CAP5415 Computer Vision

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HEC-241

Questions?

Image Segmentation

Lecture 14

Agenda

- Image segmentation basics
- Thresholding based
  - Binarization
  - Otsu
- Region based
  - Merging
  - Splitting
- Clustering based
  - K-means (SLIC)
  - Mean-shift

Image Segmentation

Lecture 14

Image segmentation basics

Image Segmentation

- Partition an image into a collection of set of pixels
  - Meaningful regions (coherent objects)
  - Linear structures (line, curve, …)
  - Shapes (circles, ellipses, …)



Image Segmentation

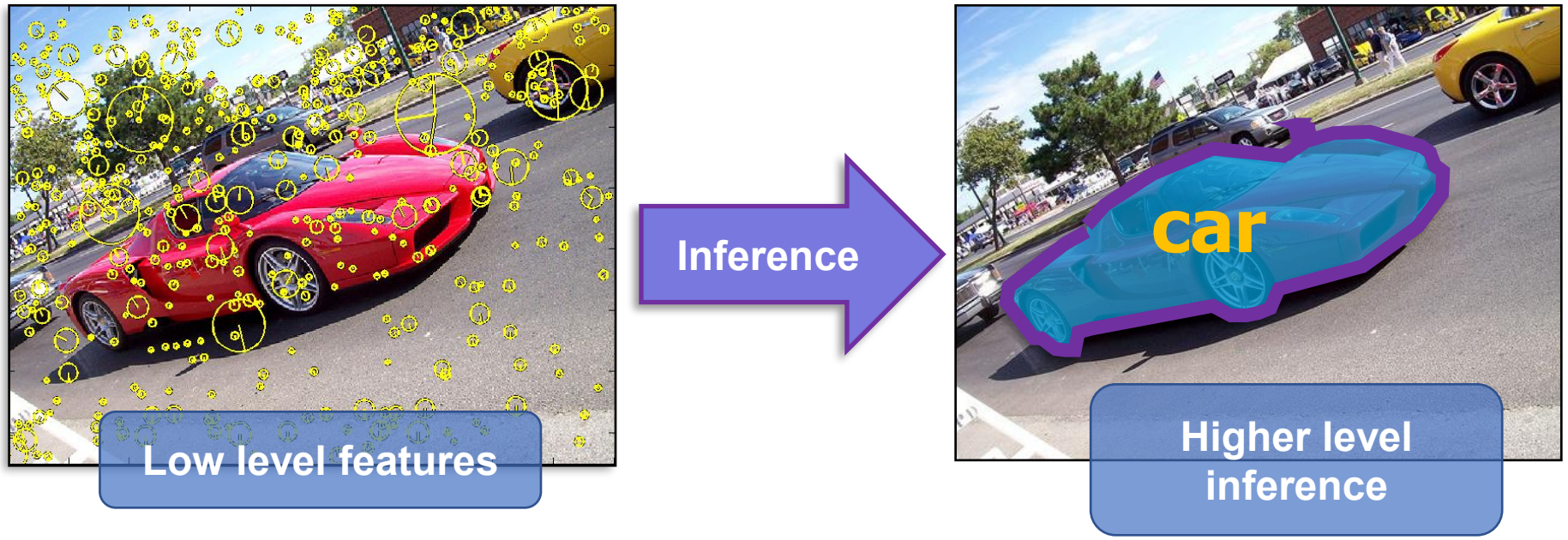
- Partition an image into a collection of set of pixels
  - Meaningful regions (coherent objects)
  - Linear structures (line, curve, …)
  - Shapes (circles, ellipses, …)

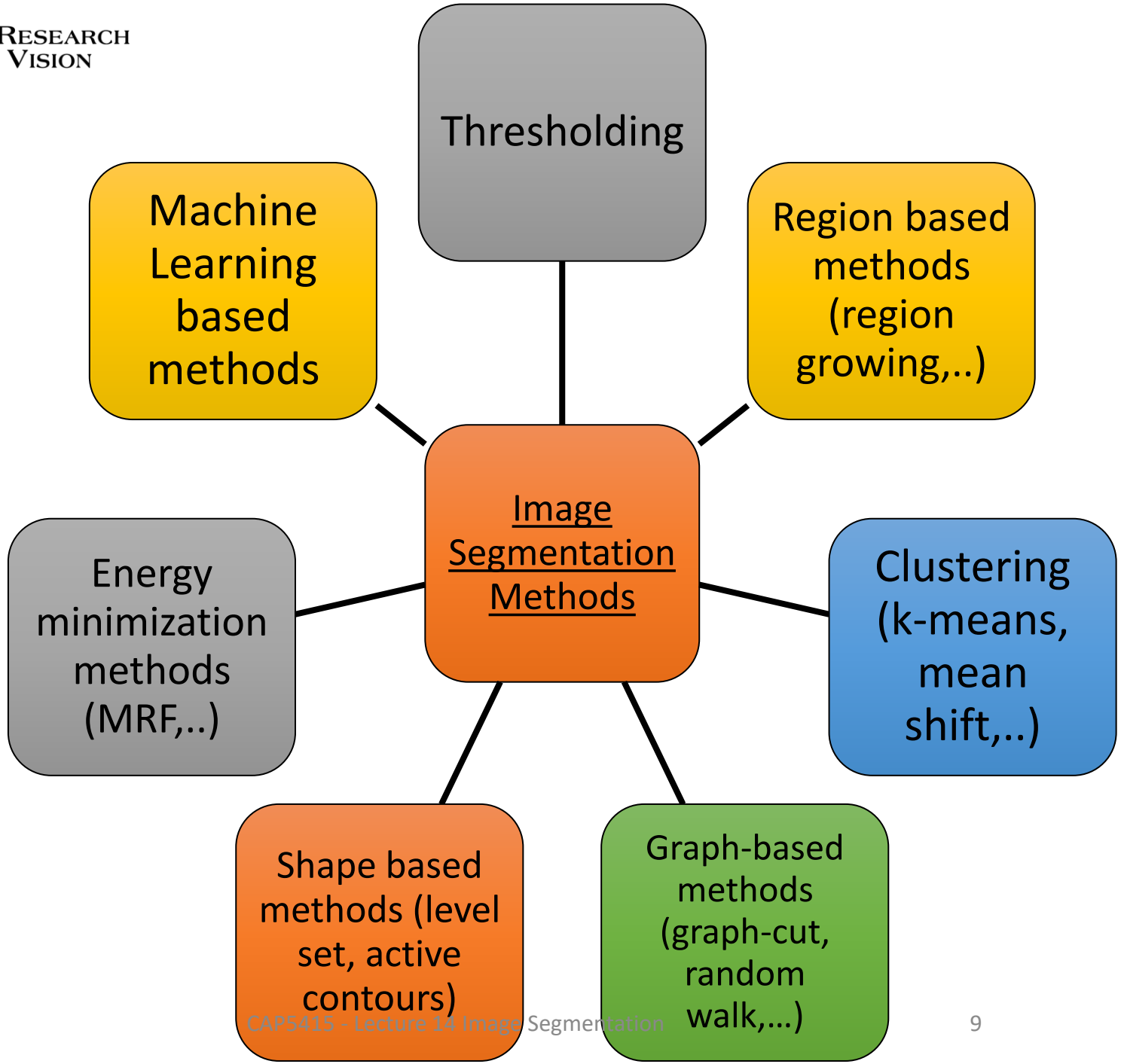
- Content based image retrieval
- Machine Vision
- Medical Imaging applications (tumor delineation,..)
- Object detection (face detection,…)
- Object/Motion Tracking
- Object-based measurements such as size and shape
- Object recognition (face recognition,…)
- Fingerprint recognition,
- Video surveillance

…

Image Segmentation

- One of the oldest and most widely studied problems
  - *Early techniques -> region splitting or merging*
  - *Recent techniques -> Energy minimization, hybrid methods, and deep learning*

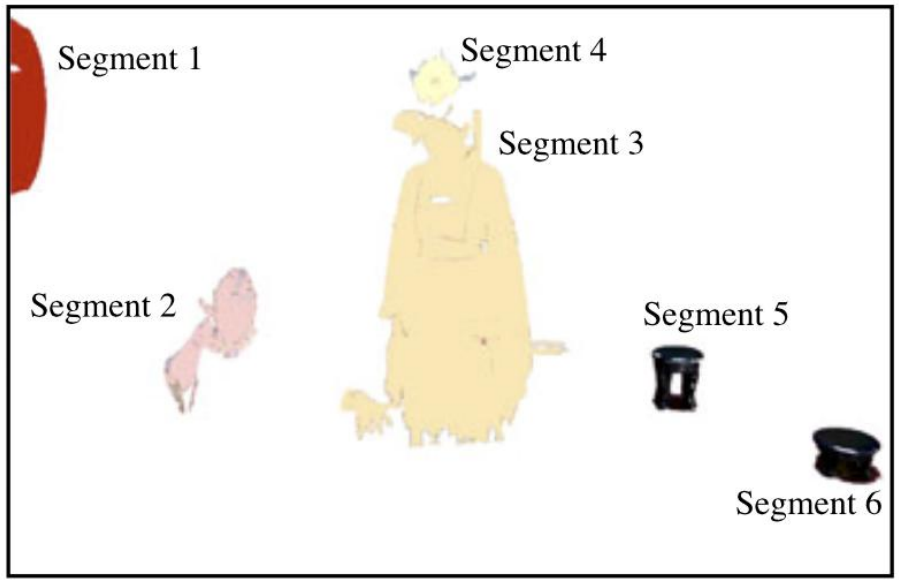



Thresholding
Machine Learning based methods
Region based methods (region growing,..)
Image Segmentation Methods
Energy minimization methods (MRF,..)
Clustering (k-means, mean shift,..)
Shape based methods (level set, active contours)
Graph-based methods (graph-cut, random walk,…)

Basics of Image Segmentation

- Definition: *Image segmentation* partitions an image into regions called segments.





Creates segments of by analyzing some similarity criteria:

- *Such as intensity, color, texture, histogram, features, …*

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$$J(x,y) = \begin{cases} 0 & \text{if } I(x,y) < T \\ 1 & \text{otherwise.} \end{cases}$$

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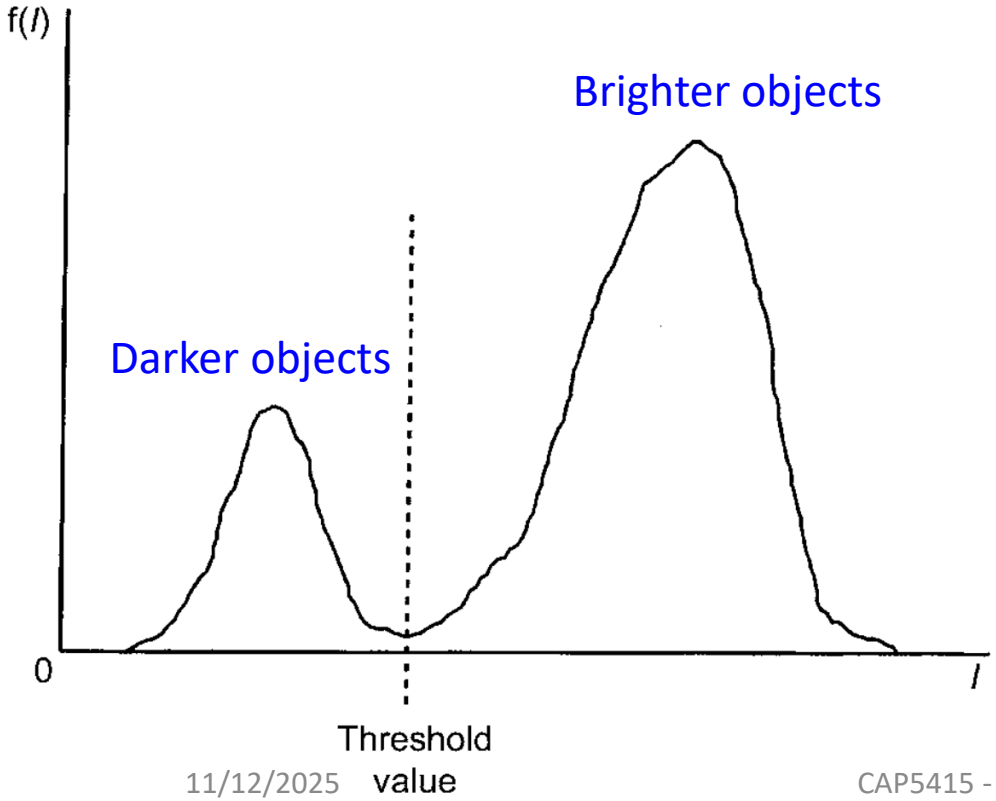
- Image binarization applies often just one global threshold T for mapping a scalar image I into a binary image

$$J(x,y) = \begin{cases} 0 & \text{if } I(x,y) < T \\ 1 & \text{otherwise.} \end{cases}$$

- The global threshold can be identified by an optimization strategy aiming at creating “large” connected regions and at reducing the number of small-sized regions, called *artifacts*.

Image Binarization

- Thresholding: Most frequently employed method for determining threshold is based on histogram analysis of intensity levels.



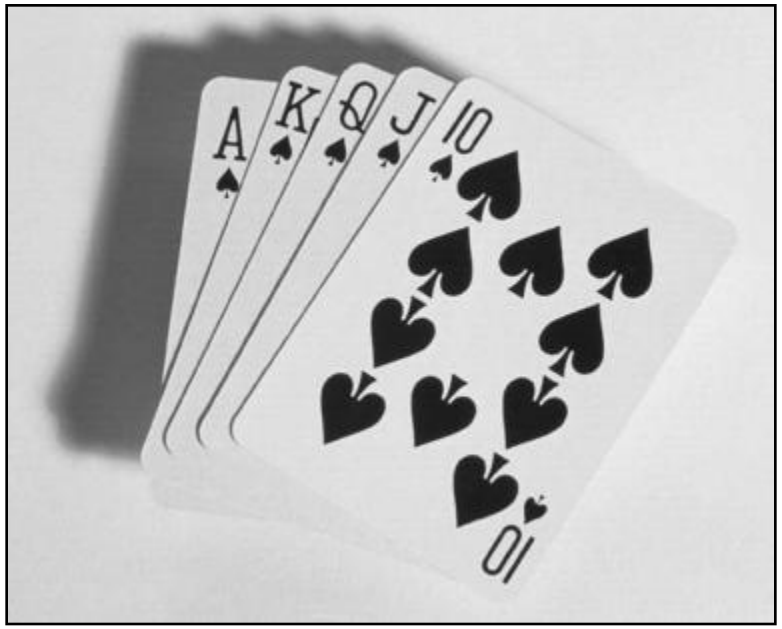
Peak on the left of the histogram corresponds to dark objects

Peak on the right of the histogram corresponds to brighter objects

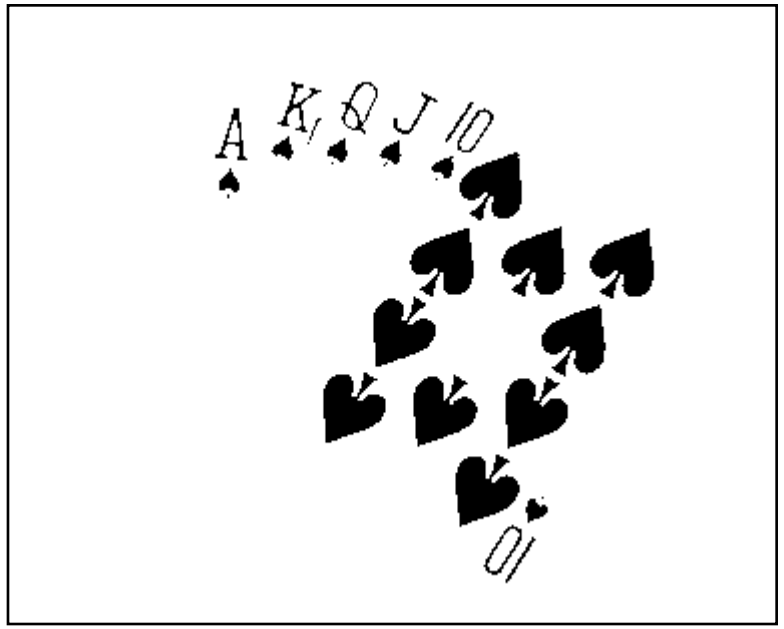
DIFFICULTIES

1. The valley may be so broad that it is difficult to locate a significant minimum
2. Number of minima due to type of details in the image
3. Noise
4. No visible valley
5. Histogram may be multi-modal

Thresholding Example

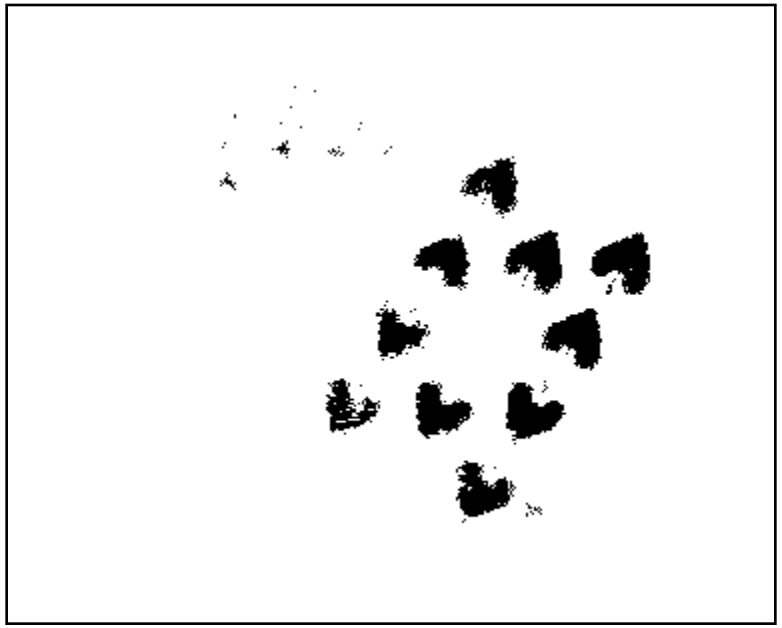


Original Image

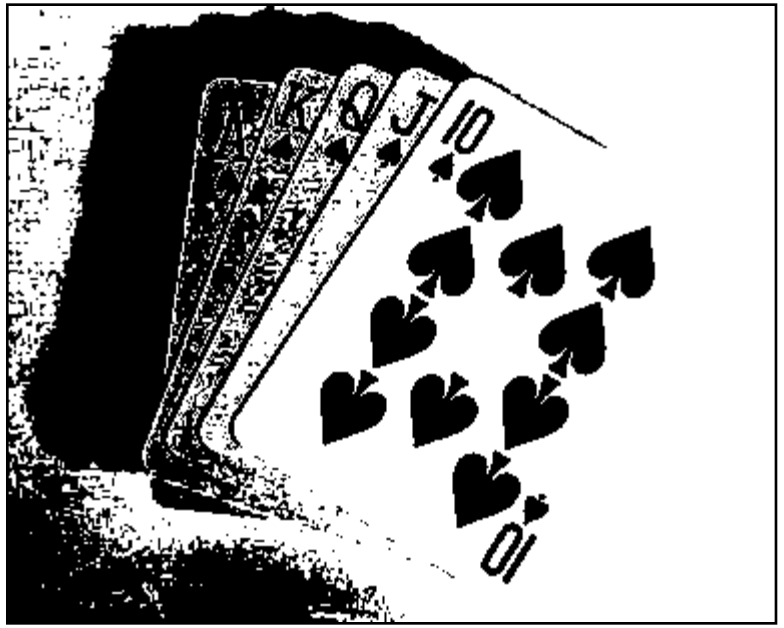


Thresholded Image

Thresholding Example 2

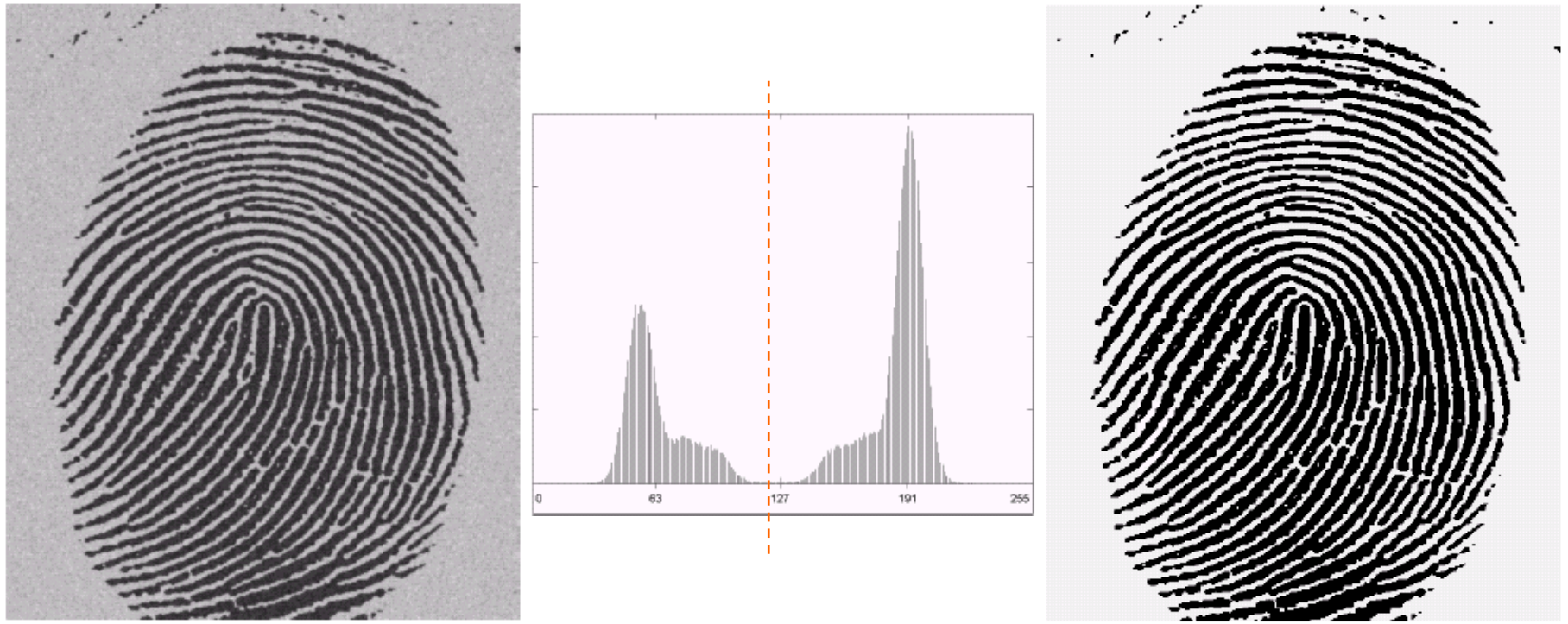


Threshold Too Low

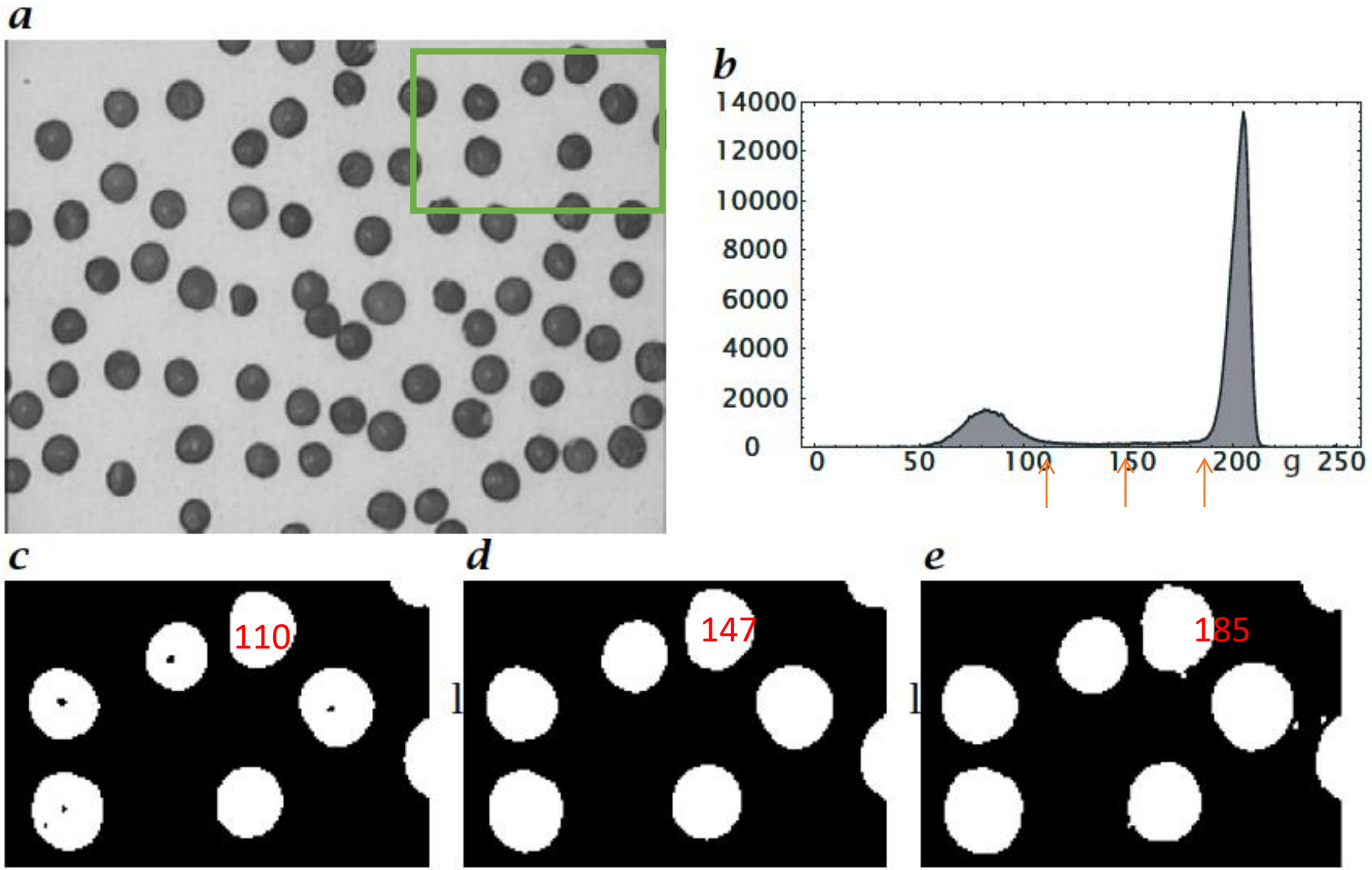


Threshold Too High

Thresholding Example 3



Thresholding Example-4



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Otsu Thresholding

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- In the case of two classes,

$$\sigma_b^2 = P_1(\mu_1 - \mu)^2 + P_2(\mu_2 - \mu)^2 = P_1 P_2(\mu_1 - \mu_2)^2$$

where P_1 and P_2 denote class probabilities, and μ_i the means of object and background classes.

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where P_1 and P_2 denote class probabilities, and μ_i the means of object and background classes.

- Let c_I be the relative cumulative histogram of an image I, then P_1 and P_2 are approximated by $c_I(u)$ and $1 - c_I(u)$, respectively.
- u is assumed to be the chosen threshold.

Otsu Thresholding Algorithm

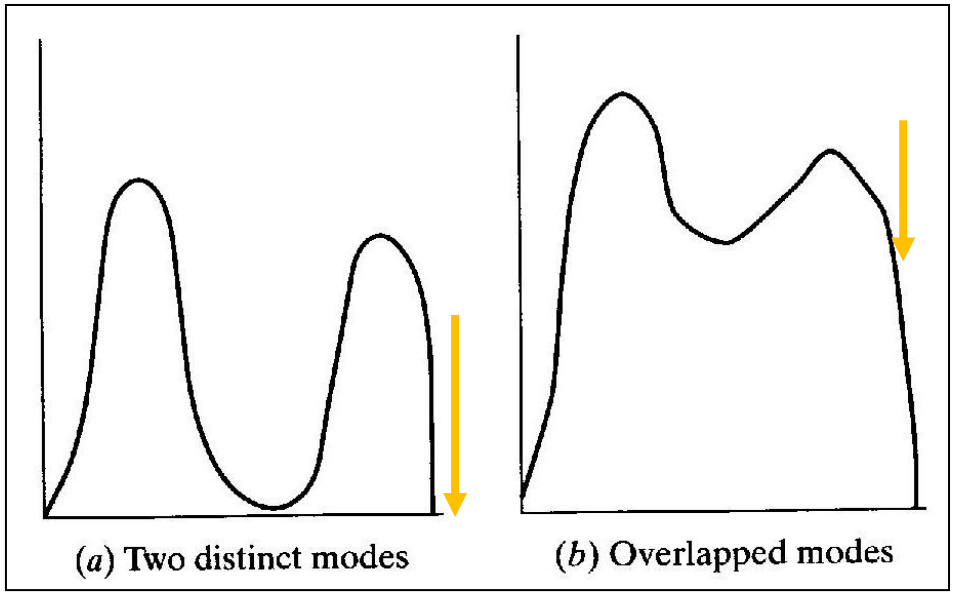
1: Compute histogram H_I for $u = 0, \ldots, G_{\max}$;
2: Let T_0 be the increment for potential thresholds; $u = T_0$; $T = u$; and $S_{\max} = 0$;
3: **while** $u < G_{\max}$ **do**
4: Compute $c_I(u)$ and $\mu_i(u)$ for $i = 1, 2$;
5: Compute $\sigma_b^2(u) = c_I(u)[1 - c_I(u)][\mu_i(u) - \mu_2(u)]^2$;
6: **if** $\sigma_b^2(u) > S_{\max}$ **then**
7: $S_{\max} = \sigma_b^2(u)$ and $T = u$;
8: **end if**
9: Set $u = u + T_0$
10: **end while**

$$P_1 = \sum_{i=0}^{u} p(i) \qquad \mu_1 = \sum_{i=0}^{u} ip(i)/P_1$$

$$P_2 = \sum_{i=u+1}^{G_{max}} p(i) \qquad \mu_2 = \sum_{i=u+1}^{G_{max}} ip(i)/P_2$$

probabilities

Class means

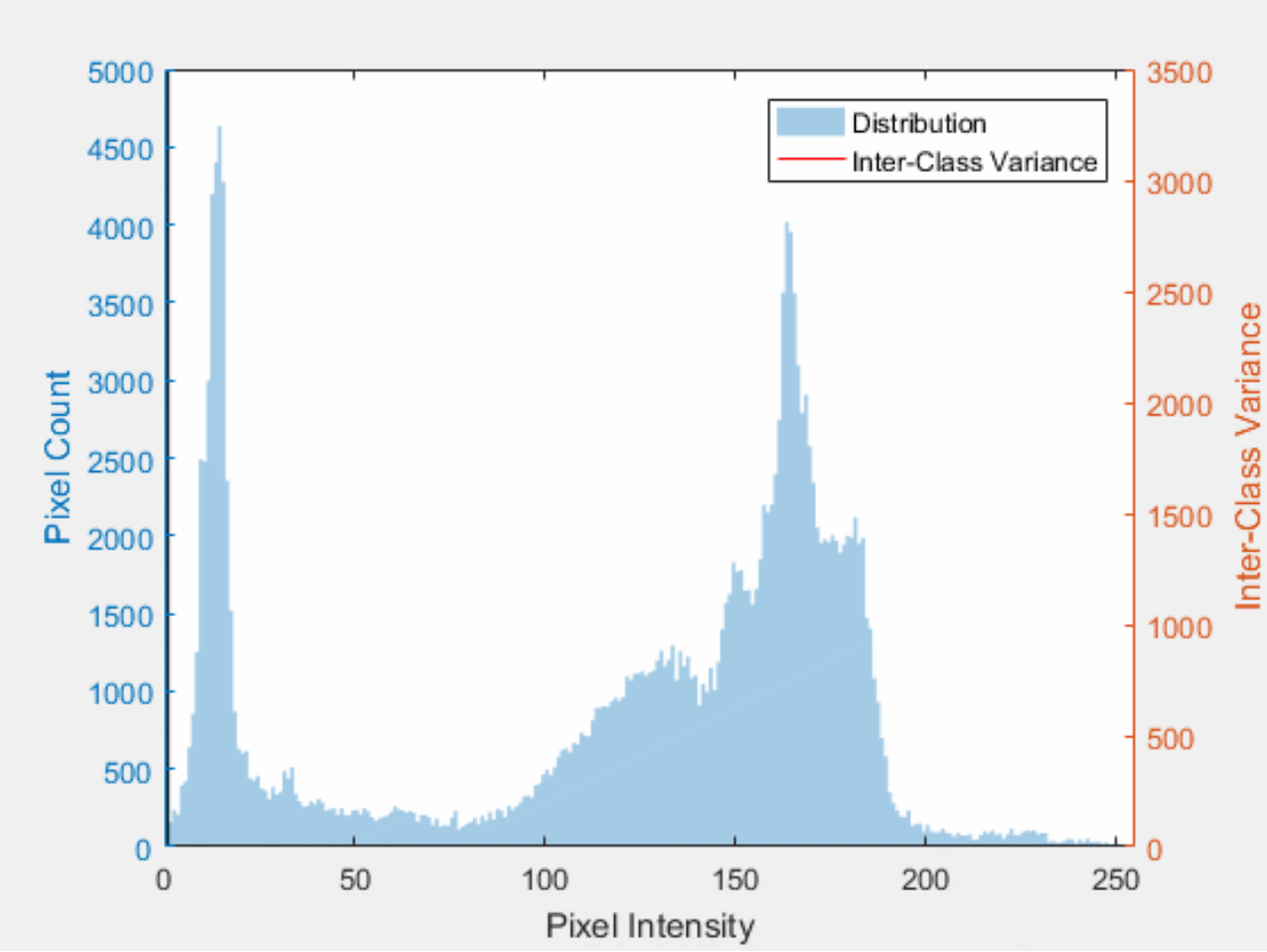


Example: Otsu Thresholding





Example: Otsu Thresholding



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Pop Quiz?

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Region based

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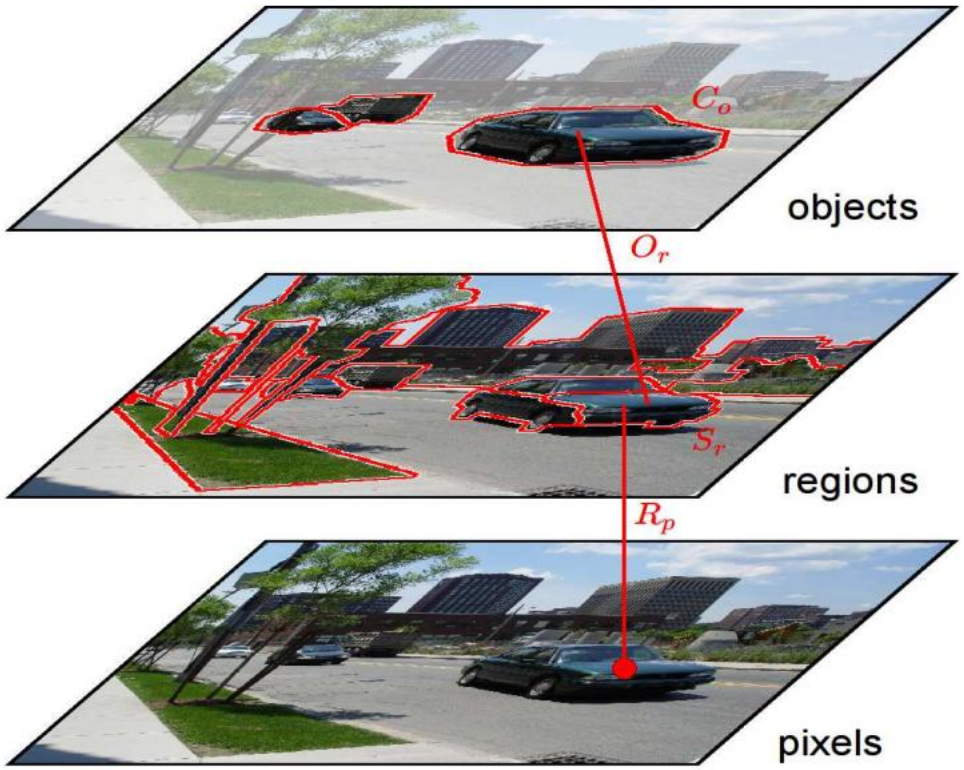
Region Based Segmentation-Basics



Region:

A group of connected pixels with similar properties

Closed boundaries

Computation of regions is based on similarity

Regions may correspond to Objects in a scene or parts of objects

Spatial proximity + similarity

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Region Growing

- For segment generation in grey-level or color images, we may start at one *seed pixel* (x,y,I(x,y)) and add recursively adjacent pixels that satisfy a “similarity criterion” with pixels contained in the so-far grown region around the *seed pixel.*

Region Growing

- For segment generation in grey-level or color images, we may start at one *seed pixel* (x,y,I(x,y)) and add recursively adjacent pixels that satisfy a "similarity criterion" with pixels contained in the so-far grown region around the *seed pixel.*

- Defining similarity criteria alone is not an effective basis for segmentation
- It is necessary to consider the adjacency spatial relationship between pixels

Region Growing

Algorithm

1. The absolute intensity difference between candidate pixel and the seed pixel must lie within a specified range
2. The absolute intensity difference between a candidate pixel and the running average intensity of the growing region must lie within a specified range;
3. The difference between the standard deviation in intensity over a specified local neighborhood of the candidate pixel and that over a local neighborhood of the candidate pixel must (or must not) exceed a certain threshold

Seeded Segmentation (Region Growing)

1. Choose the seed pixel

0	0	5	6	7
1	1	5	8	7
0	1	6	7	7
2	0	7	6	6
0	1	5	6	5

(a)

Seeded Segmentation (Region Growing)

1. Choose the seed pixel
2. Check the neighboring pixels and add them to the region if they are similar to the seed

0	0	5	6	7
1	1	5	8	7
0	1	6	7	7
2	0	7	6	6
0	1	5	6	5

(a)

a	a	b	b	b
a	a	b	b	b
a	a	b	b	b
a	a	b	b	b
a	a	b	b	b

(b)

Seeded Segmentation (Region Growing)

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

0	0	5	6	7
1	1	5	8	7
0	1	6	7	7
2	0	7	6	6
0	1	5	6	5

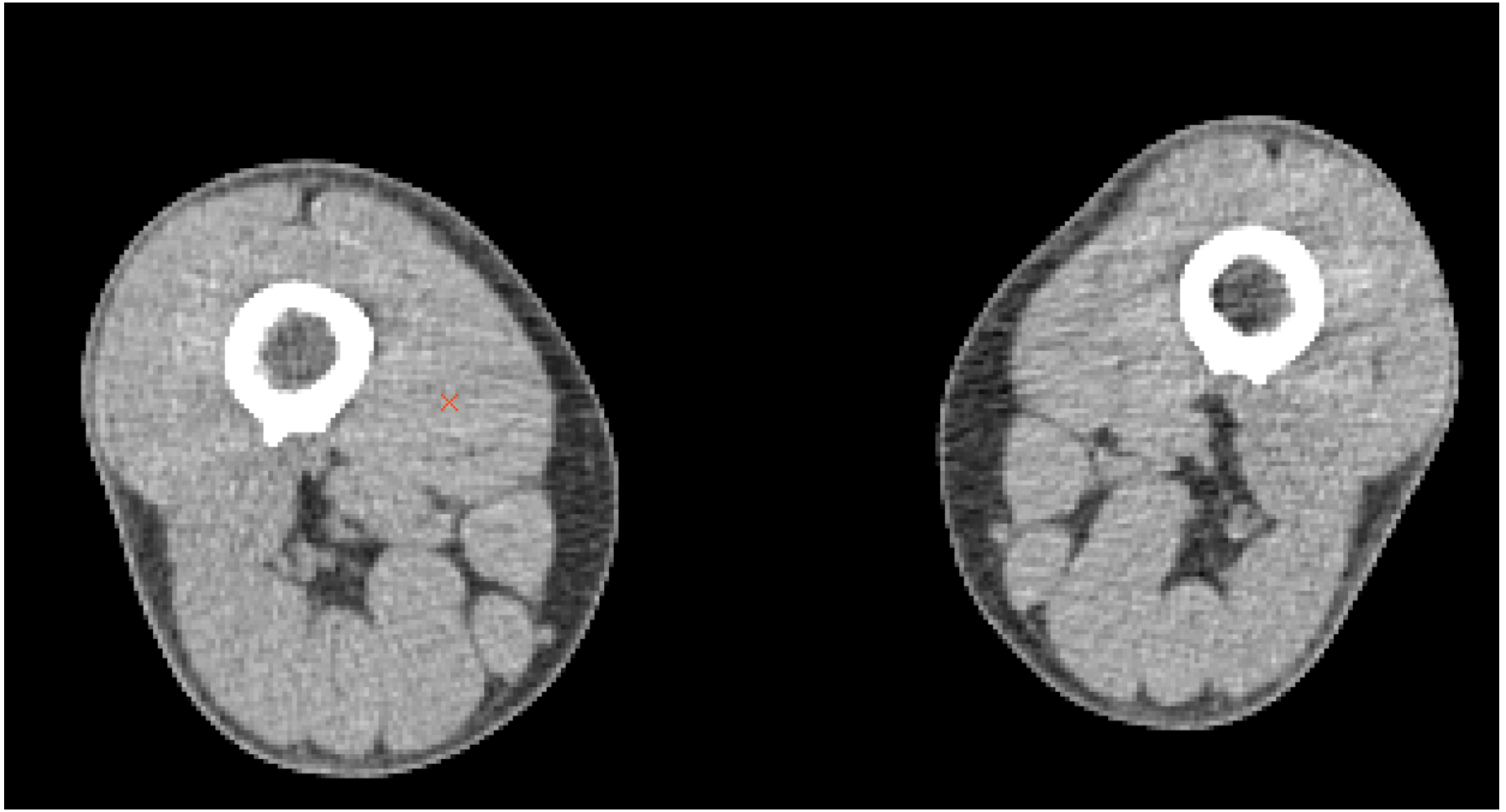
(a)

a	a	b	b	b
a	a	b	b	b
a	a	b	b	b
a	a	b	b	b
a	a	b	b	b

(b)

$$|\text{neighboring pixels} - \text{seed}| < Threshold$$

Ex: Muscle/Bone Segmentation in CT Scans



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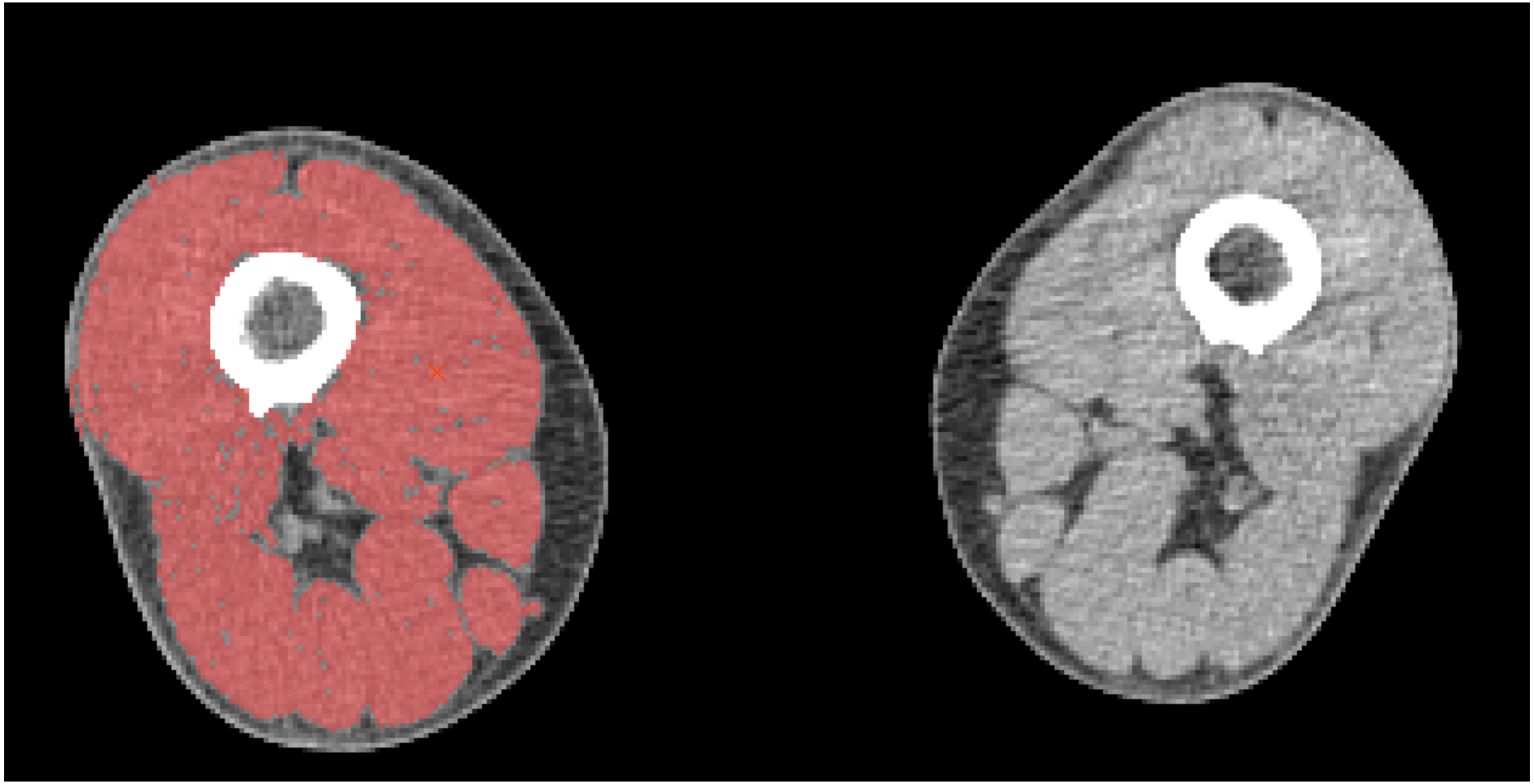

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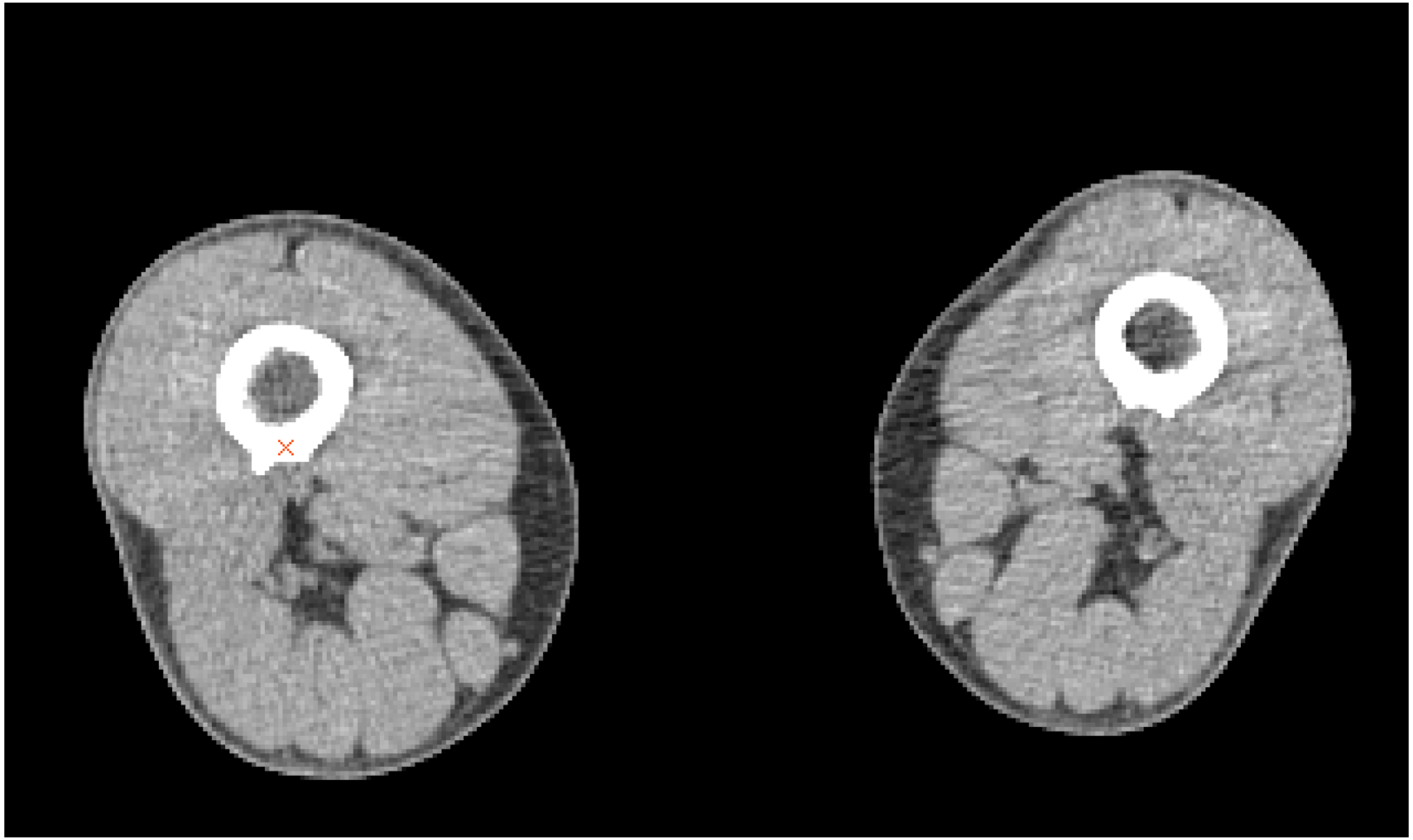

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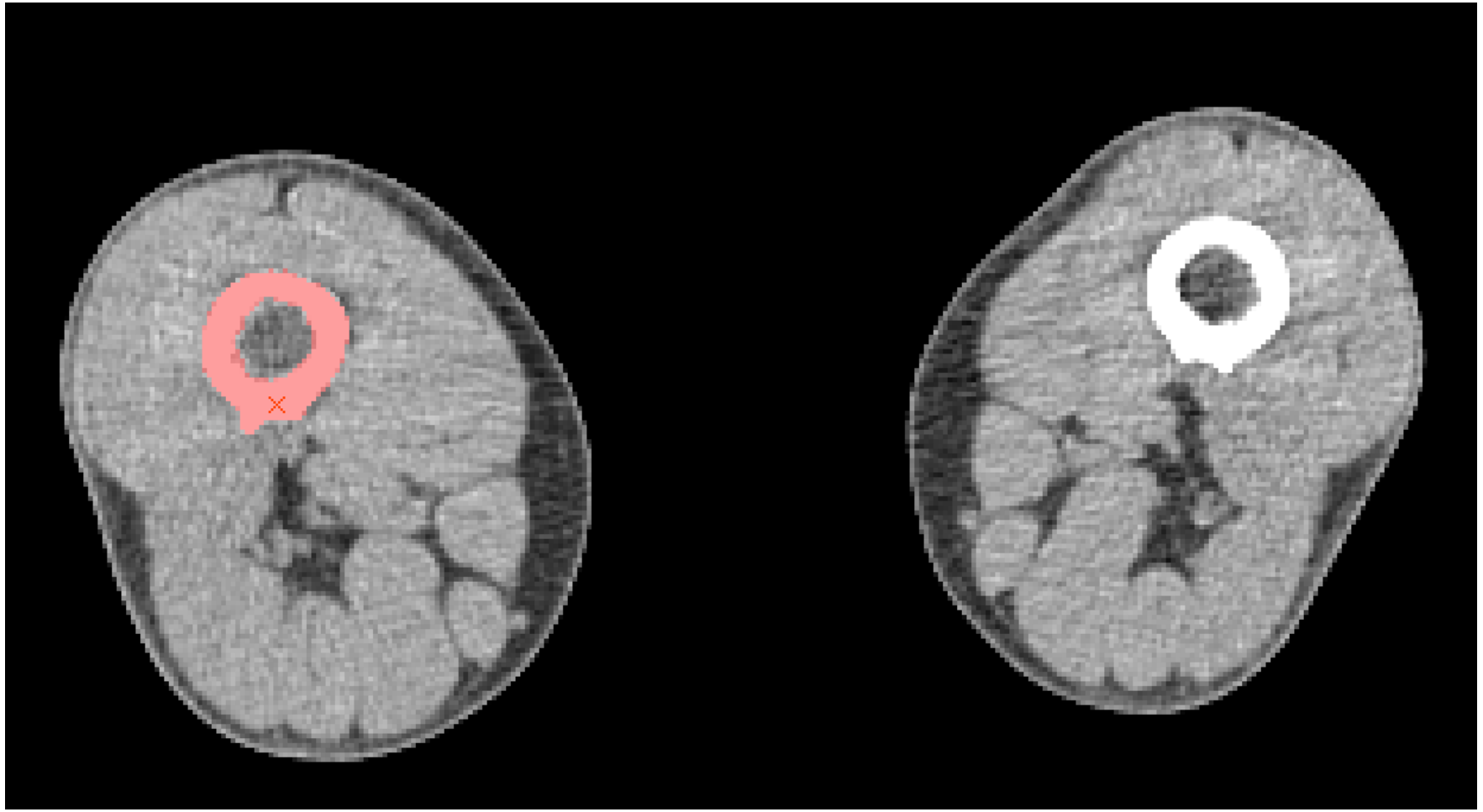
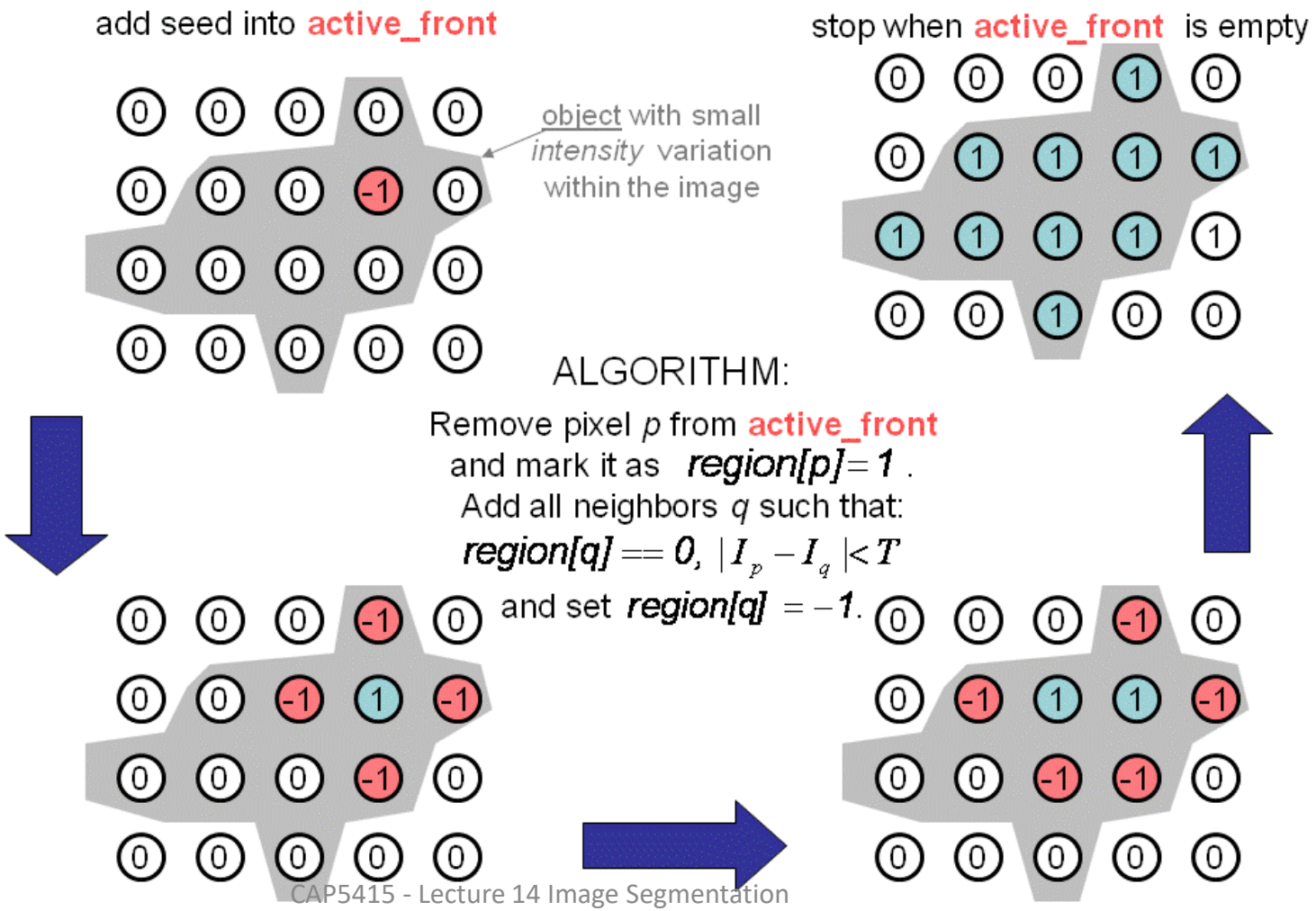


Region Growing Implementation

growRegion: red nodes are the "active_front" (queue or stack)



Comparison of Thresholding and Region Growing

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

threshold $T \geq 10$

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

threshold $T \geq 11$

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

threshold $T \geq 12$

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

3	5	7	3	4	2	1
2	4	9	10	22	9	3
3	5	12	11	15	10	3
5	6	11	9	17	19	1
2	3	11	12	18	16	2
3	6	8	10	18	9	5
4	6	7	8	3	3	1

region growing with variance of 2 in respect to value 11 with reference to threshold $T \geq 11$

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Region splitting and Merging Segmentation

- Region splitting:
  - Unlike region growing, which starts from a set of seed points, region splitting starts with the whole image as a single region and subdivides it into subsidiary regions recursively while a condition of homogeneity is not satisfied.

Region splitting and Merging Segmentation

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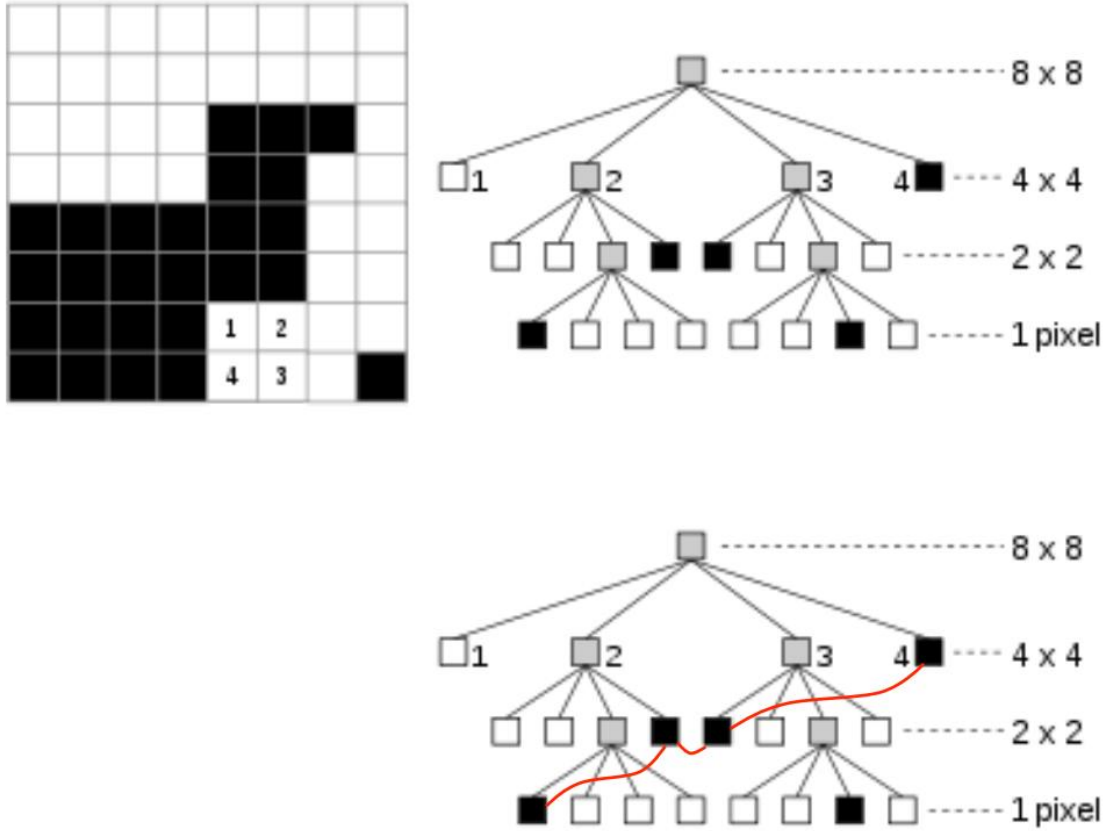
- Region merging:
  - Region merging is the opposite of splitting, and works as a way of avoiding over-segmentation

Region splitting and Merging Segmentation

- Region splitting:
  - Unlike region growing, which starts from a set of seed points, region splitting starts with the whole image as a single region and subdivides it into subsidiary regions recursively while a condition of homogeneity is not satisfied.
- Region merging:
  - Region merging is the opposite of splitting, and works as a way of avoiding over-segmentation
  - Start with small regions (2x2 or 4x4 regions) and merge the regions that have similar characteristics (such as gray level, variance).

Region splitting and Merging Segmentation



RAG with adjacency relations (in red) for big black region.

- RAG: region adjacency graph
- **Quadtree** for splitting (top-down) procedure

Region splitting and Merging Segmentation

Algorithm:

- If a region R is inhomogeneous (P (R)=FALSE), then R is split into four sub-regions.
- If two adjacent regions R_i,R_j are homogeneous (P(R_iUR_j)=TRUE), they are then merged.
- The algorithm stops when no further splitting or merging is possible.

Region splitting and Merging Segmentation

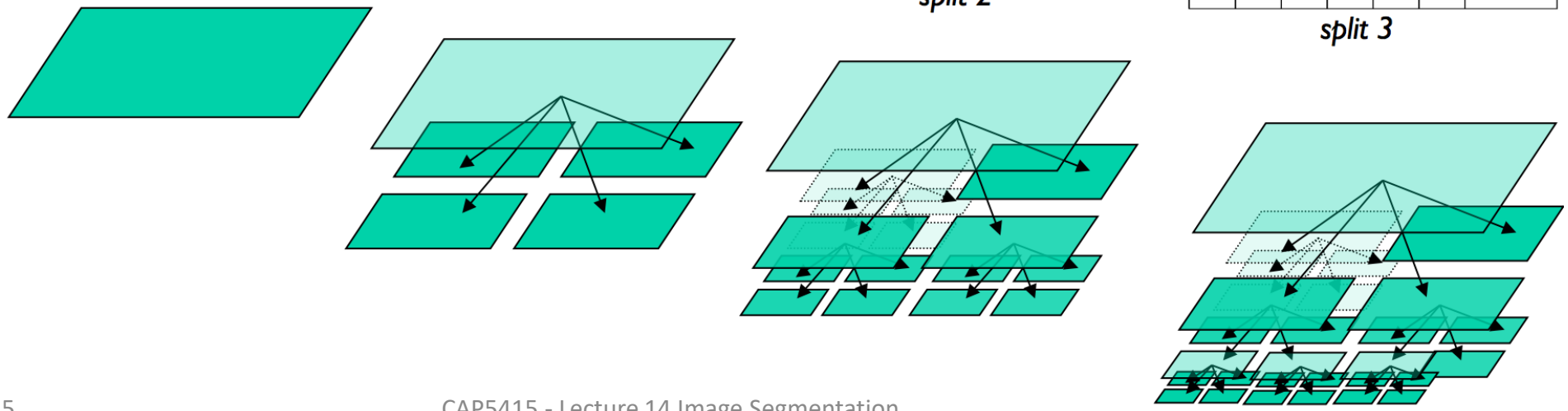
0	1	0	0	7	7	7	7
1	0	2	2	7	7	7	7
0	2	2	2	7	7	7	7
4	4	2	2	7	7	7	7
0	0	1	1	3	3	7	7
1	1	2	2	3	7	7	7
2	4	3	0	5	7	7	7
2	3	3	5	5	0	7	7

original image

split 1

split 2

split 3



http://

Questions?

CAP5415 Computer Vision

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HEC-241

SPI

- Student evaluation of course instruction (SPI)
  - Will be available on Webcourse
  - Will be available for around 15 days
- Online questionnaire includes
  - ONLY eleven (11) questions
  - 9 multiple choice and 2 open comment questions

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Clustering based

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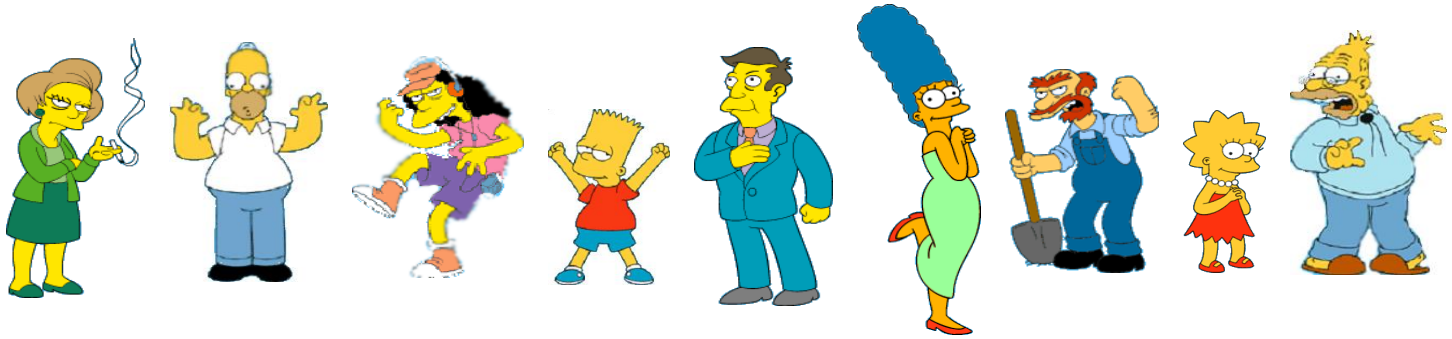
Clustering Based Segmentation Methods

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*)

What is a natural grouping?



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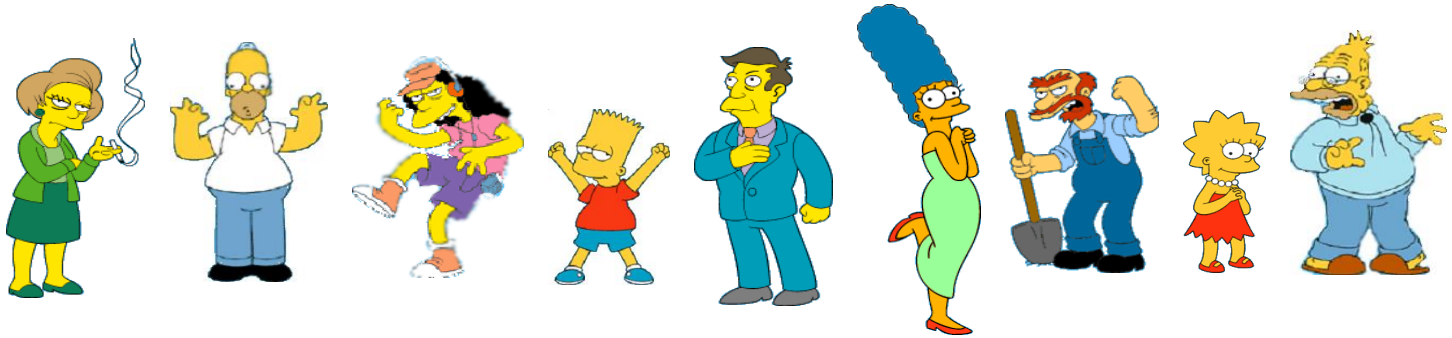
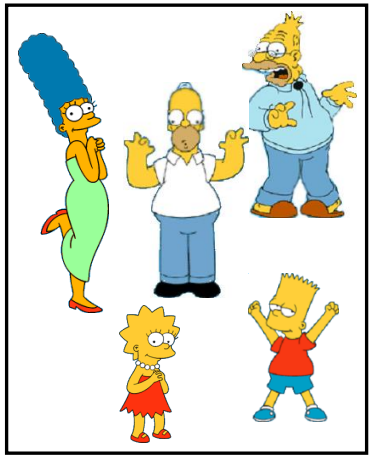


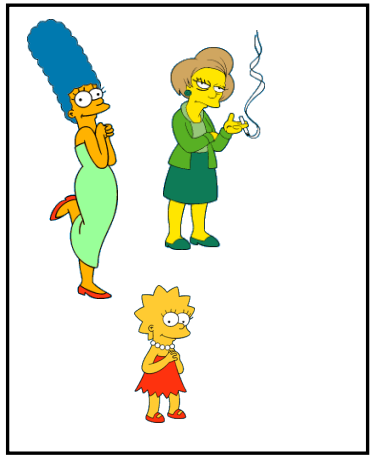
Clustering is subjective



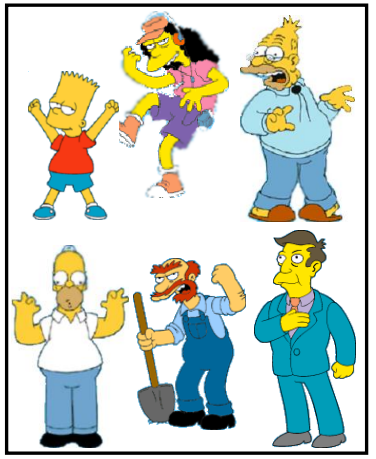
Simpson's Family



School Employees



Females



Males

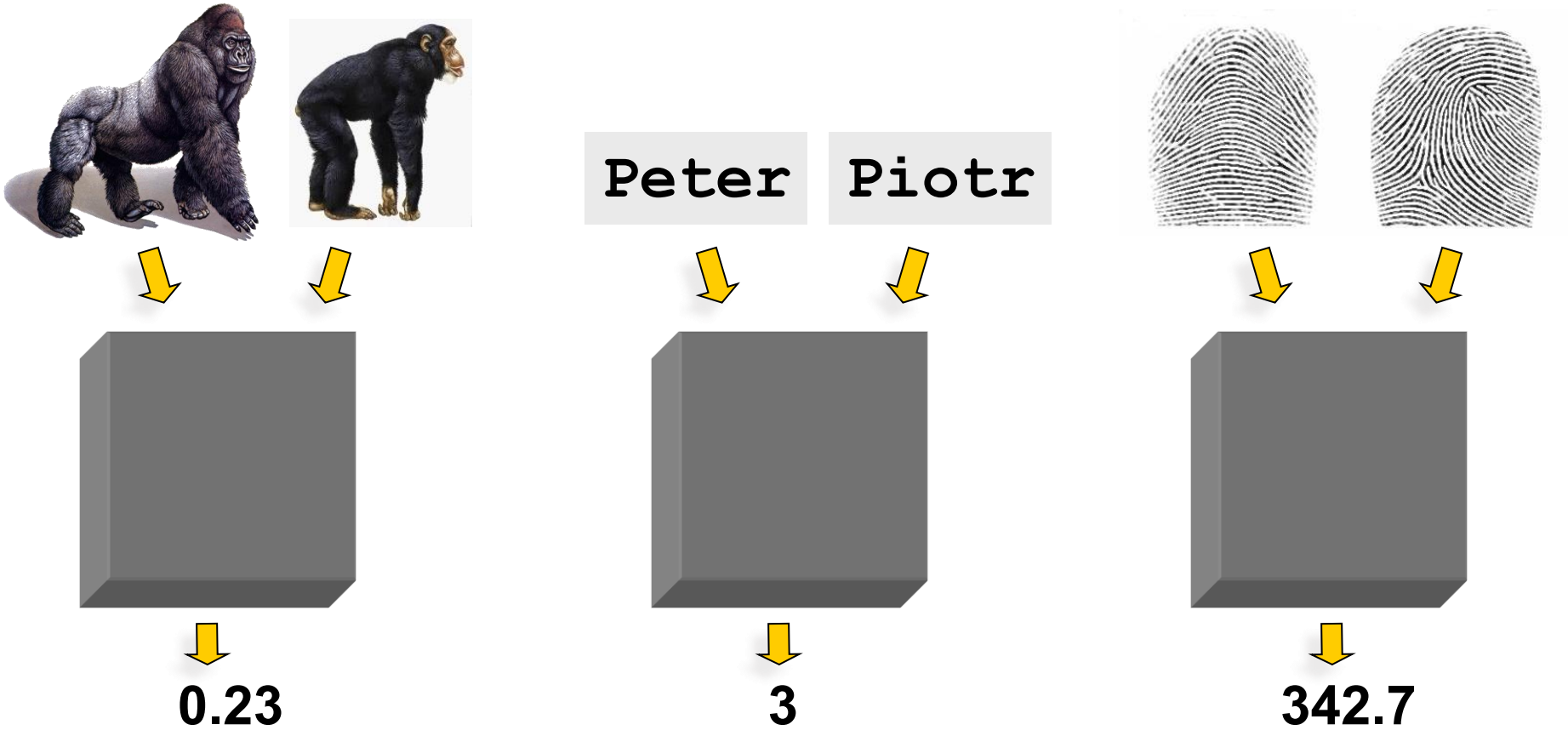
What is similarity ?



What is similarity ?



Distance metrics



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  - Merging
  - Splitting
- Clustering based
  - K-means (SLIC)
  - Mean-shift

K-means

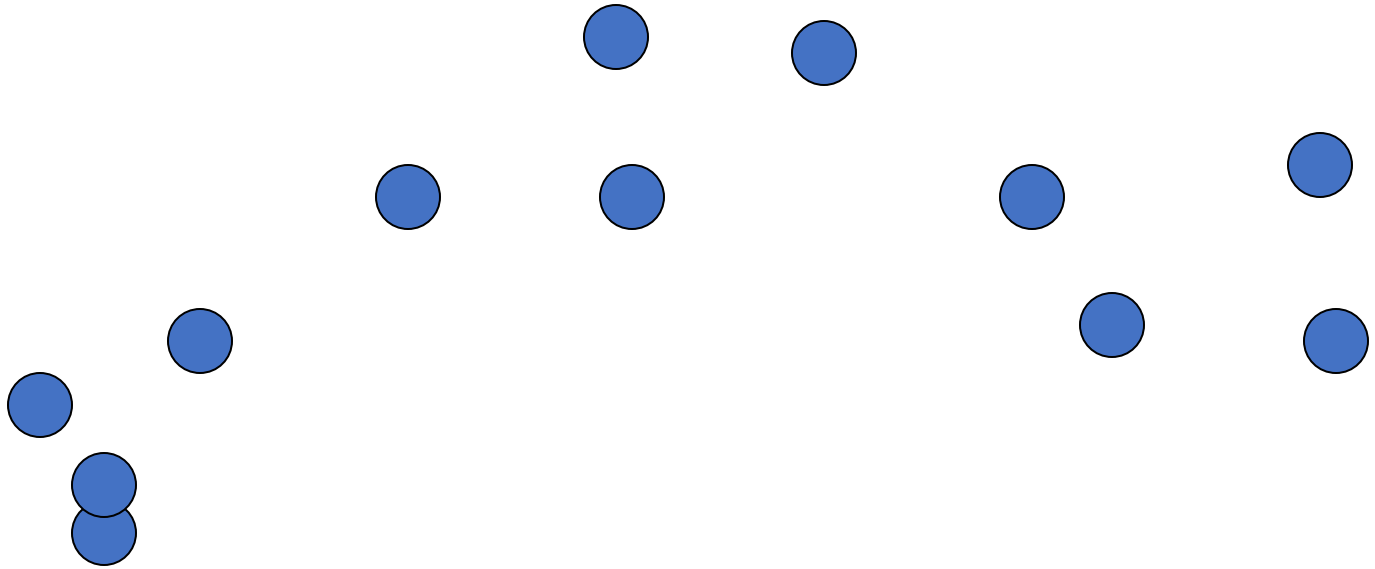
Most well-known and popular clustering algorithm:

Start with some initial cluster centers

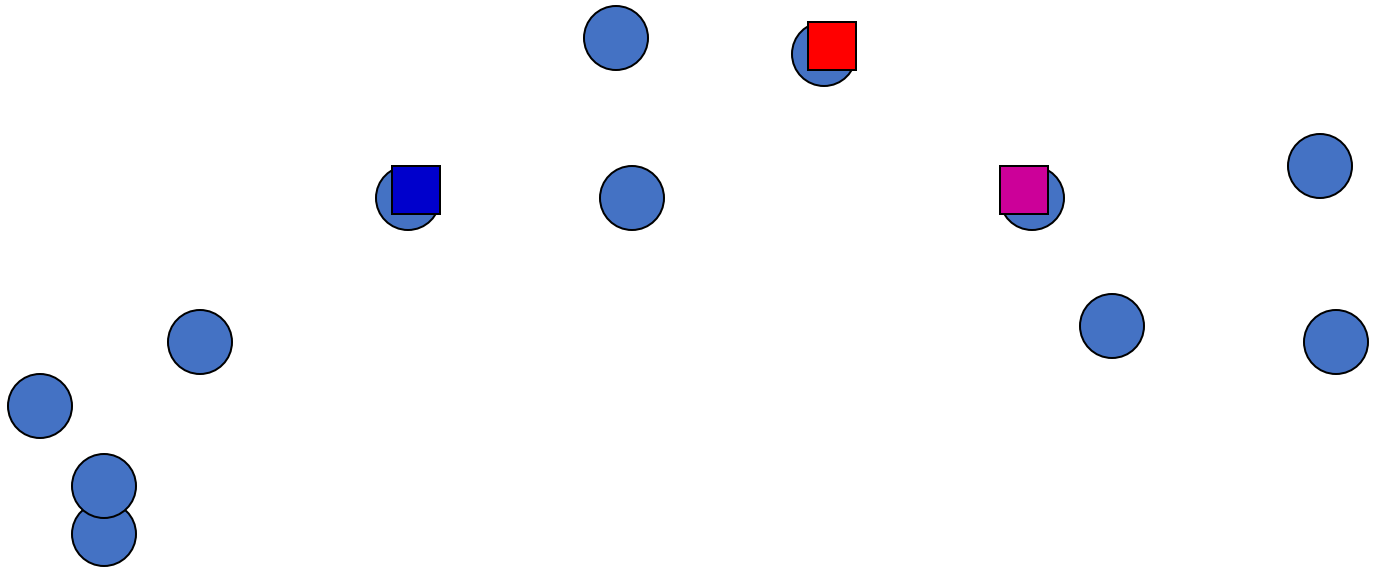
Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster

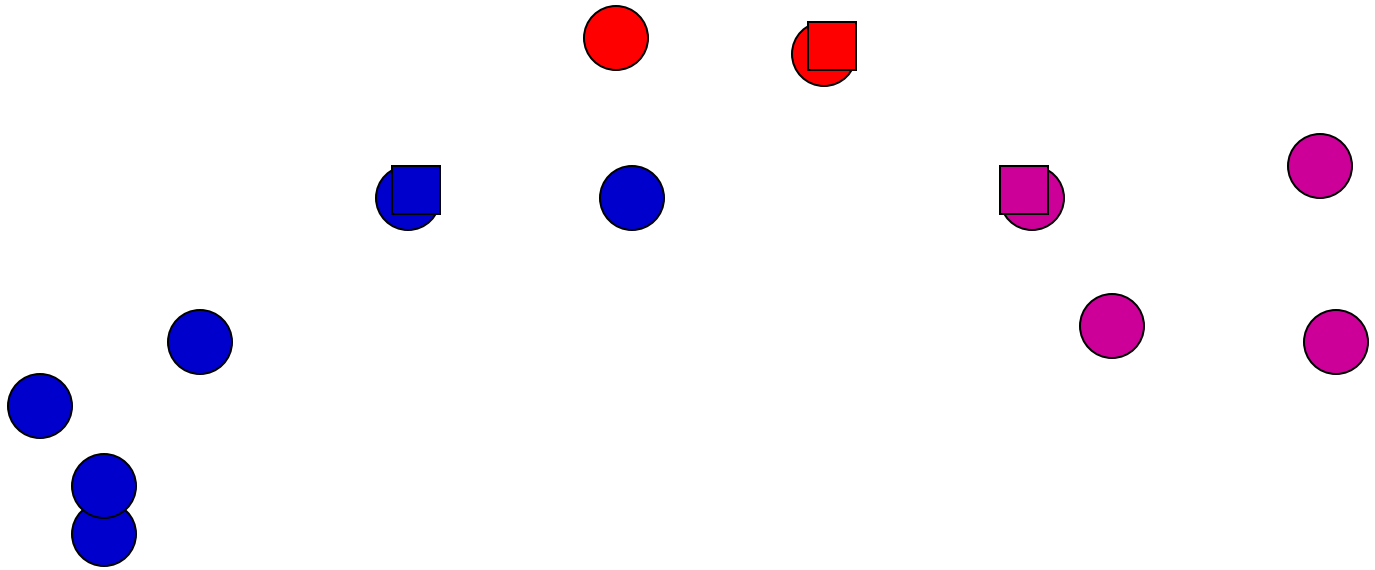
K-means: an example



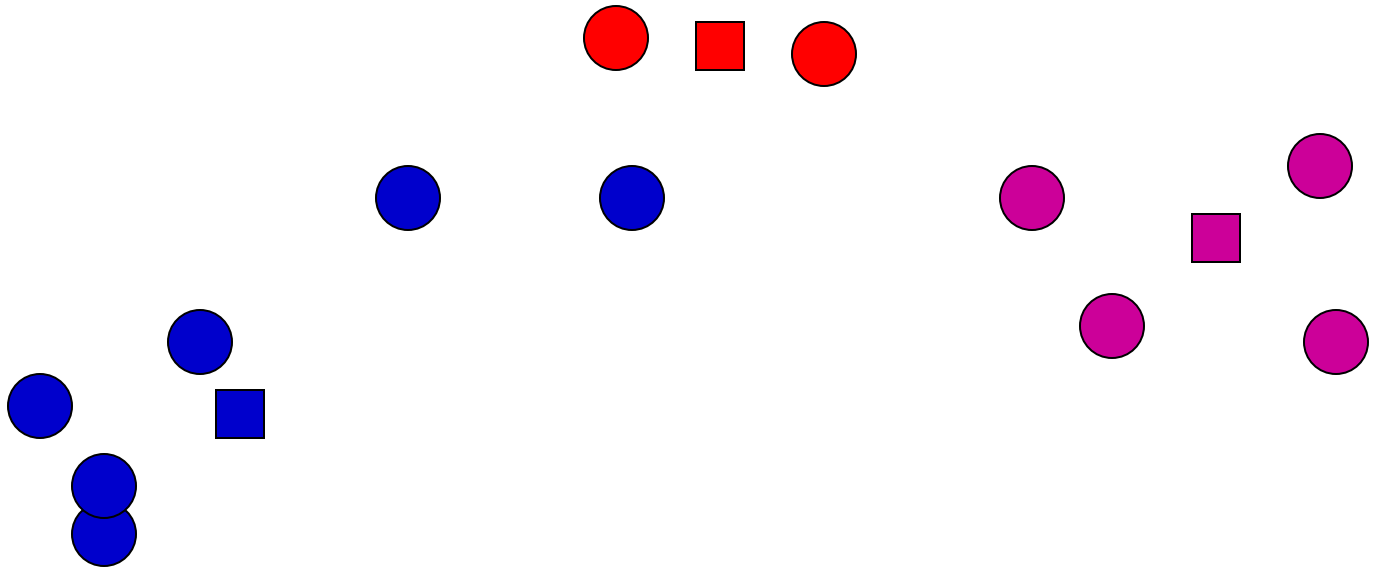
K-means: Initialize centers randomly



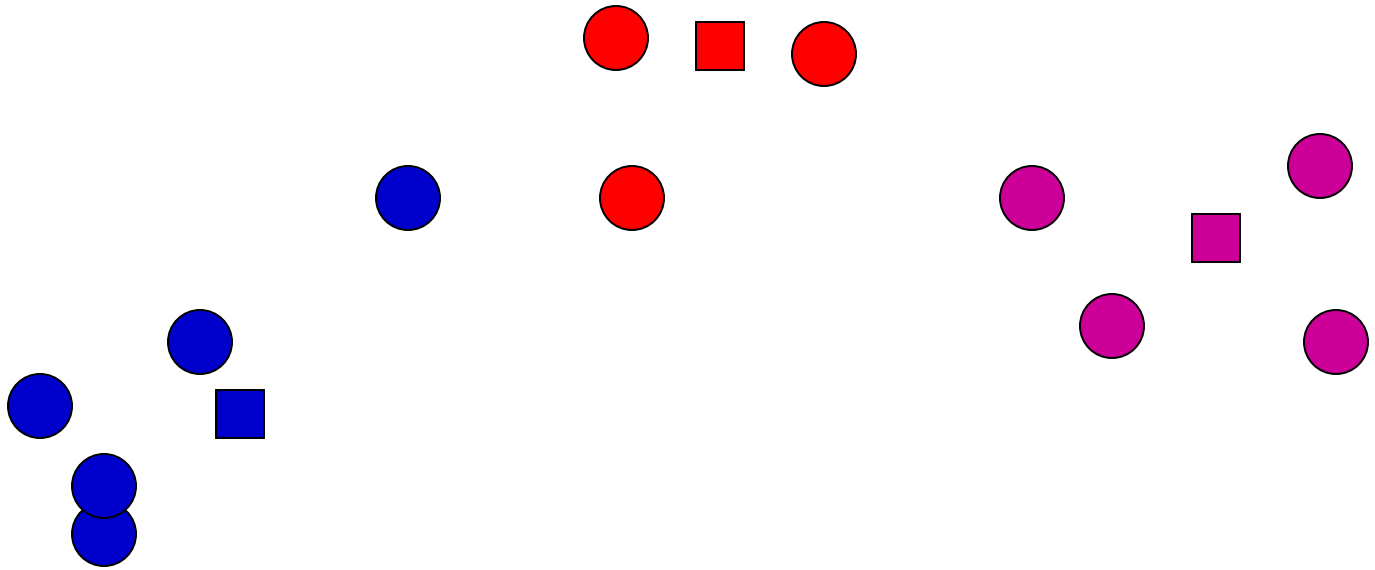
K-means: assign points to nearest center



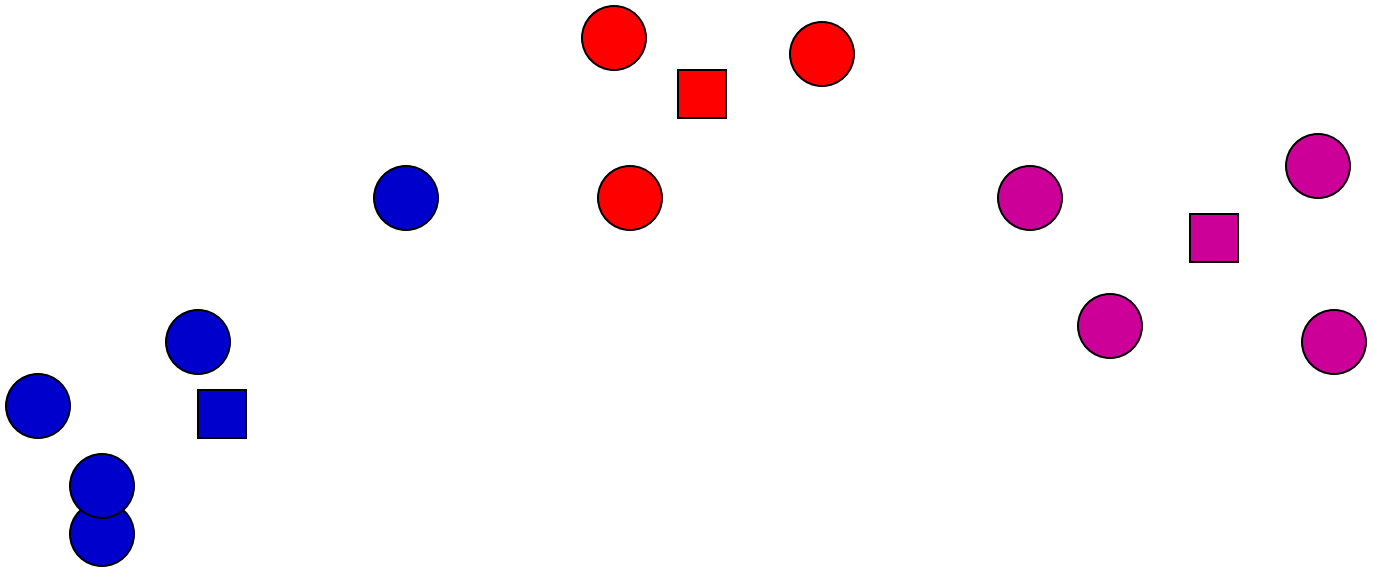
K-means: readjust centers



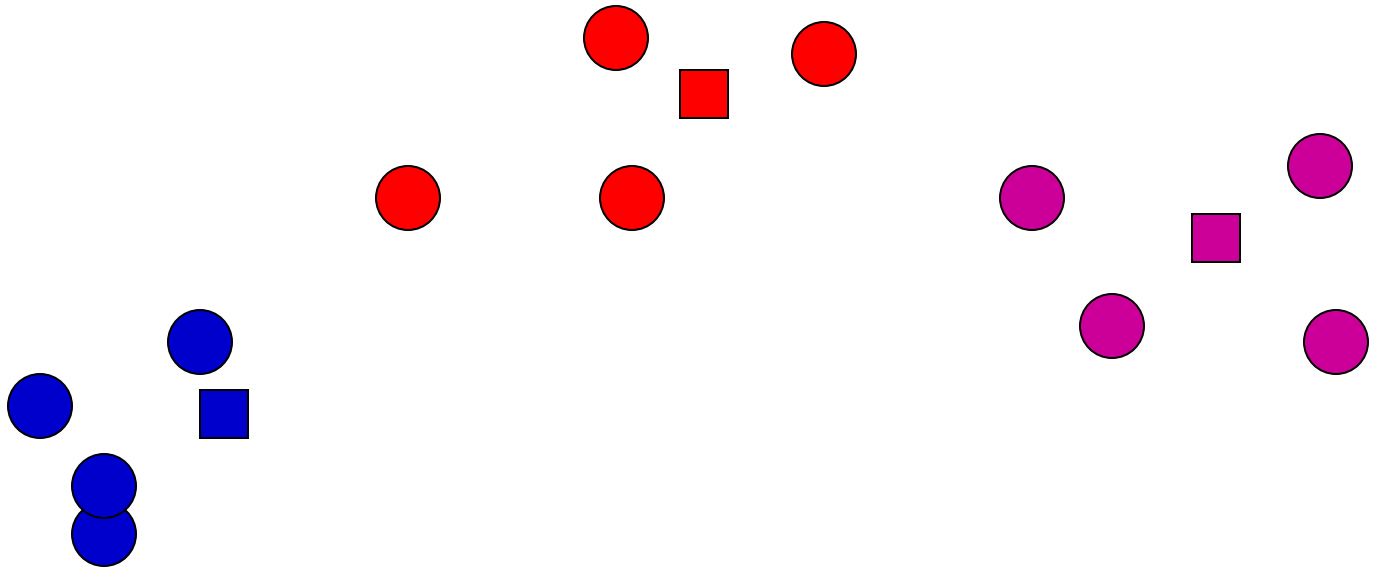
K-means: assign points to nearest center



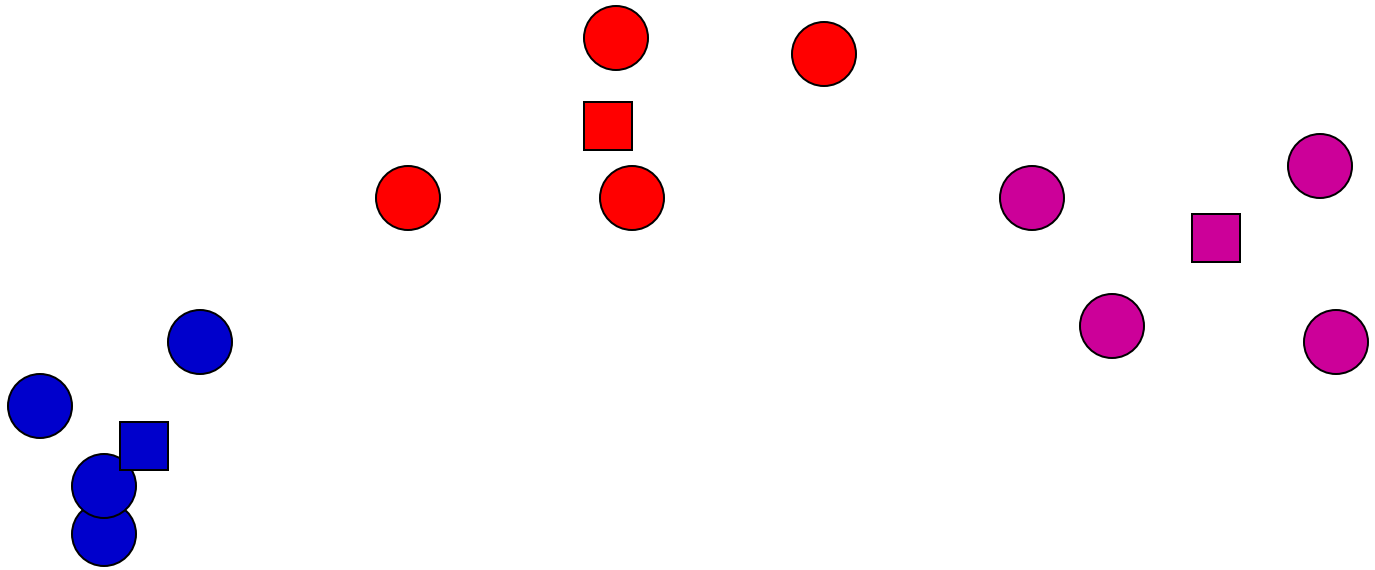
K-means: readjust centers



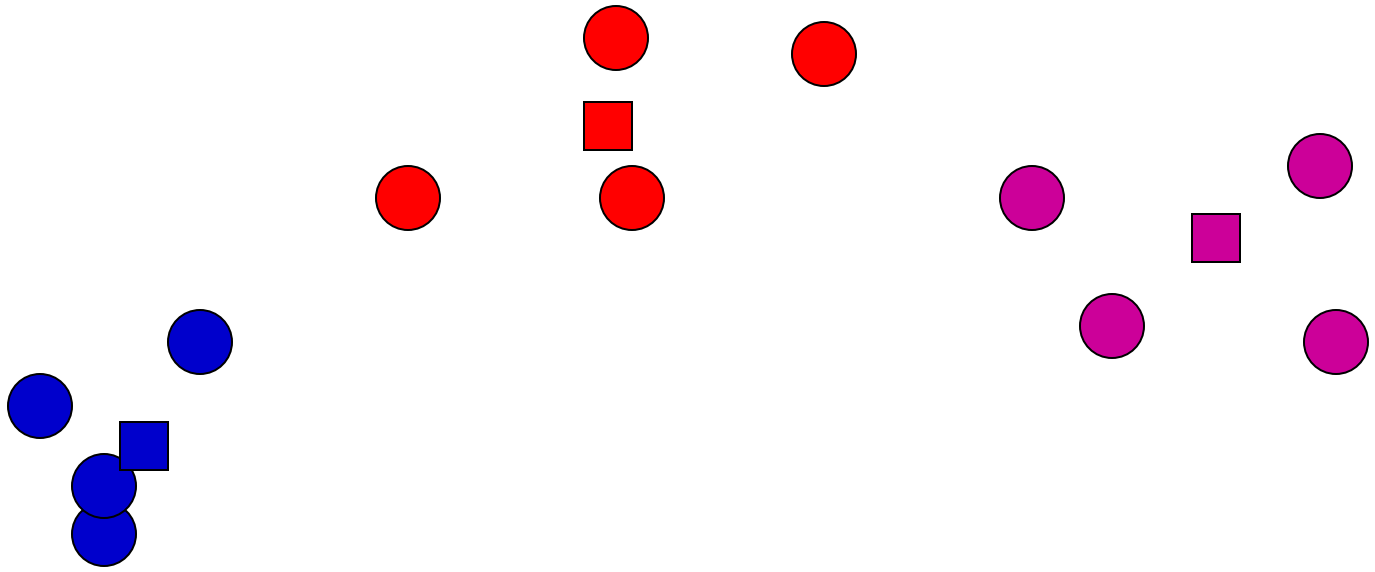
K-means: assign points to nearest center



K-means: readjust centers



K-means: assign points to nearest center

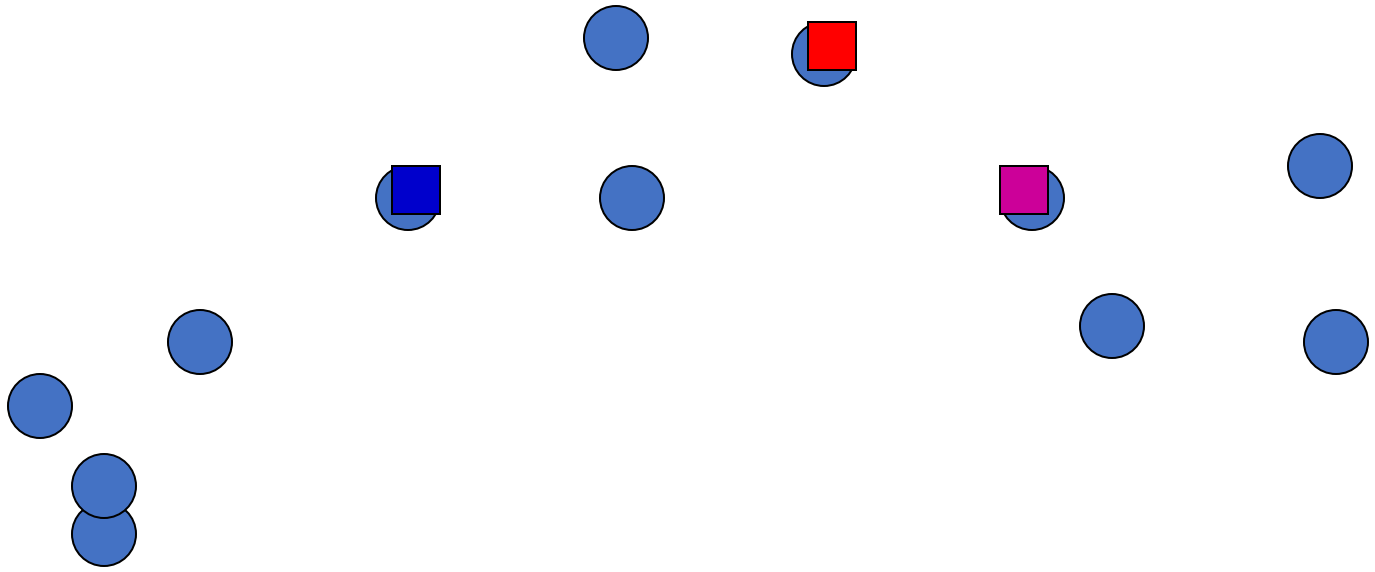


No changes: Done

K-means

Iterate:

- **Assign/cluster each example to closest center**
- Recalculate centers as the mean of the points in a cluster



How do we do this?

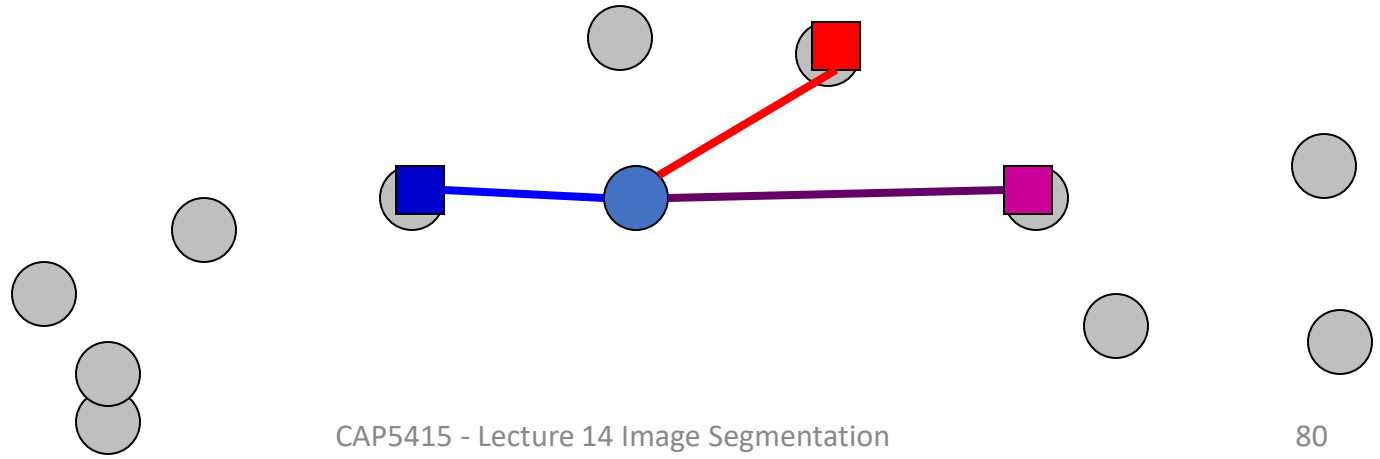
K-means

Iterate:

- **Assign/cluster each example to closest center**

  iterate over each point:
  - get distance to each cluster center
  - assign to closest center (hard cluster)

- Recalculate centers as the mean of the points in a cluster



K-means

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  iterate over each point:
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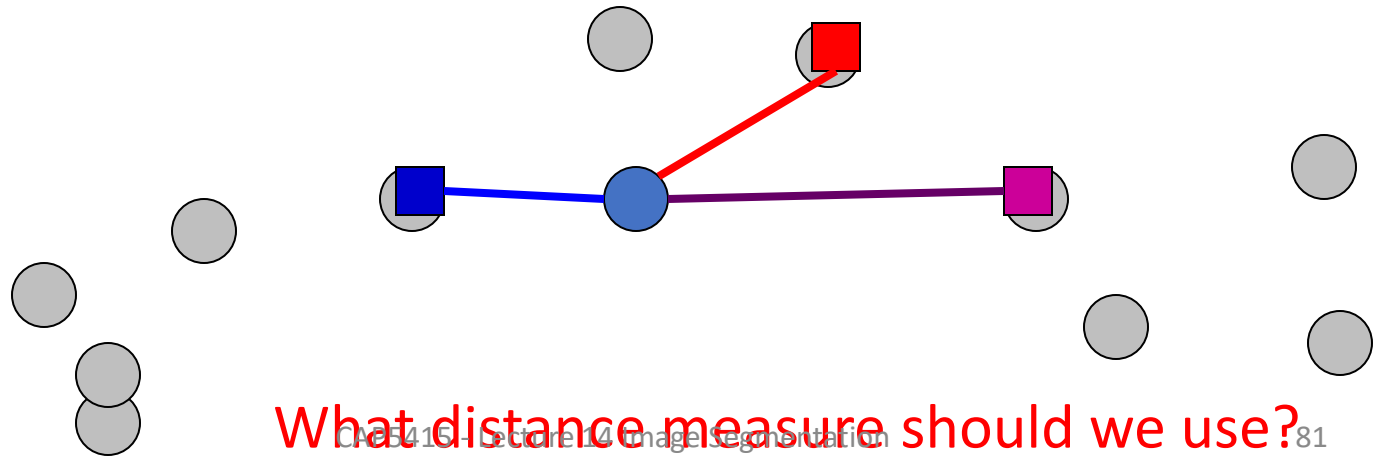


What distance measure should we use?

Distance measures

Euclidean:

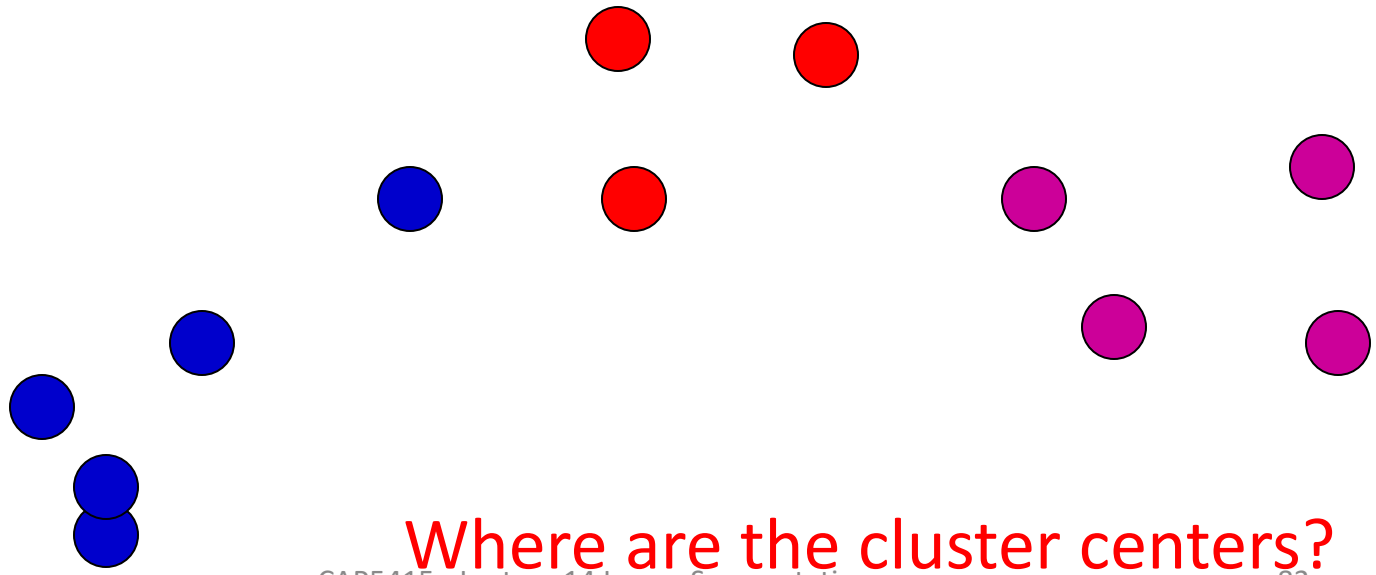
$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

good for spatial data

K-means

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster

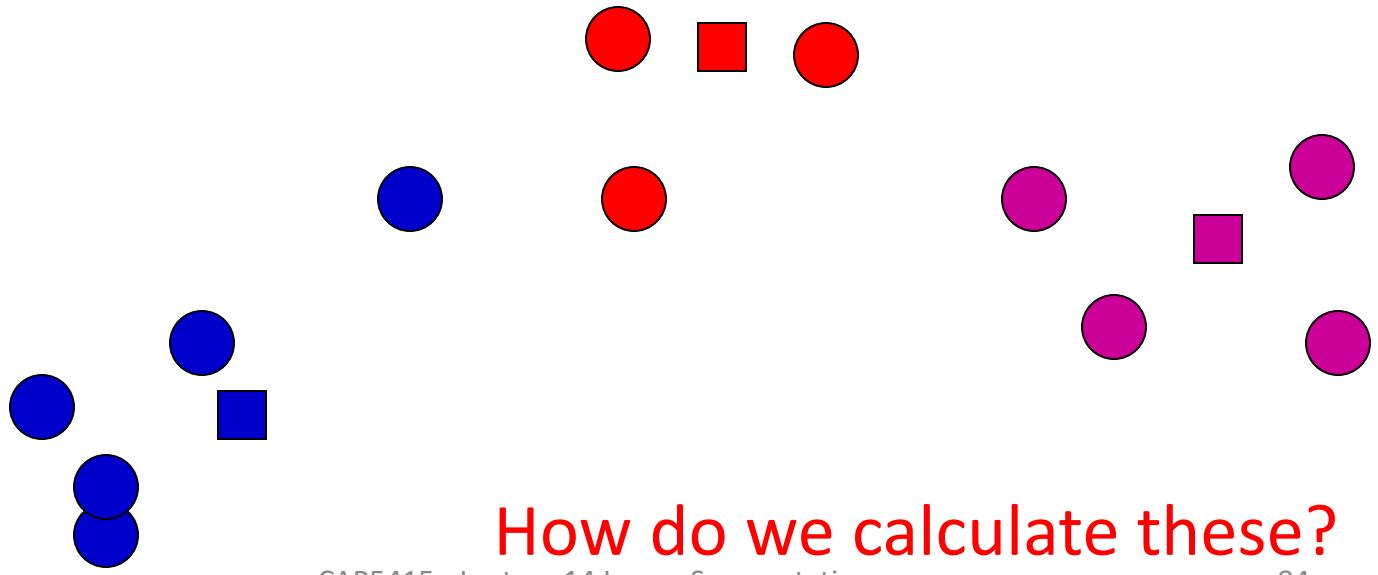


Where are the cluster centers?

K-means

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster



How do we calculate these?

K-means

Iterate:

- Assign/cluster each example to closest center
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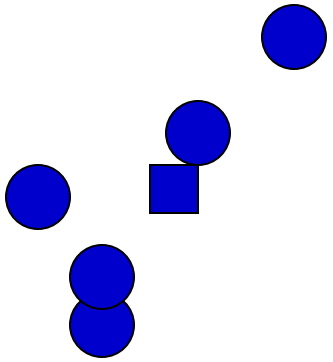


Mean of the points in the cluster:

$$\mu(C) = \frac{1}{|C|} \sum_{x \in C} x$$

where:

$$x + y = \sum_{i=1}^{n} x_i + y_i \qquad \frac{x}{|C|} = \sum_{i=1}^{n} \frac{x_i}{|C|}$$

K-means loss function

K-means tries to minimize what is called the “k-means” loss function:

$$loss = \sum_{i=1}^{n} d(x_i, \mu_k)^2 \quad \text{where } \mu_k \text{ is cluster center for } x_i$$

that is, the sum of the squared distances from each point to the associated cluster center

K-means variations/parameters

Start with some initial cluster centers

Iterate:

- Assign/cluster each example to closest center
- Recalculate centers as the mean of the points in a cluster

What are some other variations/parameters we haven't specified?

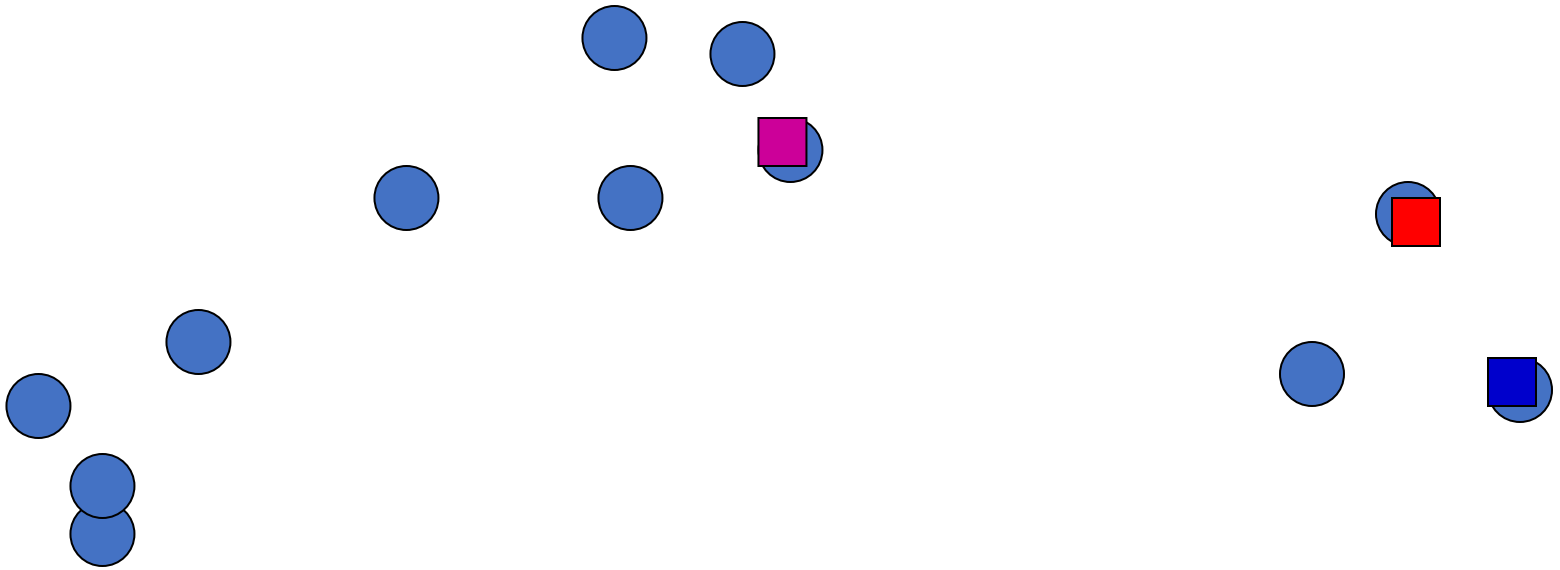
K-means variations/parameters

Initial (seed) cluster centers

Convergence

- A fixed number of iterations
- partitions unchanged
- Cluster centers don’t change

K-means: Initialize centers randomly



What would happen here?

Seed selection ideas?

Seed choice

Results can vary drastically based on random seed selection

Some seeds can result in poor convergence rate, or convergence to sub-optimal clusterings

Common heuristics

- Random centers in the space
- Randomly pick examples
- Points least similar to any existing center (furthest centers heuristic)
- **Try out multiple starting points**
- Initialize with the results of another clustering method

SLIC (Achanta et al. PAMI 2012)

1. Initialize cluster centers on pixel grid in steps S
   - Features: Lab color, x-y position
2. Move centers to position in 3x3 window with smallest gradient
3. Compare each pixel to cluster center within 2S pixel distance and assign to nearest
4. Recompute cluster centers as mean color/position of pixels belonging to each cluster
5. Stop when residual error is small



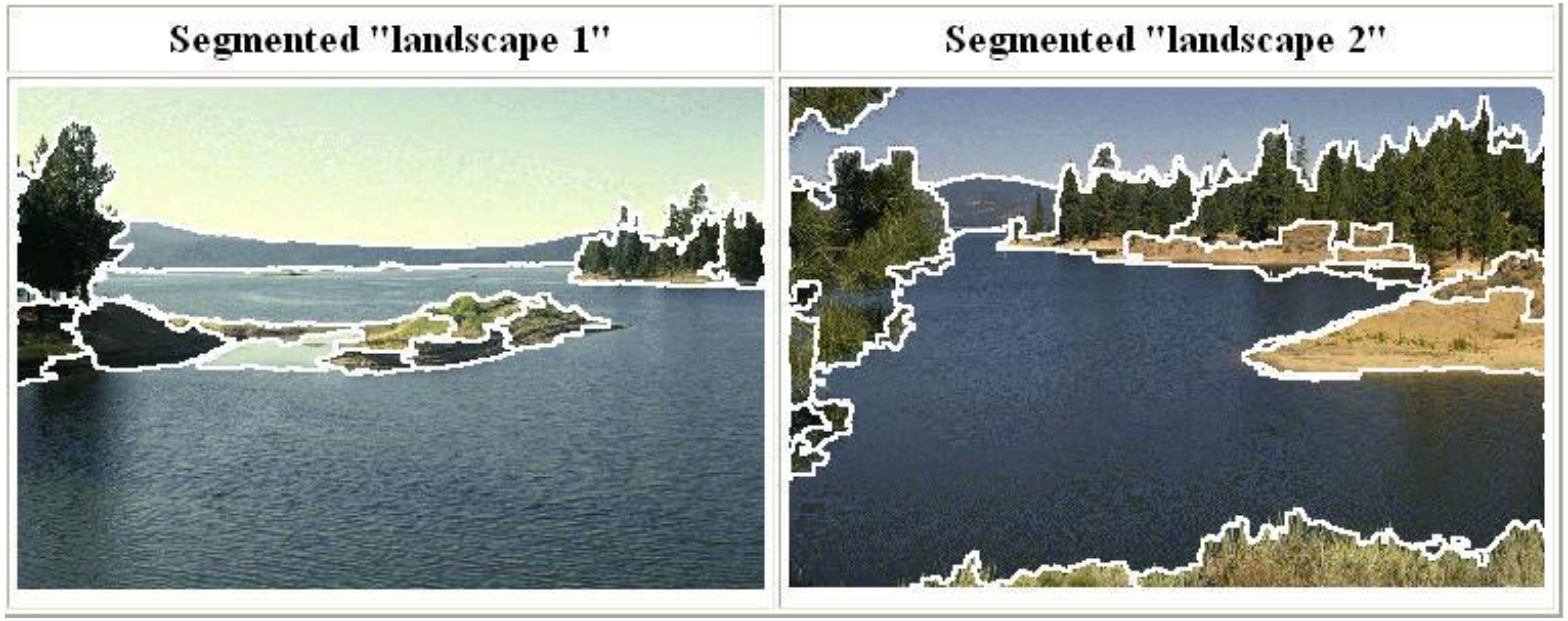
+ Fast 0.36s for 320x240
+ Regular superpixels
+ Superpixels fit boundaries
- May miss thin objects
- Large number of superpixels

Agenda

- Image segmentation basics
- Thresholding based
  - Binarization
  - Otsu
- Region based
  - Merging
  - Splitting
- Clustering based
  - K-means (SLIC)
  - Mean-shift

Mean-Shift Segmentation

- **Mean-shift** is a variant of an iterative steepest-ascent method to seek stationary points (i.e., peaks) in a density function, which is applicable in many areas of multi-dimensional data analysis.



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

Mean-Shift Segmentation

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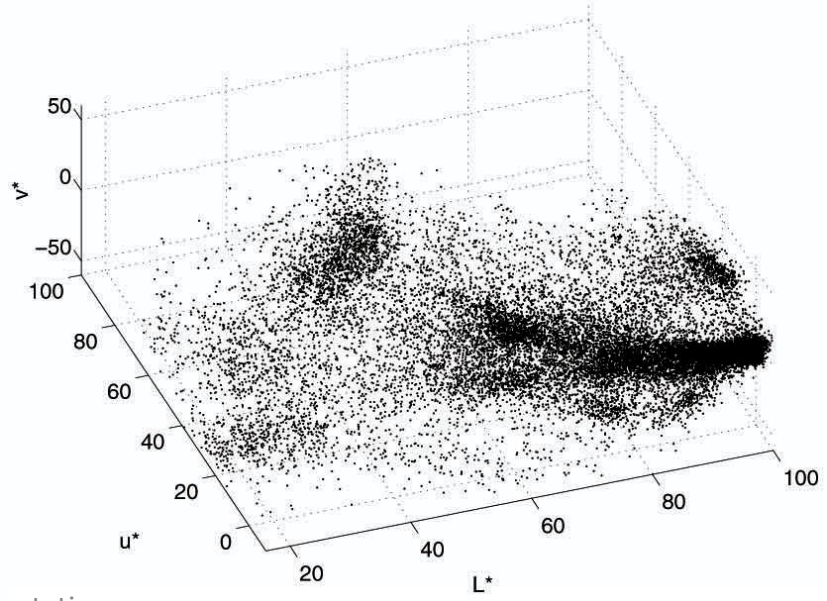
Mean-Shift Segmentation

- **Mean-shift** is a variant of an iterative steepest-ascent method to seek stationary points (i.e., peaks) in a density function, which is applicable in many areas of multi-dimensional data analysis.
- Attempts to find all possible cluster centers in feature space (unlike k-means, where there is a requirement to know the number of different clusters).

Mean-Shift Segmentation

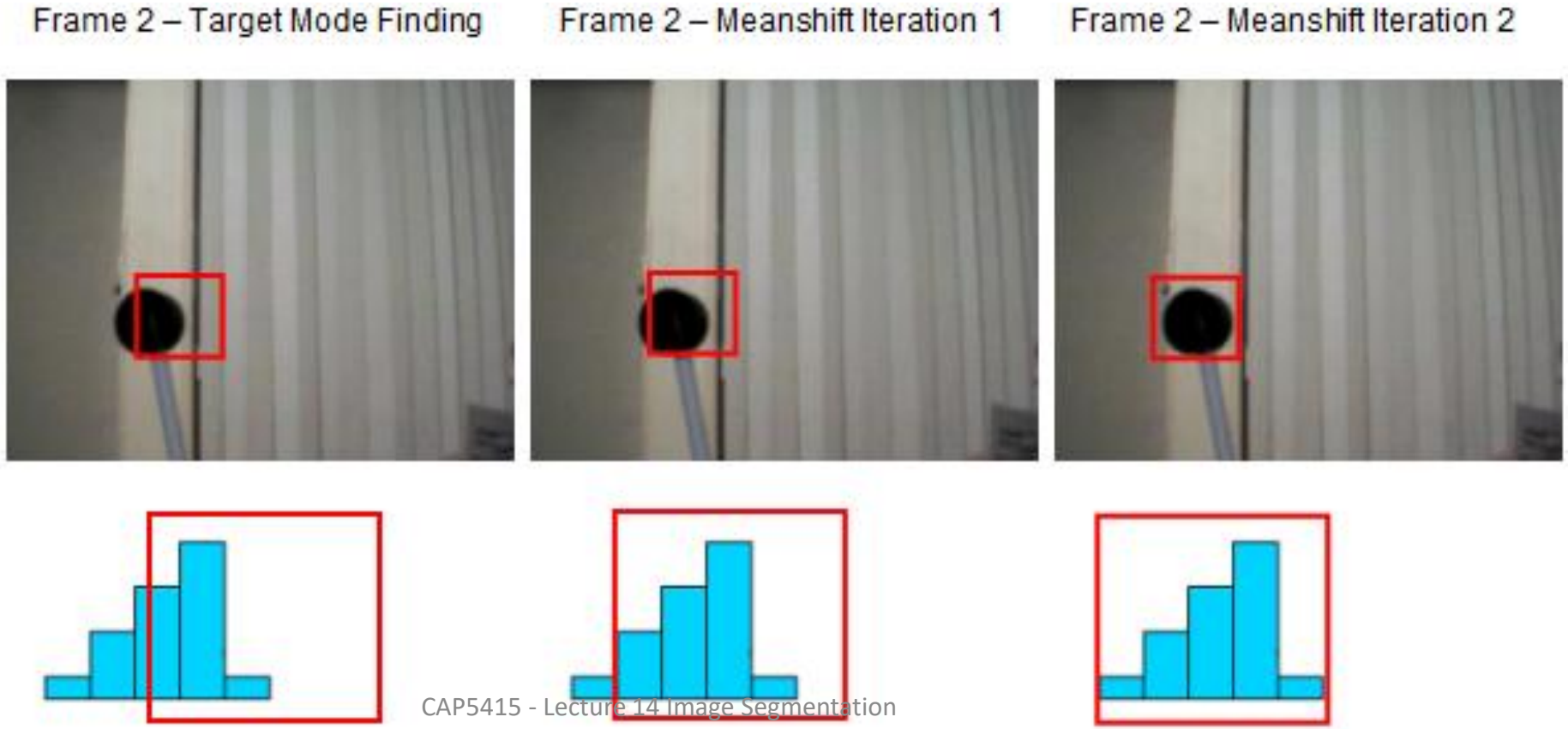
- **Mean-shift** is a variant of an iterative steepest-ascent method to seek stationary points (i.e., peaks) in a density function, which is applicable in many areas of multi-dimensional data analysis.
- The mean shift algorithm seeks *modes* or local maxima of density in the feature space





Mean-Shift Basics

- Mean-Shift is a procedure for locating maxima of a density function given discrete data samples from that function.



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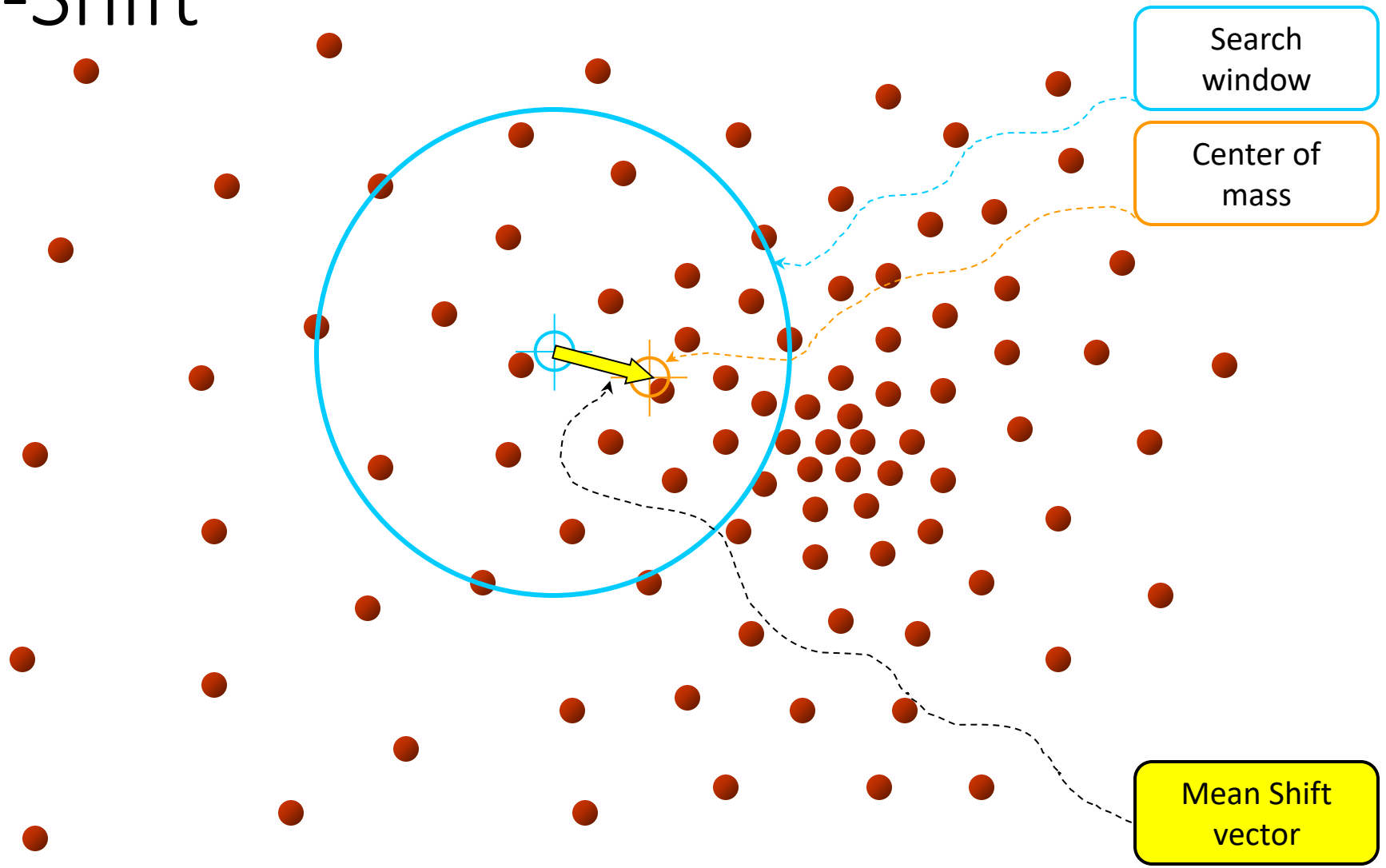
- Let a kernel function $K(x_i-x)$ be given, determining the weight of nearby points for re-estimation of the mean.
- The weighted mean of the density in the window determined by K

$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x) x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$$

N(x): neighborhood of x
m(x) – x: mean shift

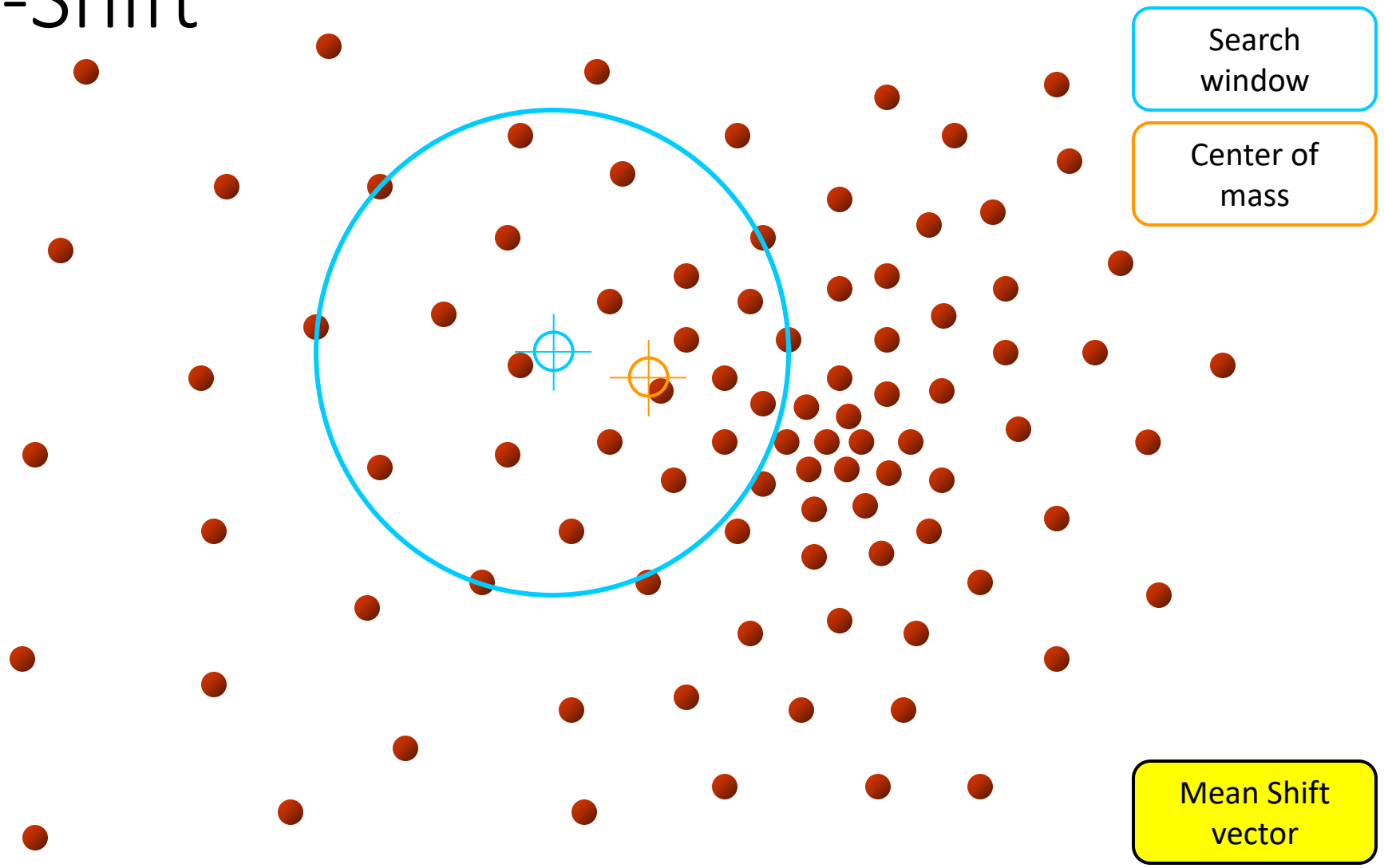
Mean-Shift



FIND DENSEST REGION!

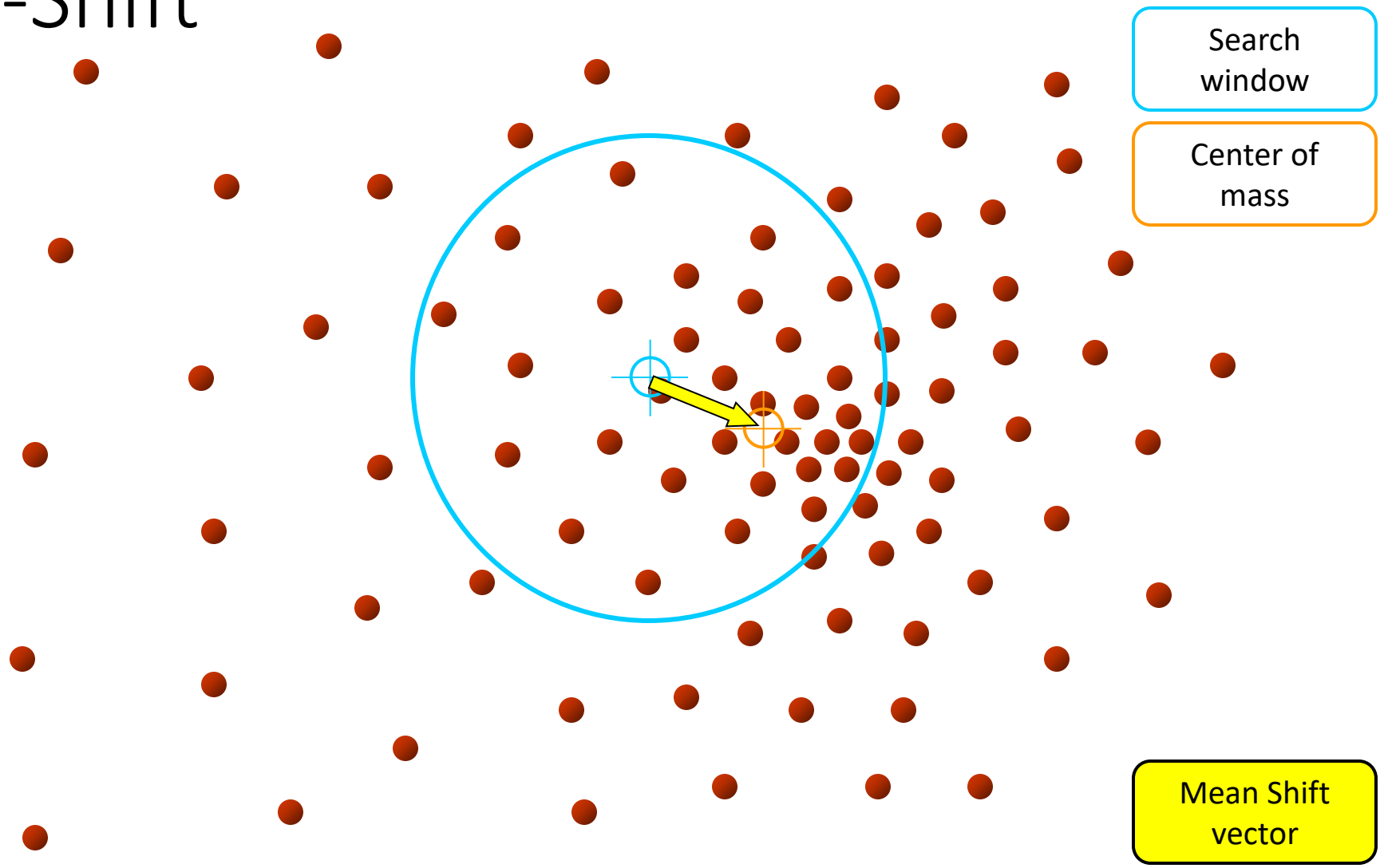
Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



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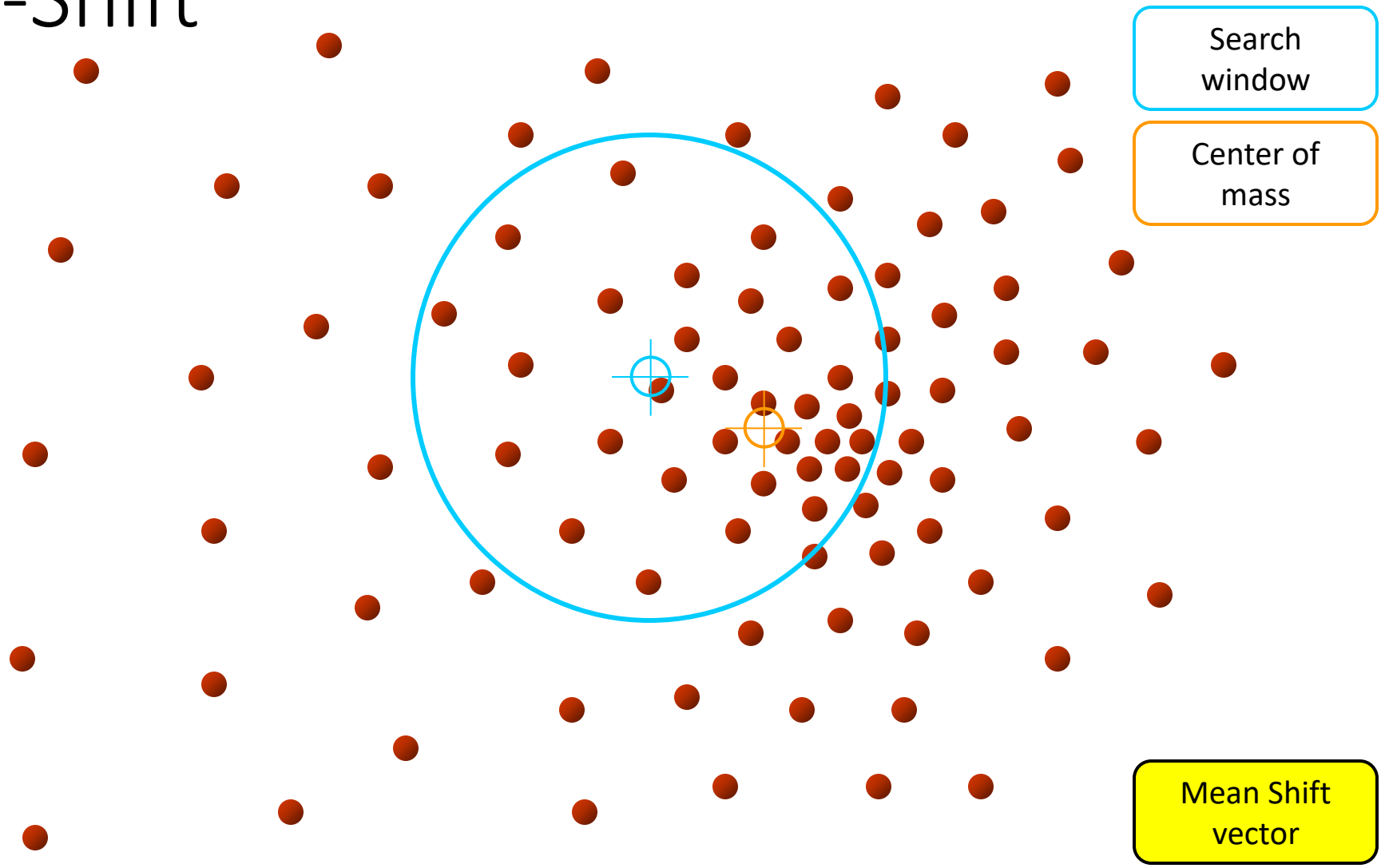

Slide by Y. Ukrainitz & B. Sarel

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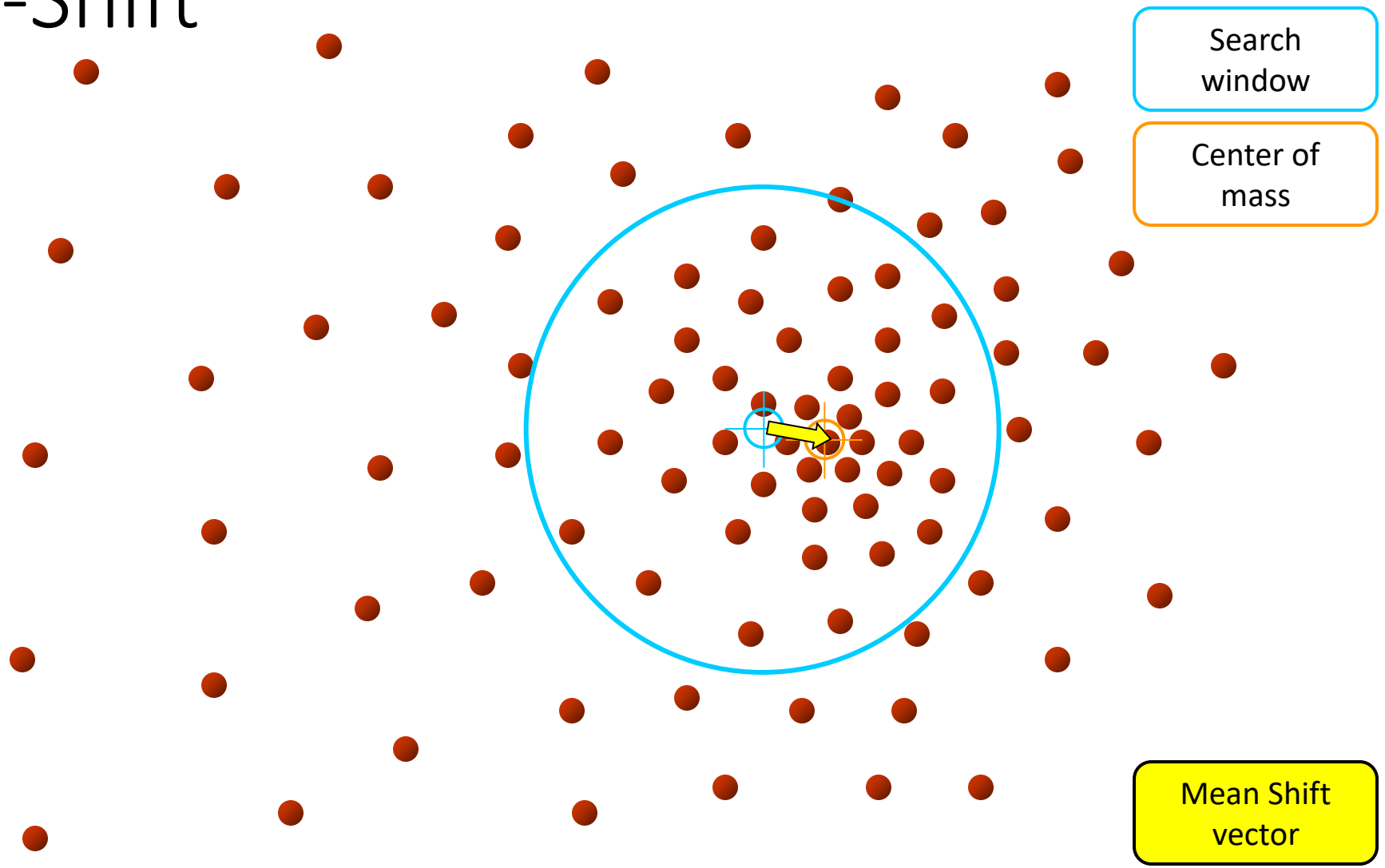

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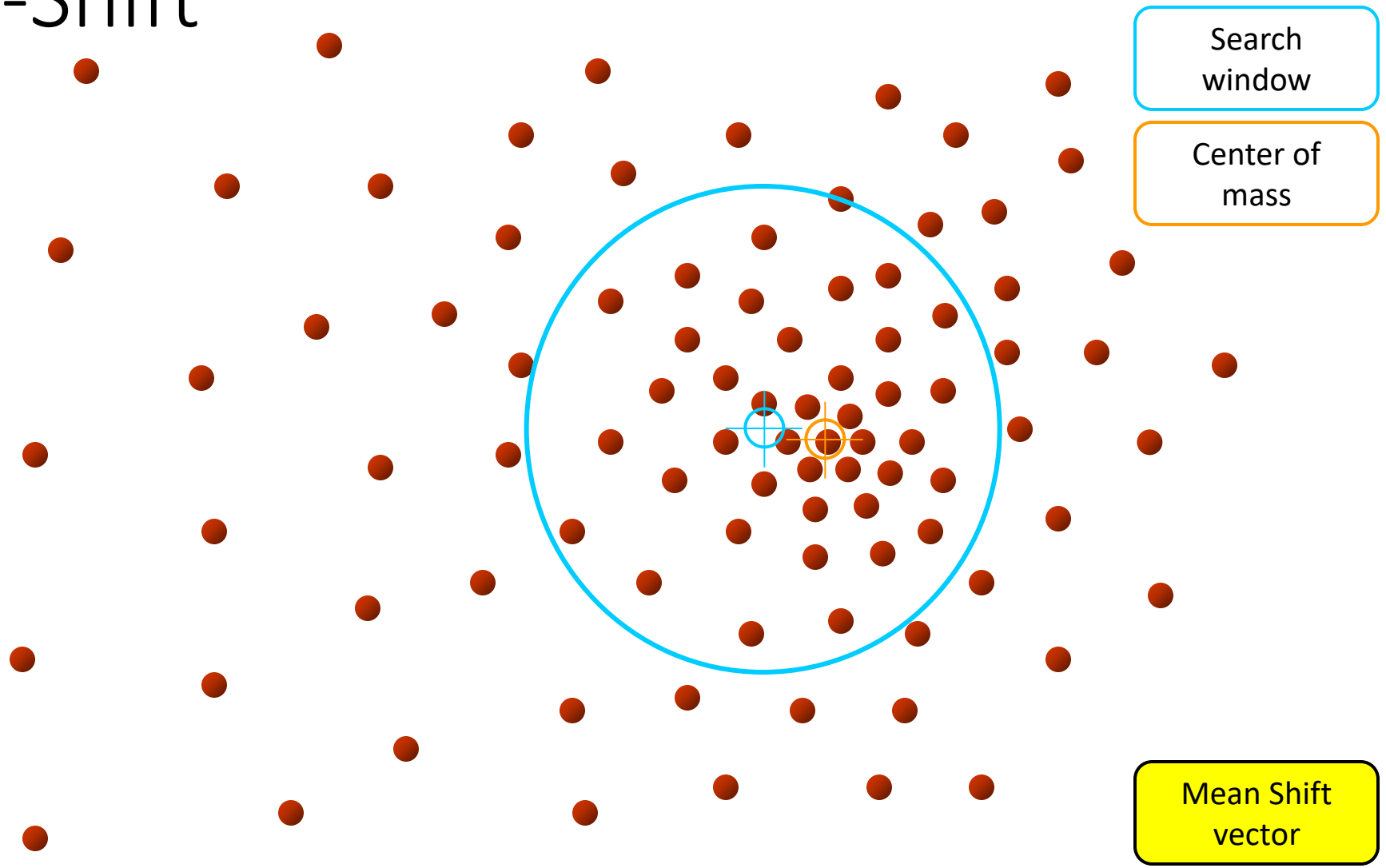
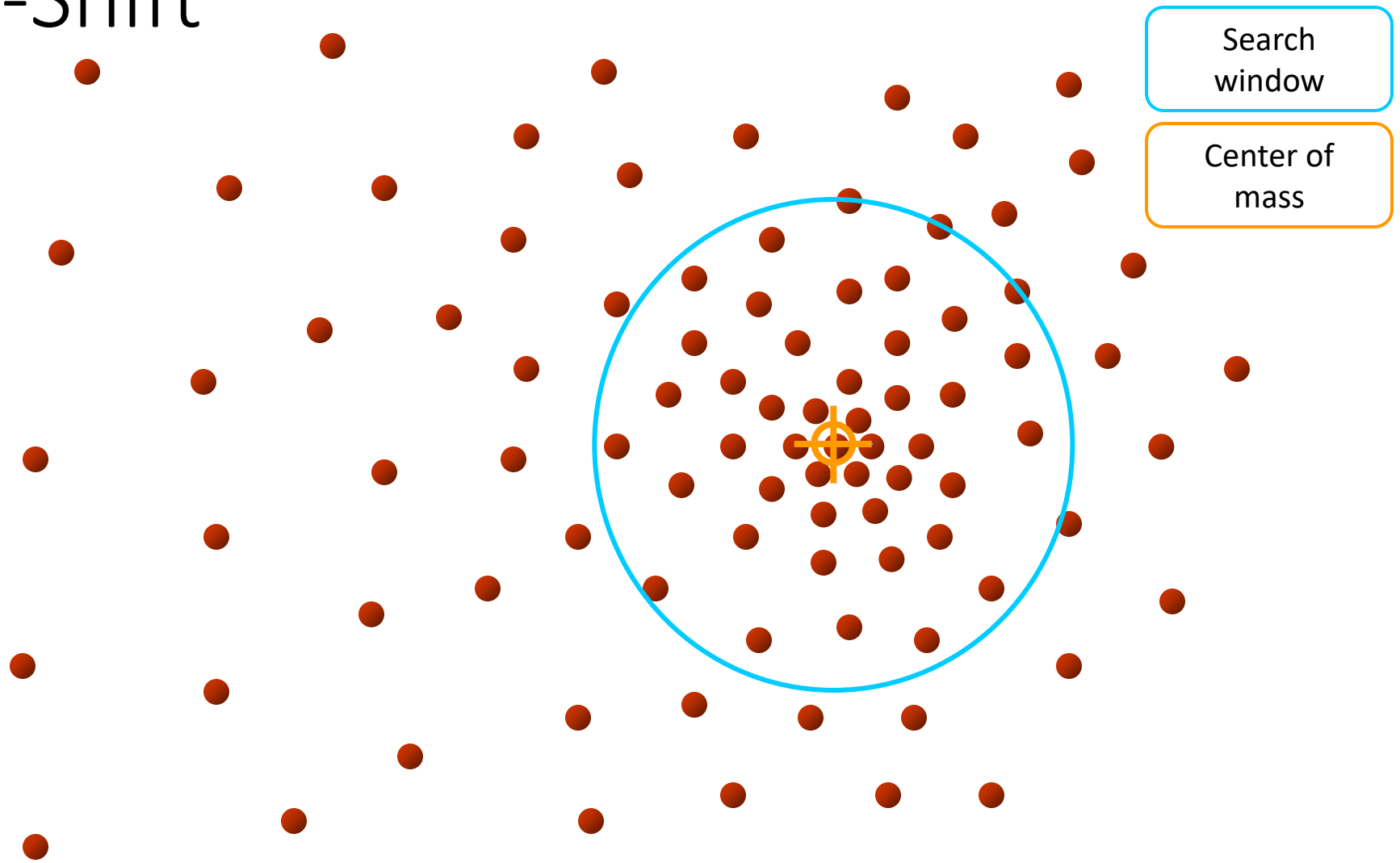


Slide by Y. Ukrainitz & B. Sarel

Mean-Shift



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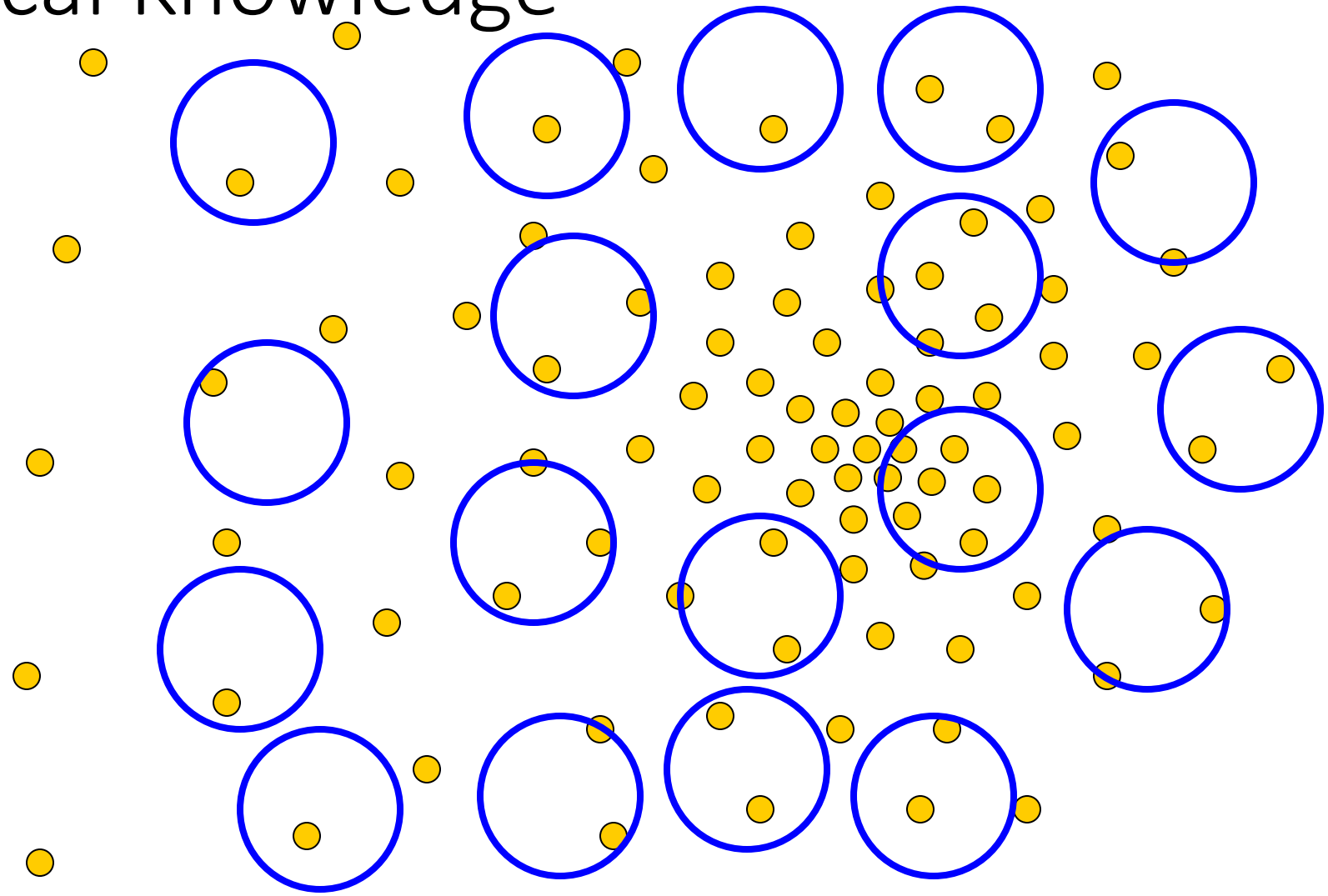
Practical Knowledge



Tessellate the space with windows

Run the procedure in parallel

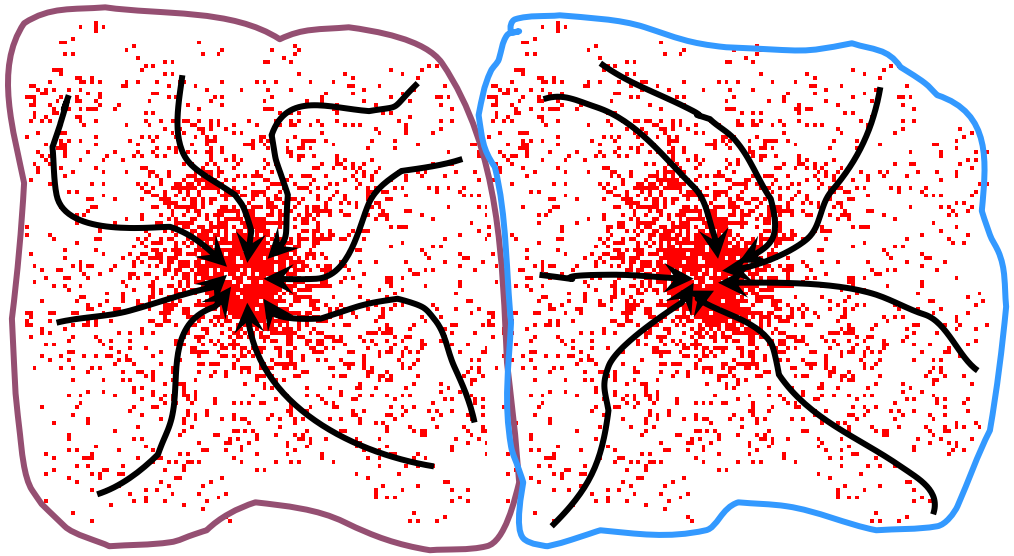
Mean shift clustering

The mean shift algorithm seeks *modes* of the given set of points

1. Choose kernel and bandwidth
2. For each point:
   a) Center a window on that point
   b) Compute the mean of the data in the search window
   c) Center the search window at the new mean location
   d) Repeat (b,c) until convergence
3. Assign points that lead to nearby modes to the same cluster

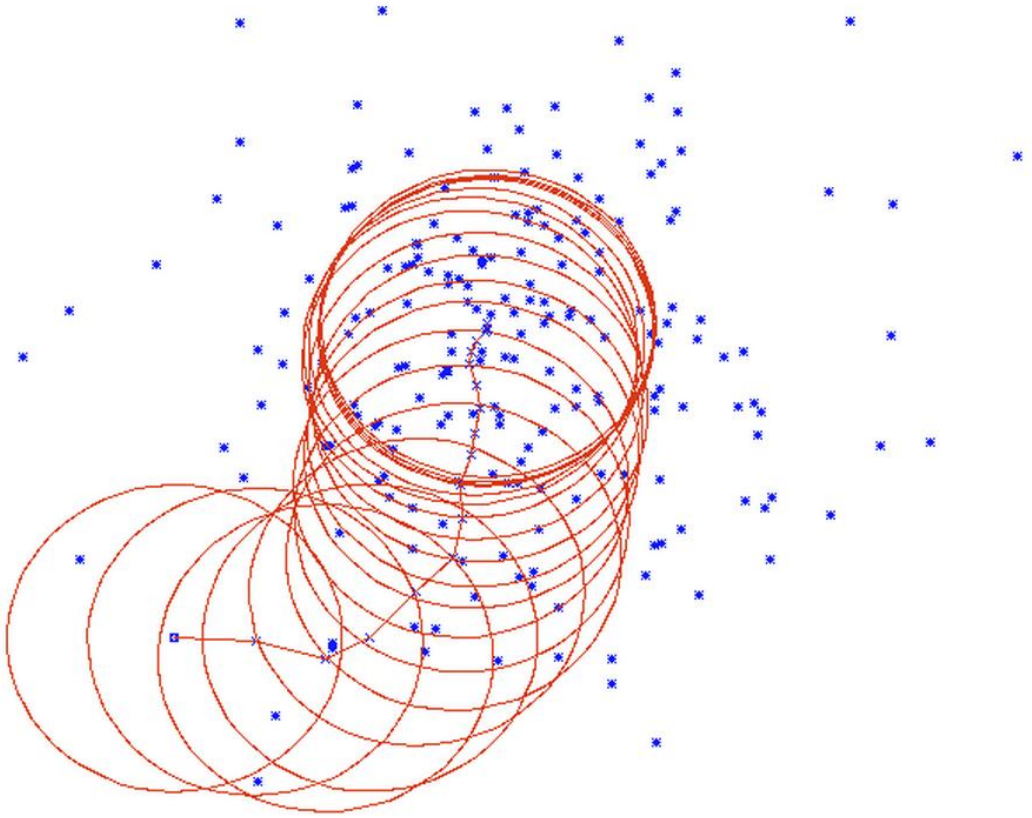
Mean-Shift Clustering

- Gradient ascent requires computing a gradient of the density function.
- Density function is only approximated by a distribution of samples, the gradient can only be approximated as well !!!
- This is done by a kernel window estimator.



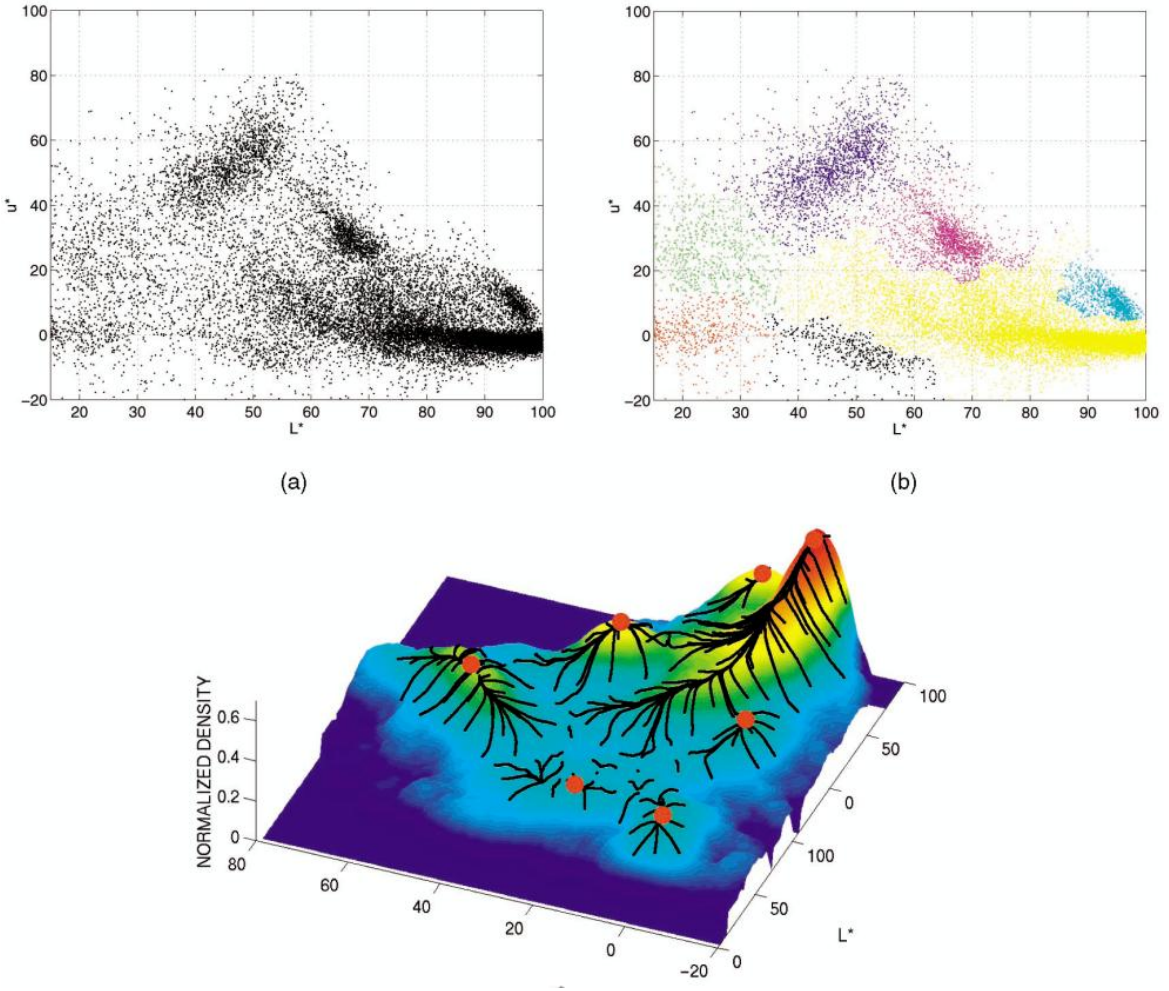
Slide by Y. Ukrainitz & B. Sarel

Trajectory: x, m(x), (m(m(x)), …..



Mean-Shift Segmentation

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



Ex: Mean-Shift Segmentation



Ex: Mean-Shift Segmentation

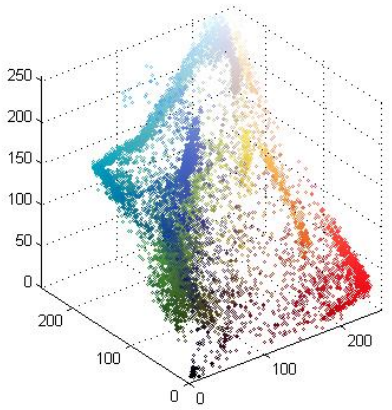


Mean-Shift Clustering

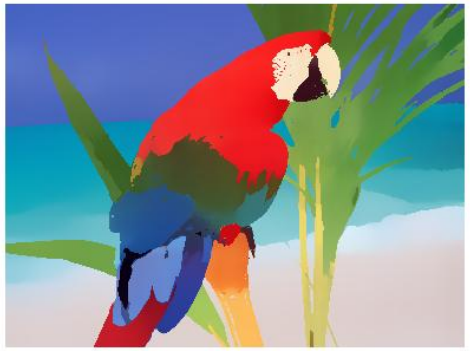
input image



Pixel Distribution Before Meanshift



output image



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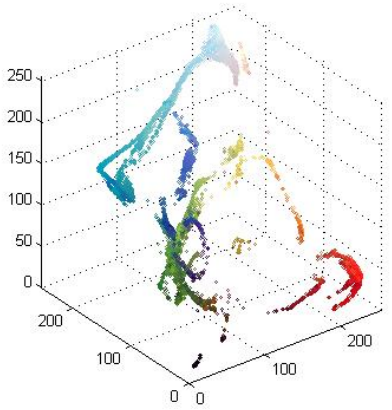
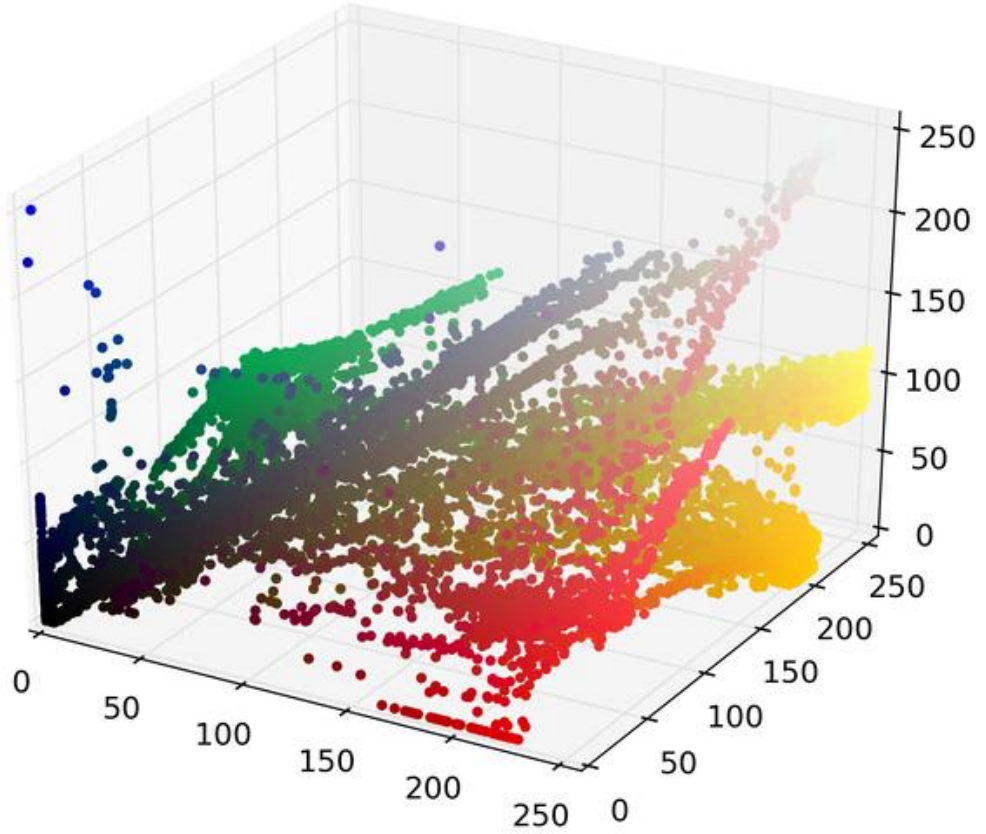


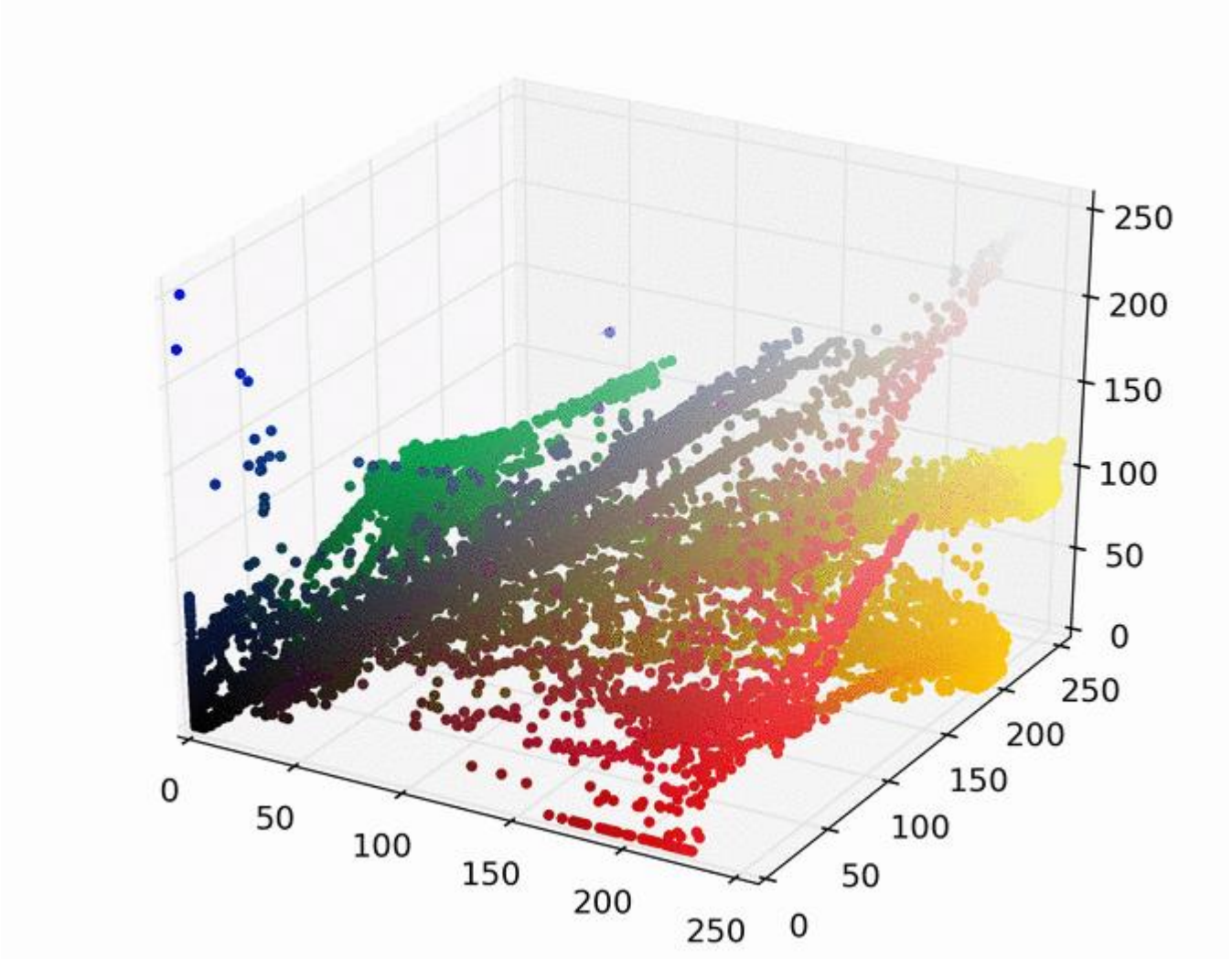
Demo





https://spin.atomicobject.com/2015/05/26/mean-shift-clustering/

Demo



https://spin.atomicobject.com/2015/05/26/mean-shift-clustering/

Demo



https://spin.atomicobject.com/2015/05/26/mean-shift-clustering/

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

Questions?

Slide Credits and References

- Ulas Bagci
- David Kauchak (k-means)
- R.Klette, Concise Computer Vision, 2014.
- Y. Ukrainitz & B. Sarel, Weizmann
- Thu Huong Nhuyen, TU Dresden
- Jens N. Kaftan and Andr`e A. Bell and Til Aach . Mean Shift Segmentation Evaluation of Optimization Techniques
- Cheng, Y. (1995). Mean Shift, Mode Seeking, and Clustering. IEEE Transactions on Pattern Analysis and Machine Intelligence, 17(8):790–799.
- KEINOSUKE FUKUNAGA, AND LARRY D. HOSTETLER. The Estimation of the Gradient of a Density Function, with Applications in Pattern – Recognition. IEEE TRANSACTIONS ON INFORMATION THEORY, VOL. IT-21, NO. 1, JANUARY 1975
- Comaniciu, D. and Meer, P. (1997). Robust Analysis of Feature Spaces: Color Image Segmentation.
- In IEEE Conference on Computer Vision and Pattern Recognition. CVPR 1997, pages 750–755.
- Comaniciu, D. and Meer, P. (1999). Mean Shift Analysis an Applications. In International Conference on Computer Vision. ICCV 1999, volume 2, pages 1197–1203.
- Comaniciu, D. and Meer, P. (2002). Mean Shift: A Robust Approach Toward Feature Space Analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(5):603–619.
- K. Fukunaga, L.D. Hostetler, The estimation of the gradient of a density function, with applications in pattern recognition, IEEE Trans. Inf. Theory 21 (1975) 3240.
- Yiping Hong , Jianqiang Yi and Dongbin Zhao . Improved mean shift segmentation approach for natural images