

Lecture 12

Image 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.

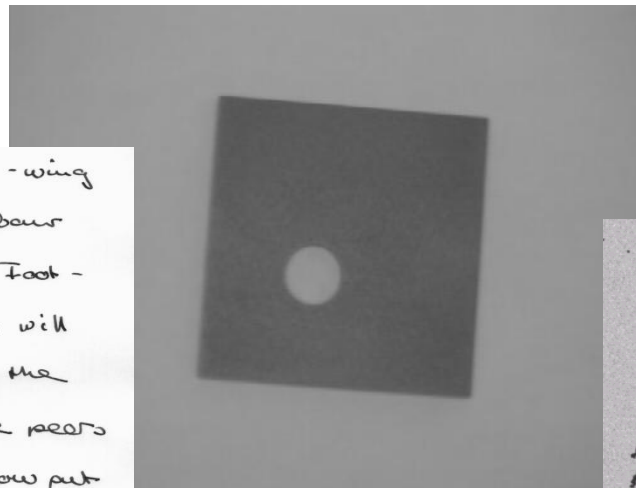
Image Segmentation

- 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.

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

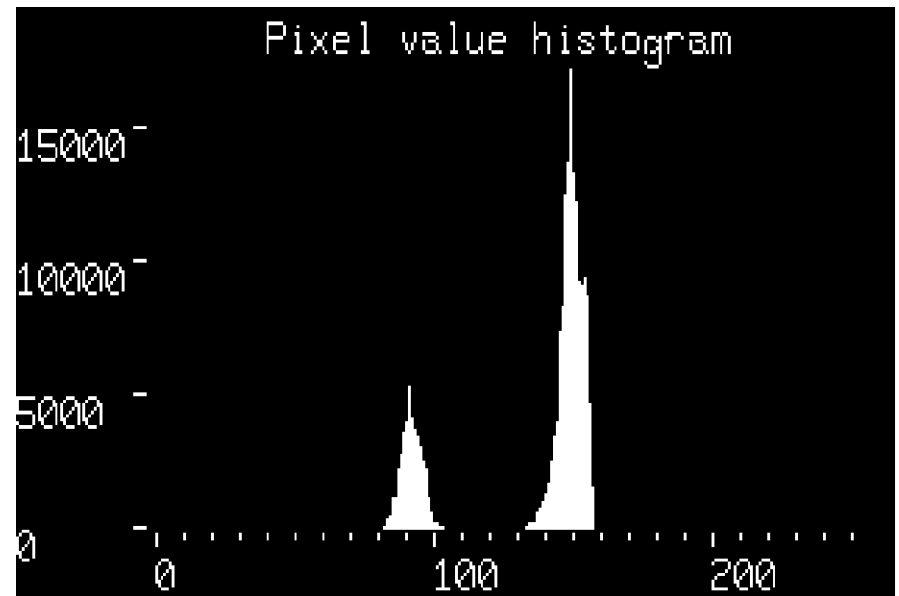
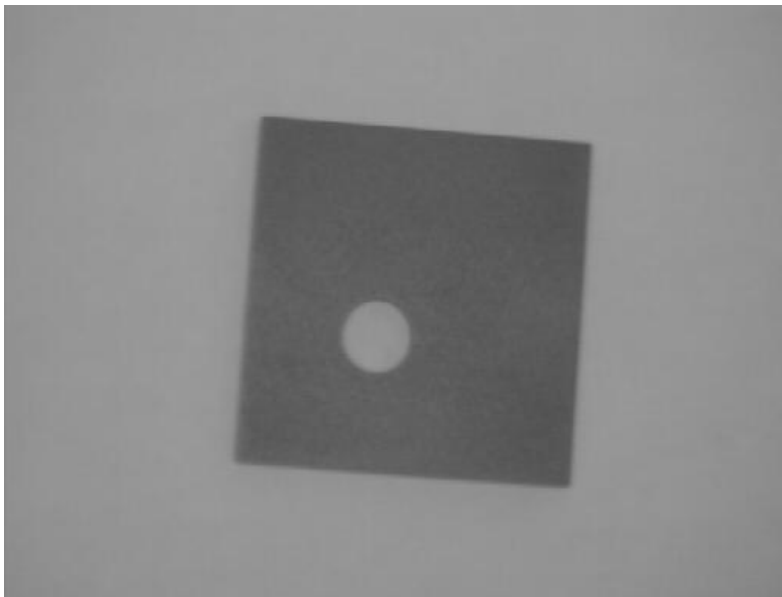
$$g(x, y) = \begin{cases} 1 & \text{if } f(x, y) > T \\ 0 & \text{if } f(x, y) \leq T \end{cases}$$

Objects & Background

- Global Thresholding
- Local/Adaptive Thresholding

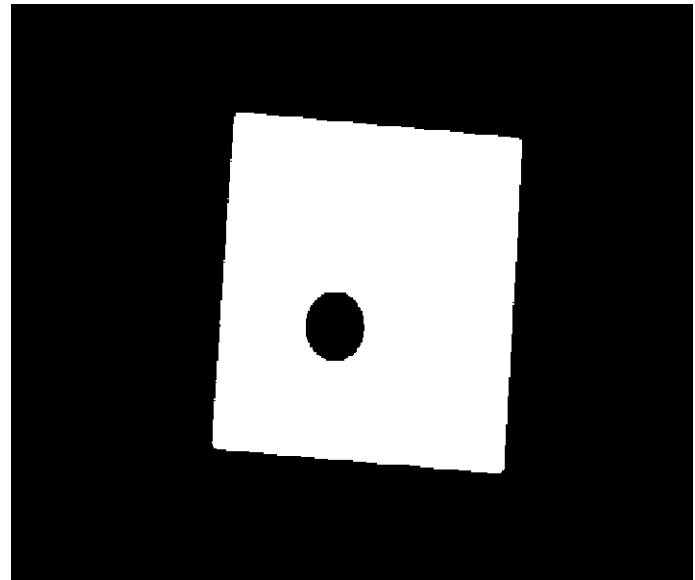
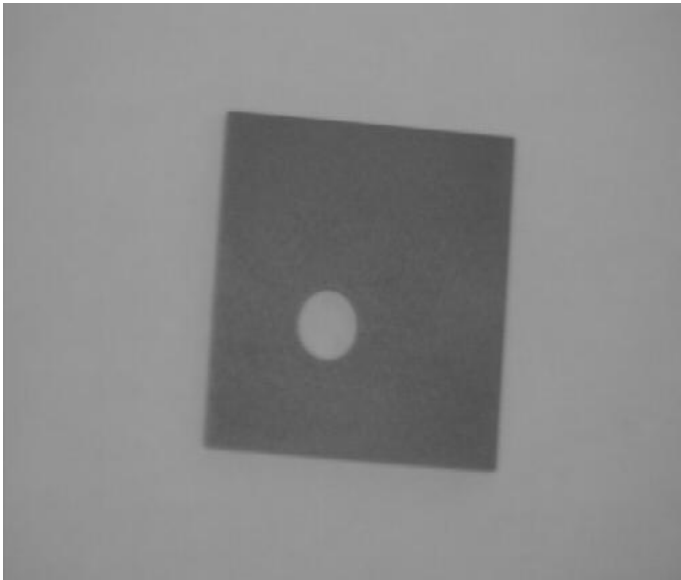
Global Thresholding

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



Global Thresholding

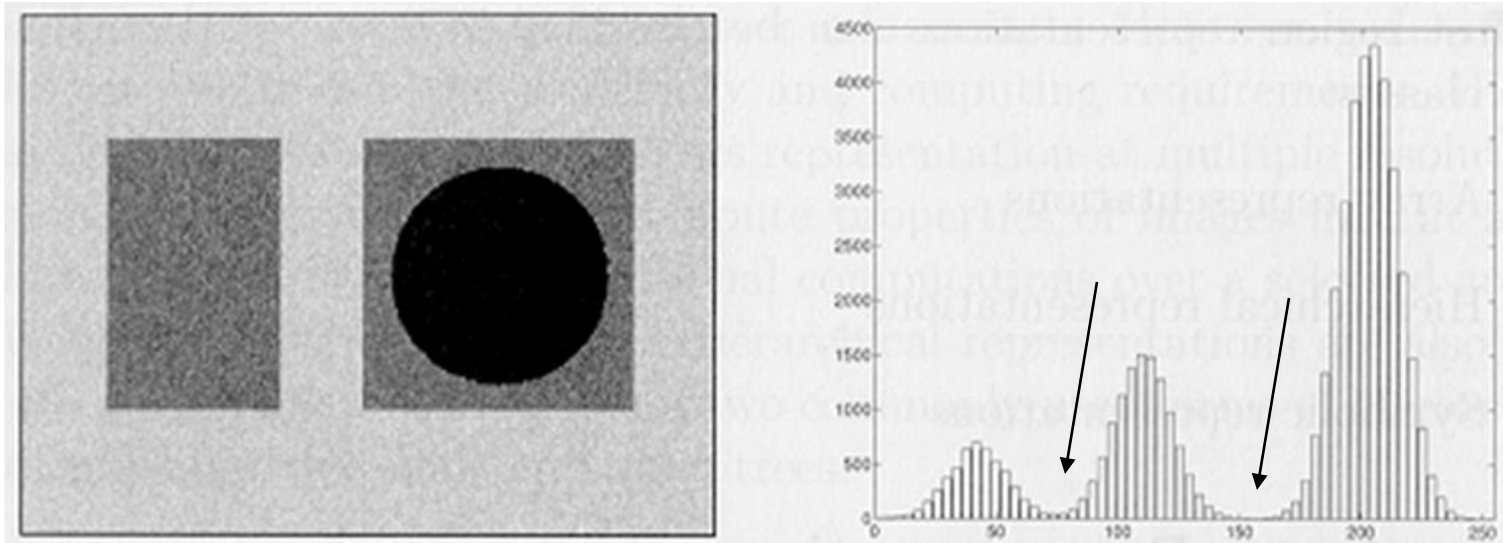
- Single threshold value for entire image
- Fixed ?
- Automatic
 - Intensity histogram



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: $\text{abs}(T_i - T_{i-1}) < \text{epsilon}$

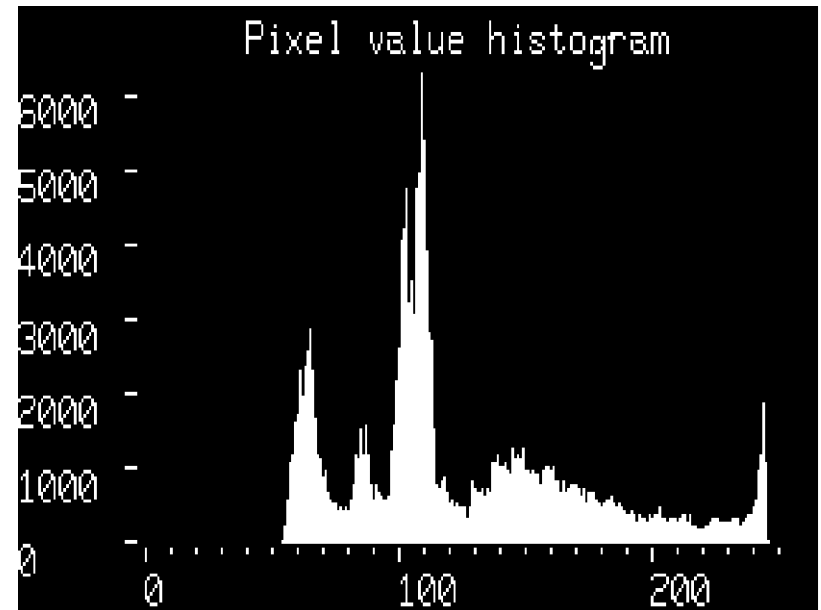
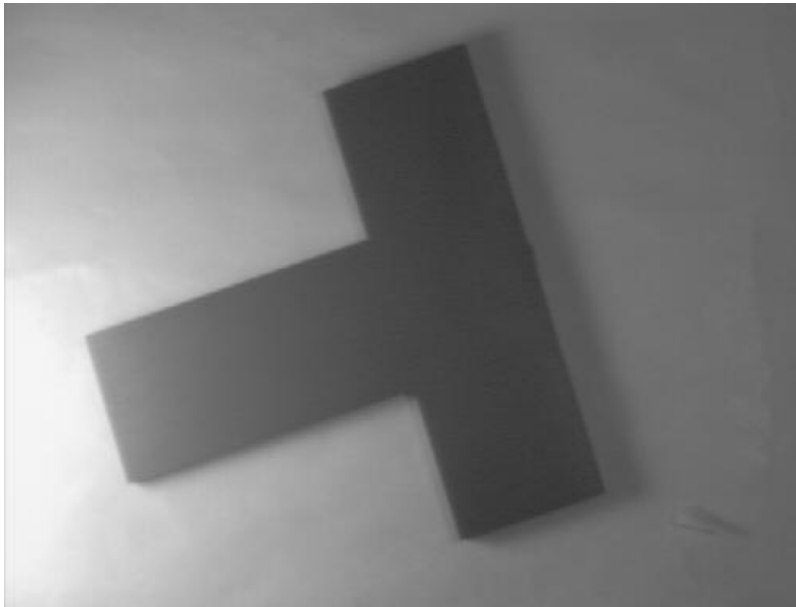
Global Thresholding



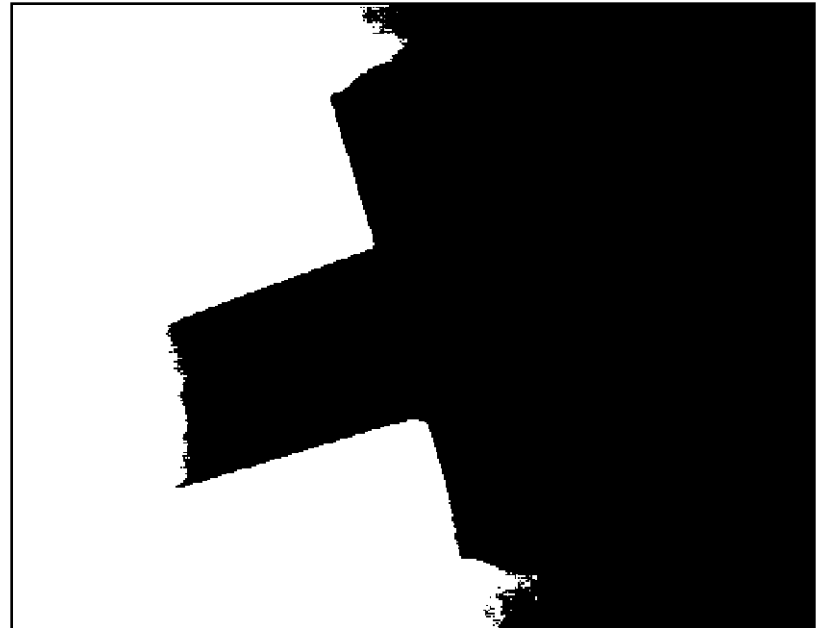
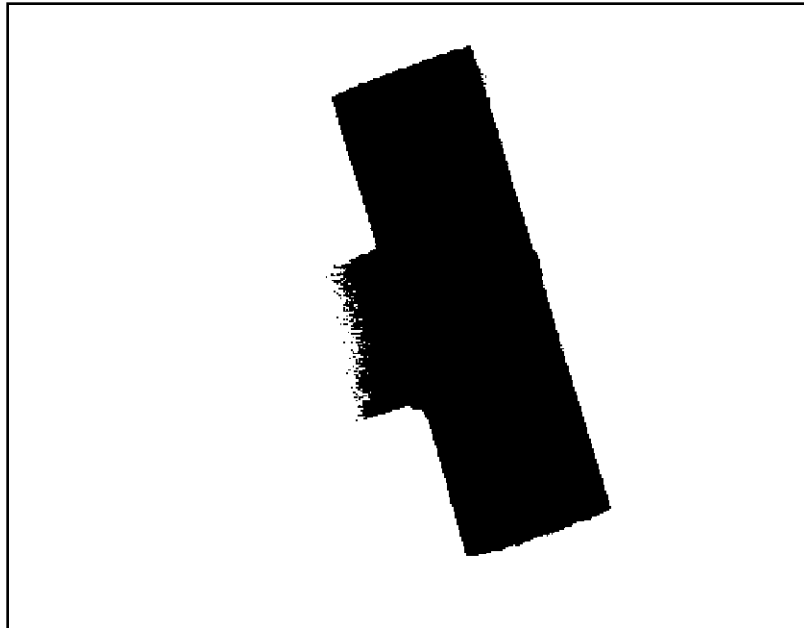
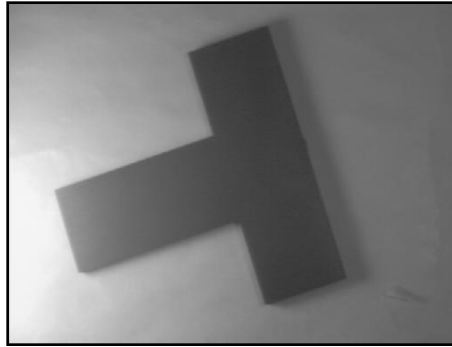
Multilevel thresholding

Thresholding

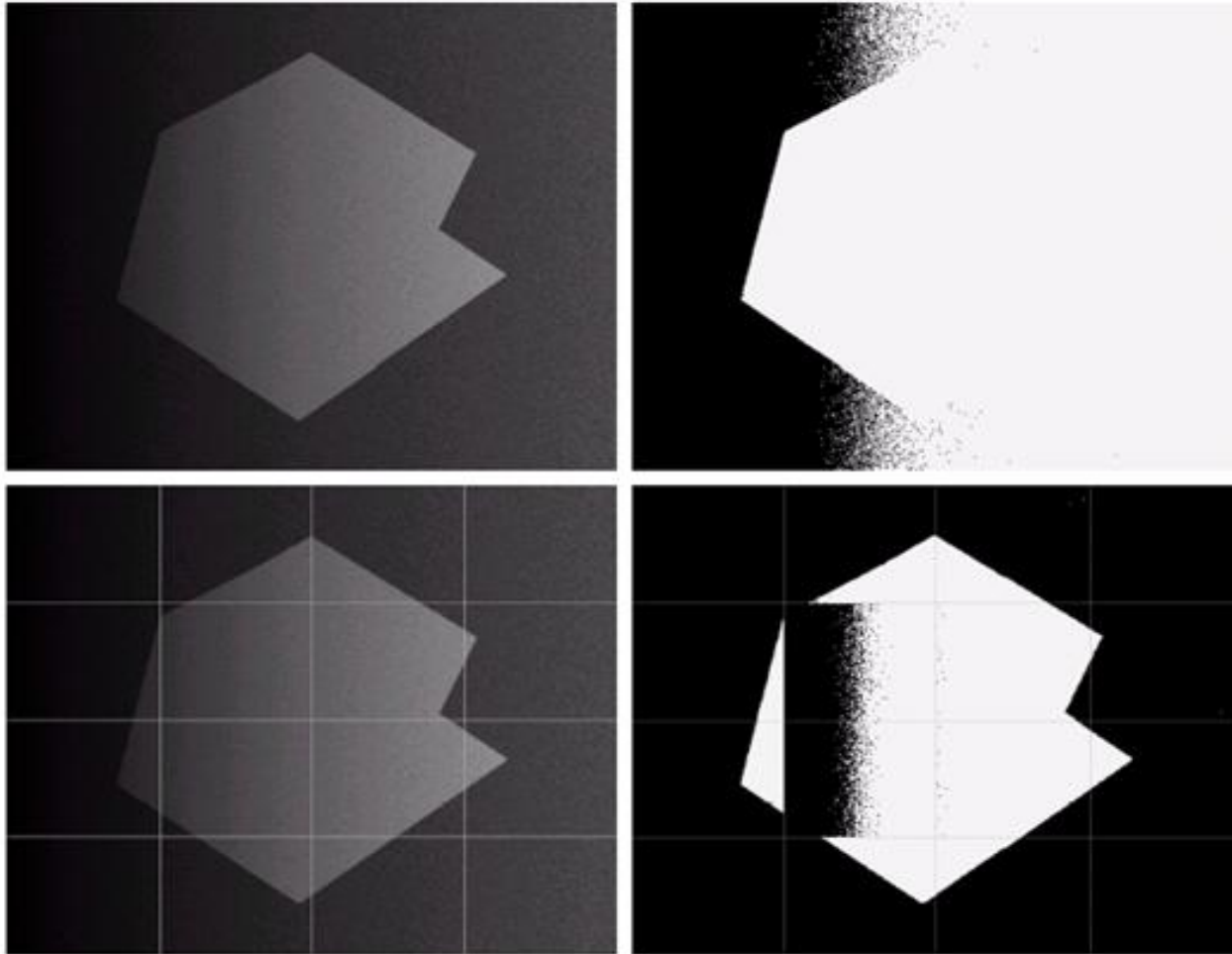
- Non-uniform illumination:



Global Thresholding



Adaptive Thresholding



Adaptive Thresholding

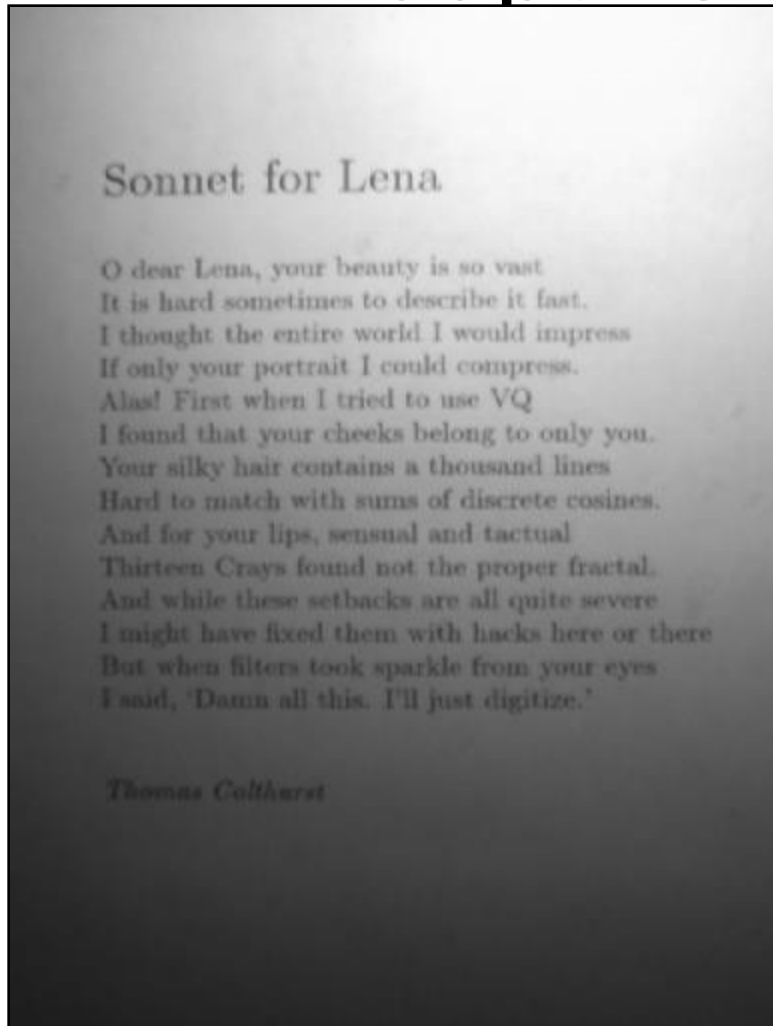
- Threshold: function of neighboring pixels

$$T = \textit{mean}$$

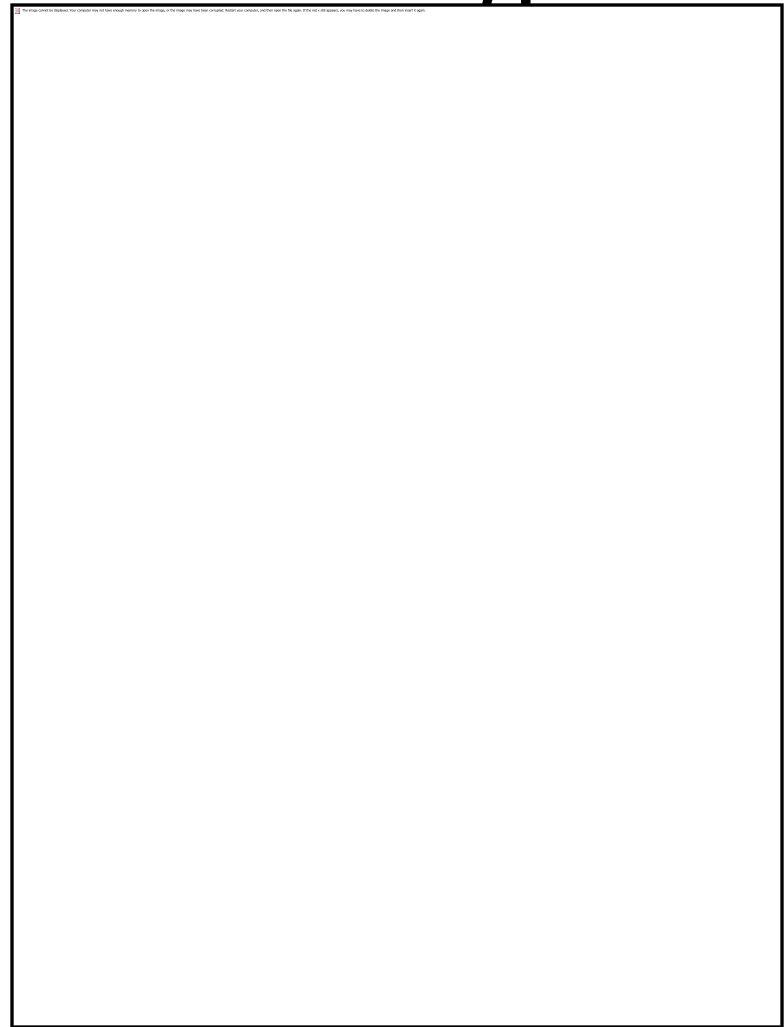
$$T = \textit{median}$$

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

Adaptive Thresholding

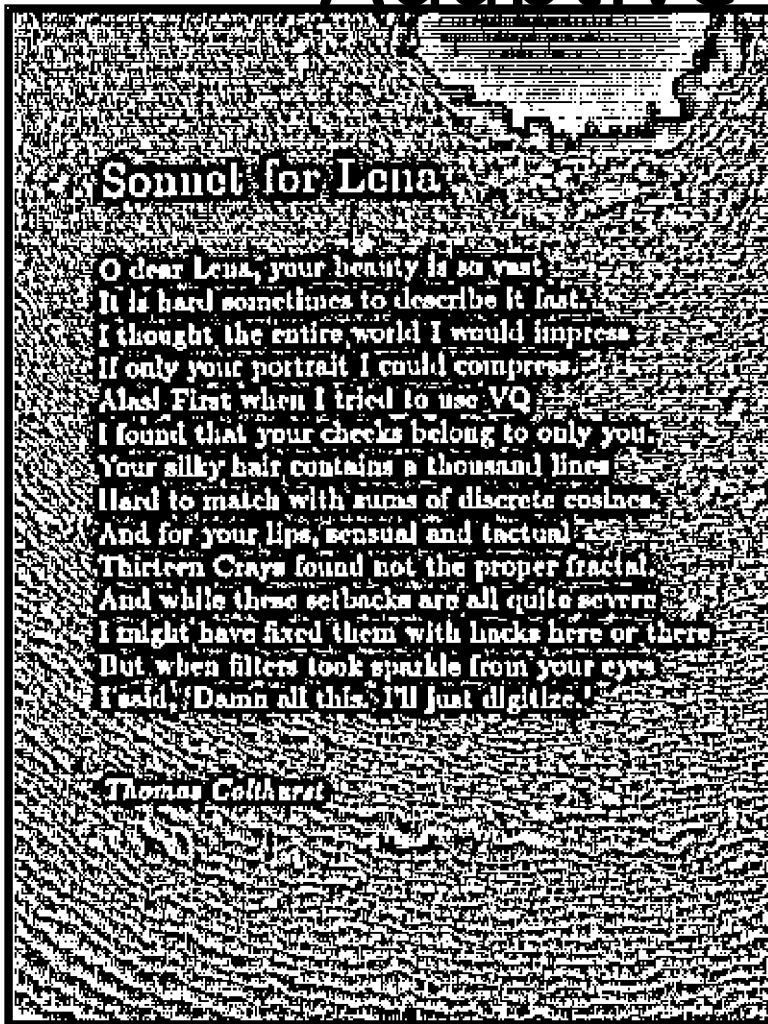


Original Image

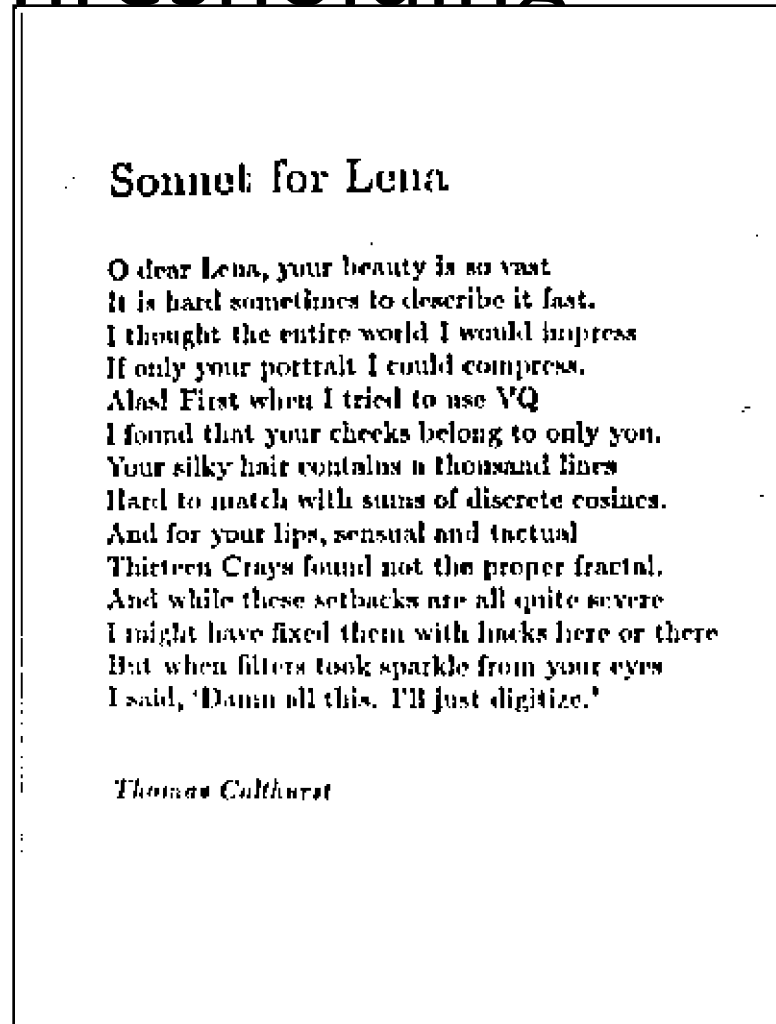


Global Thresholding

Adaptive Thresholding



T=mean, neighborhood=7x7



T=mean-Const., neighborhood=7x7

Adaptive Thresholding

- Niblack Algorithm

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

m = mean

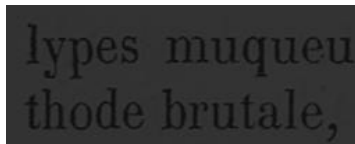
s = standard deviations

k = Niblack constant

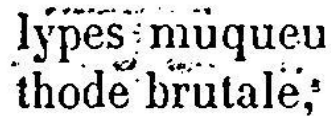
- Neighborhood size???

Document Binarization

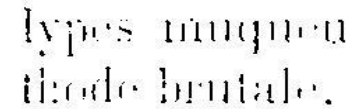
- Local Thresholding – Examples

The original document text is shown in a dark, low-contrast image where the text is almost completely obscured by the background.

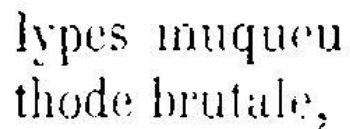
Original

The Niblack binarization method results in a high-contrast, black and white image where the text is clearly visible but has a grainy, noisy appearance.

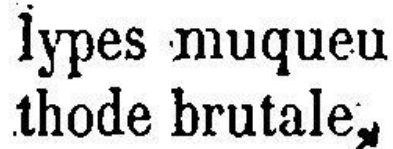
Niblack

The Sauvola binarization method produces a clean, high-contrast image where the text is clearly legible and free from noise.

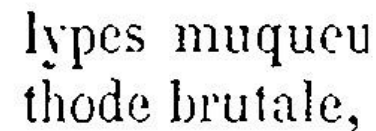
Sauvola

The Wolf binarization method results in a clean, high-contrast image where the text is clearly legible and free from noise.

Wolf

The Feng binarization method results in a high-contrast, black and white image where the text is clearly visible but has a grainy, noisy appearance.

Feng

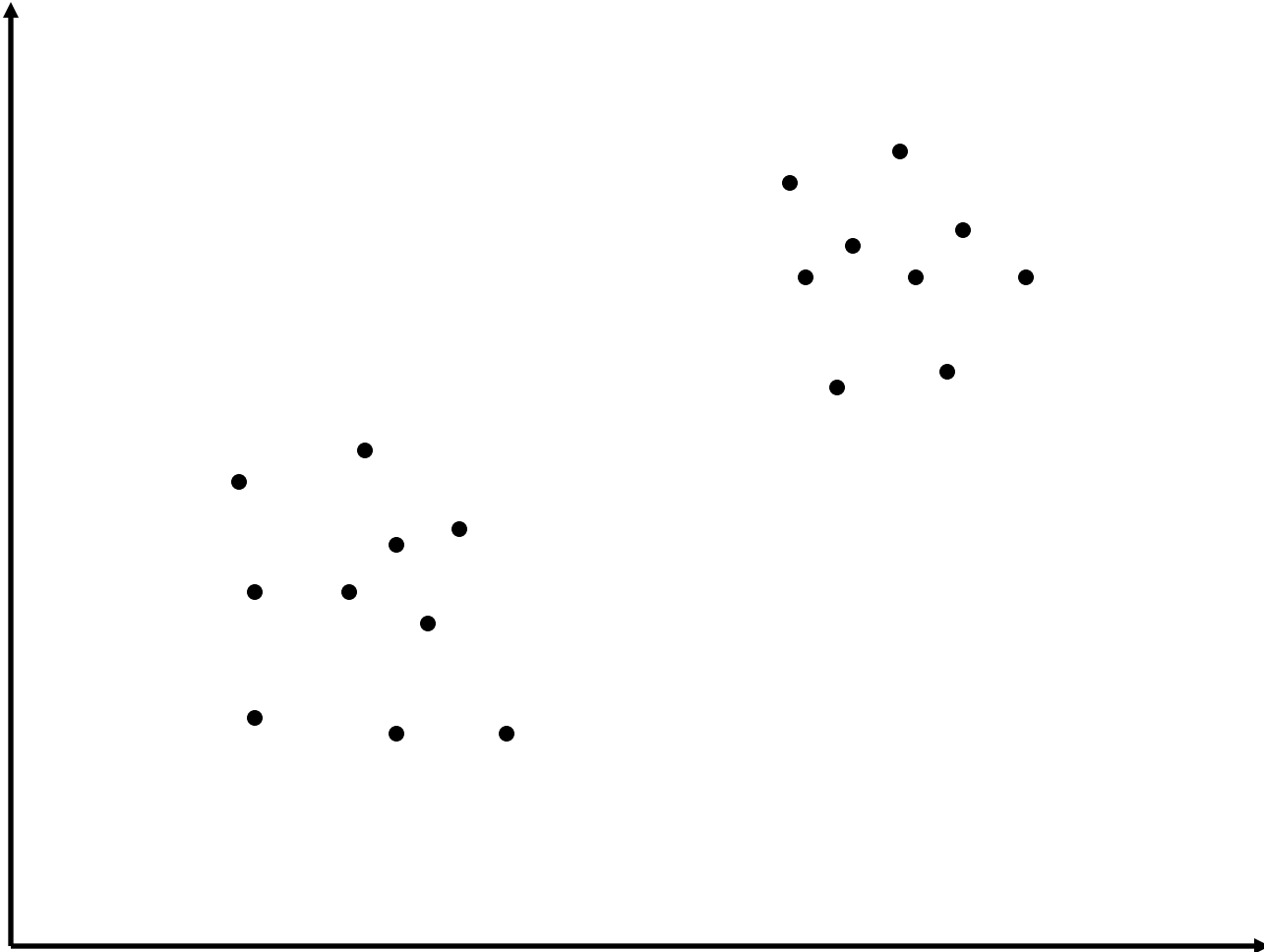
The NICK binarization method results in a clean, high-contrast image where the text is clearly legible and free from noise.

NICK

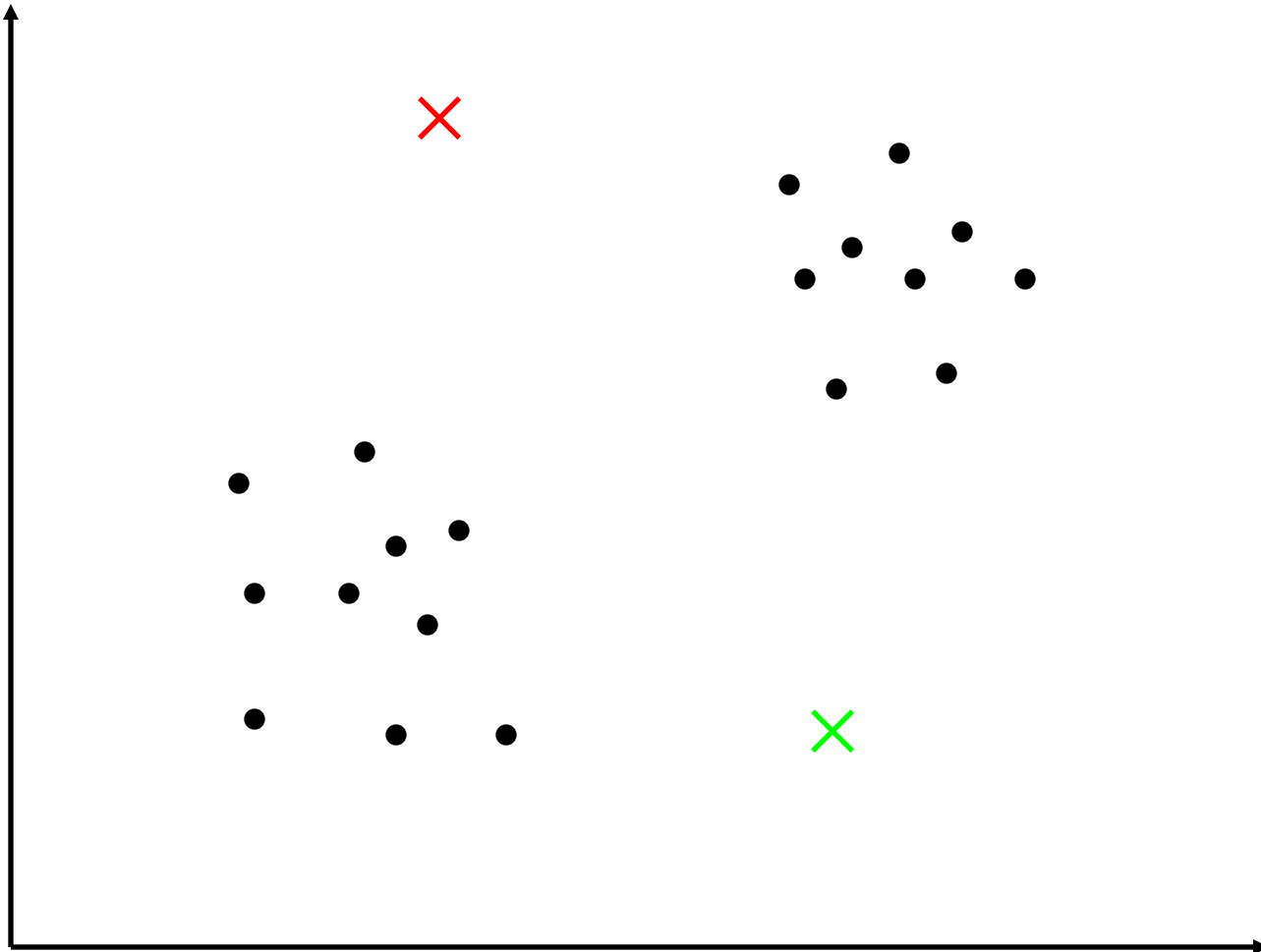
K-Means Clustering

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).

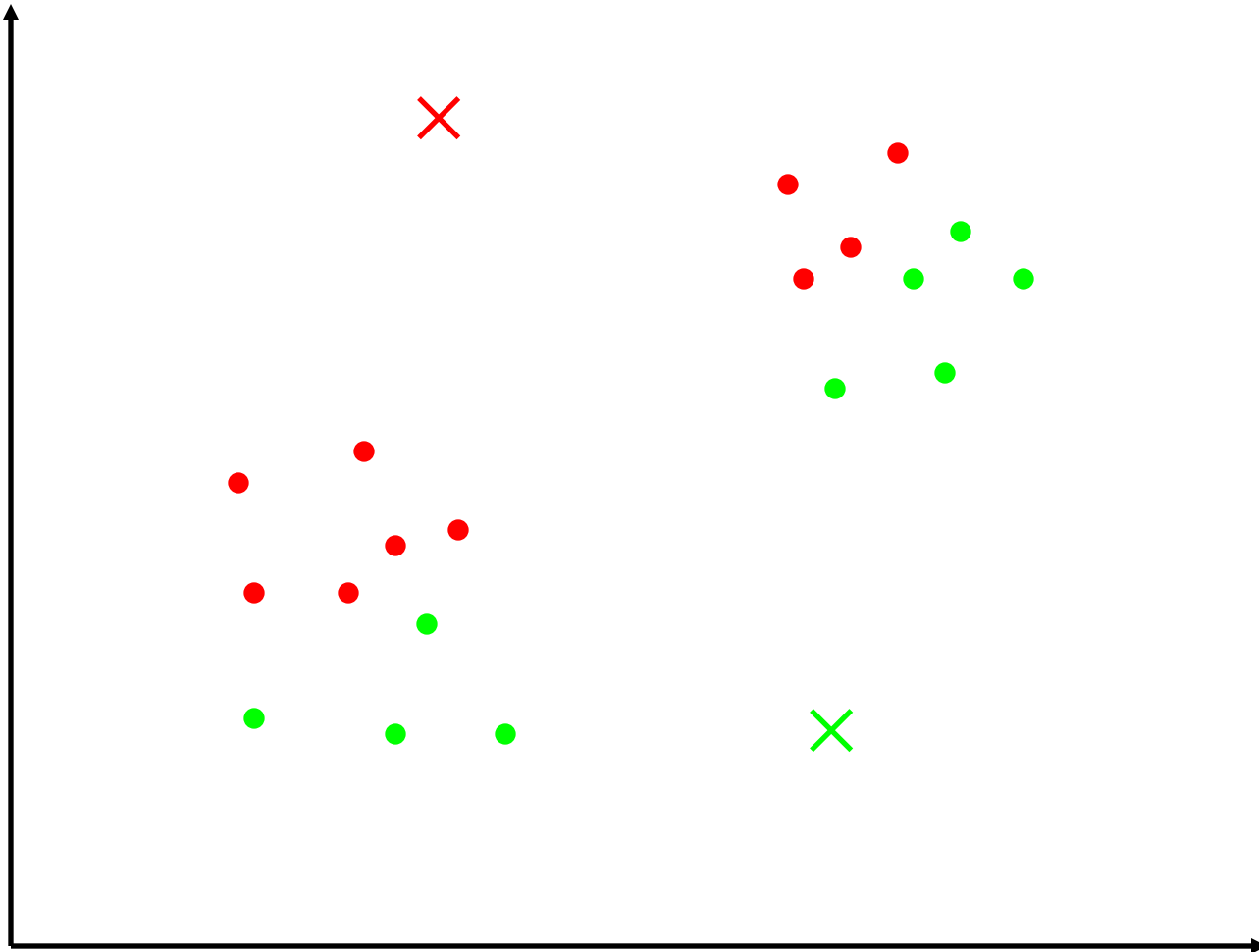
K-Means Clustering



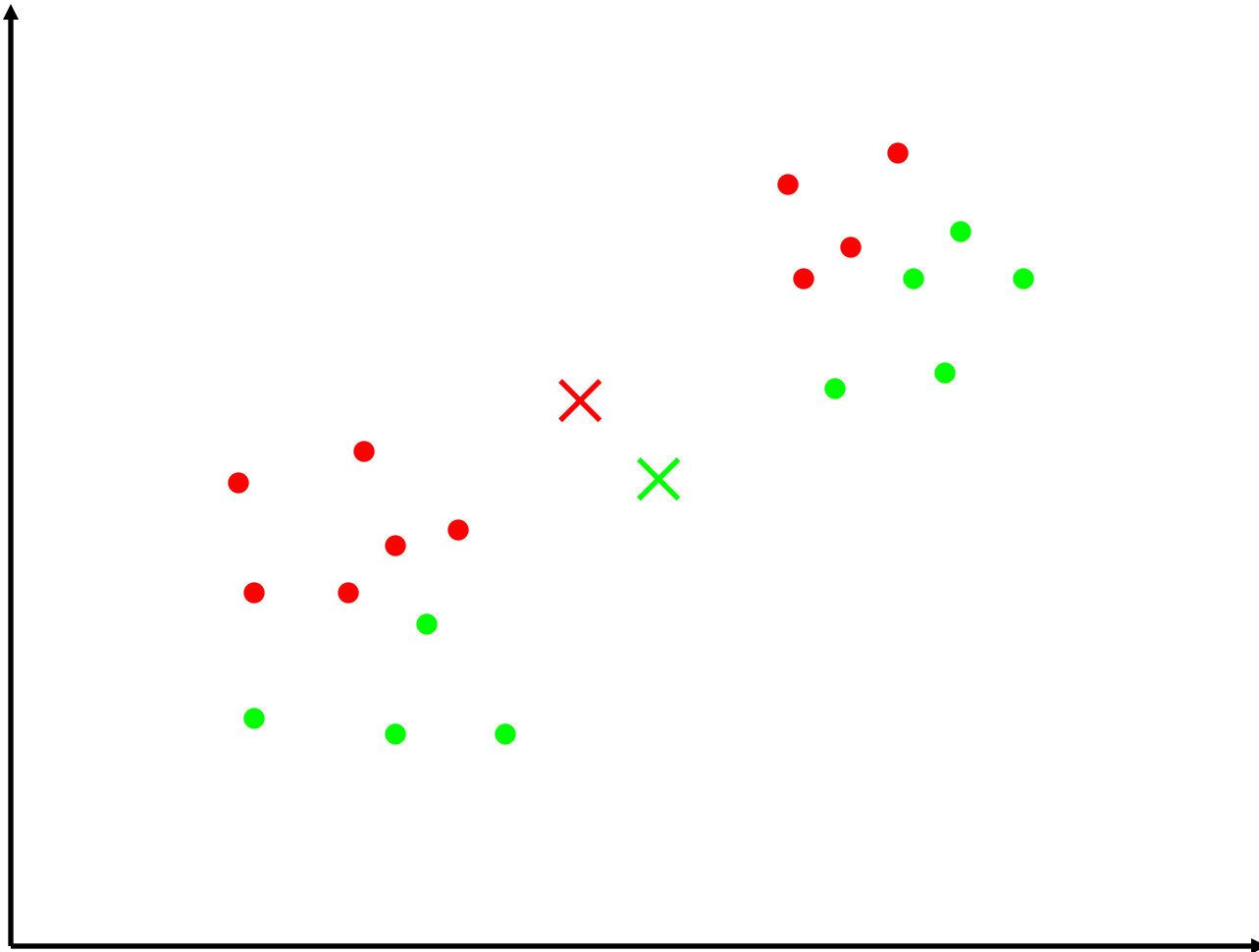
K-Means Clustering



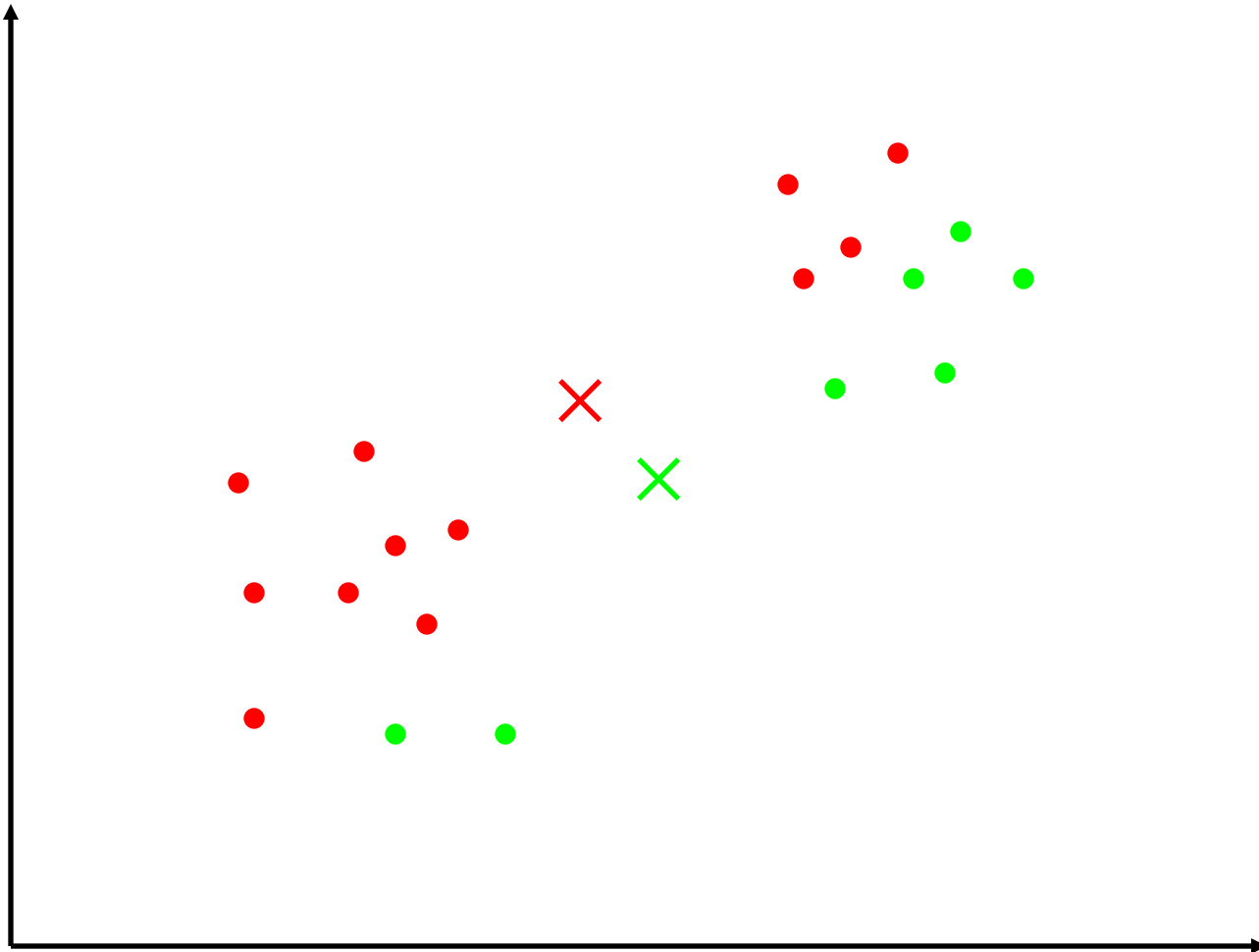
K-Means Clustering



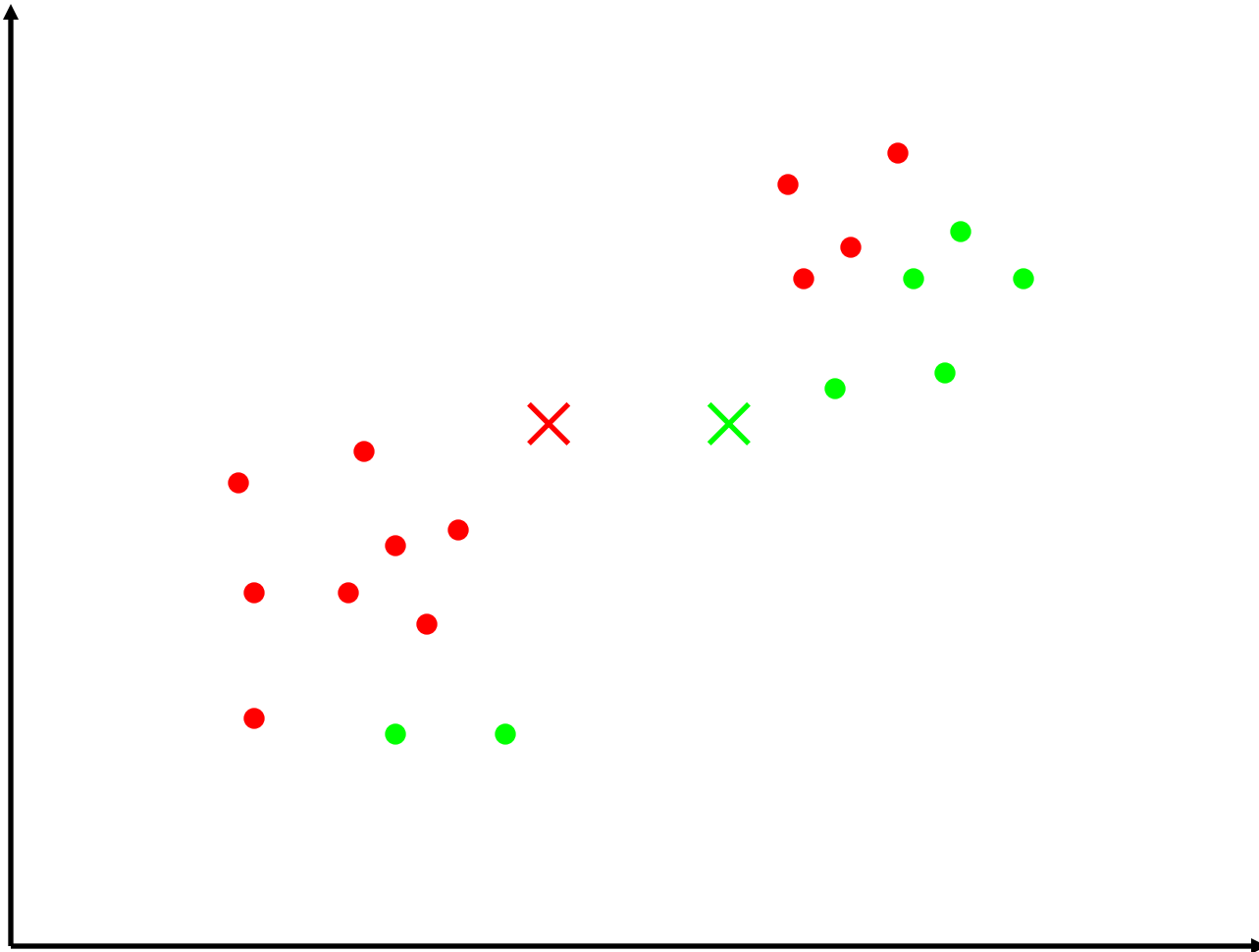
K-Means Clustering



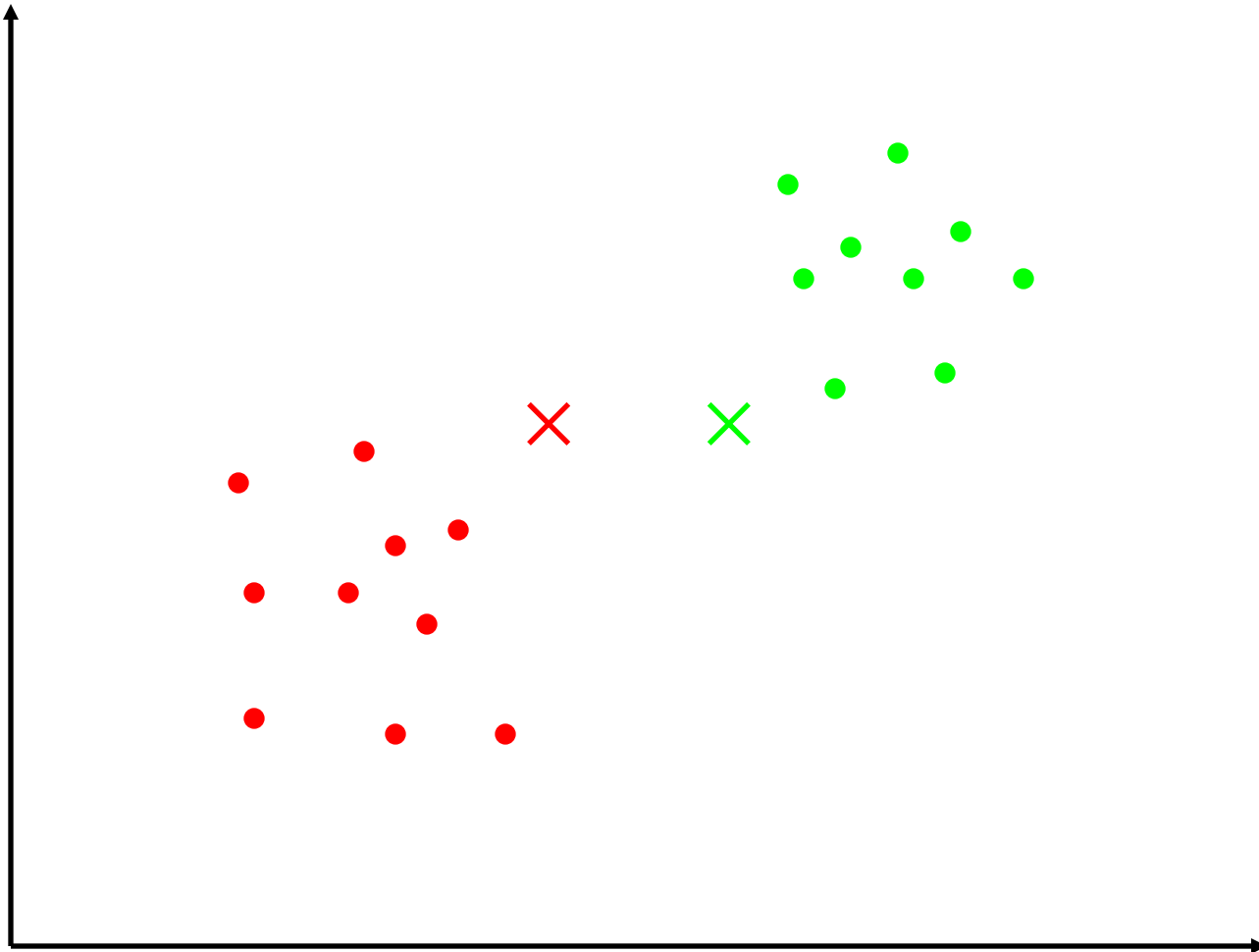
K-Means Clustering



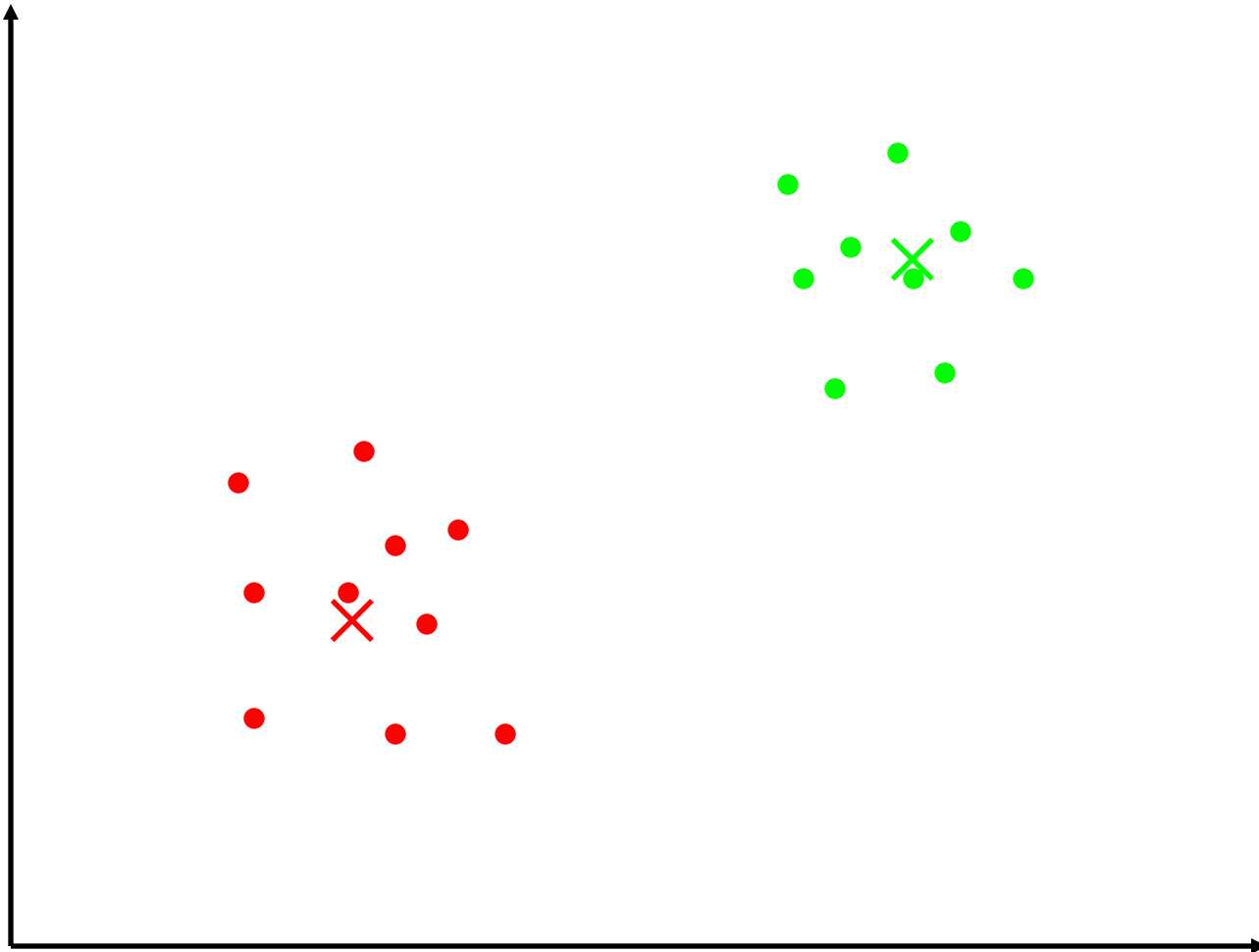
K-Means Clustering



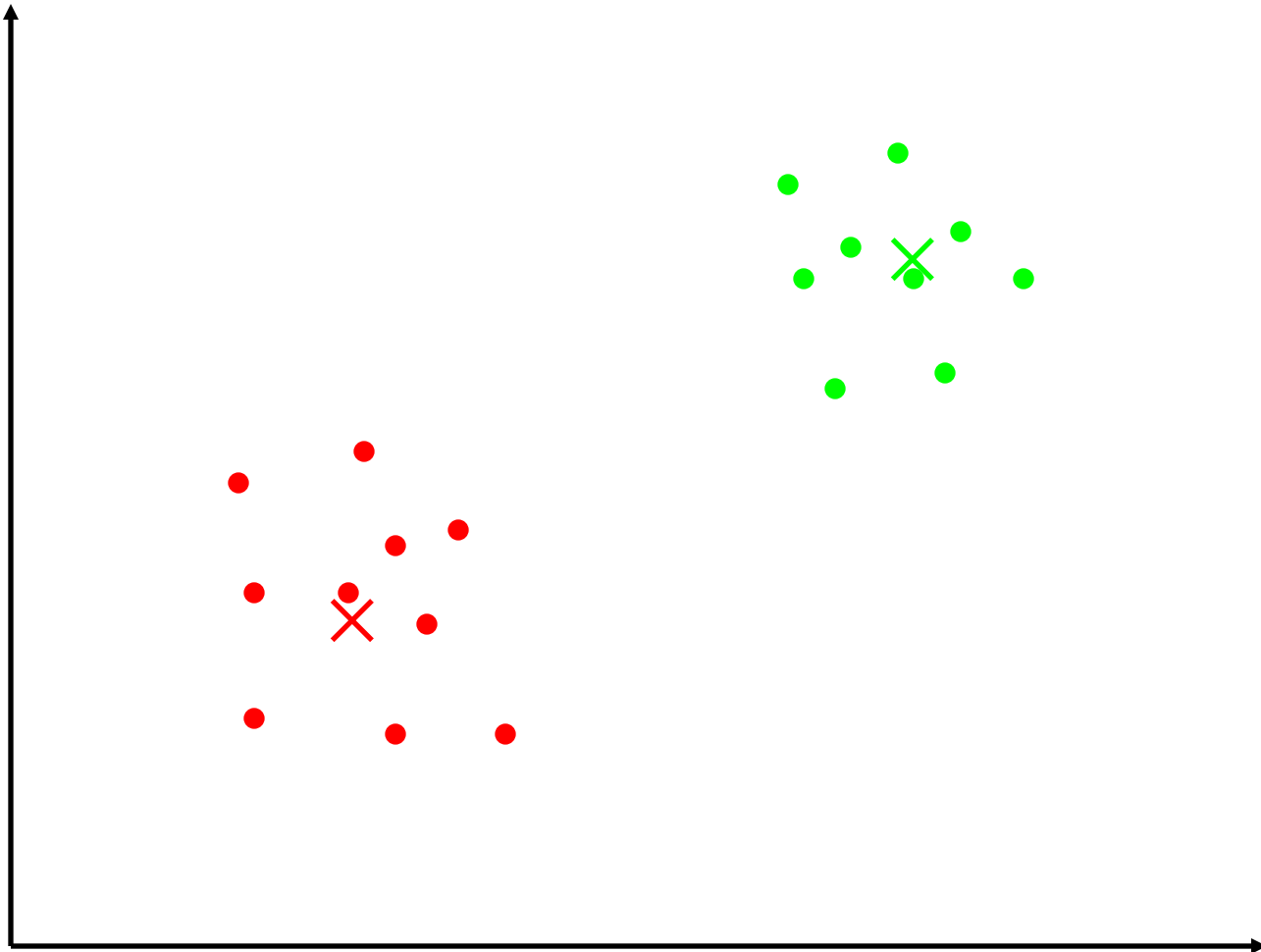
K-Means Clustering



K-Means Clustering

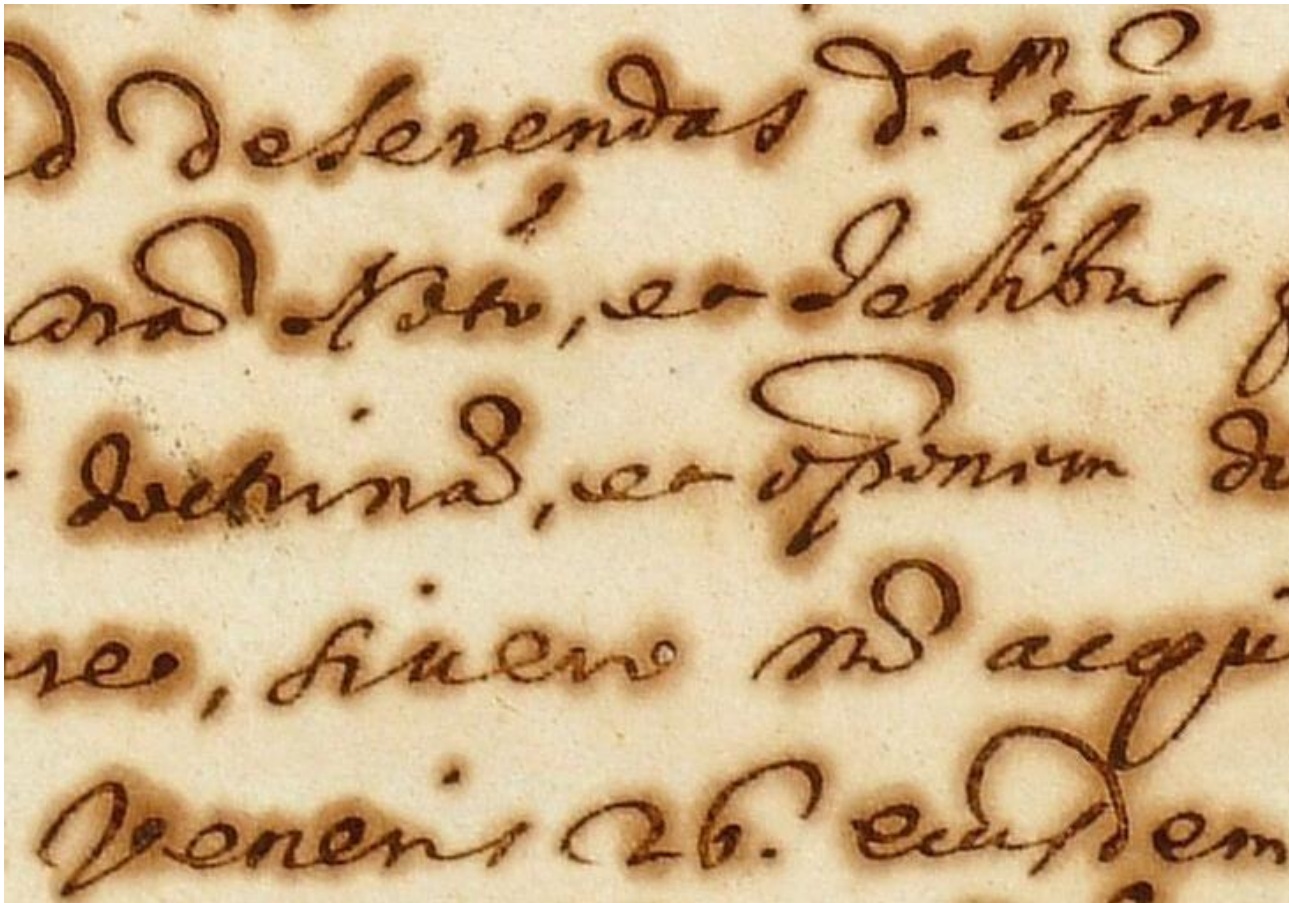


K-Means Clustering



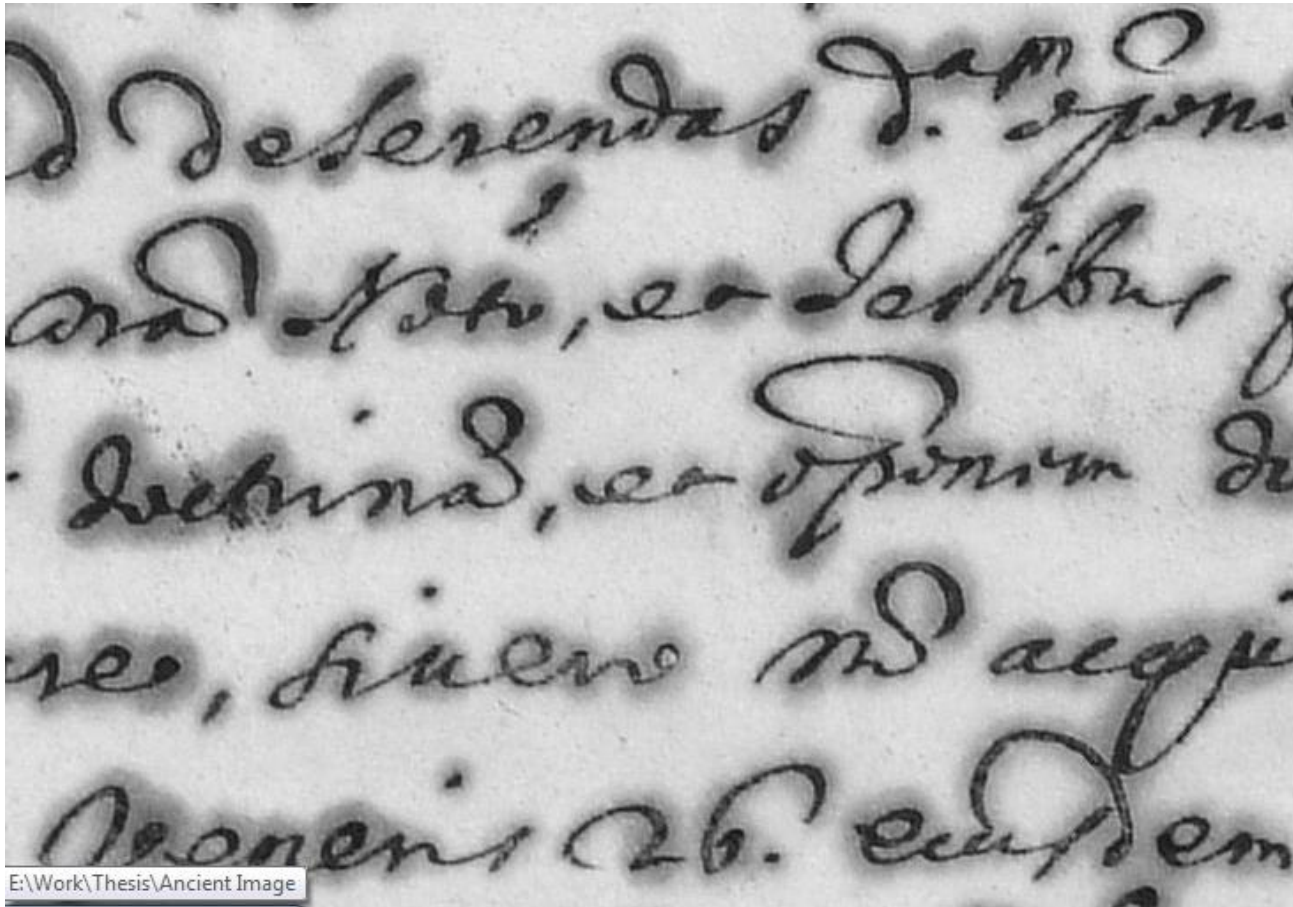
Clustering

- Example



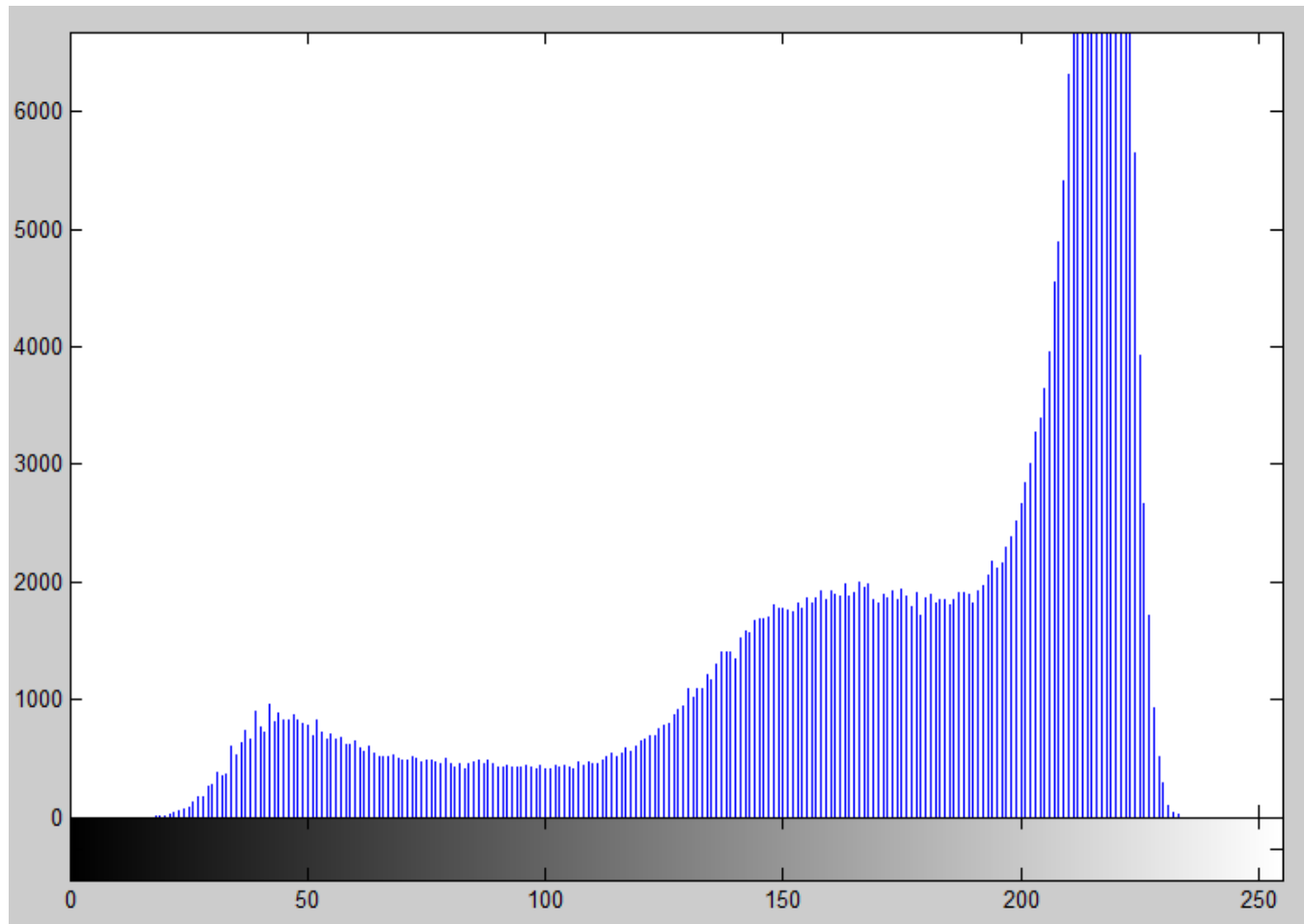
Clustering

- Example



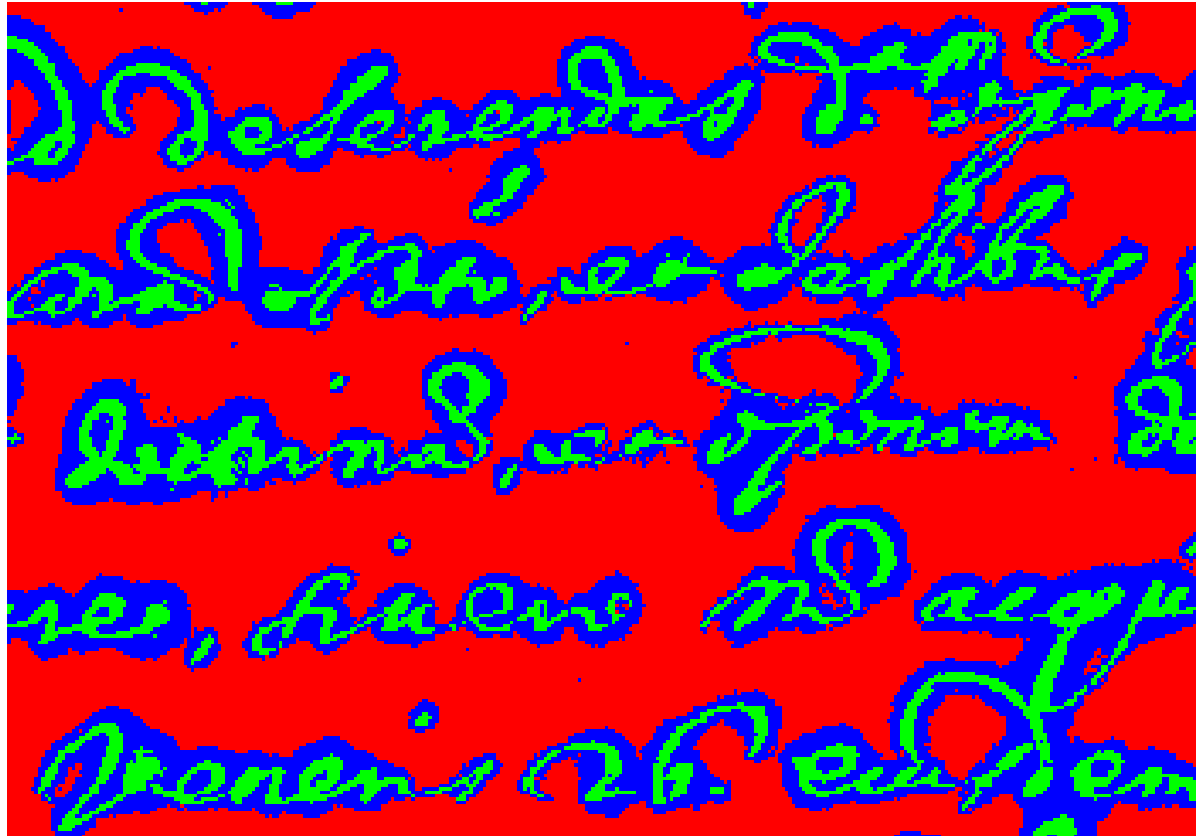
Clustering

- Example



Clustering

- Example



Clustering

- Example



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

K-Means Clustering

- Example



Original



K=5



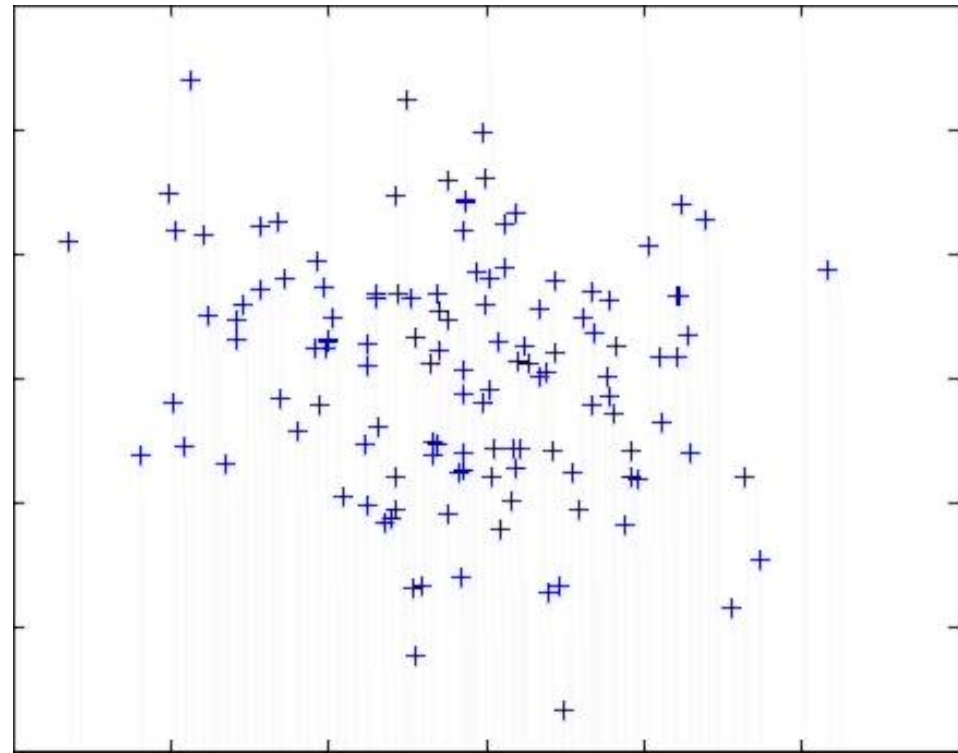
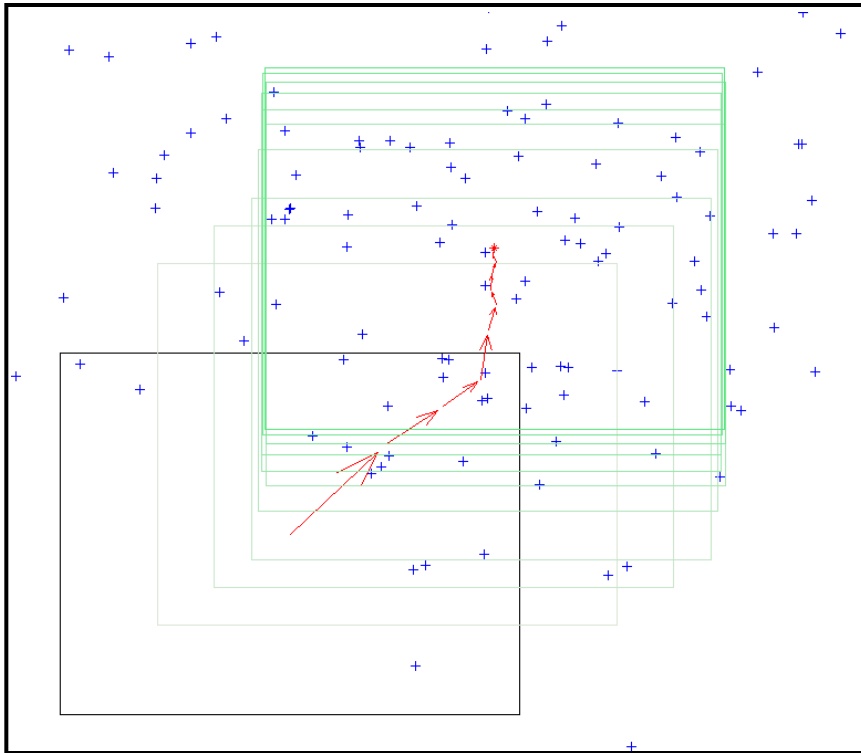
K=11

Mean Shift Algorithm

Mean Shift Algorithm

1. Choose a search window size.
2. Choose the initial location of the search window.
3. Compute the mean location (centroid of the data) in the search window.
4. Center the search window at the mean location computed in Step 3.
5. Repeat Steps 3 and 4 until convergence.

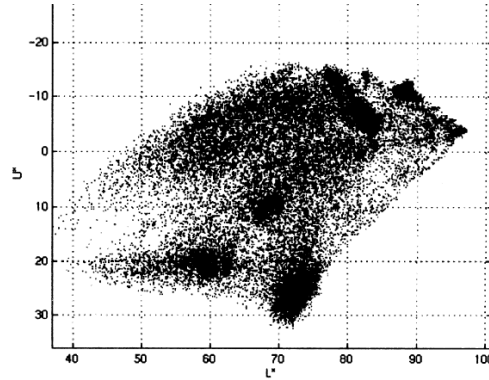
The mean shift algorithm seeks the “mode” or point of highest density of a data distribution:



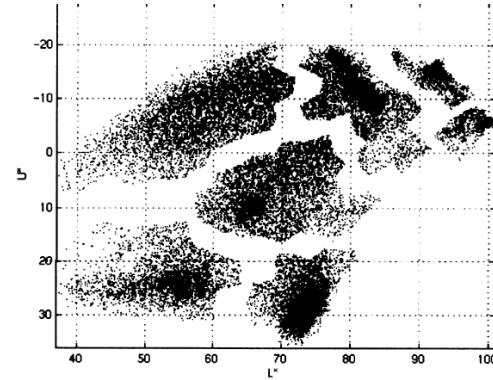
Mean Shift Segmentation

Mean Shift Segmentation Algorithm

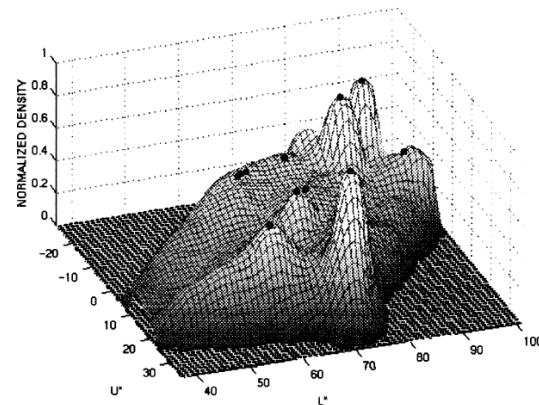
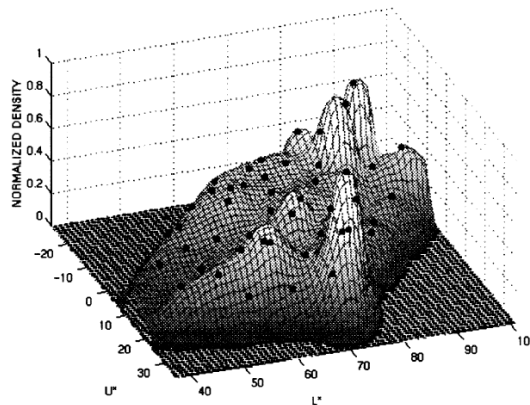
1. Convert the image into tokens (via color, gradients, texture measures etc).
2. Choose initial search window locations uniformly in the data.
3. Compute the mean shift window location for each initial position.
4. Merge windows that end up on the same “peak” or mode.
5. The data these merged windows traversed are clustered together.



(a)

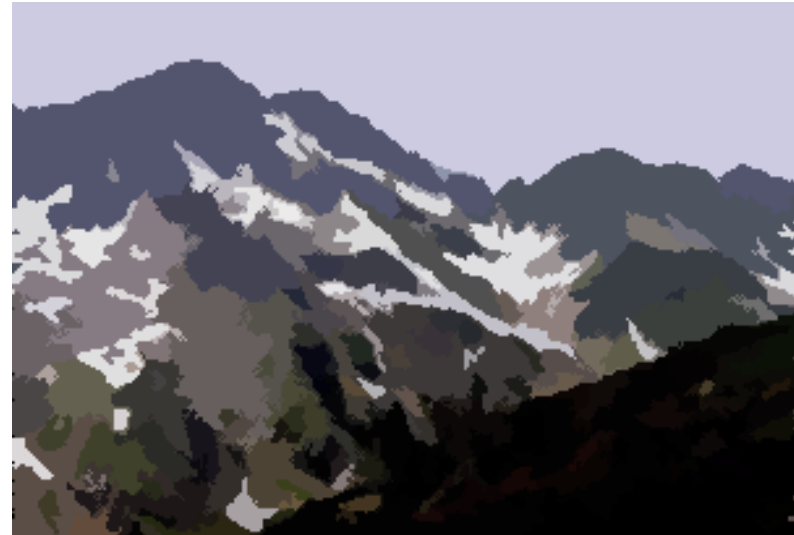


(b)



Mean Shift Segmentation

Results:



Mean Shift Segmentation

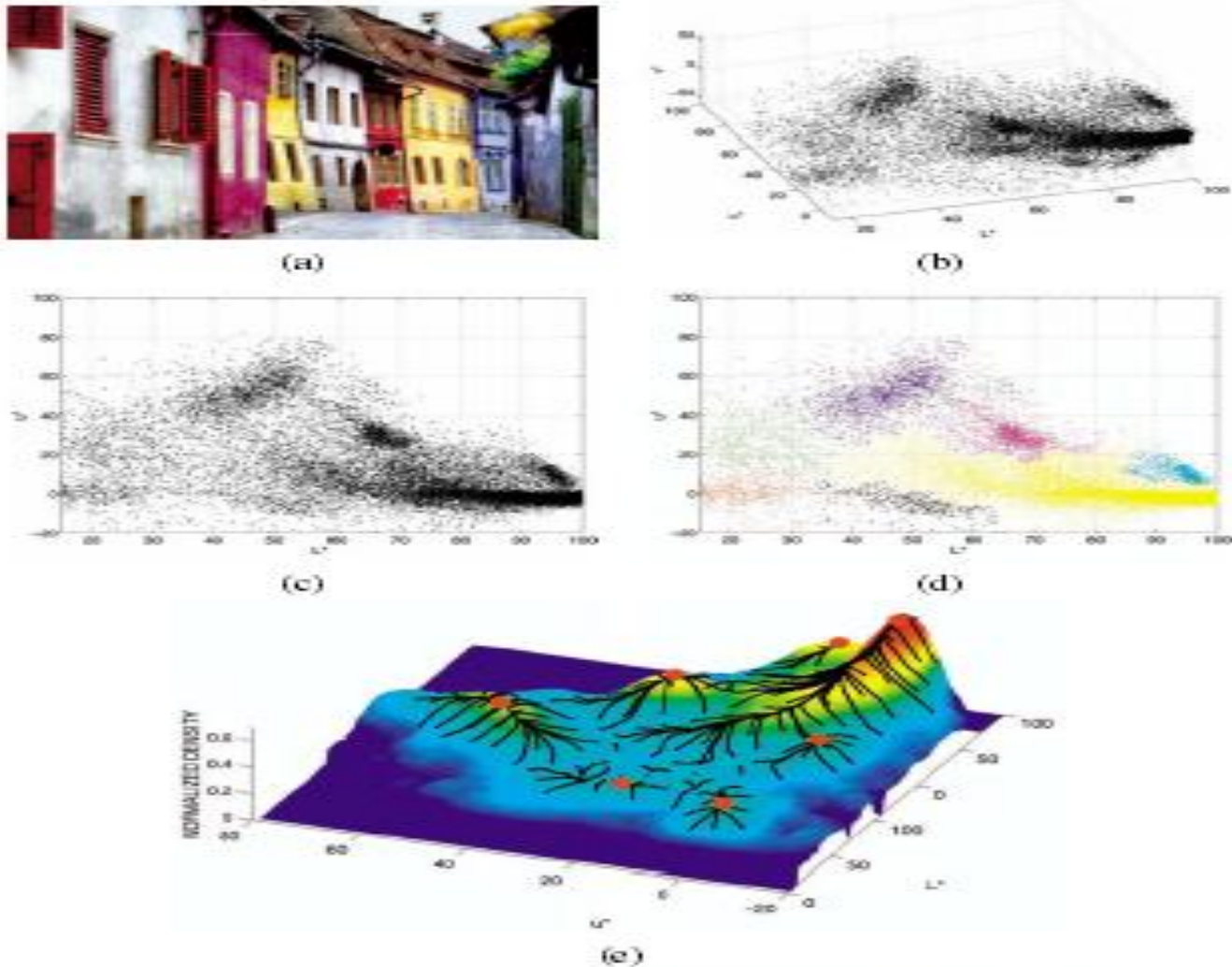
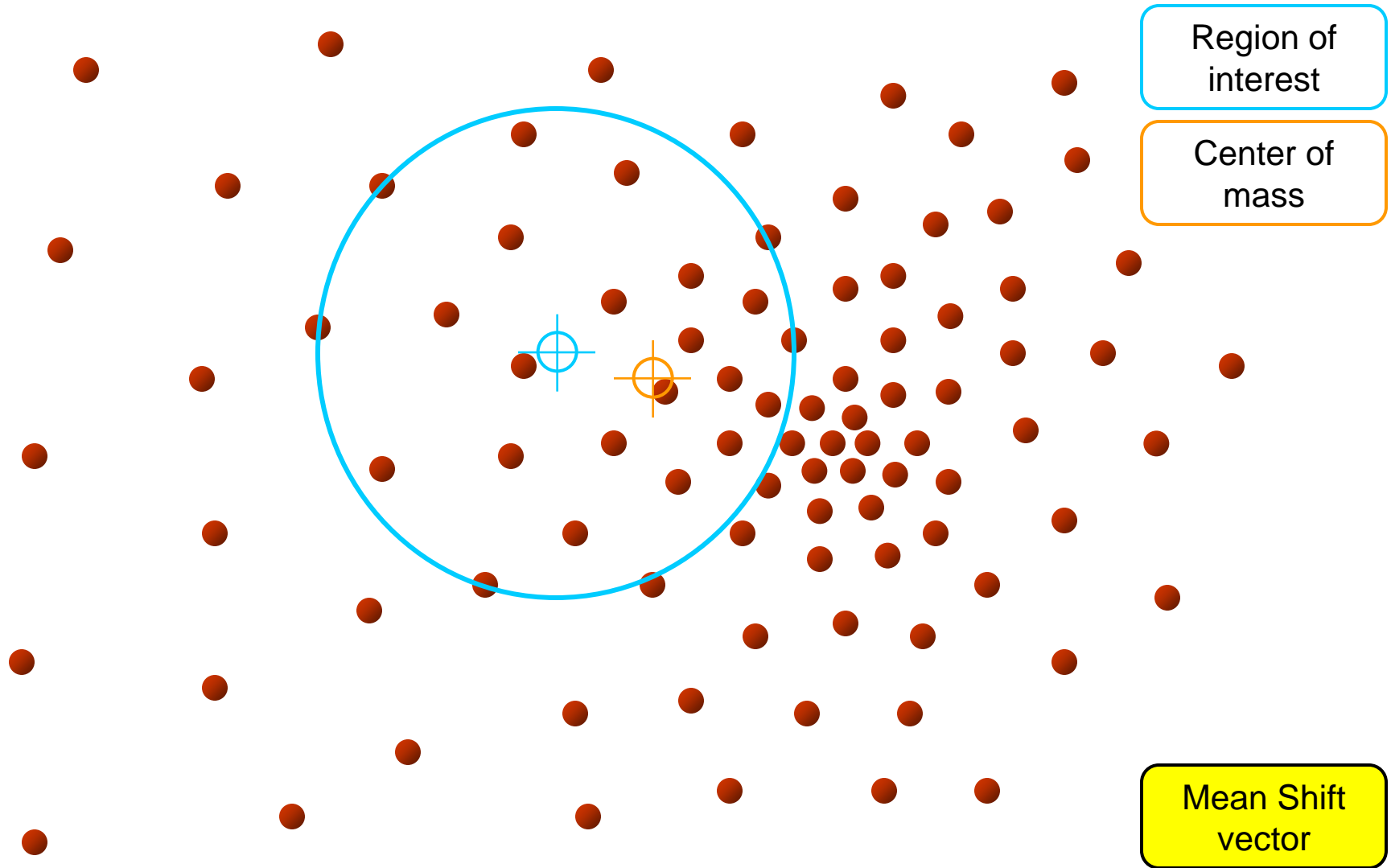


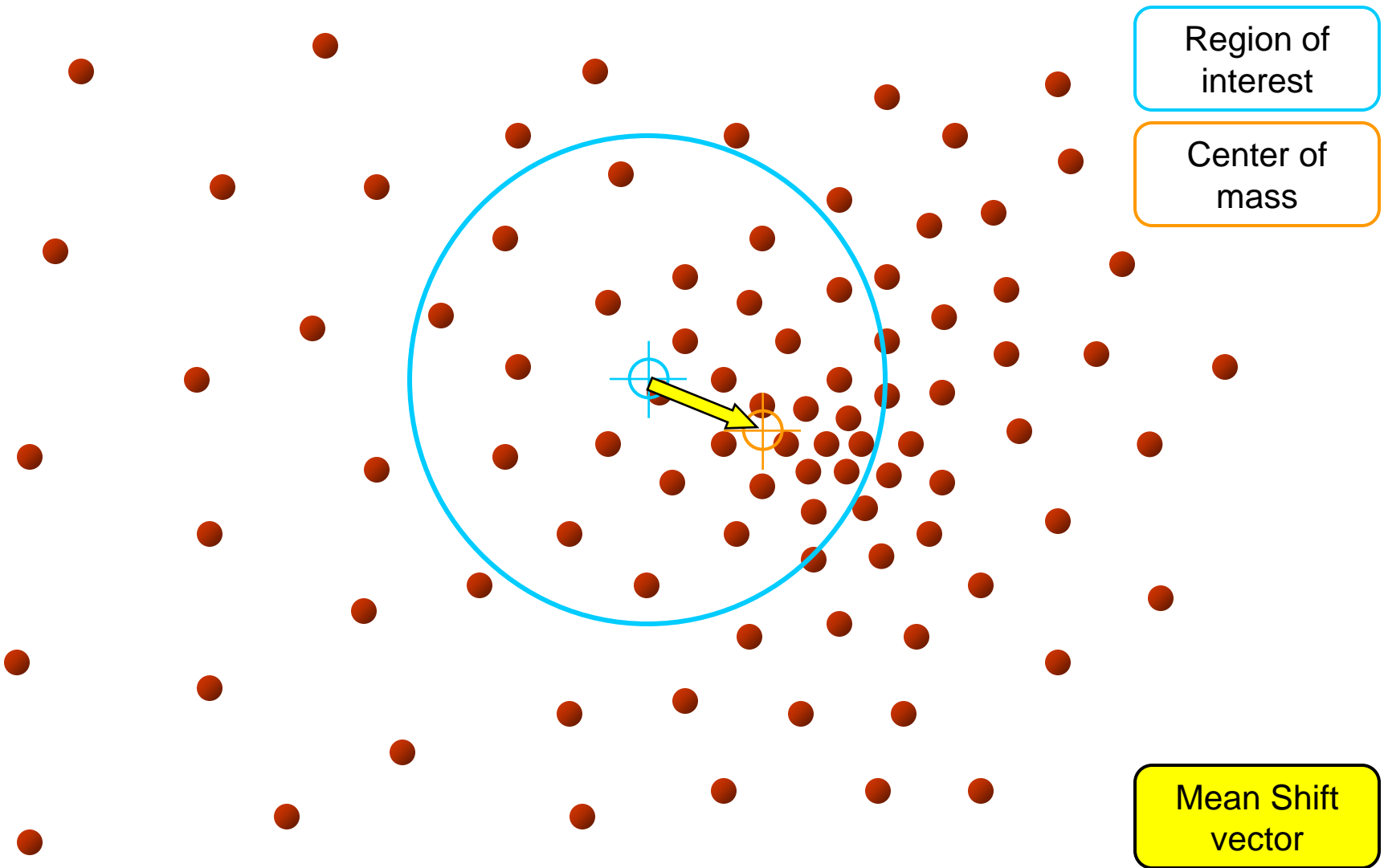
Figure 5.16 Mean-shift image segmentation (Comaniciu and Meer 2002) © 2002 IEEE: (a) input color image; (b) pixels plotted in $L^*u^*v^*$ space; (c) L^*u^* space distribution; (d) clustered results after 159 mean-shift procedures; (e) corresponding trajectories with peaks marked as red dots.

Mean-shift based tracking: intuitive description



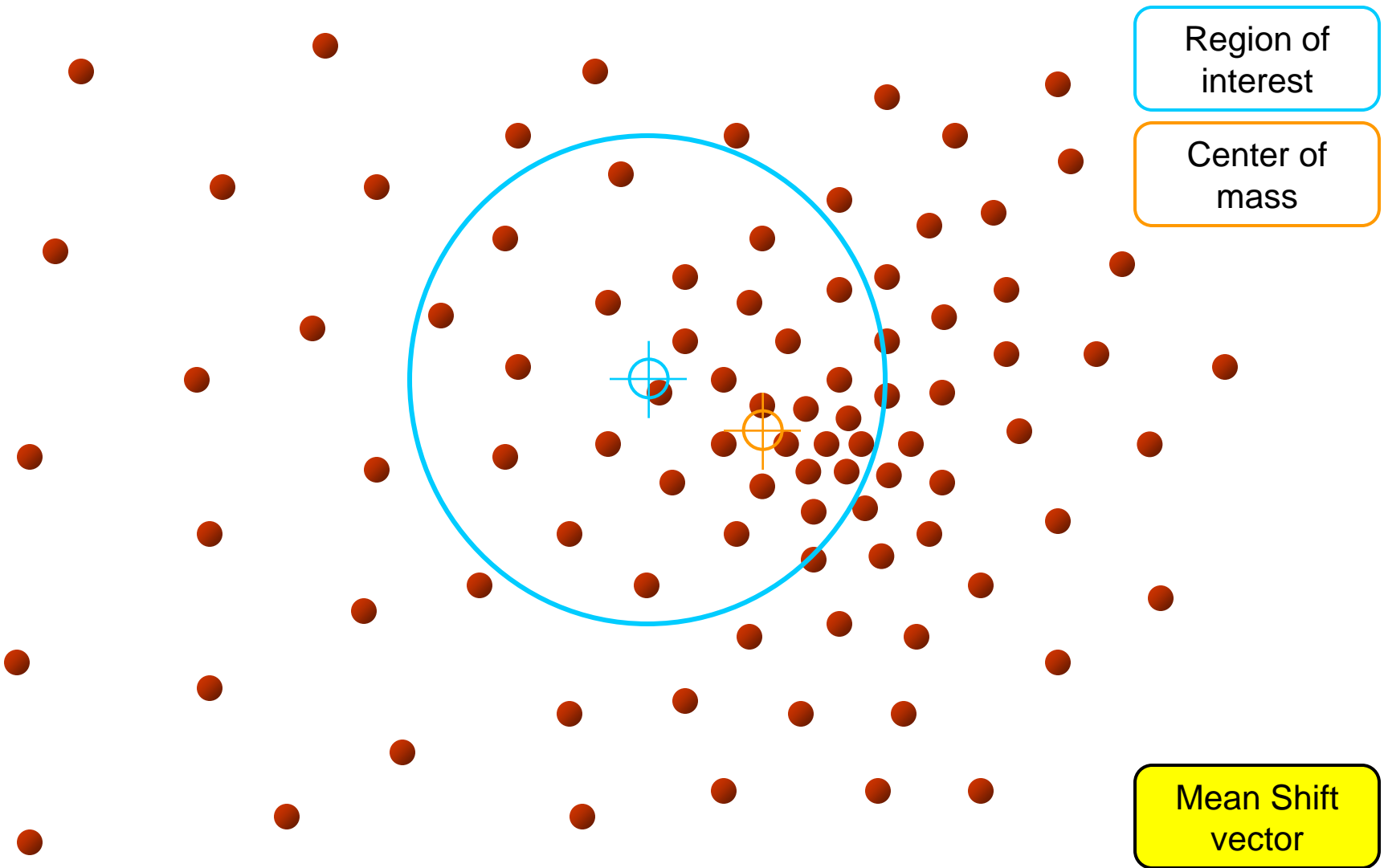
Objective : Find the densest region
Distribution of identical billiard balls

Intuitive Description



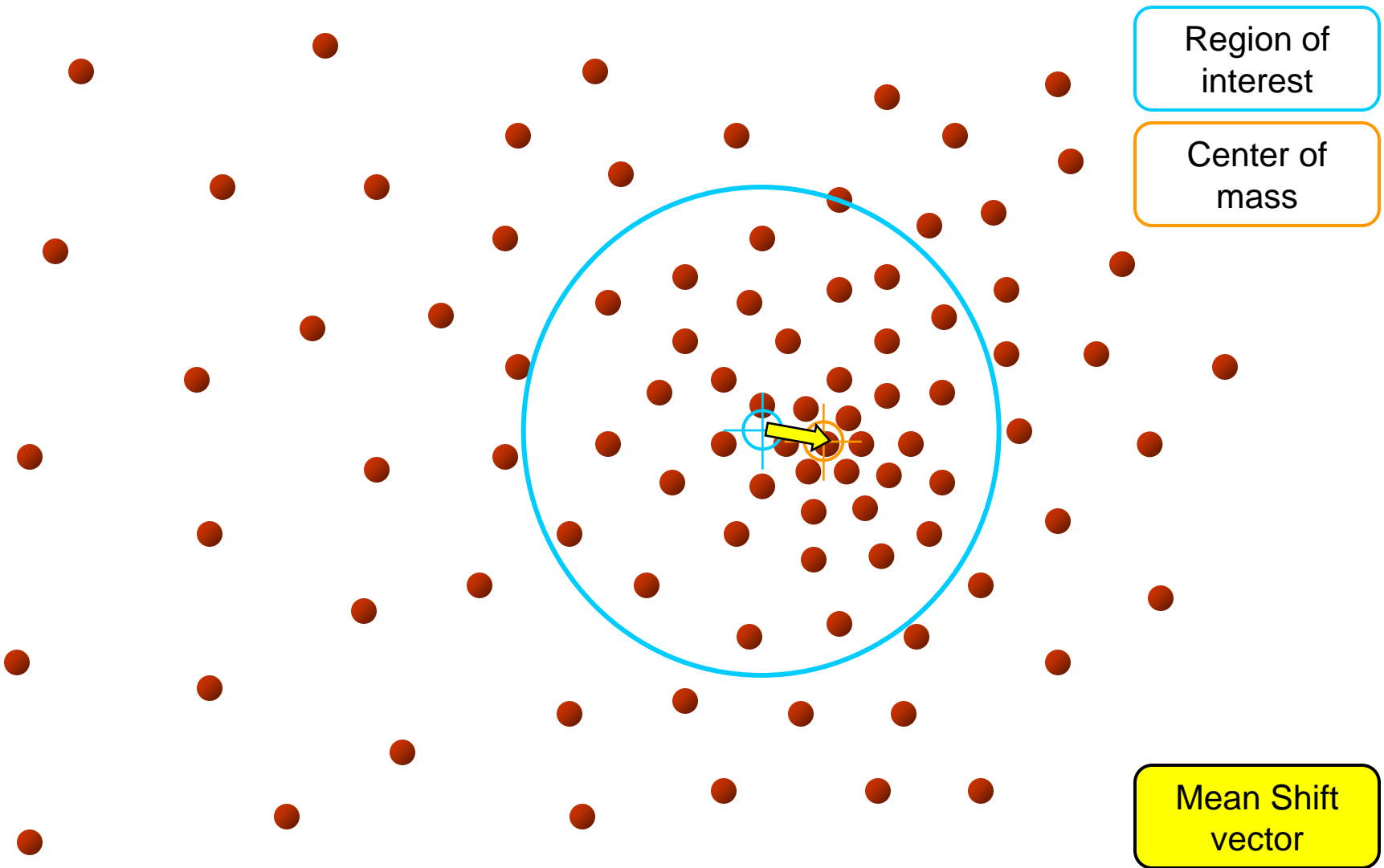
Objective : Find the densest region
Distribution of identical billiard balls

Intuitive Description



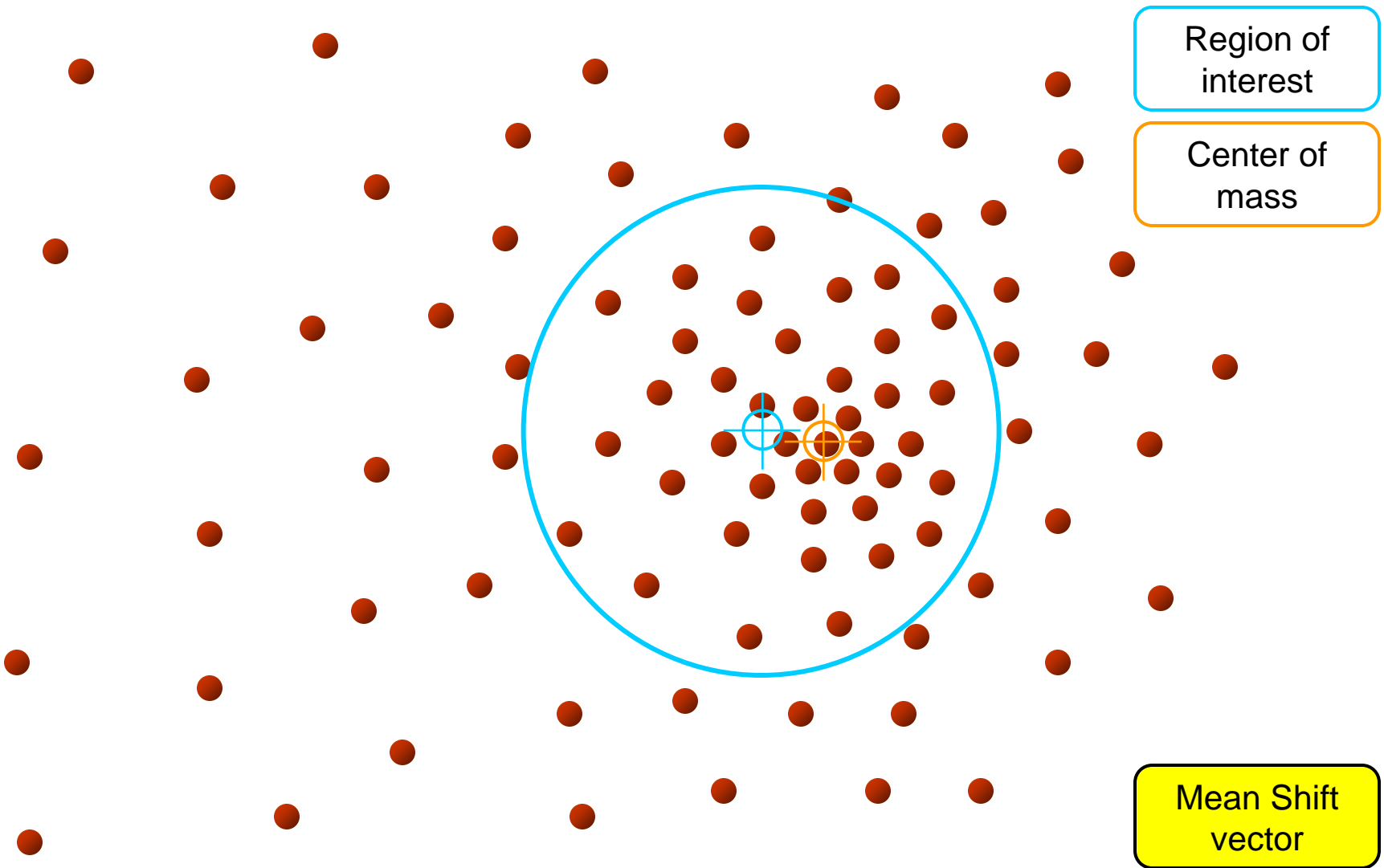
Objective : Find the densest region
Distribution of identical billiard balls

Intuitive Description



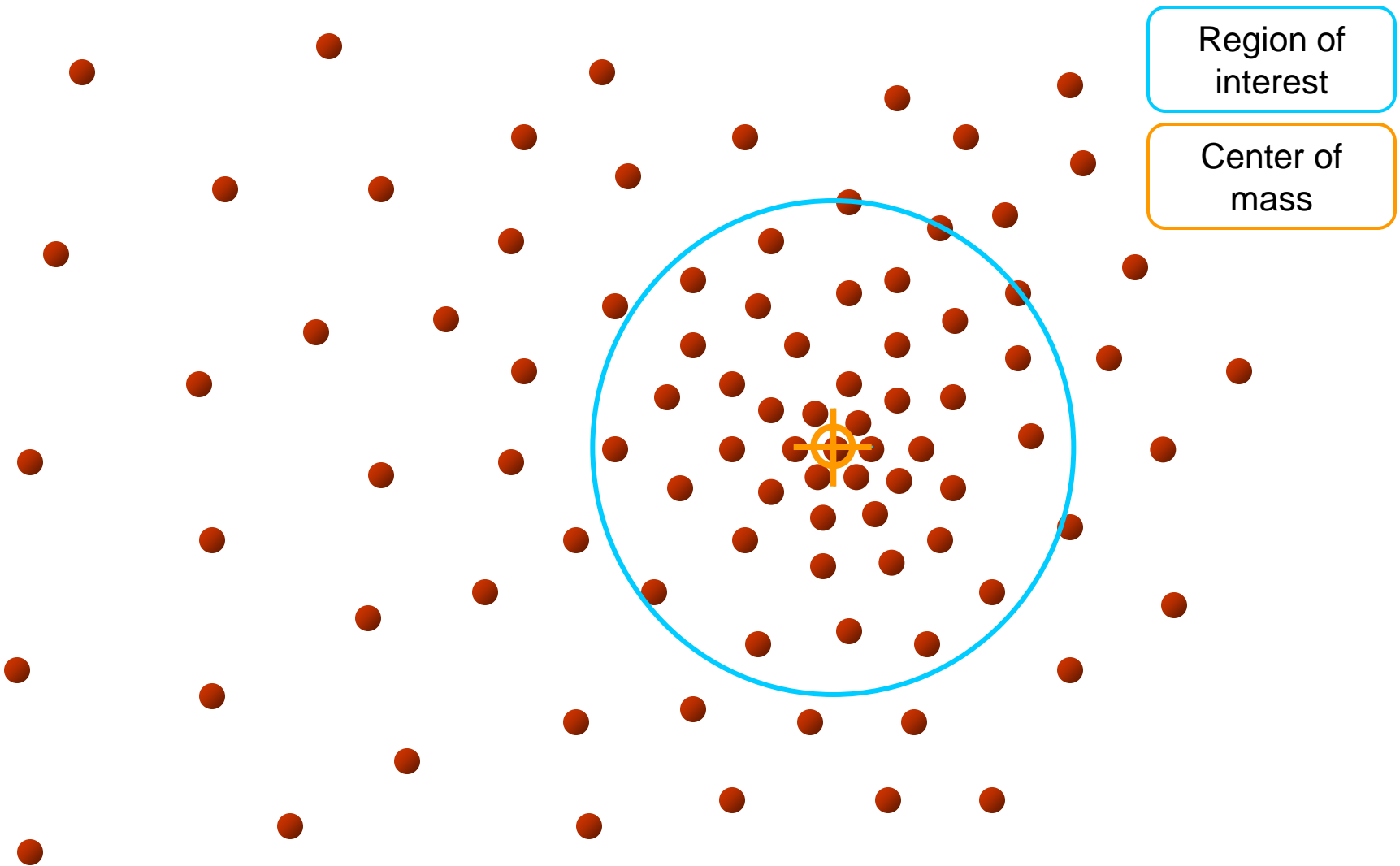
Objective : Find the densest region
Distribution of identical billiard balls

Intuitive Description



Objective : Find the densest region
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Intuitive Description



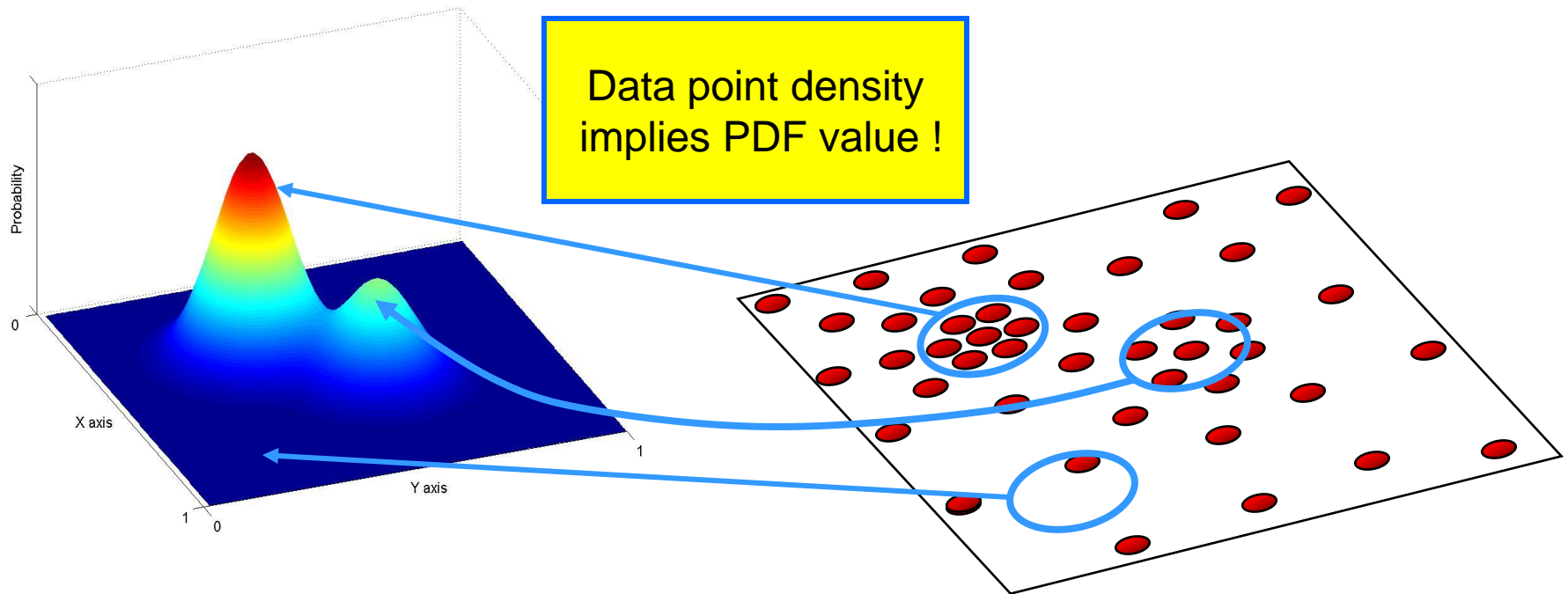
Objective : Find the densest region
Distribution of identical billiard balls

Non-Parametric Density Estimation

A tool for:

Finding modes in a set of data samples, manifesting an underlying probability density function (PDF) in R^N

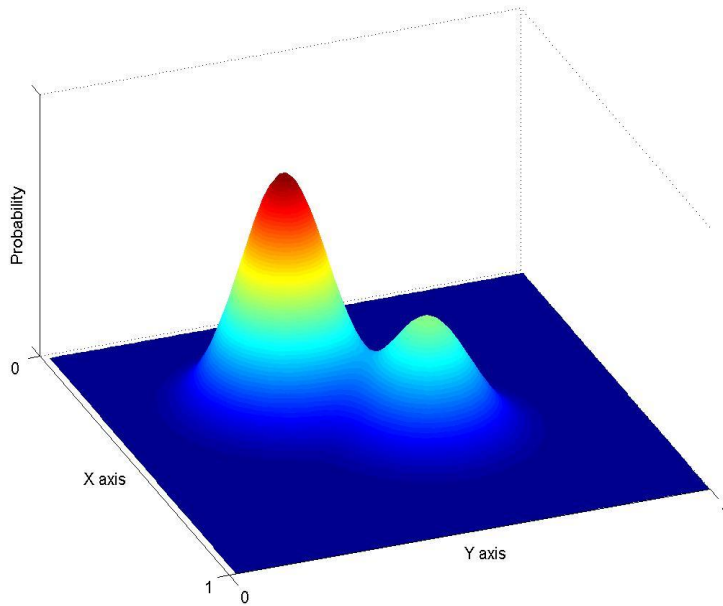
Assumption : The data points are sampled from an underlying PDF



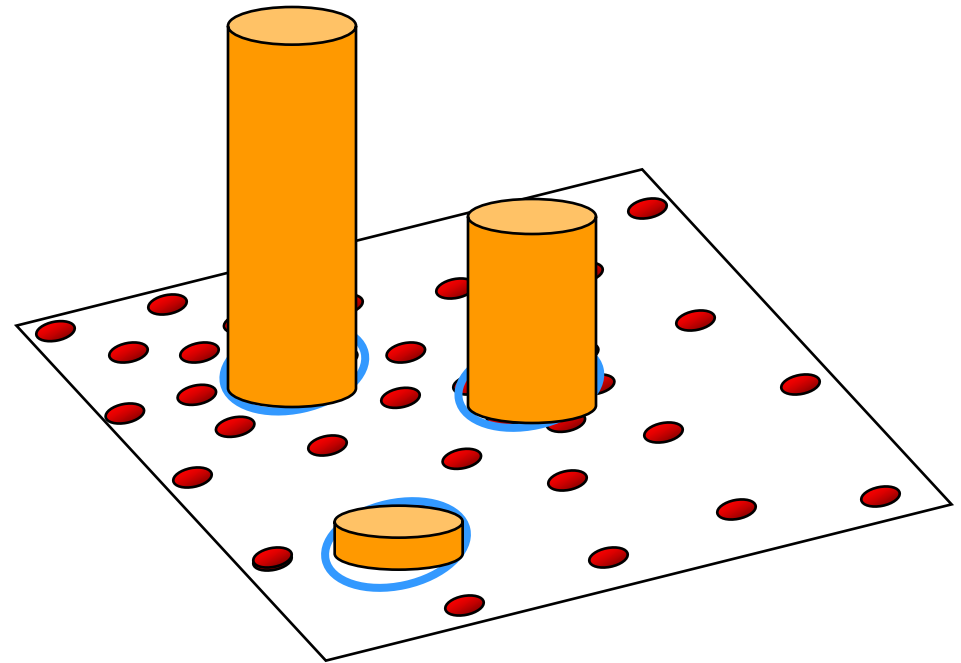
Assumed Underlying PDF

Real Data Samples

Non-Parametric Density Estimation



Assumed Underlying PDF



Real Data Samples

Mean Shift Segmentation Results:



Figure 5.18 Mean-shift color image segmentation with parameters $(h_x, h_r, M) = (16, 19, 40)$ (Comaniciu and Meer 2002) © 2002 IEEE.