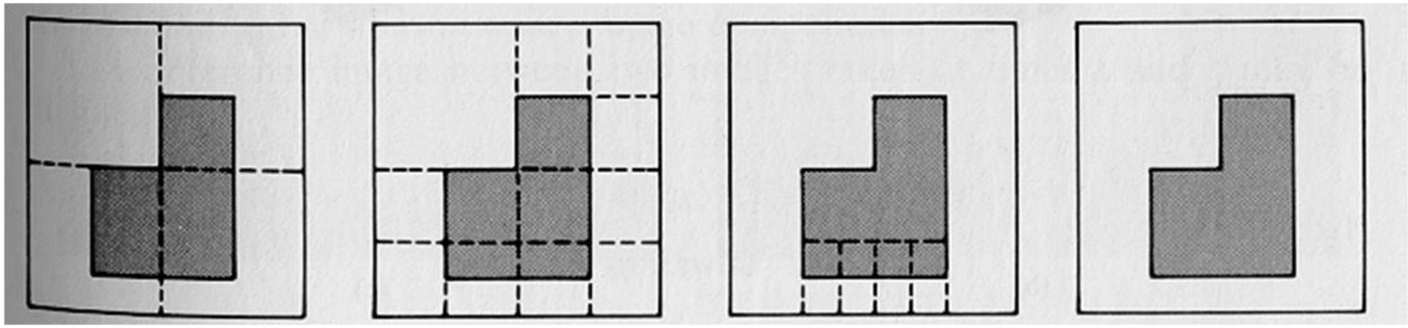
- Region Merging
  - Region merging is the opposite of region splitting.
  - Merge adjacent regions R_i and R_j for which:

$$P(R_i \cup R_j) = True$$

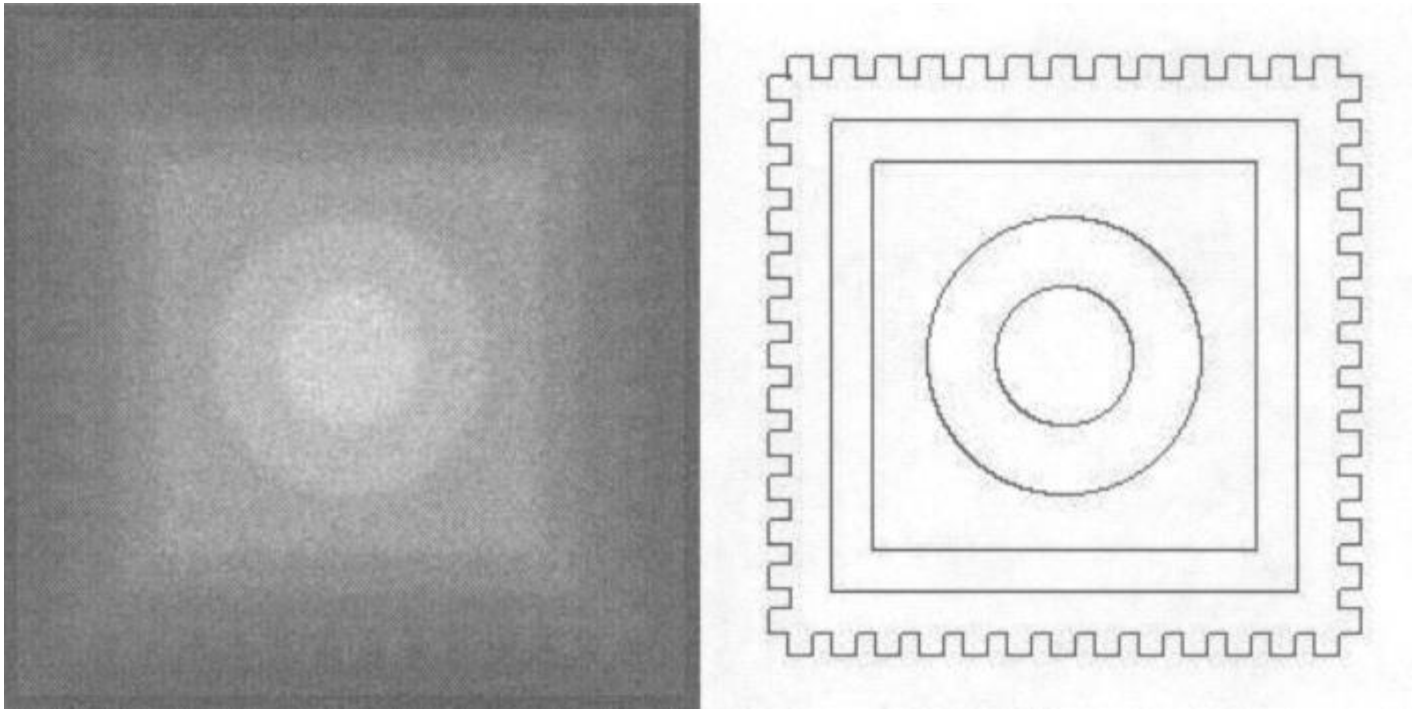
- Region Splitting/Merging
  - Stop when no further split or merge is possible

Region-Based Segmentation

- Example



1. Split into four disjointed quadrants any region R_i where $P(R_i)$=False
2. Merge any adjacent regions R_j and R_k for which $P(R_j \cup R_k)$=True
3. Stop when no further merging or splitting is possible



Finding the outline and shape of image objects,
e.g. character recognition.

The goals of segmentation

- Separate image into coherent “objects”

image | human segmentation

Berkeley segmentation database:
http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

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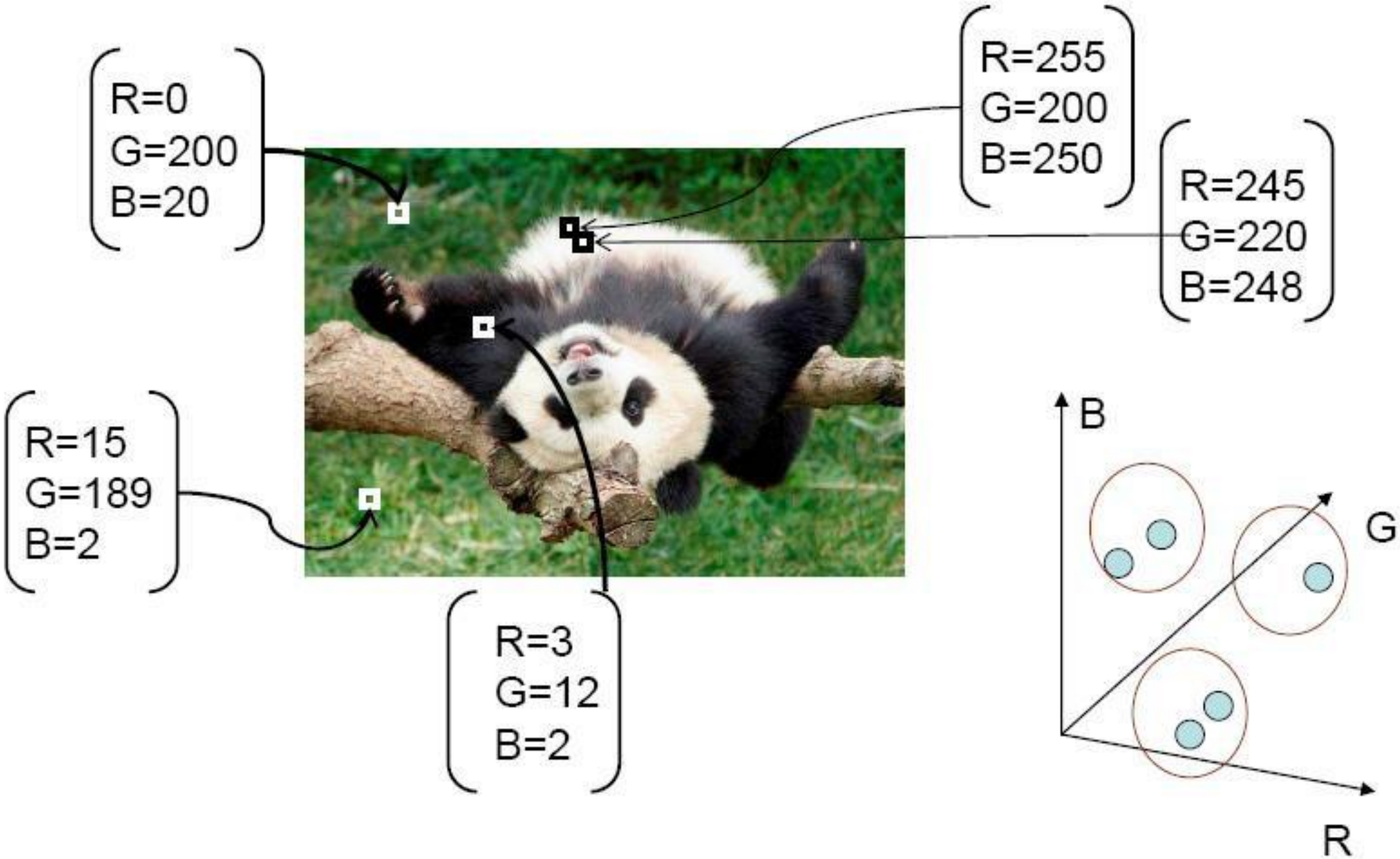
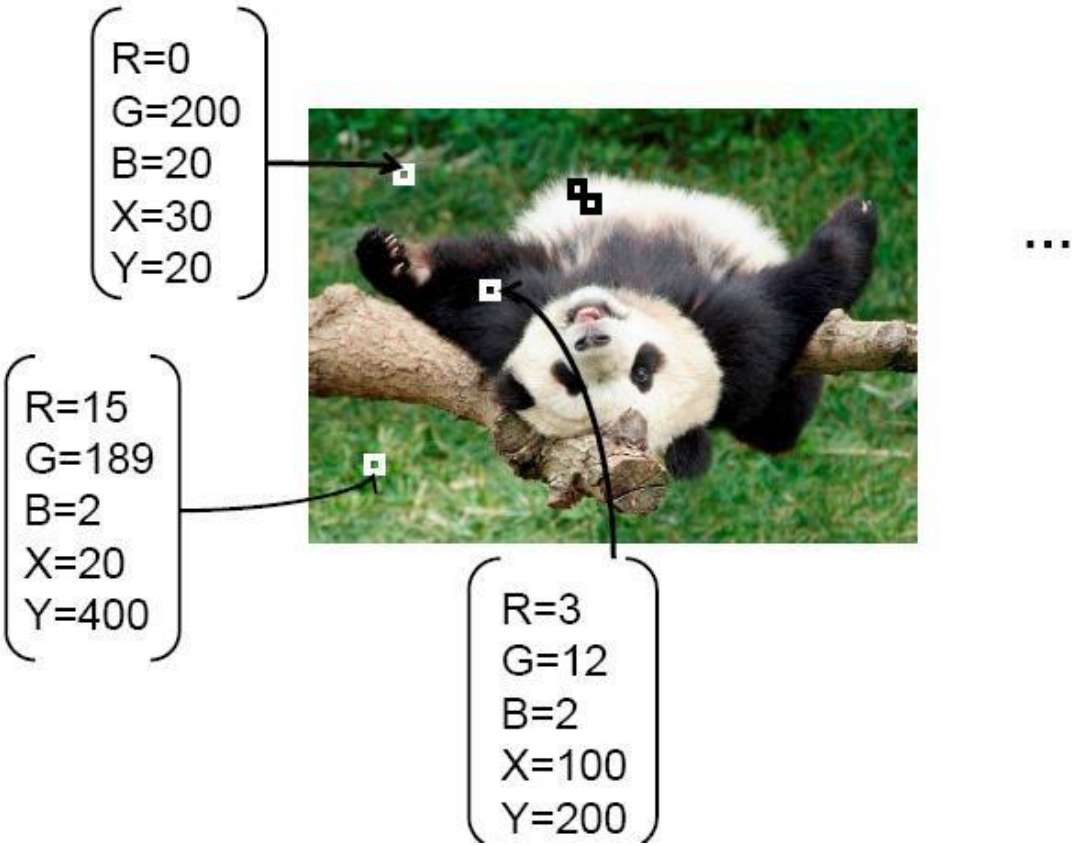
Segmentation as Clustering

- Cluster similar pixels (features) together



Segmentation as clustering

- Cluster similar pixels (features) together



Source: K. Grauman

What is Cluster Analysis?

- Cluster: a collection of data objects
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters
- Cluster analysis
  - Finding similarities between data according to the characteristics found in the data and grouping similar data objects into clusters

What is Cluster Analysis?

- Clustering analysis is an important human activity
- Early in childhood, we learn how to distinguish between cats and dogs
- Unsupervised learning: no predefined classes
- Typical applications
  - As a stand-alone tool to get insight into data distribution
  - As a preprocessing step for other algorithms

Types of Clustering

Hierarchical: clusters form a tree

- Agglomerative
- Divisive

- Hard vs. Soft
  - Hard: same object can only belong to single cluster i.e. k-Mean, k-Medoid etc.
  - Soft: same object can belong to different clusters i.e. Fuzzy C Mean Clustering.

Quality: What Is Good Clustering?

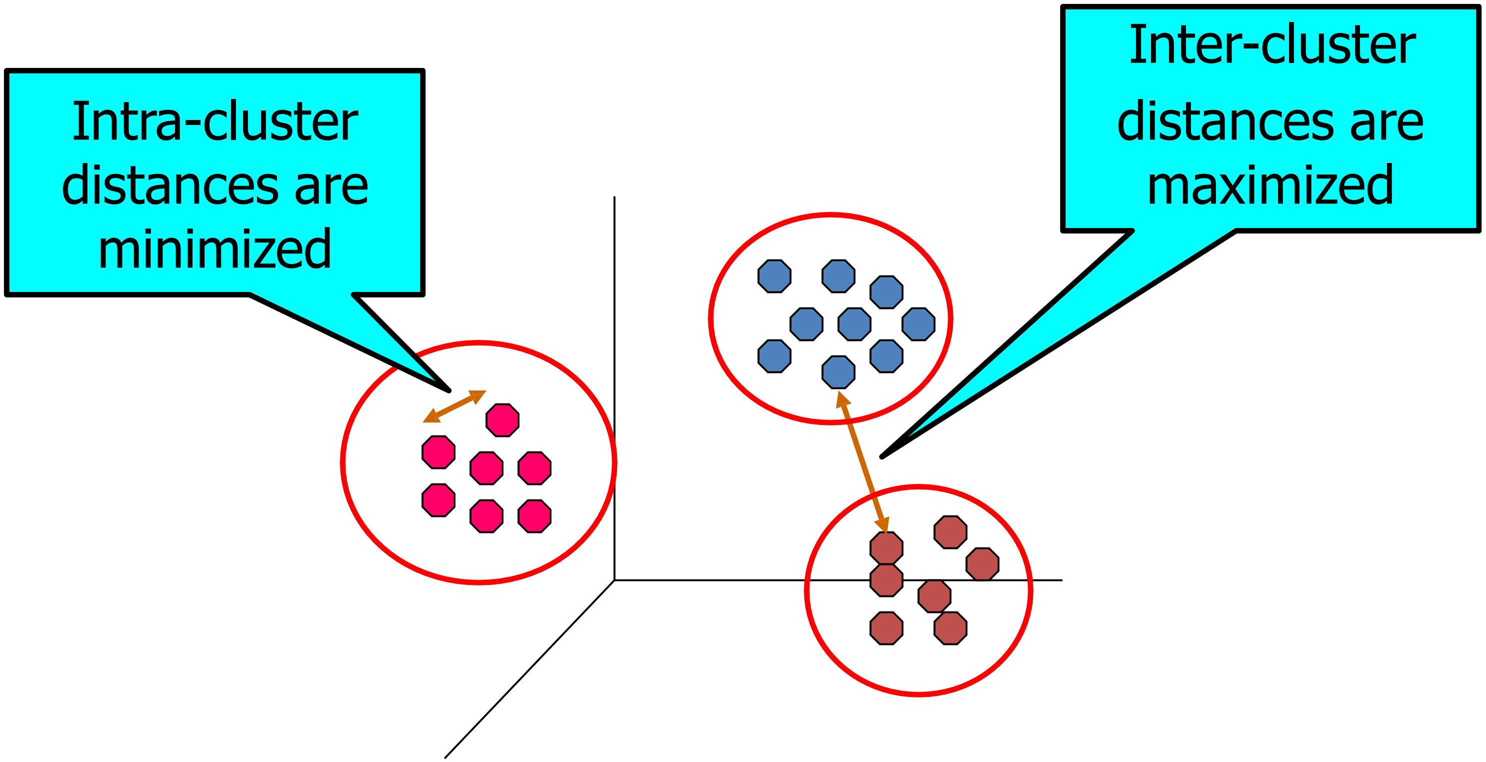
- A good clustering method will produce high quality clusters with
  - high intra-class similarity

    (Similar to one another within the same cluster)
  - low inter-class similarity

    (Dissimilar to the objects in other clusters)

Quality: What Is Good Clustering?

- Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups



Similarity and Dissimilarity Between Objects

- Distances are normally used to measure the similarity or dissimilarity between two data objects
- Some popular ones include: *Minkowski distance*:

$$d(i,j) = \sqrt[q]{(|x_{i_1} - x_{j_1}|^q + |x_{i_2} - x_{j_2}|^q + \ldots + |x_{i_p} - x_{j_p}|^q)}$$

where $i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $j = (x_{j1}, x_{j2}, \ldots, x_{jp})$ are two p-dimensional data objects, and q is a positive integer

- If $q = 1$, d is Manhattan distance

$$d(i,j) = |x_{i_1} - x_{j_1}| + |x_{i_2} - x_{j_2}| + \ldots + |x_{i_p} - x_{j_p}|$$

Similarity and Dissimilarity Between Objects

- *If q = 2, d* is Euclidean distance:

$$d(i,j) = \sqrt{(|x_{i_1} - x_{j_1}|^2 + |x_{i_2} - x_{j_2}|^2 + \ldots + |x_{i_p} - x_{j_p}|^2)}$$

- Also, one can use weighted distance, parametric Pearson correlation, or other disimilarity measures

Clustering Algorithms: Basic Concept

- Given a *k*, find a partition of *k clusters* that optimizes the chosen partitioning criterion
- *k-means* and *k-medoids* algorithms
  - <u>*k-means*</u> (MacQueen'67): Each cluster is represented by the center of the cluster
  - <u>*k-medoids*</u> or PAM (Partition around medoids) (Kaufman & Rousseeuw'87): Each cluster is represented by one of the objects in the cluster

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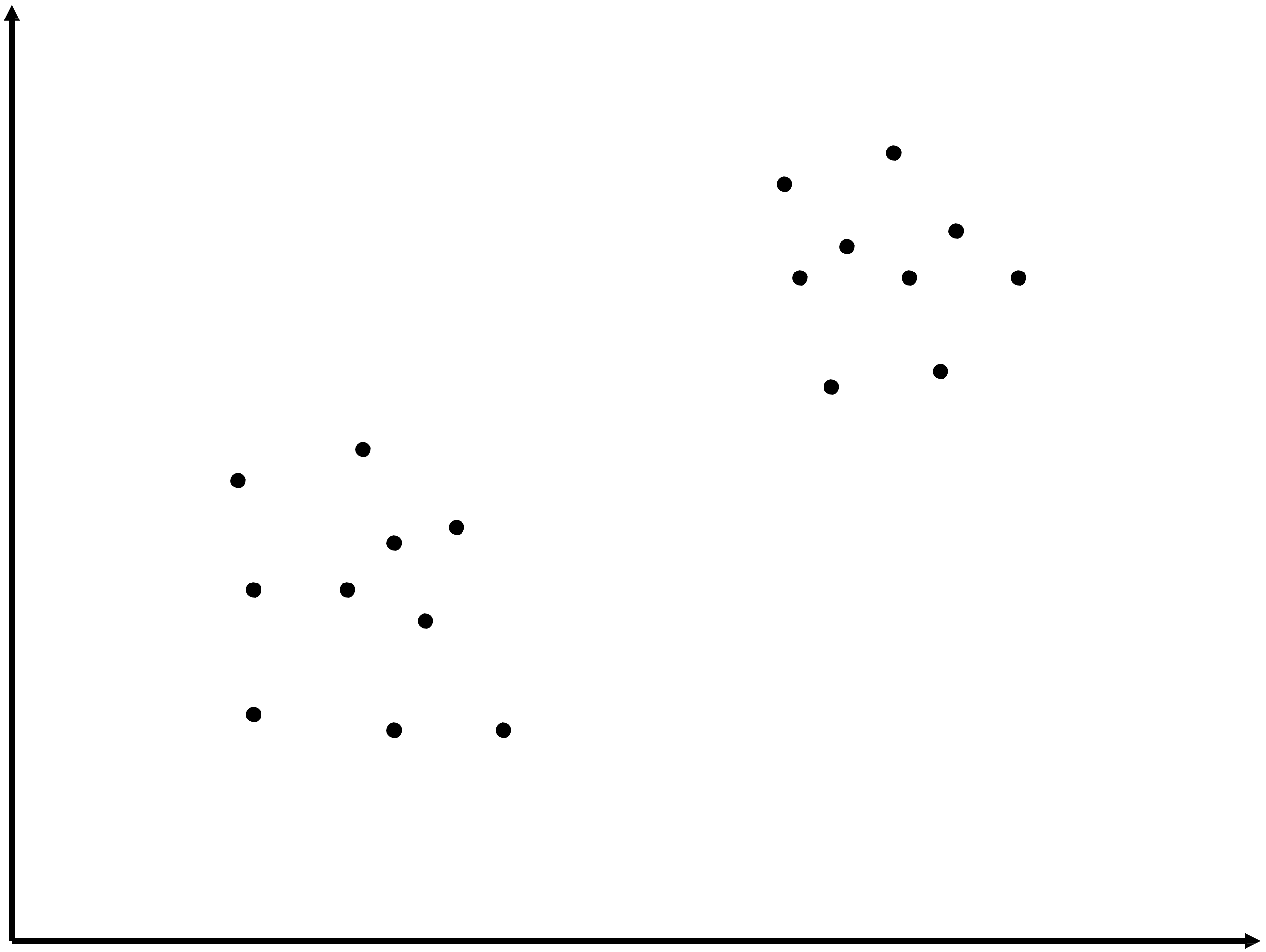
K-Means Clustering

1. Chose the number (K) of clusters and randomly select the
   centroids of each cluster.
2. For each data point:
   - Calculate the distance from the data point to each cluster.
   - Assign the data point to the closest cluster.
3. Recompute the centroid of each cluster.
4. Repeat steps 2 and 3 until there is no further change in the assignment of data points (or in the centroids).

K-Means Clustering



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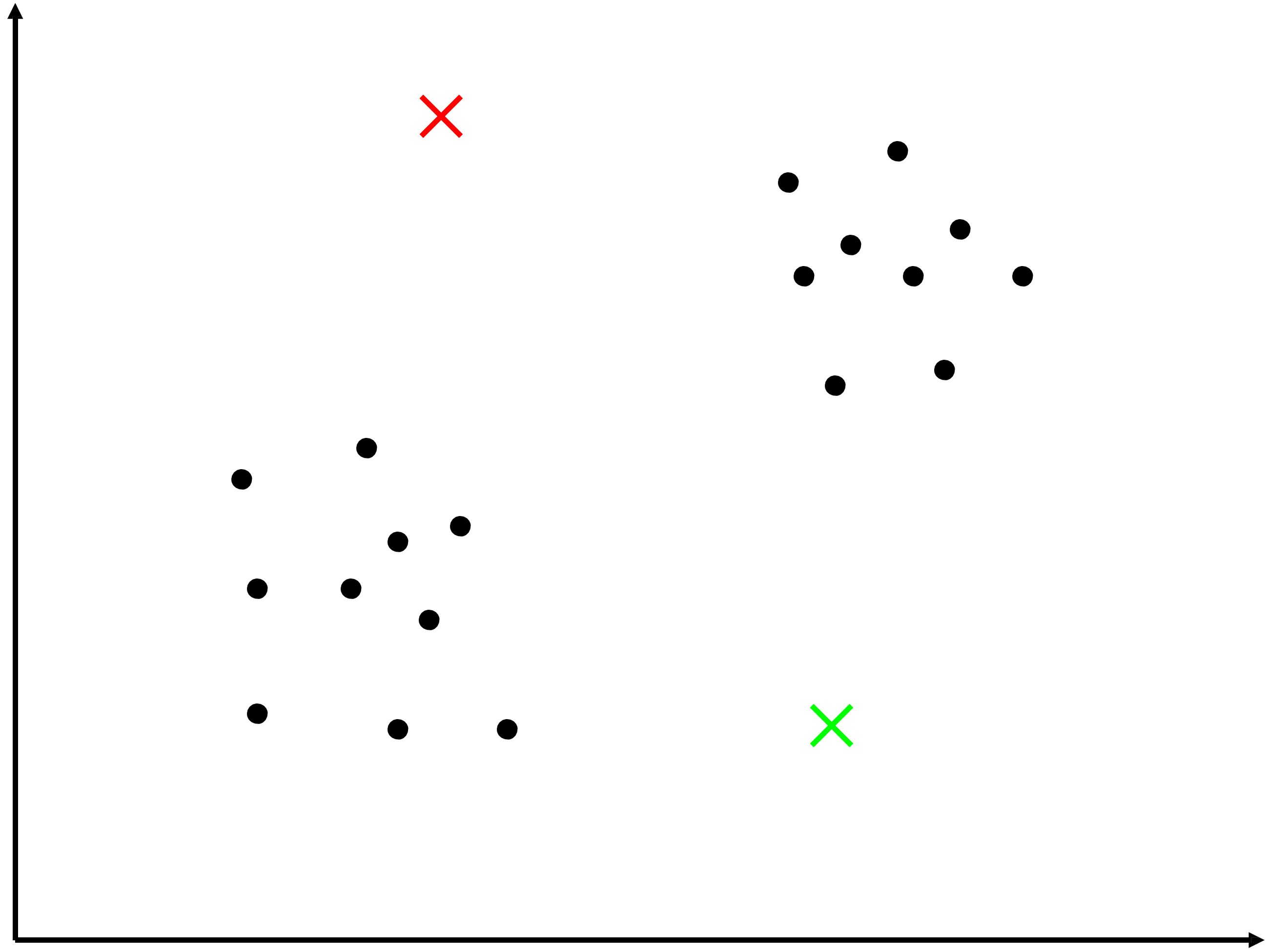

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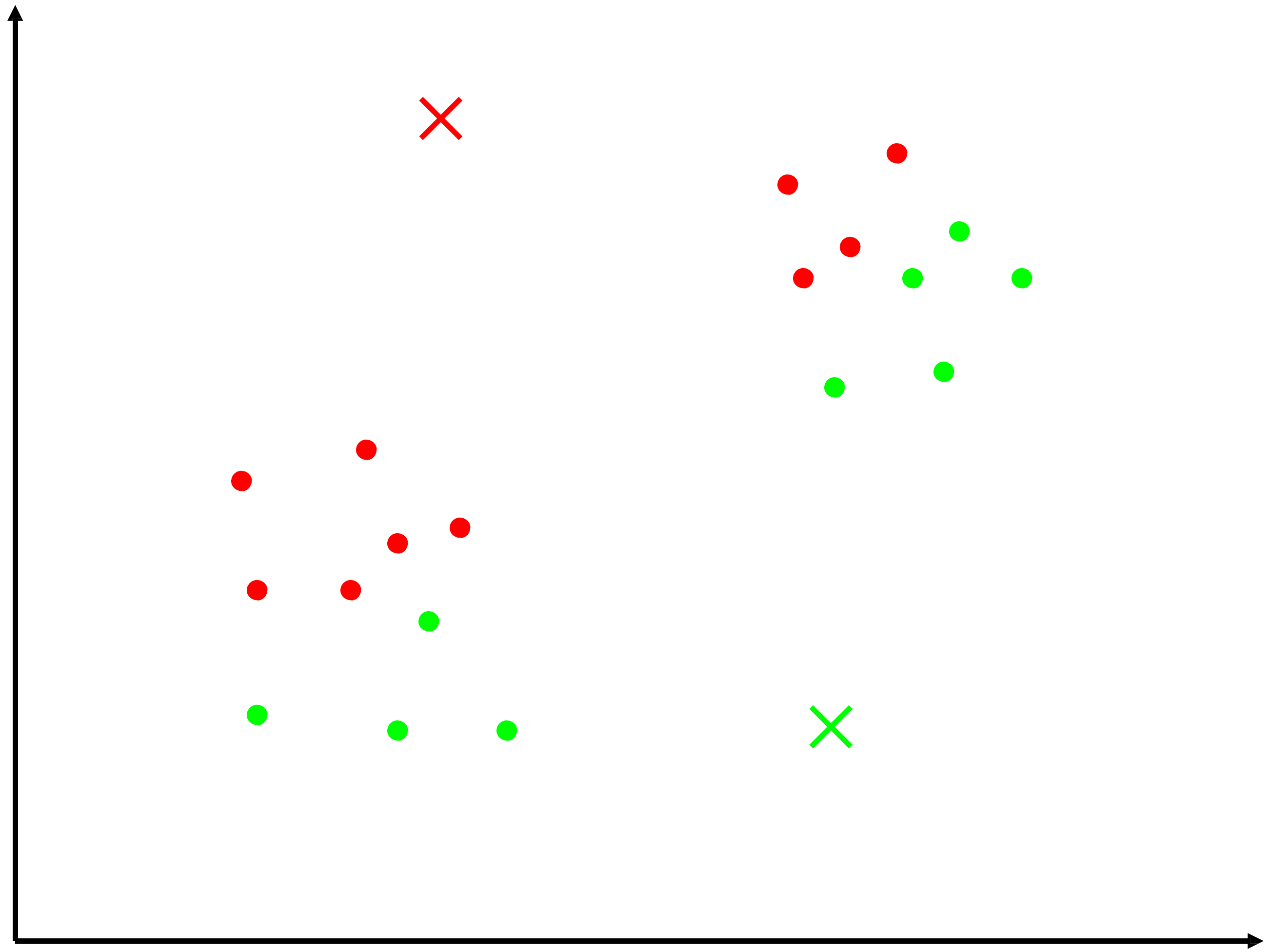

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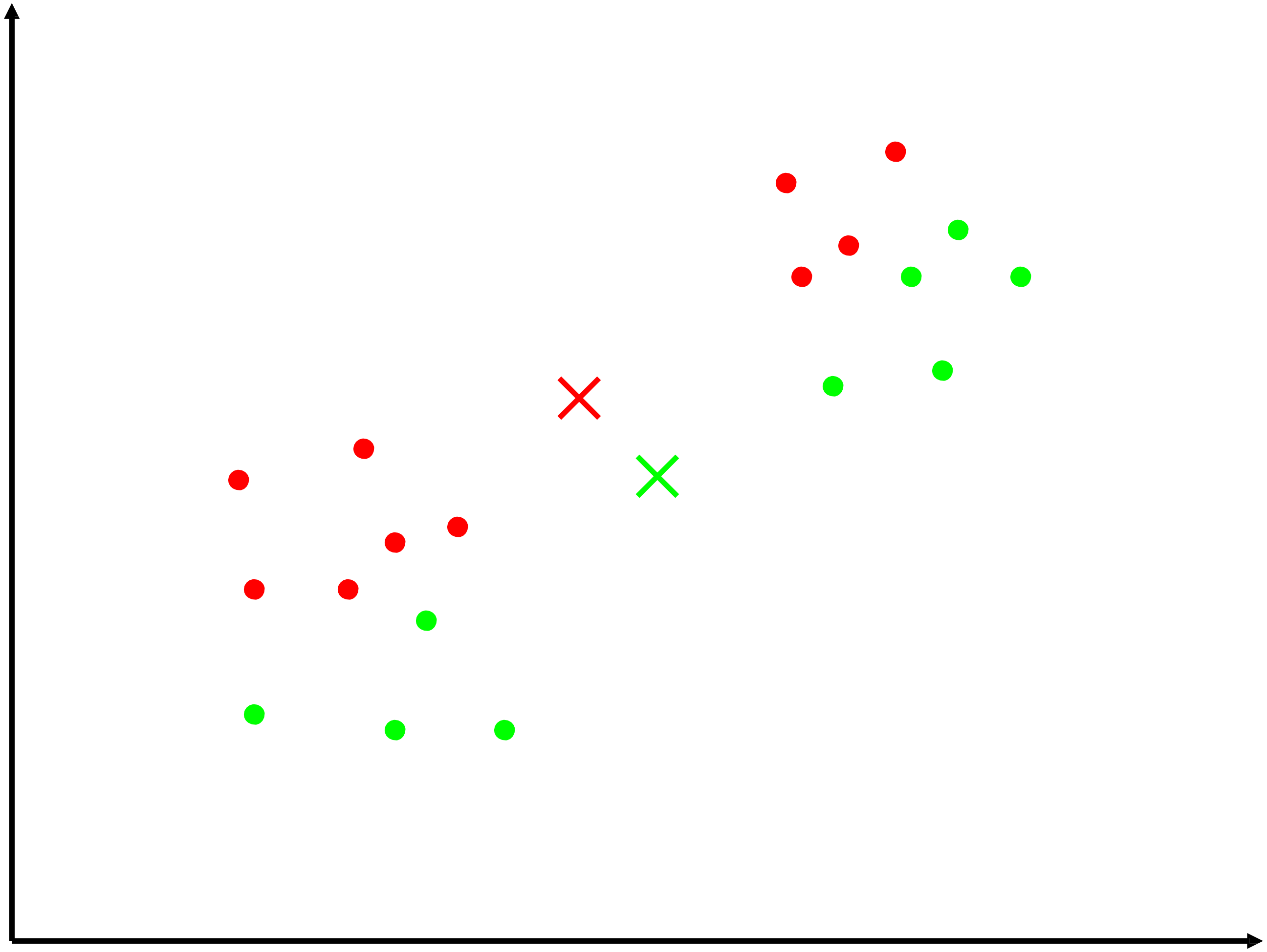

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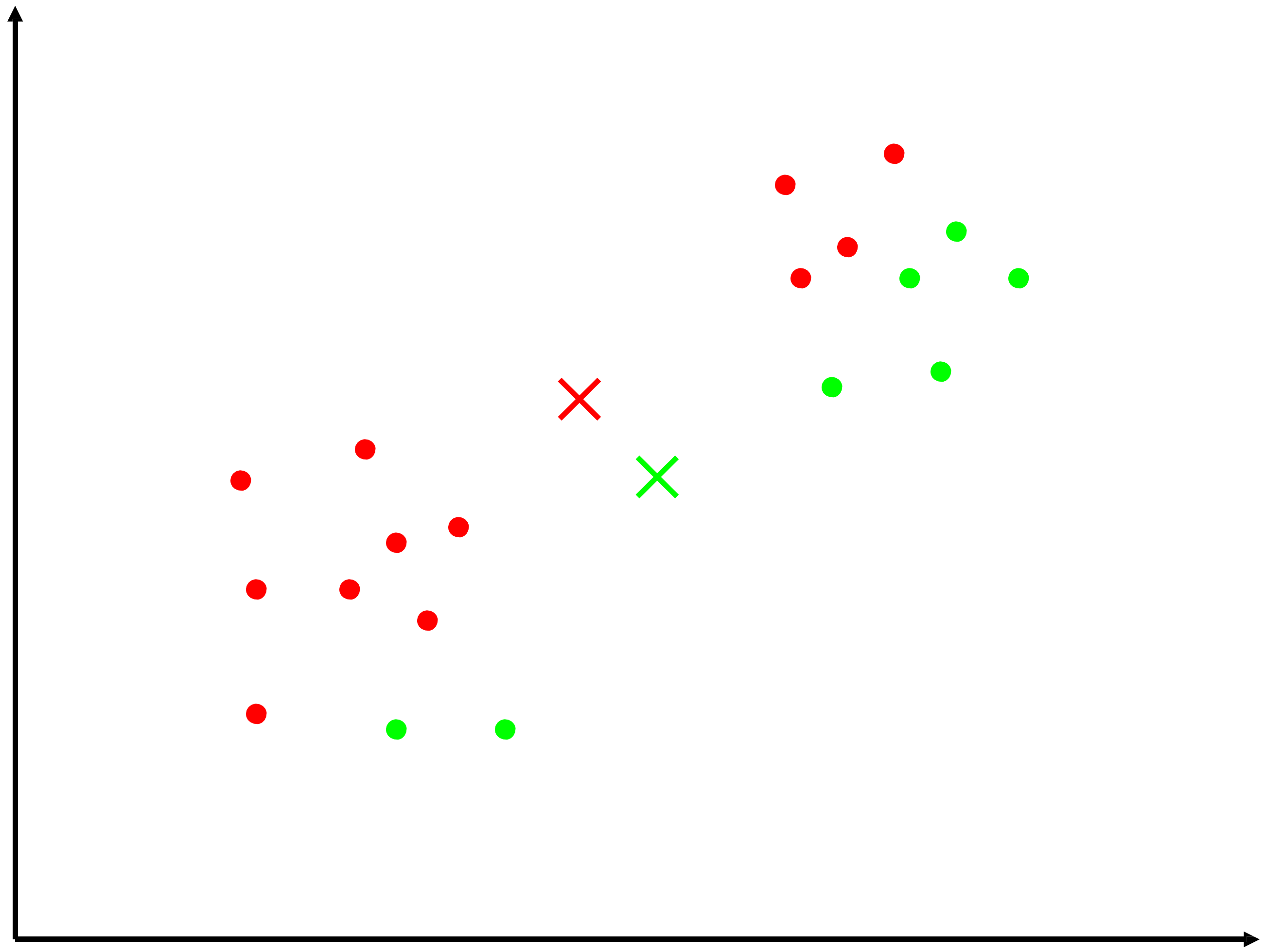

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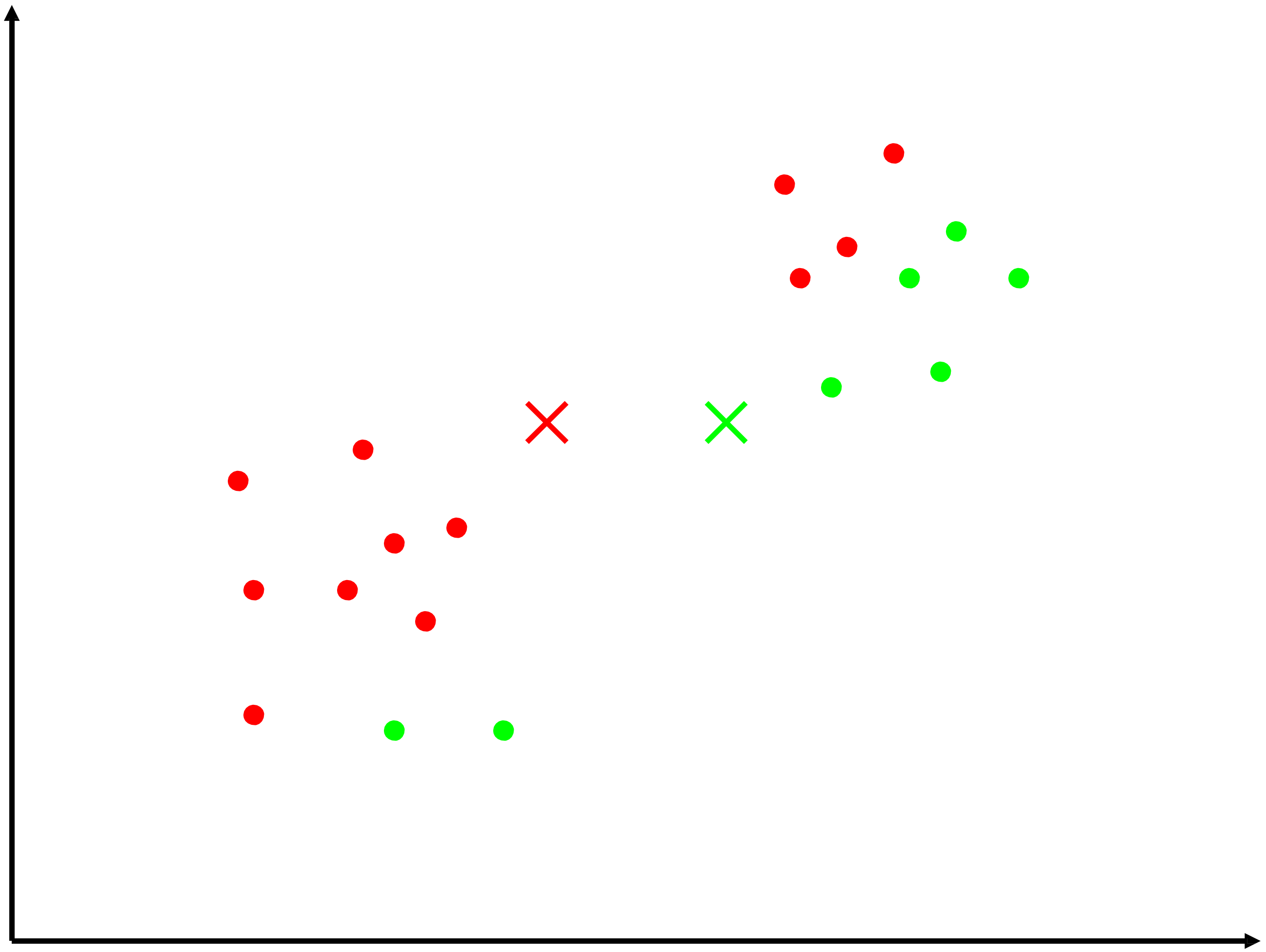

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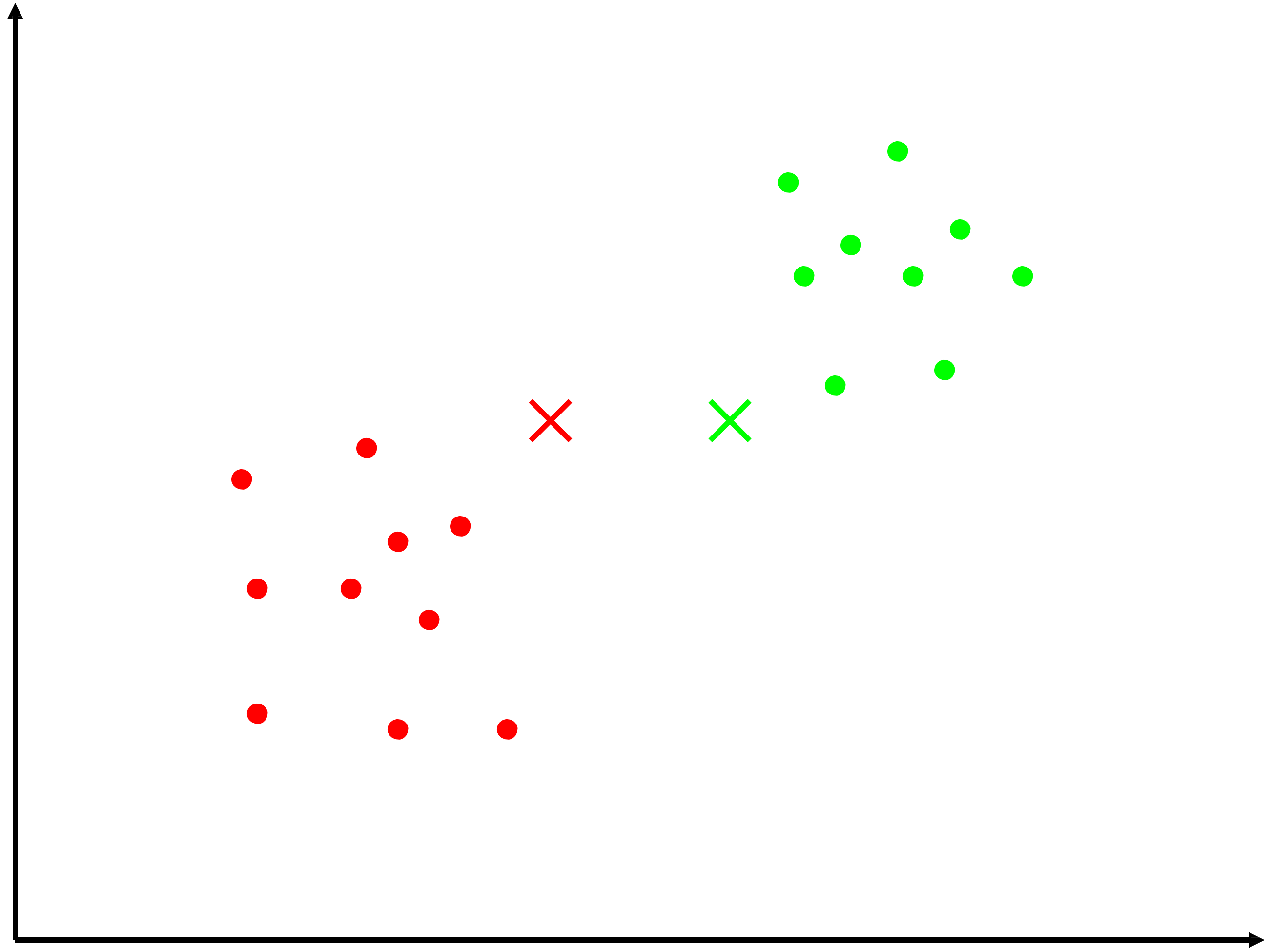

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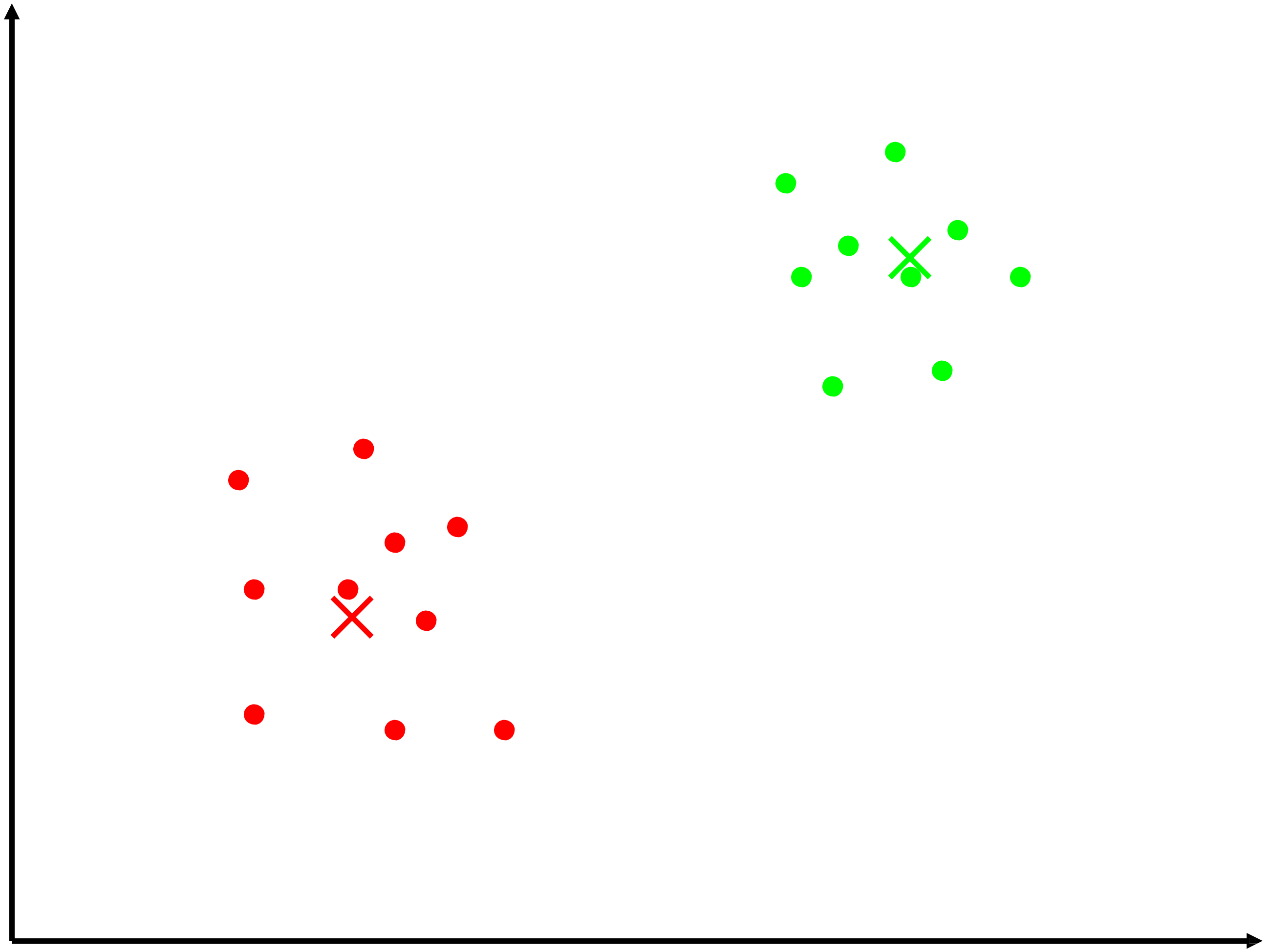

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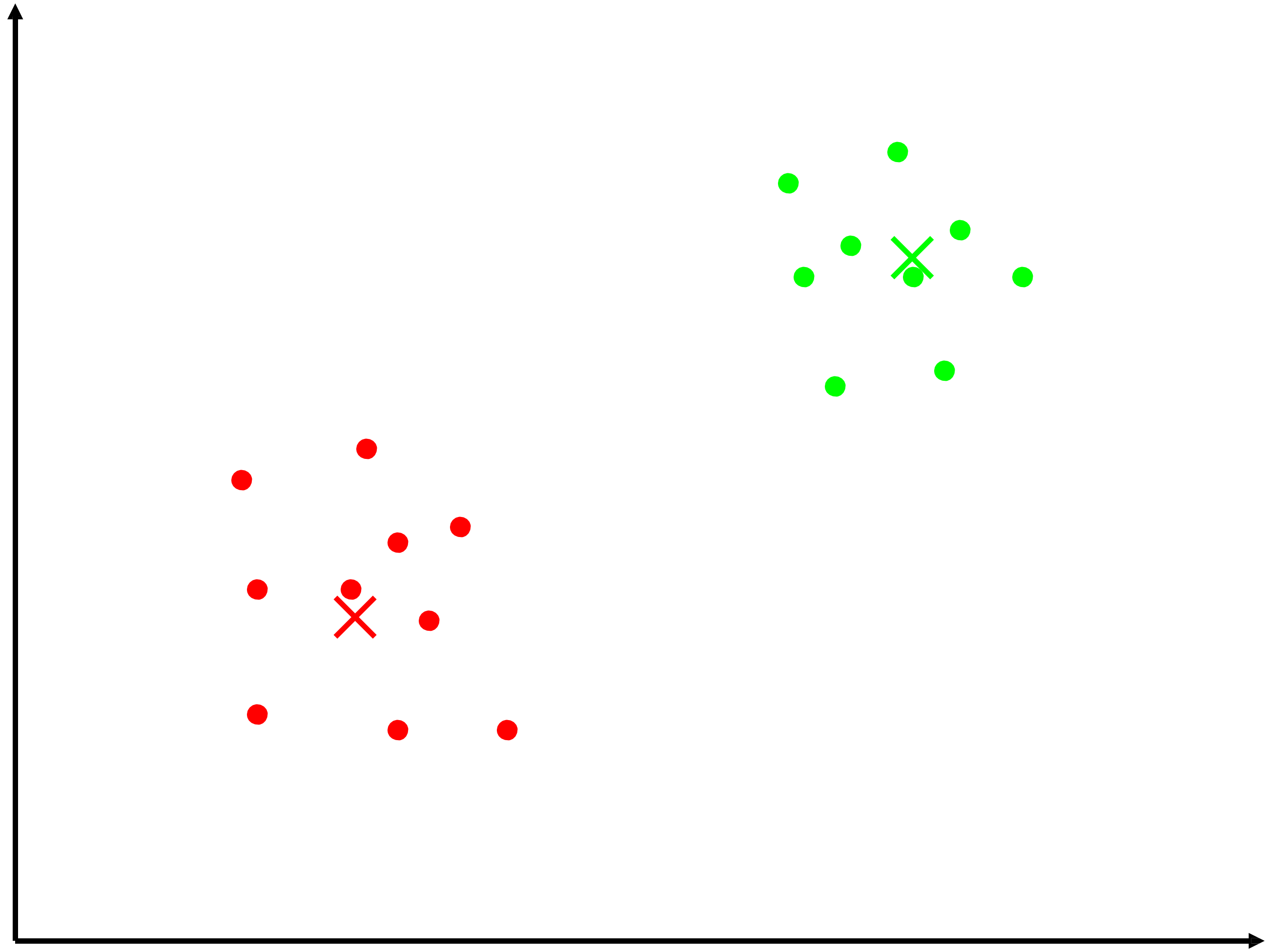
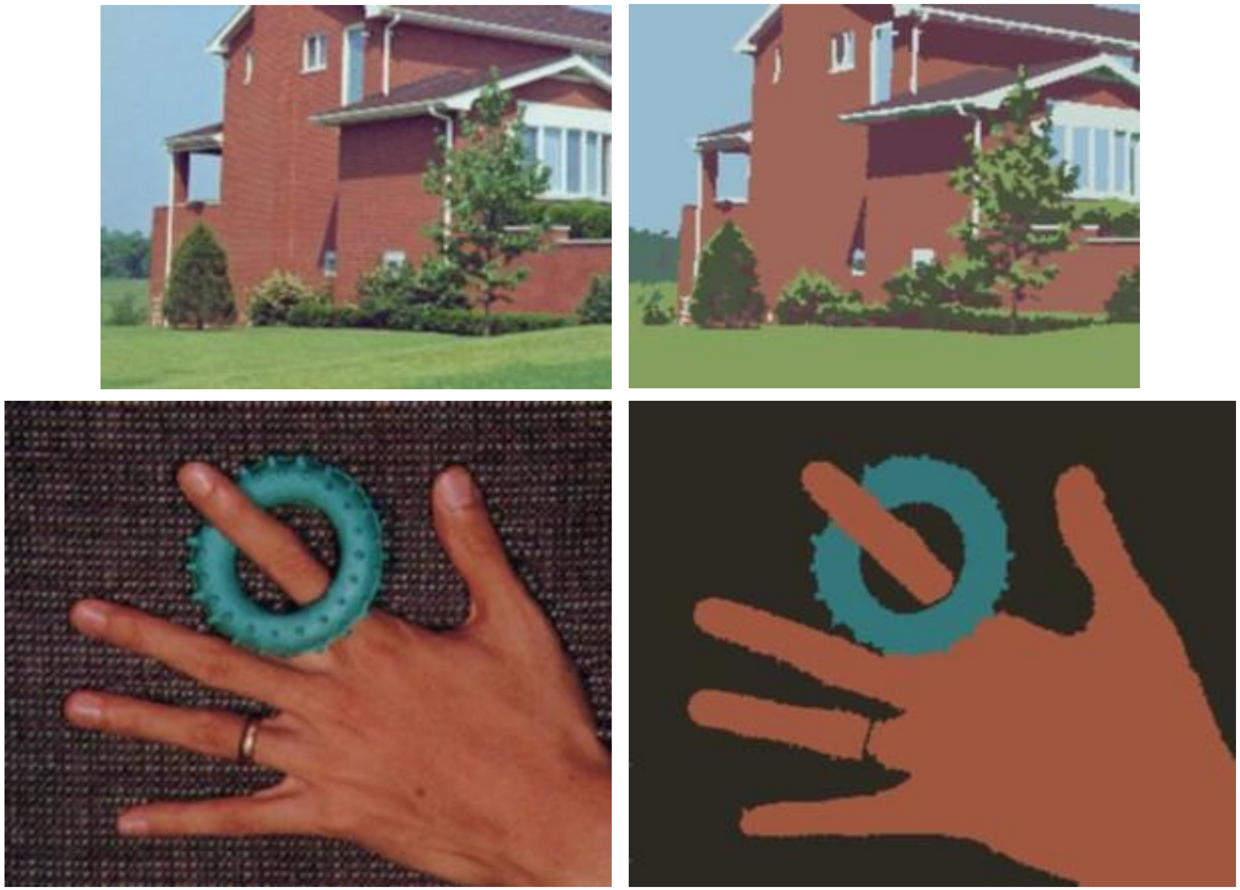


Clustering

- Example



D. Comaniciu and P. Meer, *Robust Analysis of Feature Spaces: Color Image Segmentation*, 1997.

K-Means Clustering

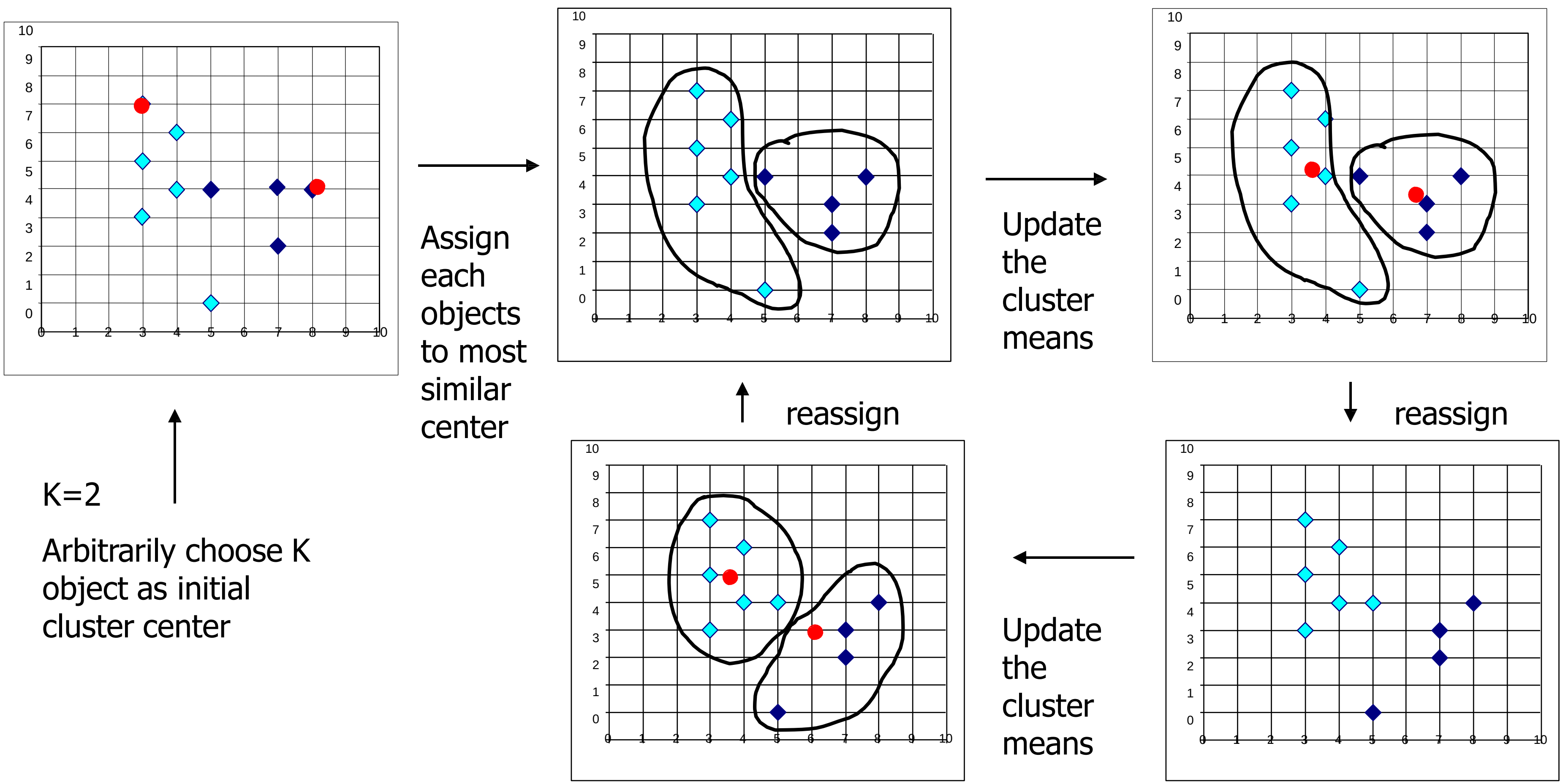
- Example

Original

K=5

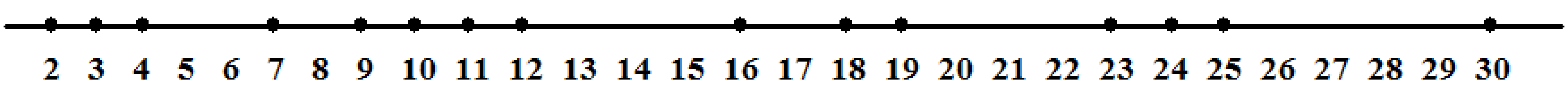
K=11

The *K-Means* Clustering Method



Example

- Run K-means clustering with 3 clusters (initial centroids: 3, 16, 25) for at least 2 iterations



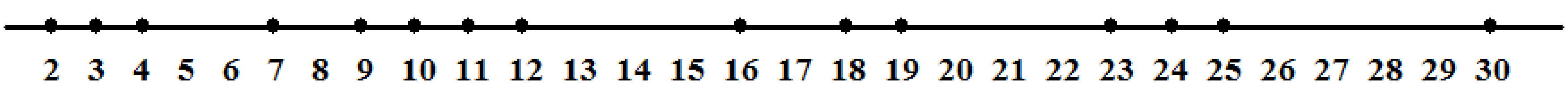
Example

- Centroids:

3 – 2 3 4 7 9 new centroid: 5

16 – 10 11 12 16 18 19 new centroid: 14.33

25 – 23 24 25 30 new centroid: 25.5



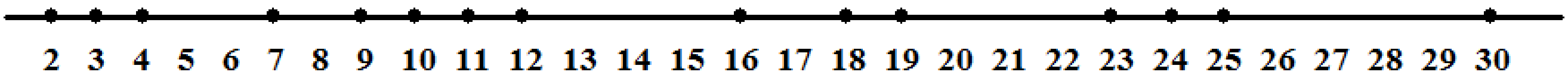
Example

- Centroids:

5 – 2 3 4 7 9 new centroid: 5

14.33 – 10 11 12 16 18 19 new centroid: 14.33

25.5 – 23 24 25 30 new centroid: 25.5



In class Practice

- Run K-means clustering with 3 clusters (initial centroids: 3, 12, 19) for at least 2 iterations

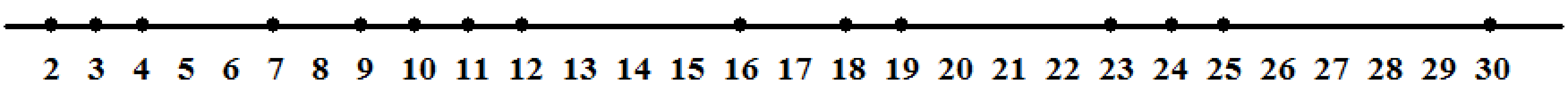


Image Segmentation Algorithms (Techniques)

- Thresholding: Global vs Adaptive.
- Region Growing
- Region Splitting and Merging
- Cluster Analysis:

  k-Mean Clustering
  k-Mode Clustering
  Hierarchical Clustering
  Fuzzy C-Mean Clustering
  Mean Shift Segmentation

Hierarchical Clustering

- **Two main types of hierarchical clustering**
  - **Agglomerative:**
    - **Start with the points as individual clusters**
    - **At each step, merge the closest pair of clusters until only one cluster (or k clusters) left**

    Matlab: Statistics Toolbox: clusterdata,

    which performs all these steps: pdist, linkage, cluster
  - **Divisive:**
    - **Start with one, all-inclusive cluster**
    - **At each step, split a cluster until each cluster contains a point (or there are k clusters)**
- **Traditional hierarchical algorithms use a similarity or distance matrix**
  - **Merge or split one cluster at a time**
  - **Image segmentation mostly uses simultaneous merge/split**

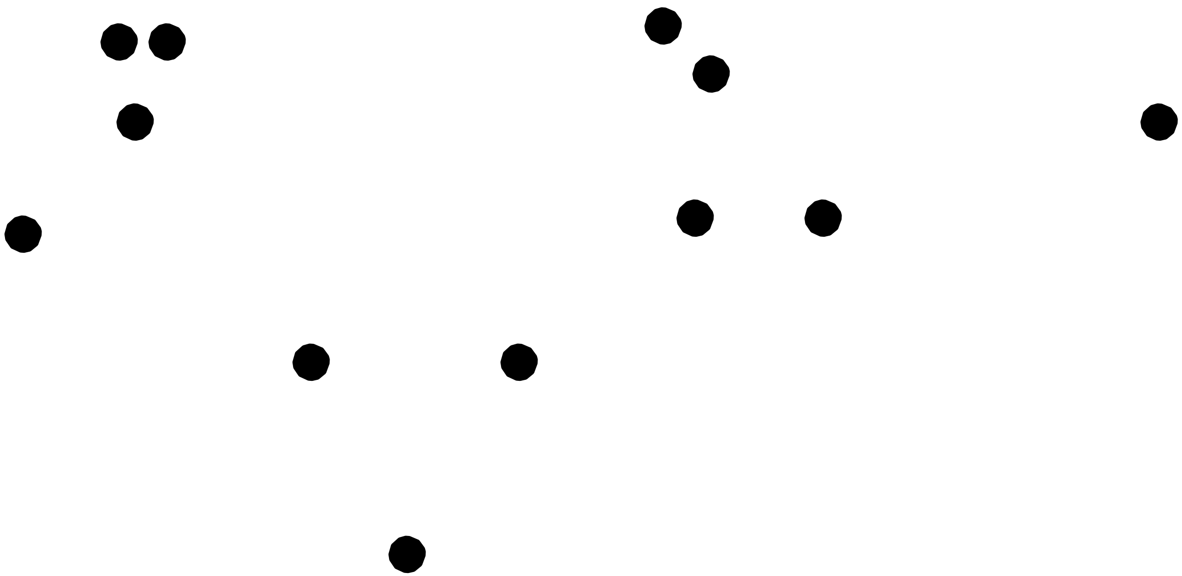
Hierarchical Clustering

- Agglomerative (Bottom-up)
  - Compute all pair-wise pattern-pattern similarity coefficients
  - Place each of *n* patterns into a class of its own
  - Merge the two most similar clusters into one
    - Replace the two clusters into the new cluster
    - Re-compute inter-cluster similarity scores w.r.t. the new cluster
  - Repeat the above step until there are *k* clusters

left (*k* can be 1)

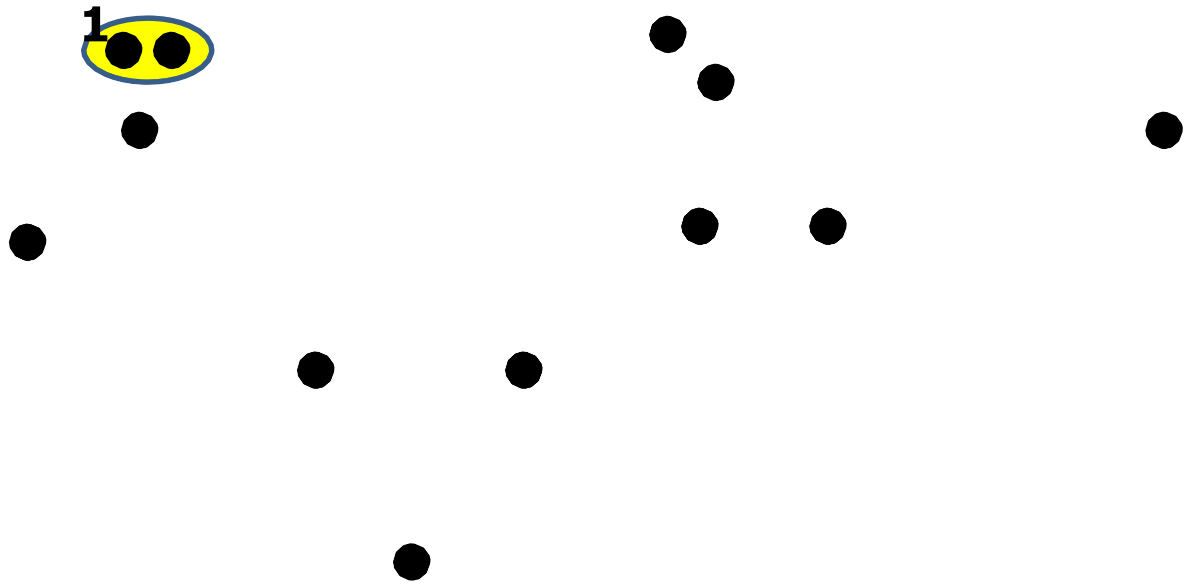
Hierarchical Clustering

- Agglomerative (Bottom up)



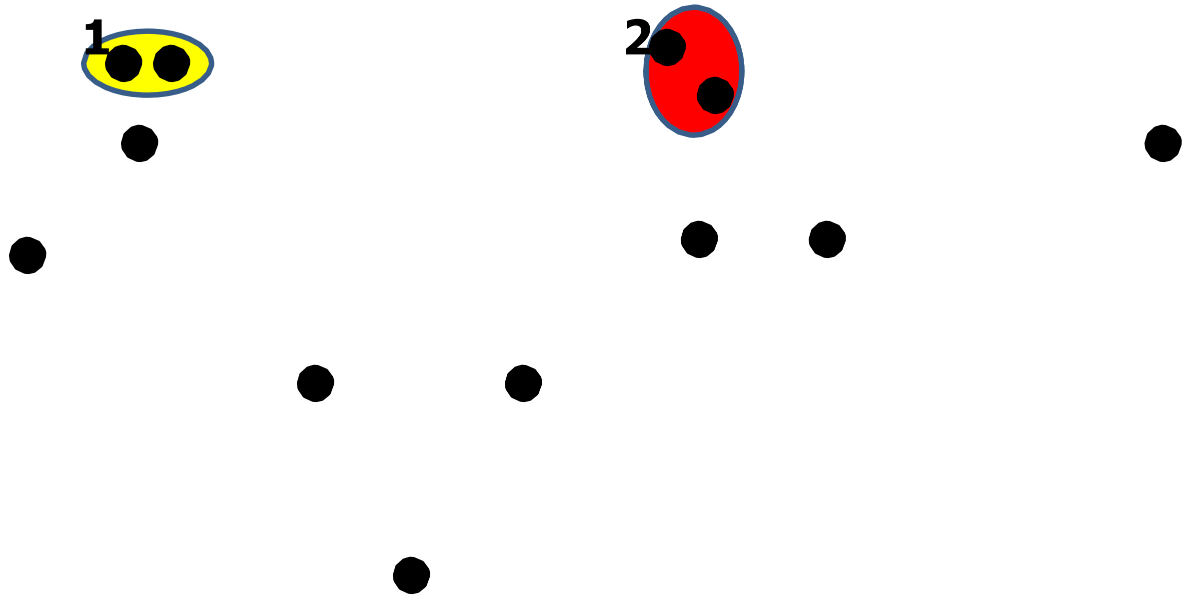
Hierarchical clustering

- Agglomerative (Bottom up)
- 1st iteration



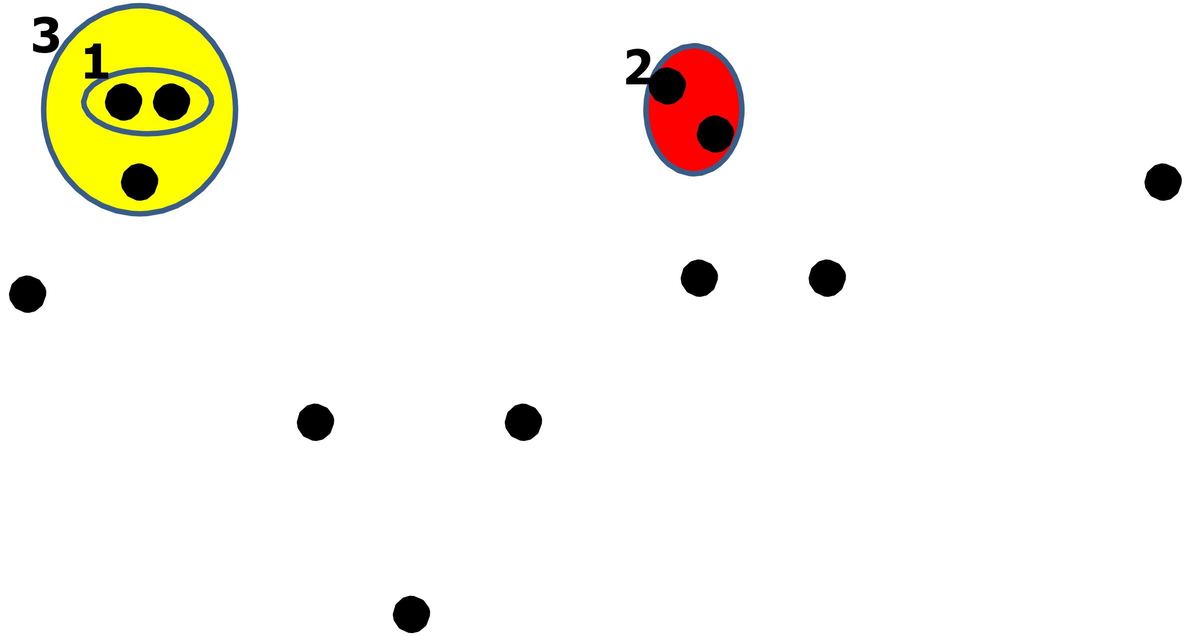
Hierarchical clustering

- Agglomerative (Bottom up)
- 2nd iteration



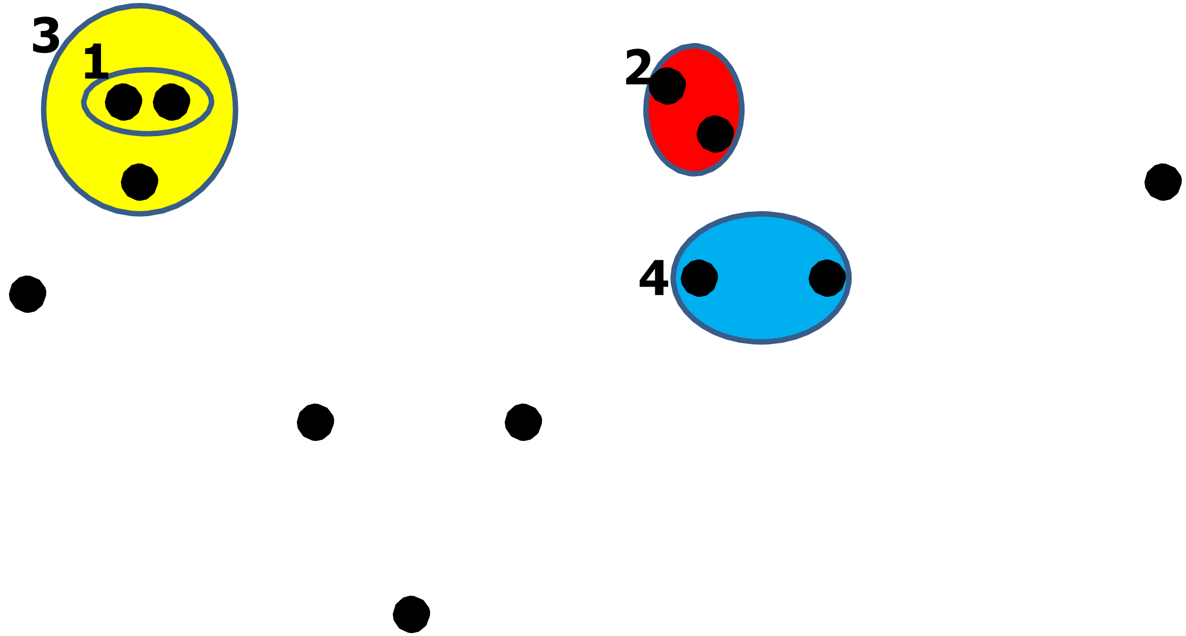
Hierarchical clustering

- Agglomerative (Bottom up)
- 3rd iteration



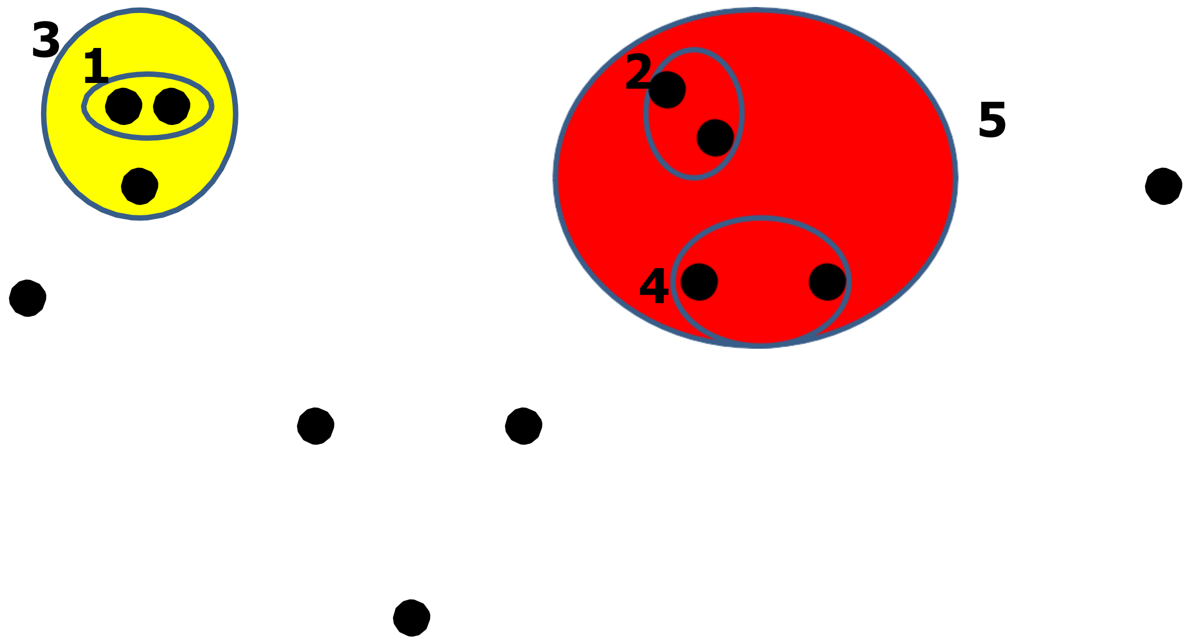
Hierarchical clustering

- Agglomerative (Bottom up)
- 4th iteration



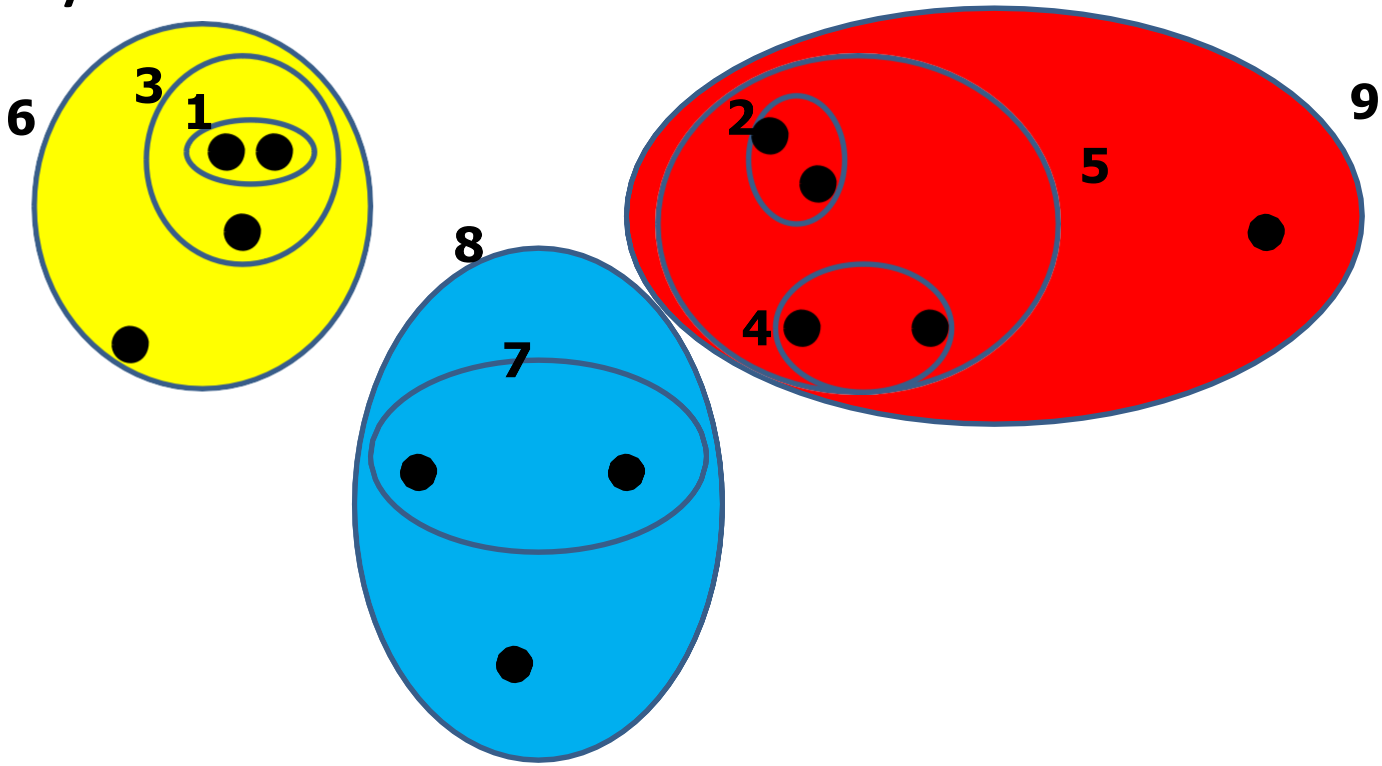
Hierarchical clustering

- Agglomerative (Bottom up)
- 5th iteration



Hierarchical clustering

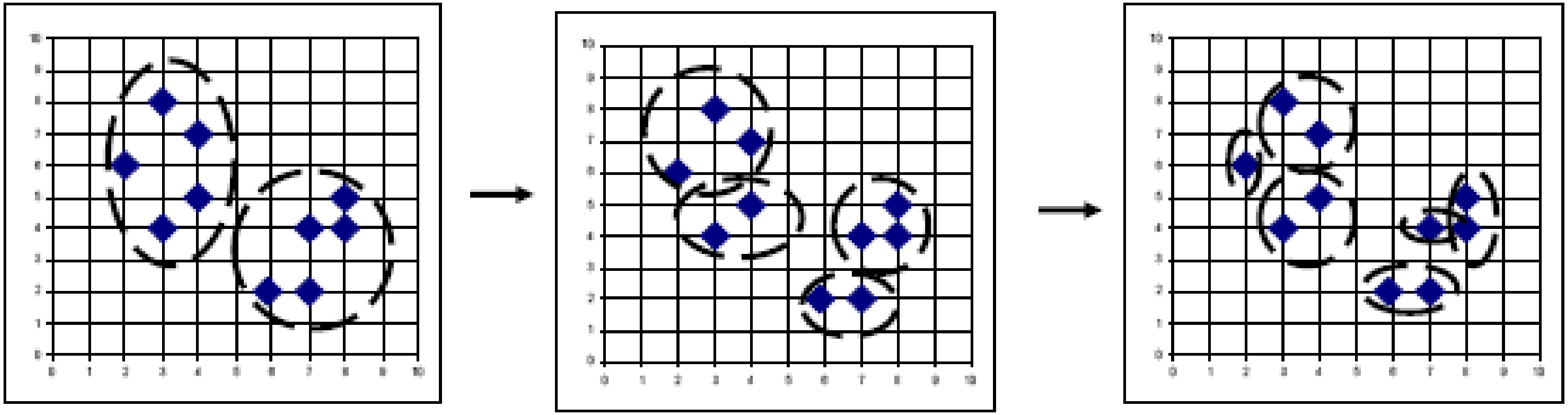
- Agglomerative (Bottom up)
- Finally k clusters left



- Divisive (Top-down)
  - Start at the top with all patterns in one cluster
  - The cluster is split using a flat clustering algorithm
  - This procedure is applied recursively until each pattern is in its own singleton cluster

Hierarchical clustering

- Divisive (Top-down)



Hierarchical Clustering: The Algorithm

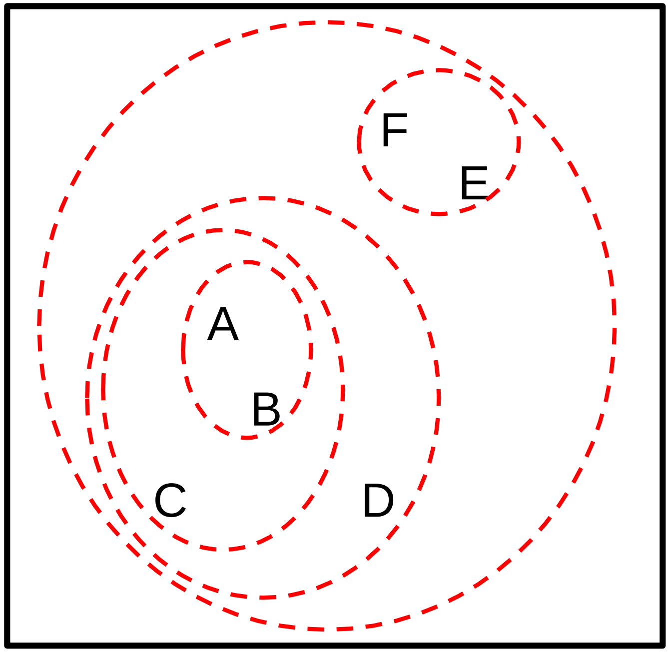
- Hierarchical clustering takes as input a set of points
- It creates a tree in which the points are leaves and the internal nodes reveal the similarity structure of the points.
  - The tree is often called a “dendogram.”
- The method is summarized below:

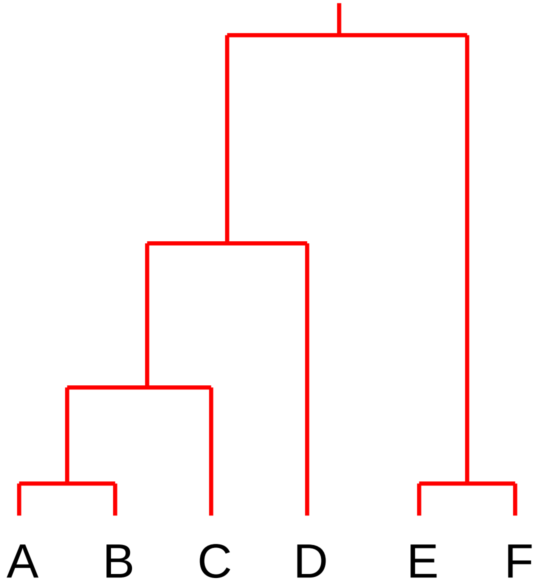
```
Place all points into their own clusters
While there is more than one cluster, do
    Merge the closest pair of clusters
```

- The behavior of the algorithm depends on how “closest pair of clusters” is defined

Hierarchical Clustering: Example

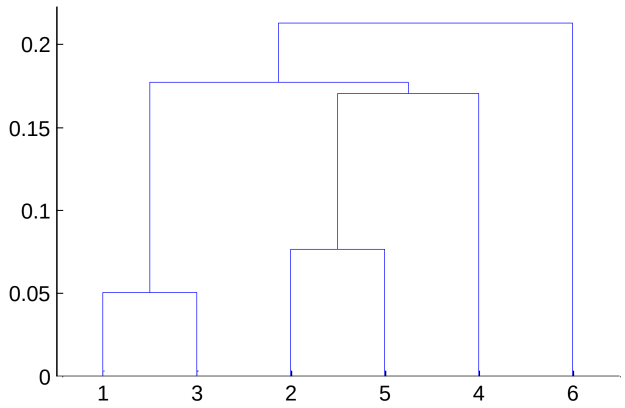
This example illustrates single-link clustering in Euclidean space on 6 points.

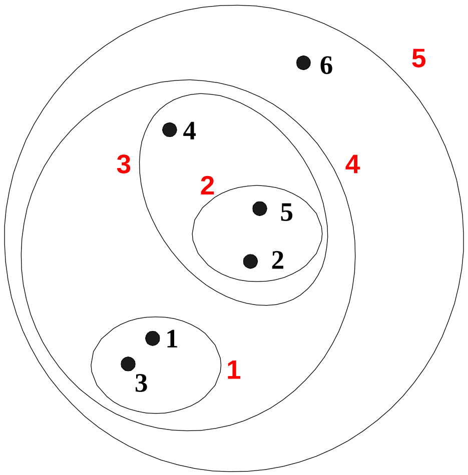




Hierarchical clustering

- Produces a set of nested clusters organized as a hierarchical tree
- Can be visualized as a dendrogram
  - A tree like diagram that records the sequences of merges or splits

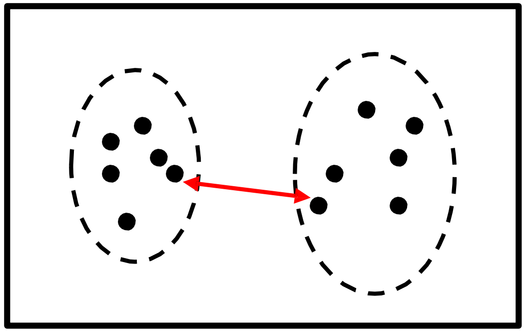




Strengths of Hierarchical Clustering

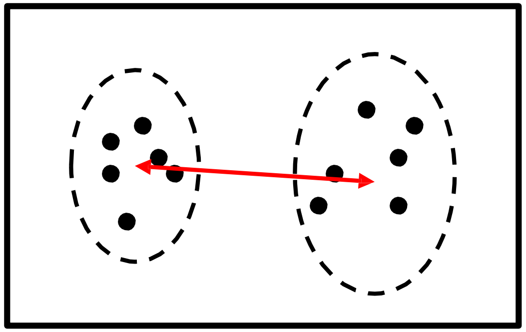
- Do not have to assume any particular number of clusters
  - Any desired number of clusters can be obtained by ‘cutting’ the dendogram at the proper level

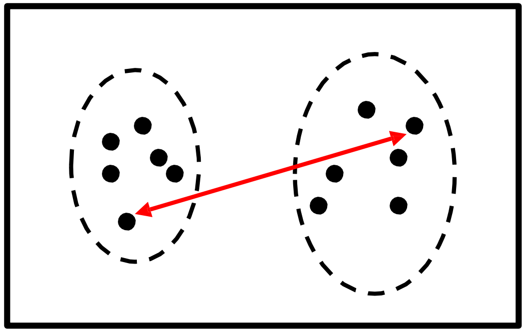
Hierarchical Clustering: Merging Clusters



Single Link: Distance between two clusters is the distance between the closest points. Also called "neighbor joining."

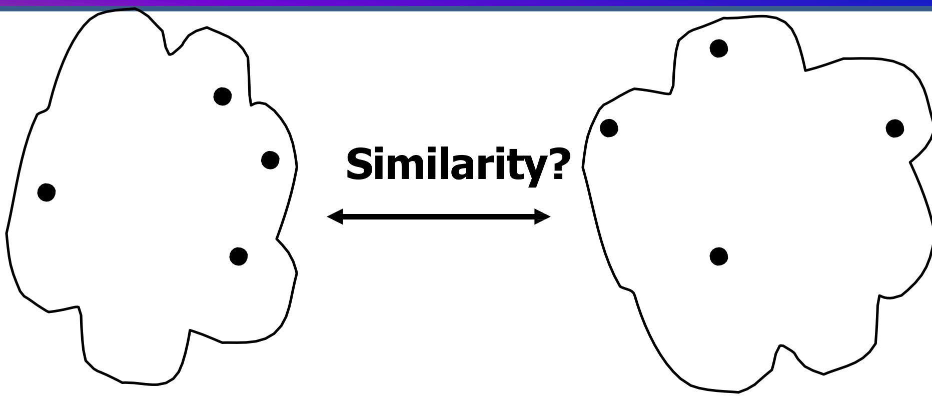
Average Link: Distance between clusters is distance between the cluster centroids.





Complete Link: Distance between clusters is distance between farthest pair of points.

How to Define Inter-Cluster Similarity

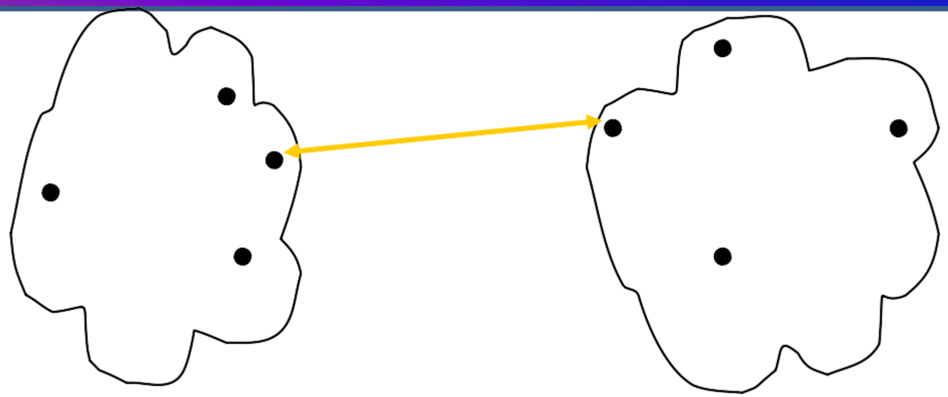


	p1	p2	p3	p4	p5	. . .
p1						
p2						
p3						
p4						
p5						
. . .						

Proximity Matrix

- MIN
- MAX
- Group Average
- Distance Between Centroids

How to Define Inter-Cluster Similarity

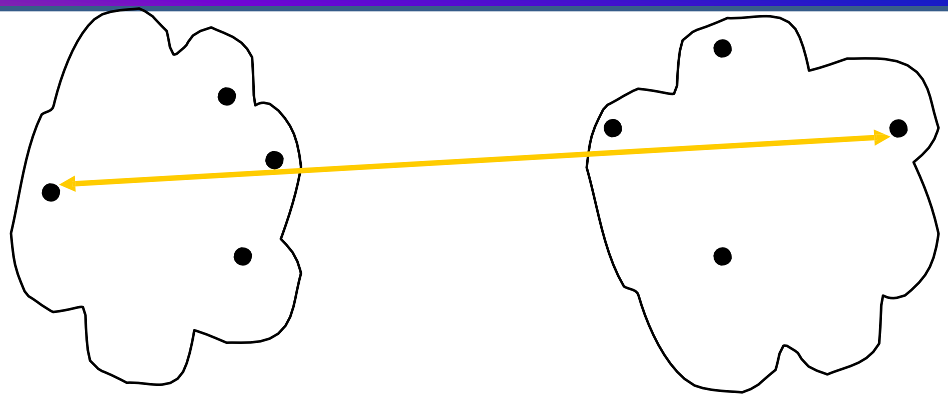


- MIN
- MAX
- Group Average
- Distance Between Centroids

	p1	p2	p3	p4	p5	. . .
p1						
p2						
p3						
p4						
p5						
.						
.						
.						

Proximity Matrix

How to Define Inter-Cluster Similarity



	p1	p2	p3	p4	p5	. . .
p1						
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.						
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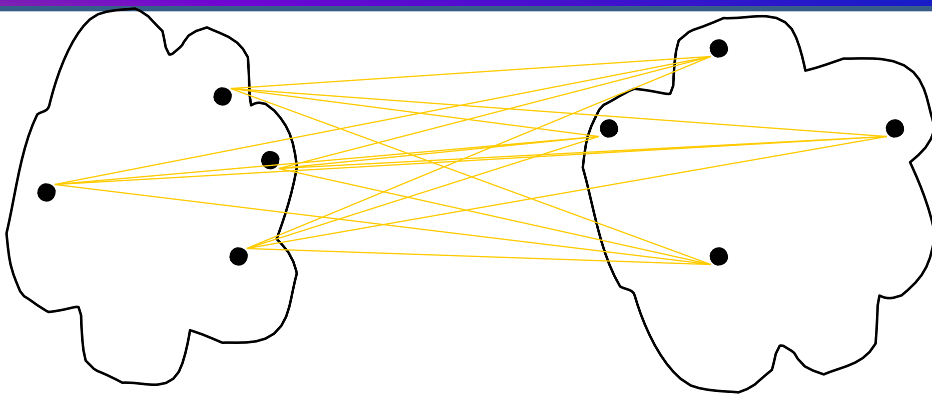

	p1	p2	p3	p4	p5	. . .
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.						
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Proximity Matrix

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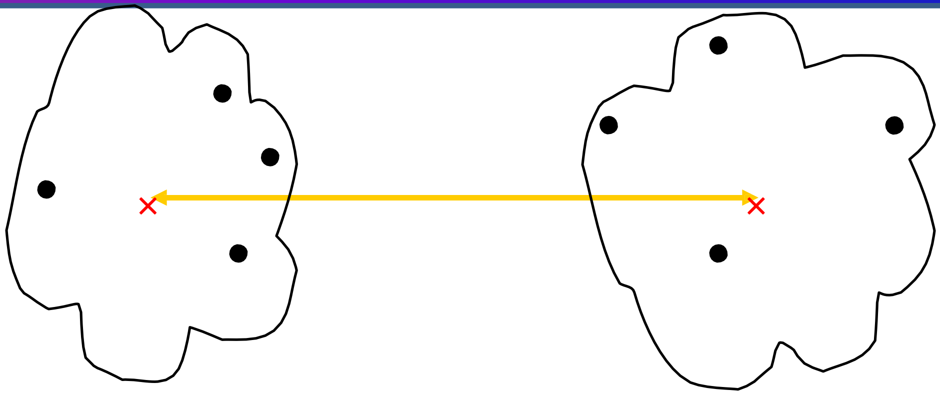
How to Define Inter-Cluster Similarity



- MIN
- MAX
- Group Average
- Distance Between Centroids

	p1	p2	p3	p4	p5	. . .
p1						
p2						
p3						
p4						
p5						
.						
.						
.						

Proximity Matrix

Example

Let us consider a gene measured in a set of 5 experiments: A,B,C,D and E. The values measured in the 5 experiments are:

A=100 B=200 C=500 D=900 E=1100

We will construct the hierarchical clustering of these values using Euclidean distance, centroid linkage and an agglomerative approach.

Example

SOLUTION:

- The closest two values are 100 and 200

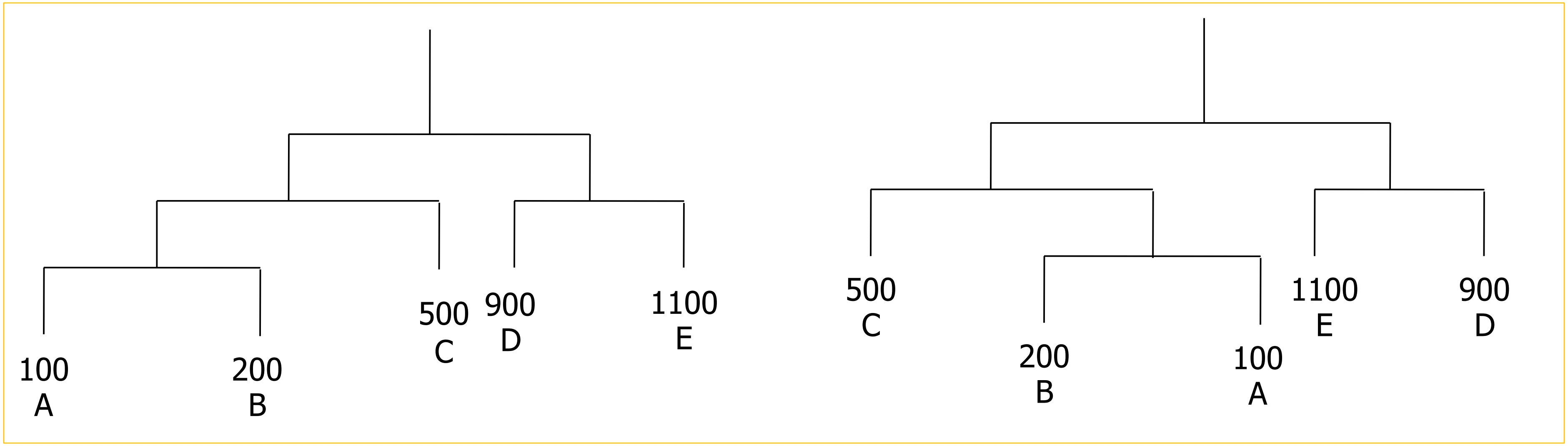
  =>the centroid of these two values is 150.
- Now we are clustering the values: 150, 500, 900, 1100
- The closest two values are 900 and 1100

  =>the centroid of these two values is 1000.
- The remaining values to be joined are: 150, 500, 1000.
- The closest two values are 150 and 500

  =>the centroid of these two values is 325.
- Finally, the two resulting subtrees are joined in the root of the tree.

An example:

Two hierarchical clusters of the expression values of a single gene measured in 5 experiments.

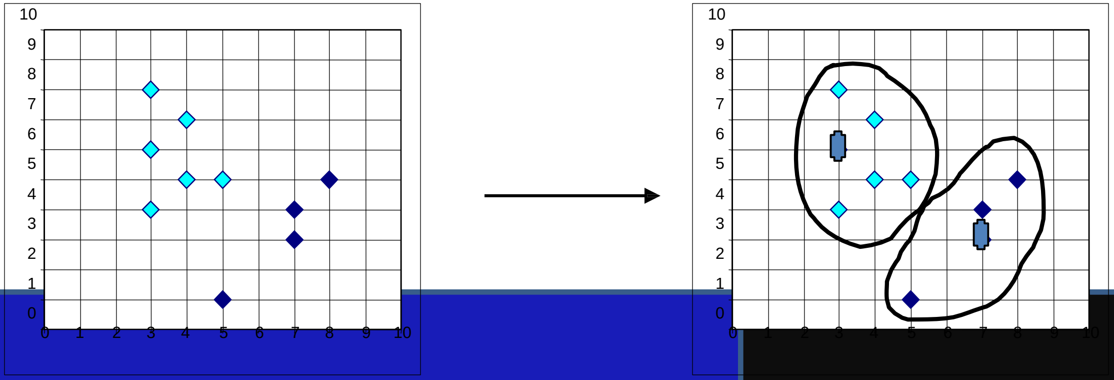


- ➢<u>The dendograms are identical</u>: both diagrams show that:
  - •A is most similar to B
  - •C is most similar to the group (A,B)
  - •D is most similar to E
- ➢In the left dendogram A and E are plotted far from each other
- ➢In the right dendogram A and E are immediate neighbors

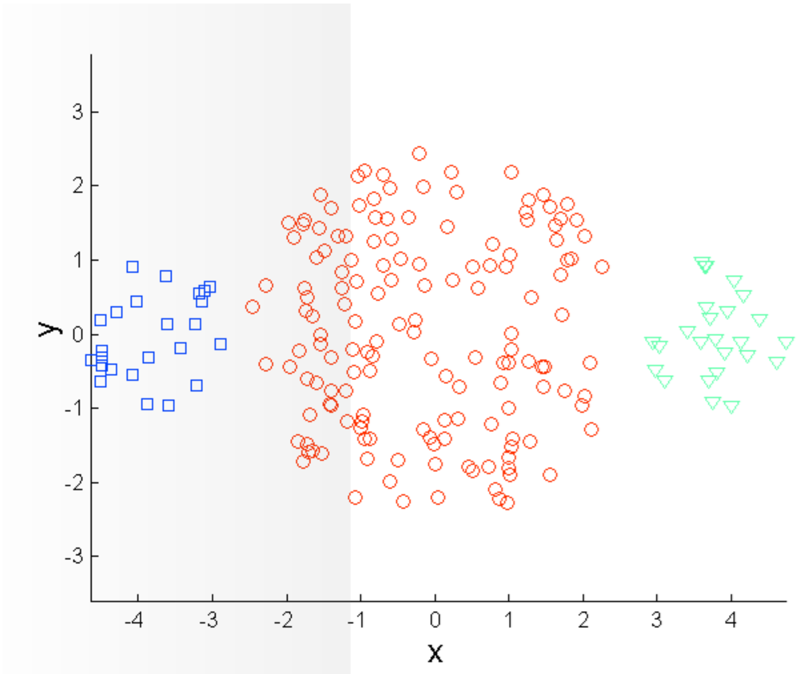
THE PROXIMITY IN A HIERARCHICAL CLUSTERING DOES NOT NECESSARILY CORRESPOND TO SIMILARITY

What Is the Problem of the K- Means Method?

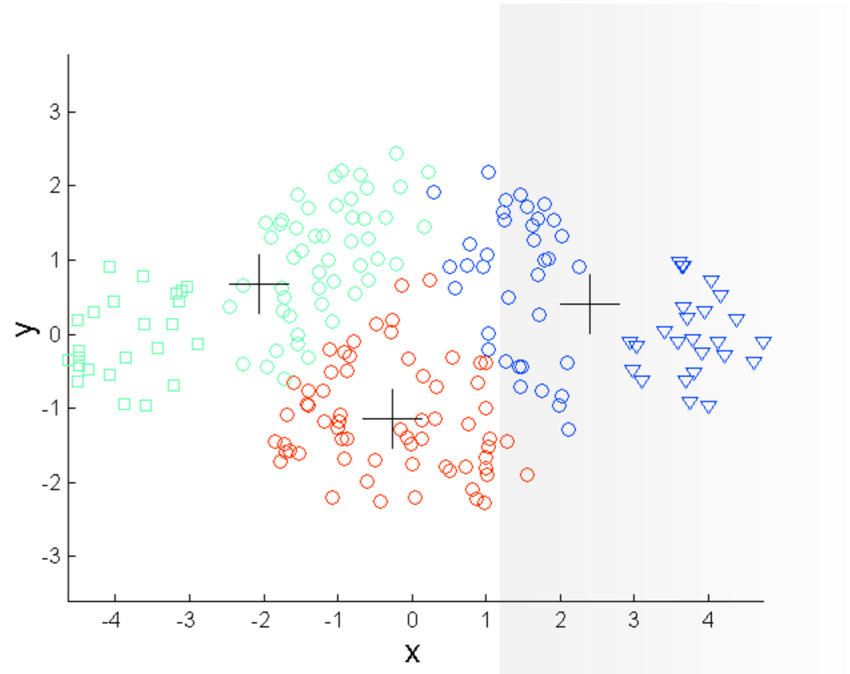
- The k-means algorithm is sensitive to outliers !
  - Since an object with an extremely large value may substantially distort the distribution of the data.
- K-Medoids: Instead of taking the **mean** value of the object in a cluster as a reference point, **medoids** can be used, which is the **most centrally located** object in a cluster.



Limitations of K-means: Differing Sizes

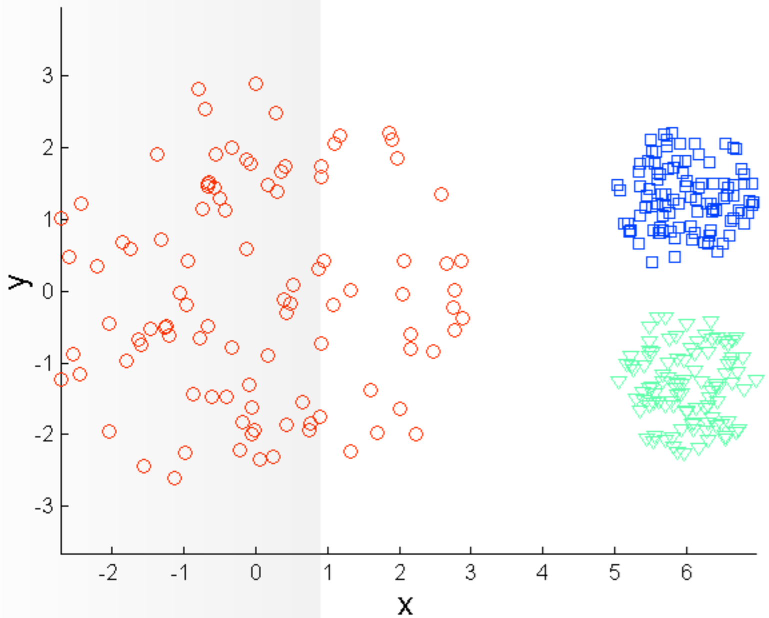


Original Points

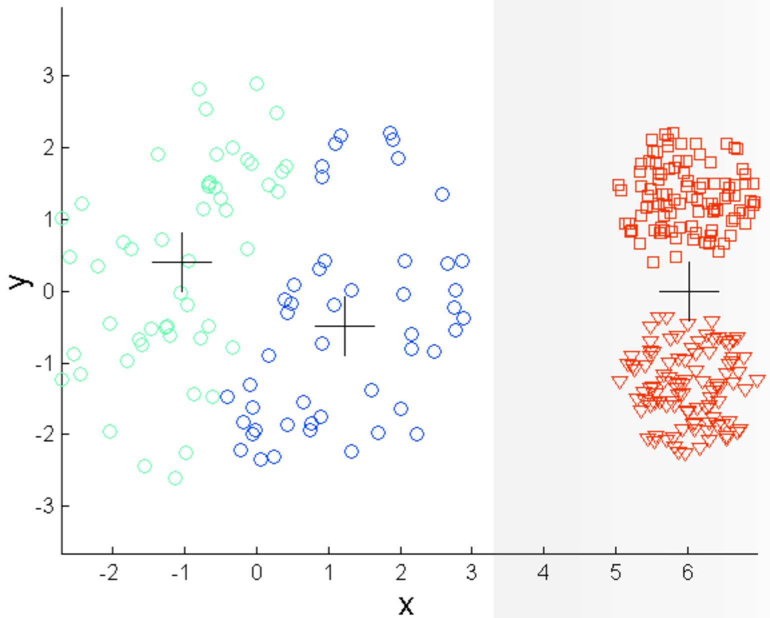


K-means (3 Clusters)

Limitations of K-means: Differing Density

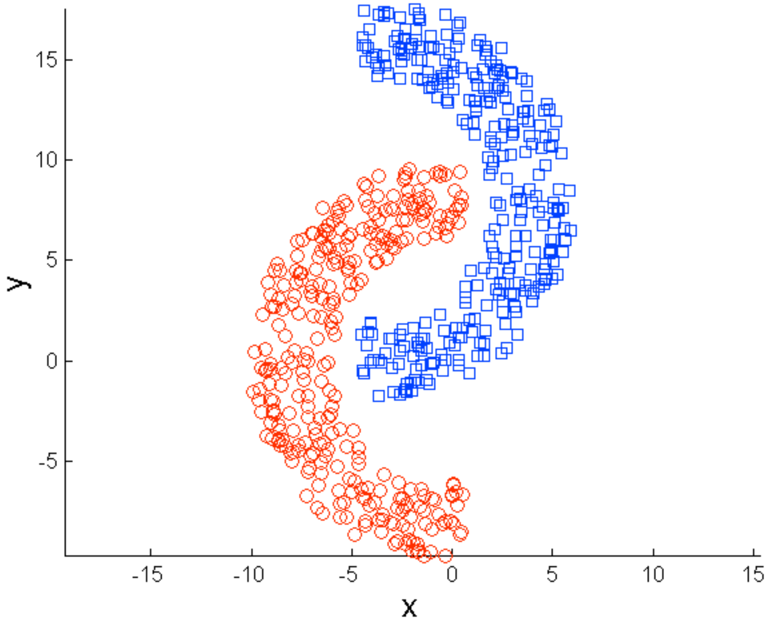


Original Points

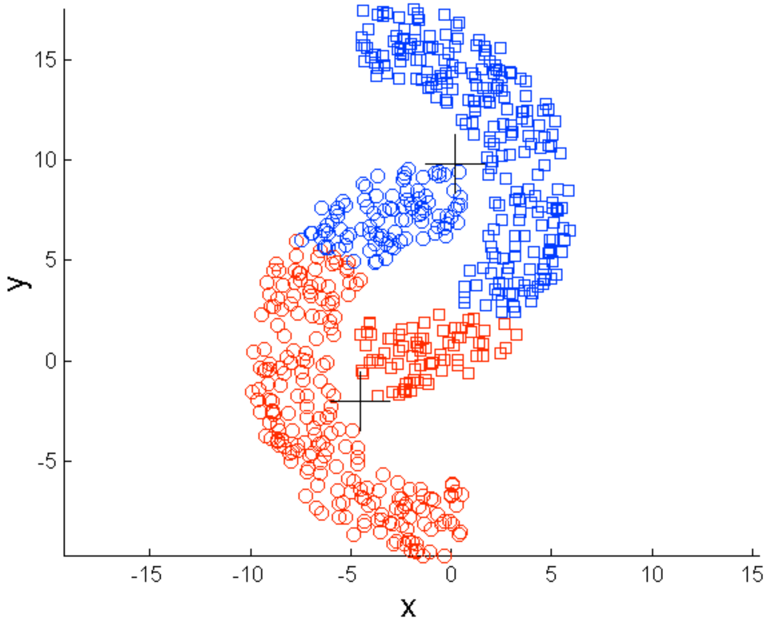


K-means (3 Clusters)

Limitations of K-means: Non-globular Shapes



Original Points



K-means (2 Clusters)

Image Segmentation Algorithms (Techniques)

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  k-Mode Clustering
  Hierarchical Clustering
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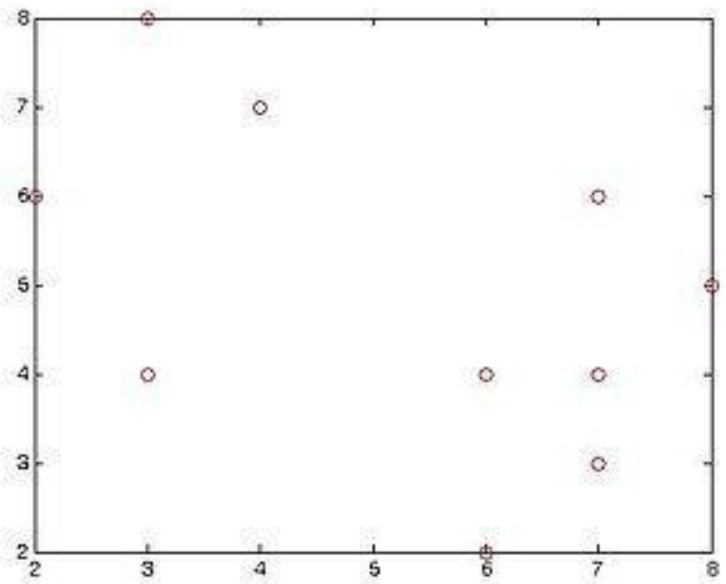
K-Mode

- Handling categorical data: *k-modes* (Huang’98)
  - Replacing means of clusters with <u>modes</u>
    - Mode of an attribute: most frequent value
    - Mode of instances: for an attribute A, mode(A)= most frequent value
    - K-mode is equivalent to K-means
  - Using a <u>frequency</u>-based method to update modes of clusters
  - A mixture of categorical and numerical data: *k-prototype* method

K-mediods example

X_1	2	6
X_2	3	4
X_3	3	8
X_4	4	7
X_5	6	2
X_6	6	4
X_7	7	3
X_8	7	4
X_9	8	5
X_{10}	7	6



K-mediods example

- Initialize *k* mediods
- Let us assume $c_1 = (3,4)$ and $c_2 = (7,4)$
- Calculate distance so as to associate each data object to its nearest medoid.

i	c_1		Data ts objec (X_i)		Cost (distance)
1	3	4	2	6	**3**
3	3	4	3	8	**4**
4	3	4	4	7	**4**
5	3	4	6	2	5
6	3	4	6	4	3
7	3	4	7	3	5
9	3	4	8	5	6
10	3	4	7	6	6

i	c_2		Data s object (X_i)		Cost (distance)
1	7	4	2	6	7
3	7	4	3	8	8
4	7	4	4	7	6
5	7	4	6	2	**3**
6	7	4	6	4	**1**
7	7	4	7	3	**1**
9	7	4	8	5	**2**
10	7	4	7	6	**2**

$Cluster_1$ = {(3,4)(2,6)(3,8)(4,7)}

$Cluster_2$ = {(7,4)(6,2)(6,4)(7,3)(8,5)(7,6)}

$$\mathrm{cost}(x,c) = \sum_{i=1}^{d} |x_i - c_i|$$

$$\begin{aligned}
\text{total cost} &= \{\mathrm{cost}((3,4),(2,6)) + \mathrm{cost}((3,4),(3,8)) + \mathrm{cost}((3,4),(4,7))\} \\
&\quad + \{\mathrm{cost}((7,4),(6,2)) + \mathrm{cost}((7,4),(6,4)) + \mathrm{cost}((7,4),(7,3)) \\
&\quad + \mathrm{cost}((7,4),(8,5)) + \mathrm{cost}((7,4),(7,6))\} \\
&= (3+4+4) + (3+1+1+2+2) \\
&= 20
\end{aligned}$$

- **Select one of the nonmedoids O′. Let us assume O′ = (7,3)**
- **Now the medoids are c_1(3,4) and O′(7,3)**

i	c_1		Data ts objec (X_i)		Cost (distance)
1	3	4	2	6	**3**
3	3	4	3	8	**4**
4	3	4	4	7	**4**
5	3	4	6	2	5
6	3	4	6	4	3
8	3	4	7	4	4
9	3	4	8	5	6
10	3	4	7	6	6

i	O′		Data objects (X_i)		Cost (distance)
1	7	3	2	6	8
3	7	3	3	8	9
4	7	3	4	7	7
5	7	3	6	2	**2**
6	7	3	6	4	**2**
8	7	3	7	4	**1**
9	7	3	8	5	**3**
10	7	3	7	6	**3**

$$\text{total cost} = 3 + 4 + 4 + 2 + 2 + 1 + 3 + 3 = 22$$

$$S = \text{current total cost} - \text{past total cost} = 22 - 20 = 2 > 0.$$

- Do not change the mediod as S > 0

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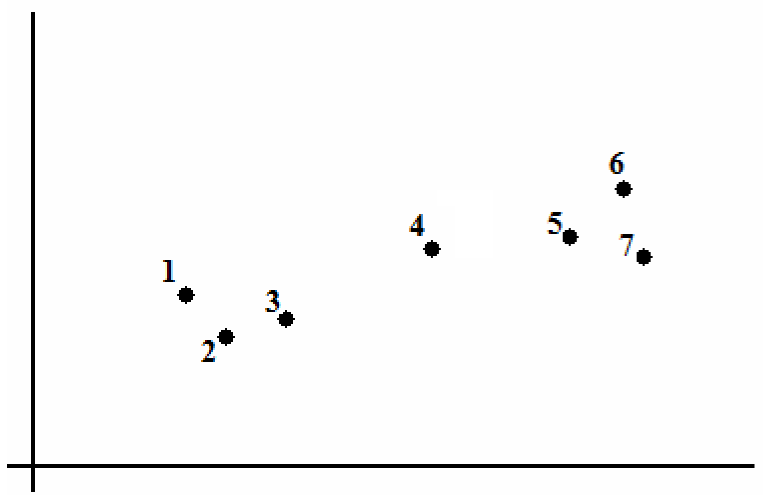
Fuzzy C-means Clustering

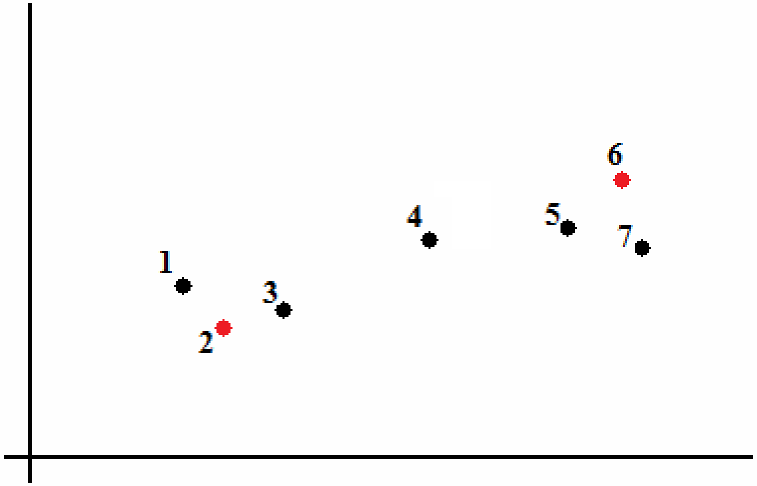
- Fuzzy C-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters.

- This method (developed by Dunn in 1973 and improved by Bezdek in 1981) is frequently used in pattern recognition.

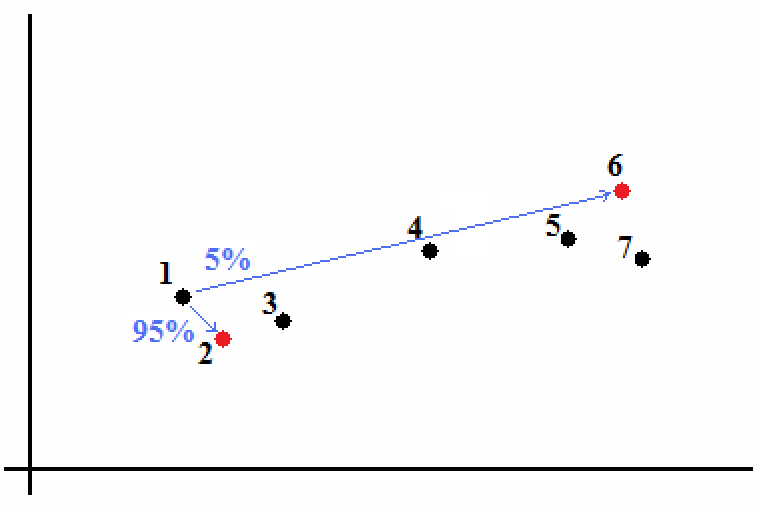
Fuzzy C-means Clustering



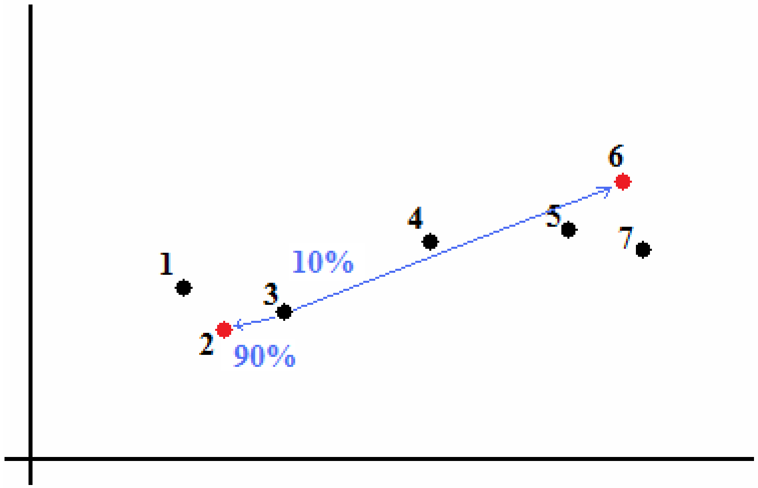
Fuzzy C-means Clustering



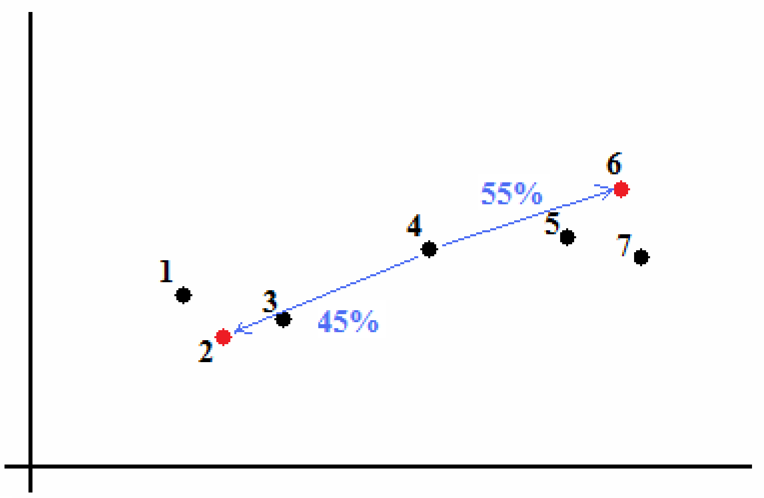
Fuzzy C-means Clustering



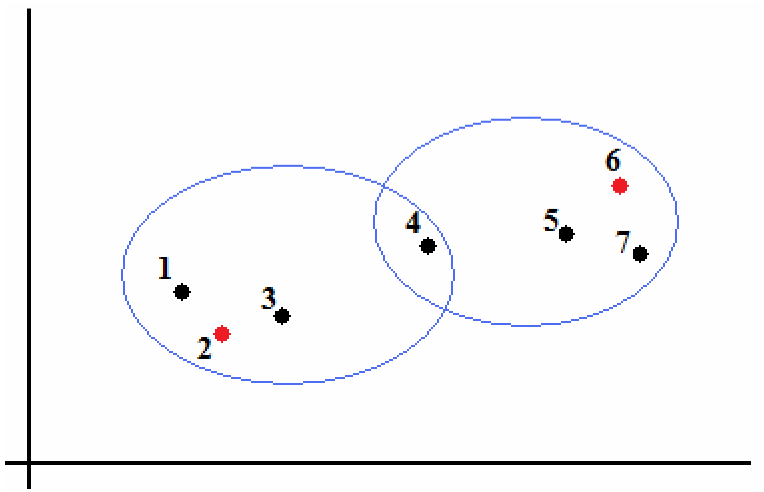
Fuzzy C-means Clustering



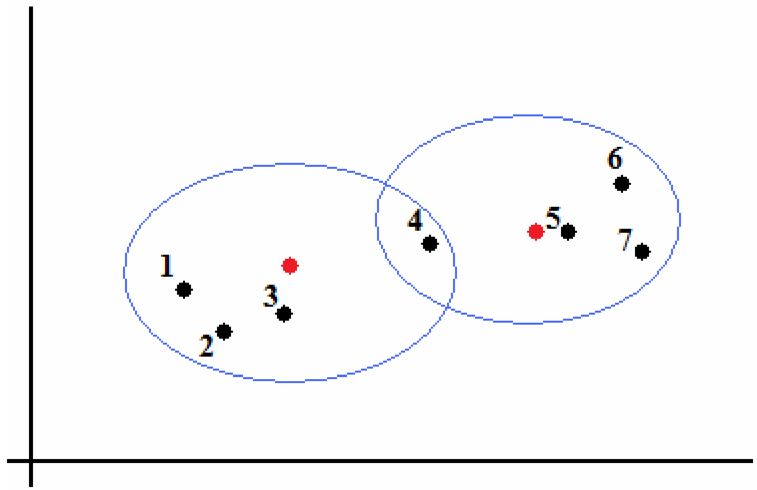
Fuzzy C-means Clustering



Fuzzy C-means Clustering



Fuzzy C-means Clustering



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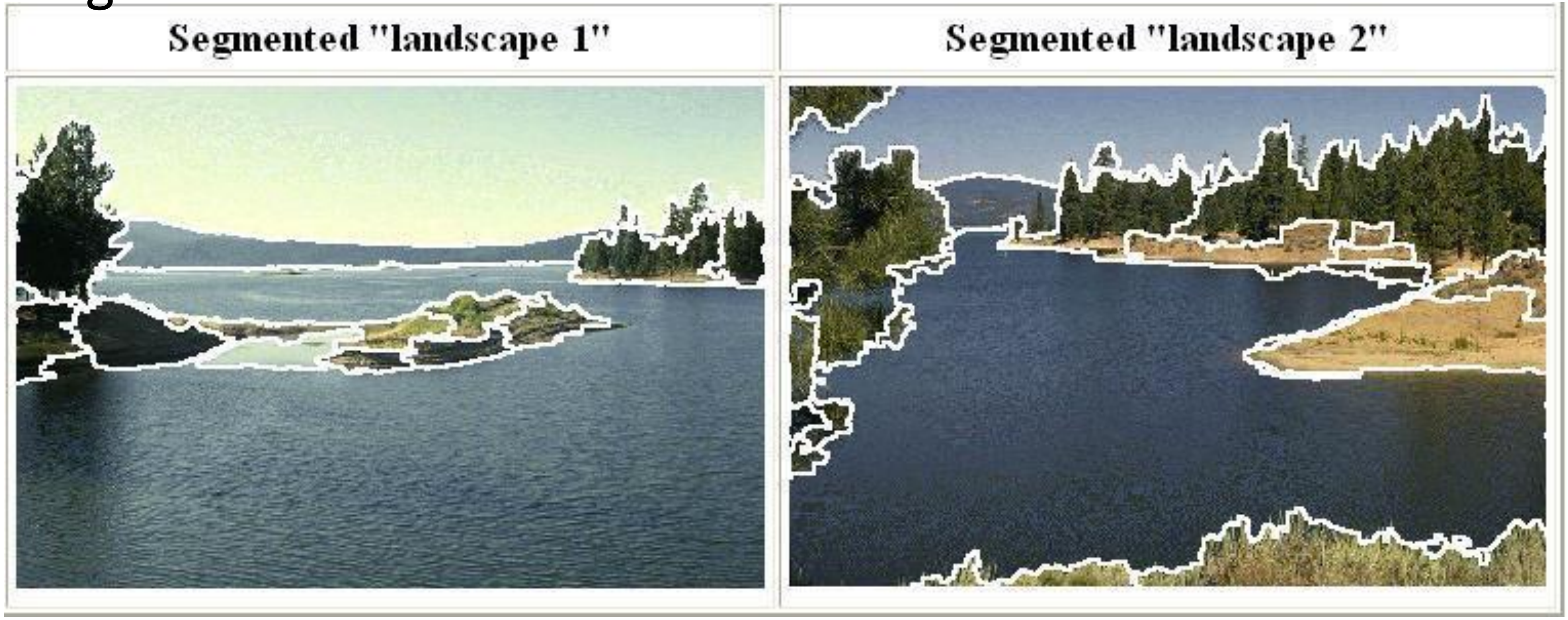
  Mean Shift Segmentation

Mean Shift Segmentation

- An advanced and versatile technique for clustering-based segmentation

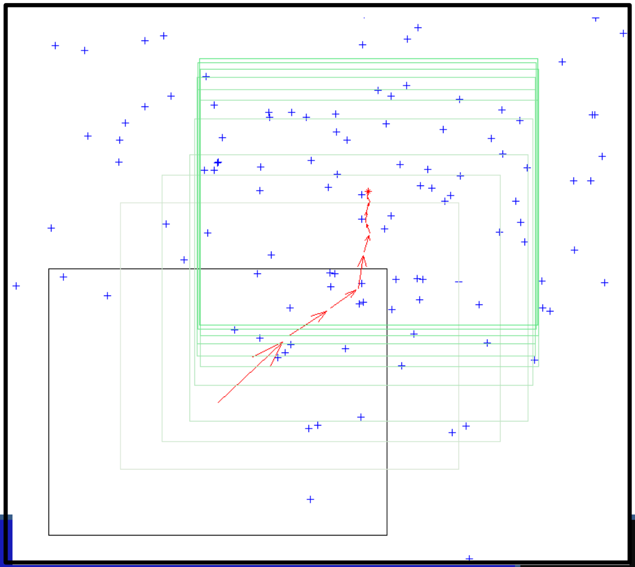


http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

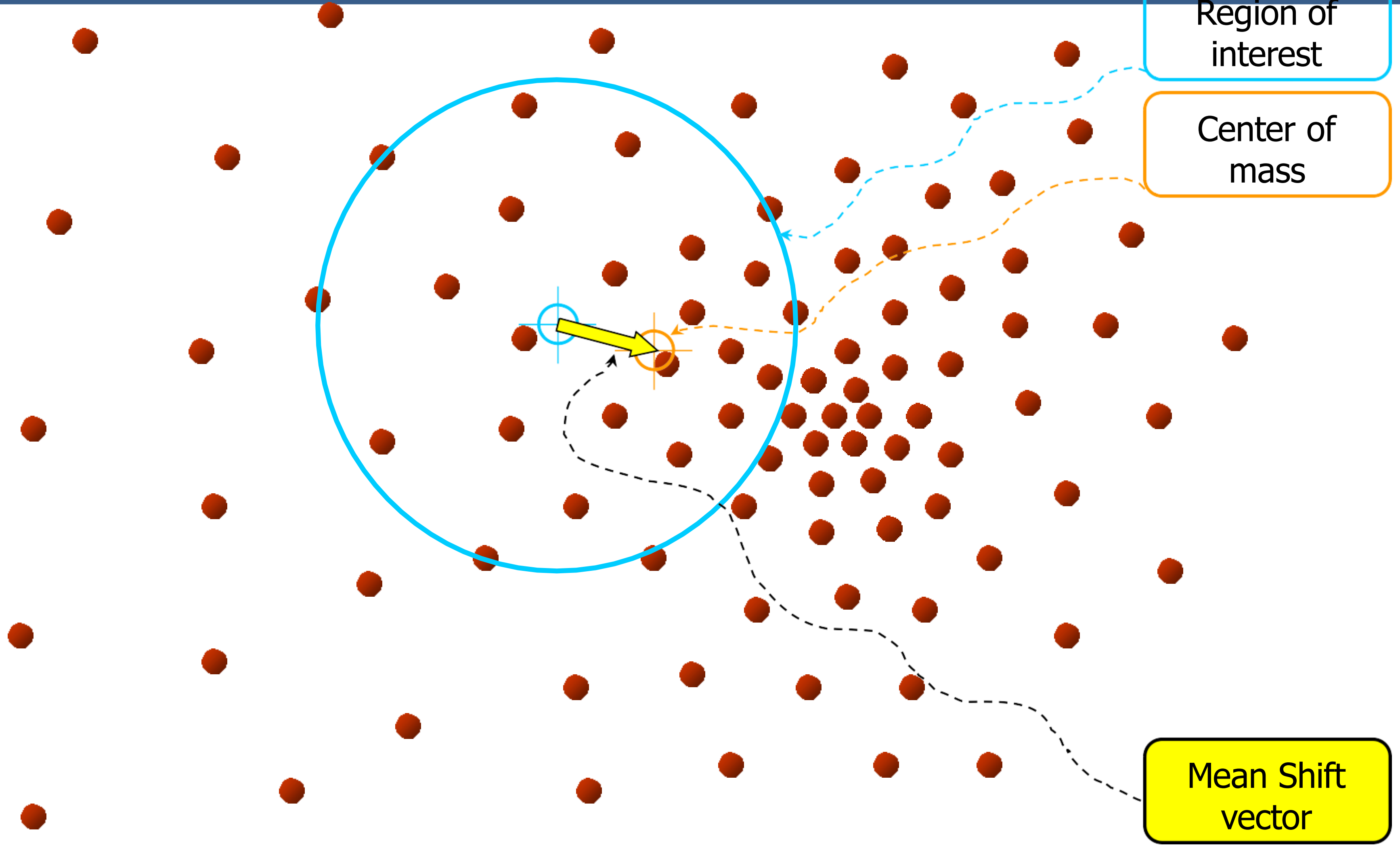
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean Shift Segmentation

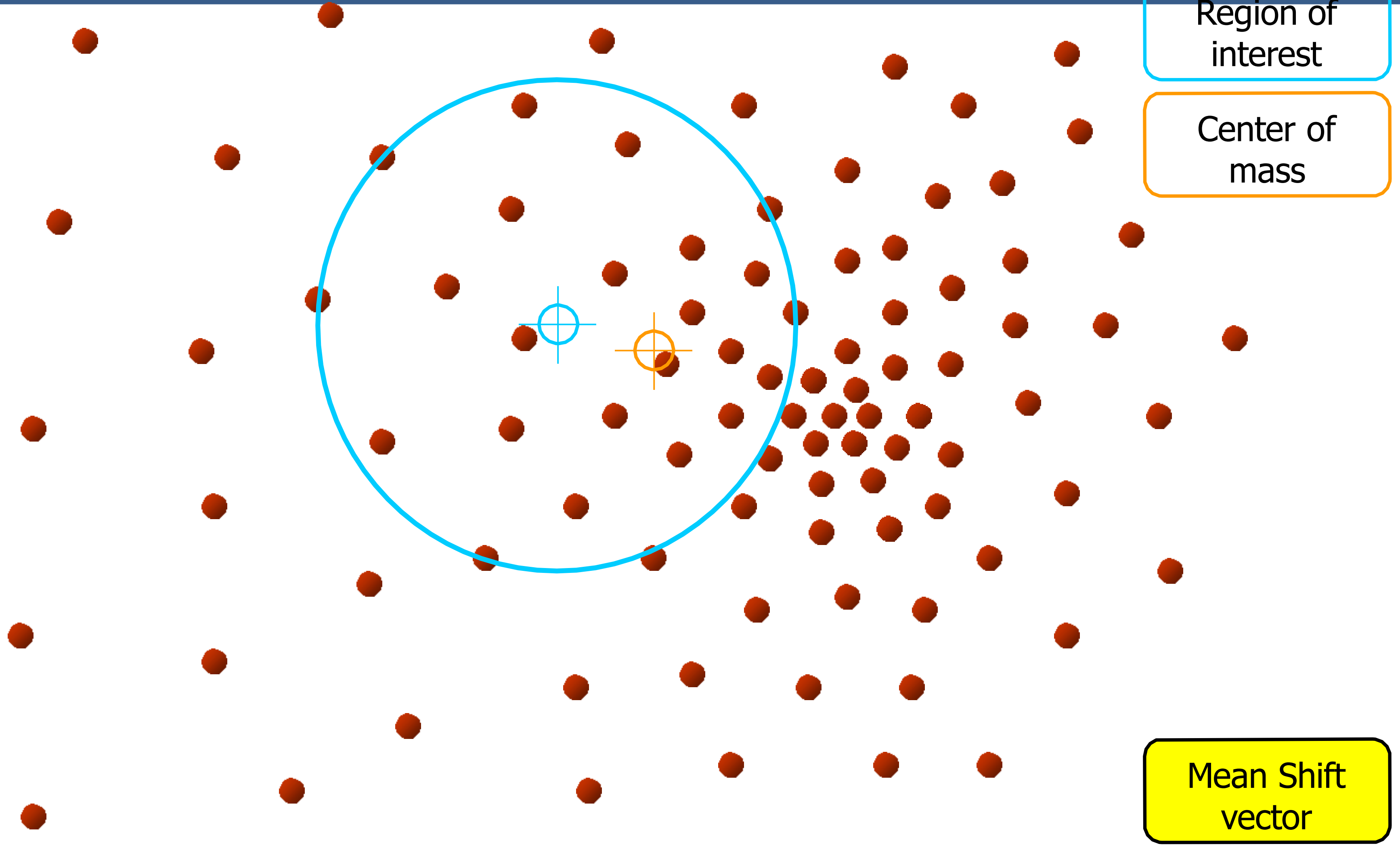
- The mean shift algorithm seeks a *mode* or local maximum of density of a given distribution
  - Choose a search window (width and location)
  - Compute the mean of the data in the search window
  - Center the search window at the new mean location
  - Repeat until convergence



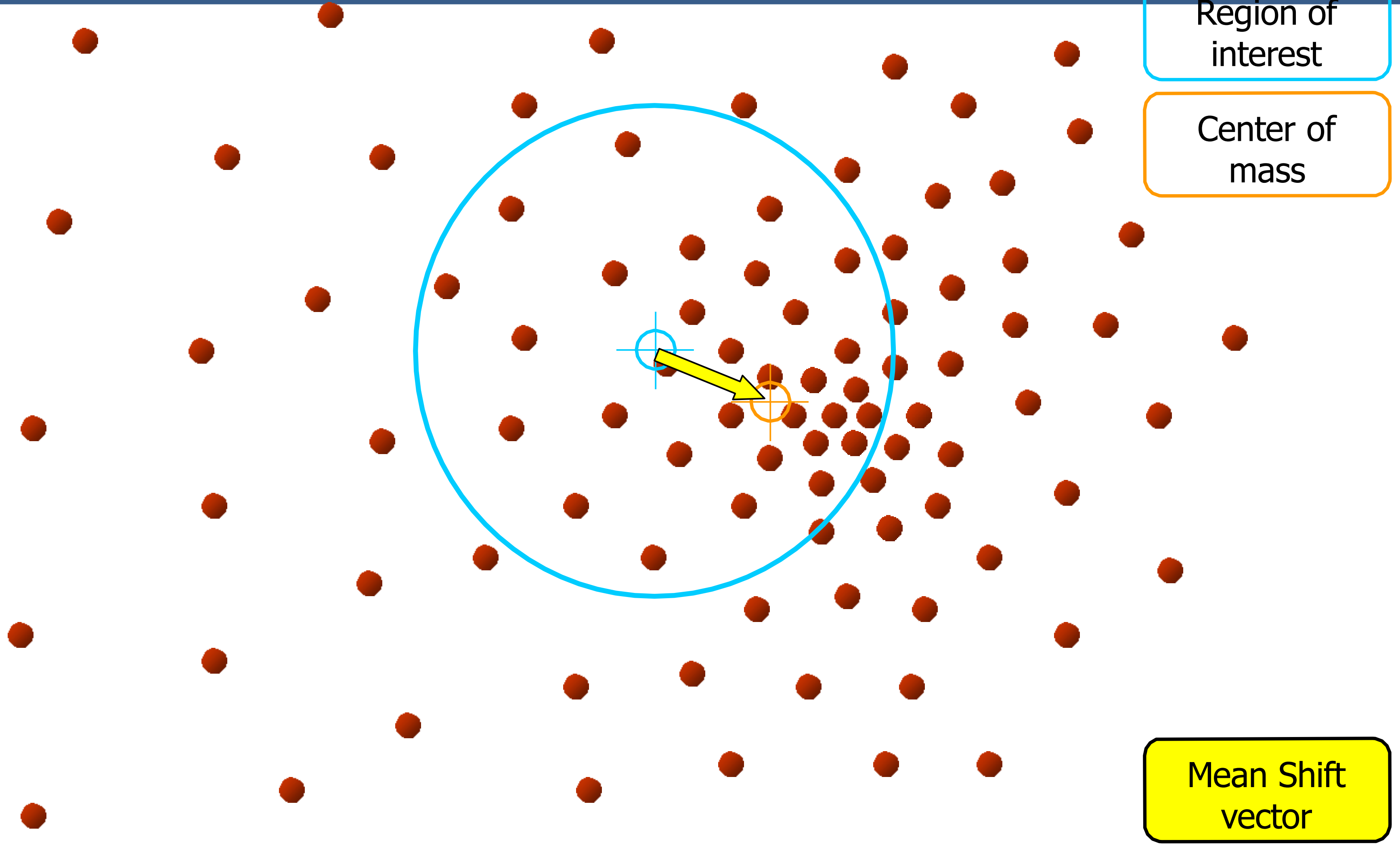
Mean Shift Segmentation



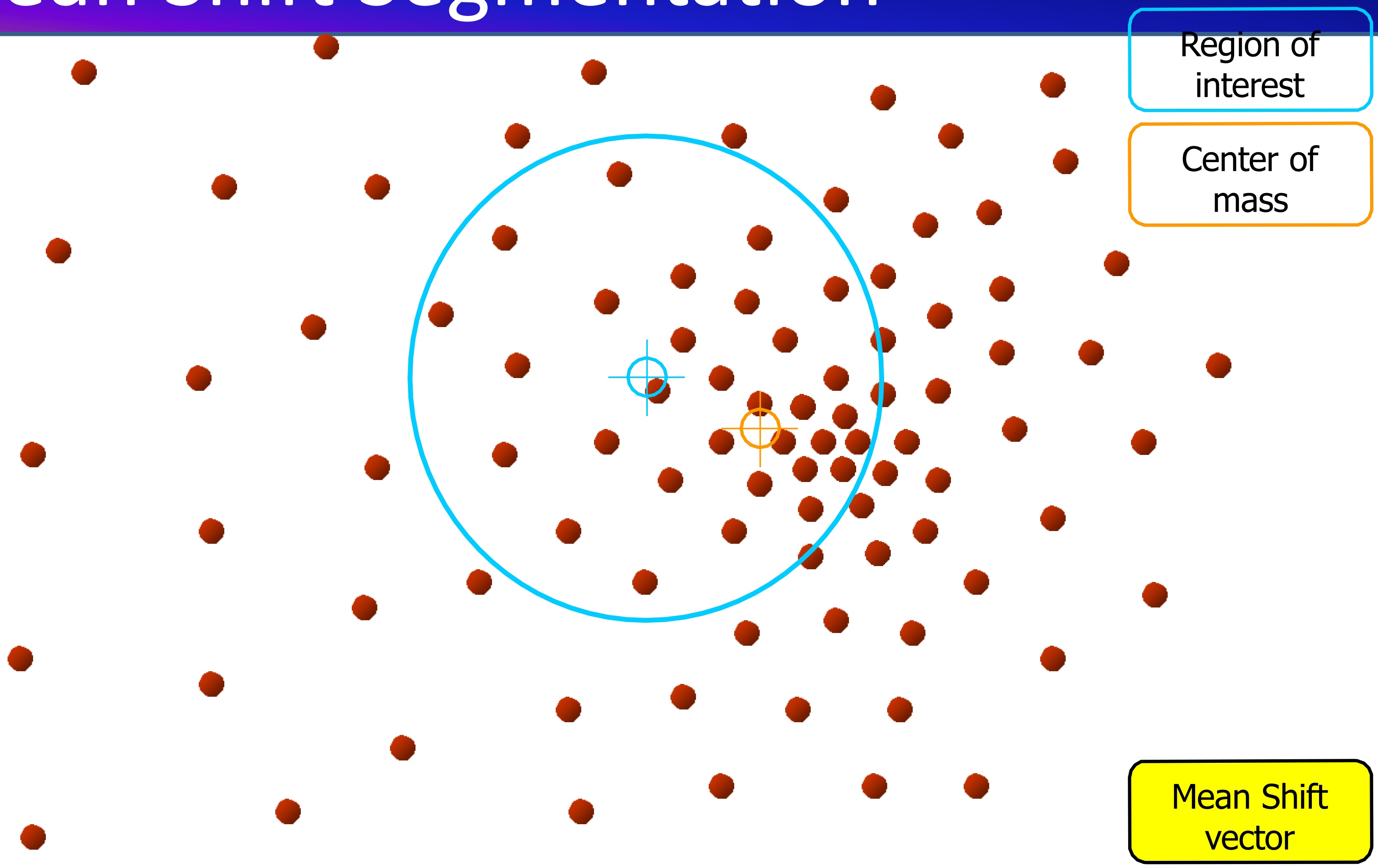
Mean Shift Segmentation



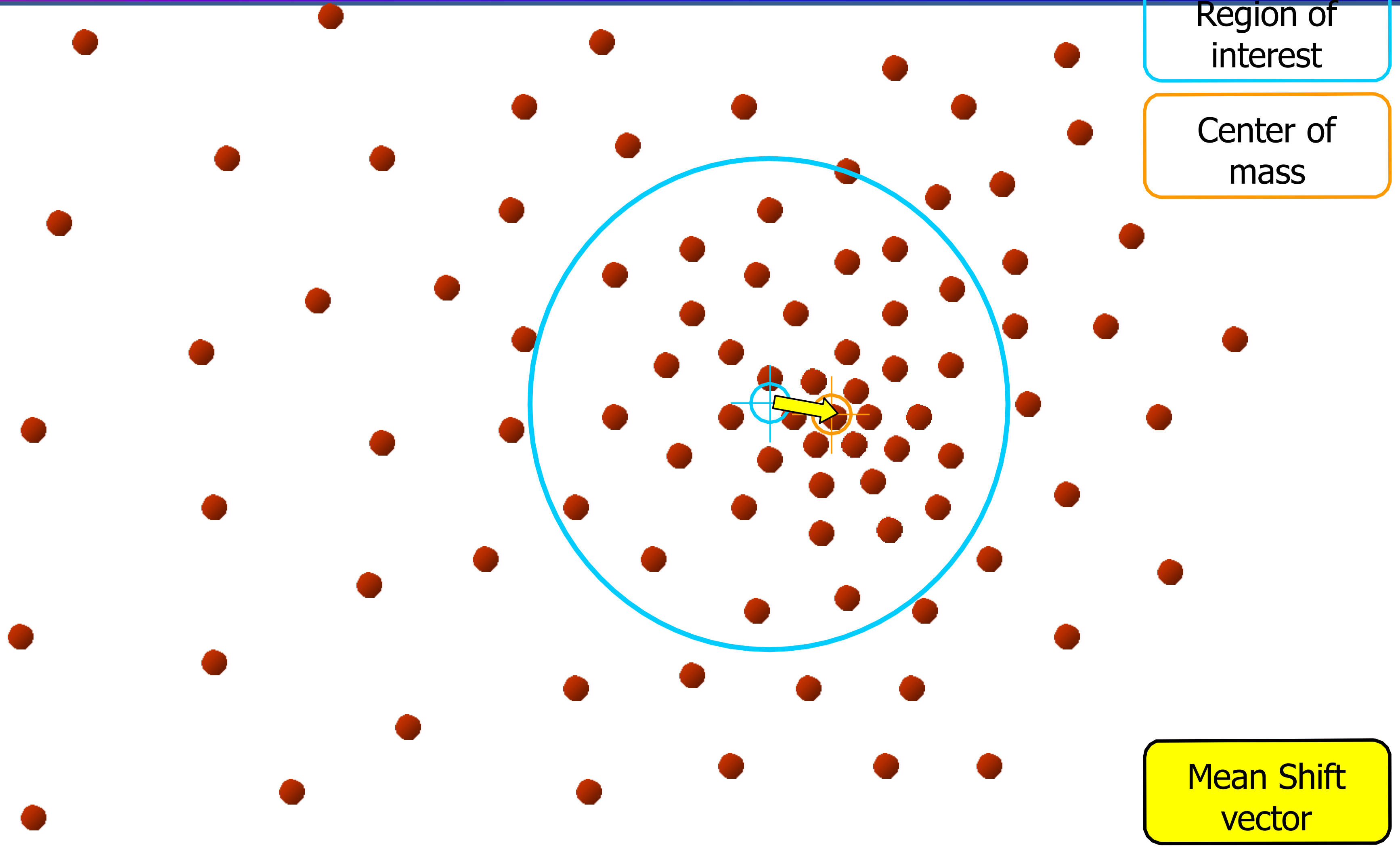
Mean Shift Segmentation



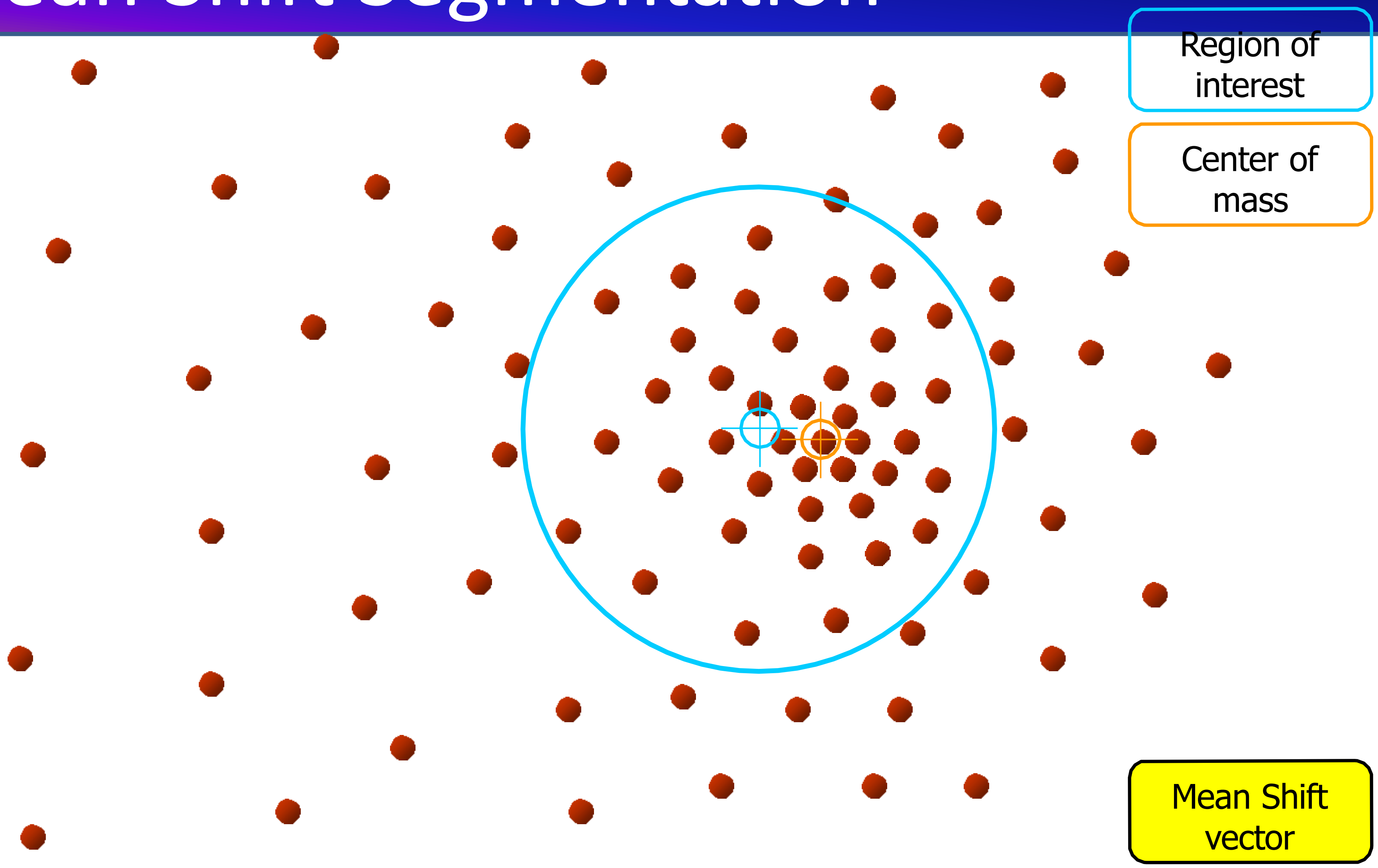
Mean Shift Segmentation



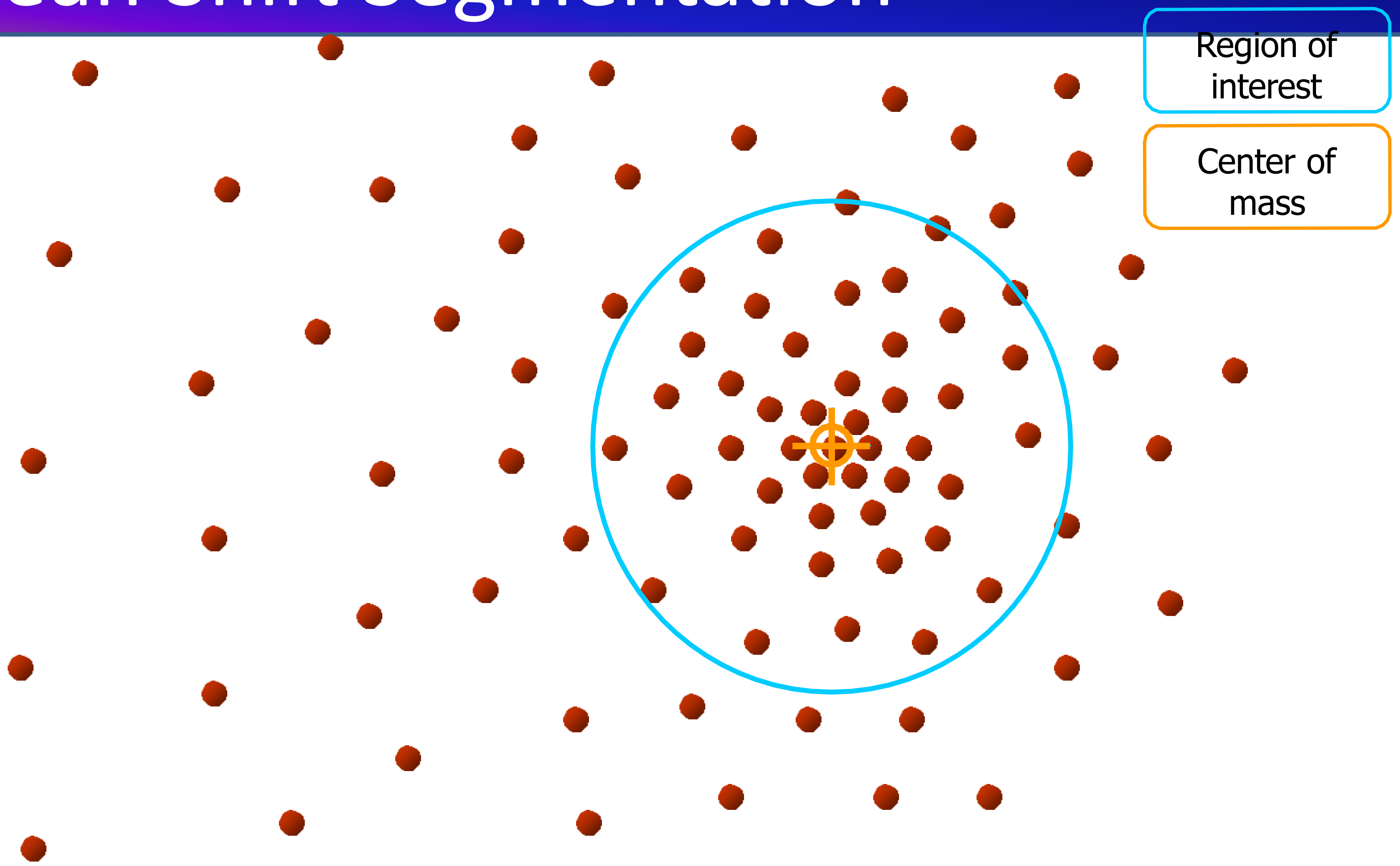
Mean Shift Segmentation



Mean Shift Segmentation

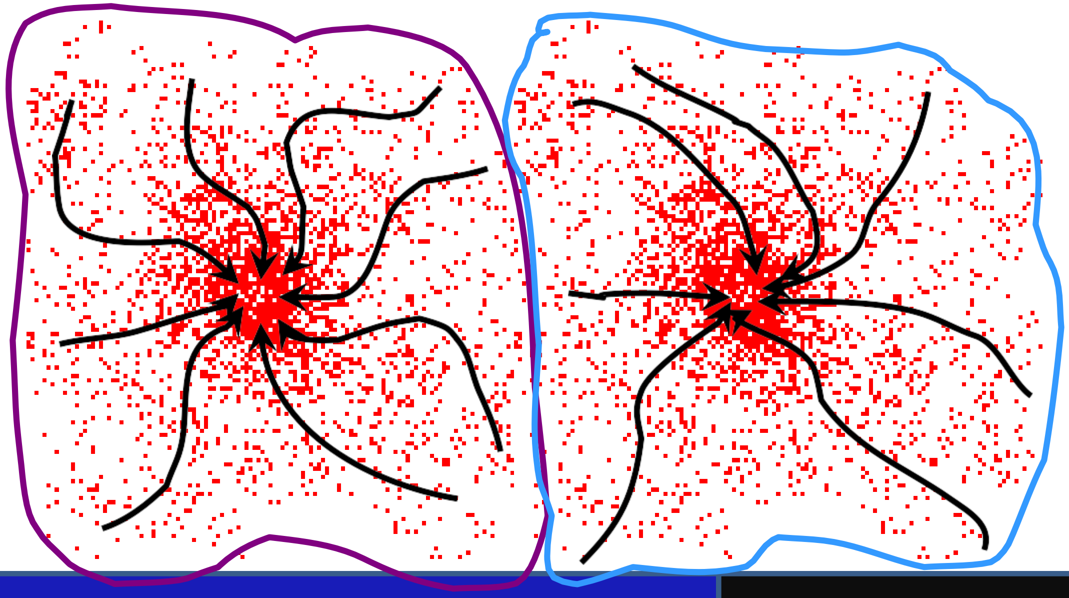


Mean Shift Segmentation



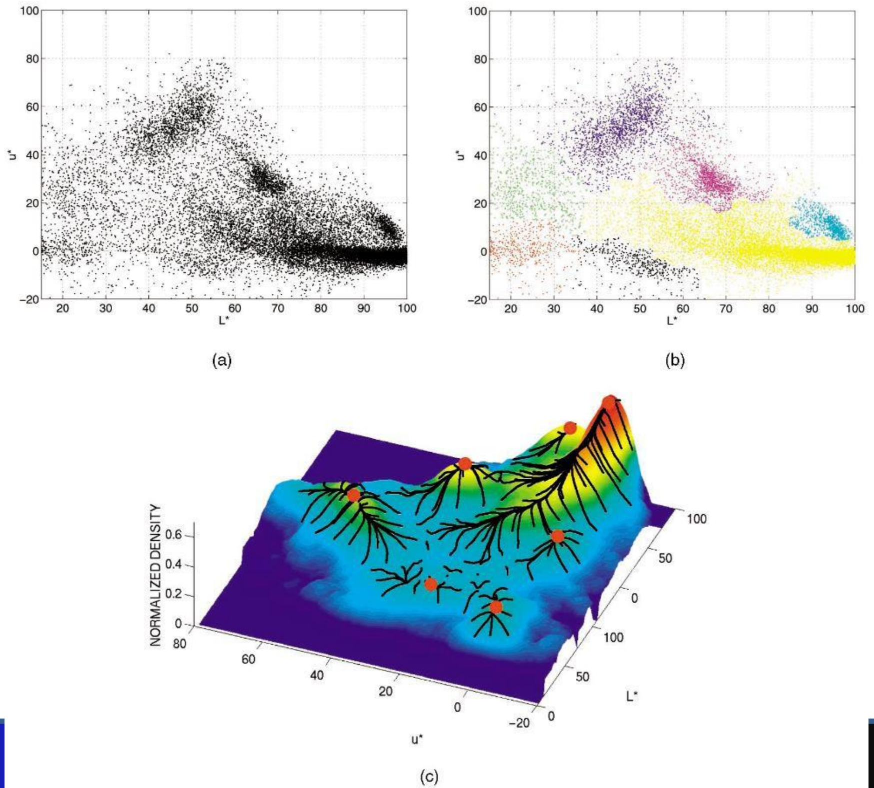
Mean Shift Segmentation

- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajectories lead to the same mode

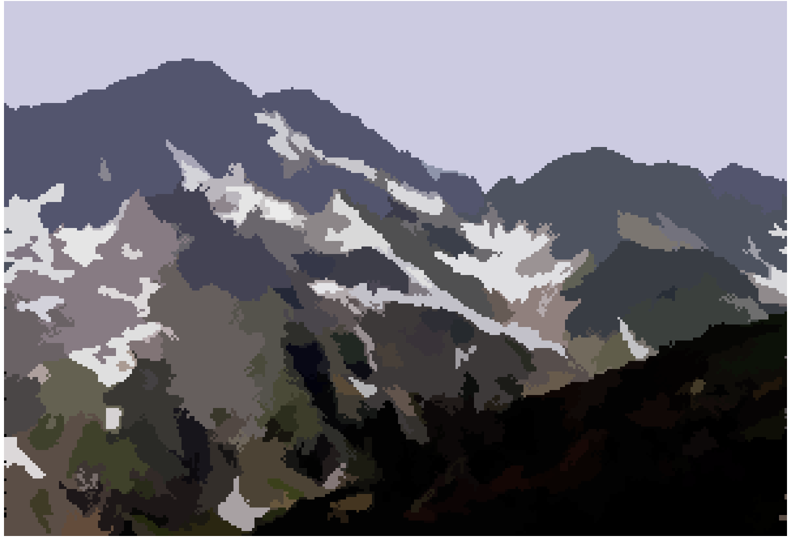


Mean shift clustering/segmentation

- Find features (color, gradients, texture, etc)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same "peak" or mode

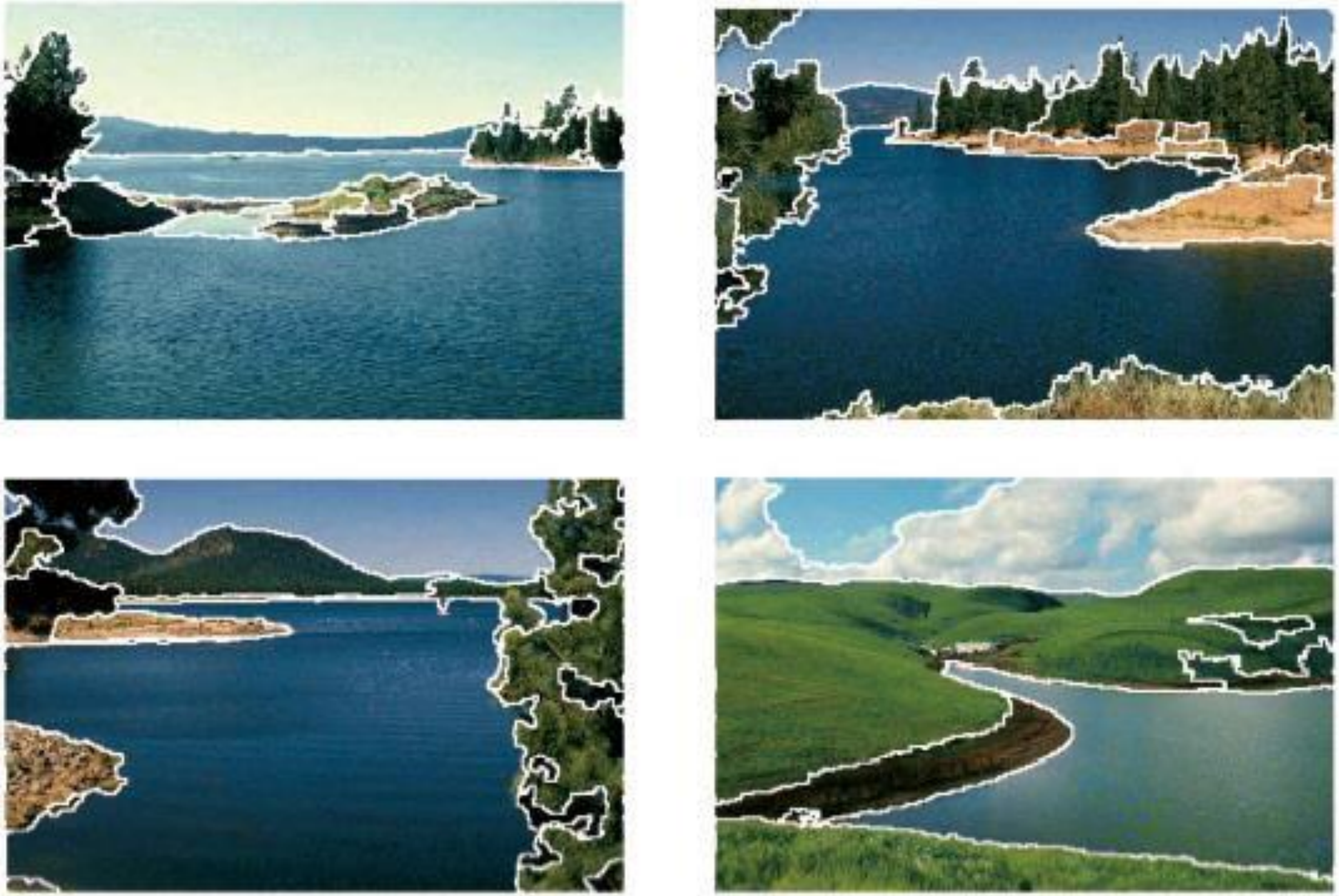


Mean shift segmentation results



http://www.caip.rutgers.edu/~comanici/MSPAMI/msPamiResults.html

More results



Mean shift pros and cons

- Pros
  - Does not assume spherical clusters
  - Just a single parameter (window size)
  - Finds variable number of modes
  - Robust to outliers
- Cons
  - Output depends on window size
  - Computationally expensive
  - Does not scale well with dimension of feature space

References

- Some Slide material has been taken from Dr M. Usman Akram Computer Vision Lectures
- CSCI 1430: Introduction to Computer Vision by James Tompkin
- Statistical Pattern Recognition: A Review – A.K Jain et al., PAMI (22) 2000
- Pattern Recognition and Analysis Course – A.K. Jain, MSU
- *Pattern Classification"* by Duda et al., John Wiley & Sons.
- Digital Image Processing", Rafael C. Gonzalez & Richard E. Woods, Addison-Wesley, 2002
- Machine Vision: Automated Visual Inspection and Robot Vision", David Vernon, Prentice Hall, 1991
- www.eu.aibo.com/
- Advances in Human Computer Interaction, Shane Pinder, InTech, Austria, October 2008
- Computer Vision A modern Approach by Frosyth
- http://www.cs.cmu.edu/~16385/s18/