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Image Segmentation



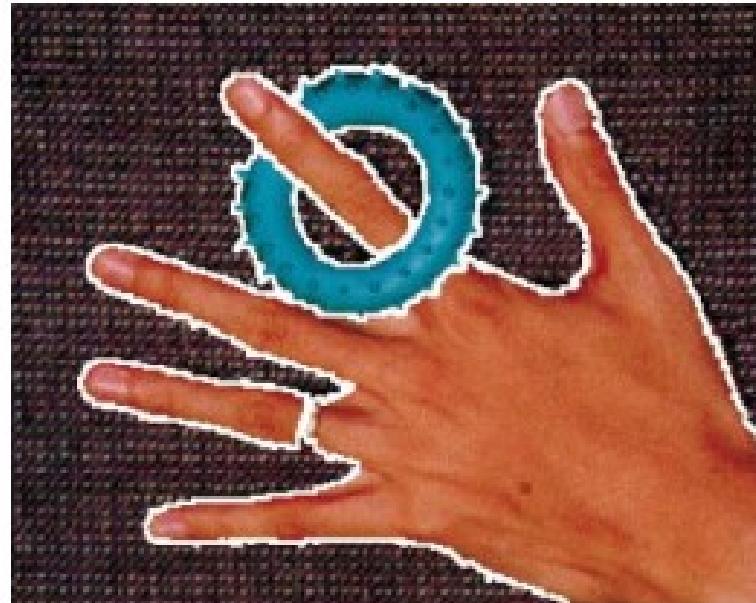
- What does “segmentation” means?
- K-Means
- Mean-shift

- [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 → **components**
- Usually a more compact representation of an image



Why we use segmentation?



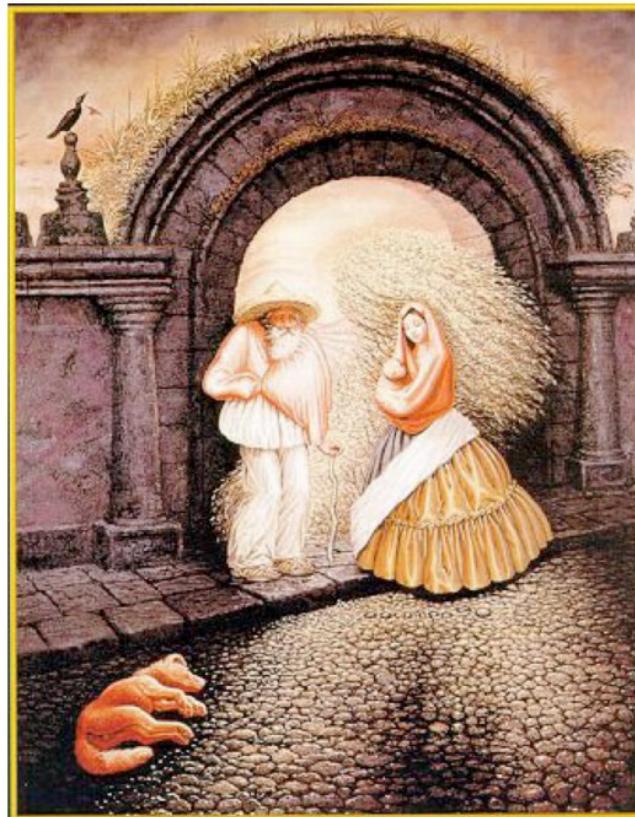
- From image to description
 - Low level → medium level
- Components are often blocks for other algorithms



What does segmentation means?

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

What does segmentation means?

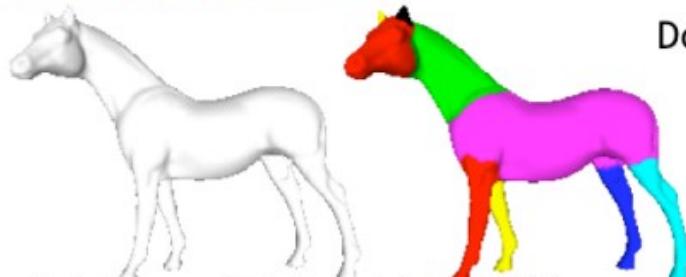


Source: Silvio Savarese

What does segmentation means?



Douillard, et al. ICRA 2011



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

How do humans segment?

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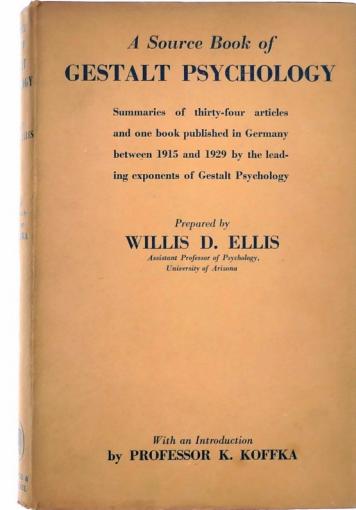
How do humans segment?

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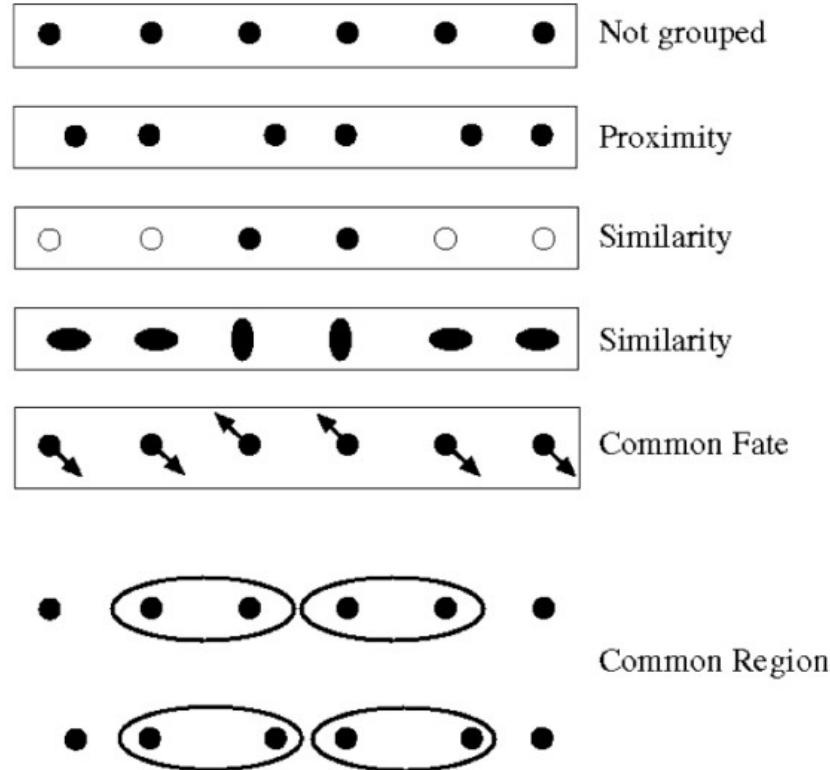


- German word for “shape”, “structure”
- The brain is holistic and parallel
 - Namely no “simple steps” as for algorithms
- Whole is greater than the sum of its parts
 - We perceive objects in their entirety
 - Only after that we perceive details
- What are the principles that allow us to do so?





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



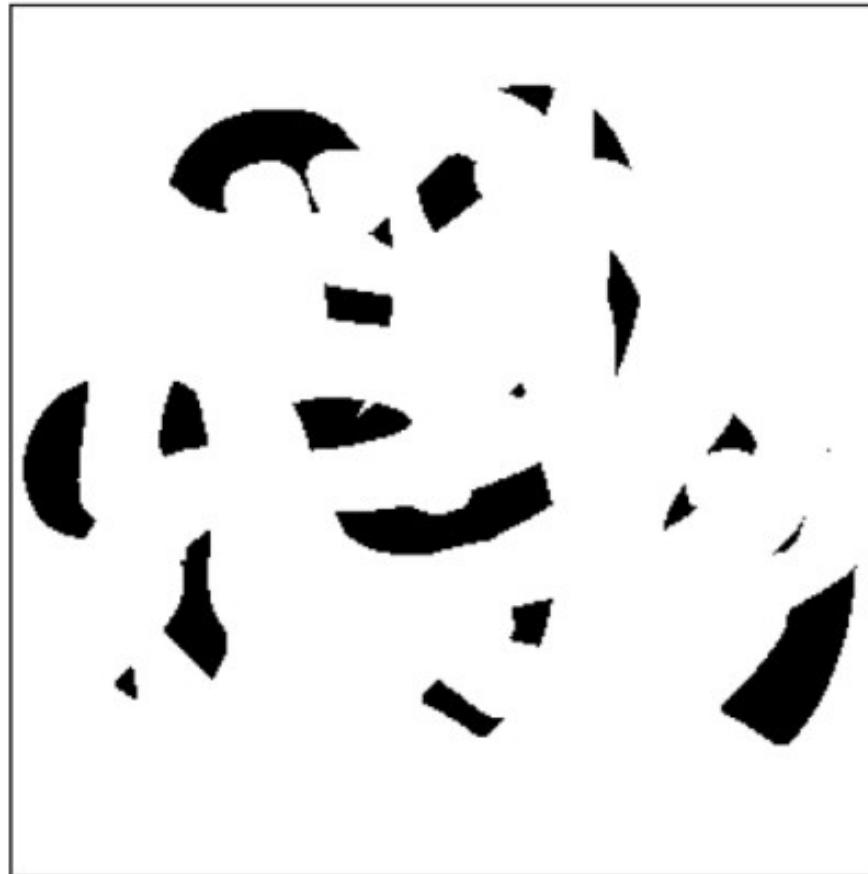


Grouping
by occlusions



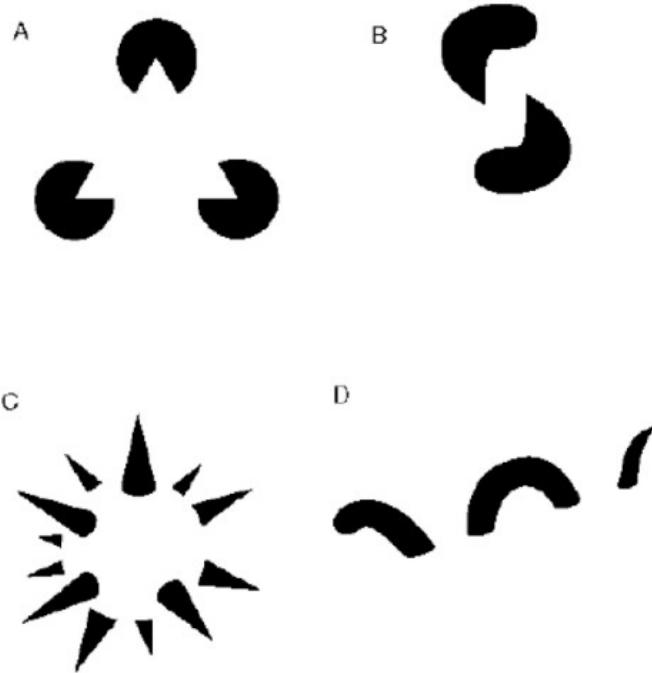


Grouping by occlusions

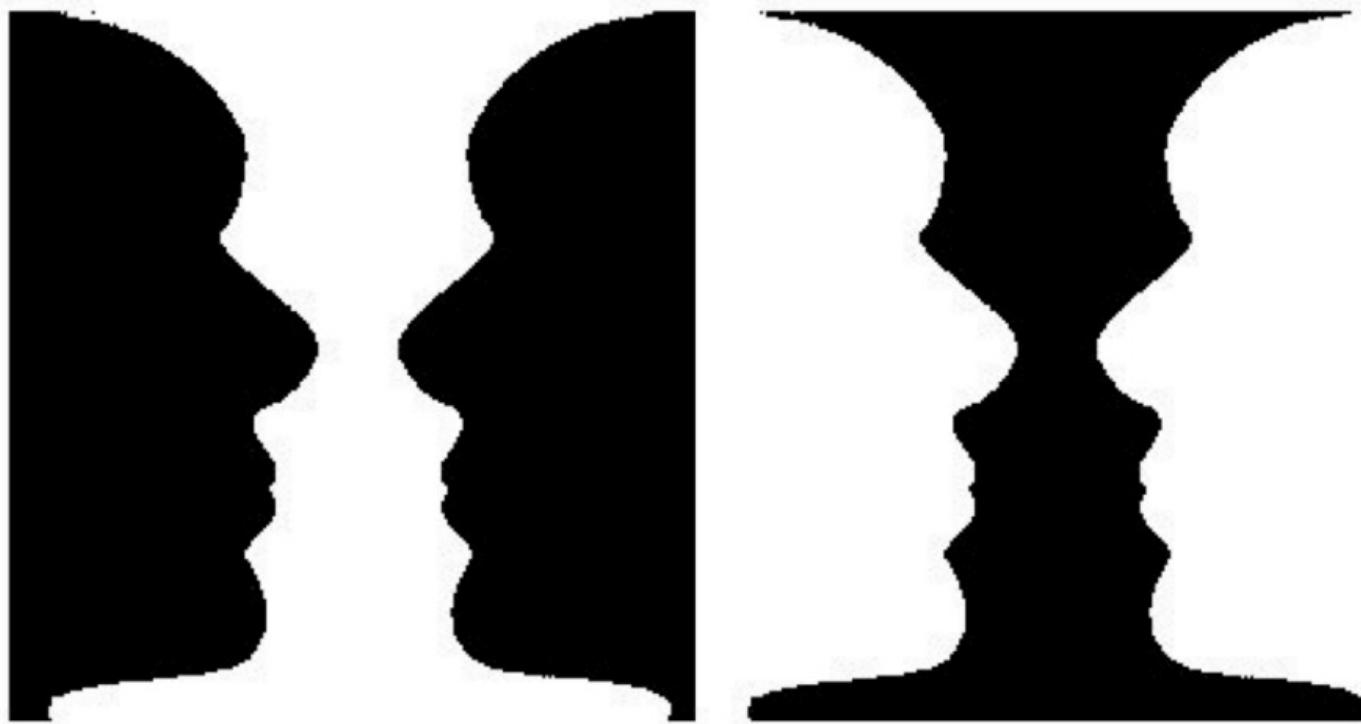




Grouping
by invisible
completions



Gestalt

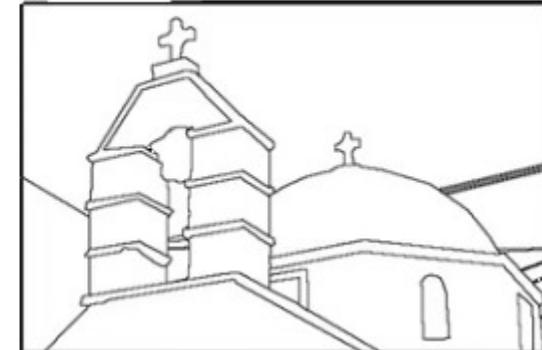
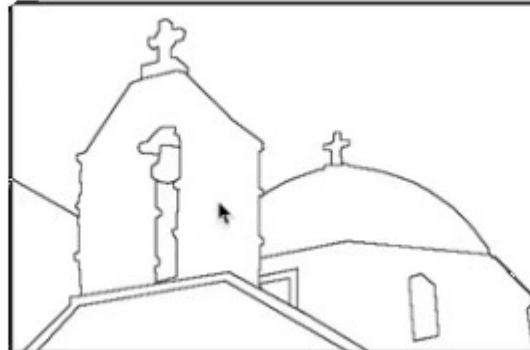
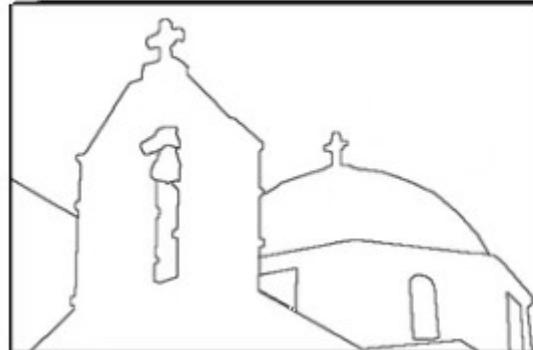




If we ask to different users to segmentate, different results are obtained



**Segmentation is
HIGHLY
Subjective!**

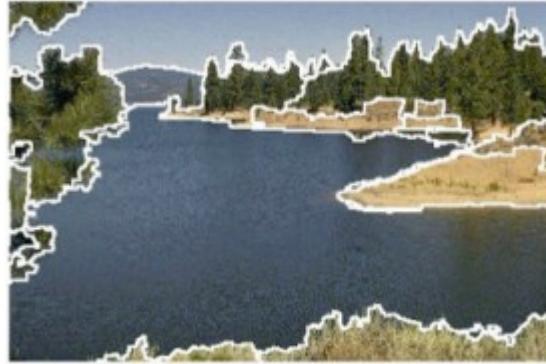


- Segmentation is intuitive for us
 - Even if highly subjective
- Very hard to translate it to an algorithm!
 - If we do not know how it works, how we can write an algorithm?
- Anyway two basic approaches

Strategies



- Bottom-up: components are locally coherent



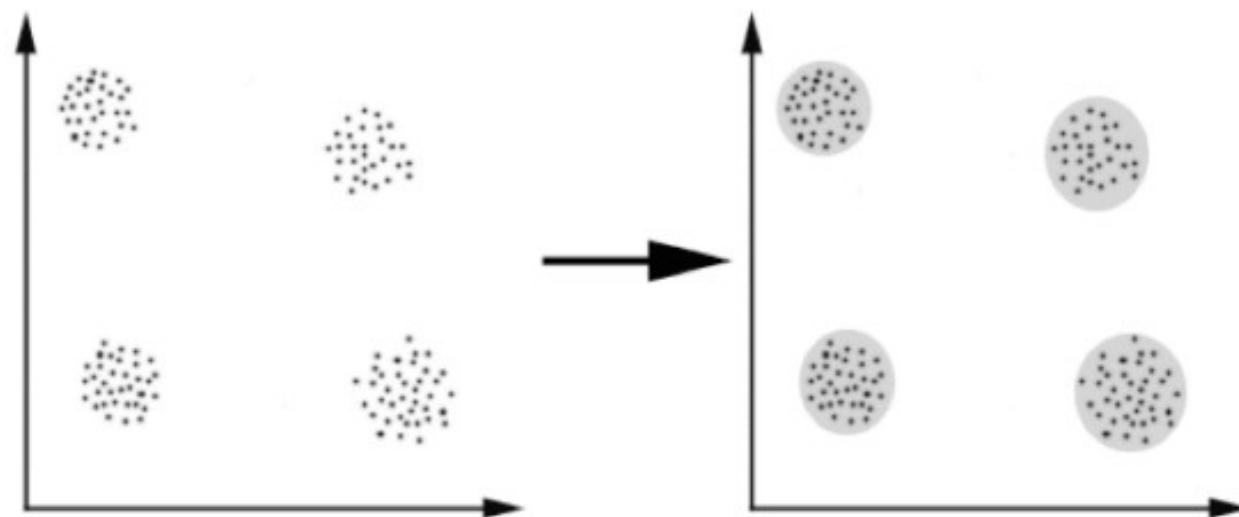
- Top-down: components belong to same entity (object, scene...)



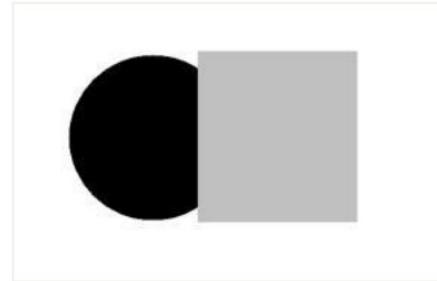
Clustering



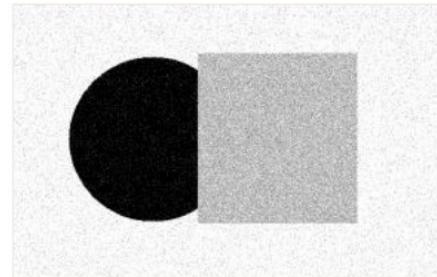
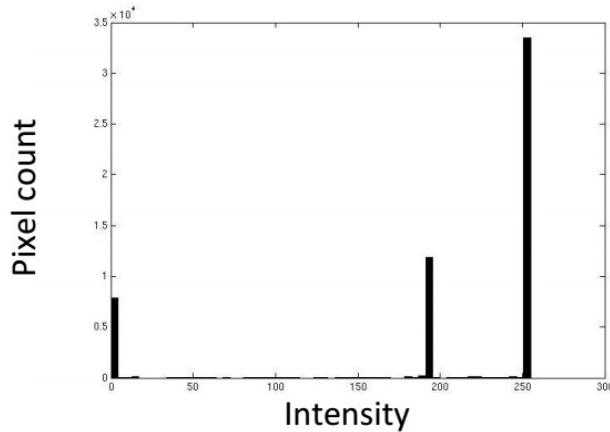
- Each point belongs to a specific “cluster”
- It depends on points visual characteristics
 - A “vector”



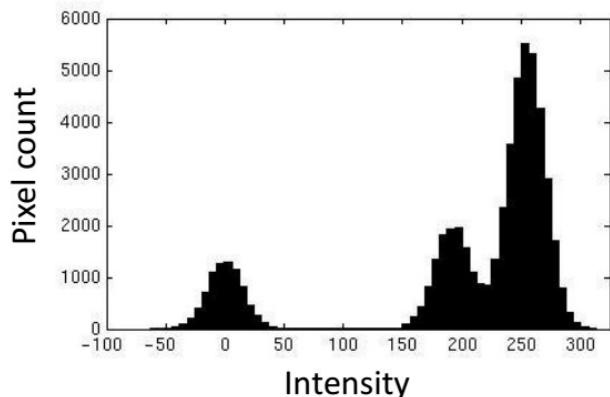
Clustering



Input image



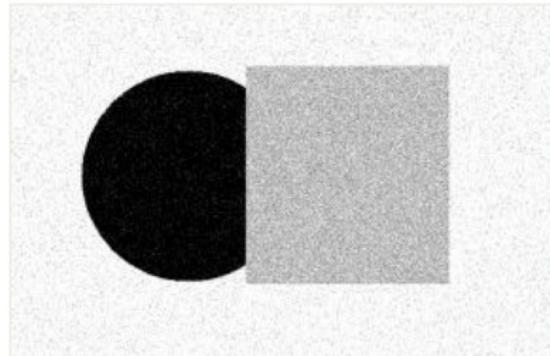
Input image



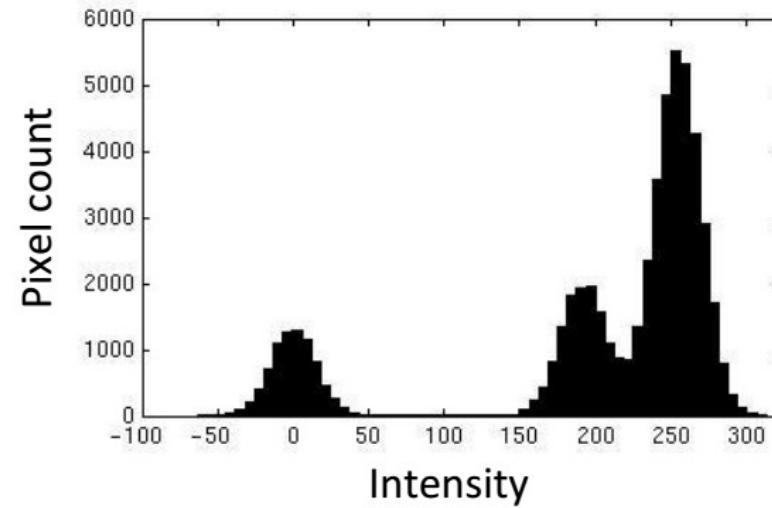
Clustering



- Clustering → identify different luminance levels



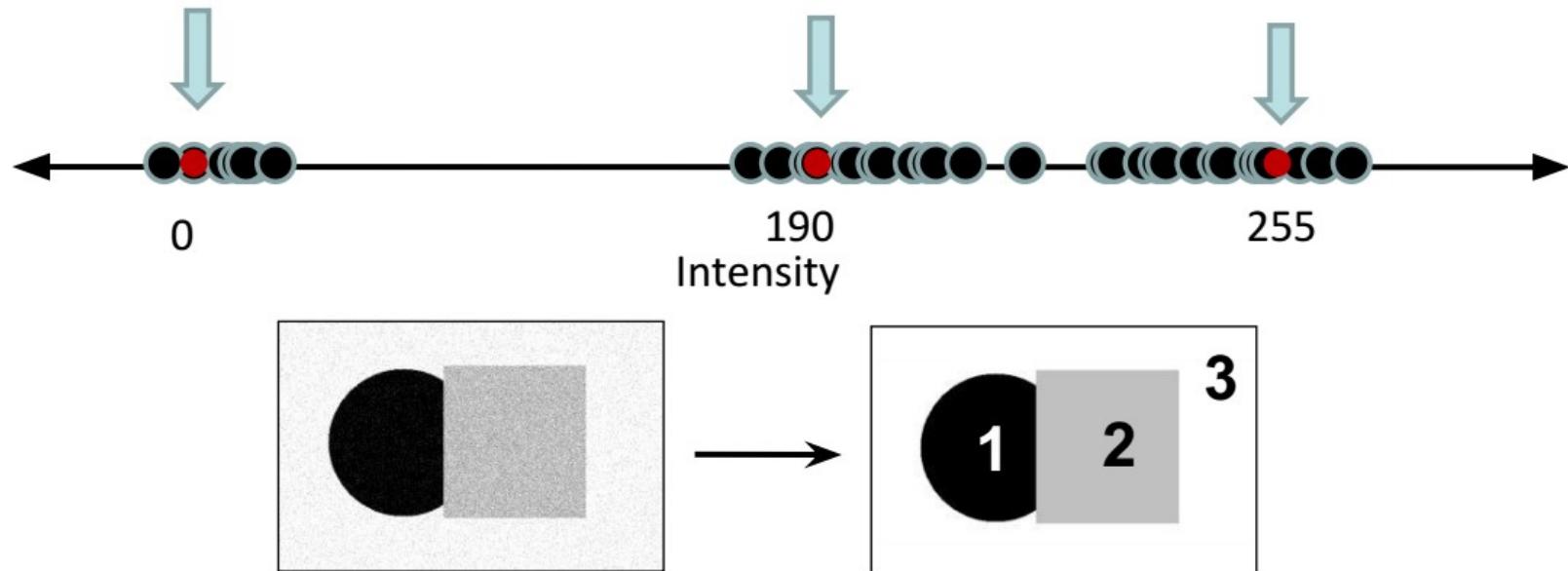
Input image



Clustering



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

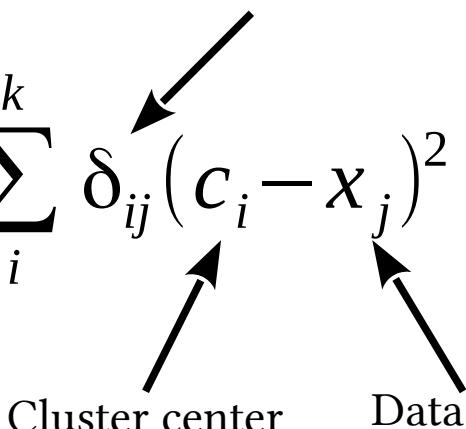




- Underlying idea: minimize “distance” of each “pixel” from cluster center
 - Given N data & k clusters:

$$c^*, \delta^* = \arg \min_{c, \delta} \frac{1}{N} \sum_j^N \sum_i^k \delta_{ij} (c_i - x_j)^2$$

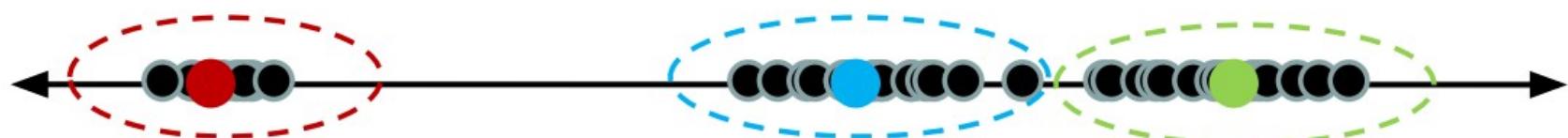
Is x_j belonging to c_i ?



The diagram illustrates the components of the clustering cost function. It shows a mathematical expression where the term δ_{ij} is highlighted with three arrows pointing to its components: "Cluster center" (pointing to c_i), "Data" (pointing to x_j), and "Is x_j belonging to c_i ?".



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



Clustering techniques

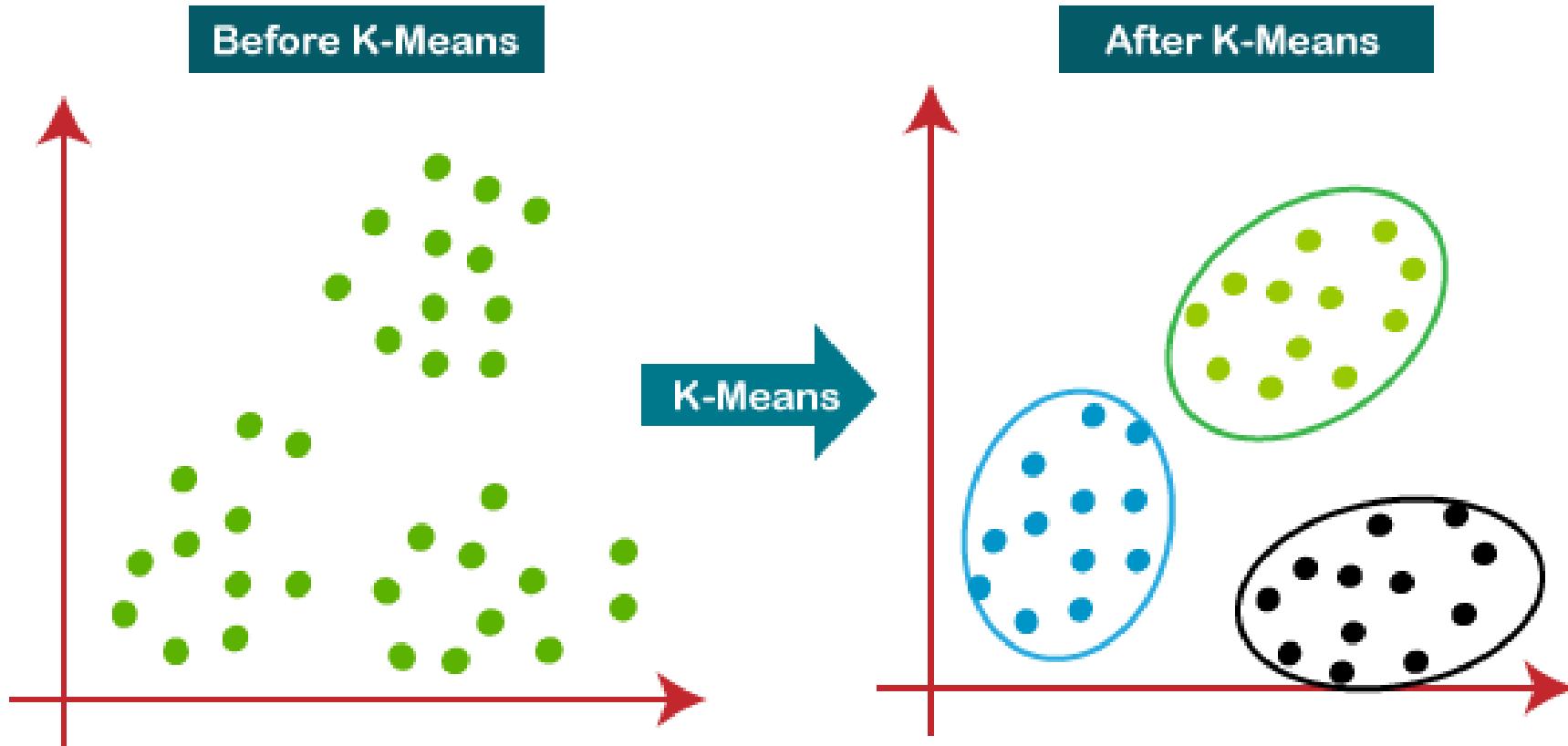
- K-Means
 - Predefined number of clusters
 - “Spherical” clusters
- Mean-shift
 - Variable number of clusters
 - No a priori shape assumptions
 - Slow



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K-means clustering

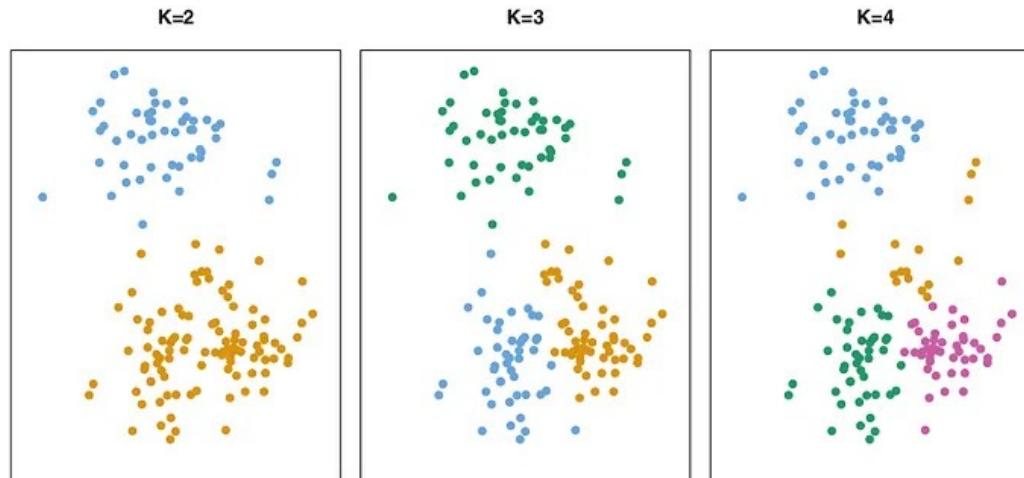
K-Means clustering



K-Means clustering



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



K-Means clustering

- Initialization
 - Choose k cluster centers
- Repeat
 - Assignment 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 Assignment step



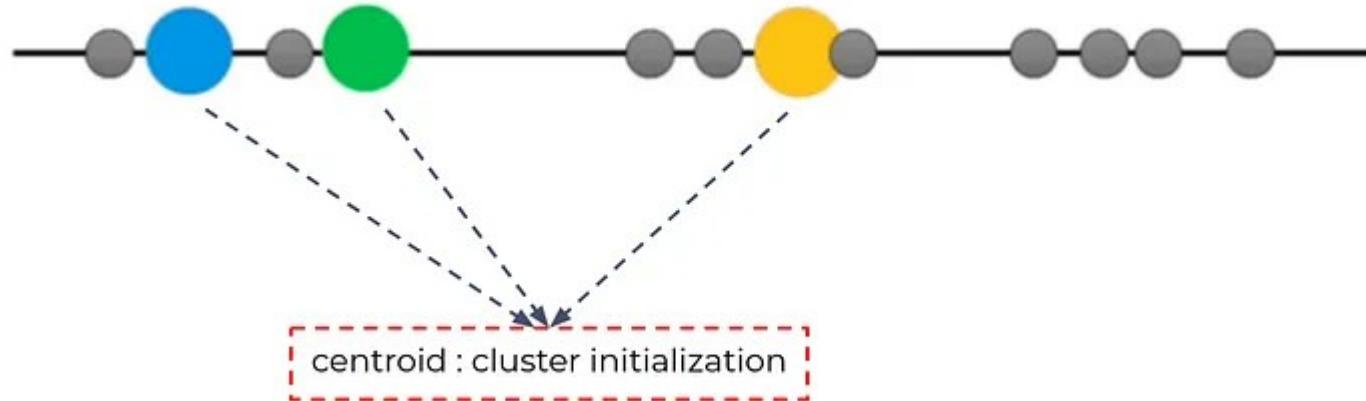
- Initialization
 - Choose k cluster centers
 - The value can be critical, since it can lead to completely different results
- How to select them?
 - randomly
 - k points of the set



K-Means clustering



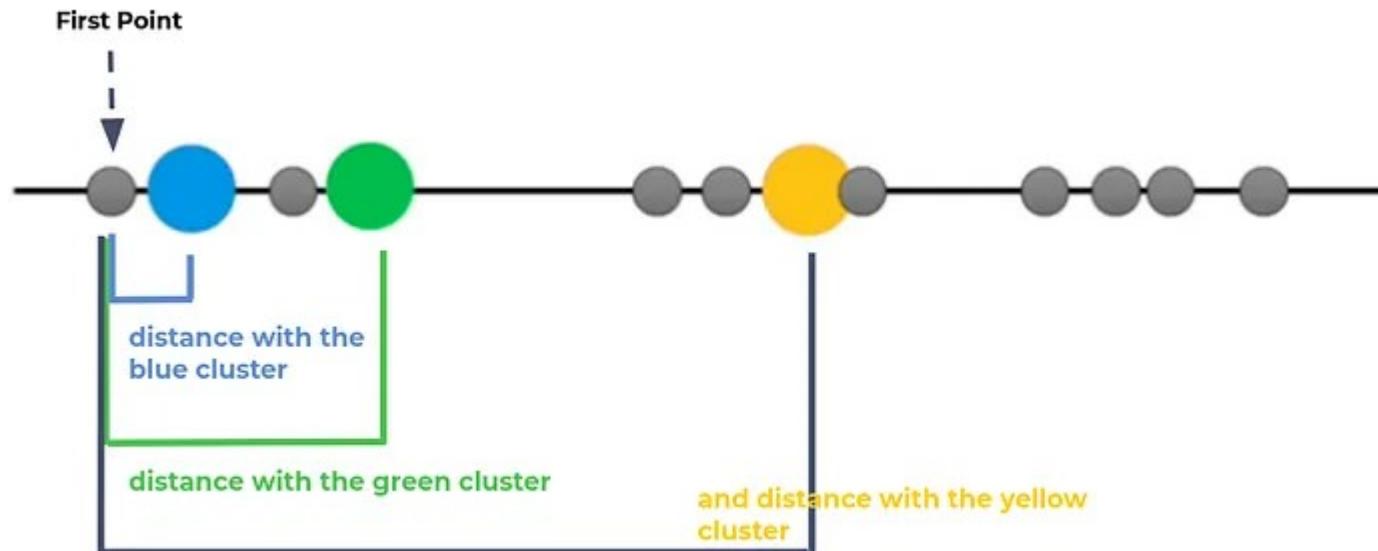
- In our example
 - $k = 3$
 - 3 points are selected as center of clusters



K-Means clustering



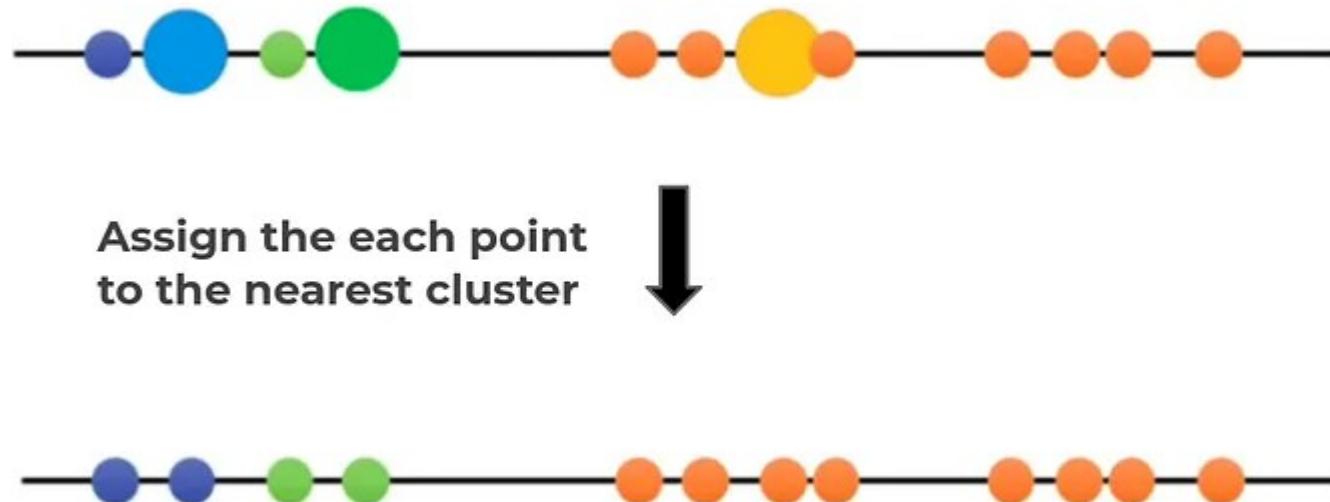
- Assignment
 - For each point find the closest center
 - In our case euclidean distance is used



K-Means clustering



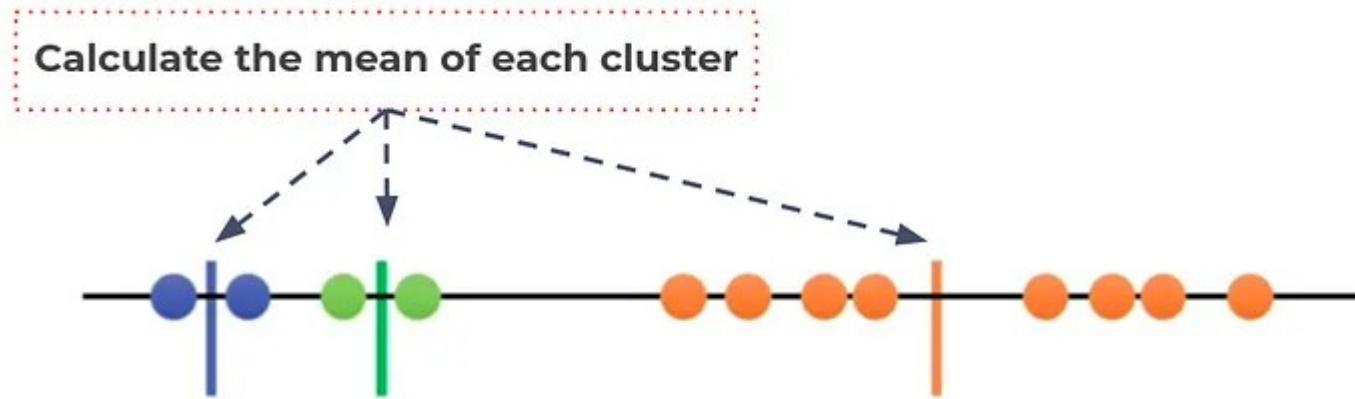
- Assignment
 - For each point find the closest center
 - In our case euclidean distance is used



K-Means clustering



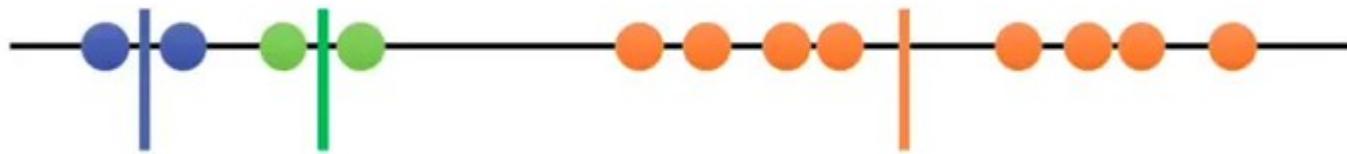
- Update step
 - Update every center as the mean of its points



K-Means clustering



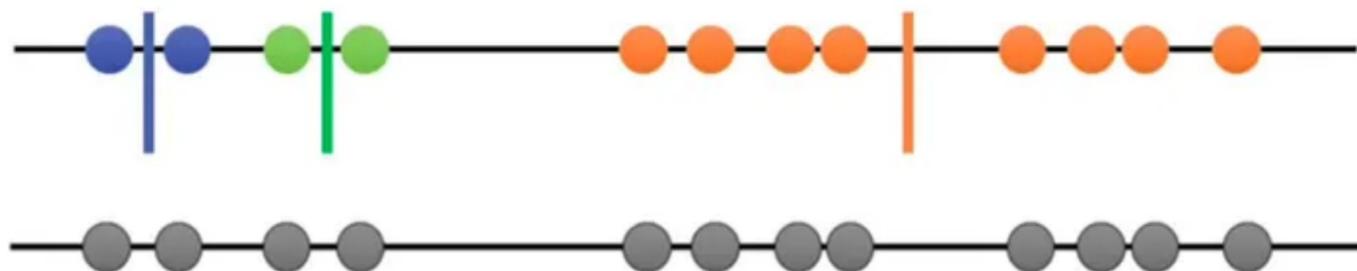
- Repeat
 - Assignment & Update
 - Until no or little changes or a fixed amount of iterations



K-Means clustering



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



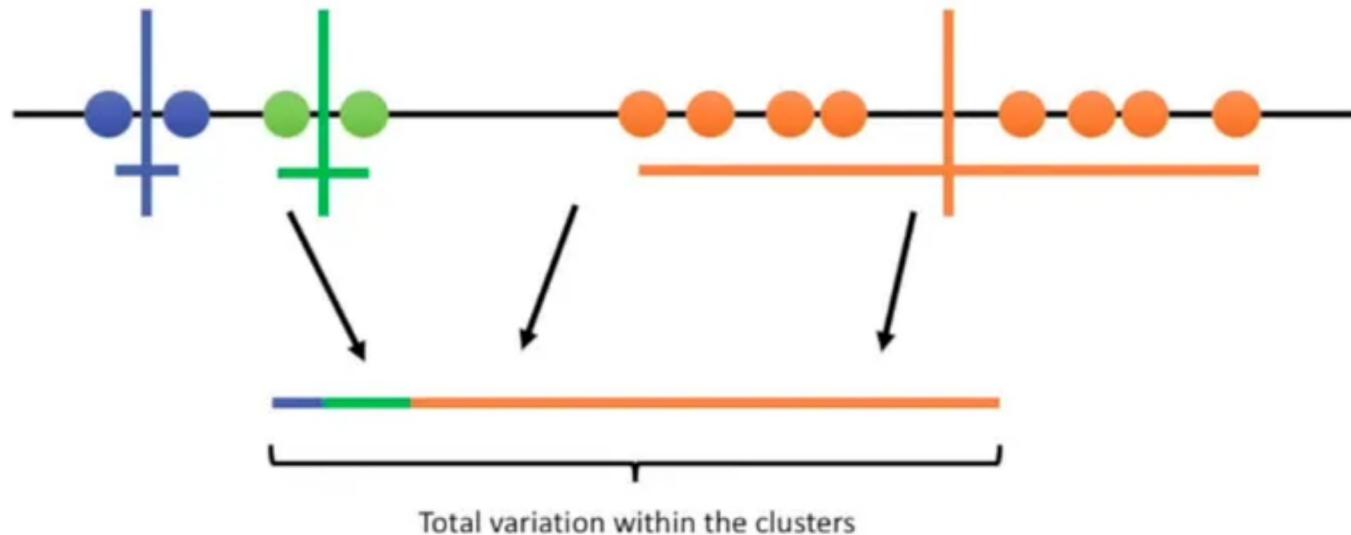
K-Means clustering

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

K-Means clustering



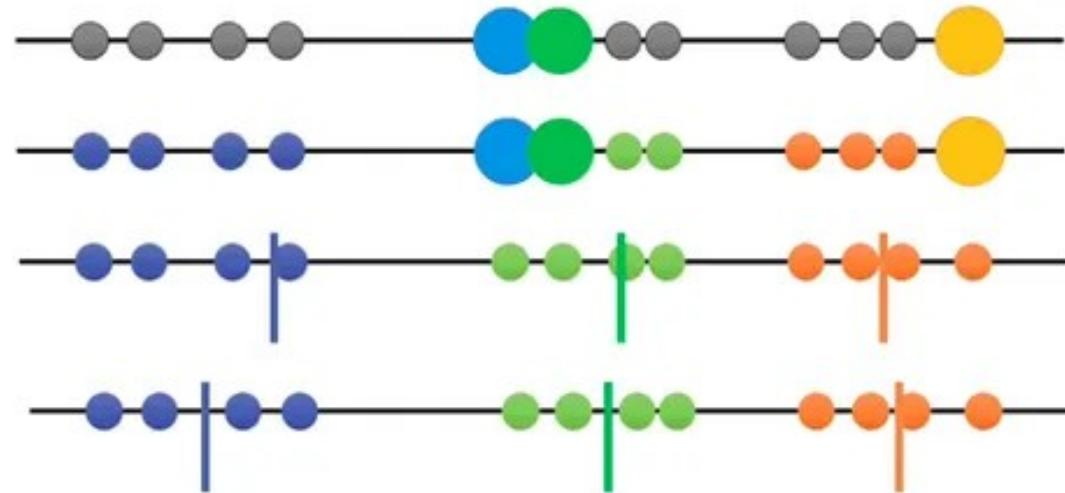
- Multiple initializations
 - Given a first try, asses the quality of the result
 - Compute the variance of each cluster



K-Means clustering



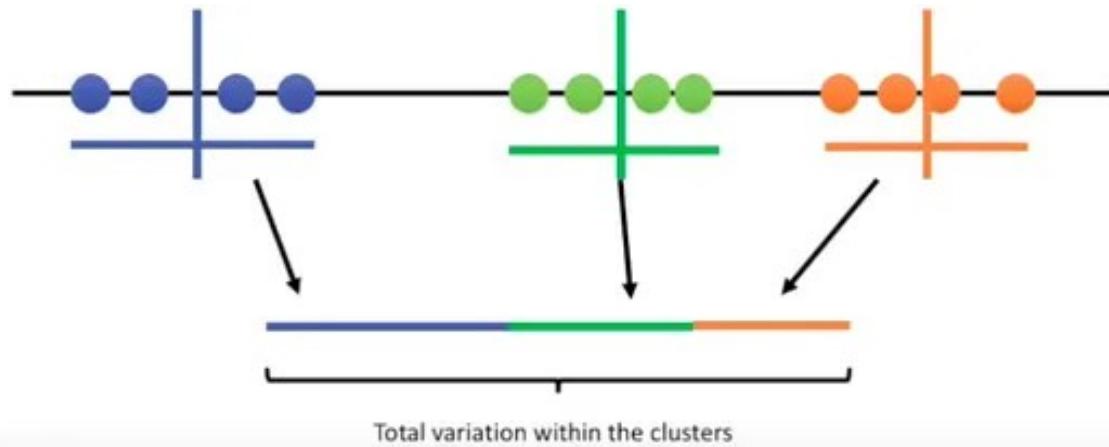
- Repeat again “until” we obtain the minimum variance



K-Means clustering

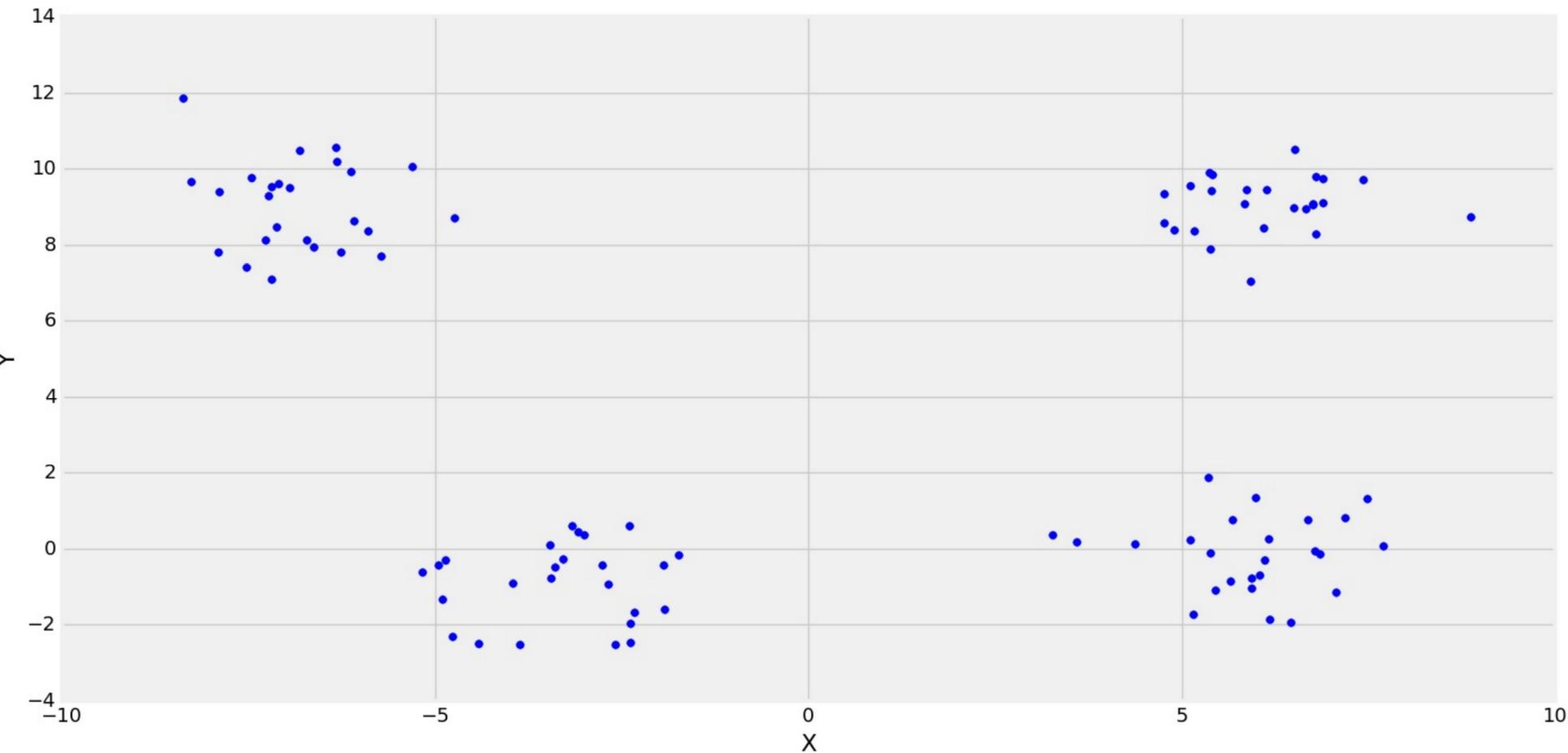


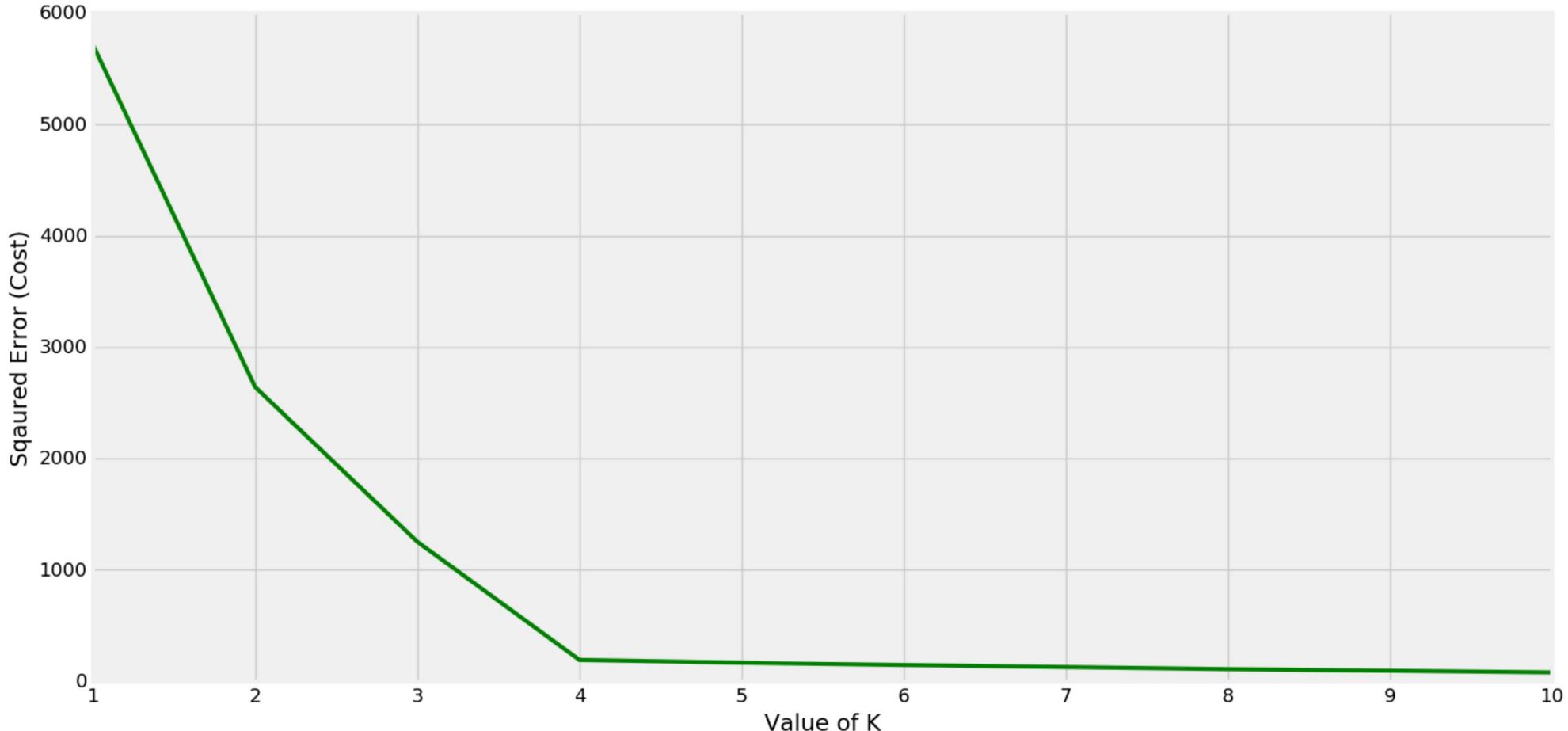
- Repeat again until we obtain the minimum variance



K-Means clustering

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





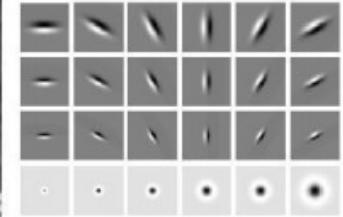
Features



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

.
s.

$$\begin{cases} R=255 \\ G=200 \end{cases}$$



Filter bank of
24 filters

Features



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

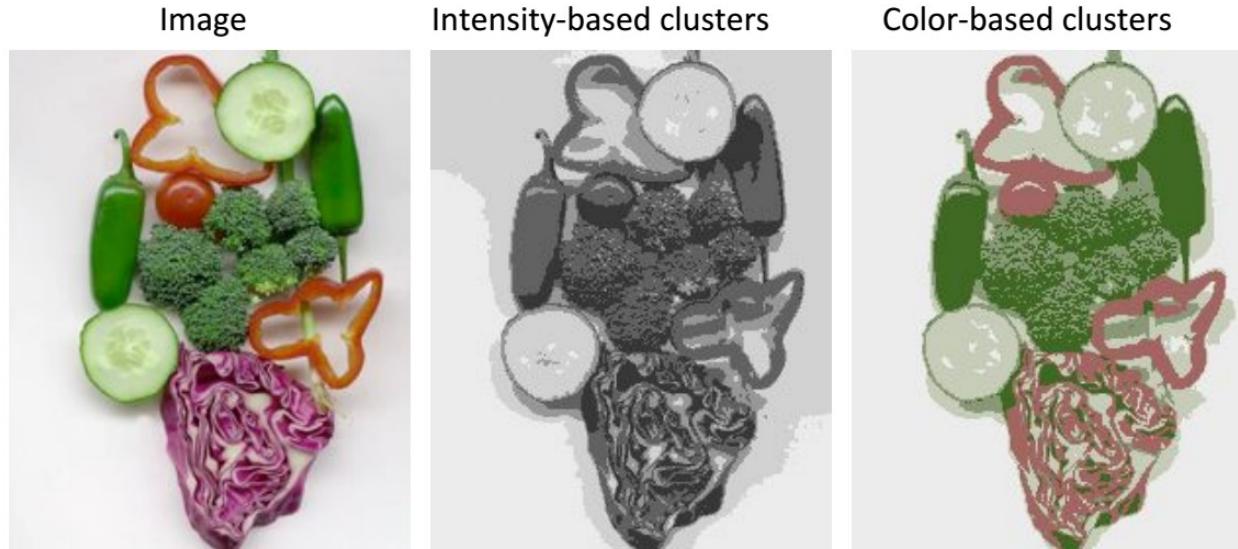
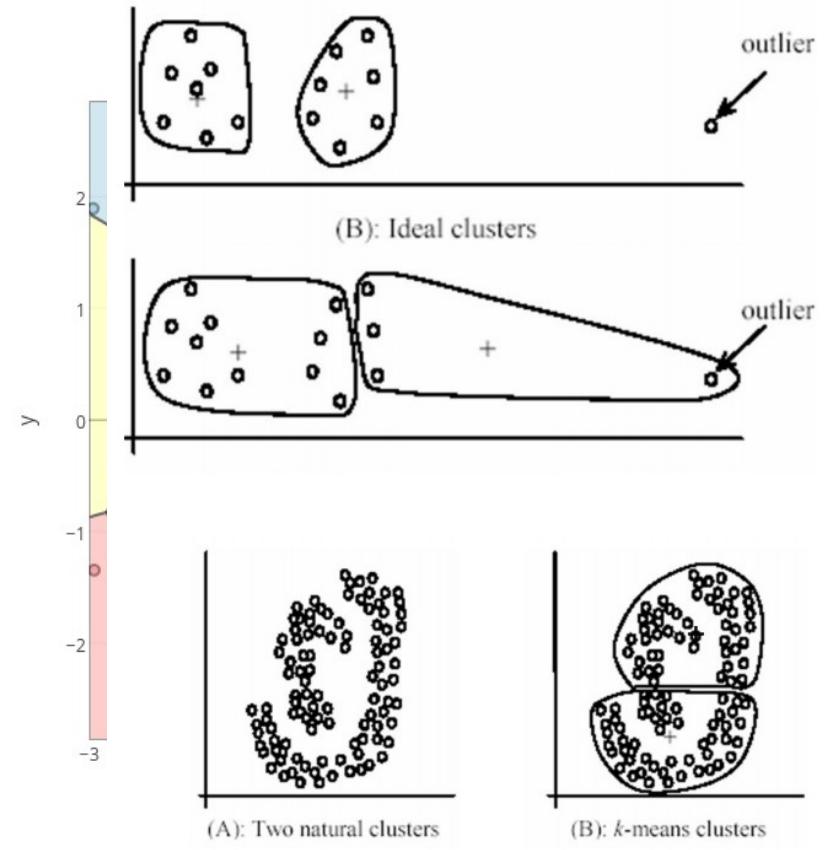


Image source: Forsyth & Ponce

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



- Images can not be a suitable data for clustering
- We need to extract relevant data → 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
)
```



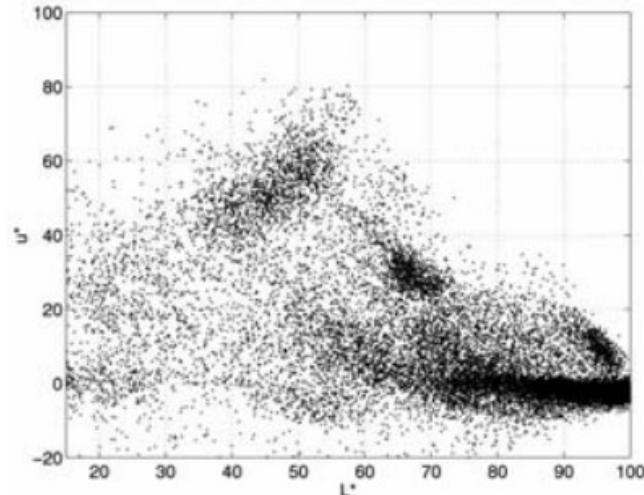
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Mean-shift clustering

Mean shift



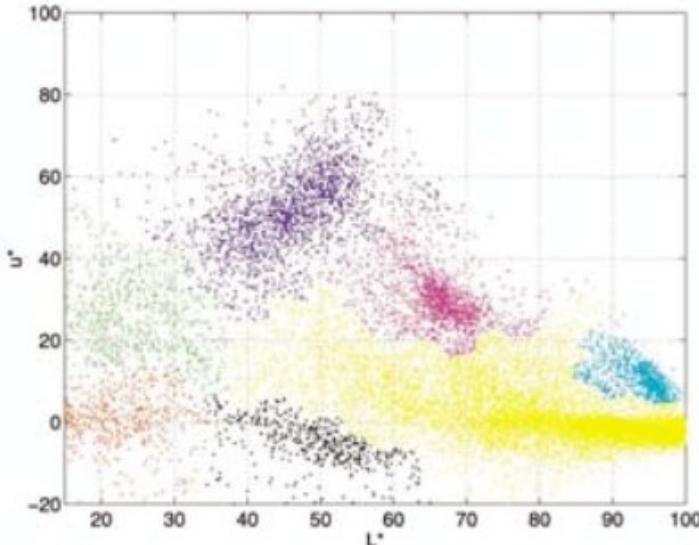
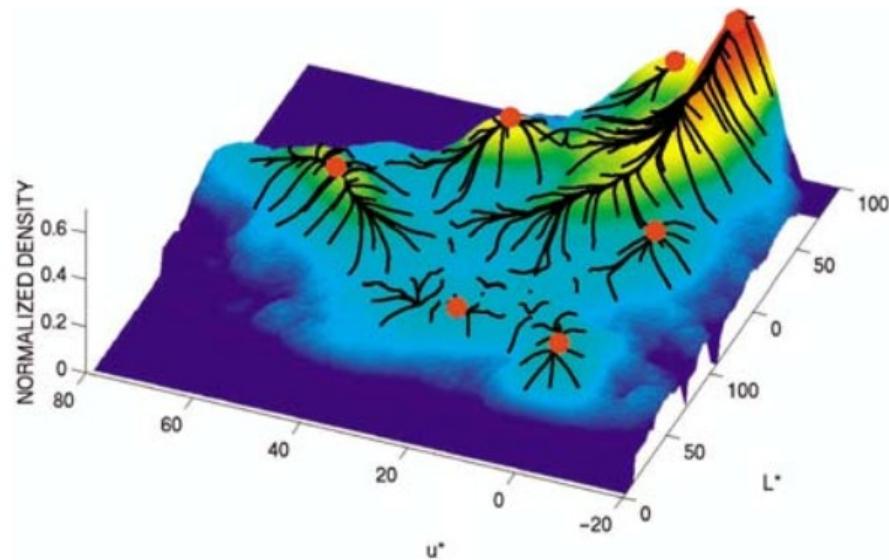
- As for k-means we work on data, not directly on images
 - For simplicity we assume a 2D data
 - Higher dimensionality is anyway possible



Mean shift

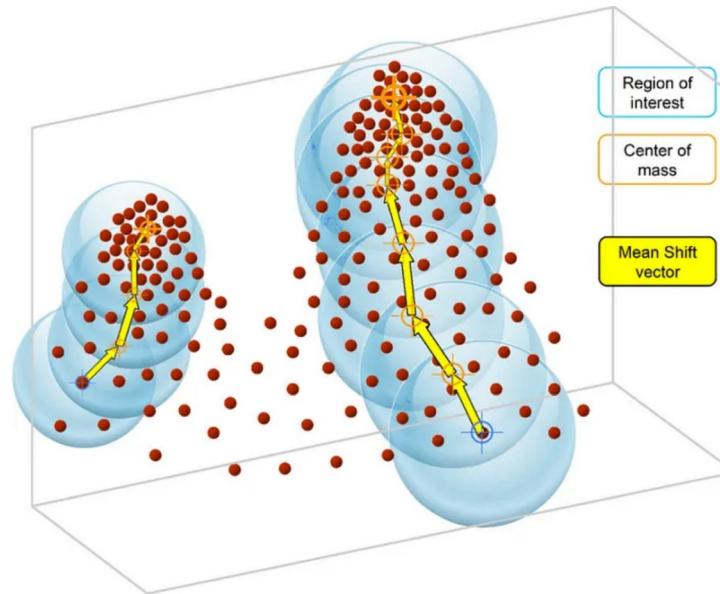
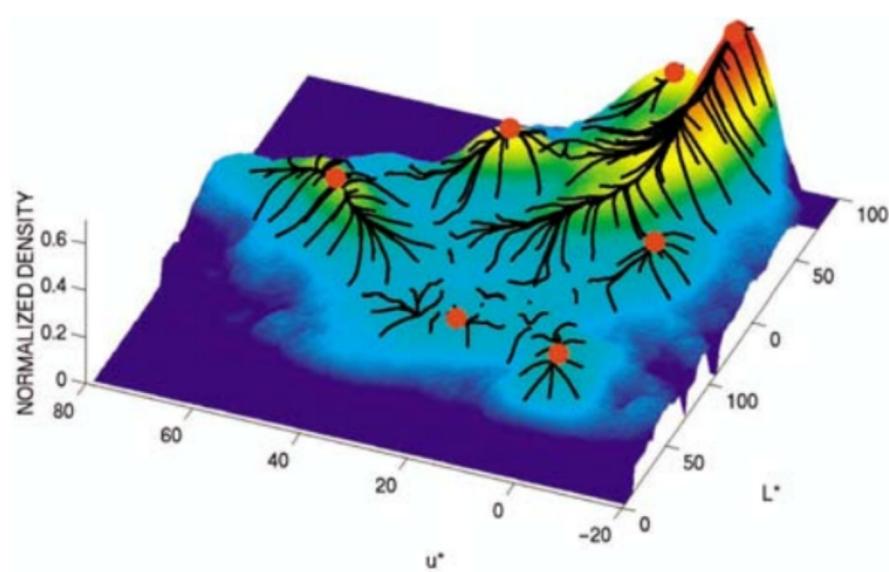


- Looking at data we can imagine a potential clustering
 - Density based
 - Consider density as a third “dimension”



Mean shift

- 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



- 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 $K()$

$$\sum_{x \in W} x \cdot K'(x)$$

- 3) Shift W to the mean
- 4) Repeat (2) until convergence

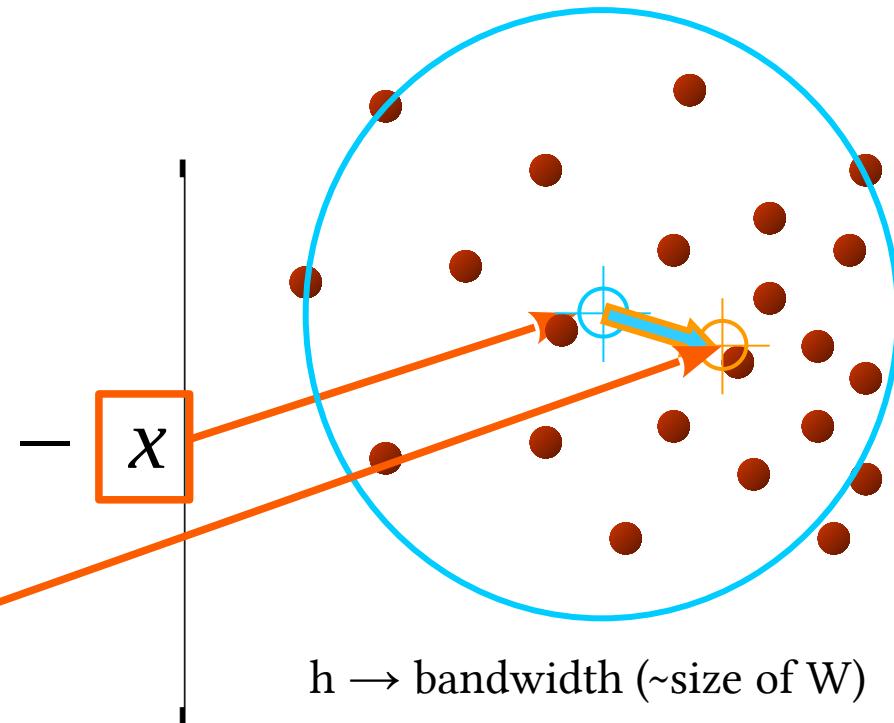
Mean shift

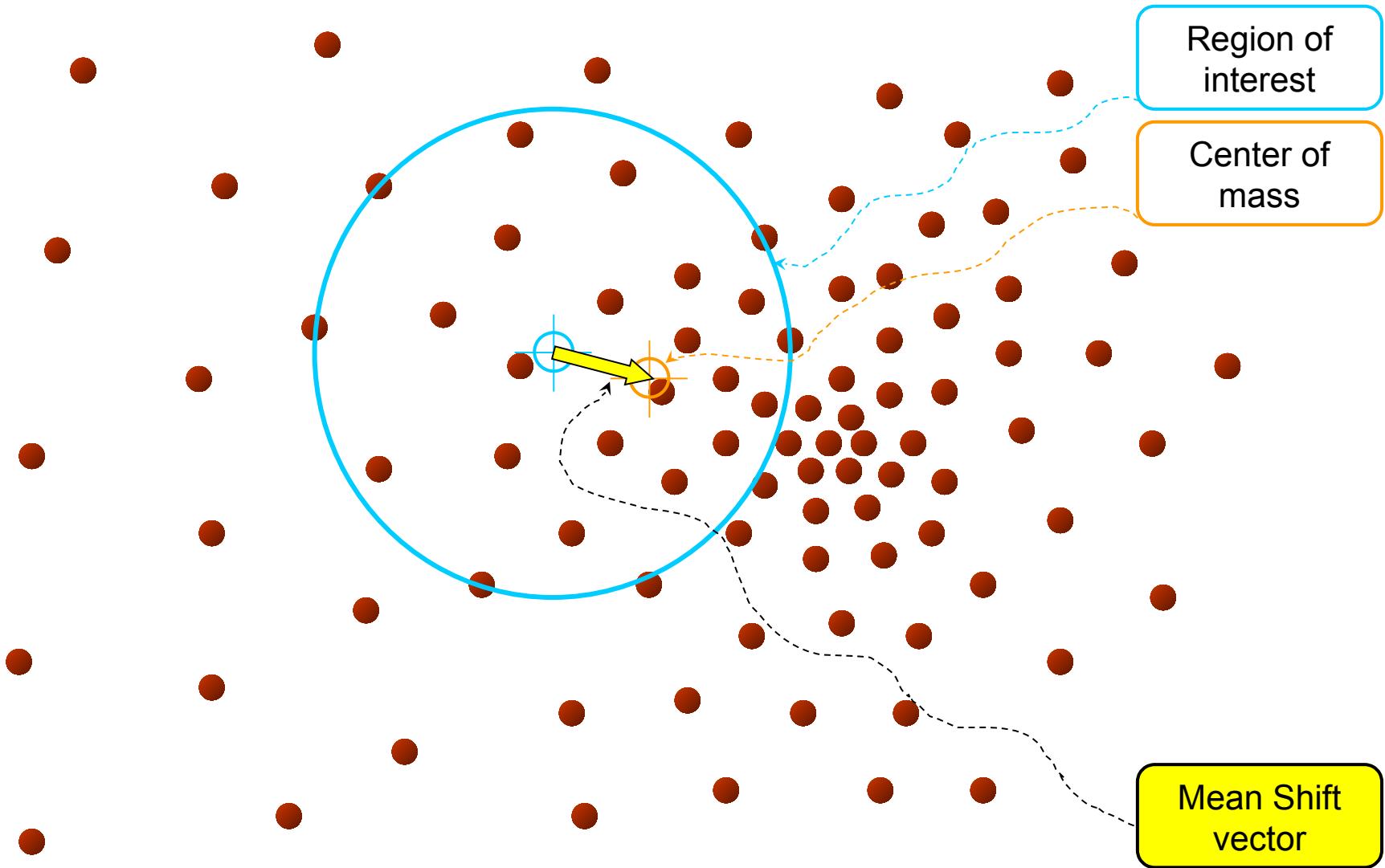


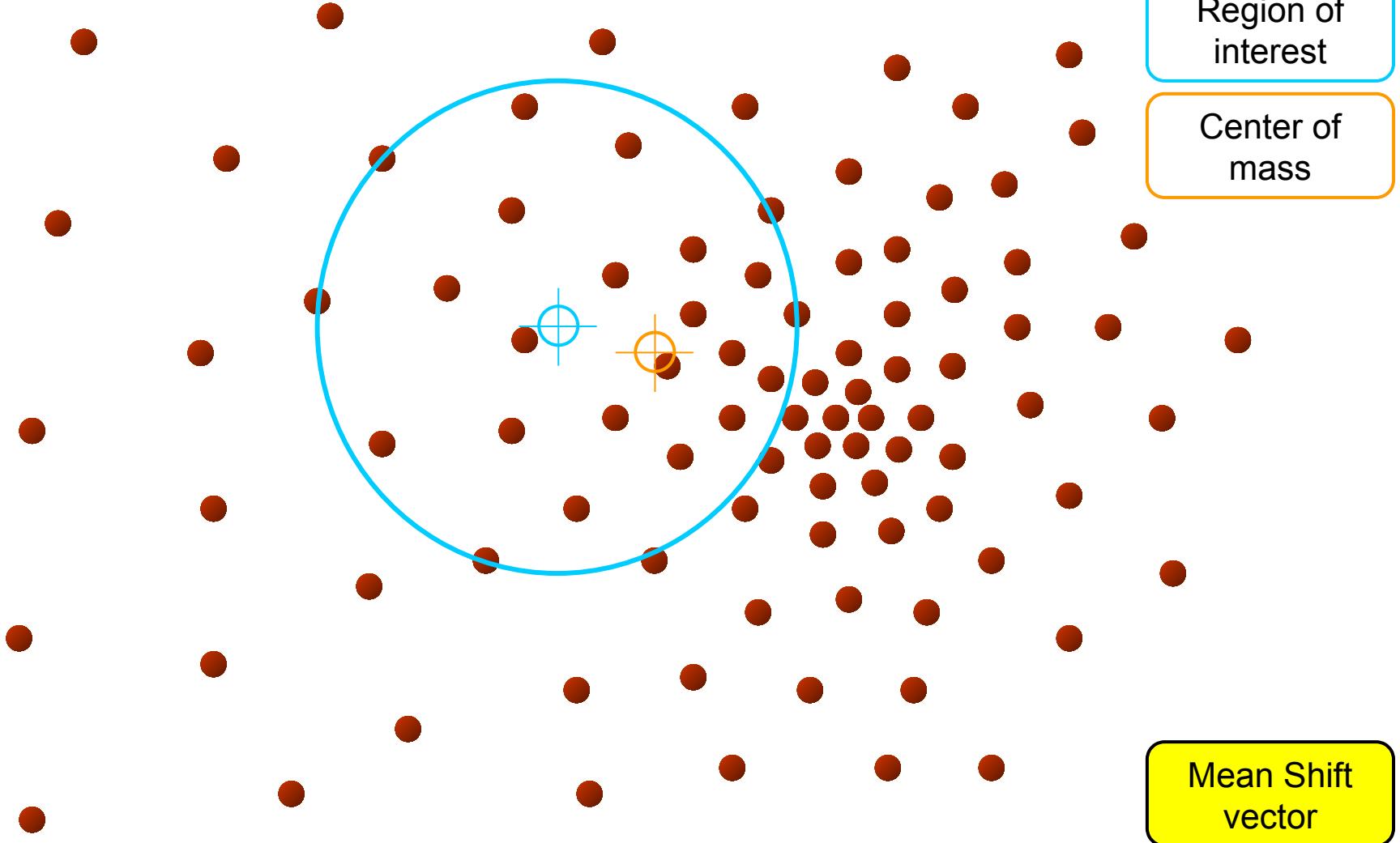
- Compute mean shift
 - Usually a Gaussian approach is used
- Translate W by $m(x)$

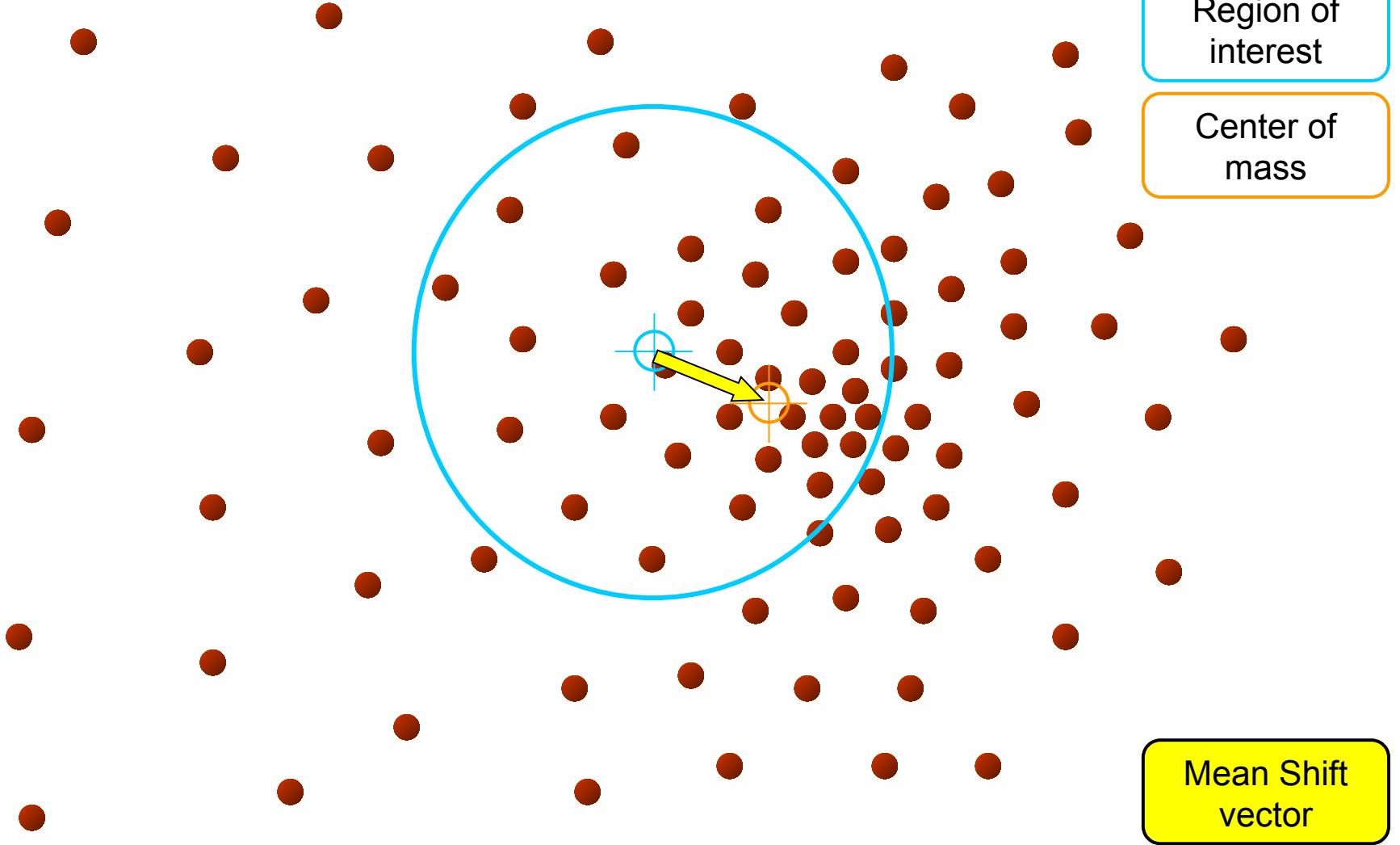
$$m(x) = \frac{\sum_{i=1}^n x_i g\left(\frac{\|x - x_i\|^2}{h}\right)}{\sum_{i=1}^n g\left(\frac{\|x - x_i\|^2}{h}\right)}$$

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





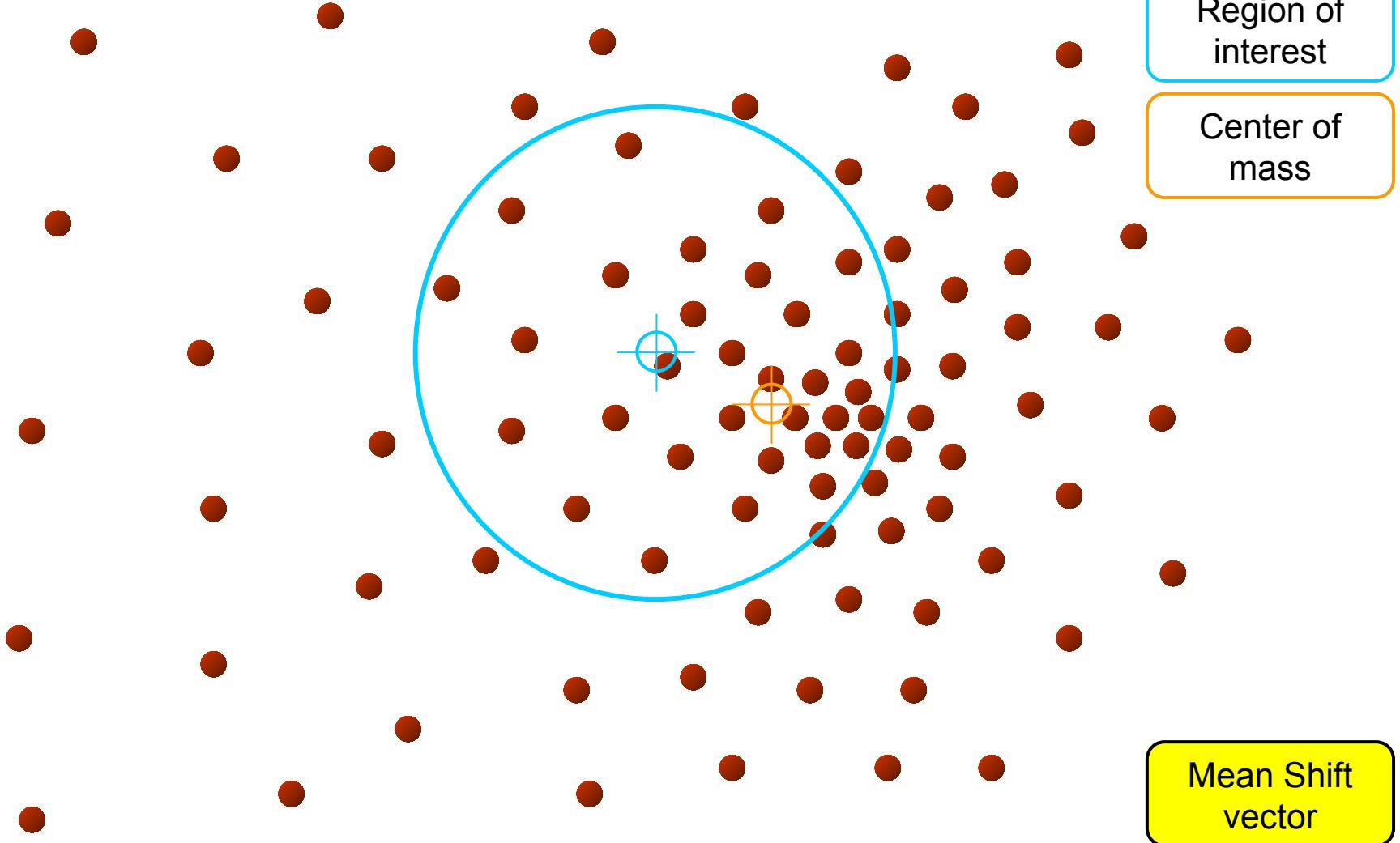


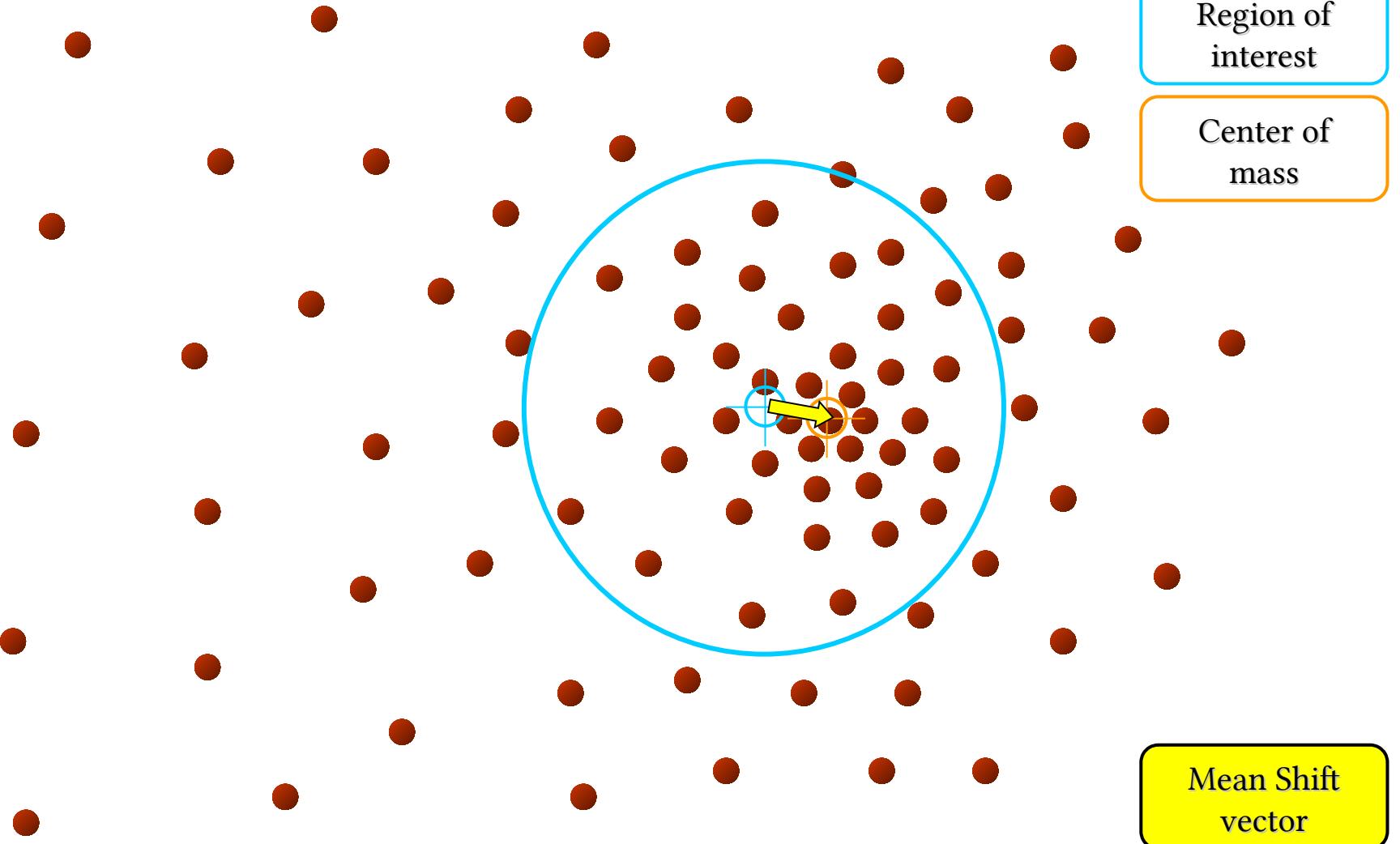


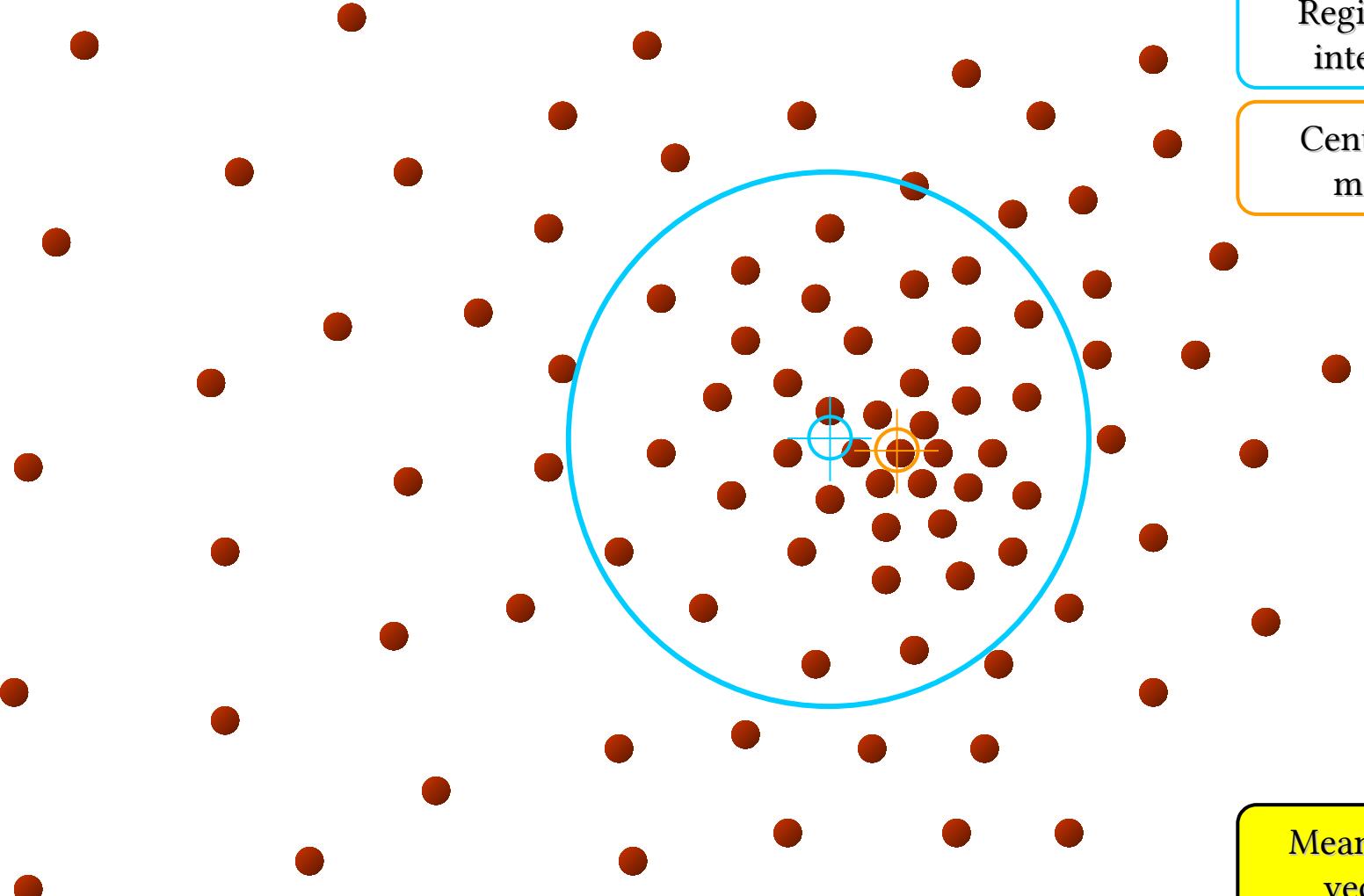
Region of
interest

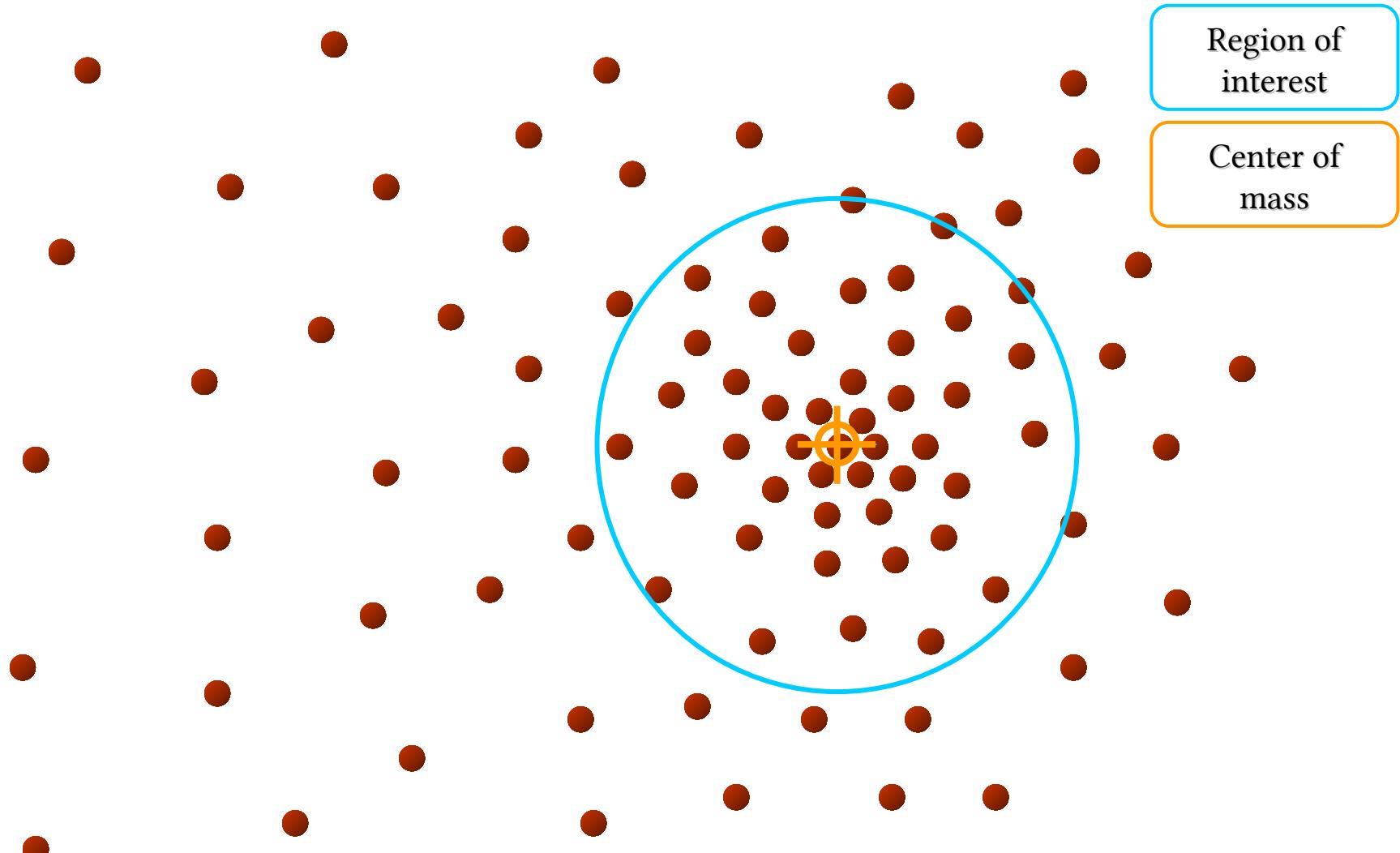
Center of
mass

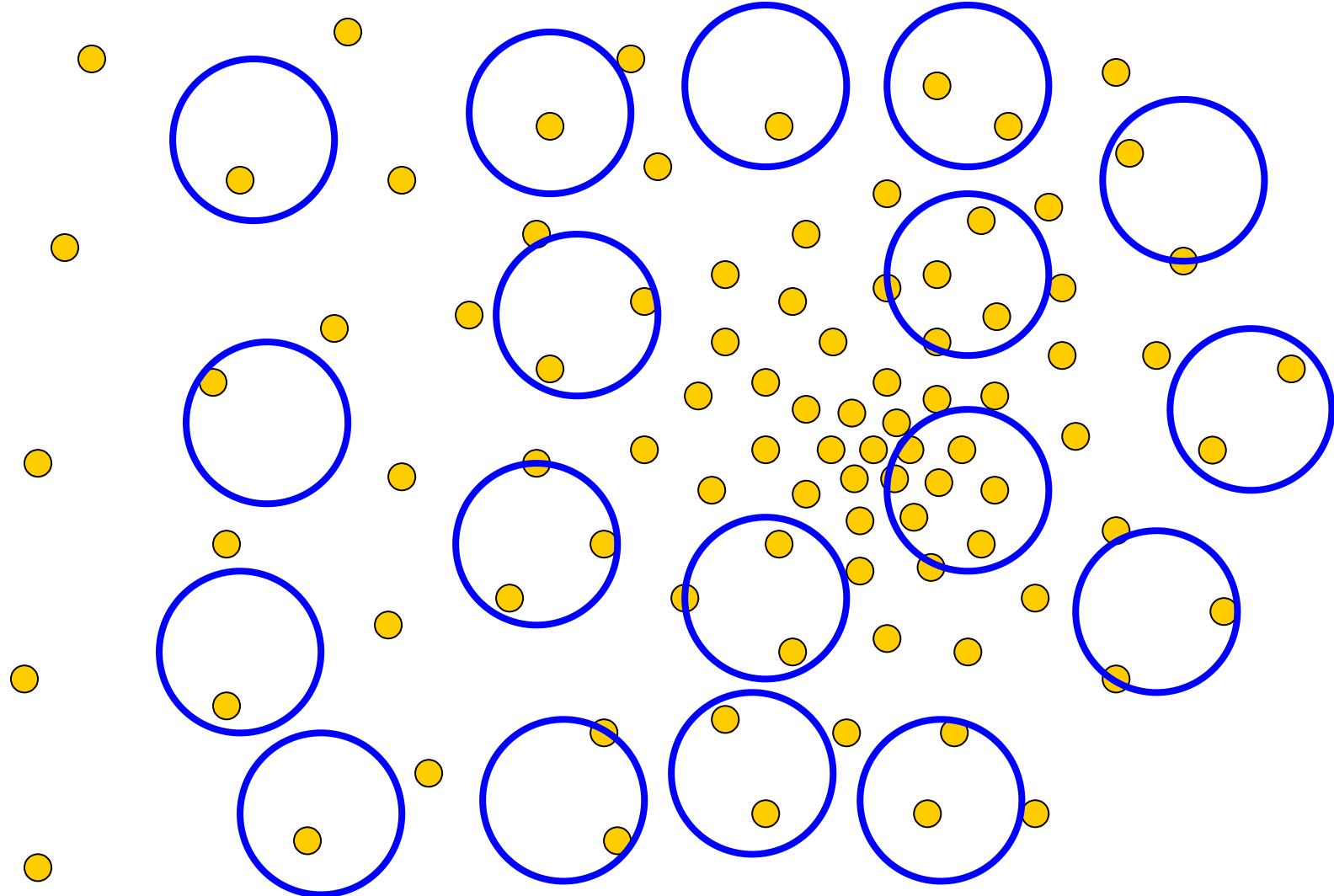
Mean Shift
vector





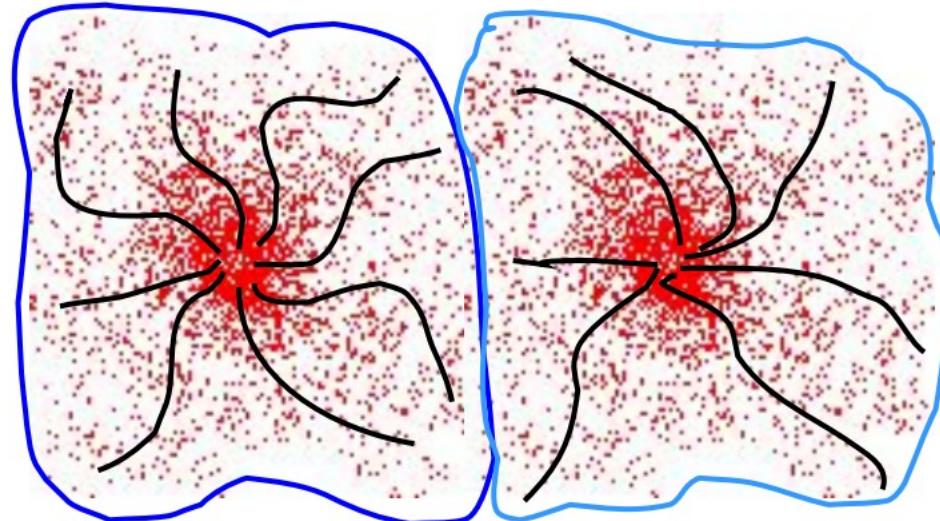








- Attraction basins → region where all trajectories lead to the same node
- Cluster → all points in the attraction basin of each node

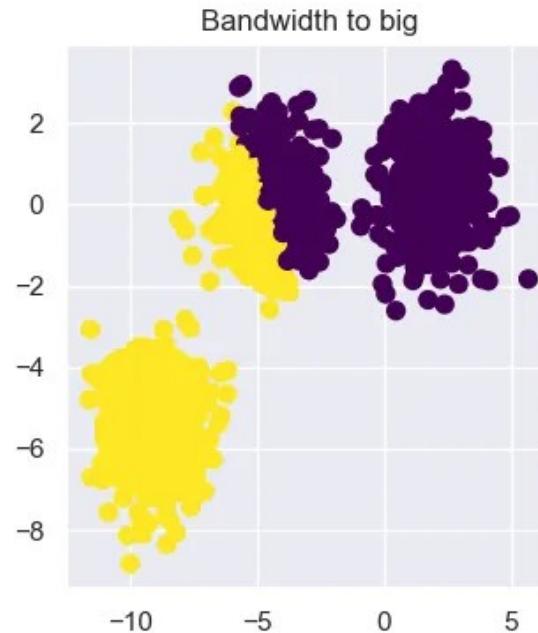
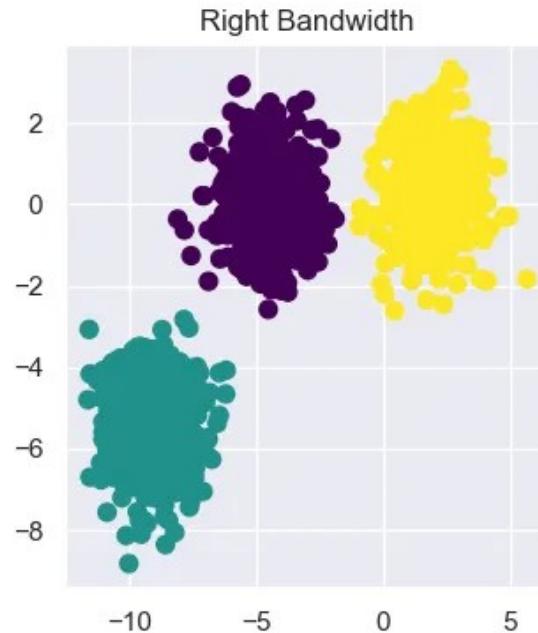
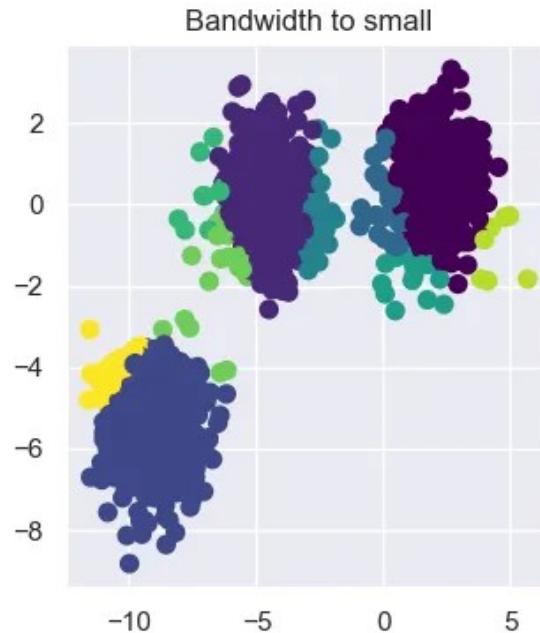


Mean Shift examples



- 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

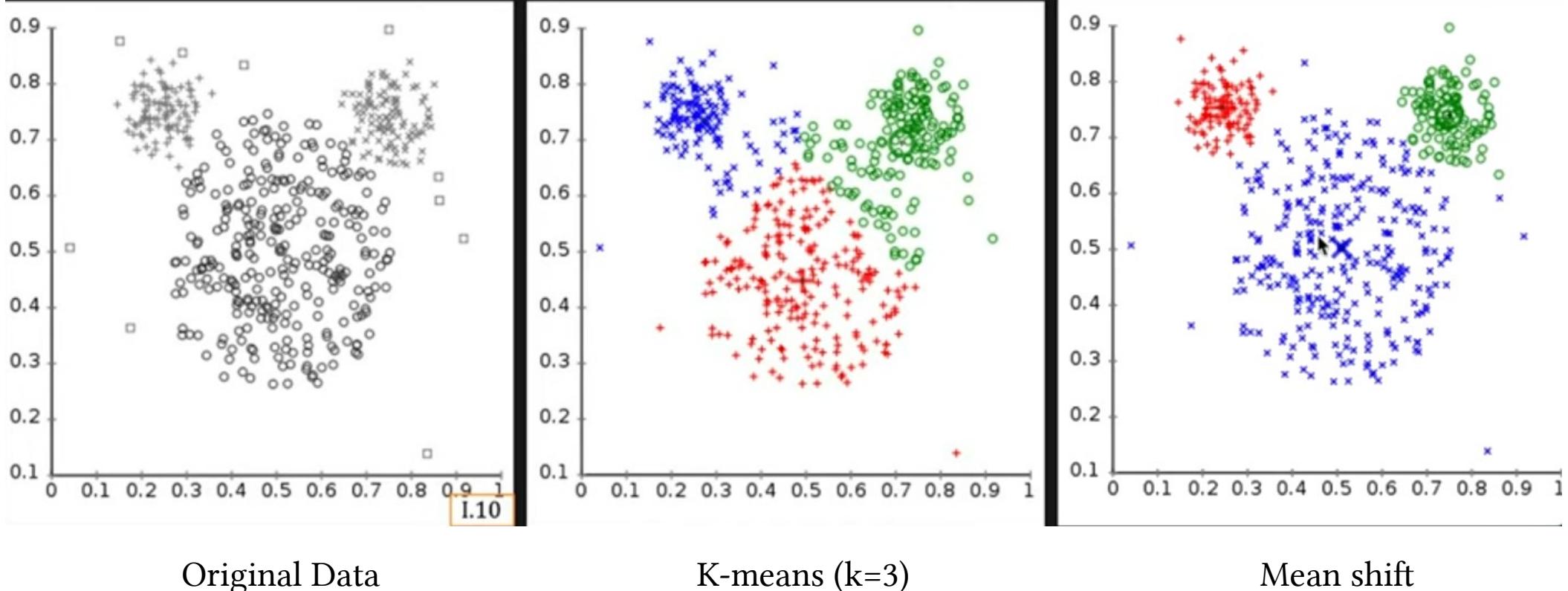




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K-means vs mean shift

K-means vs mean shift



K-means vs mean shift



Original Data



K-means (k=16)



Mean shift



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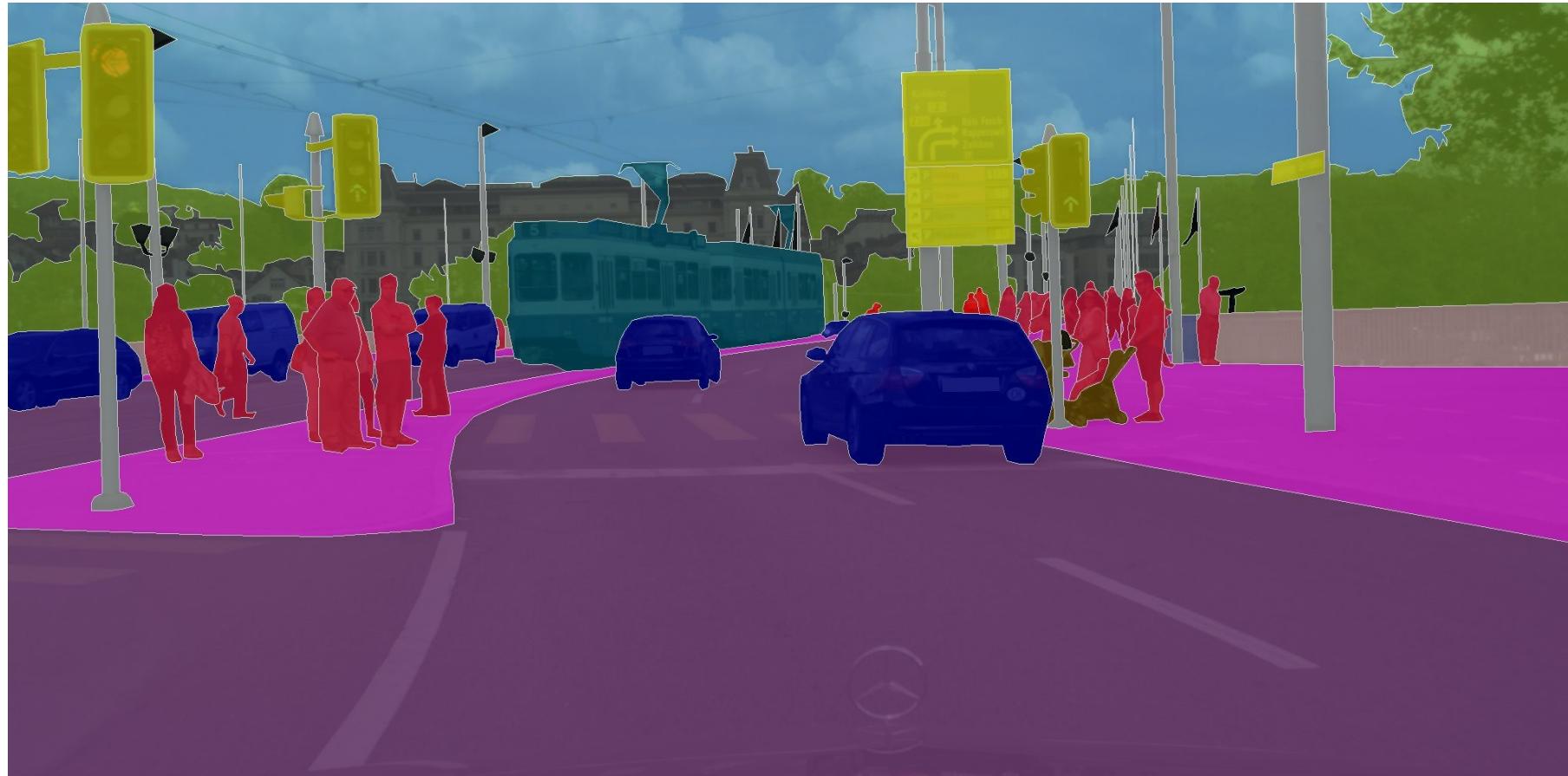
Other clustering approaches

Other clustering approaches

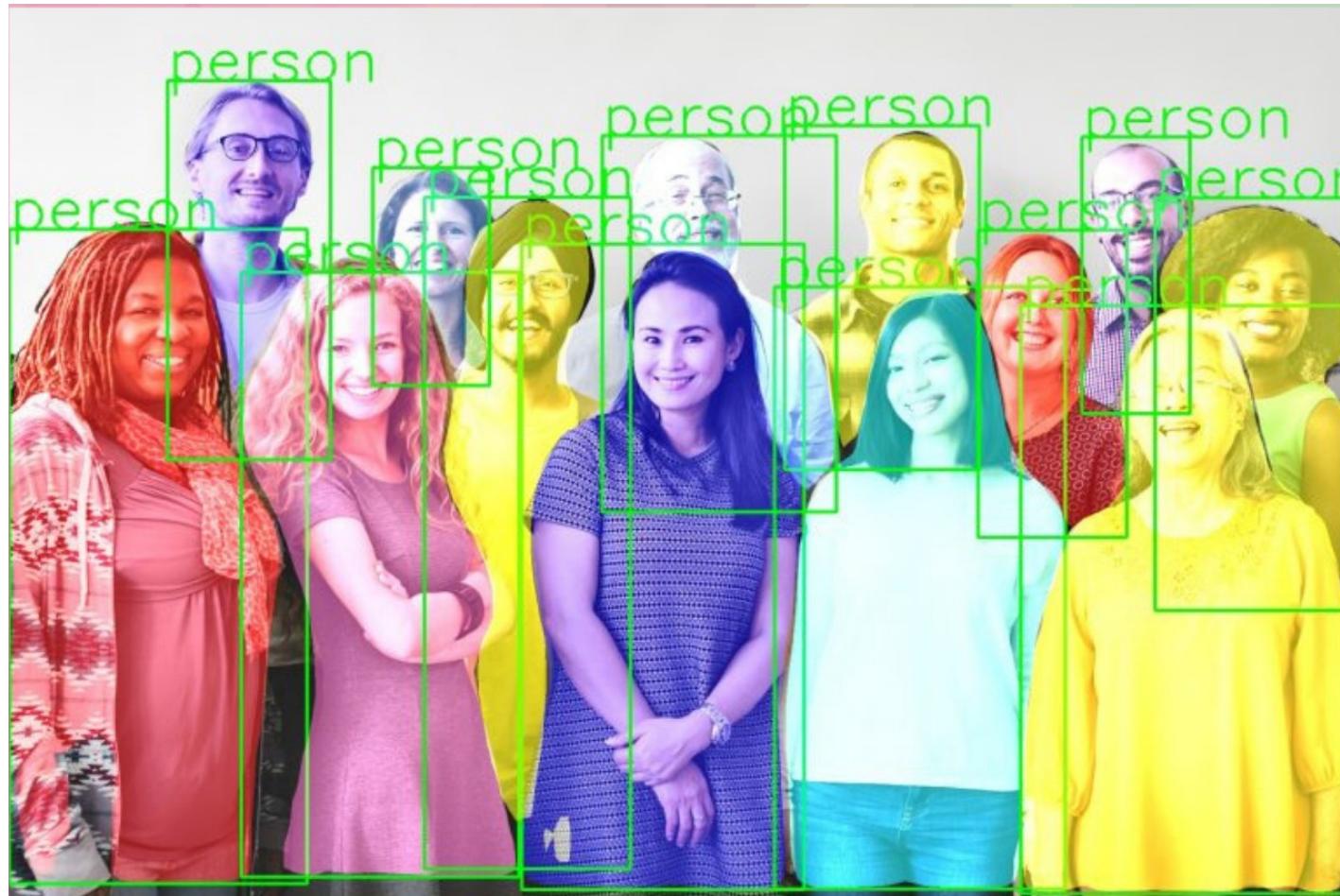


- Spectral clustering
- Agglomerative clustering
- Graph cut
- ...
- All bottom-up approaches!

Semantic segmentation (DL)



Instance segmentation (DL)





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Image Segmentation

Question time!

