

# Grouping and Segmentation

Computer Vision  
CS 543 / ECE 549  
University of Illinois

Derek Hoiem

# Last week

- EM
- Mixture of Gaussians
- Segmentation using EM and graph cuts

# Today's class

- Segmentation and grouping
  - Gestalt cues
  - By clustering (mean-shift)
  - By boundaries (watershed)

# Gestalt grouping

# Gestalt psychology or gestaltism

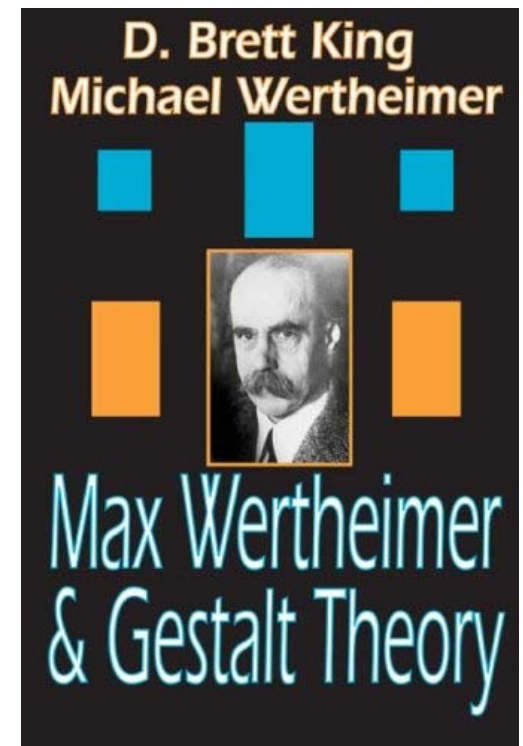
German: *Gestalt* - "form" or "whole"

Berlin School, early 20th century

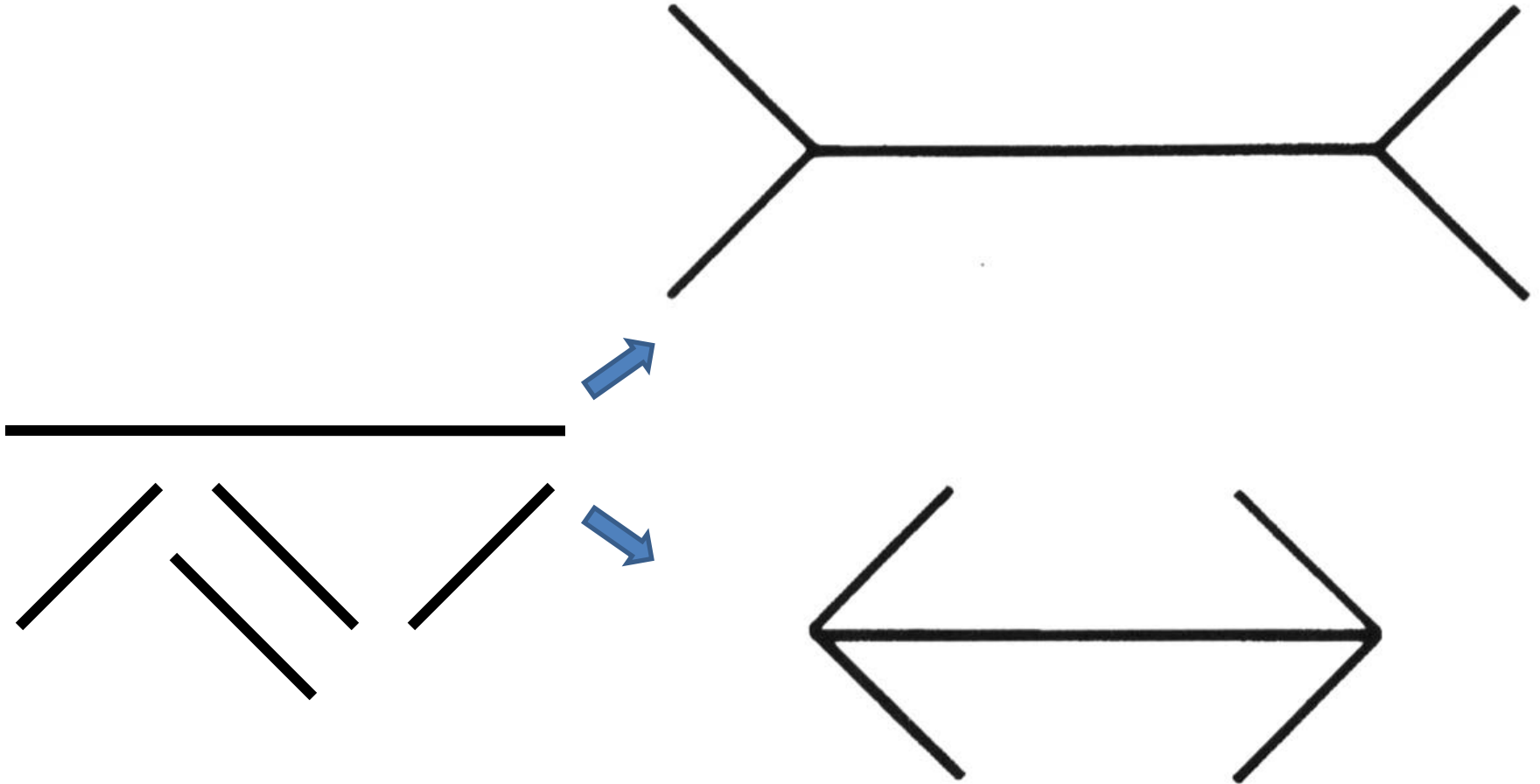
Kurt Koffka, Max Wertheimer, and Wolfgang Köhler

View of brain:

- whole is more than the sum of its parts
- holistic
- parallel
- analog
- self-organizing tendencies

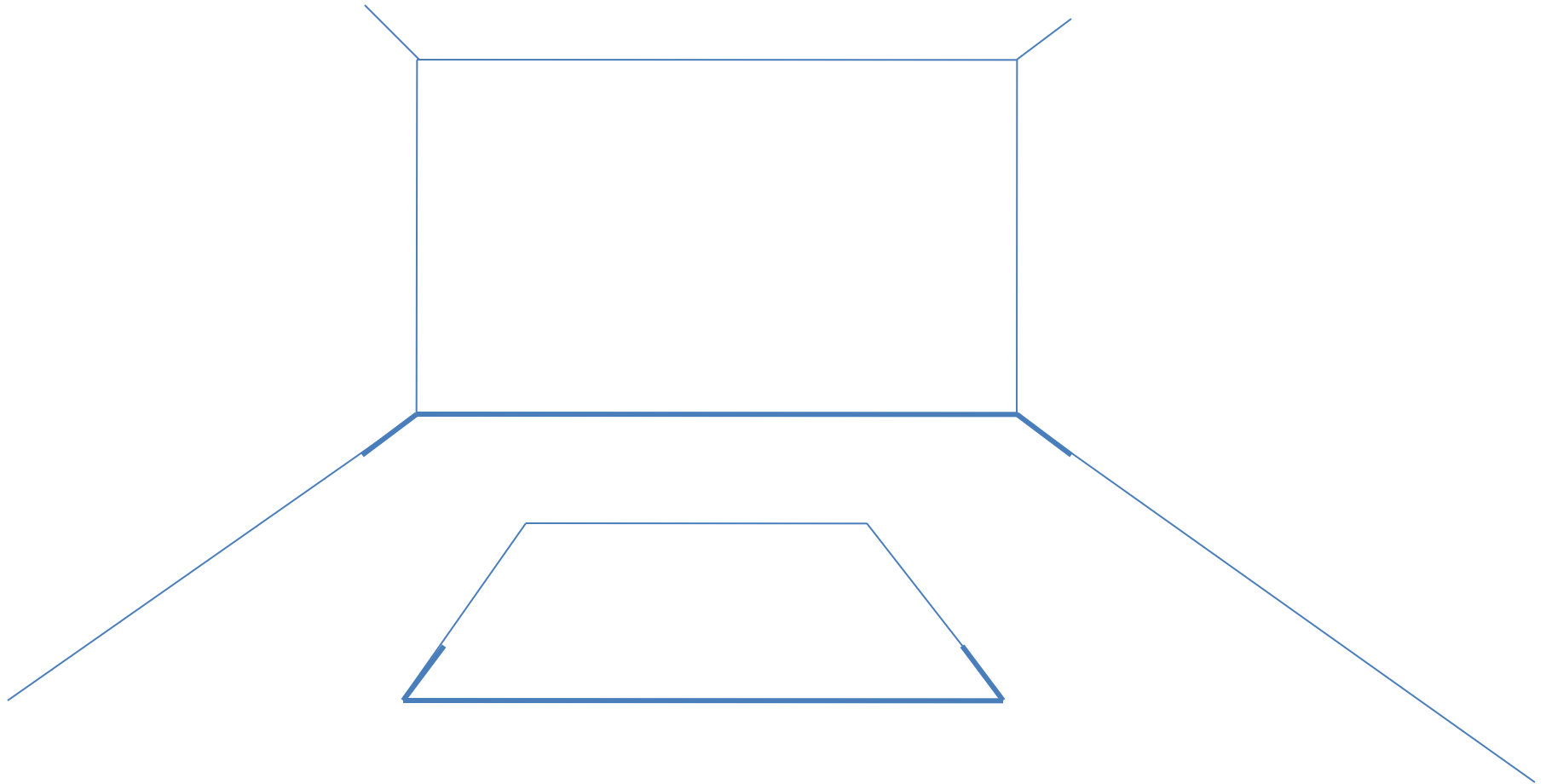


# Gestaltism



The Muller-Lyer illusion

We perceive the interpretation, not the  
senses



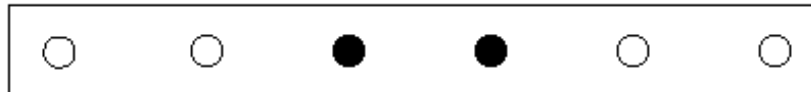
# Principles of perceptual organization



Not grouped



Proximity



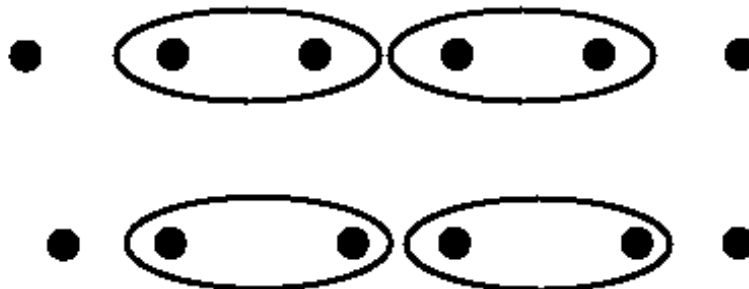
Similarity



Similarity



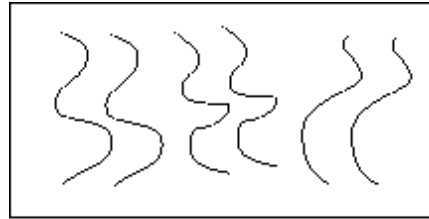
Common Fate



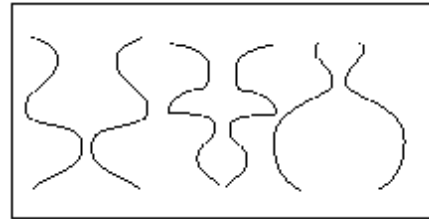
Common Region



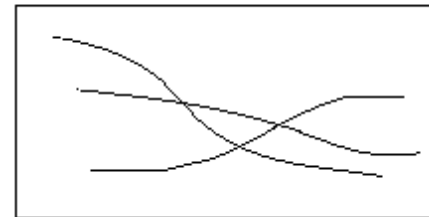
# Principles of perceptual organization



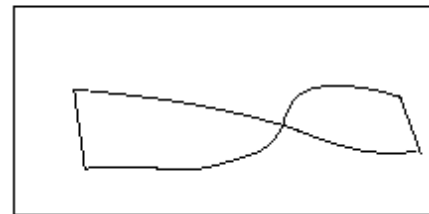
Parallelism



Symmetry

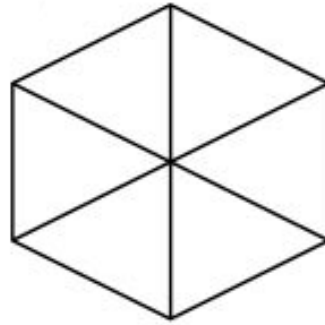


Continuity

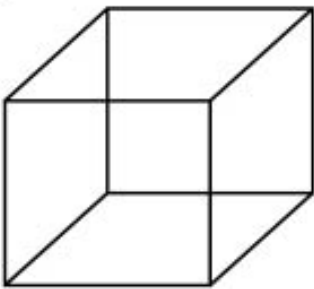


Closure

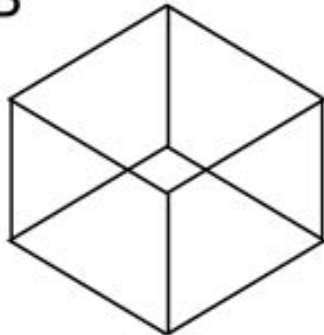
# Gestaltists do not believe in coincidence



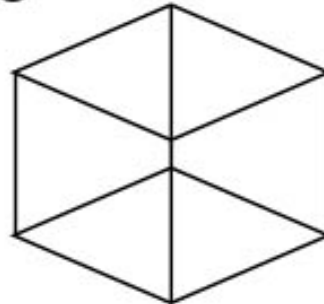
A



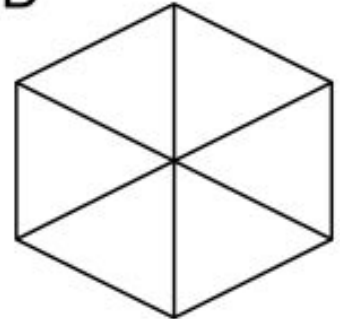
B



C



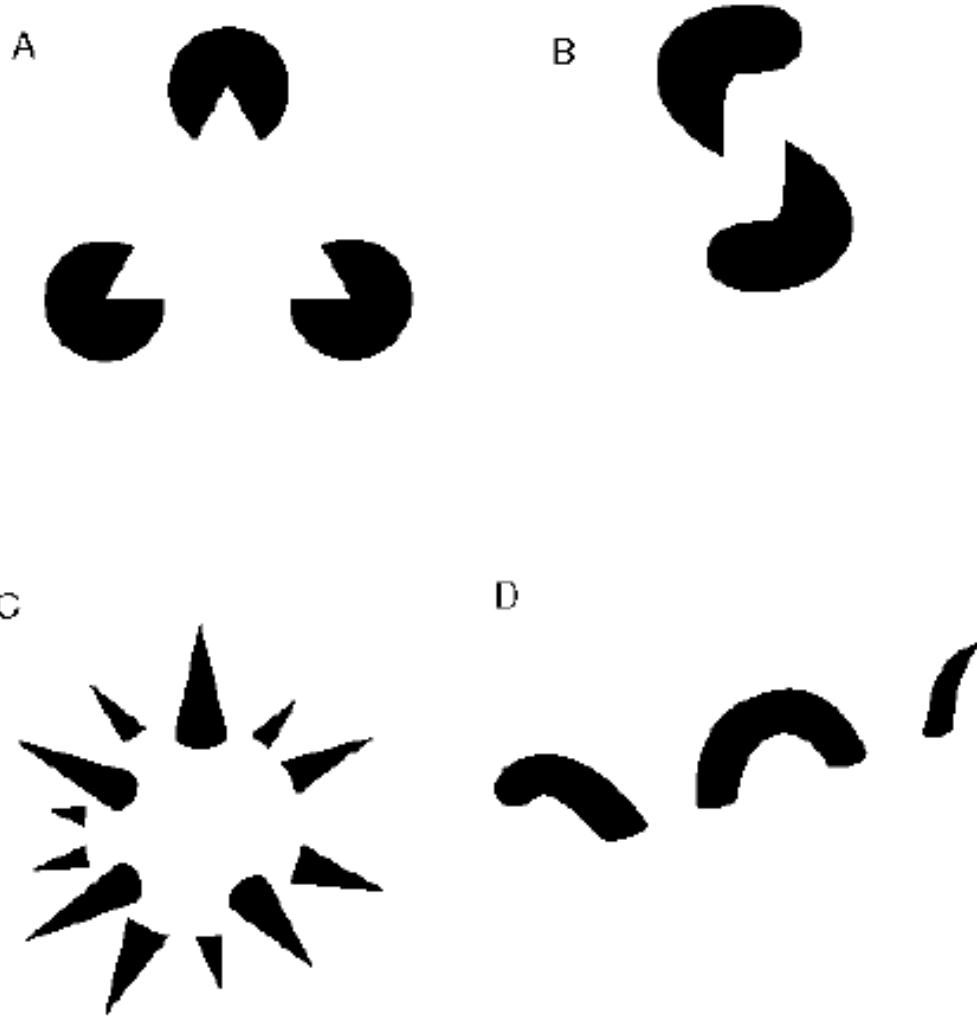
D



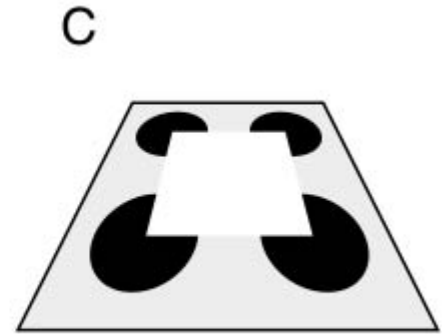
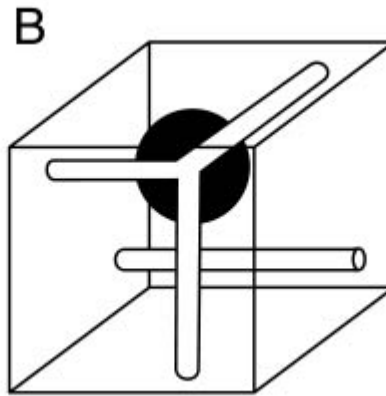
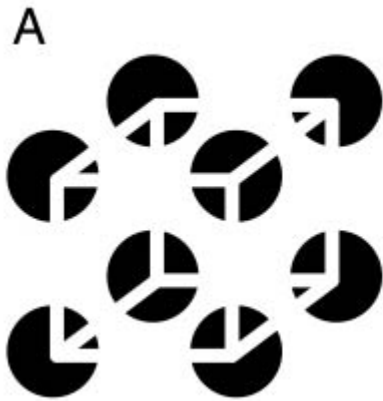
# Emergence



# Grouping by invisible completion

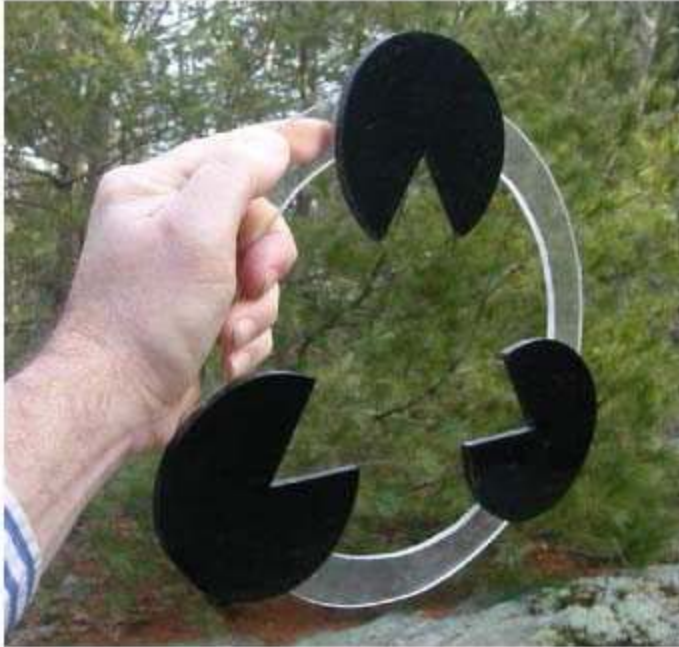


# Grouping involves global interpretation



# Grouping involves global interpretation

A



B



# Gestalt cues

- Good intuition and basic principles for grouping
- Basis for many ideas in segmentation and occlusion reasoning
- Some (e.g., symmetry) are difficult to implement in practice

# Moving on to image segmentation ...

Goal: Break up the image into meaningful or perceptually similar regions

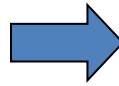




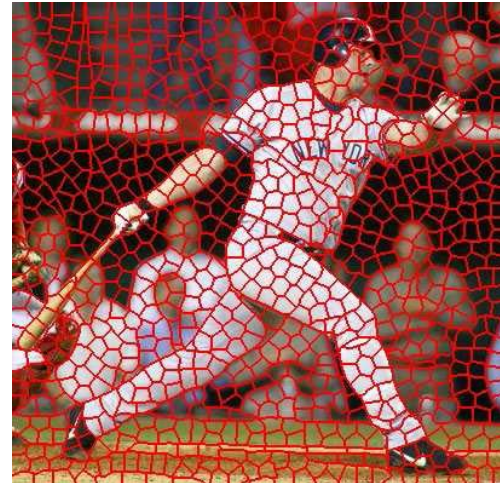
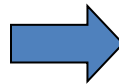
# Segmentation for feature support



# Segmentation for efficiency



[Felzenszwalb and Huttenlocher 2004]



[Shi and Malik 2001]

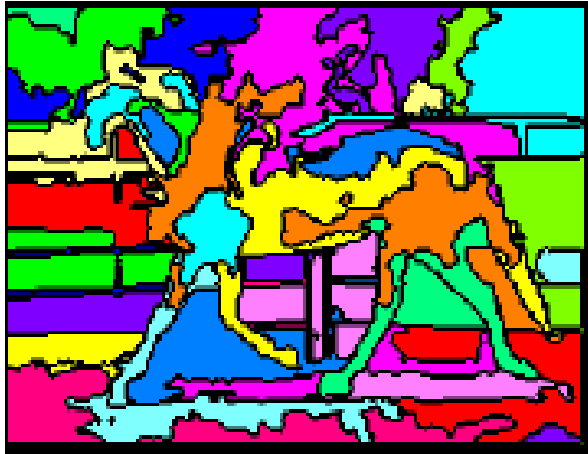
[Hoiem et al. 2005, Mori 2005]

# Segmentation as a result

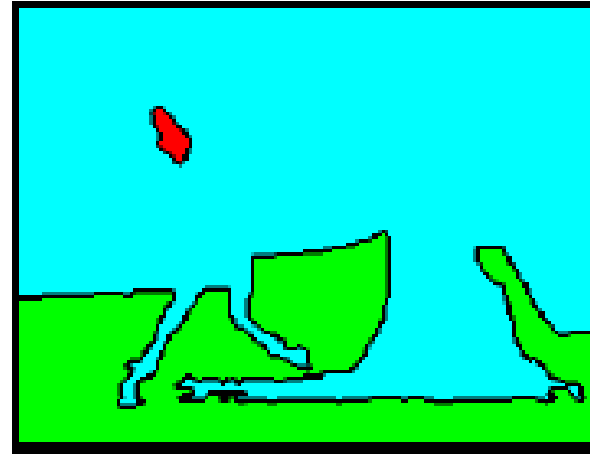




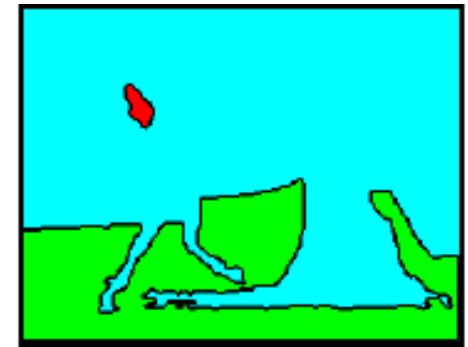
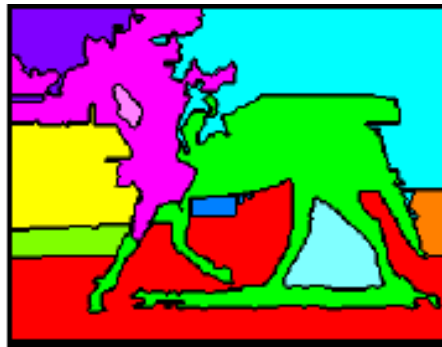
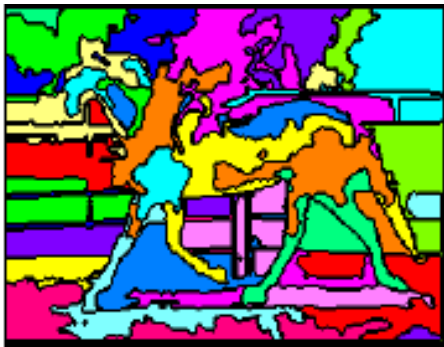
# Types of segmentations



Oversegmentation



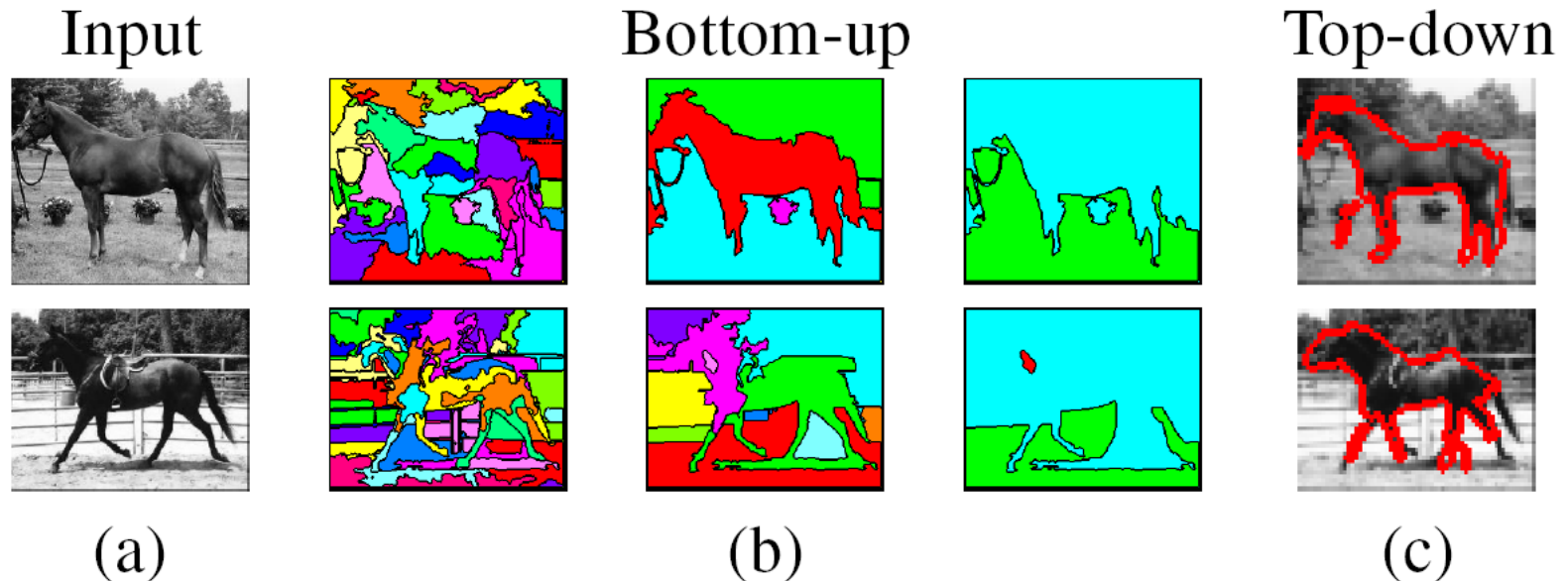
Undersegmentation



Multiple Segmentations

# Major processes for segmentation

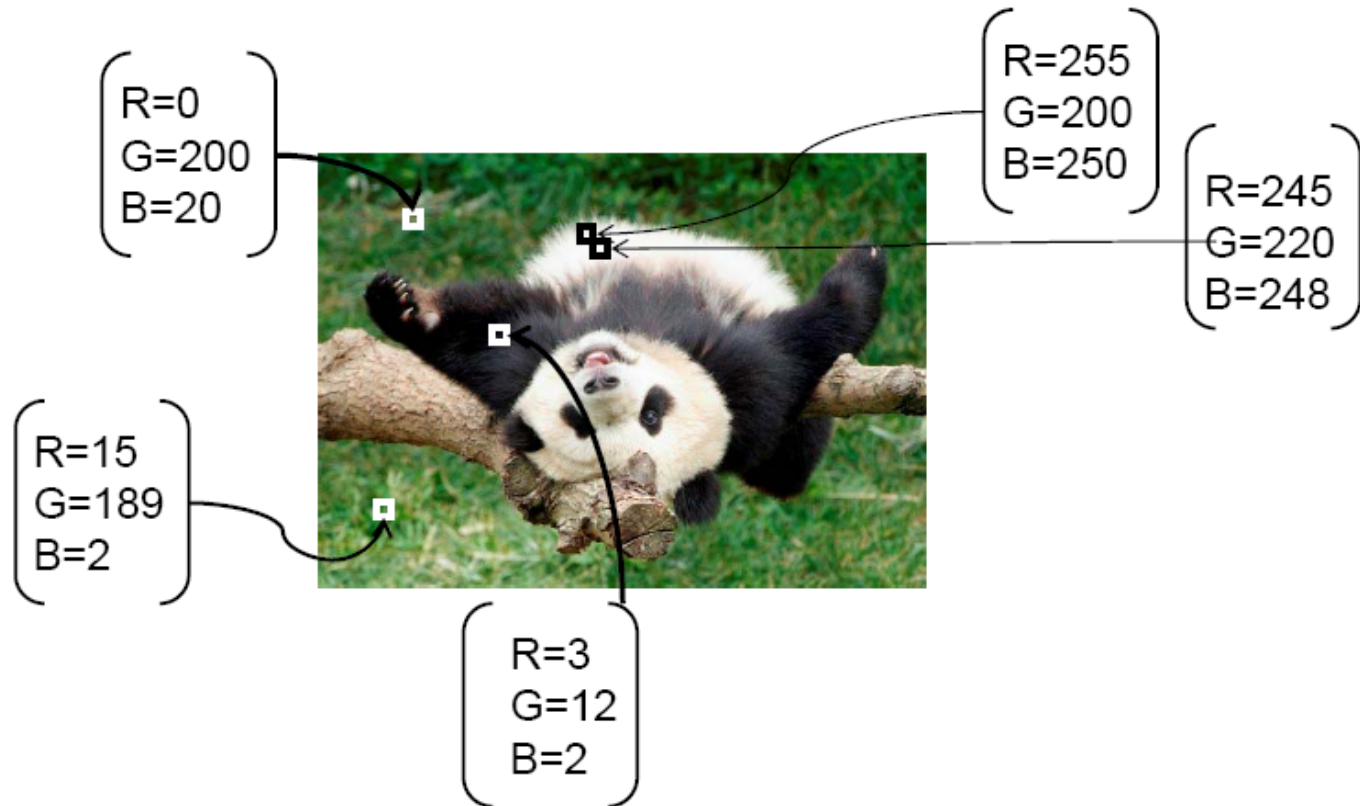
- Bottom-up: group tokens with similar features
- Top-down: group tokens that likely belong to the same object



# Segmentation using clustering

- Kmeans
- Mean-shift

# Feature Space



# K-means clustering using intensity alone and color alone

Image



Clusters on intensity



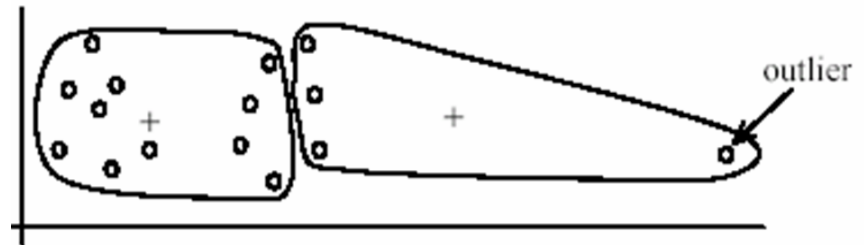
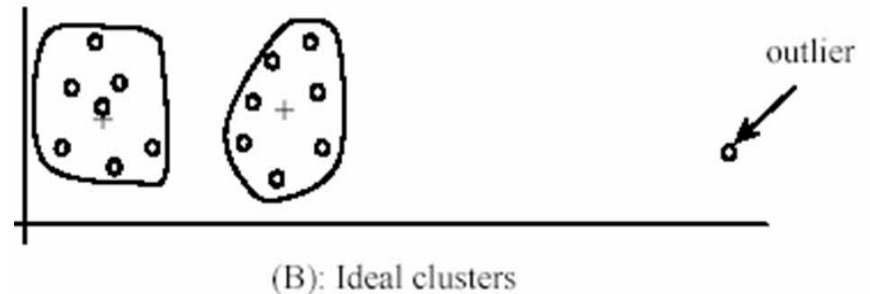
Clusters on color





# K-Means pros and cons

- Pros
  - Simple and fast
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers
- Usage
  - Rarely used for pixel segmentation



# Mean shift segmentation

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

- Versatile technique for clustering-based segmentation

**Segmented "landscape 1"**

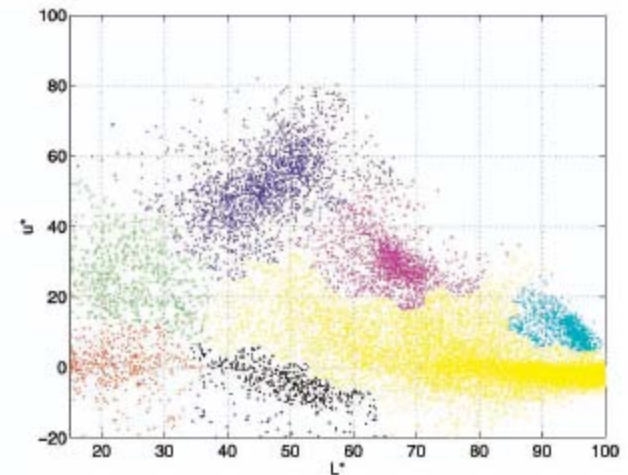
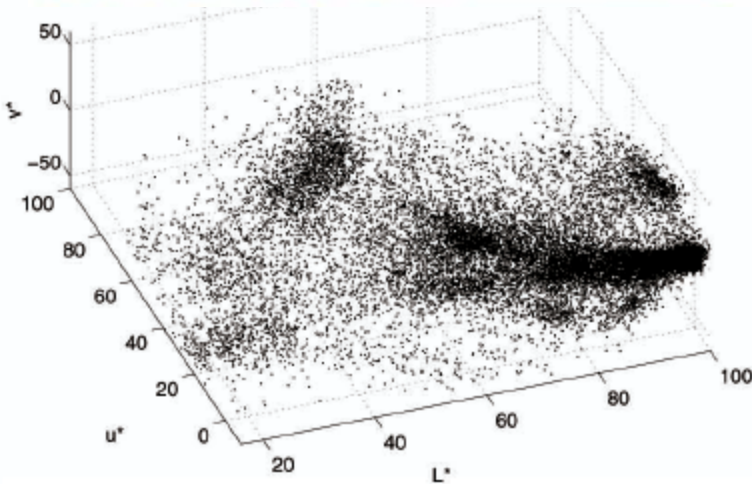
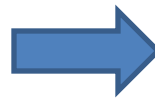
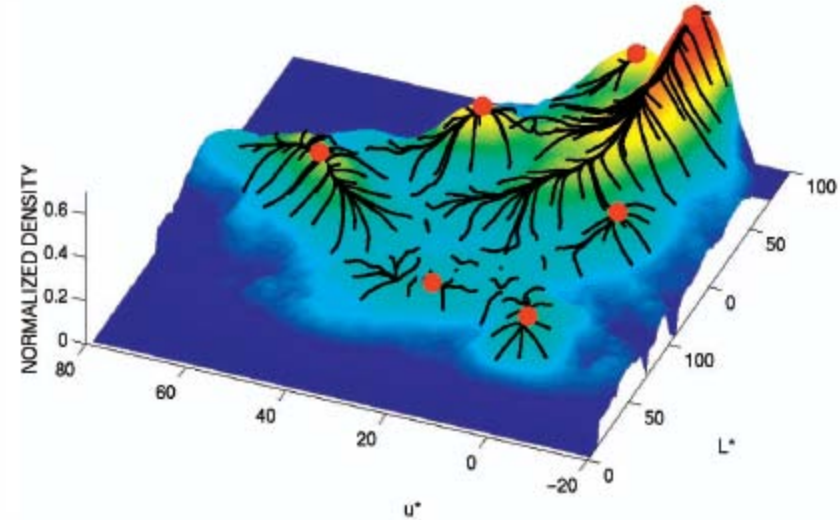


**Segmented "landscape 2"**



# Mean shift algorithm

- Try to find *modes* of this non-parametric density



# Kernel density estimation

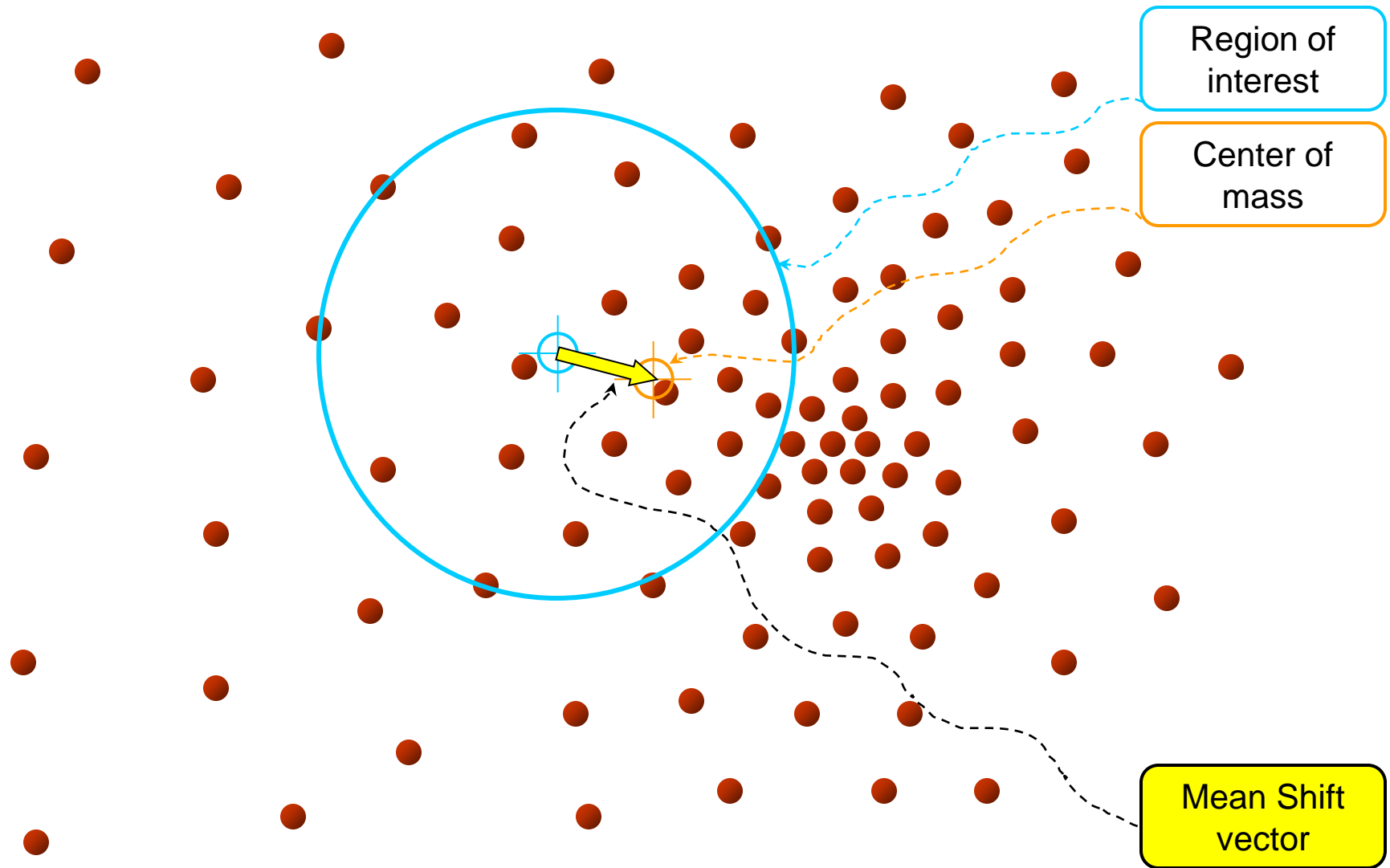
Kernel density estimation function

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right)$$

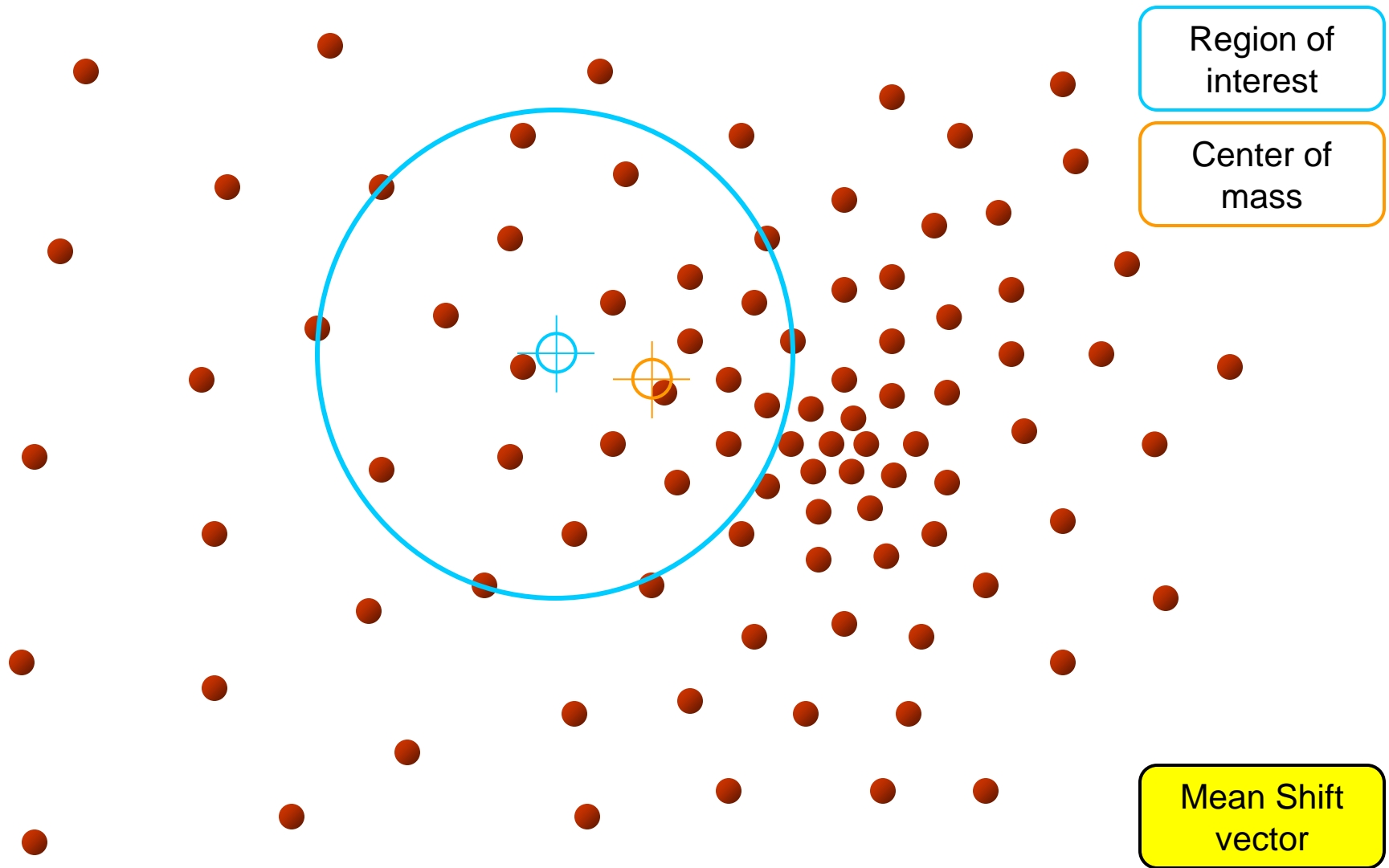
Gaussian kernel

$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x - x_i)^2}{2h^2}}.$$

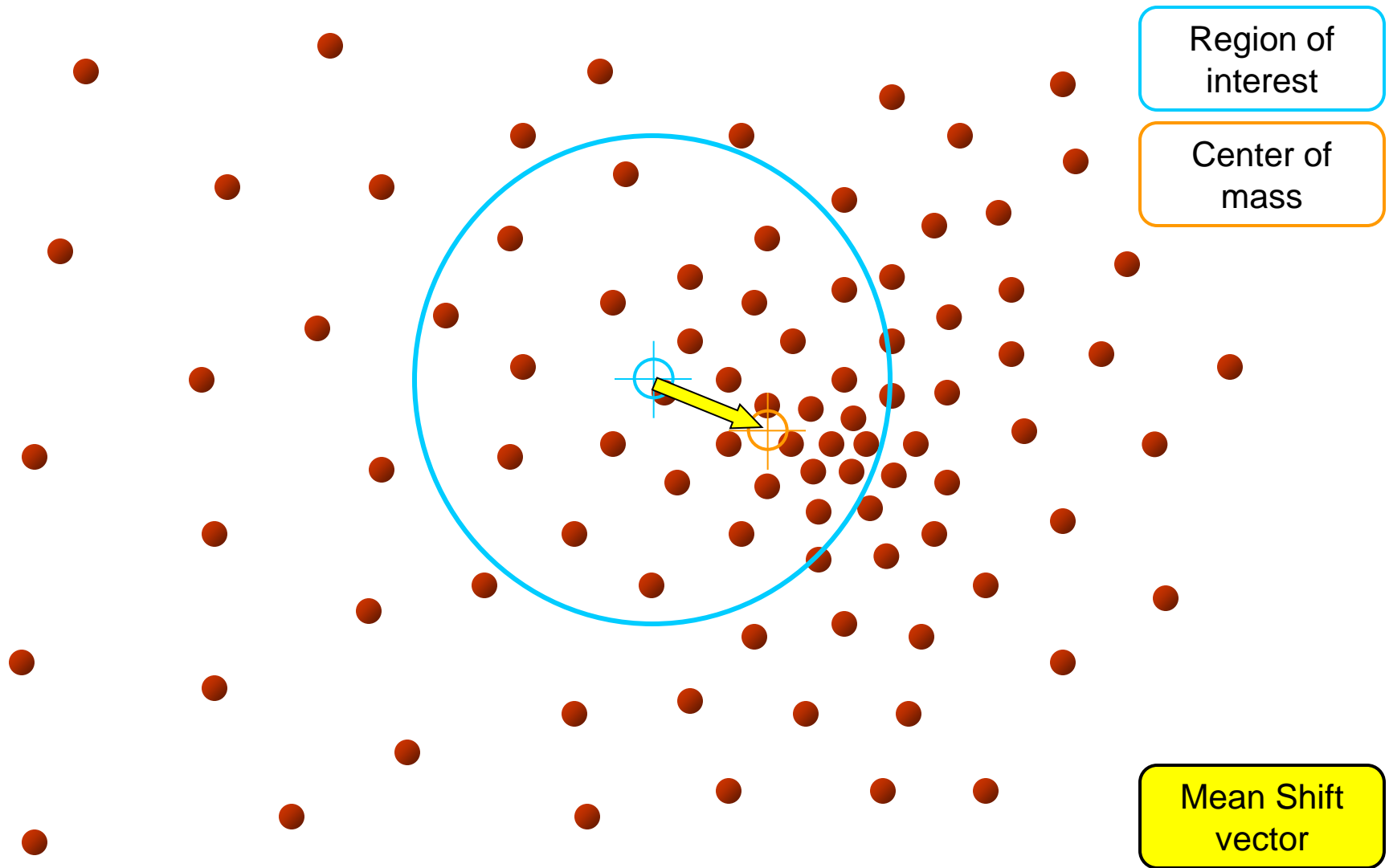
# Mean shift



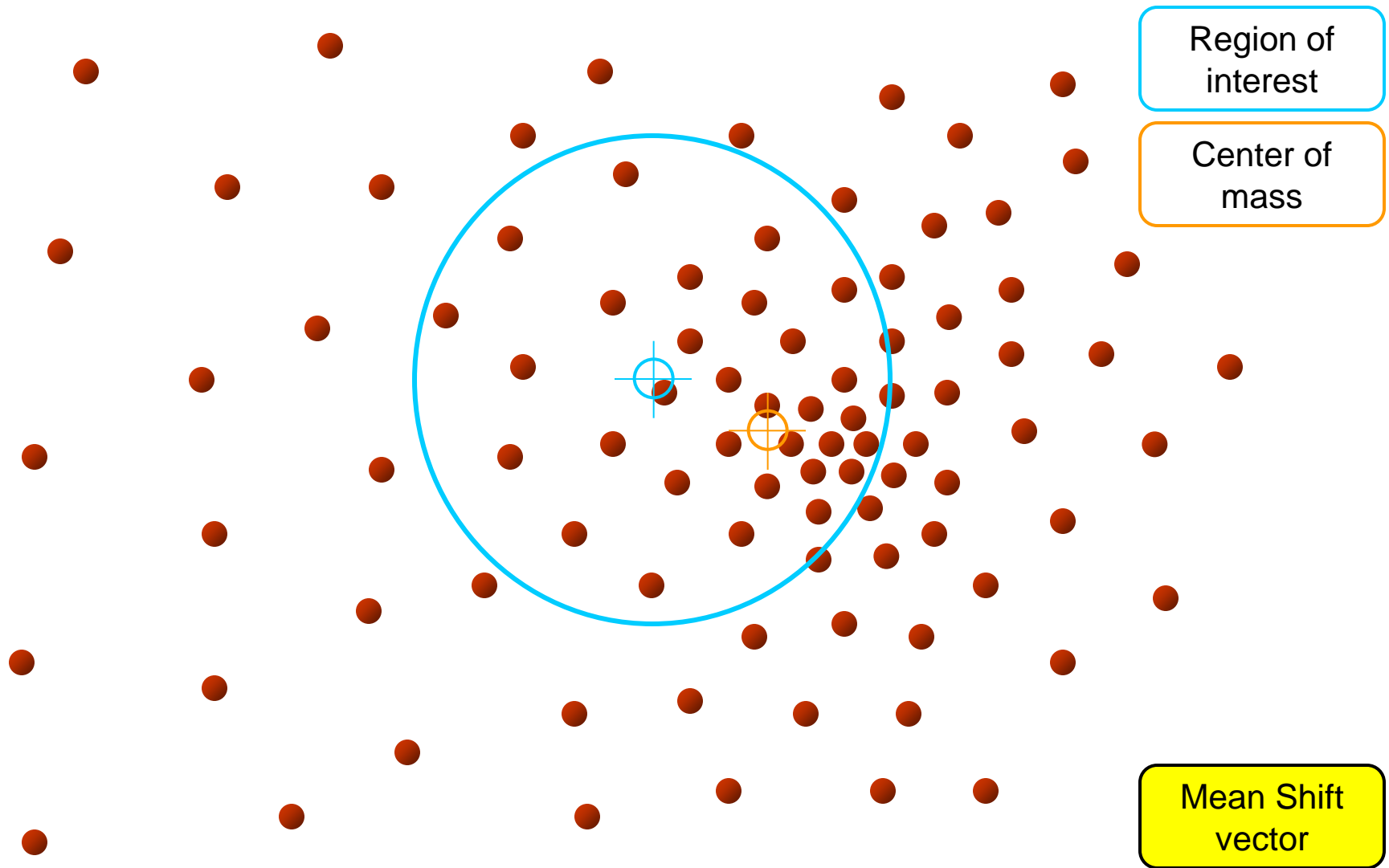
# Mean shift



# Mean shift

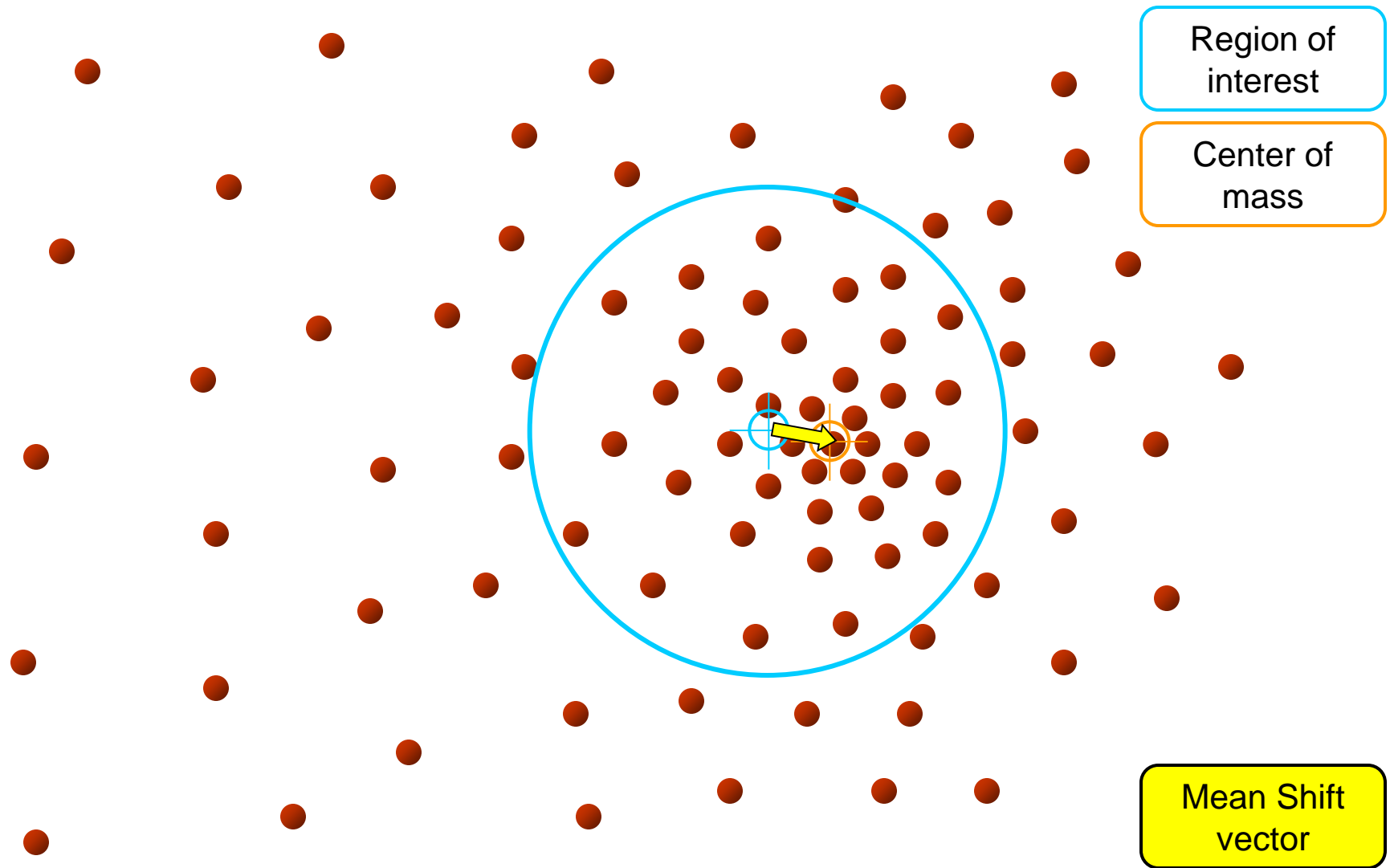


# Mean shift

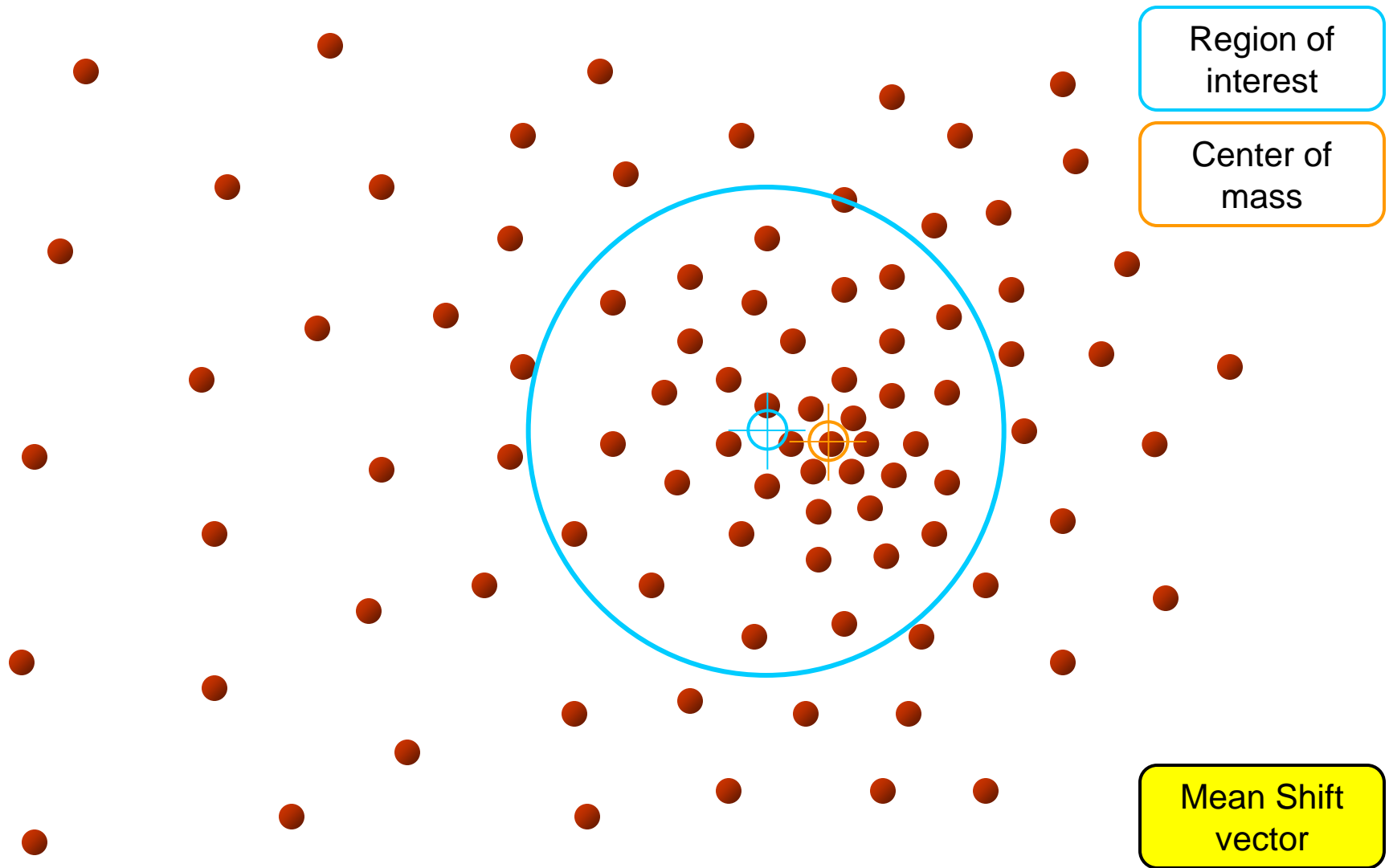




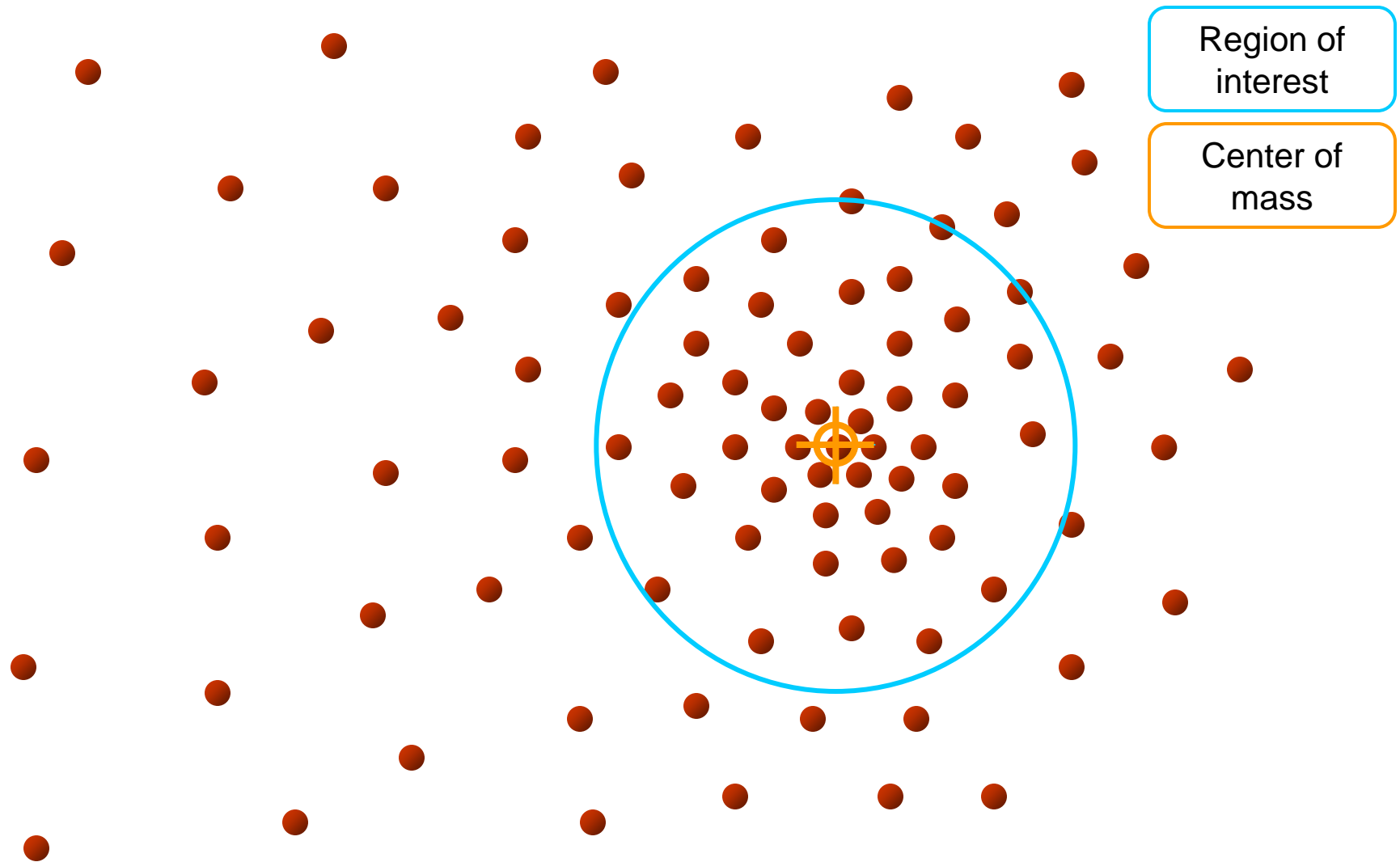
# Mean shift



# Mean shift



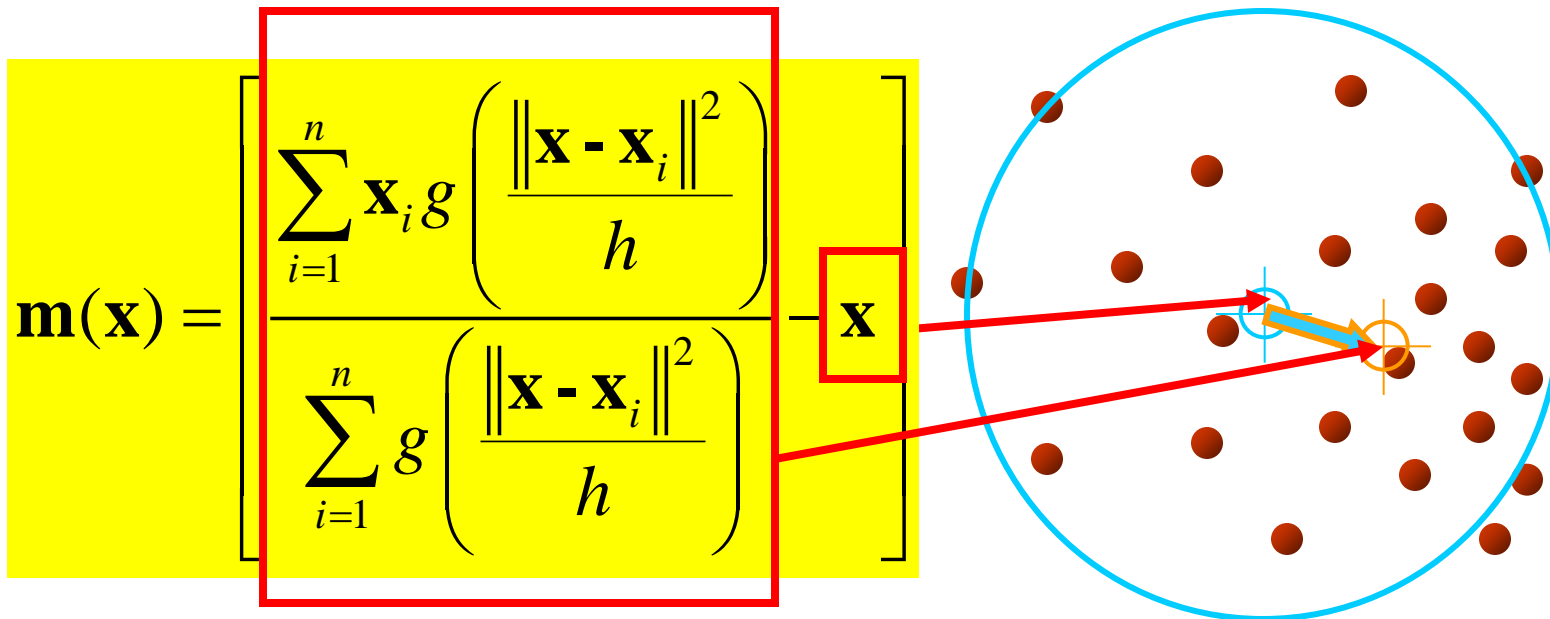
# Mean shift



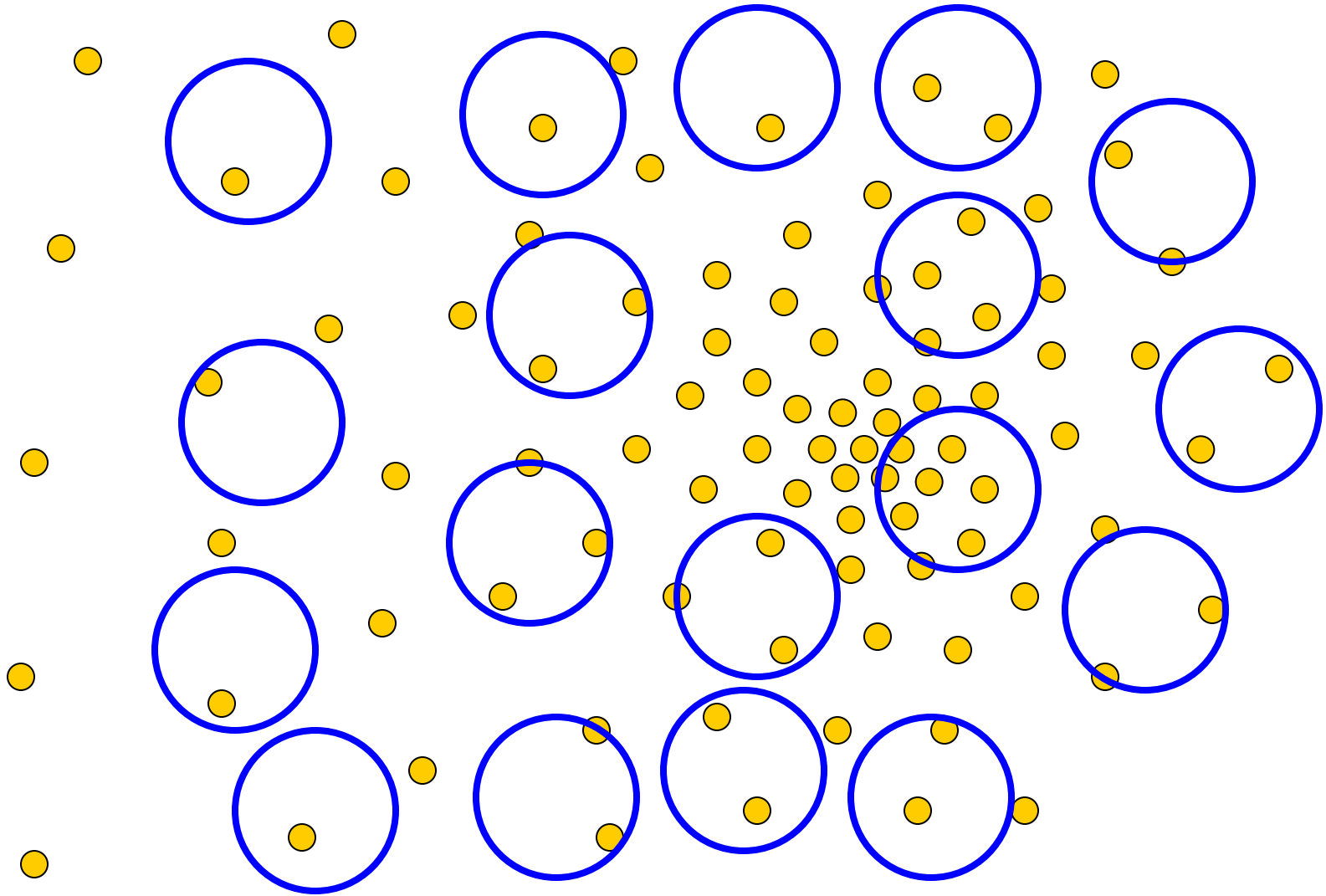
# Computing the Mean Shift

Simple Mean Shift procedure:

- Compute mean shift vector
- Translate the Kernel window by  $\mathbf{m}(\mathbf{x})$

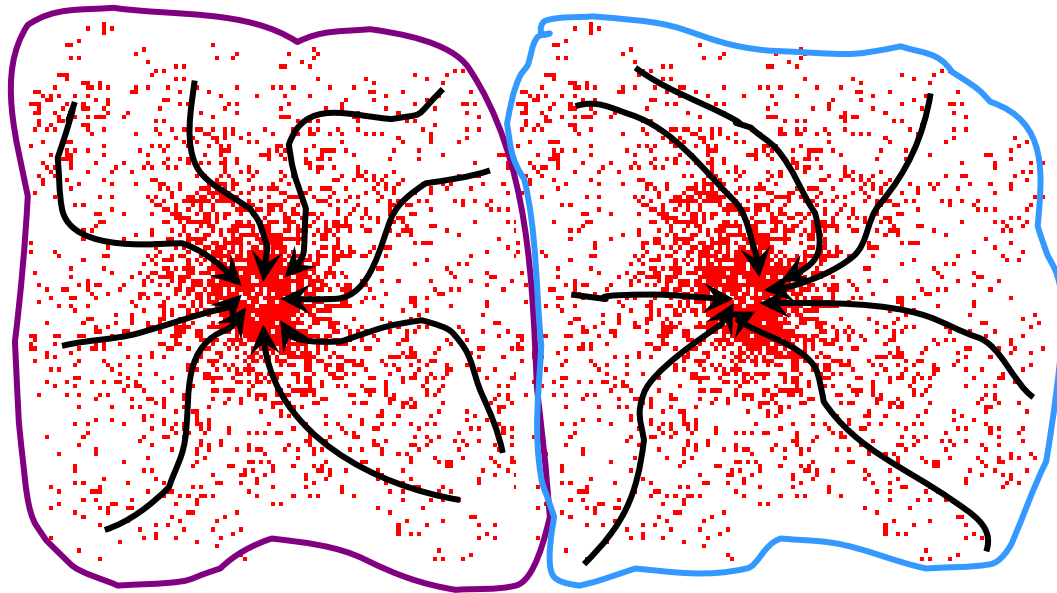


# Real Modality Analysis

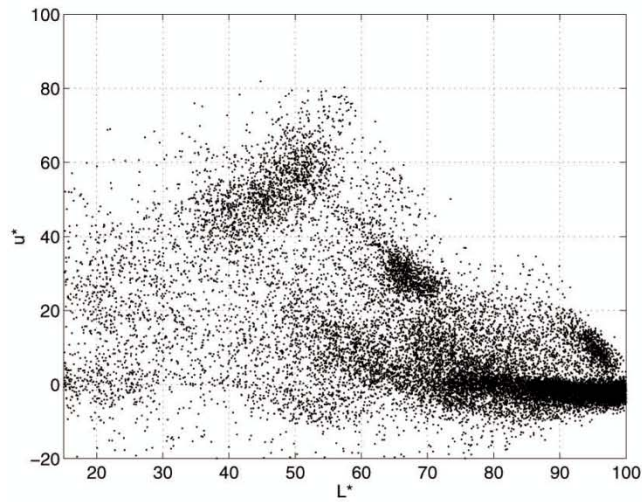


# Attraction basin

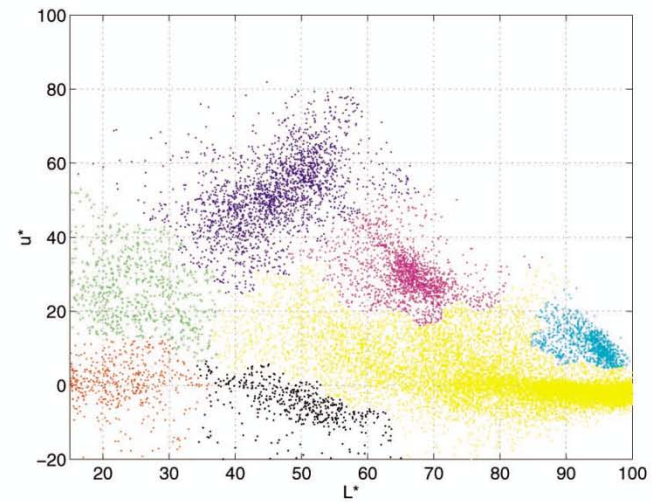
- **Attraction basin:** the region for which all trajectories lead to the same mode
- **Cluster:** all data points in the attraction basin of a mode



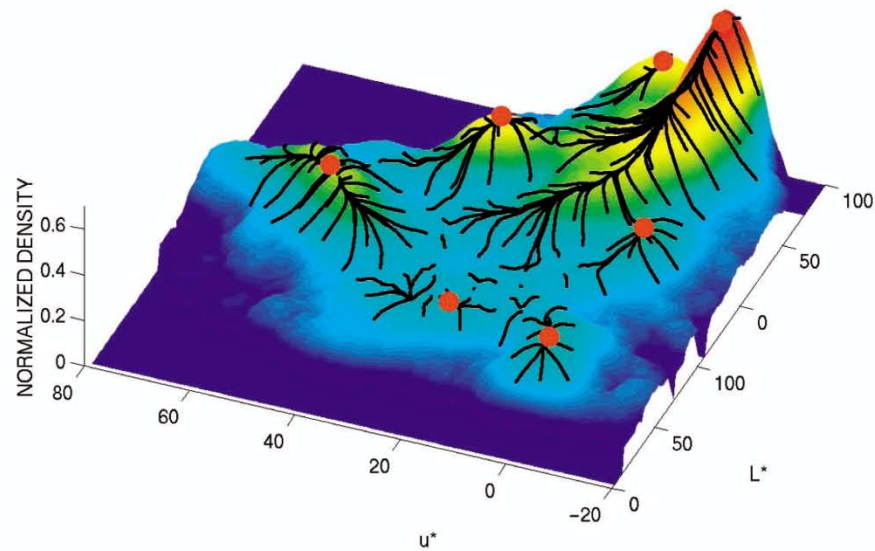
# Attraction basin



(a)



(b)



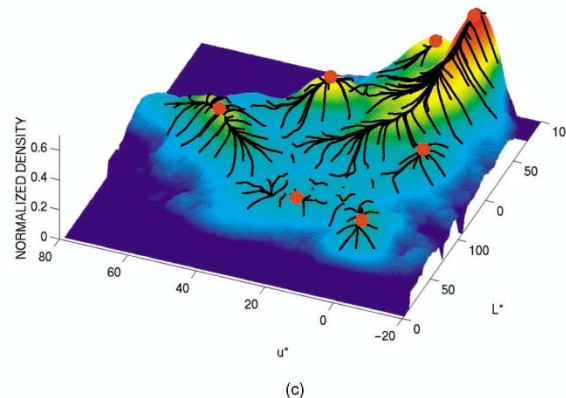
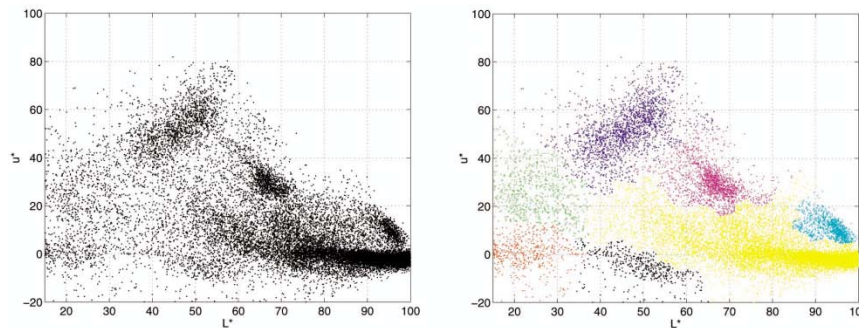
# Mean shift clustering

- 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

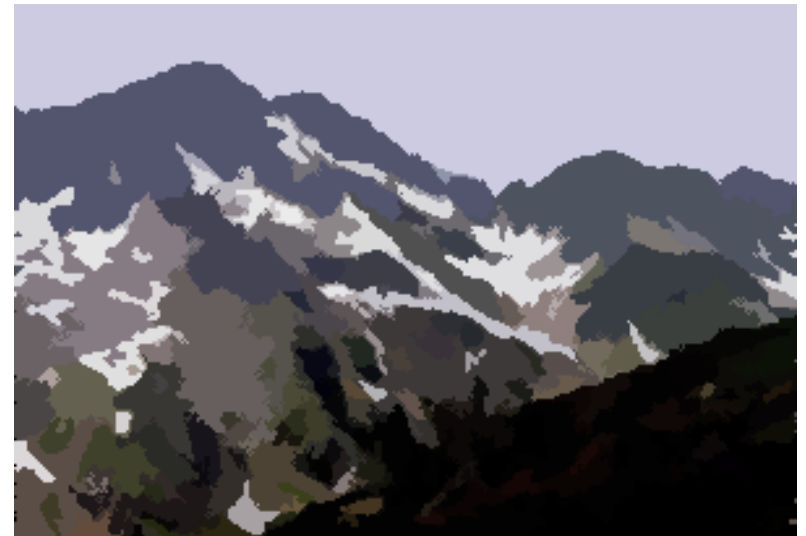


# Segmentation by Mean Shift

- Compute features for each pixel (color, gradients, texture, etc)
- Set kernel size for features  $K_f$  and position  $K_s$
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that are within width of  $K_f$  and  $K_s$



# Mean shift segmentation results



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



# Mean-shift: other issues

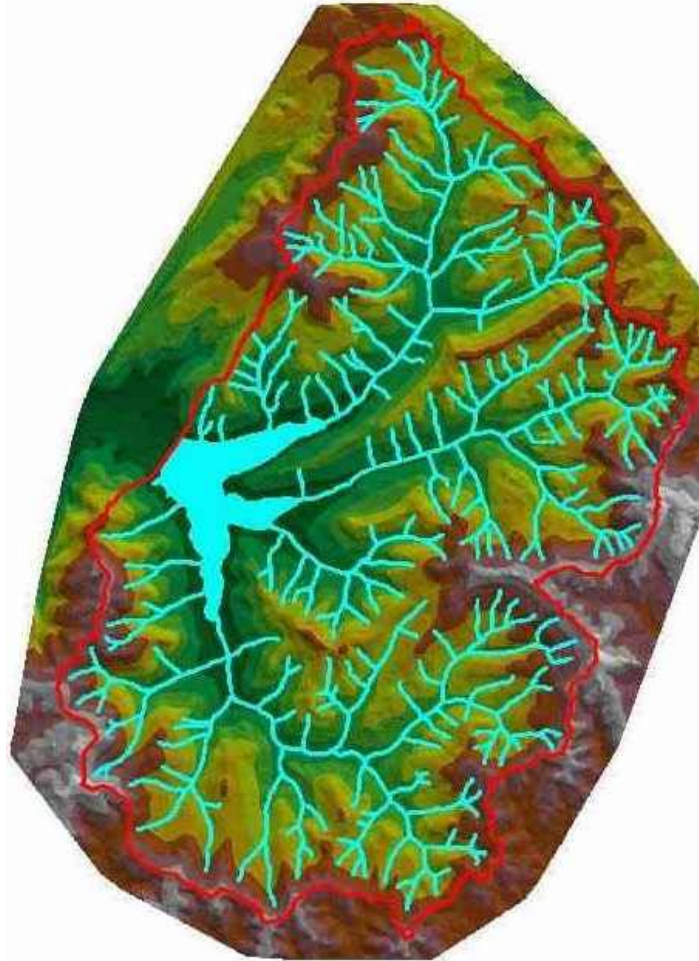
- Speedups
  - Binned estimation
  - Fast search of neighbors
  - Update each window in each iteration (faster convergence)
- Other tricks
  - Use kNN to determine window sizes adaptively
- Lots of theoretical support

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

# Mean shift pros and cons

- Pros
  - Good general-practice segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
- Cons
  - Have to choose kernel size in advance
  - Not suitable for high-dimensional features
- When to use it
  - Oversegmentation
  - Multiple segmentations
  - Tracking, clustering, filtering applications

# Watershed algorithm





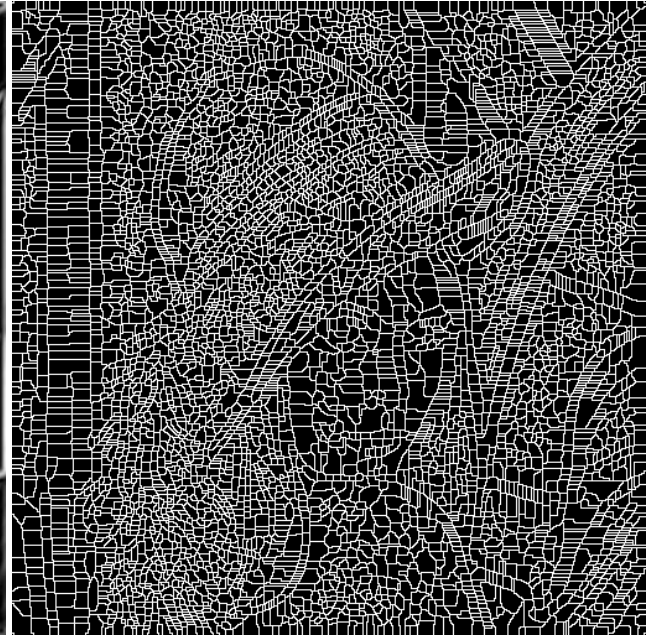
# Watershed segmentation



Image



Gradient



Watershed boundaries

# Meyer's watershed segmentation

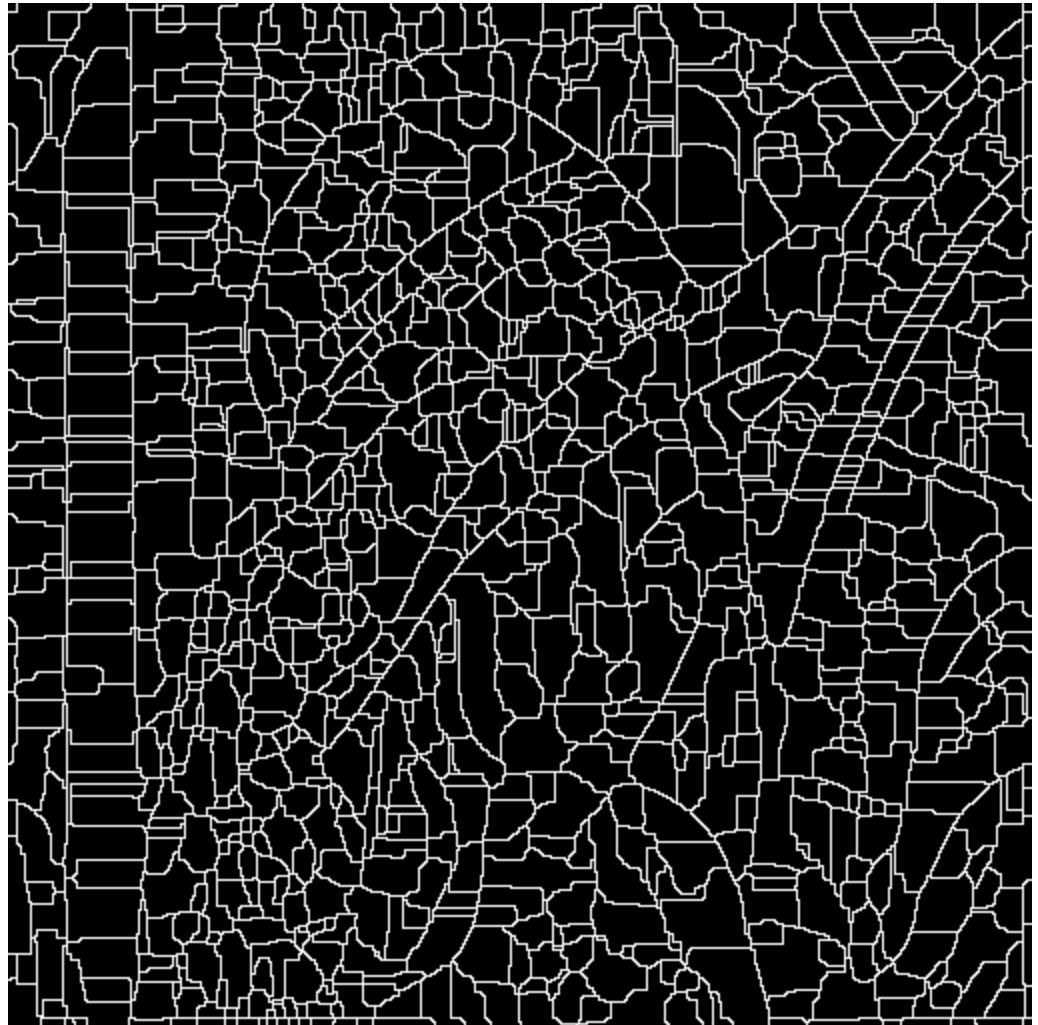
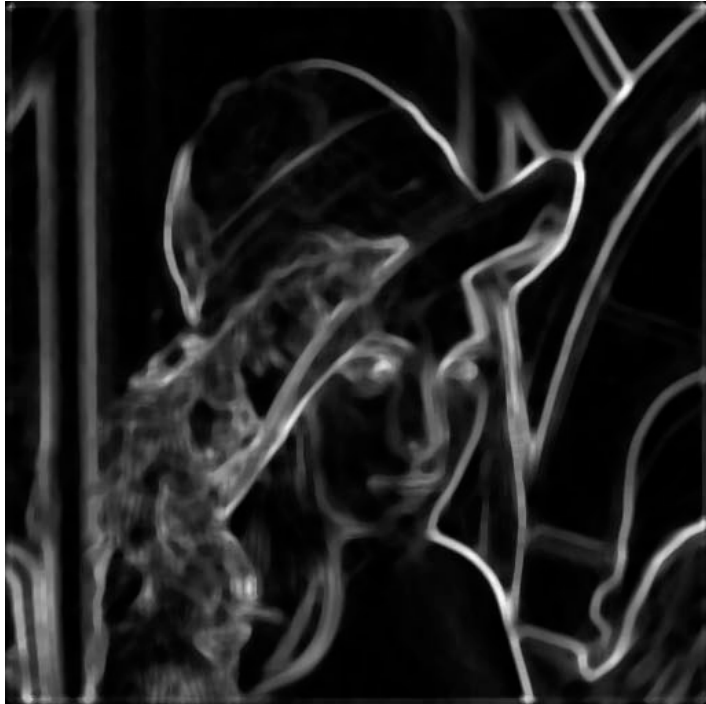
1. Choose local minima as region seeds
2. Add neighbors to priority queue, sorted by value
3. Take top priority pixel from queue
  1. If all labeled neighbors have same label, assign to pixel
  2. Add all non-marked neighbors
4. Repeat step 3 until finished

Matlab: `seg = watershed(bnd_im)`



# Simple trick

- Use Gaussian or median filter to reduce number of regions



# Watershed usage

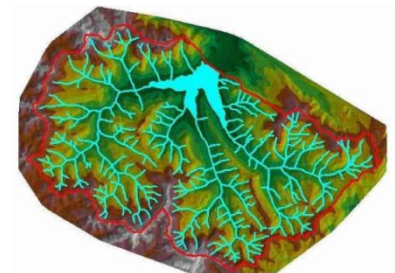
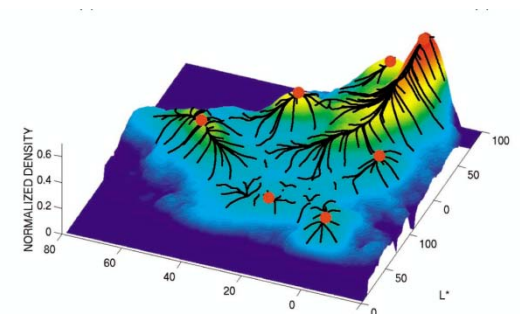
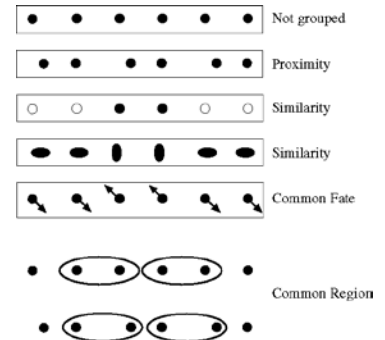
- Use as a starting point for hierarchical segmentation
  - Ultrametric contour map (Arbelaez 2006)
- Works with any soft boundaries
  - Pb
  - Canny
  - Etc.

# Watershed pros and cons

- Pros
  - Fast (< 1 sec for 512x512 image)
  - Among best methods for hierarchical segmentation
- Cons
  - Only as good as the soft boundaries
  - Not easy to get variety of regions for multiple segmentations
  - No top-down information
- Usage
  - Preferred algorithm for hierarchical segmentation

# Things to remember

- Gestalt cues and principles of organization
- Uses of segmentation
  - Efficiency
  - Better features
  - Want the segmented object
- Mean-shift segmentation
  - Good general-purpose segmentation method
  - Generally useful clustering, tracking technique
- Watershed segmentation
  - Good for hierarchical segmentation
  - Use in combination with boundary prediction



# Further reading

- Nicely written mean-shift explanation (with math)

<http://saravananthirumuruganathan.wordpress.com/2010/04/01/introduction-to-mean-shift-algorithm/>

- Mean-shift paper by Comaniciu and Meer

<http://www.caip.rutgers.edu/~comanici/Papers/MsRobustApproach.pdf>

- Adaptive mean shift in higher dimensions

<http://mis.hevra.haifa.ac.il/~ishimshoni/papers/chap9.pdf>

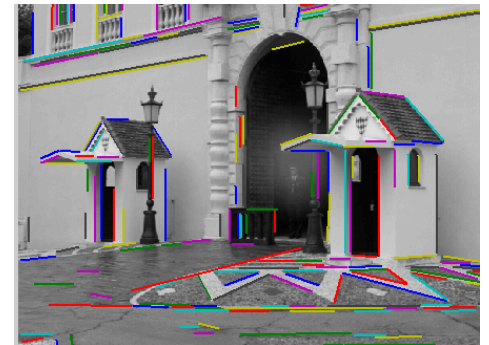
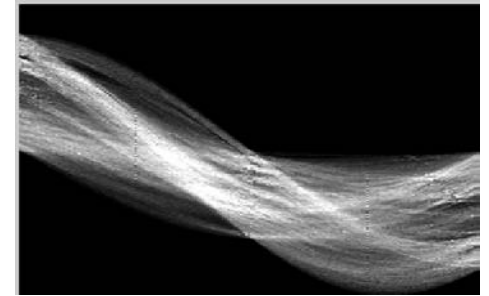
- Contours to regions (watershed): Arbelaez et al. 2009

[http://www.eecs.berkeley.edu/~arbelaez/publications/Arbelaez\\_Maire\\_Fowlkes\\_Malik\\_CVPR2009.pdf](http://www.eecs.berkeley.edu/~arbelaez/publications/Arbelaez_Maire_Fowlkes_Malik_CVPR2009.pdf)

# Recap of Grouping and Fitting

# Edge and line detection

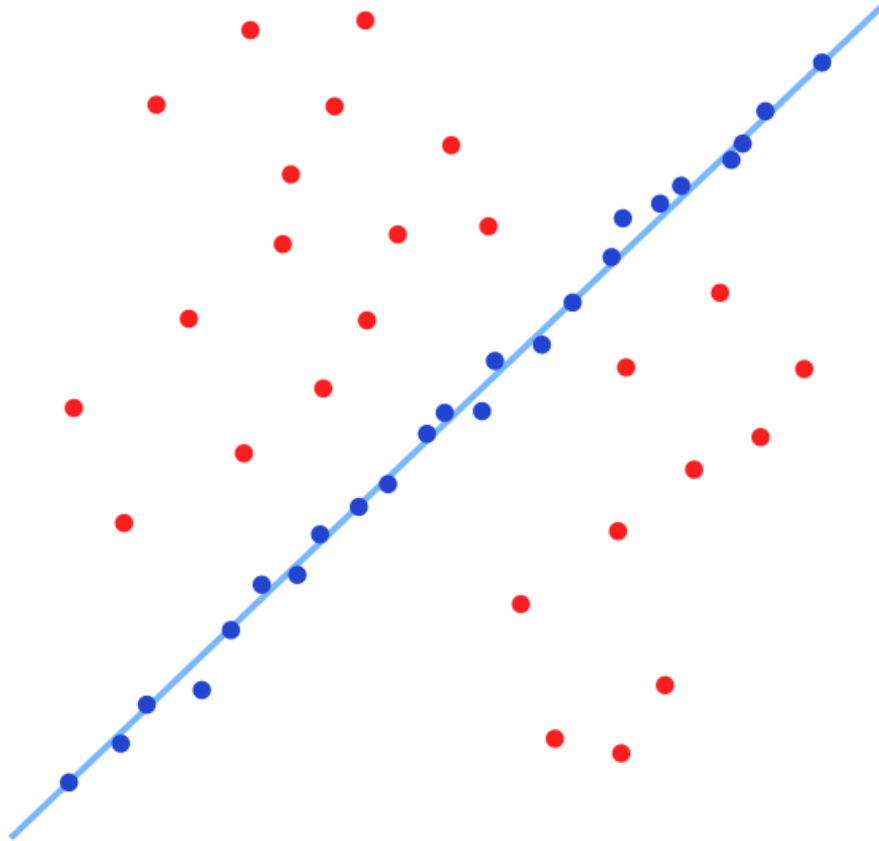
- Canny edge detector =  
smooth  $\rightarrow$  derivative  $\rightarrow$  thin  $\rightarrow$   
threshold  $\rightarrow$  link
- Generalized Hough transform =  
points vote for shape parameters
- Straight line detector =  
canny + gradient orientations  $\rightarrow$   
orientation binning  $\rightarrow$  linking  $\rightarrow$   
check for straightness



# Robust fitting and registration

## Key algorithms

- RANSAC, Hough Transform

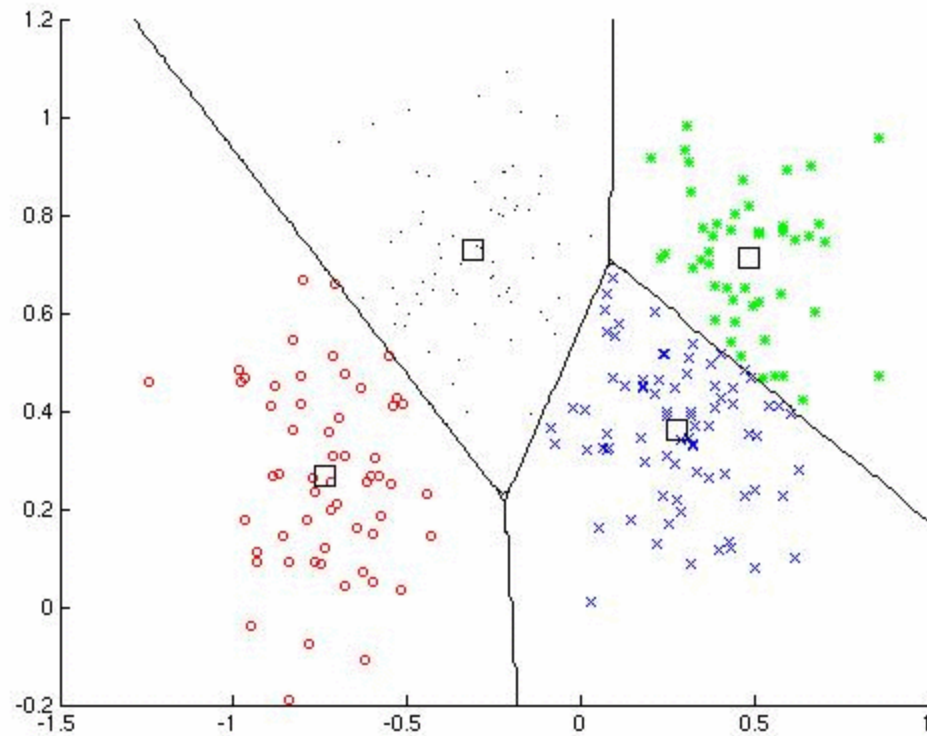




# Clustering

## Key algorithm

- K-means

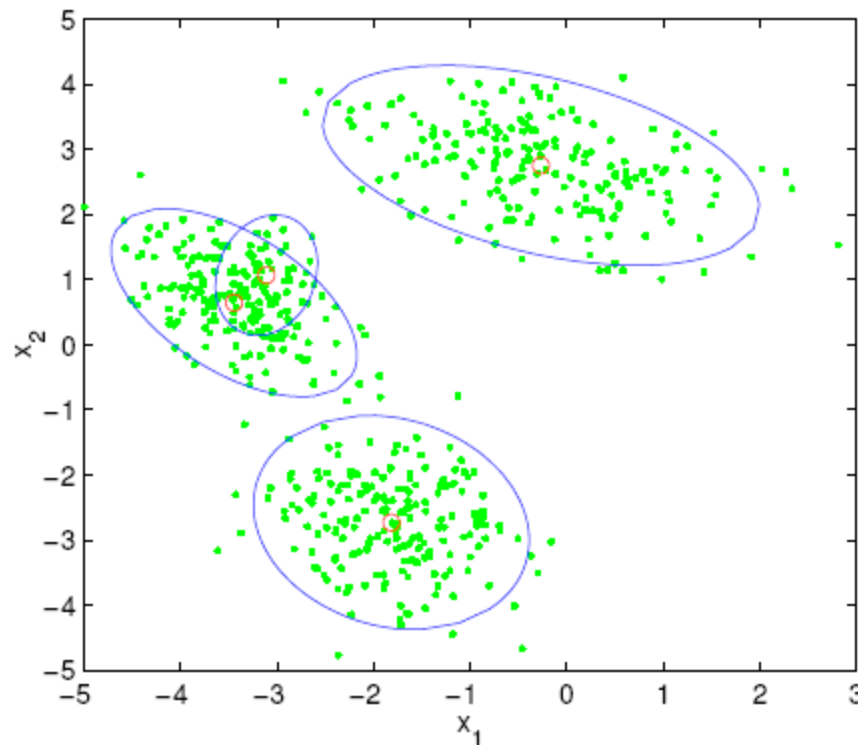


# EM and Mixture of Gaussians

## Tutorials:

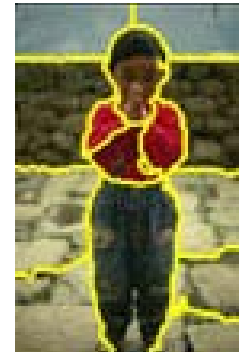
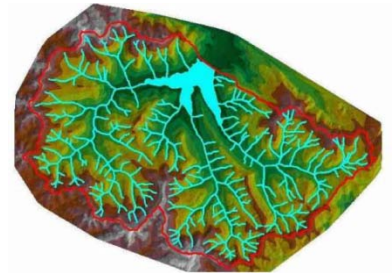
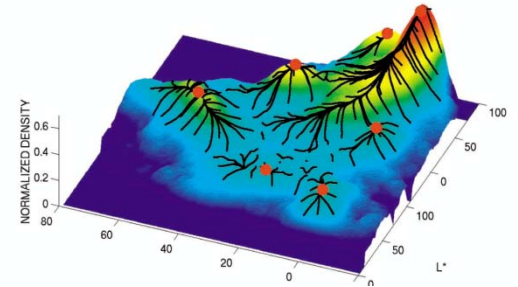
<http://www.cs.duke.edu/courses/spring04/cps196.1/.../EM/tomasiEM.pdf>

[http://www-clmc.usc.edu/~adsouza/notes/mix\\_gauss.pdf](http://www-clmc.usc.edu/~adsouza/notes/mix_gauss.pdf)



# Segmentation

- Mean-shift segmentation
  - Flexible clustering method, good segmentation
- Watershed segmentation
  - Hierarchical segmentation from soft boundaries
- Normalized cuts
  - Produces regular regions
  - Slow but good for oversegmentation
- MRFs with Graph Cut
  - Incorporates foreground/background/object model and prefers to cut at image boundaries
  - Good for interactive segmentation or recognition



# Next section: Recognition

- How to recognize
  - Specific object instances
  - Faces
  - Scenes
  - Object categories