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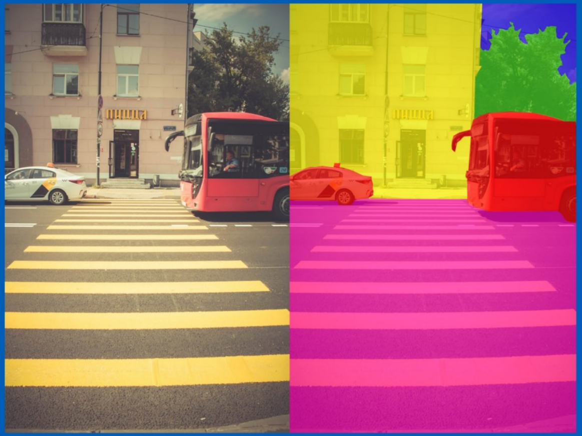
Image Segmentation



Summary

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- What does “segmentation” means?
- K-Means
- Mean-shift

References

- [FP] D. A. Forsyth and J. Ponce. Computer Vision: A Modern Approach (2nd Edition). Prentice Hall, 2011.
- CS231A · Computer Vision: from 3D reconstruction to recognition
  - Prof. Silvio Savarese – Stanford University
- CS131 · Computer Vision: Foundations and Applications
  - Prof. Fei-Fei Li – Stanford University
- Elementi di Analisi per Visione Artificiale
  - Paolo Medici http://www.ce.unipr.it/people/medici

What does segmentation means?

- Extraction of homogeneous parts of an image $\longrightarrow$ **components**
- Usually a more compact representation of an image

 

Source: Silvio Savarese

Why we use segmentation?

- From image to description
  - Low level $\longrightarrow$ medium level
- Components are often blocks for other algorithms


What does segmentation means?

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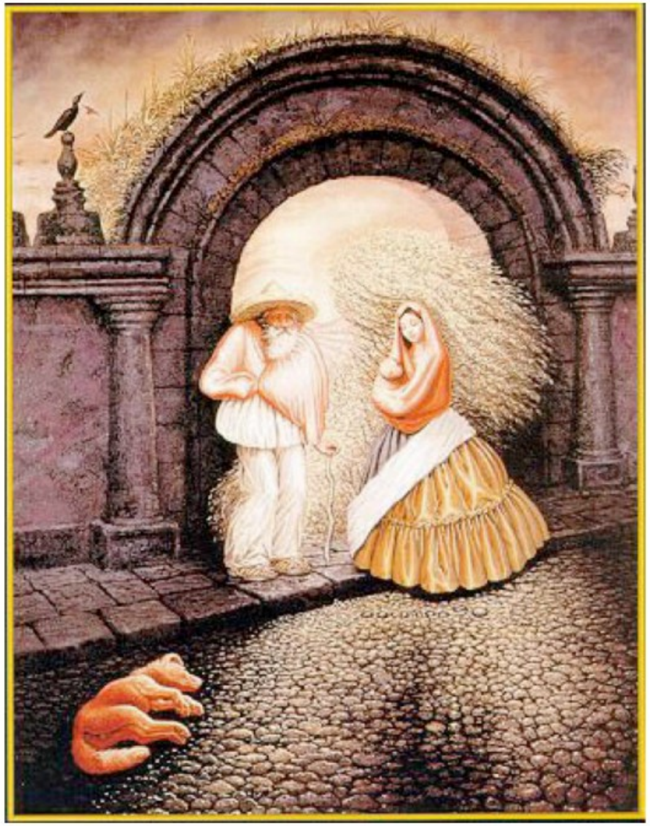
- Extraction of homogeneous parts of an image $\longrightarrow$ **components**
- Usually a more compact representation of an image
- Components share common properties
- Different levels of abstraction for properties

Source: Silvio Savarese

What does segmentation means?

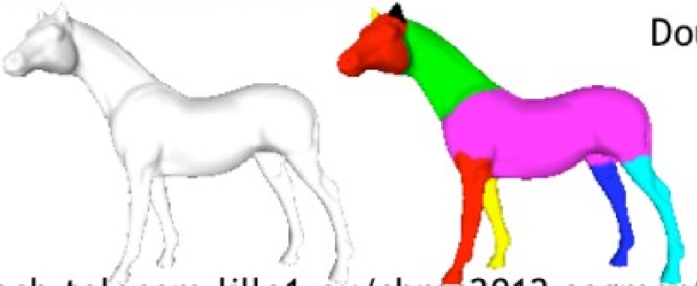


Source: Silvio Savarese

What does segmentation means?

Instance vs **Semantic** Segmentation

Douillard, et al. ICRA 2011



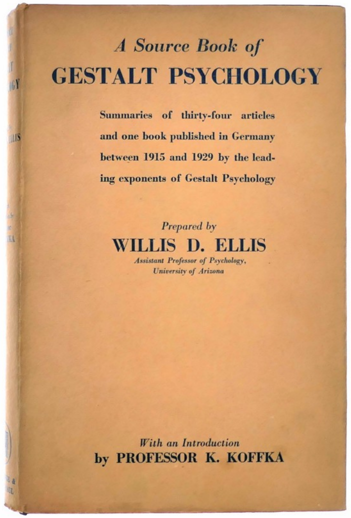
http://www-rech.telecom-lille1.eu/shrec2012-segmentation/

How do humans segment?

How do humans segment?

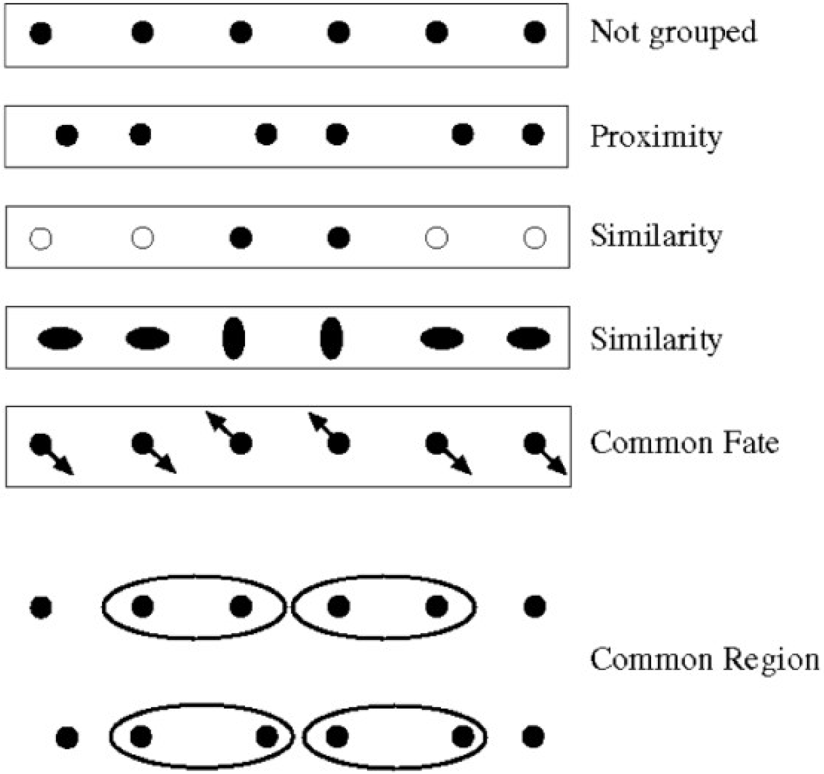
Gestalt

- German word for “shape”, “structure”
- The brain is holistic and parallel
  - Namely no “simple steps” as for algorithms
- Whole is greater than the sum of its parts
  - We perceive objects in their entirety
  - Only after that we perceive details
- What are the principles that allow us to do so?



Gestalt

–A series of factors affect whether elements should be grouped together



Source: Silvio Savarese

Gestalt

Grouping
by occlusions

Source: Silvio Savarese

Gestalt

Grouping
by occlusions

Source: Silvio Savarese

Gestalt

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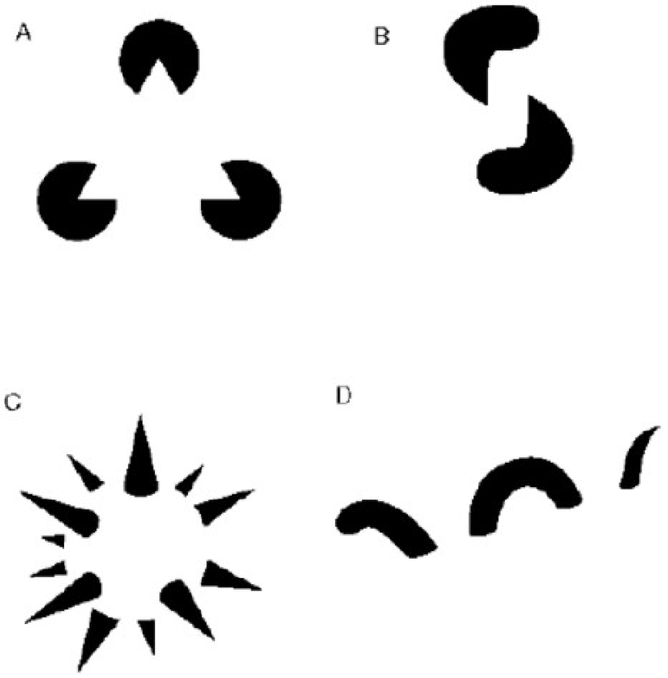
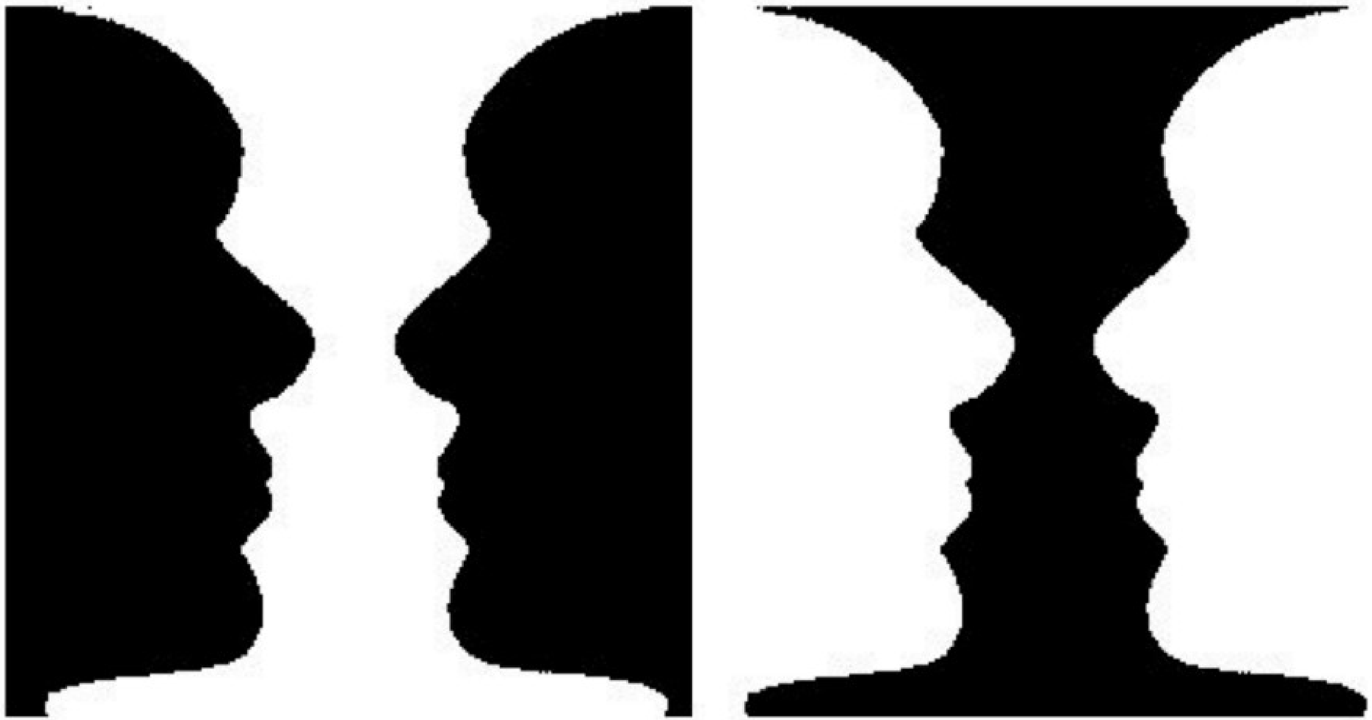
Grouping
by invisible
completions



Source: Silvio Savarese

Gestalt

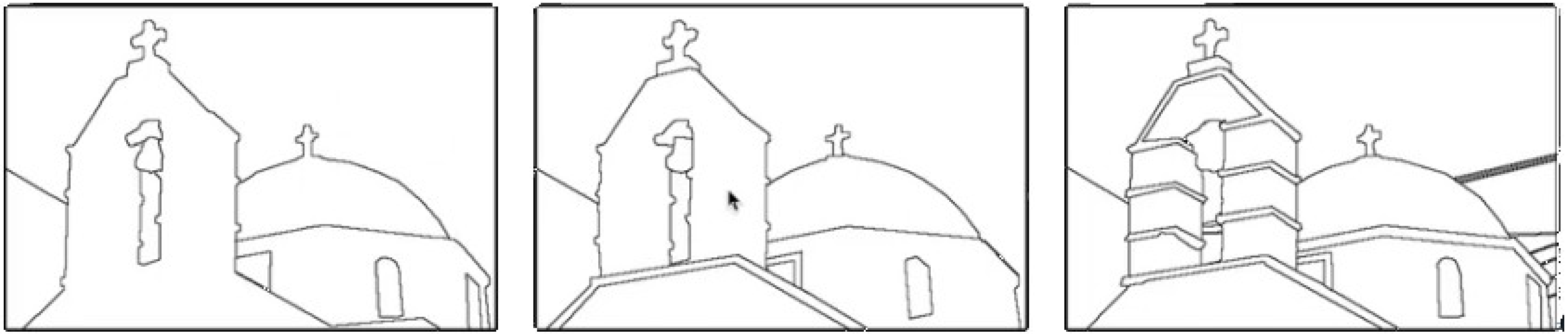


Source: Silvio Savarese

Gestalt

If we ask to different users to segmentate, different results are obtained

Segmentation is HIGHLY Subjective!



Source: Shree Nayar

Gestalt

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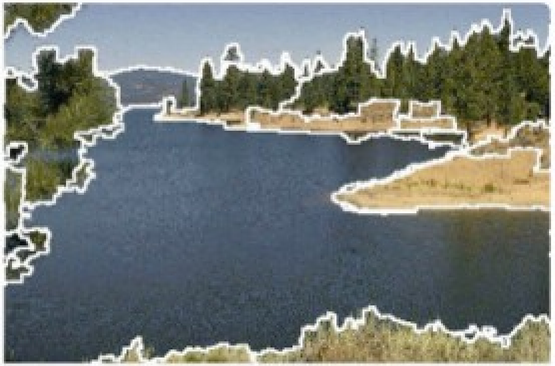
- Segmentation is intuitive for us
  - Even if highly subjective
- Very hard to translate it to an algorithm!
  - If we do not know how it works, how we can write an algorithm?
- Anyway two basic approaches

Strategies

- Bottom-up: components are locally coherent

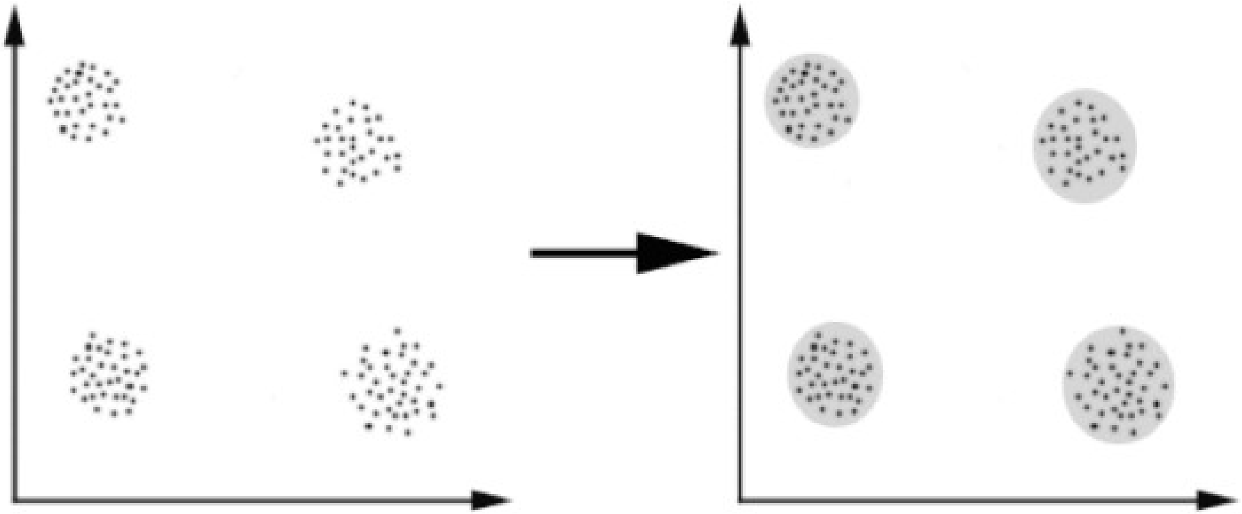


- Top-down: components belong to same entity (object, scene…)

Source: Silvio Savarese

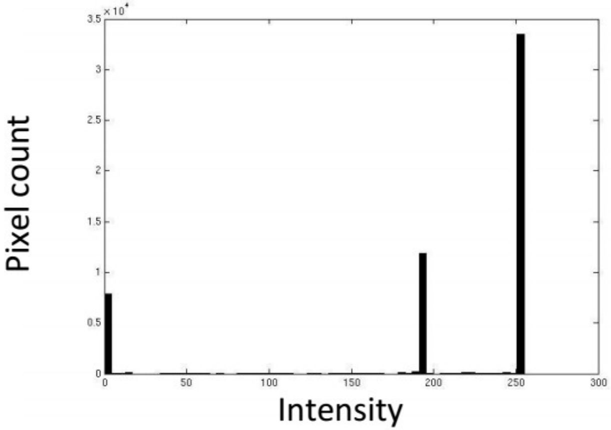
Bottom-up: clustering

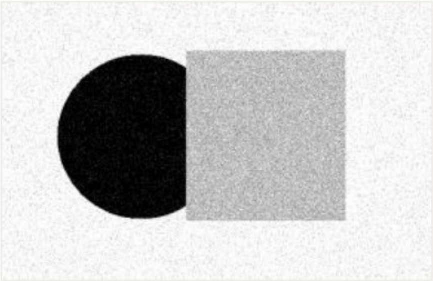
- "Locally coherent": each point belongs to a specific "cluster"
- It depends on points visual characteristics
  - A "vector"



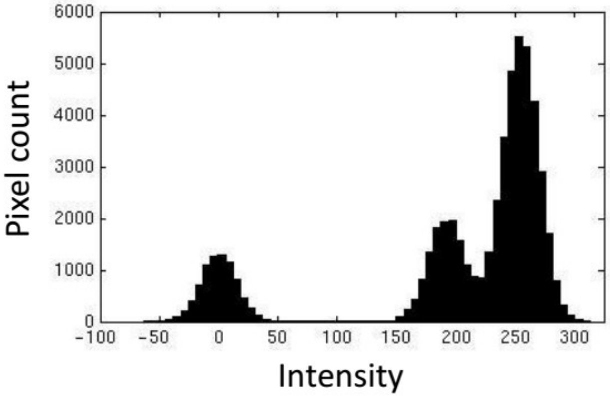
Clustering

Input image





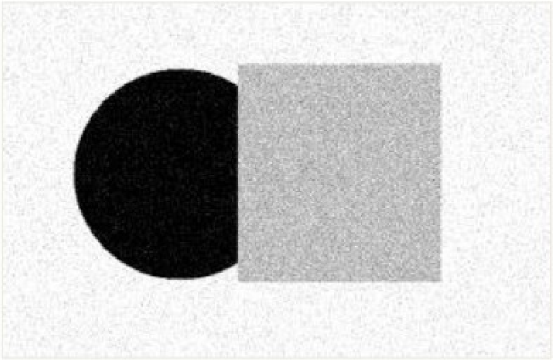
Input image



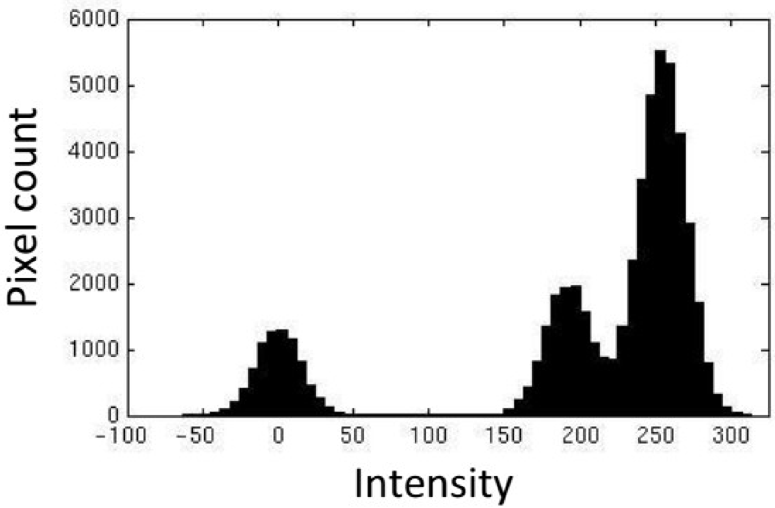
Slide credit: Kristen Grauman

Clustering

- Clustering $\longrightarrow$ identify different luminance levels

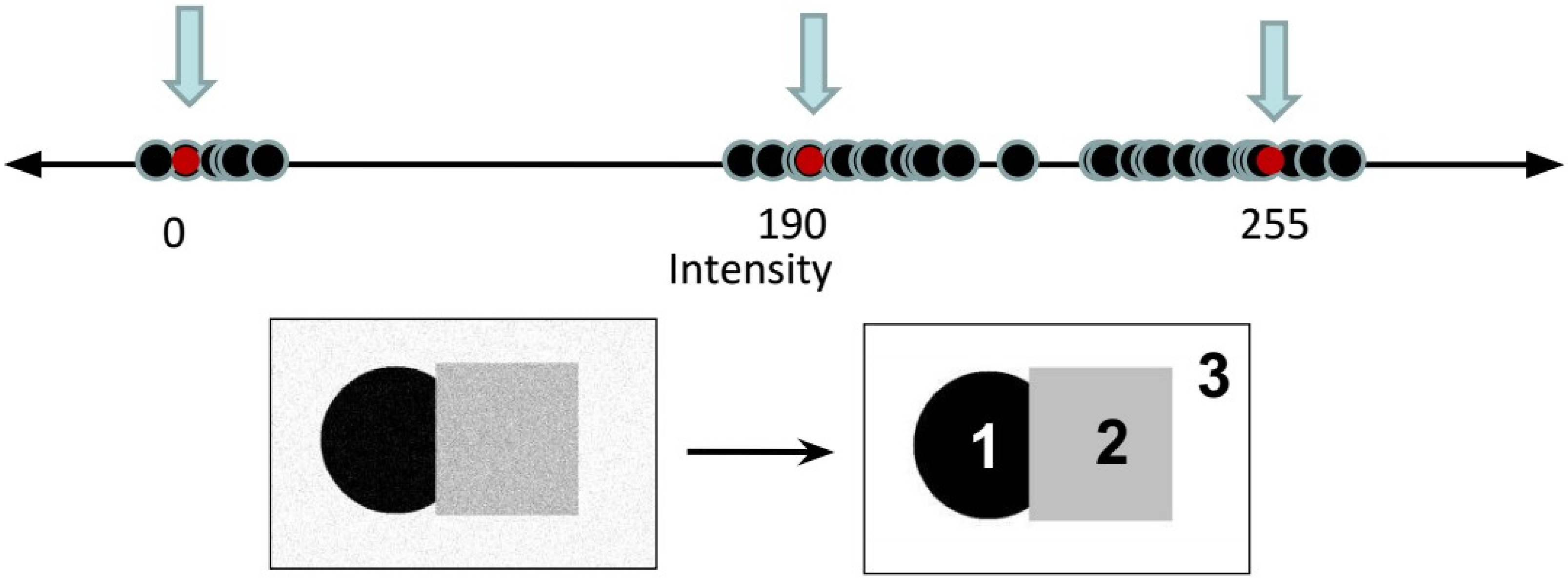


Input image



Clustering

- Clustering → identify different luminance levels
  - Associate each pixel to a specific cluster



Clustering

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- Underlying idea: minimize "distance" of each "pixel" from cluster center ("centroids")
  - Given N data & k clusters
  - We want to minimize both centroids **c** and cluster membership **δ**

Is x_j belonging to c_i?

$$c^*, \delta^* = \underset{c,\delta}{arg\ min} \frac{1}{N} \sum_{j}^{N} \sum_{i}^{k} \delta_{ij} (c_i - x_j)^2$$

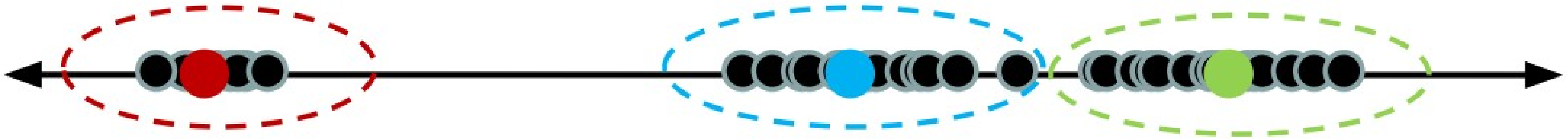
Cluster center

Data

Source: Silvio Savarese

Clustering

- Not well defined...
  - If we know cluster centers → easy points assignment
  - If we know groups → easy to compute centroids



Clustering techniques

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- K-Means
  - Predefined number of clusters
  - “Spherical” clusters
- Mean-shift
  - Variable number of clusters
  - No a priori shape assumptions
  - Slow

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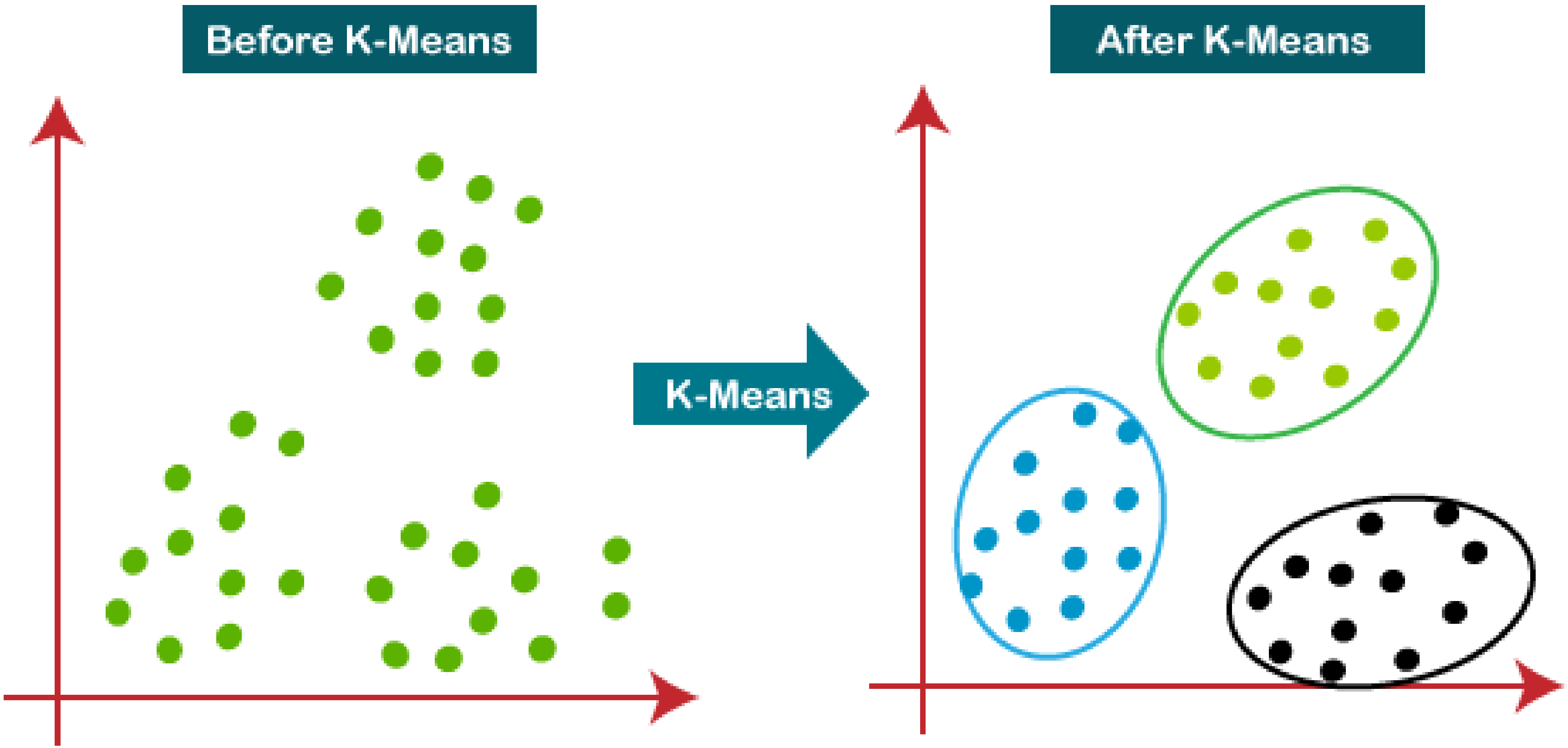
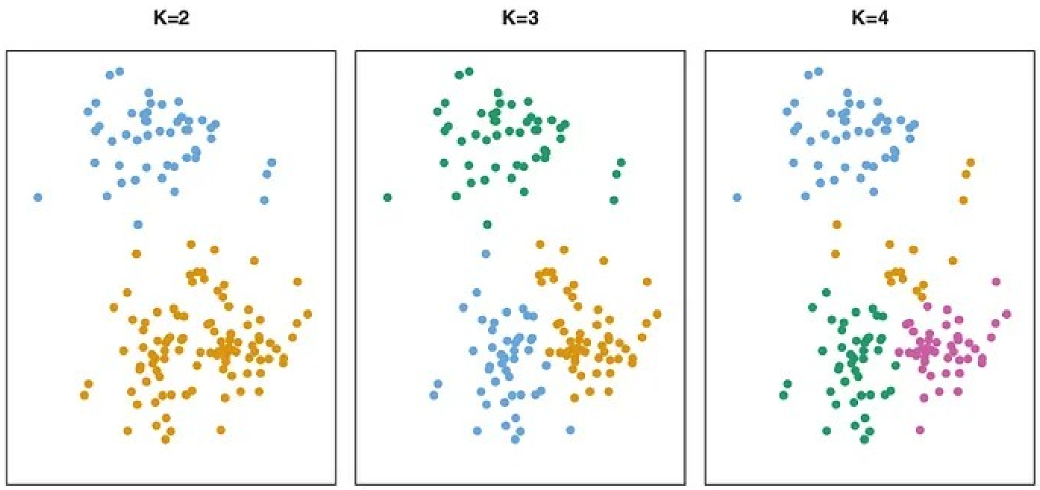
K-means clustering

K-Means clustering



K-Means clustering

- The underlying idea under k-means clustering is to guess the number of clusters
  - Namely the “k” in k-means



Source: Introduction to Statistical Learning with Applications in R page 387

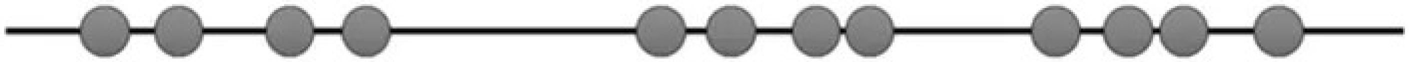
K-Means clustering

- Initialization
  - Choose k cluster centers
- Repeat
  - Assignement step:
    - For each point find the closest center
  - Update step
    - Update every center as the mean of its points
- Until
  - A maximum number of iterations is reached
  - No or little changes during Assignement step

Source: Pranshu Sharma

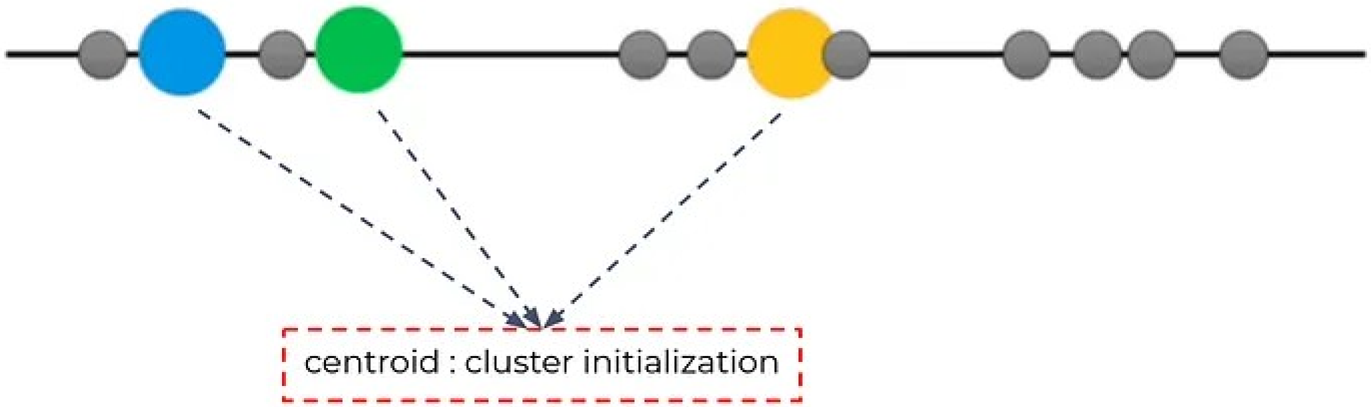
K-Means clustering

- Initialization
  - Choose k cluster centers
  - The value can be critical, since it can lead to completely different results
- How to select them?
  - randomly
  - k points of the set



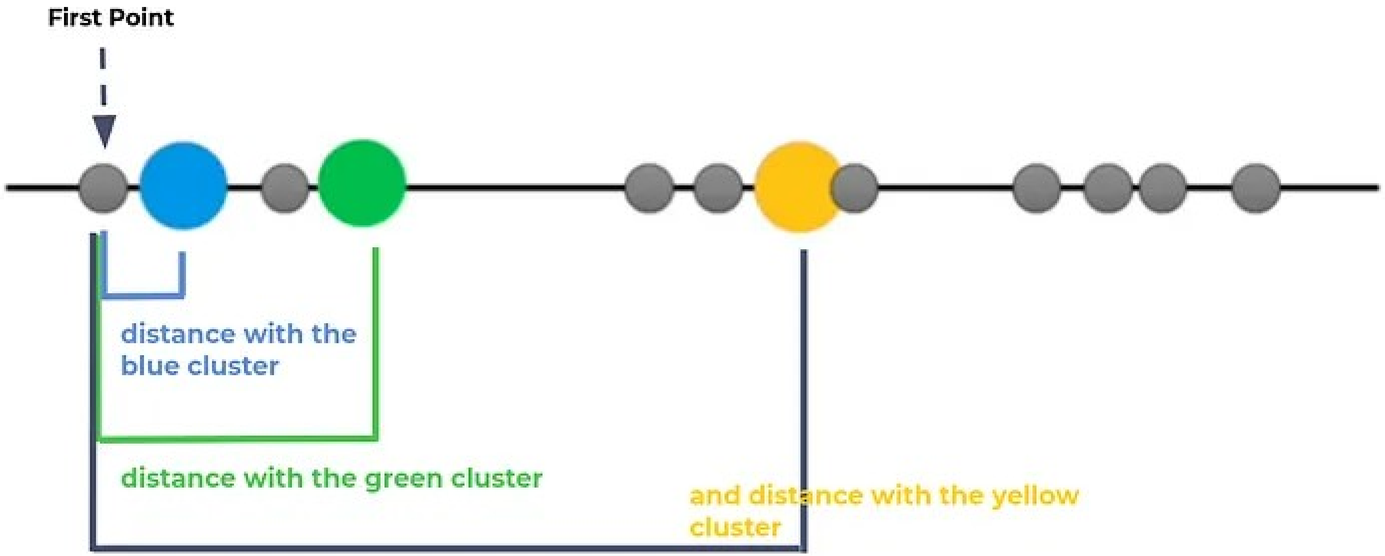
K-Means clustering

- In our example
  - $k = 3$
  - 3 points are selected as center of clusters



K-Means clustering

- Assignement
  - For each point find the closest center
  - In our case euclidean distance is used



K-Means clustering

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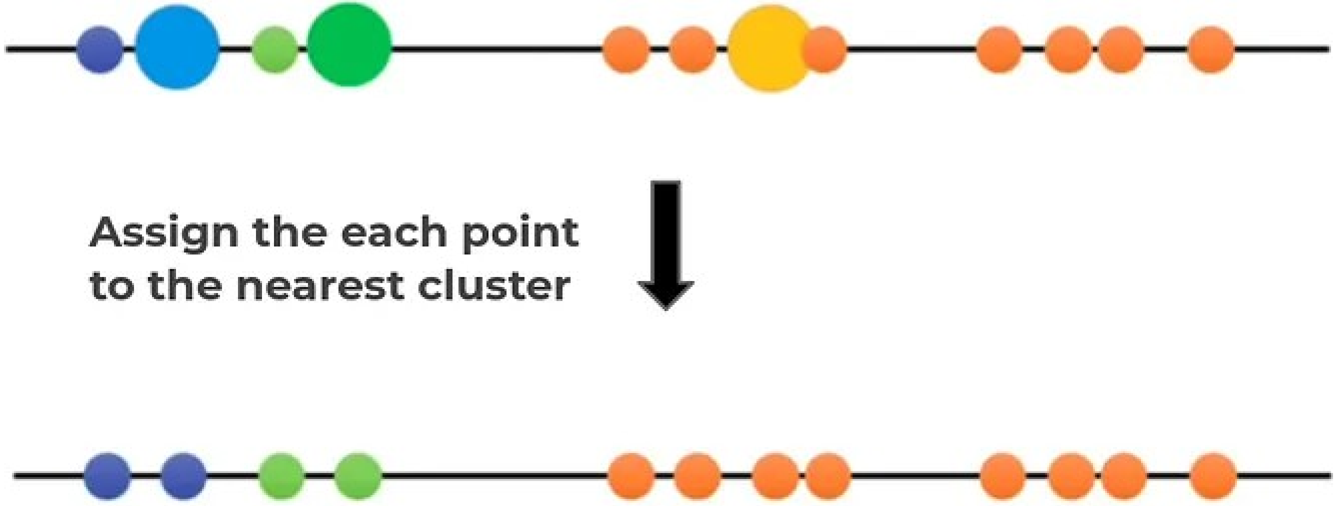
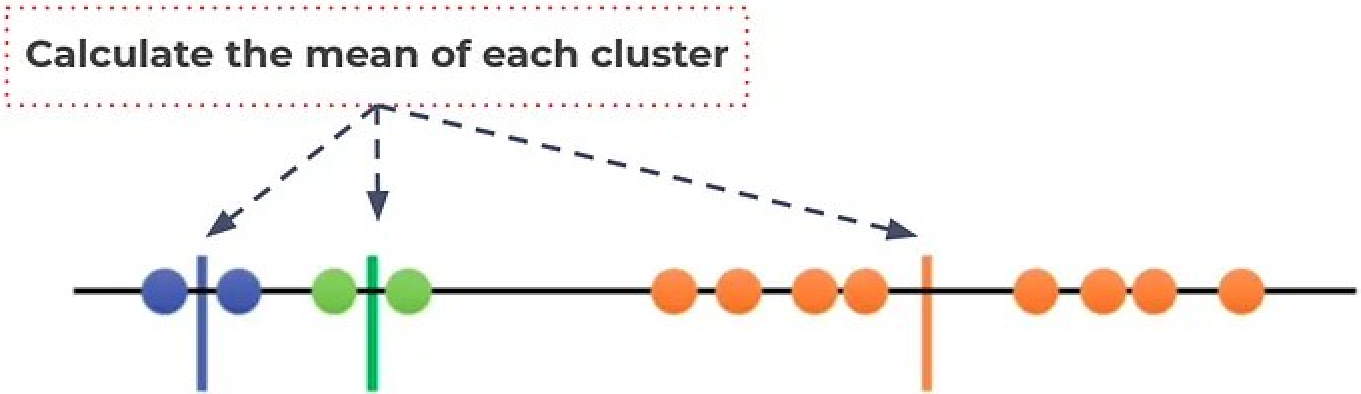
- Assignement
  - For each point find the closest center
  - In our case euclidean distance is used



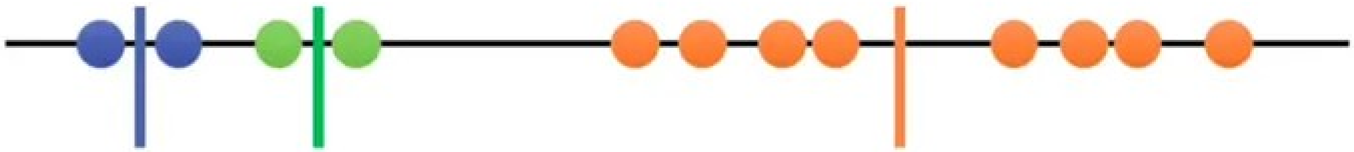
K-Means clustering

- Update step
  - Update every center as the mean of its points



K-Means clustering

- Repeat
  - Assignement & Update
  - Until no or little changes or a fixed amount of iterations



K-Means clustering

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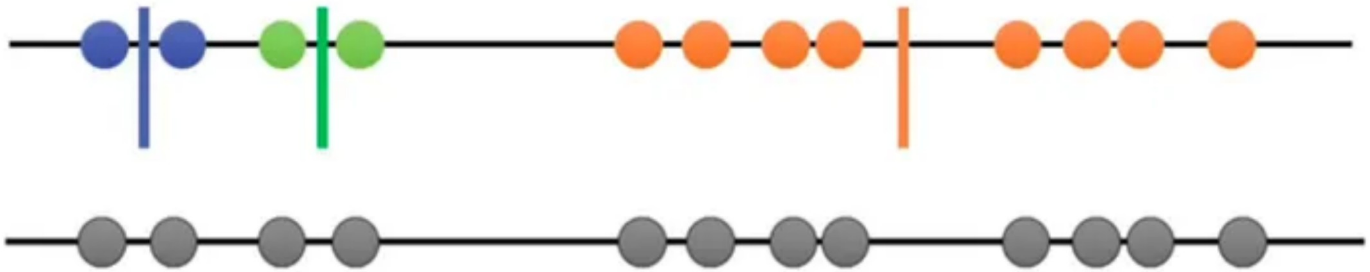
- K-means is extremely sensitive to initialization
- Bad initialization $\longrightarrow$ bad overall clustering
- Potential solutions:
  - K “spread out” points (k-means++)
  - Try multiple inizializations

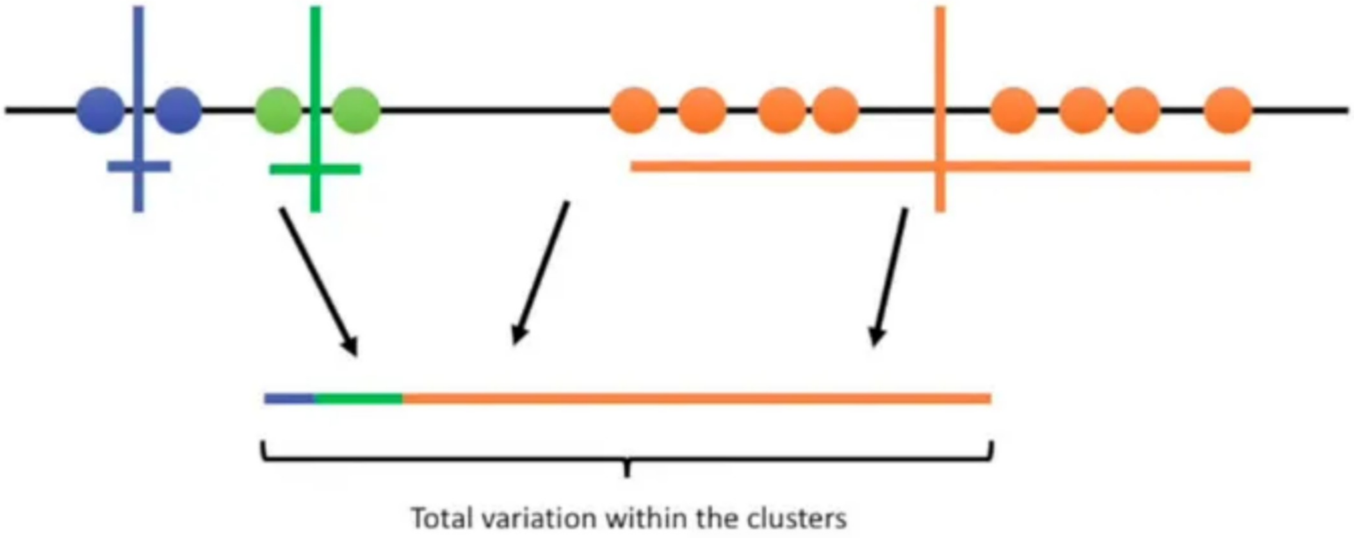


K-Means clustering

- K-means++ approach for initialization
  - Randomly select first center
  - Pick other centers using a probability proportional to $\Sigma_i(x - c_i)^2$
  - Expected error ~ log(k)

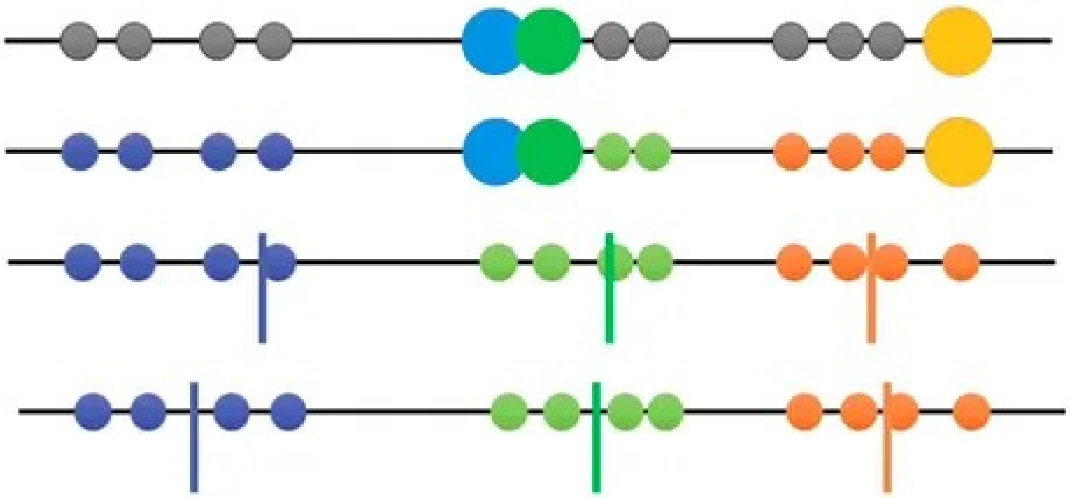
K-Means clustering

- Multiple initializations
  - Given a first try, asses the quality of the result
  - Compute the variance of each cluster



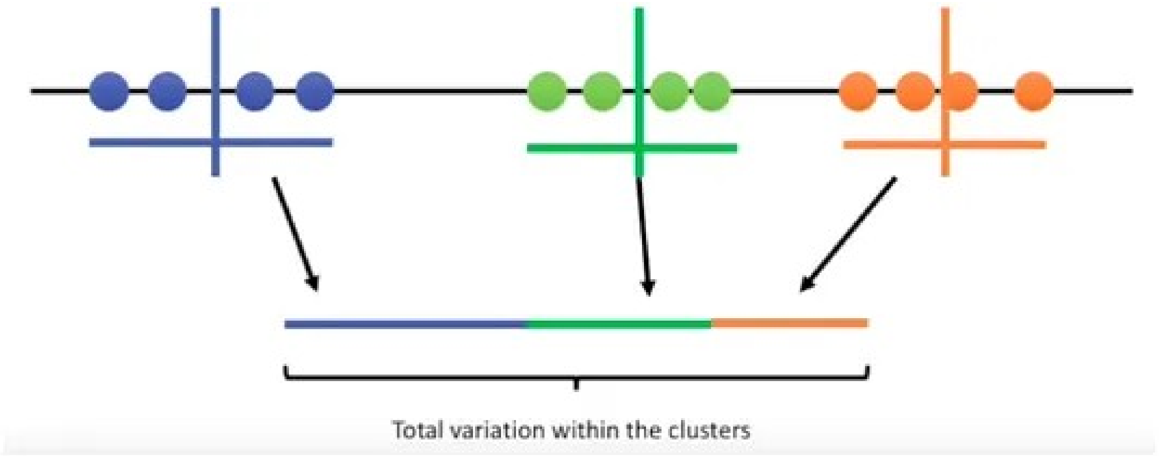
K-Means clustering

- Repeat again "until" we obtain the minimum variance



K-Means clustering

- Repeat again until we obtain the minimum variance



K-Means clustering

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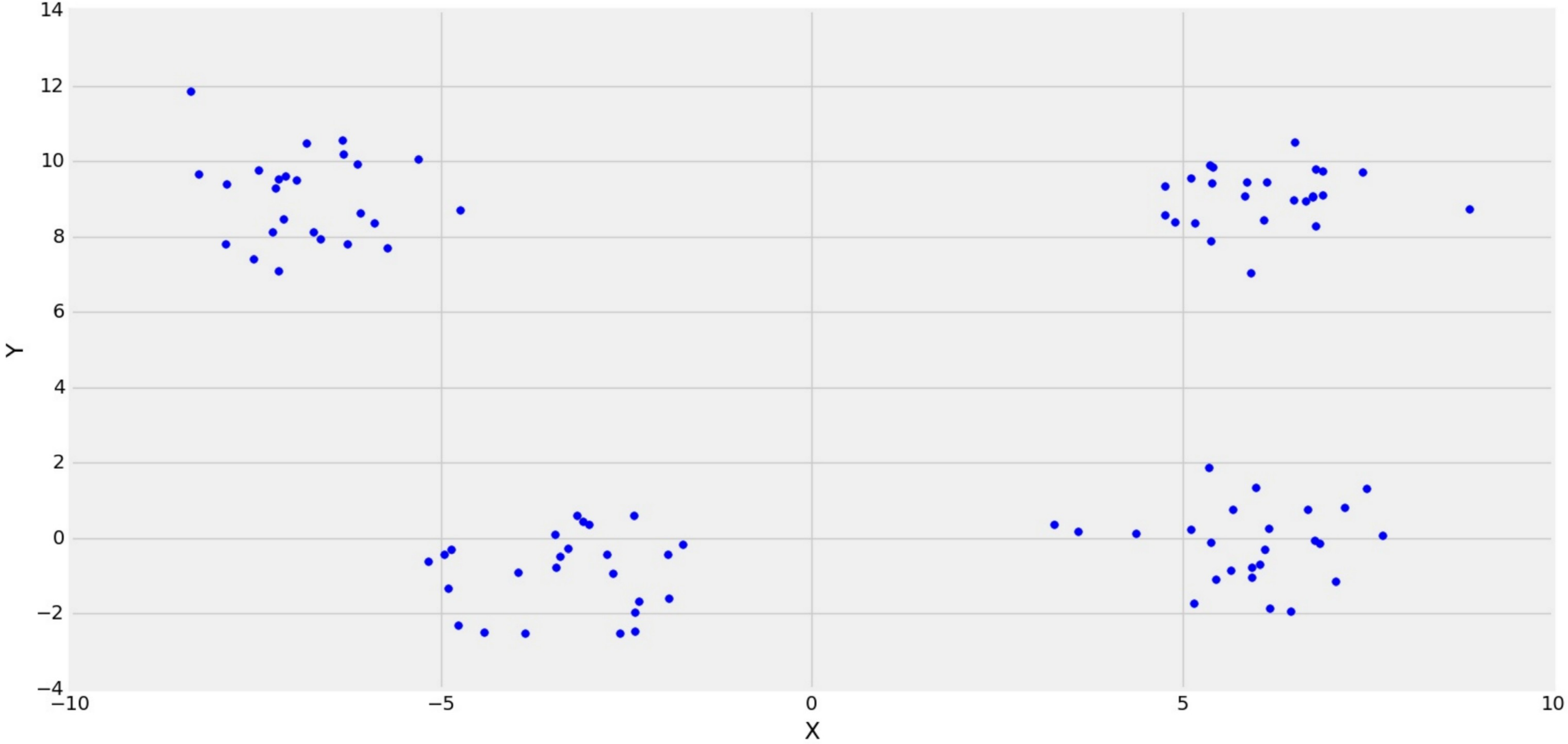
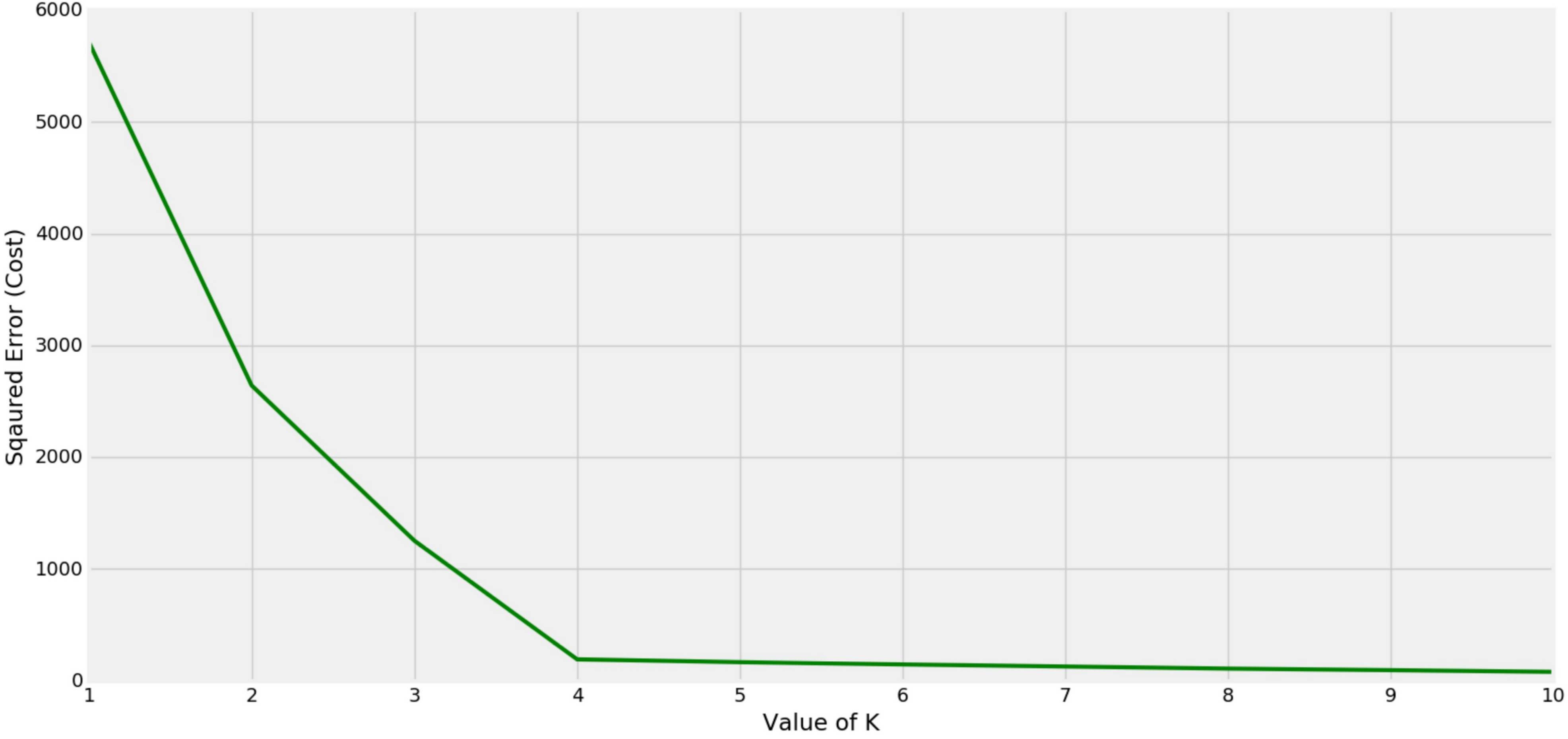
- How to choose a proper value for k?
- Test different ks
  - When k increases $\longrightarrow$ fewer elements in each cluster
    - Also variance declines
  - The k value where variance declines the most is the “elbow” point



14
12
10
8
6
4
2
0
−2
−4
Y
−10
−5
0
5
10
X

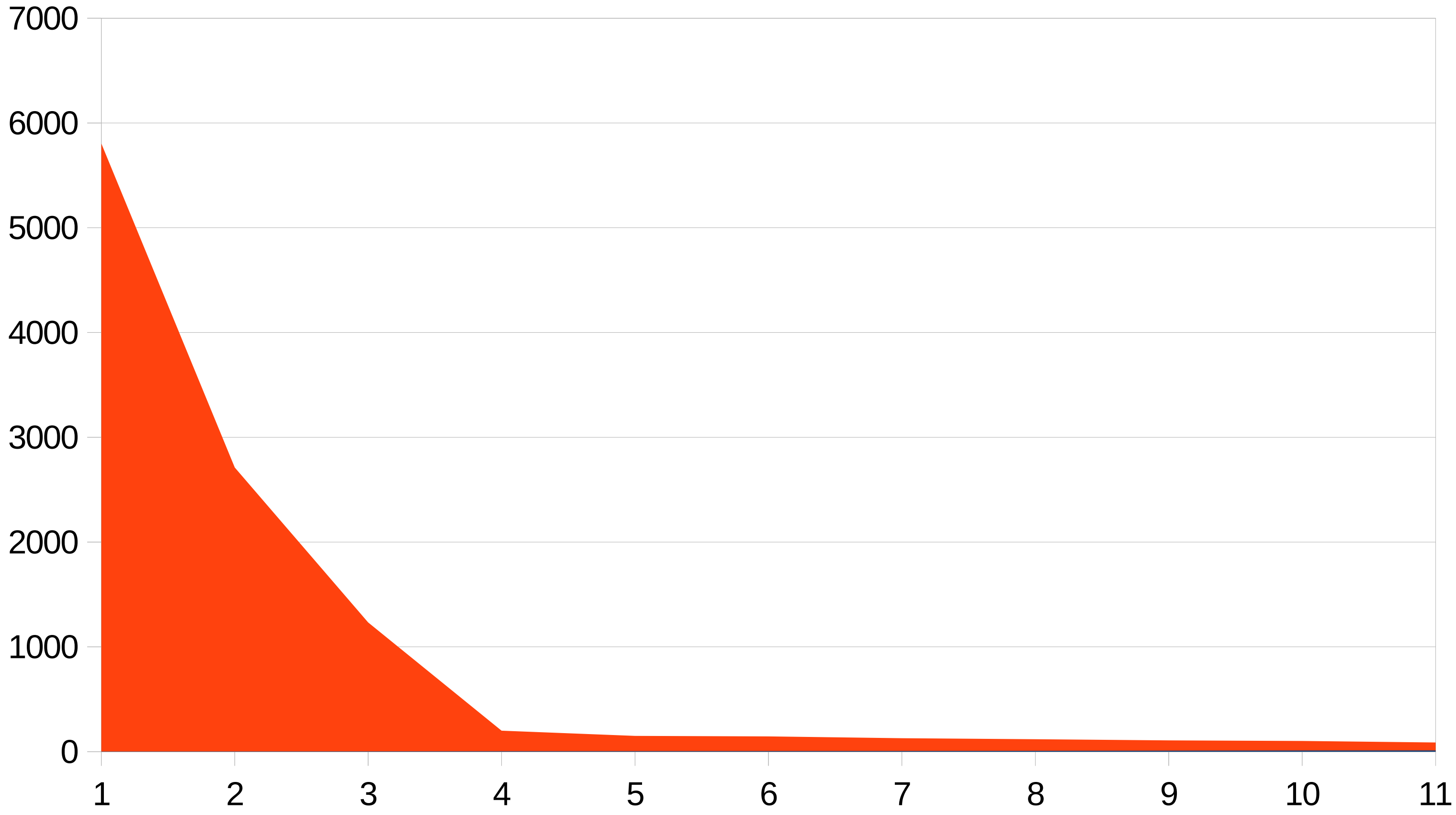


6000
5000
4000
3000
2000
1000
0
Sqaured Error (Cost)
1
2
3
4
5
6
7
8
9
10
Value of K

Computing Elbow point

- For each k/cost compute:
  - Delta1 as delta between k and k-1 costs
  - Delta2 as delta between k and k-1 Delta1s
  - Strength as delta between k+1 Delta2 and Delta1
- Maximum strength $\longrightarrow$ elbow point
- Beware! $\longrightarrow$ not always optimal result!

Example

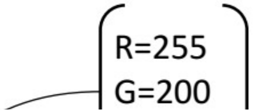


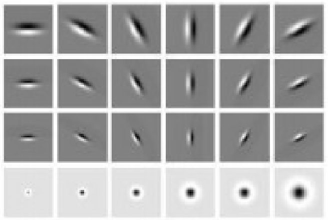
Example

K	Cost	Delta1	Delta2	Elbow?	Strenght
1	5804				
2	2712	3.092			136
3	1234	1.478	1.614		-590
4	200	1.034	444	x	934
5	150	50	984	x	40
6	145	5	45		-29
7	128	17	-12		-3
8	118	10	7		-12
9	107	11	-1	x	1
10	102	5	6		-23
11	88	14	-9		

Features

- In previous slides we used Euclidean distance as a cost function
- We can select other approaches
  - Intensity clustering
  - Color clustering
  - Texture clustering
  - …





Filter bank of 24 filters

Features

- Not always image space coherence
- As example when using color clustering we have a vector clustering

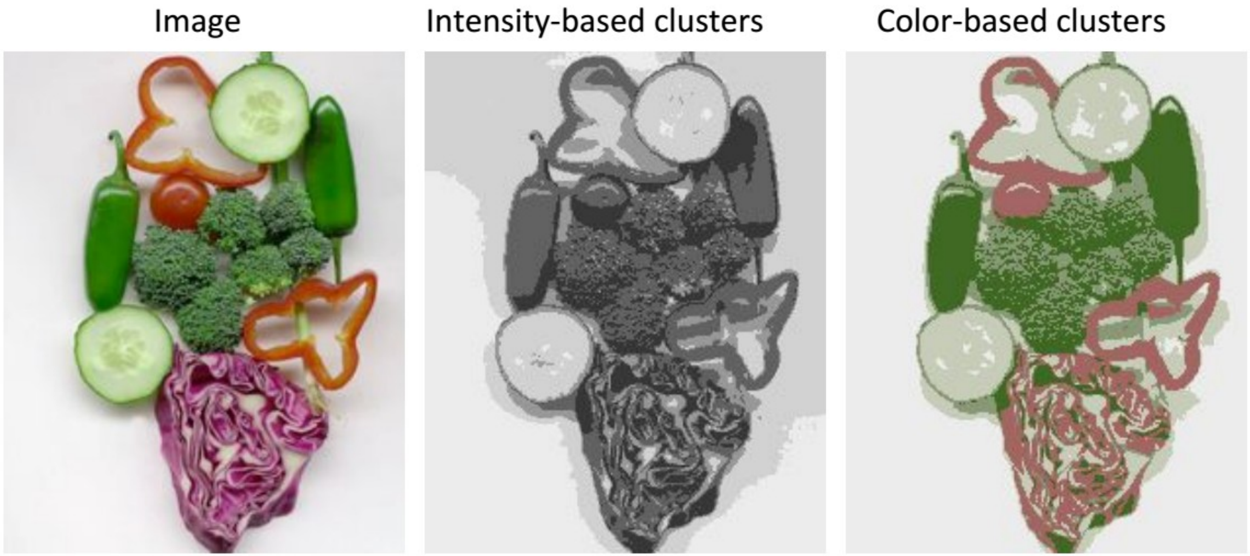
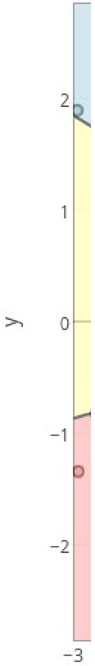


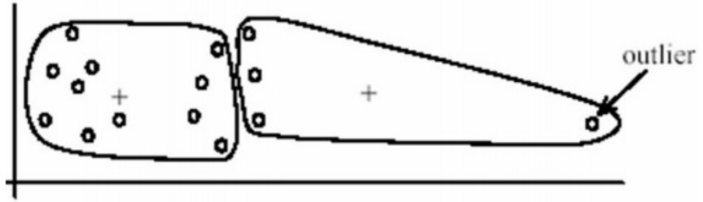
Image source: Forsyth & Ponce

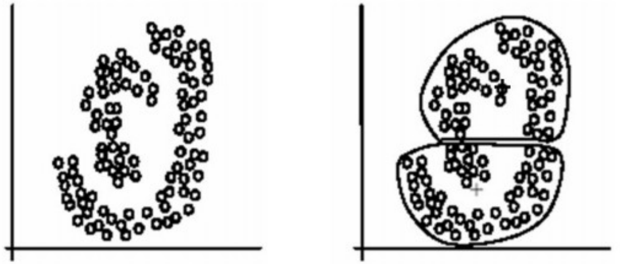
K-means limits

- Each point is assigned to a given cluster
  - No probability function
- Very sensitive to outliers
  - Centroids are affected
  - K-Medians is a K-Means variant to cope with this
- Good with “round shaped” clusters
- Bad with convex distributions
  - Voronoid space



(B): Ideal clusters





(A): Two natural clusters (B): *k*-means clusters

K-means steps

- Images can not be a suitable data for clustering
- We need to extract relevant data $\longrightarrow$ vector
- The output of k-means us then
  - A list of centroids
  - Labelled data
  - Compactness measure (quality of the result)

K-means OpenCV

```
double cv::kmeans   (
    InputArray data,                       // vector of data
      int K,                               // the K in K-means
      InputOutputArray bestLabels,         // labels (output/input)
      TermCriteria criteria,               // termination criteria
      int attempts,                        // number of tries
      int flags,                           // flags
      OutputArray centers = noArray()      // centroids list
  )
```

K-means OpenCV

- The function returns a “compactness” index
- Labels can be also used to input the initial centroids estimation
- Flags can be used to
  - Initialization method for centroids. KMEANS_RANDOM_CENTERS, KMEANS_PP_CENTERS
  - How to manage labels: KMEANS_USE_INITIAL_LABELS
- cv::TermCriteria: specific class for iterative methods:
  - Type (flag), maxCount, Espsilon (for accuracy)

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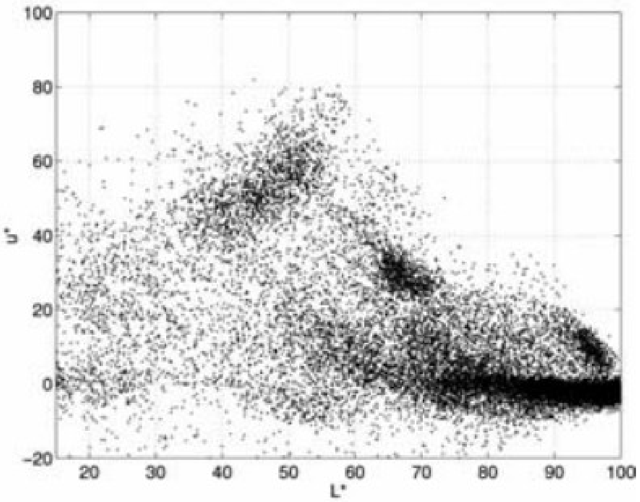
Mean-shift clustering

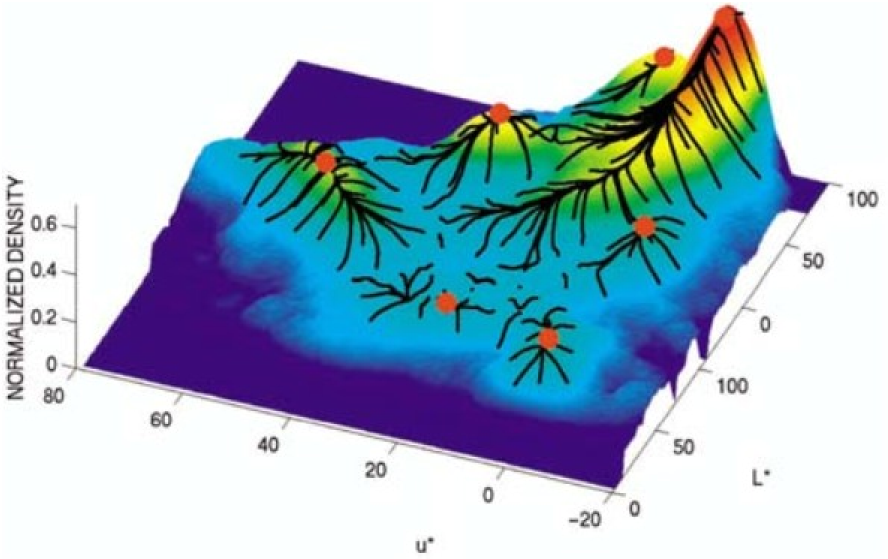
Mean shift

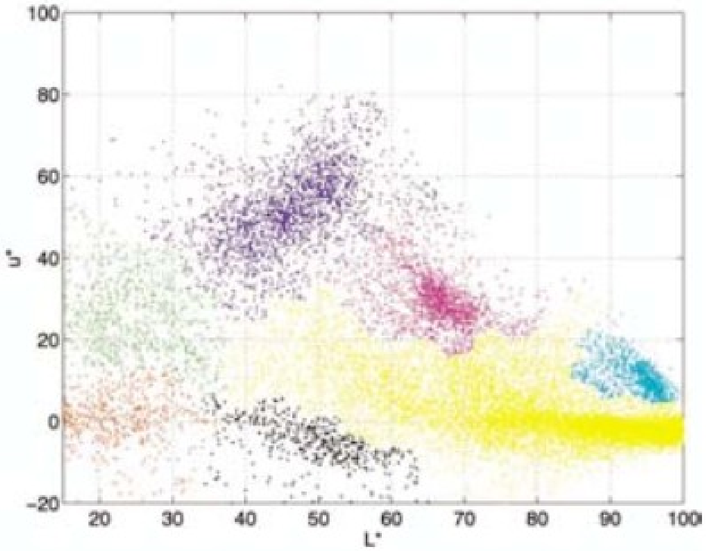
- As for k-means we work on data, not directly on images
  - For simplicity we assume a 2D data
  - Higher dimensionality is anyway possible



Mean shift

- Looking at data we can imagine a potential clustering
  - Density based
  - Consider density as a third "dimension"





Mean shift

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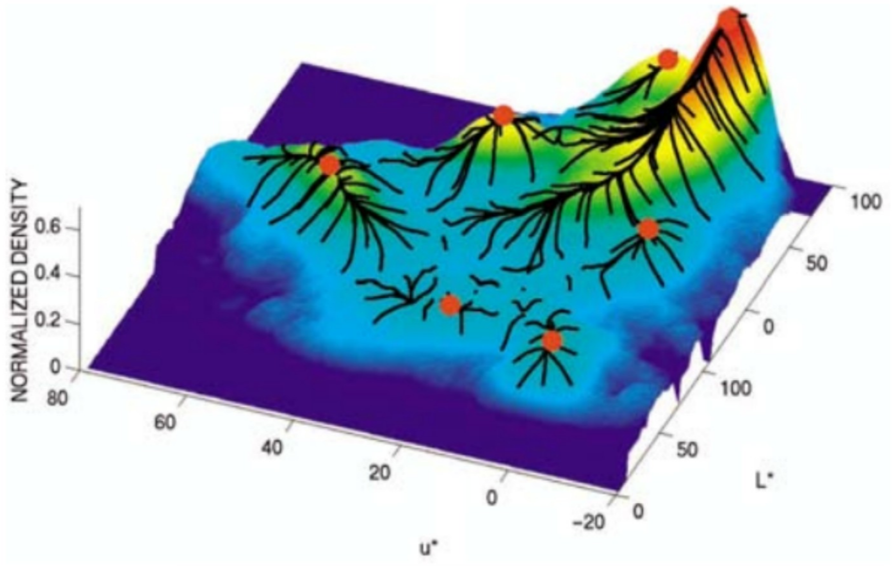
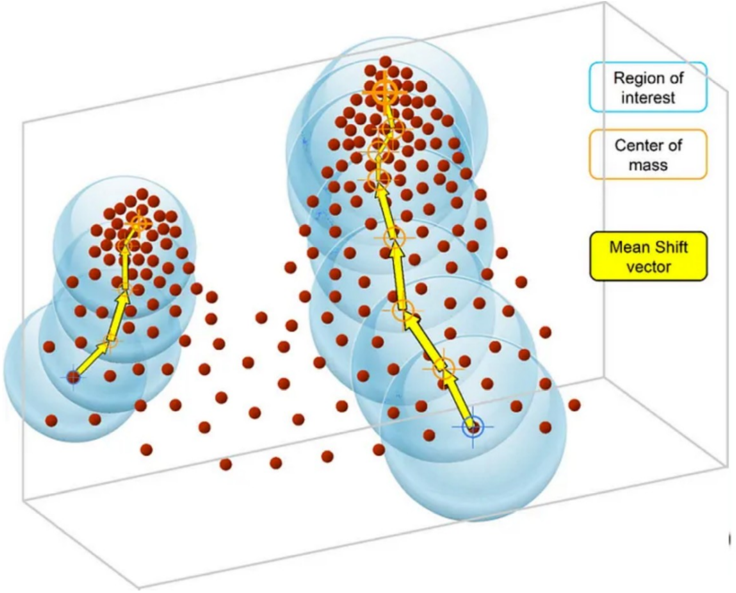
- Iteratively we can have each datum to "climb" the hill
  - Expensive when a large or complex dataset is used
  - The use a reduced set of "seeds" is possible





Mean shift

1) Initialize random seed and a search window W around it
2) Compute center of gravity (the "mean") of W using a kernel density estimation function K()
   - Typically a Gaussian
3) Shift W to the mean
4) Repeat (2) until convergence

Mean shift

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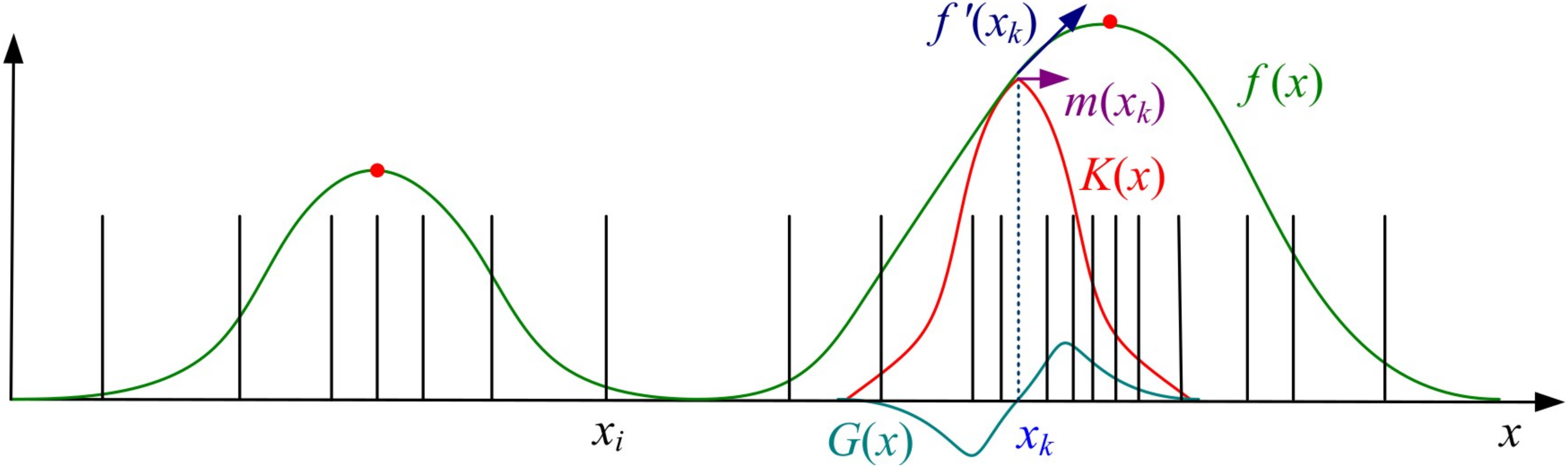
- Mean shift (m(x)) of "sampled" data f(x) using a K() window

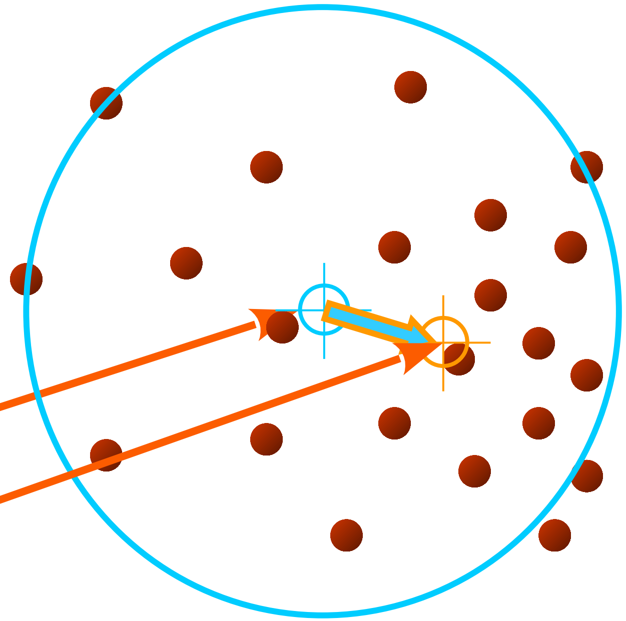


Mean shift

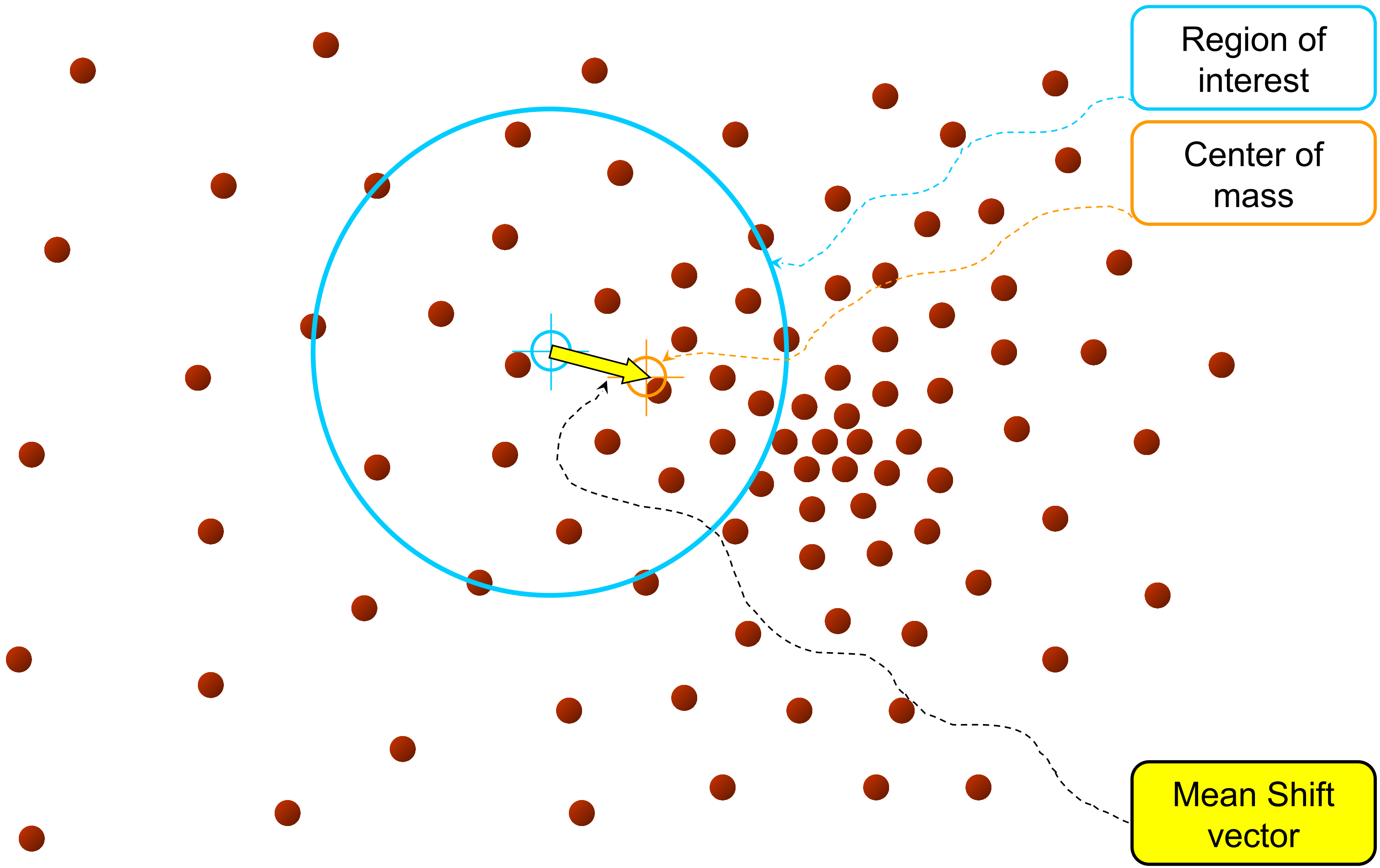
- Compute mean shift
  - Usually a Gaussian approach is used
- Translate W by m(x)

$$G(x) = -K'(x)$$

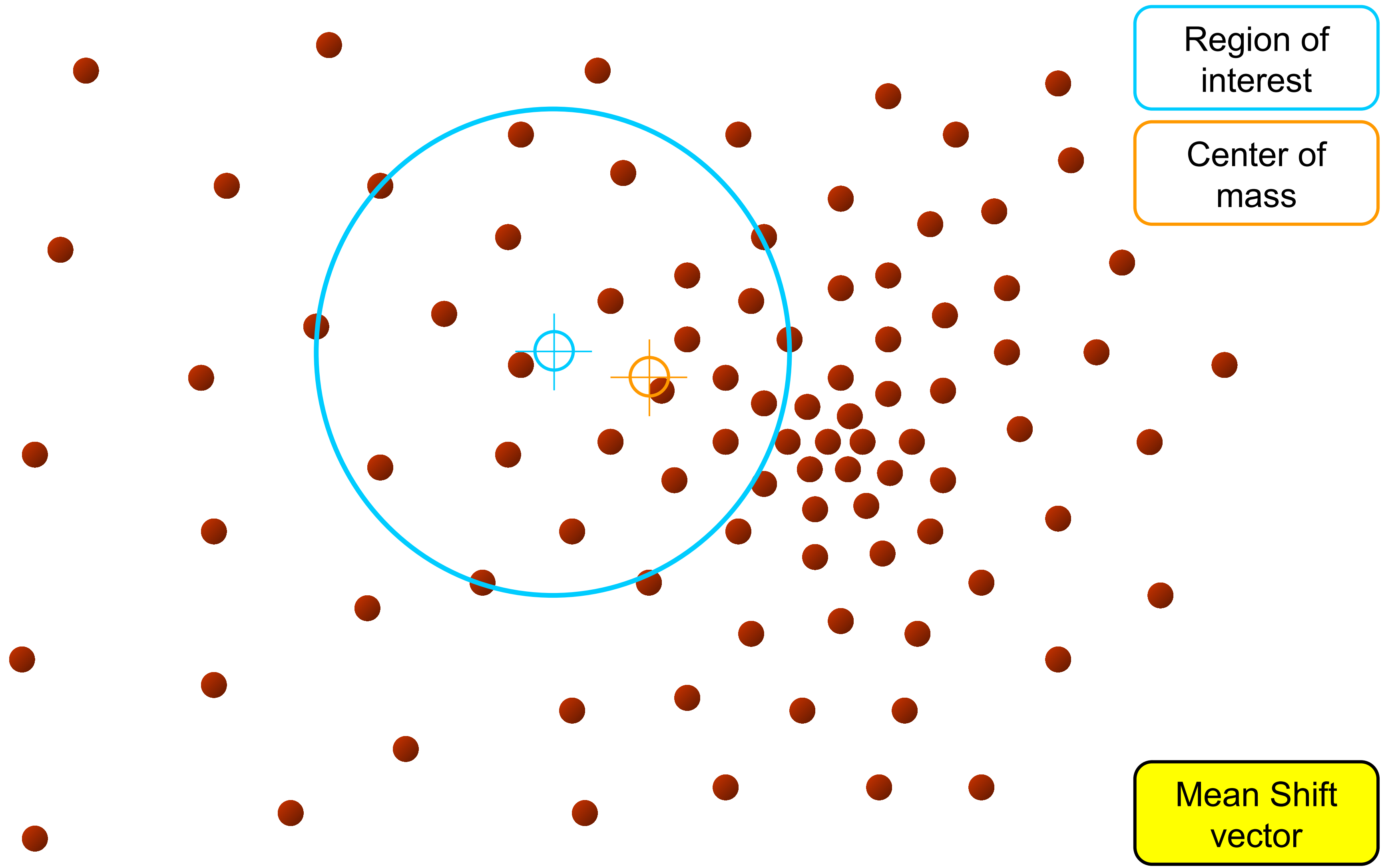
$$m(x) = \left[\boxed{\frac{\sum_{i=1}^{n} x_i G\left(\frac{\|x - x_i\|^2}{h}\right)}{\sum_{i=1}^{n} G\left(\frac{\|x - x_i\|^2}{h}\right)}} - \boxed{x} \right]$$



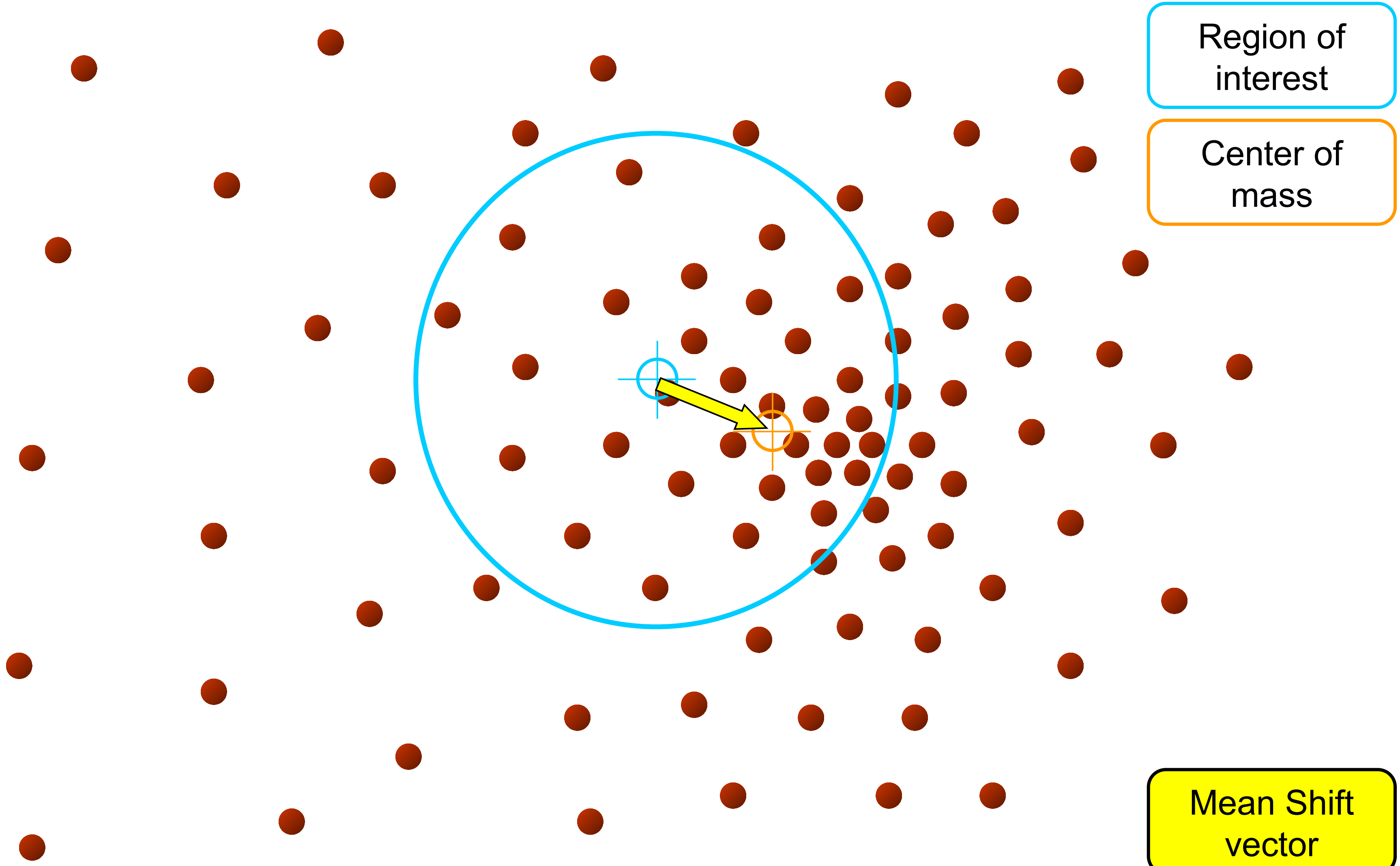
h ⟶ bandwidth (~size of W)

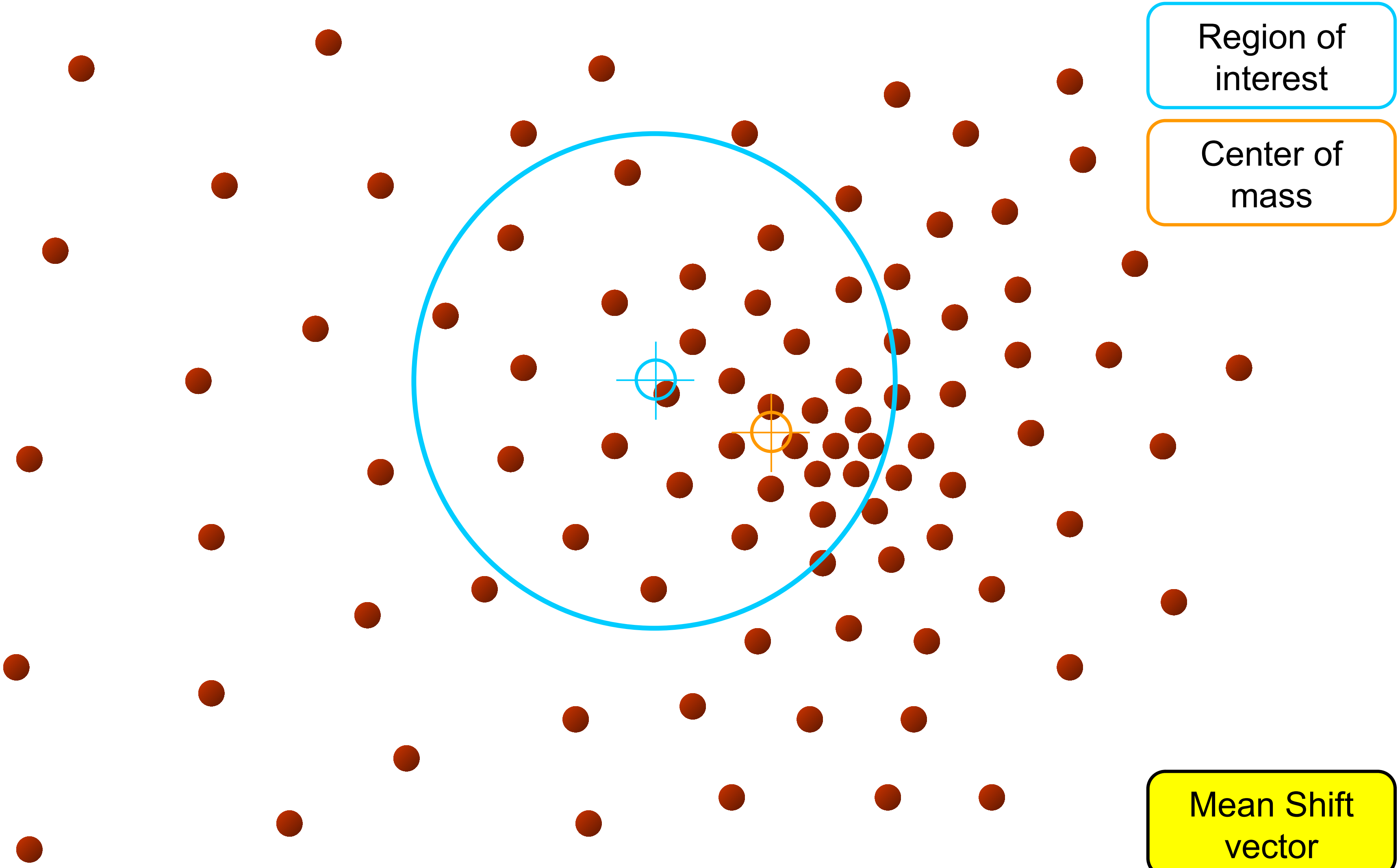


Slide by Y. Ukrainitz & B. Sarel



Slide by Y. Ukrainitz & B. Sarel


Region of interest
Center of mass
Mean Shift vector



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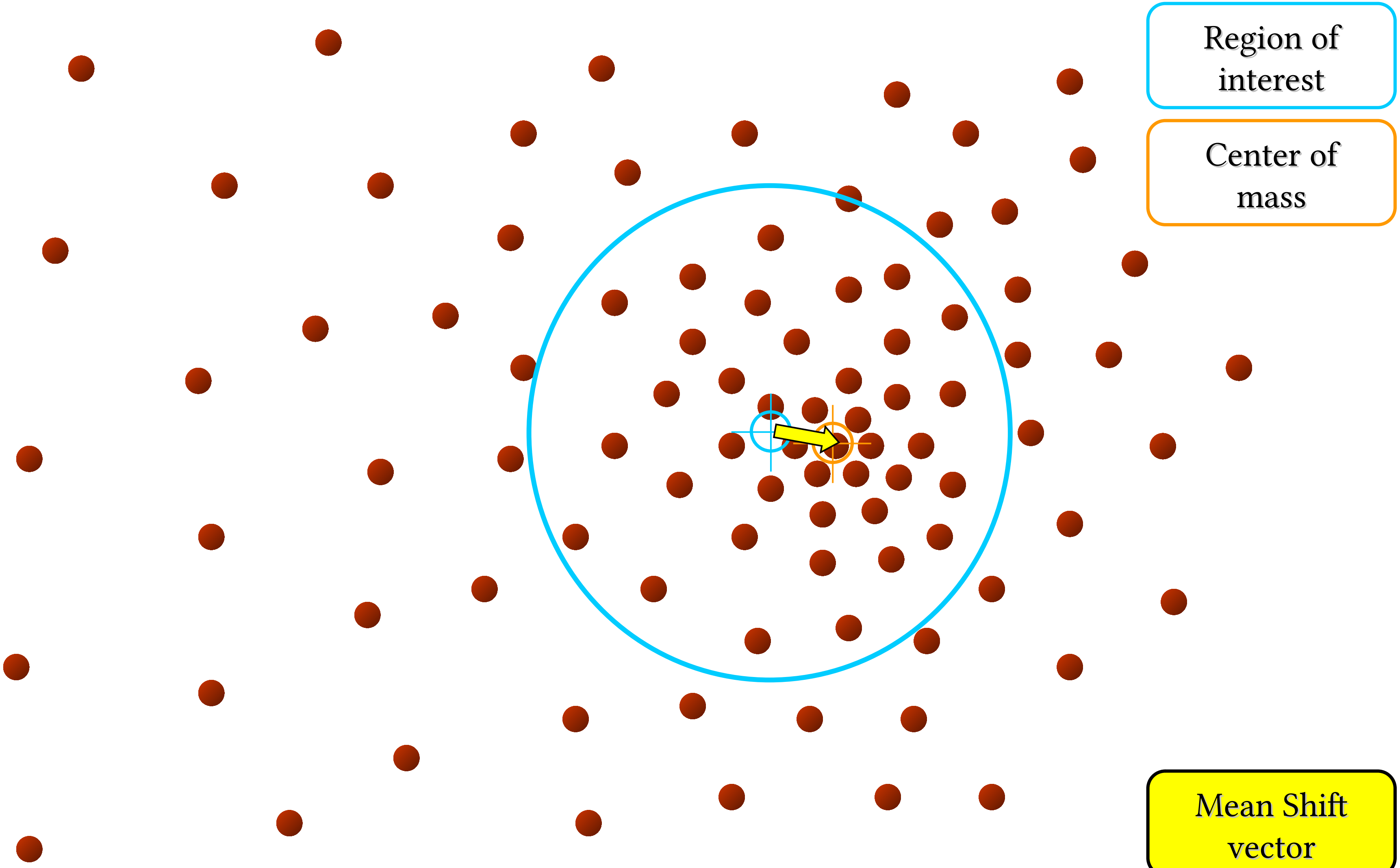

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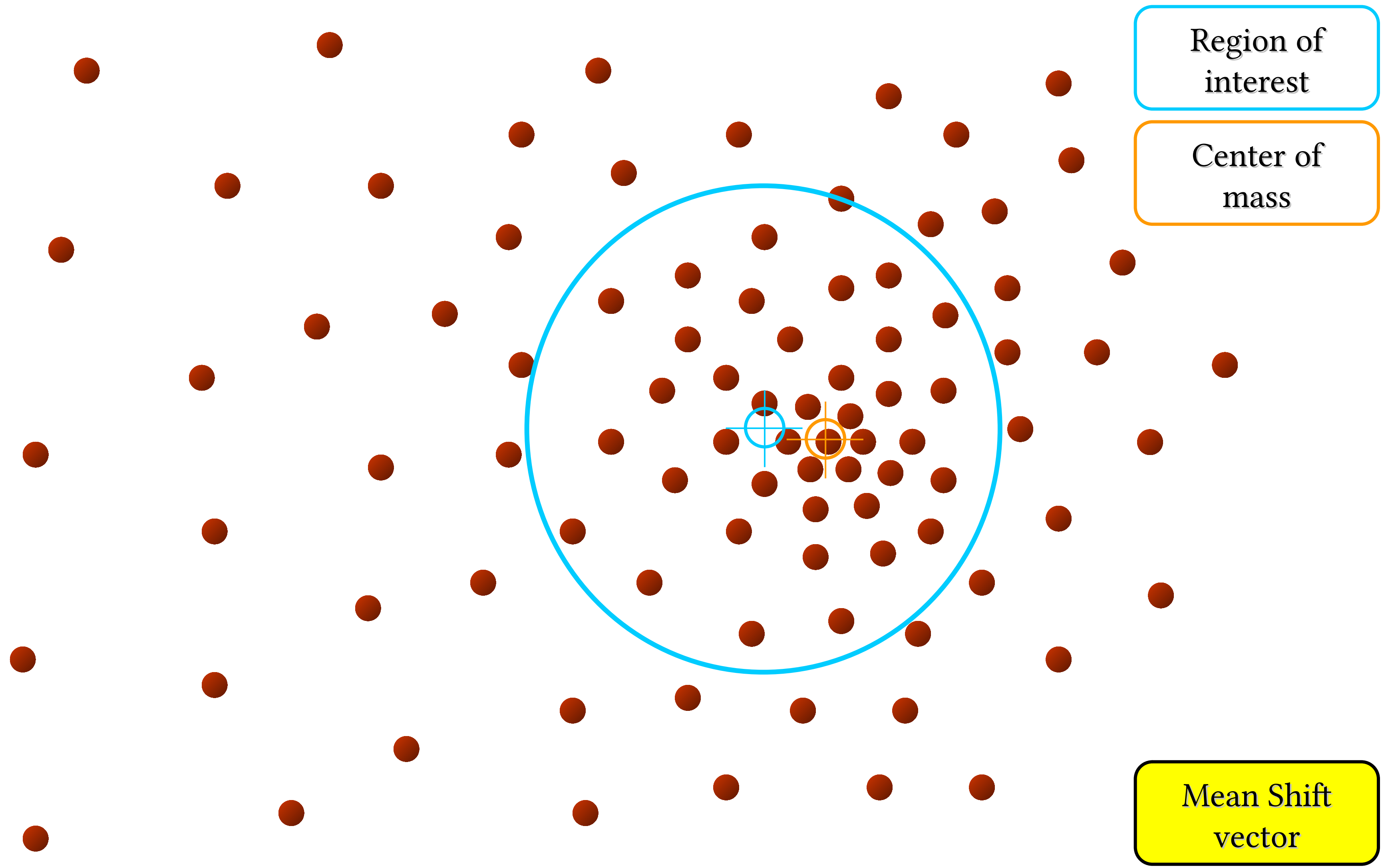

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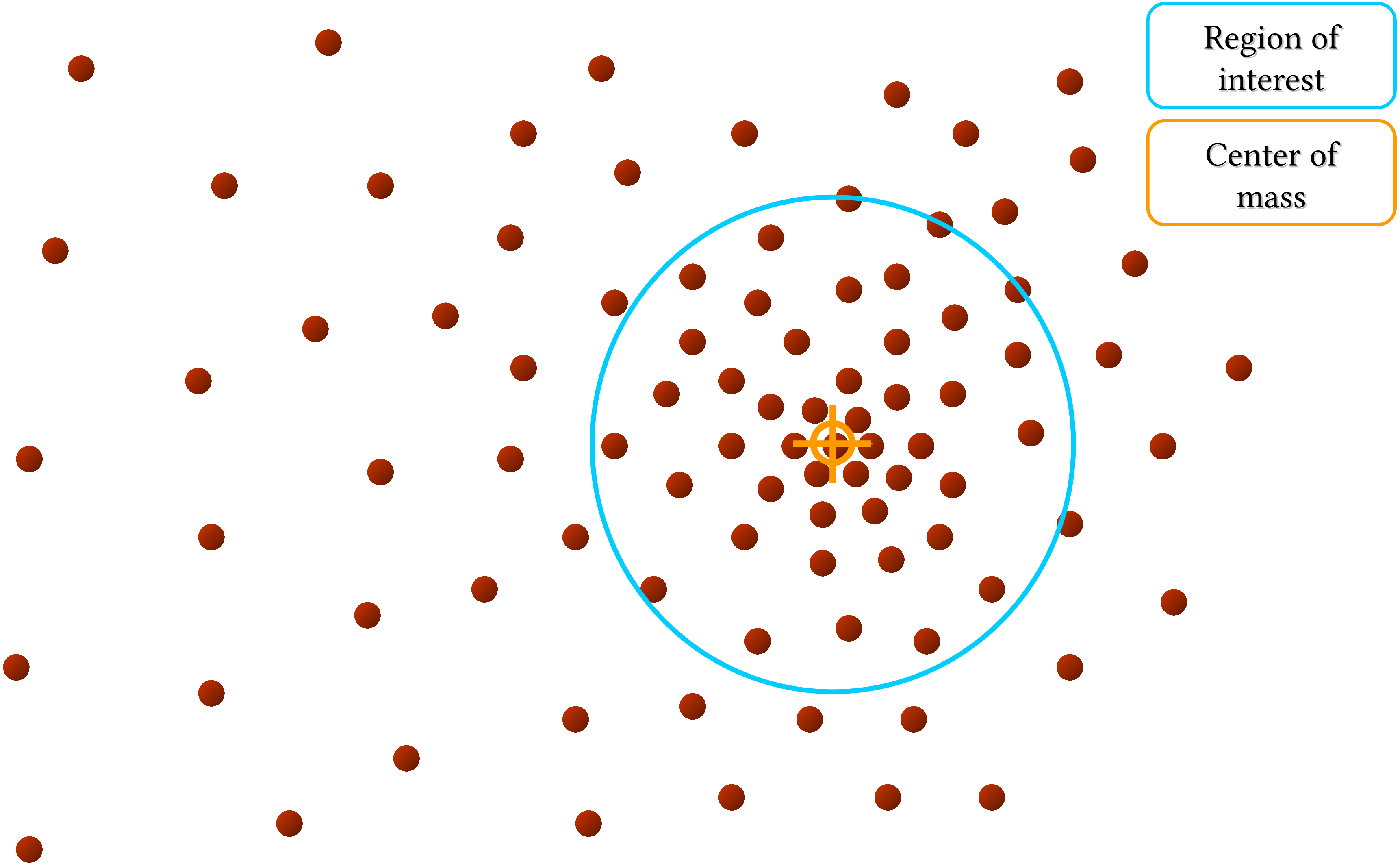
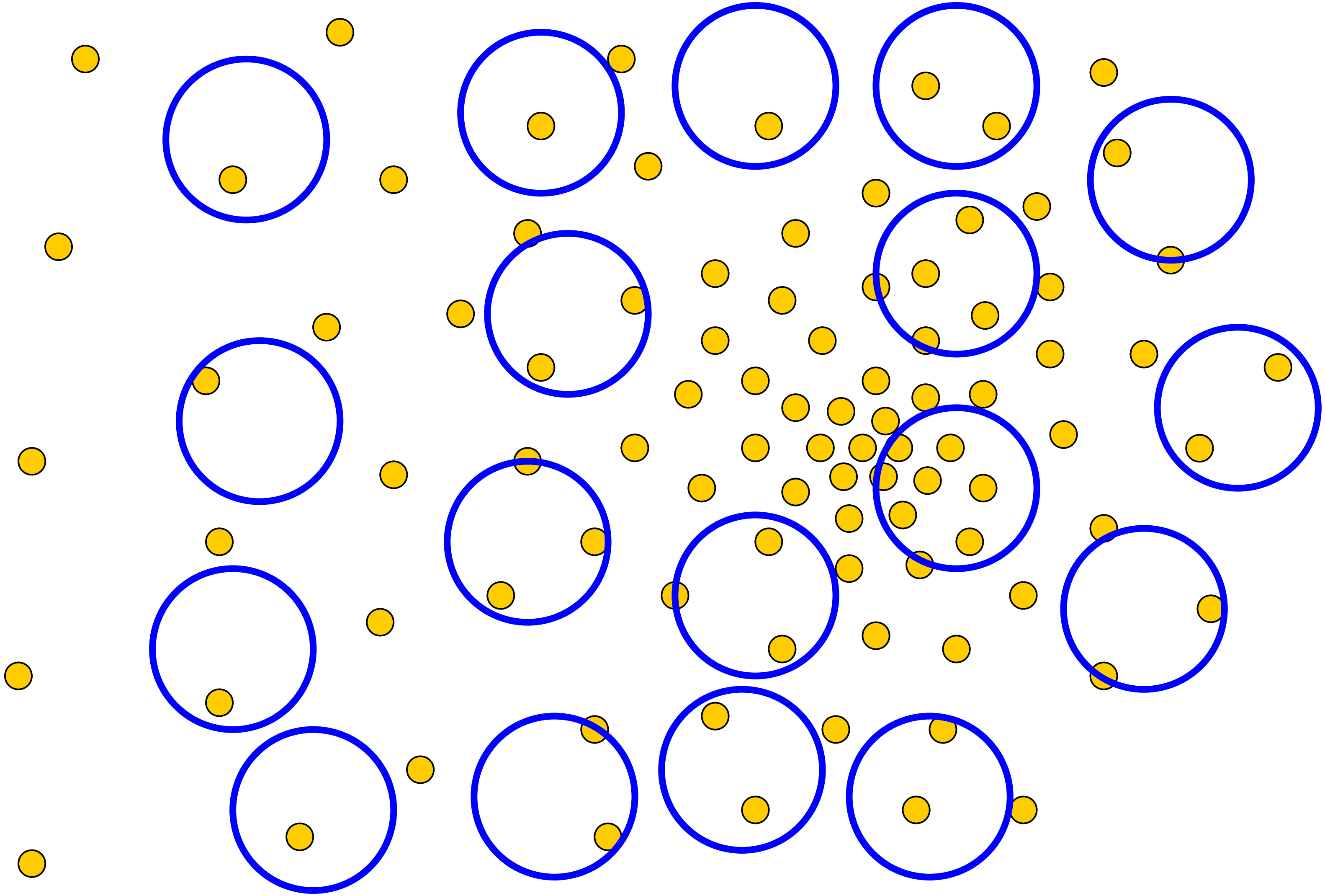
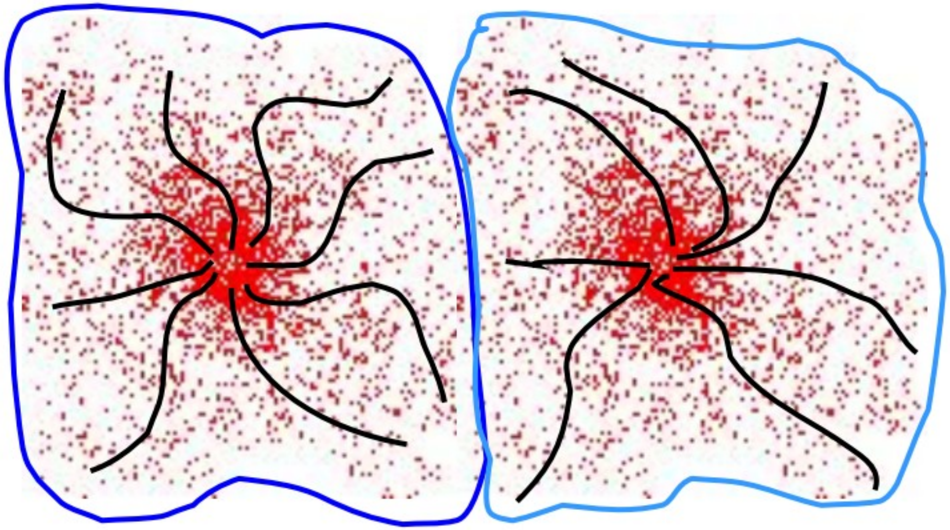


Slide by Y. Ukrainitz & B. Sarel



Mean Shift

- Attraction basins → region where all trajectories lead to the same node
- Cluster → all points in the attraction basin of each node

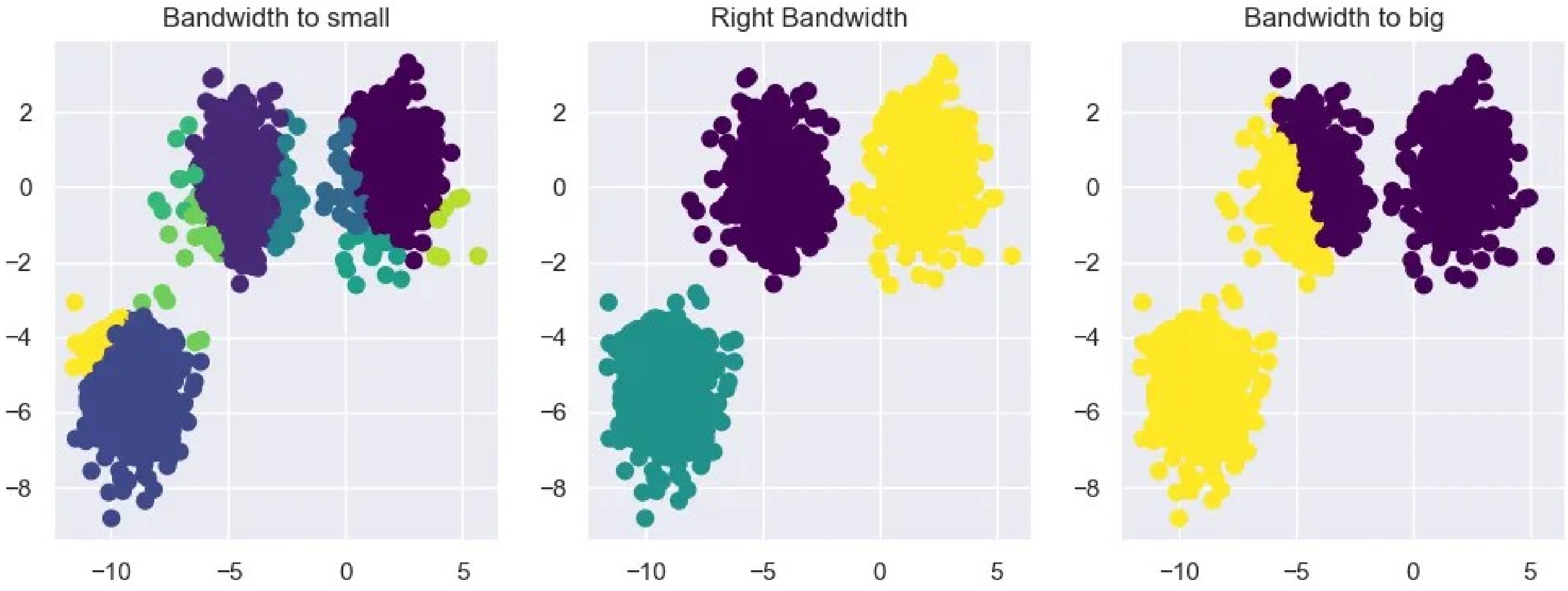


Mean Shift examples

Mean Shift: summary

- Pros
  - Good results
  - Flexible
  - Robust to outliers
- Cons
  - We have to choose kernel size
  - Not suitable for high dimensional features
  - Slow

Mean shift: bandwidth selection



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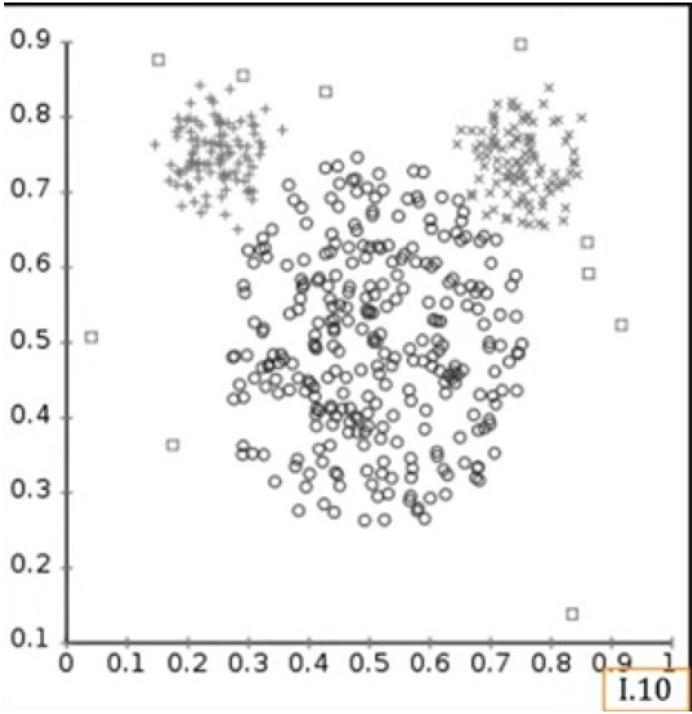
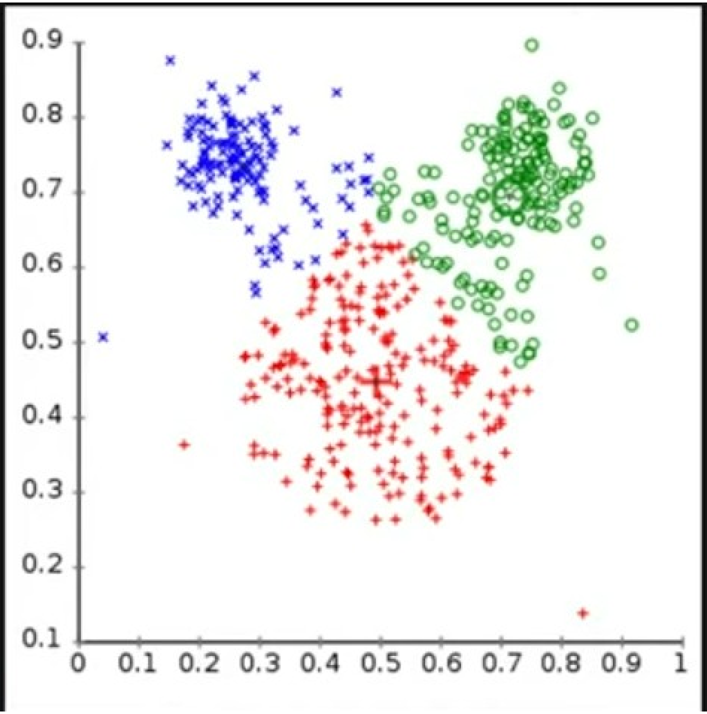
K-means vs mean shift

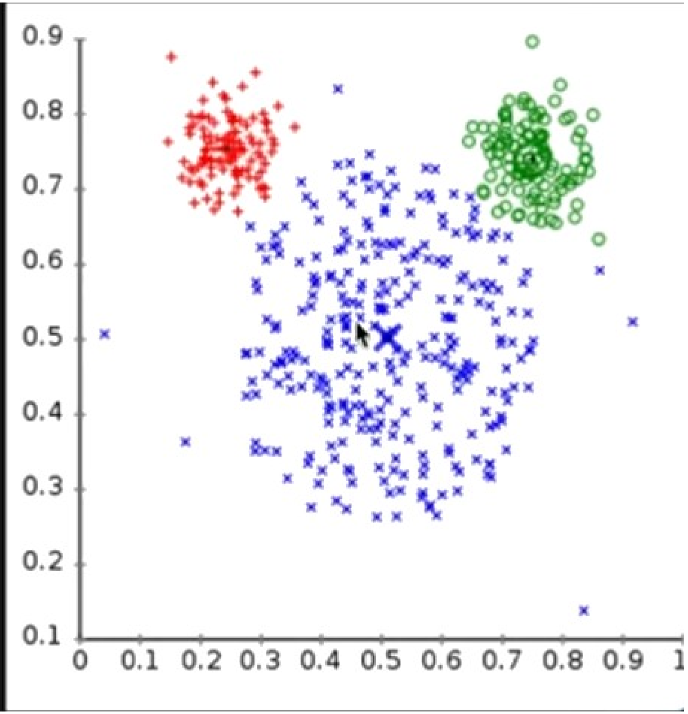
K-means vs mean shift



Original Data



K-means (k=3)



Mean shift

K-means vs mean shift

Original Data

K-means (k=16)

Mean shift

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Other clustering approaches

Other clustering approaches

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- Spectral clustering
- Agglomerative clustering
- Graph cut
- …
- All bottom-up approaches!

Semantic segmentation (DL)

Instance segmentation (DL)

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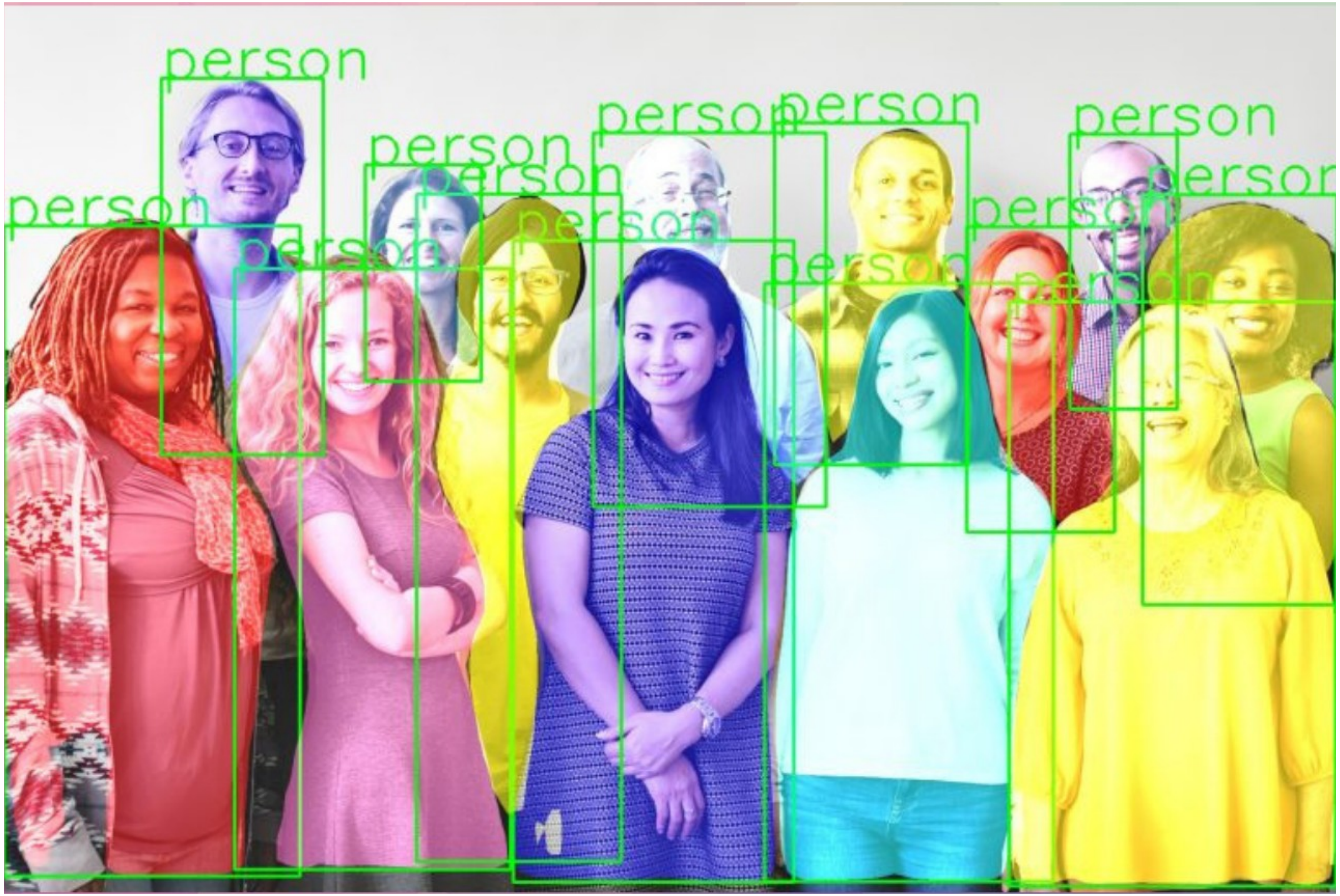

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Image Segmentation

Question time!