10A – Image Segmentation

Image Segmentation

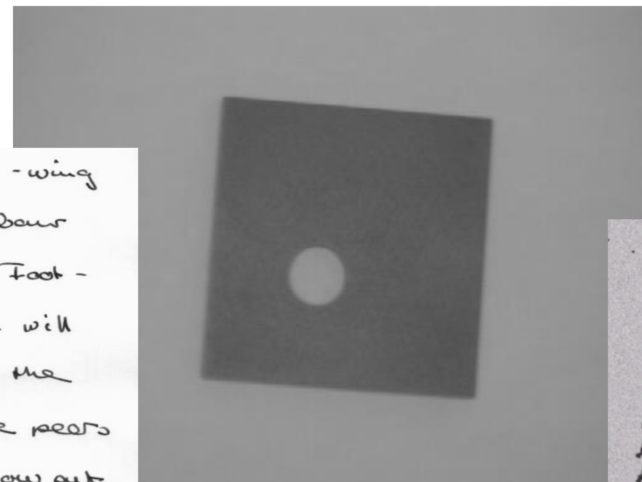
- Group similar components (such as, pixels in an image, image frames in a video)
- Applications: Finding tumors, veins, etc. in medical images, finding targets in satellite/aerial images, finding people in surveillance images, summarizing video, etc.

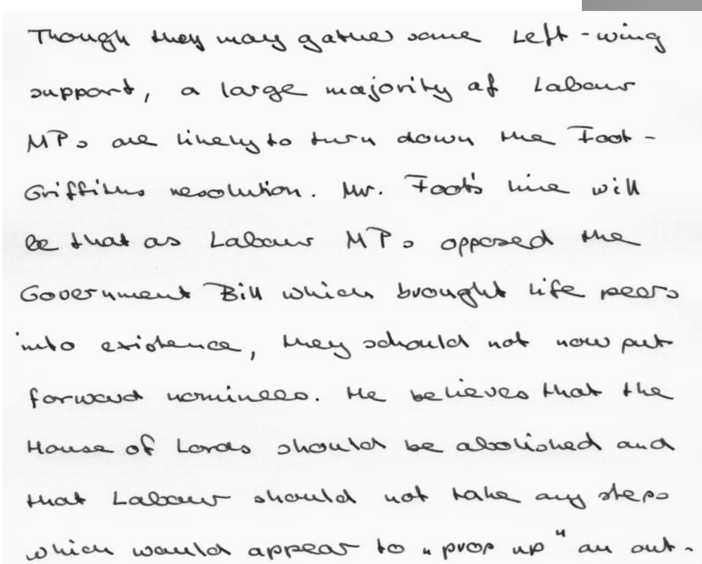
Image Segmentation

- 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





Thresholding

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

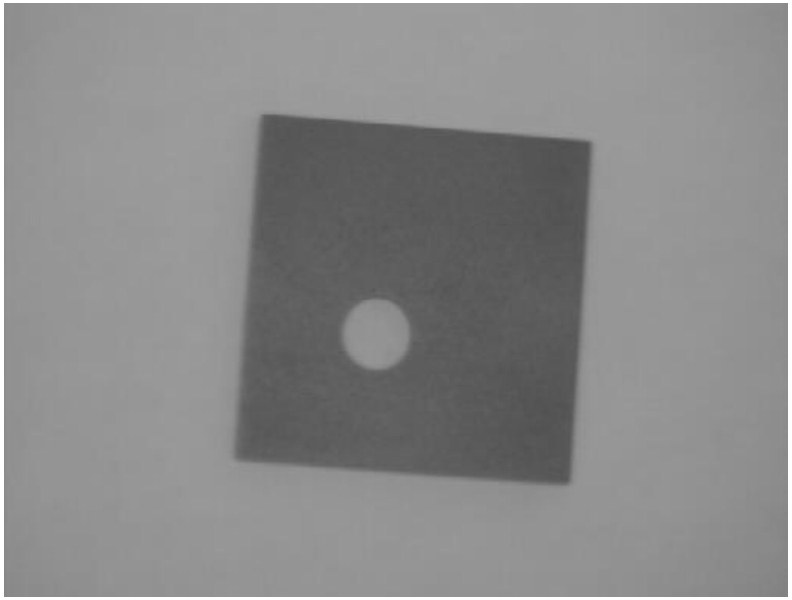
Objects & Background

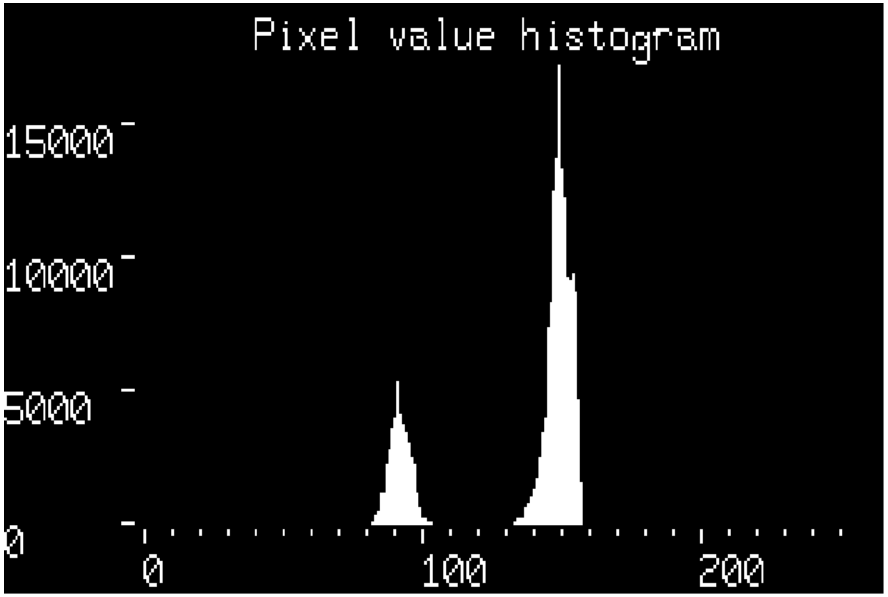
Thresholding

- GLOBAL
- ADAPTIVE
- LOCAL

Global Thresholding

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





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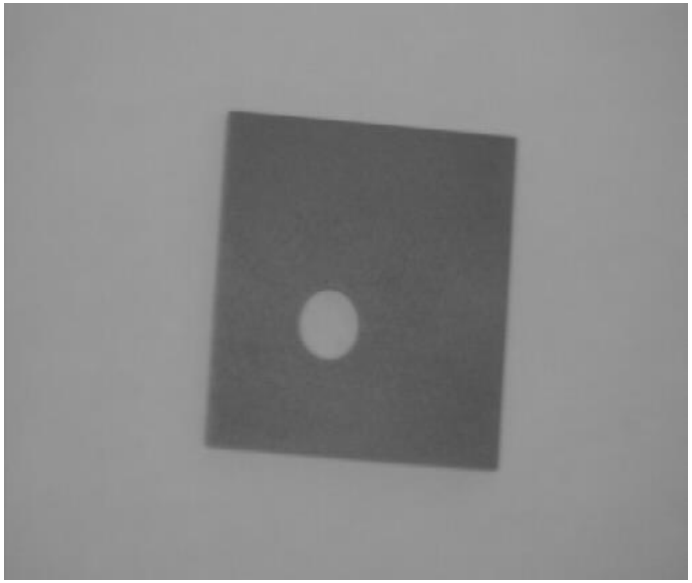
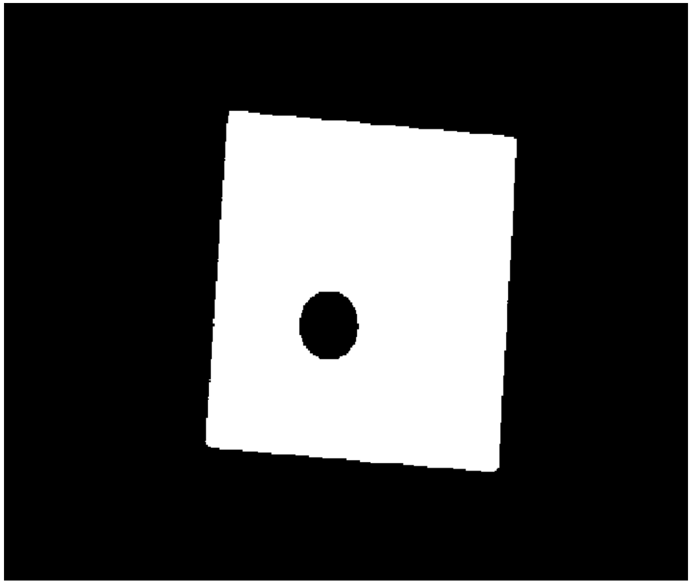
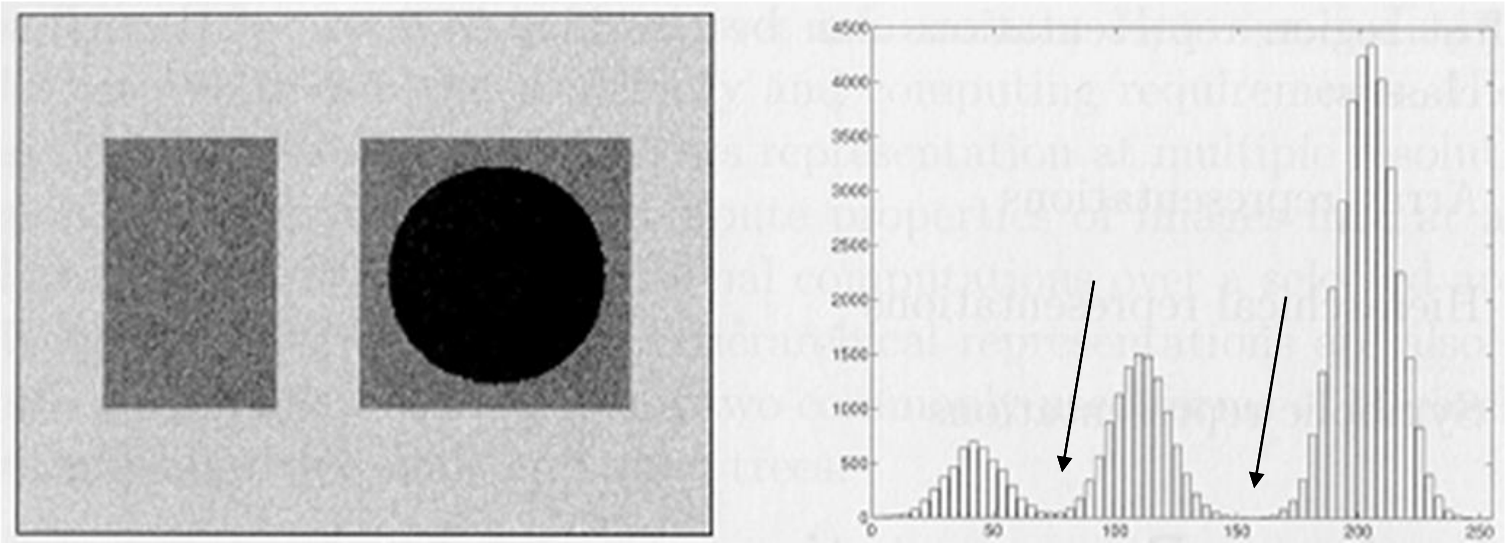




Global Thresholding

- 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

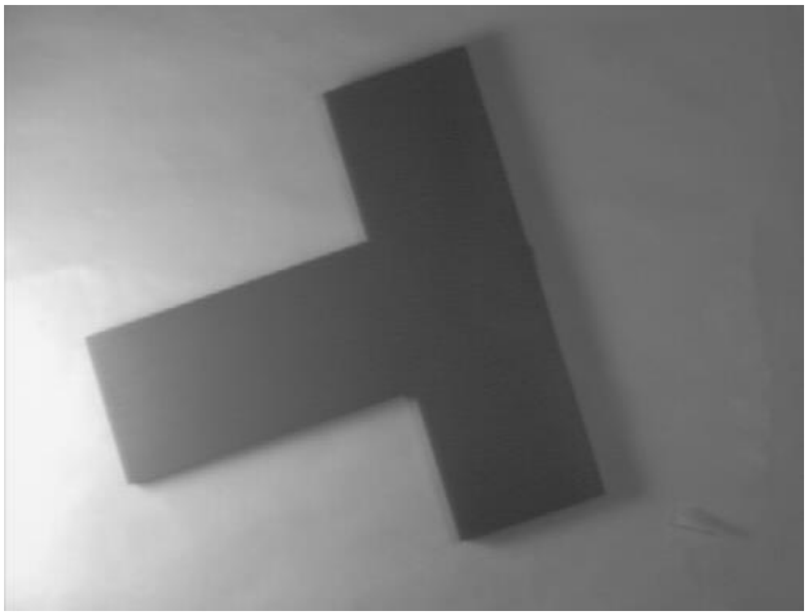
Global Thresholding

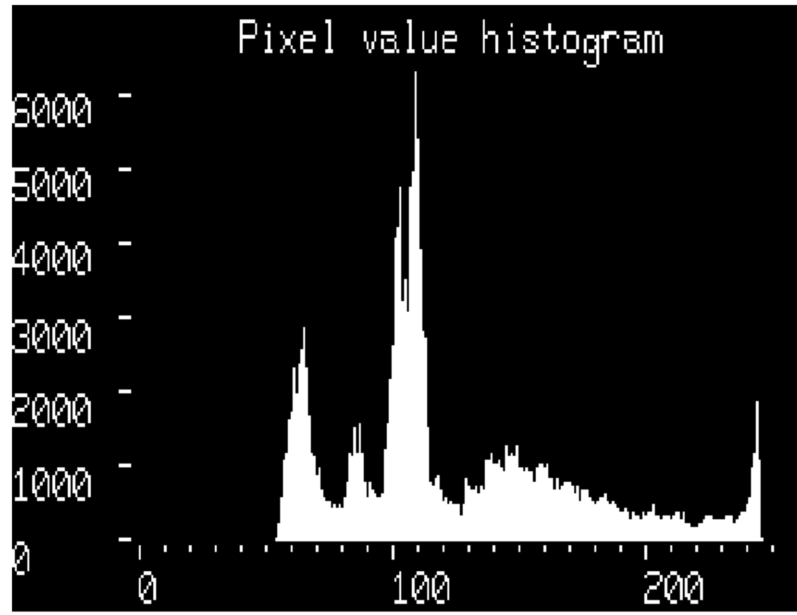


Multilevel thresholding

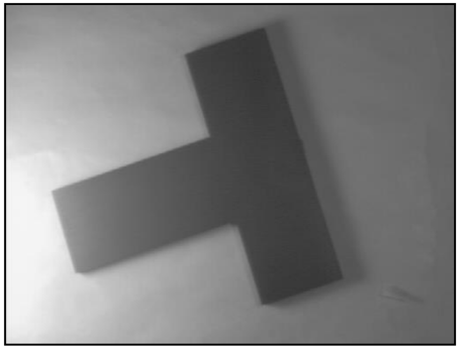
Thresholding

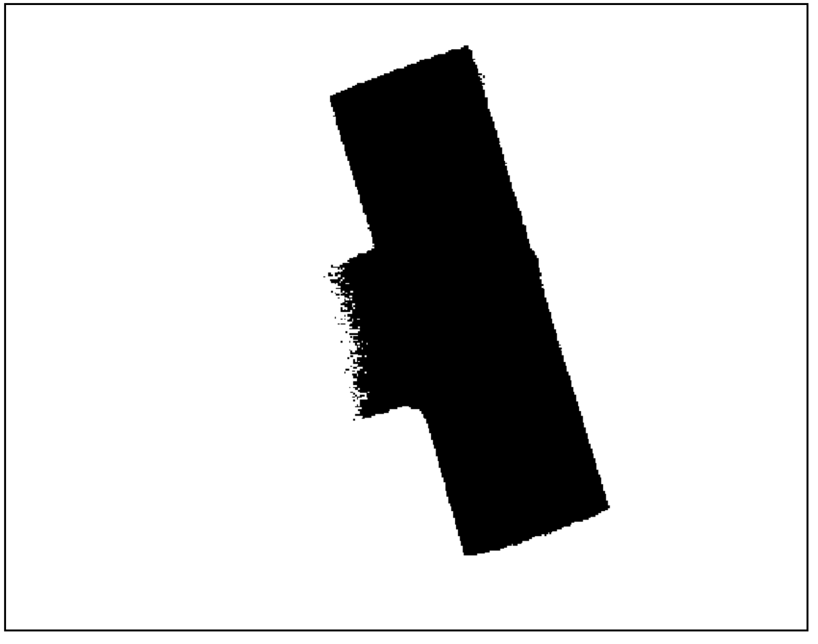
- Non-uniform illumination:

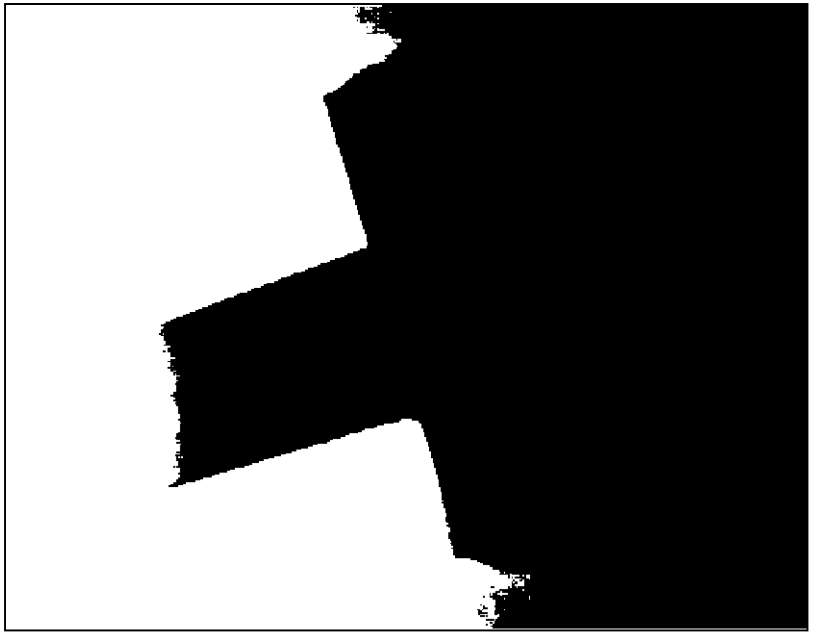




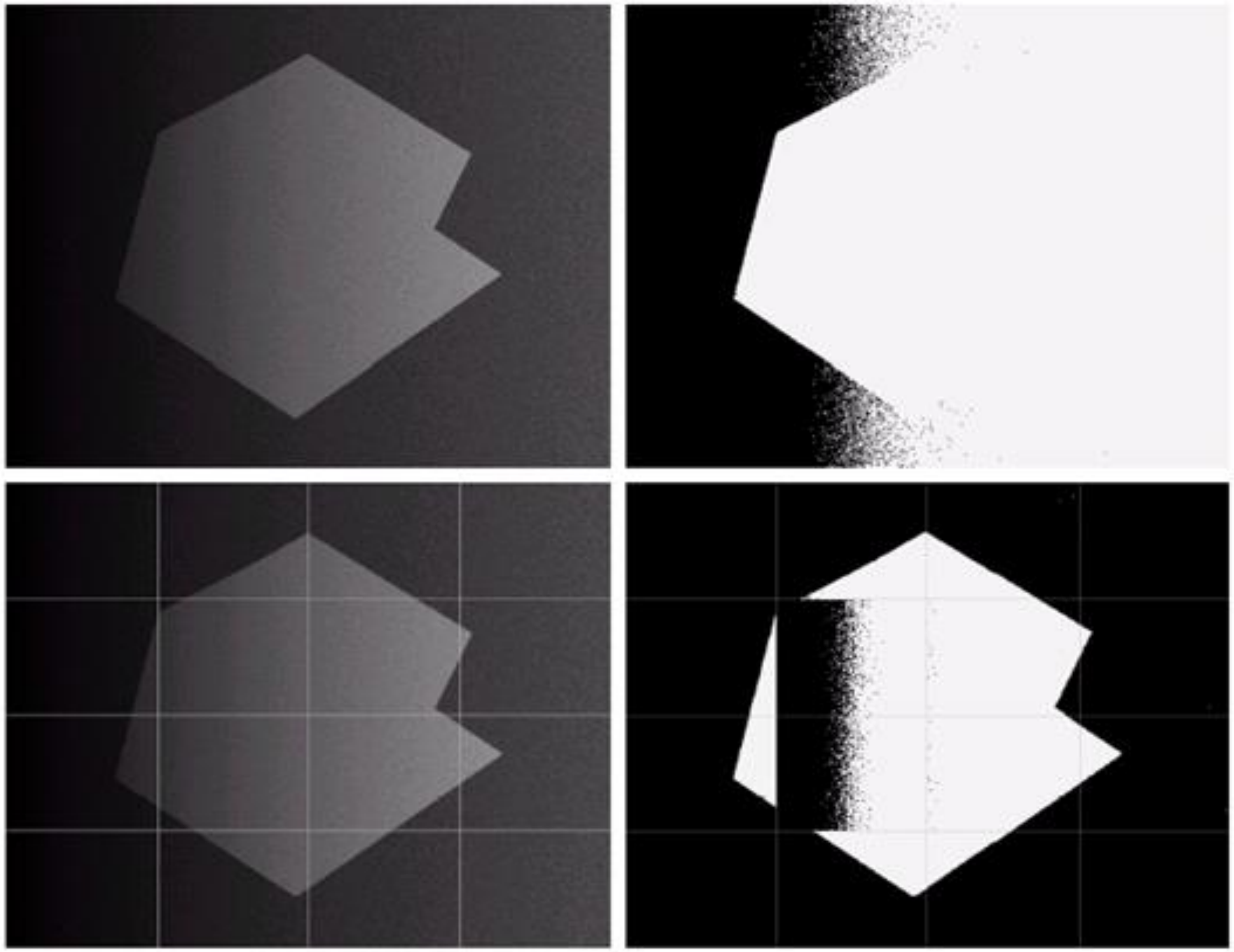
Global Thresholding







Adaptive Thresholding



Local Adaptive Thresholding

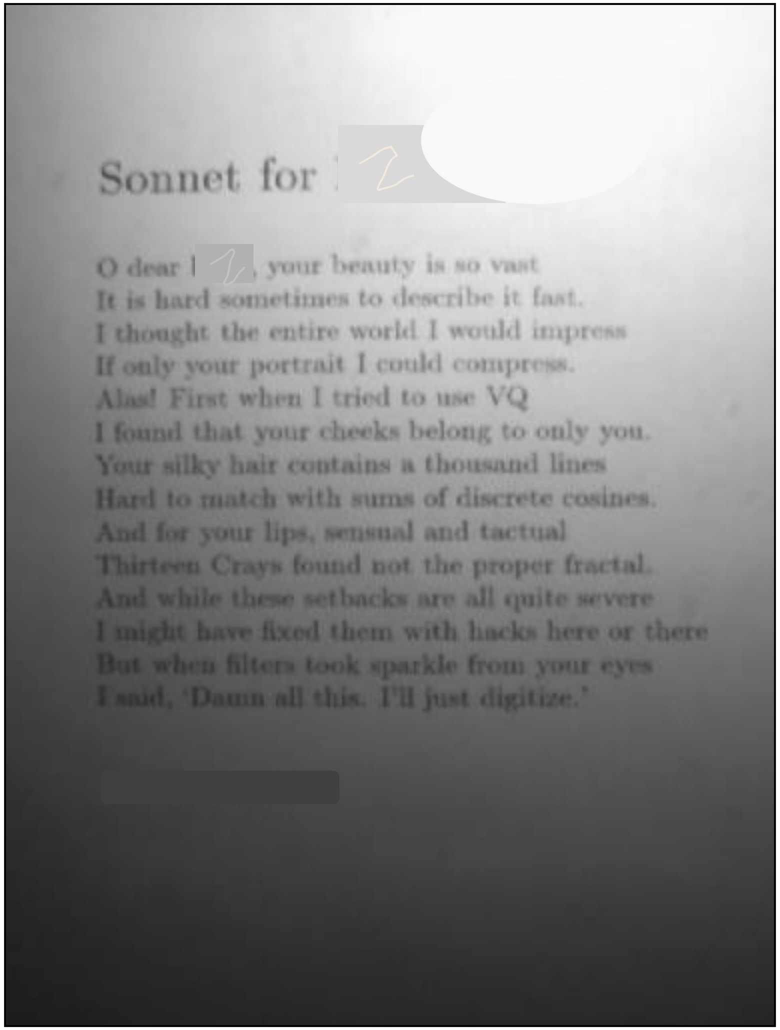
- Threshold: function of neighboring pixels

$$T = mean$$

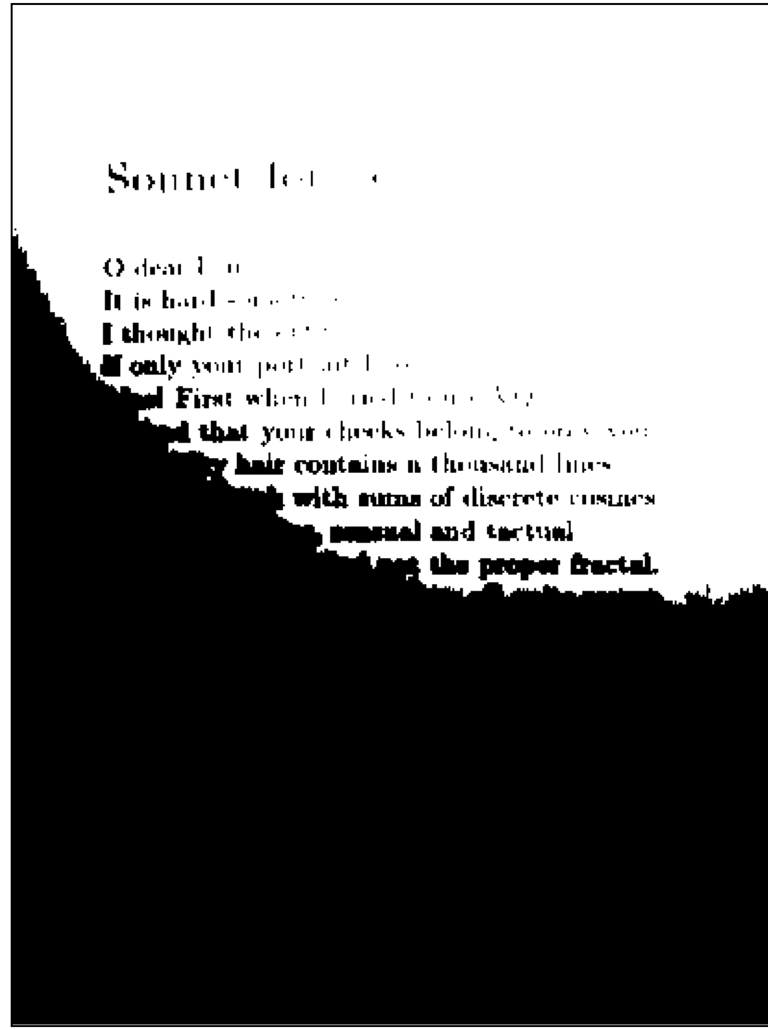
$$T = median$$

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

Local Adaptive Thresholding

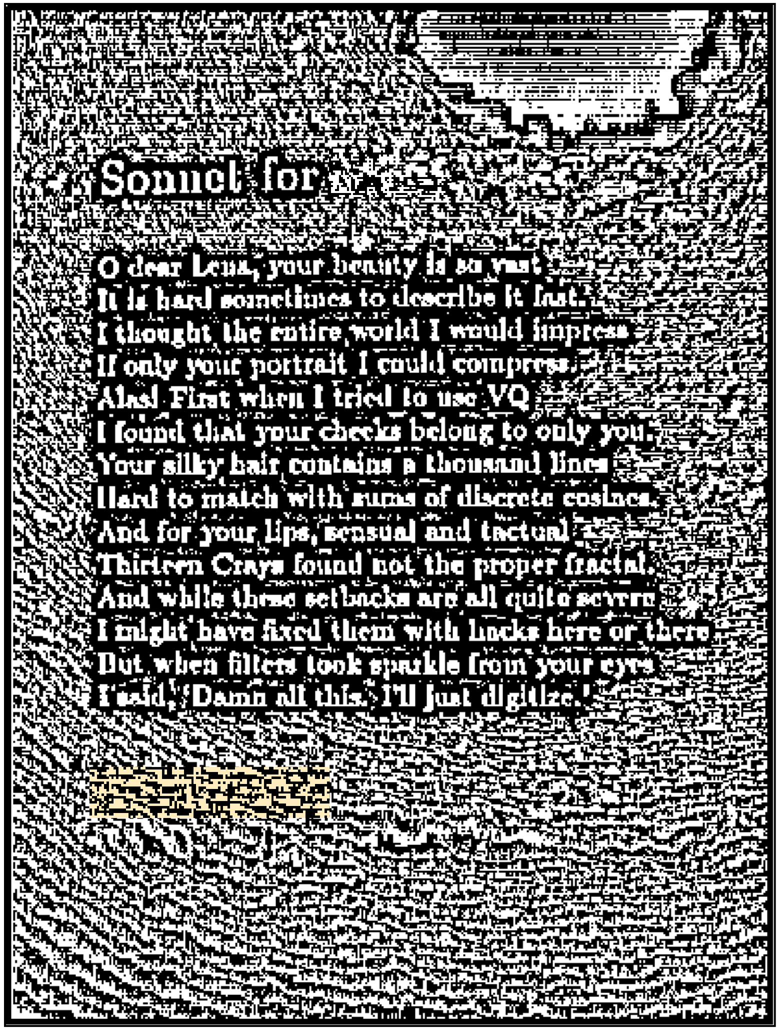


Original Image



Global Thresholding

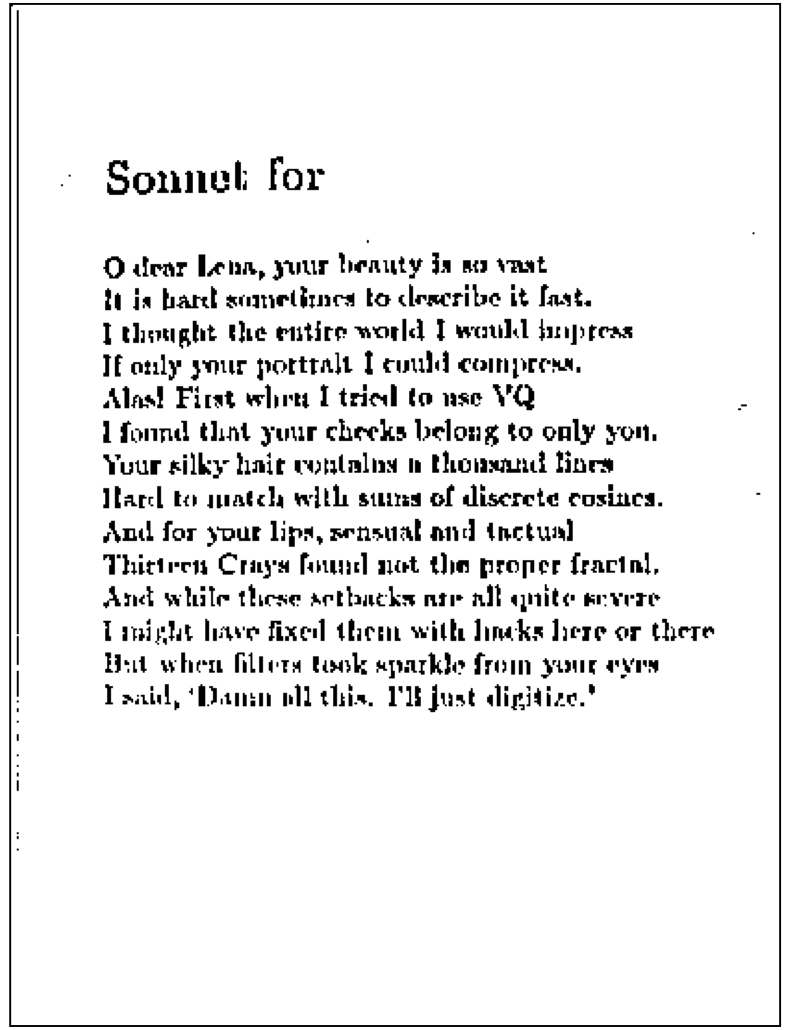
Local Adaptive Thresholding



Sonnet for

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.'

T=mean, neighborhood=7x7



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T=mean-Const., neighborhood=7x7

Local Adaptive Thresholding

- Niblack Algorithm

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

$$m = \text{mean}$$

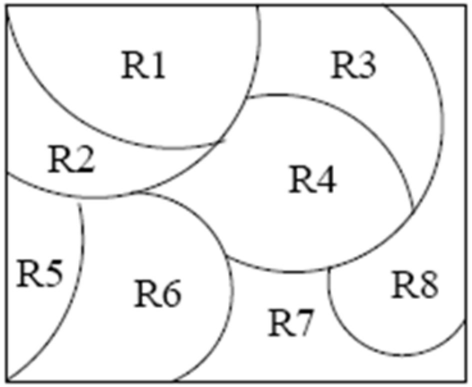
$$s = \text{standard deviations}$$

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

- Neighborhood size???

Region-Based Segmentation

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



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

$$(2)\ R_i \text{ is connected}$$

$$(3)\ R_i \cap R_j = empty$$

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

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

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.
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 $\text{abs}(z_j - \text{seed}) < \text{Epsilon}$

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

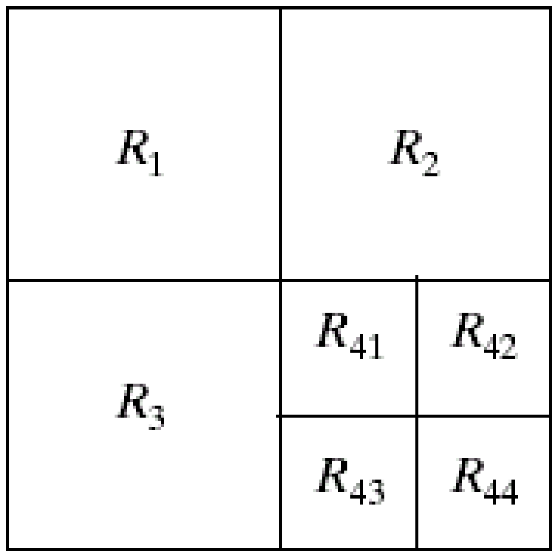
Region-Based Segmentation

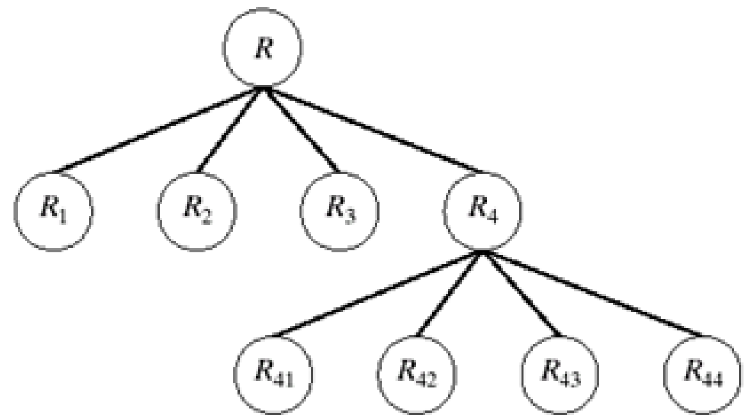
- Region Splitting
  - Region growing: Starts from a set of seed points.
  - Region Splitting: Starts with the whole image as a single region and subdivide the regions that do not satisfy a condition.
  - Image = One Region R
  - Select a predicate P (gray values etc.)
  - Successively divide each region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

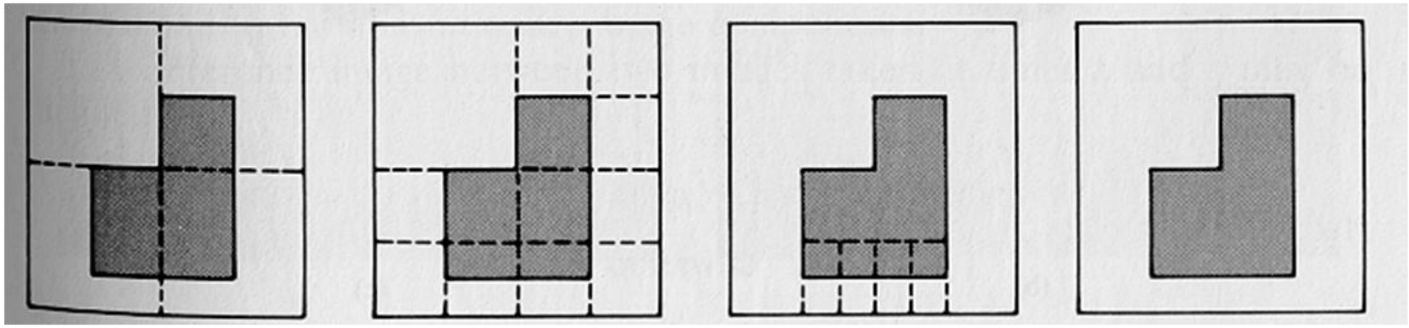
- Region Merging
  - Region merging is the opposite of region splitting.
  - Merge adjacent regions R_i and R_j for which:

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

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

Region-Based Segmentation

- Example

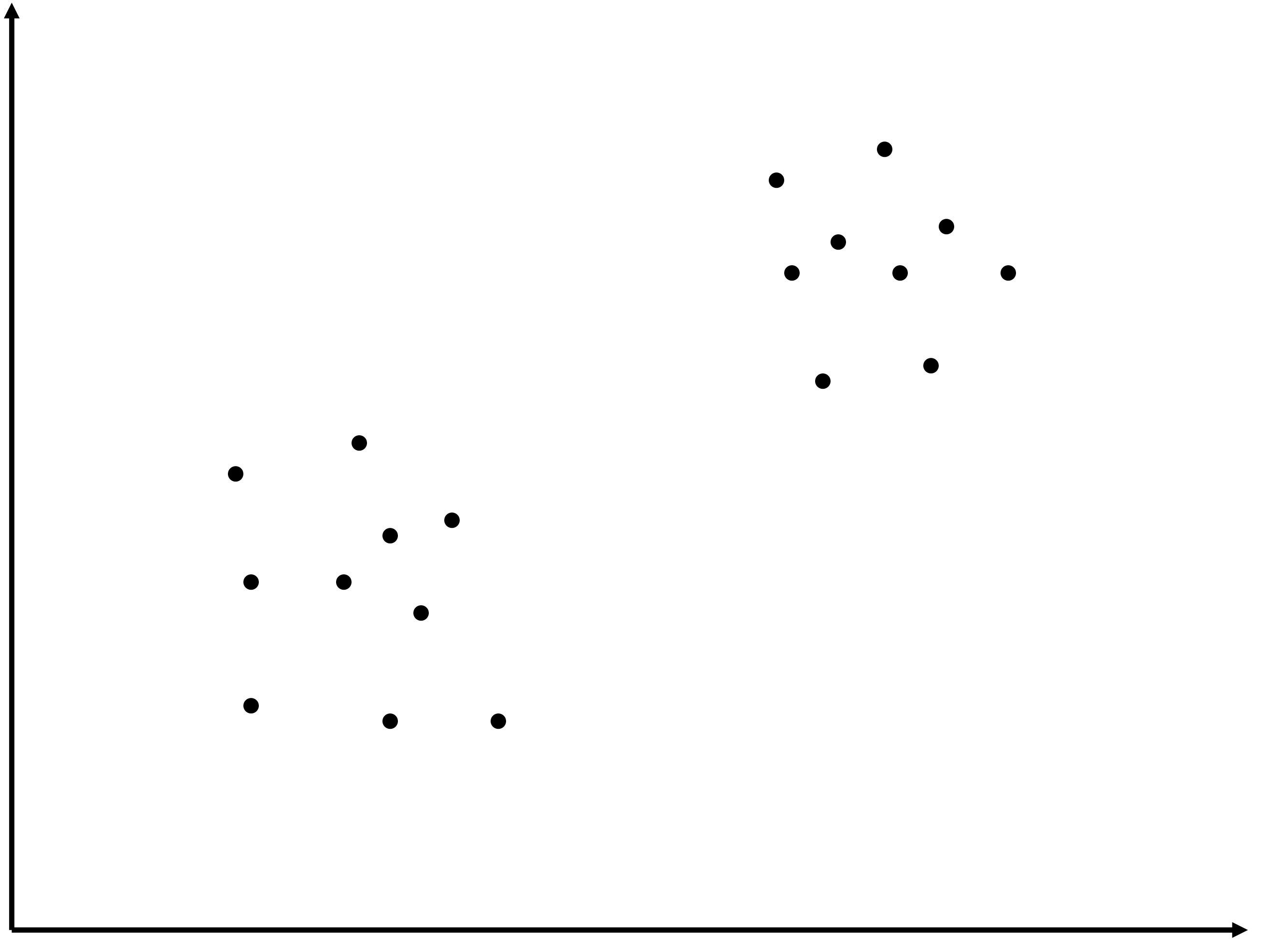


1. Split into four disjointed quadrants any region R_i where $P(R_i)$=False
2. Merge any adjacent regions R_j and R_k for which $P(R_j \cup R_k)$=True
3. Stop when no further merging or splitting is possible

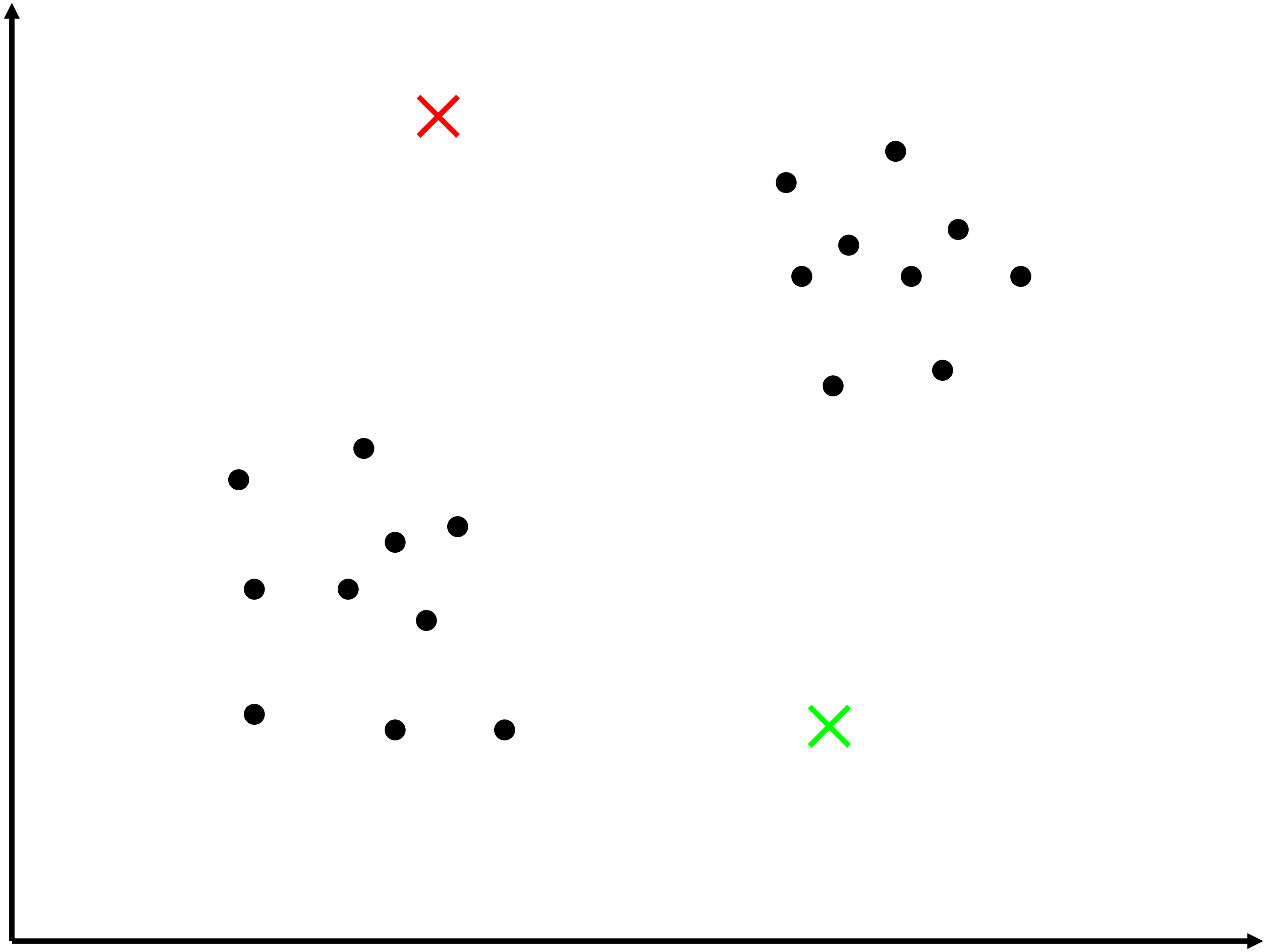
K-Means Clustering

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).

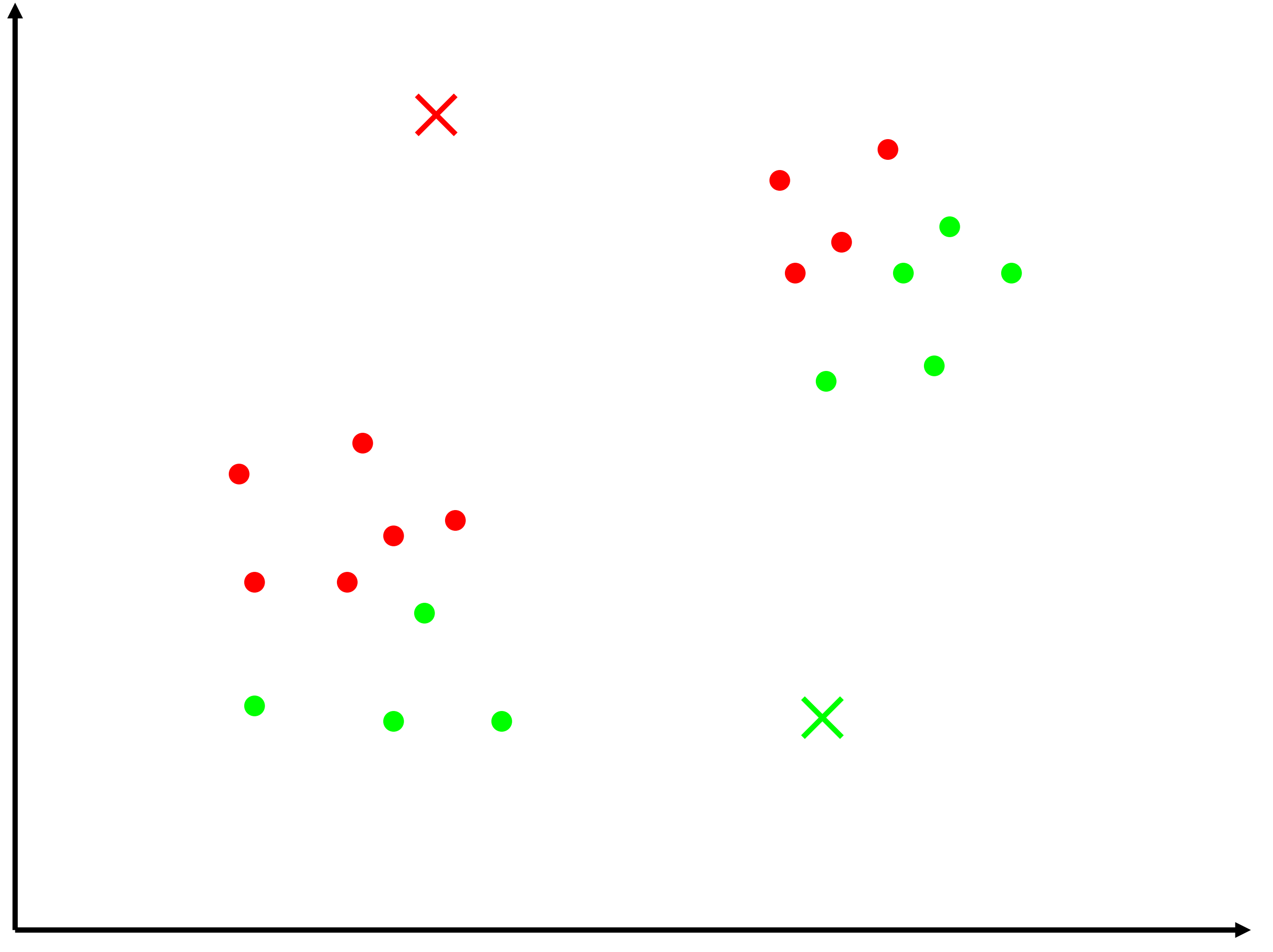
K-Means Clustering



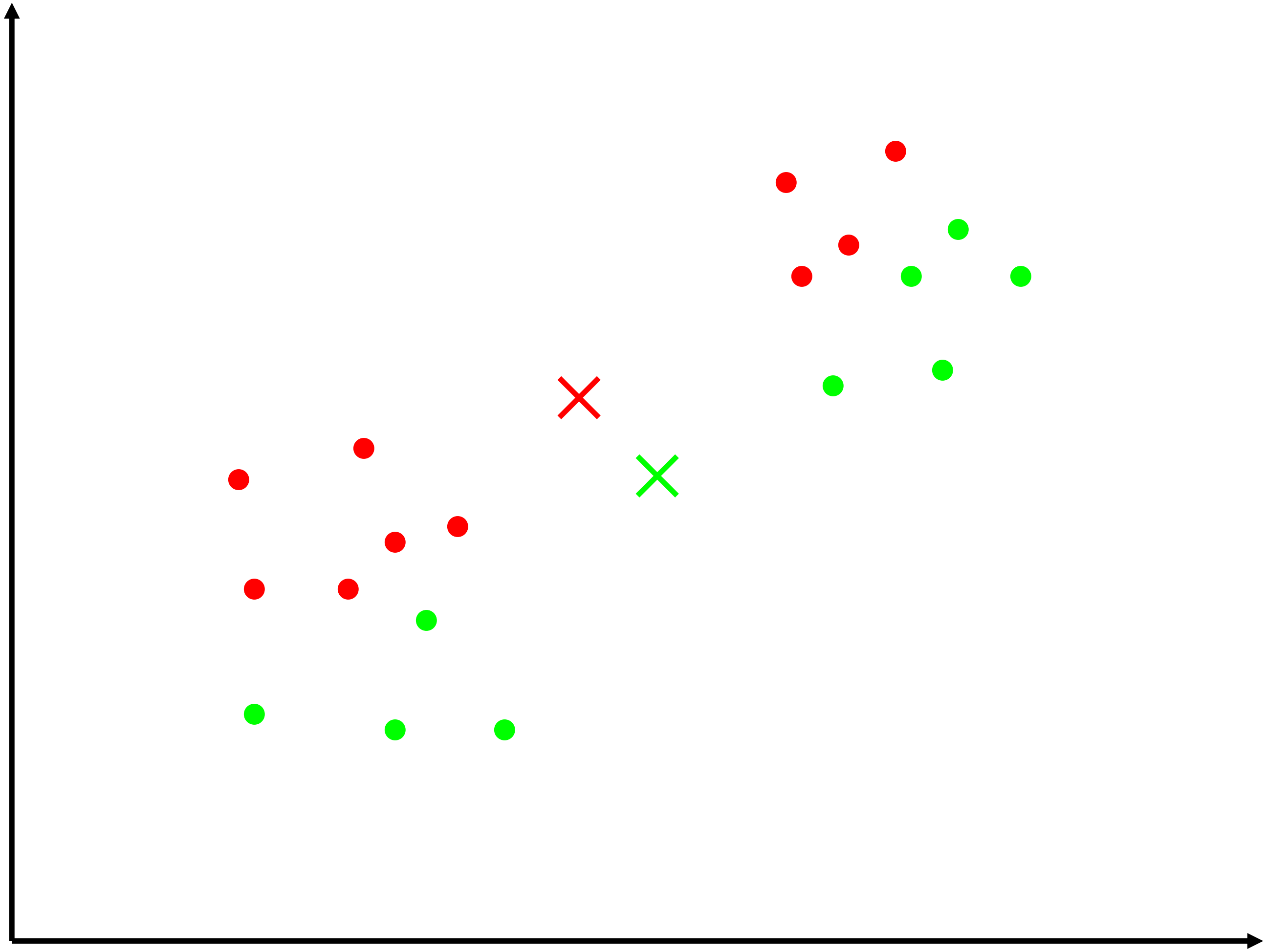
K-Means Clustering



K-Means Clustering



K-Means Clustering



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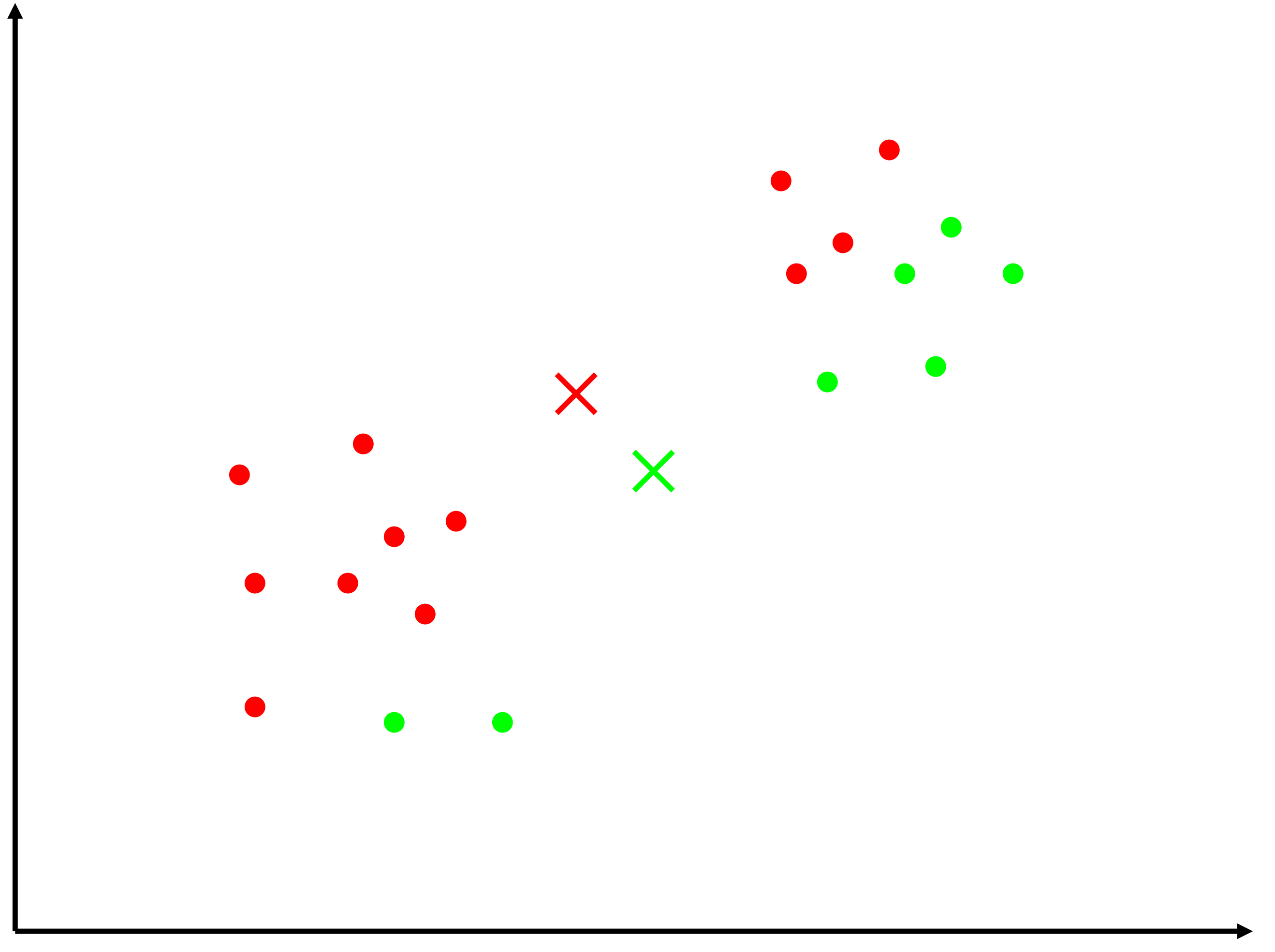
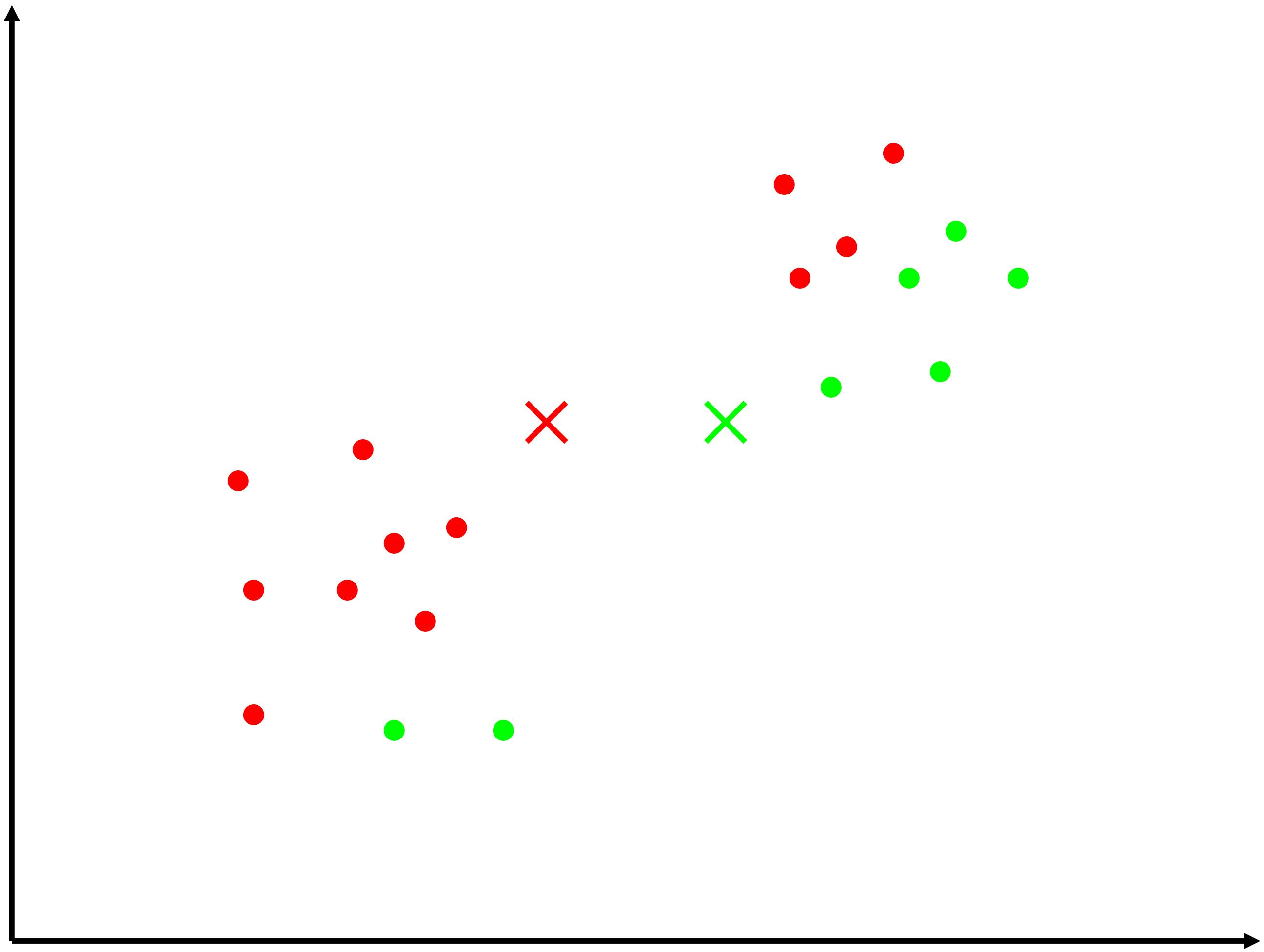


K-Means Clustering



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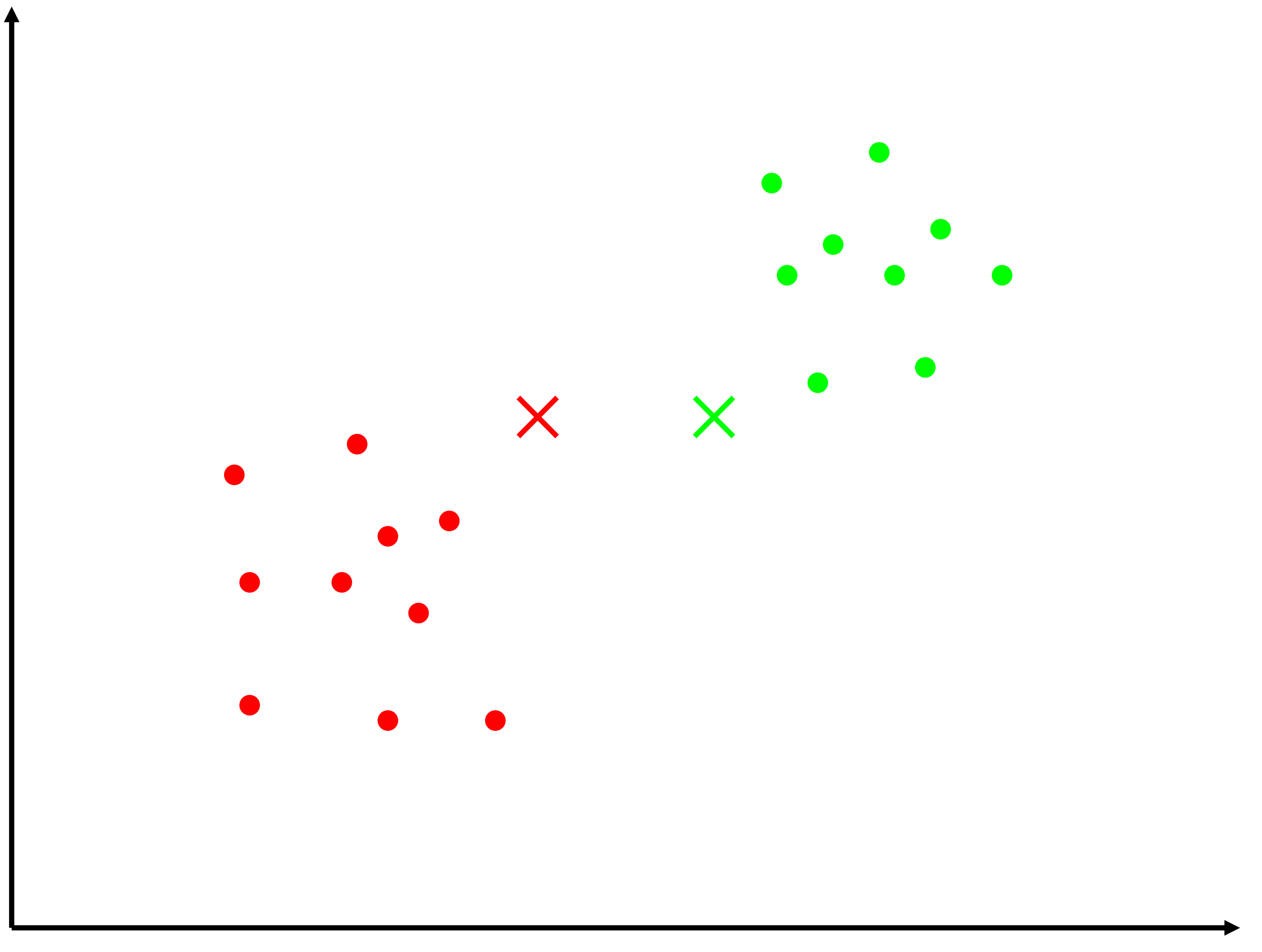

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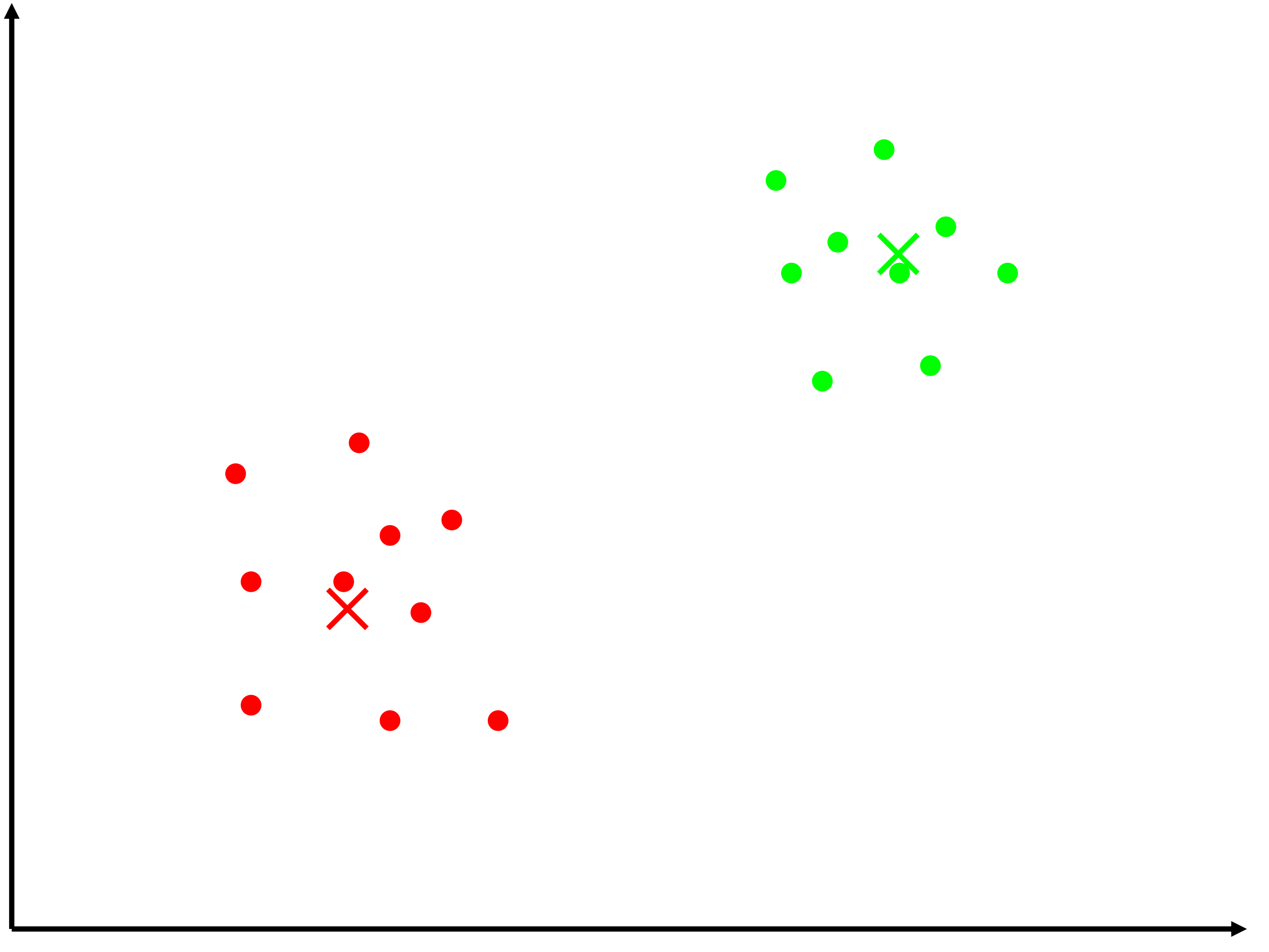
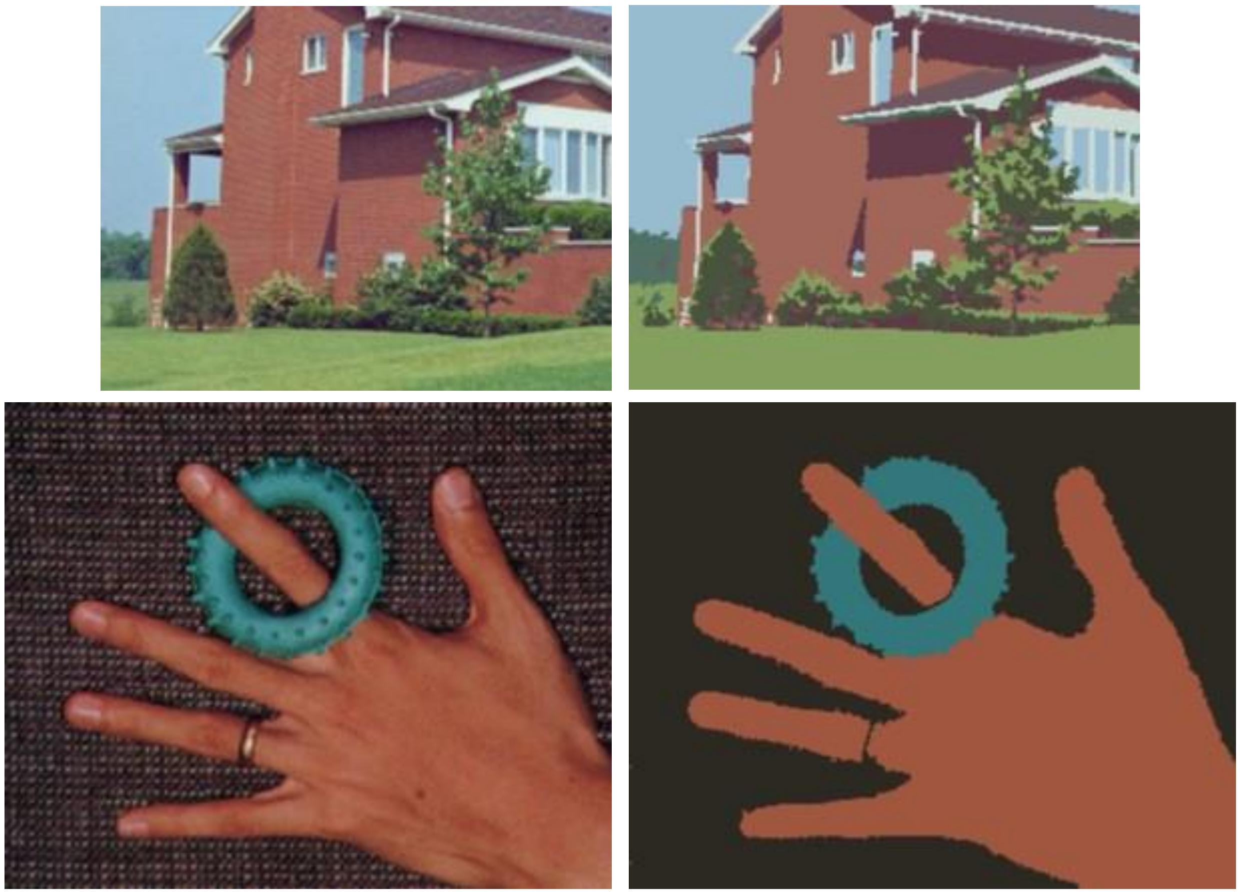


Clustering

- Example



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

K-Means Clustering

- Example

Original

K=5

K=11

References

- Chapter # 10, DIP by Gonzalez & Woods
- Lecture slides by Prof. George Bebis
  - University of Nevada
- Lecture slides by Prof. Bahadir K. Gunturk
  - Louisiana State University
- http://homepages.inf.ed.ac.uk/rbf/HIPR2/