Segmentation and Clustering

EECS 442 Computer Vision, Fall 2012

Outline

- Image Segmentation with Clustering
  - K-means
  - Mean-shift

- Graph-based Segmentation
  - Normalized-cut
  - Felzenszwalb *et al*.

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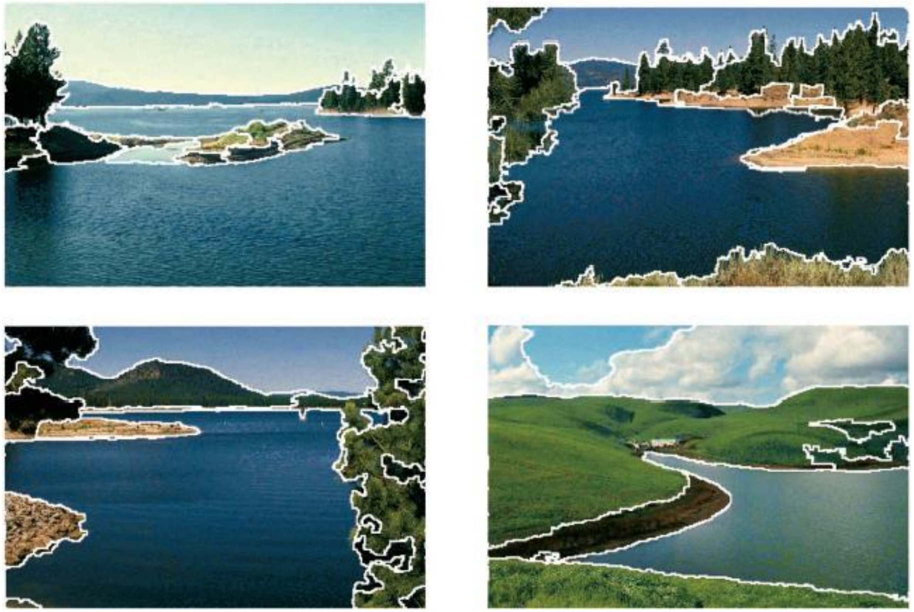
Image Segmentation

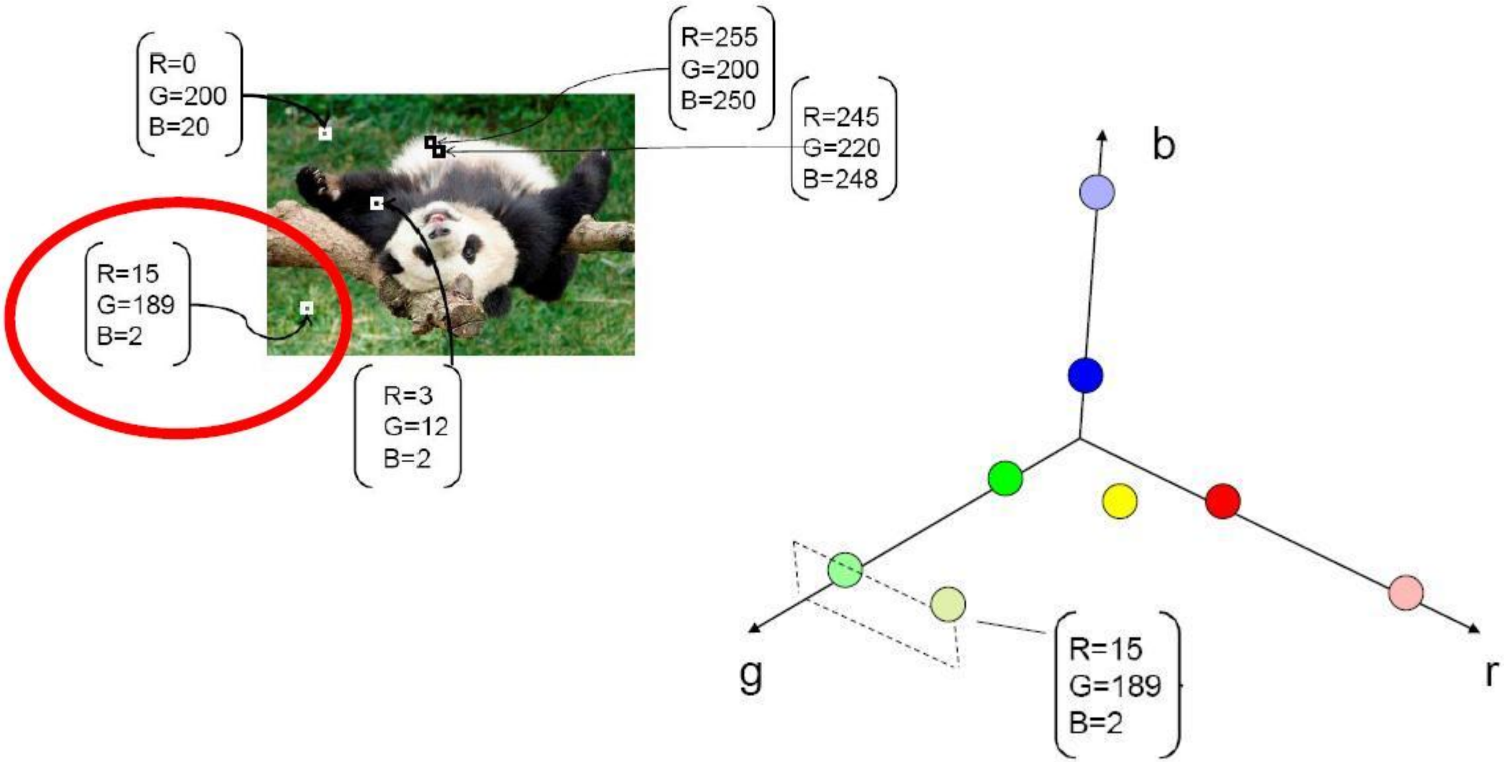
- Partitioning
  – Divide into regions/sequences with coherent internal properties
- Grouping
  – Identify sets of coherent tokens in image



D. Comaniciu and P. Meer. Mean Shift: A Robust Approach Toward Feature Space Analysis? *PAMI,* 2002.

Segmentation as Clustering

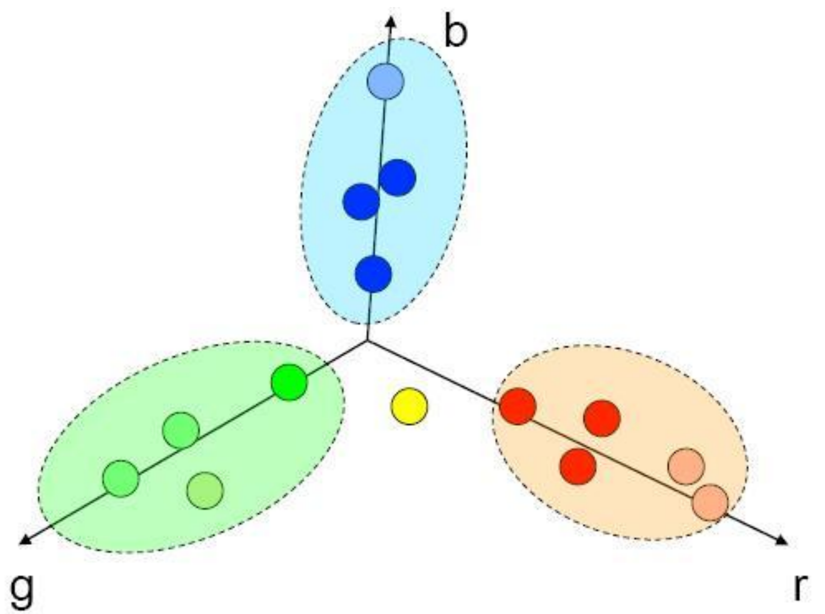
- Feature space (ex: RGB values)



Source: K. Grauman

Segmentation as Clustering

- Cluster together tokens with high similarity (small distance in feature space)

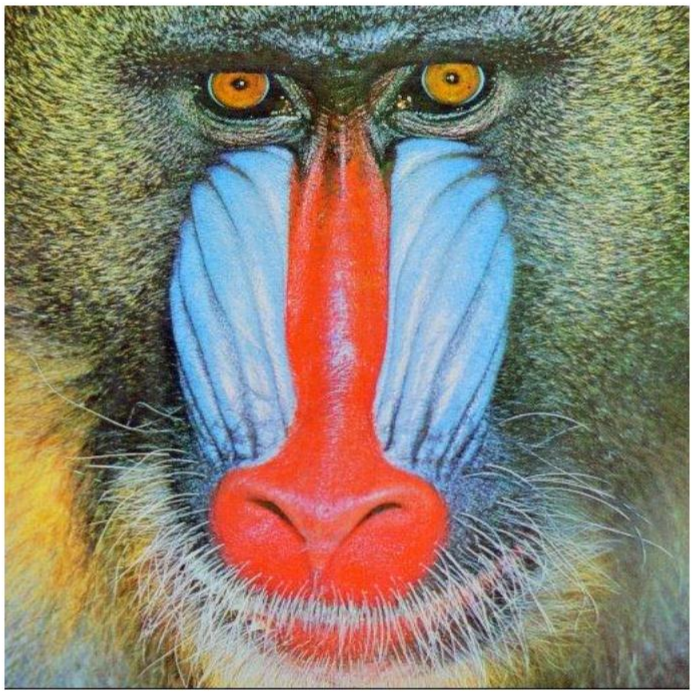


Questions:

1. How many clusters?
2. Which data belongs to which group?

Segmentation as Clustering

- Cluster together tokens with high similarity (small distance in feature space)



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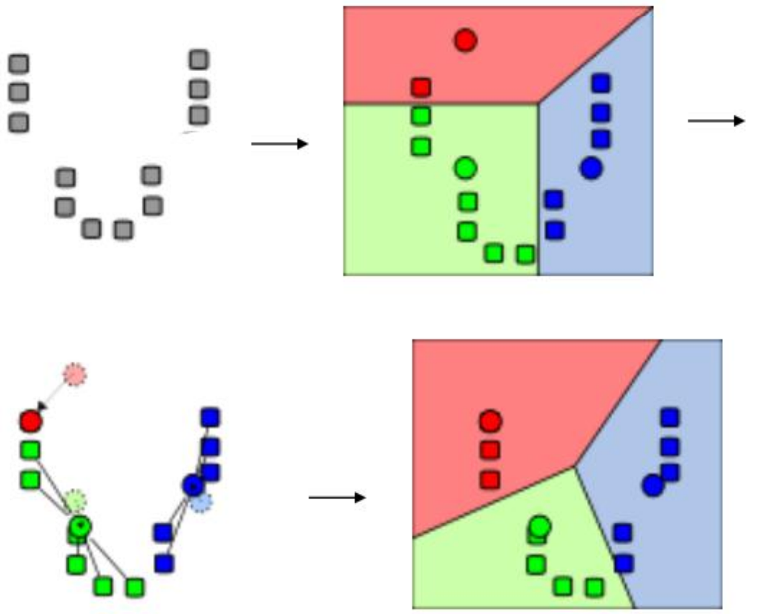
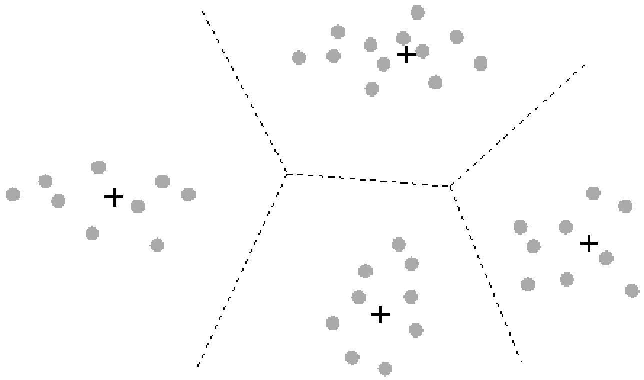
K-means



- Assign each of the N points, $\mathbf{x}_j$, to clusters by nearest $\boldsymbol{\mu}_i$
- Re-compute mean $\boldsymbol{\mu}_i$ of each cluster from its member points
- If no mean has changed more than some ε, stop

Source: Wikipedia

K-means



Source:
http://www.heikohoffmann.de/htmlthesis/node28.html

- Solving the optimization problem

$$\underset{\mathbf{S}}{\arg\min} \boxed{\sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \|\mathbf{x}_j - \boldsymbol{\mu}_i\|^2} \quad e(\boldsymbol{\mu}_i)$$

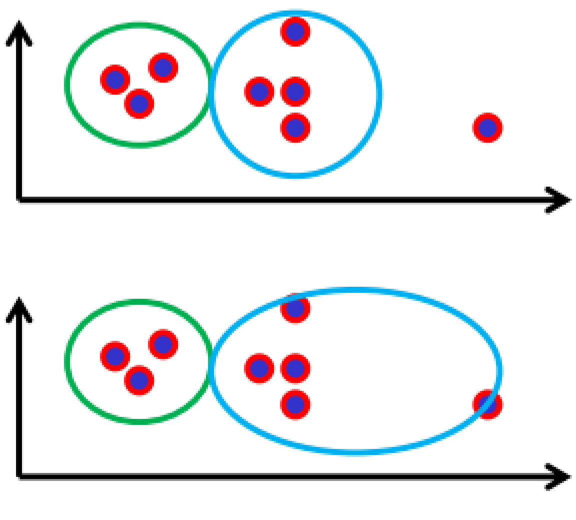
- Every iteration is a step of gradient descent

$$\frac{\partial e}{\partial \boldsymbol{\mu}_i} = 0 \longrightarrow \boxed{\boldsymbol{\mu}_i^{t+1} = \frac{1}{|S_i^{(t)}|} \sum_{\mathbf{x}_j \in S_i^{(t)}} \mathbf{x}_j}$$

K-means

- Pros
  - Simple and fast
  - Converges to a local minimum of the error function
  - K-means in matlab

- Cons
  - Need to pick K
  - Sensitive to initialization
  - Only finds “spherical” clusters
  - Sensitive to outliers



K-means

- Demo
  - Image segmentation with K-means

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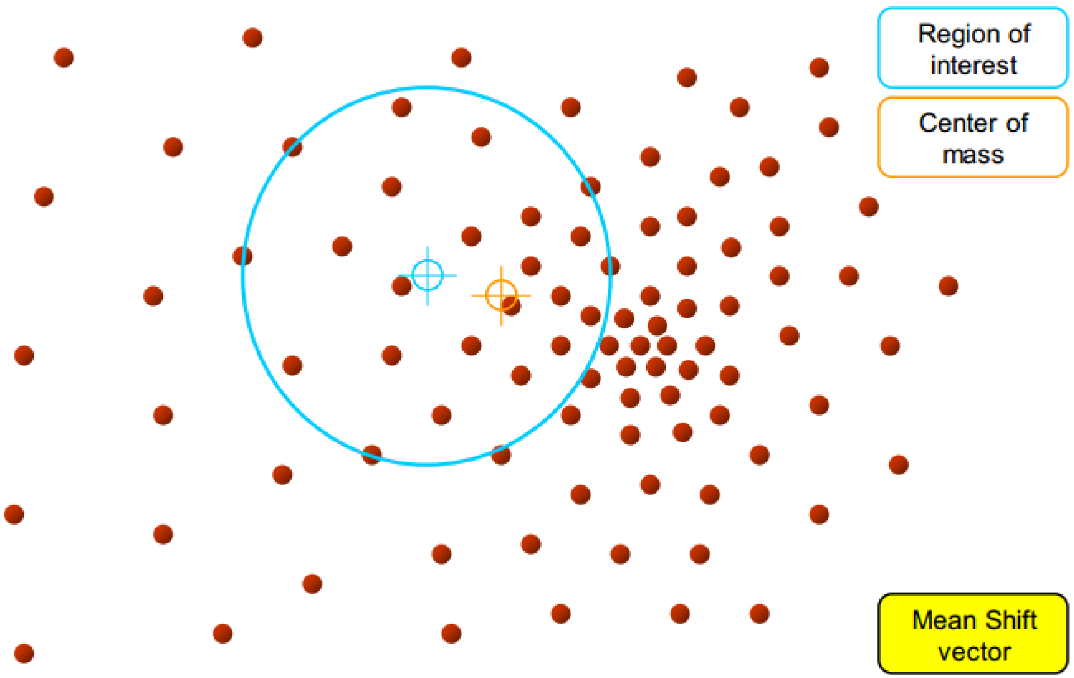
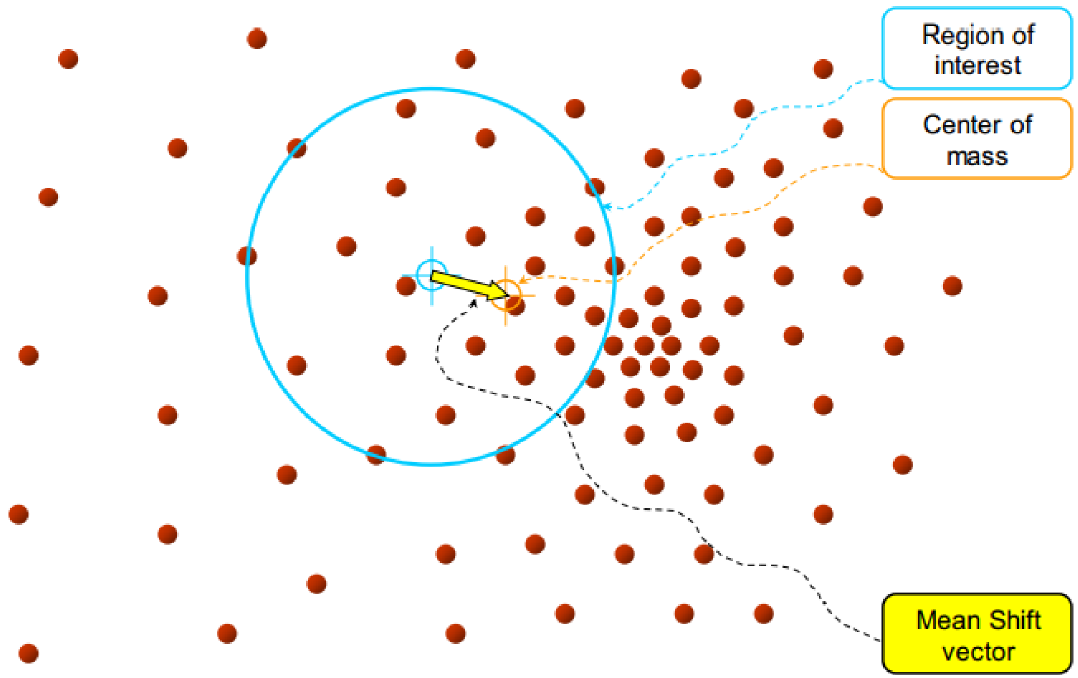
Mean-shift



Slide by Y. Ukrainitz & B. Sarel

Mean-shift



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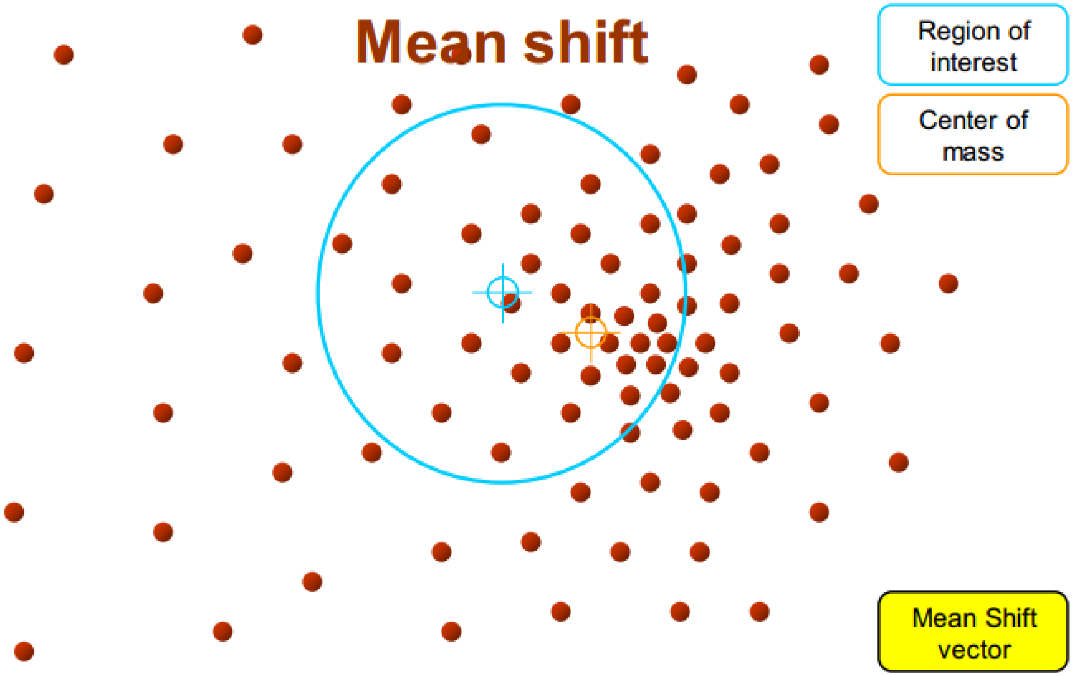
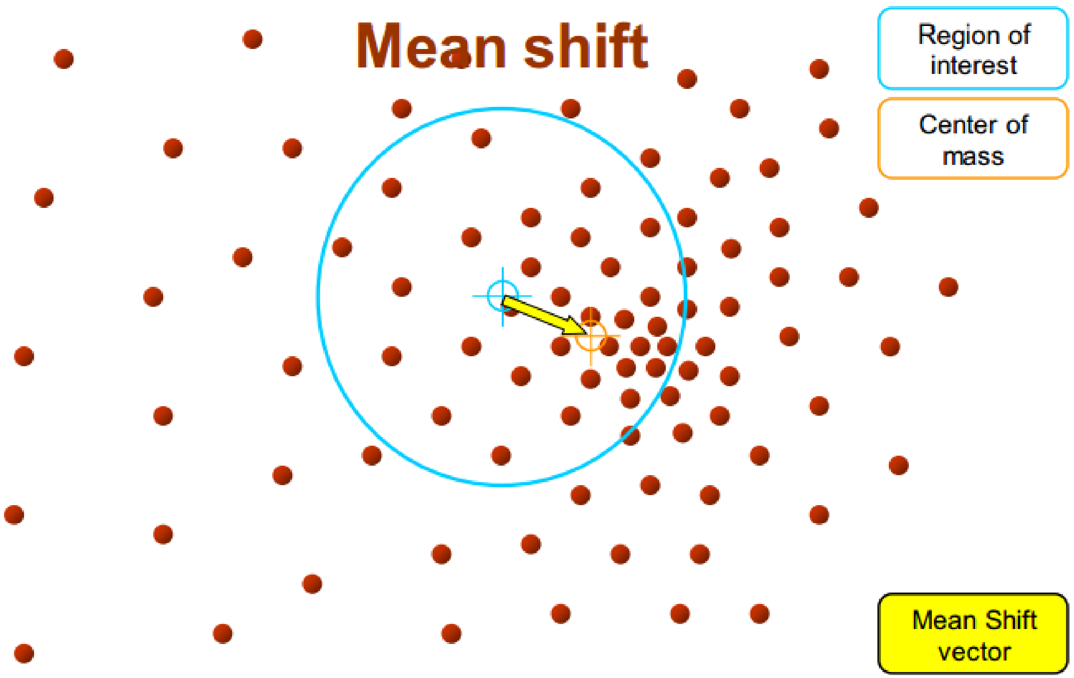
Mean-shift



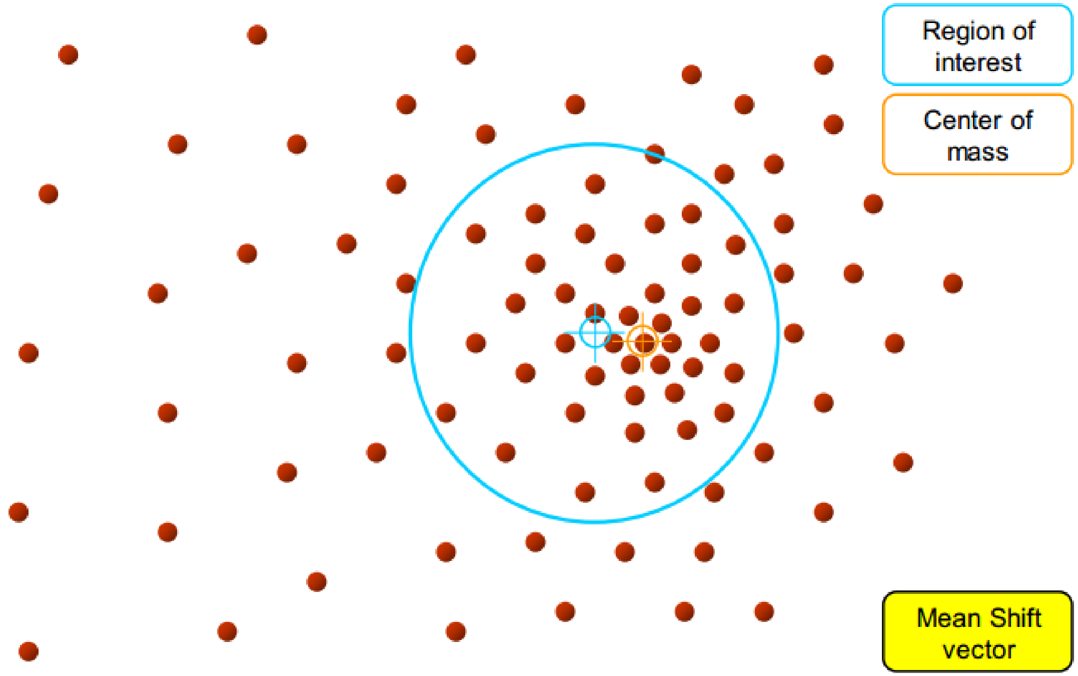
Slide by Y. Ukrainitz & B. Sarel

Mean-shift



Slide by Y. Ukrainitz & B. Sarel

Mean-shift



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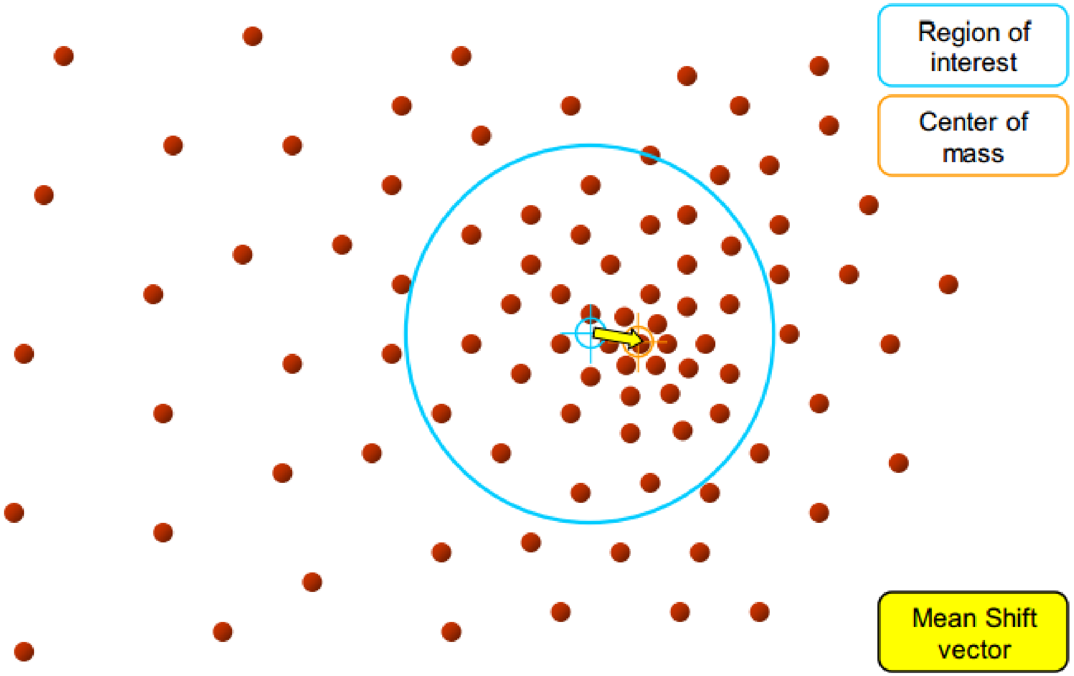
Mean-shift



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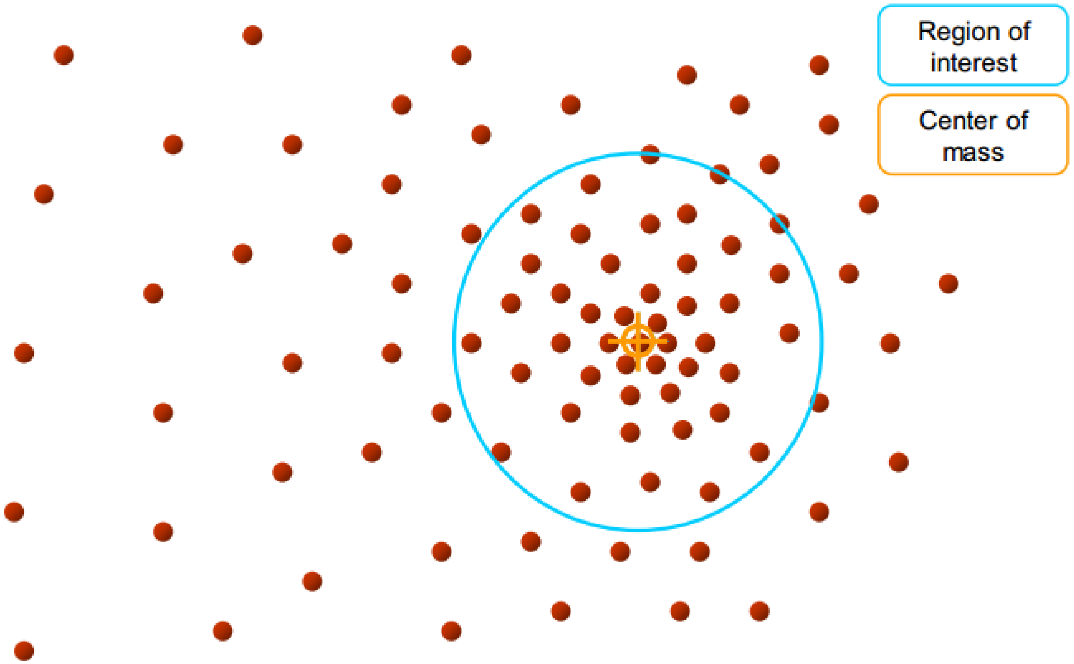
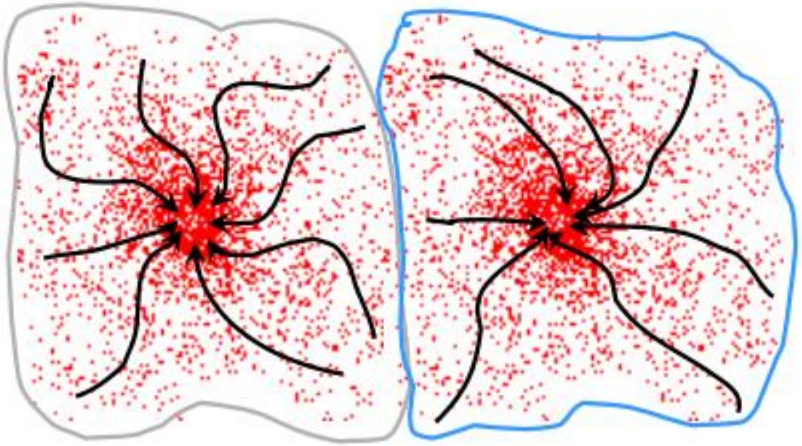
Mean-shift



Slide by Y. Ukrainitz & B. Sarel

Mean-shift

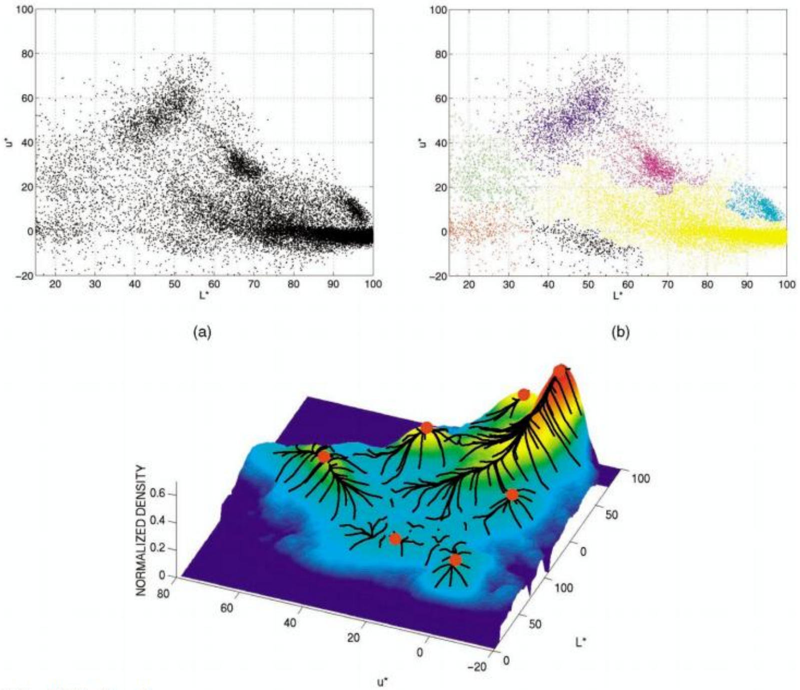
- Attraction basin: the region for which all trajectories lead to the same mode
- Cluster: all data points in the attraction basin of a mode



Slide by Y. Ukrainitz & B. Sarel

Segmentation by Mean-shift

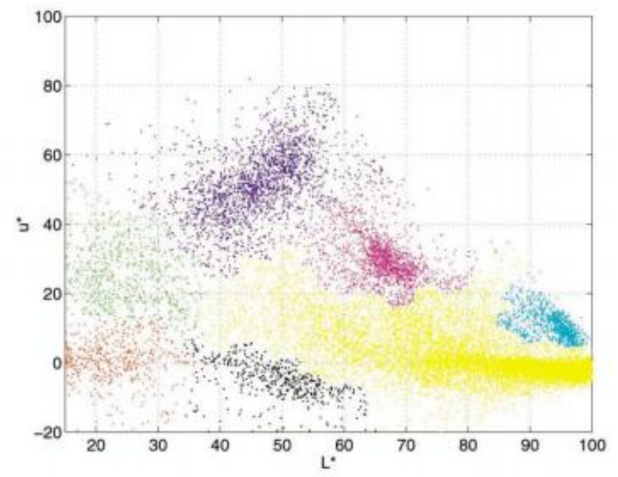
- Find features (color, gradients, texture, etc)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode



Slide by Y. Ukrainitz & B. Sarel

Segmentation by Mean-shift

- 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



(b)

Mean-shift

- Demo
  - Image segmentation with mean-shift
  - Mean-shift tracking (camshift in OpenCV)

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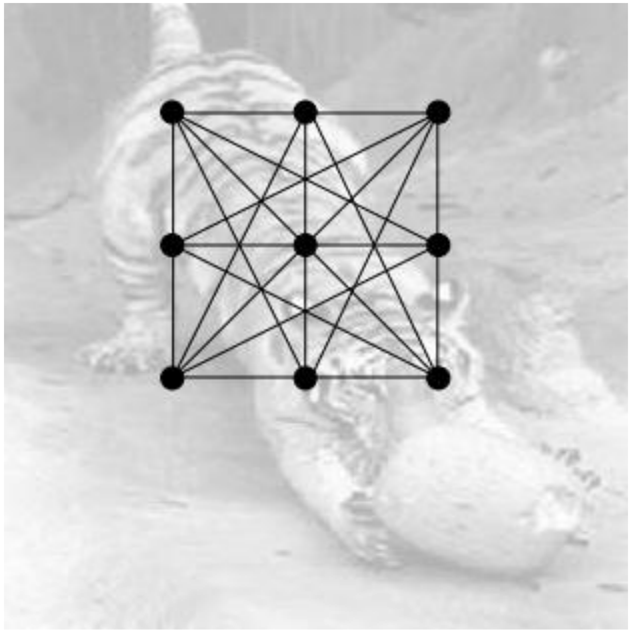
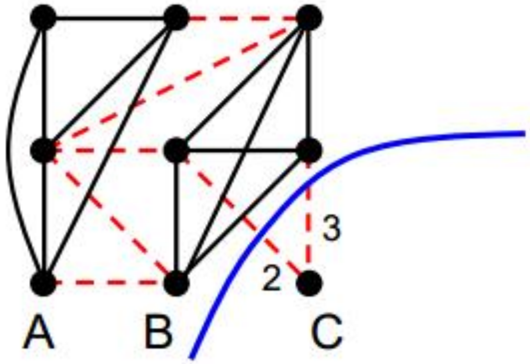
Graph-based Segmentation

- Images as graphs
  - Node for every pixel
  - Edge between every pair of pixels
  - Each edge is weighted by the affinity or similarity of the two nodes



Source: S. Seitz

Graph-based Segmentation

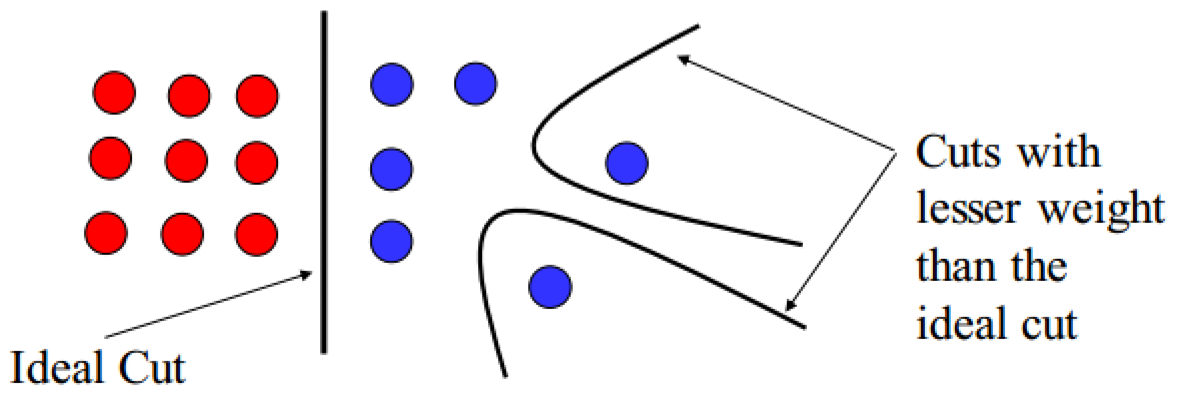


- CUT: Set of edges whose removal makes a graph disconnected
- Cost of a cut: sum of weights of cut edges
- Example: Cost of the blue cut?

Source: S. Seitz

Minimum Cut

- We can do segmentation by finding the *minimum cut* in a graph
  - Efficient algorithms exist for doing this
- Drawback: minimum cut tends to cut off very small, isolated components



* Slide from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Normalized Cut

- IDEA: normalizing the cut by component size
- The *normalized cut* cost is:

$$\frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

assoc(*A*, *V*) = sum of weights of all edges in V that touch A

J. Shi and J. Malik. Normalized cuts and image segmentation. PAMI 2000

Normalized Cut

- Demo
  - Image segmentation with normalized cut
    http://timotheecour.com/software/ncut/ncut.html

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Other State-of-the-art Algorithm

- Efficient Graph-Based Image Segmentation.
  Pedro F. Felzenszwalb and Daniel P. Huttenlocher
  IJCV, 2004

- Demo
  - http://www.cs.brown.edu/~pff/segment/