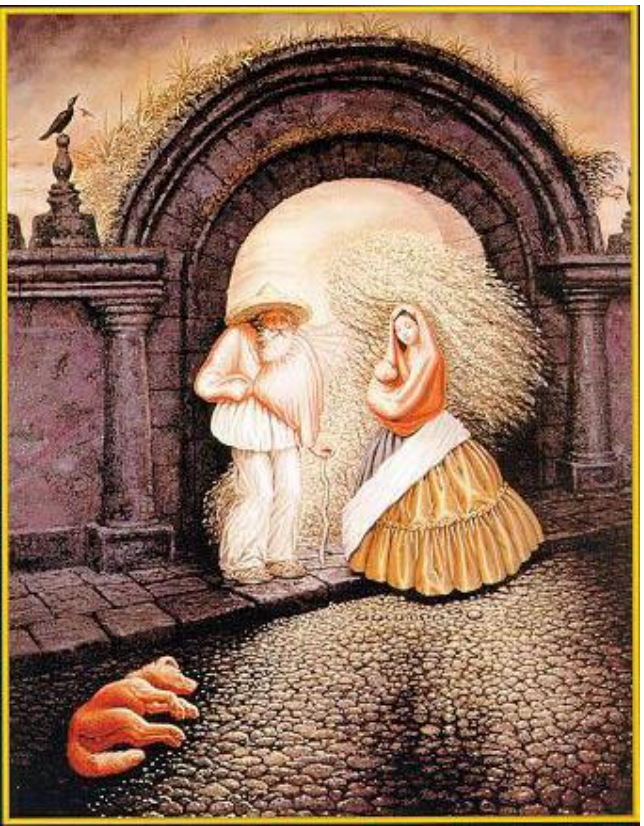
# Grouping and Segmentation



Computer Vision

CS 543 / ECE 549

University of Illinois

Derek Hoiem

# Today's class

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

- Superpixels and multiple segmentations

# **Gestalt psychology** or **gestaltism**

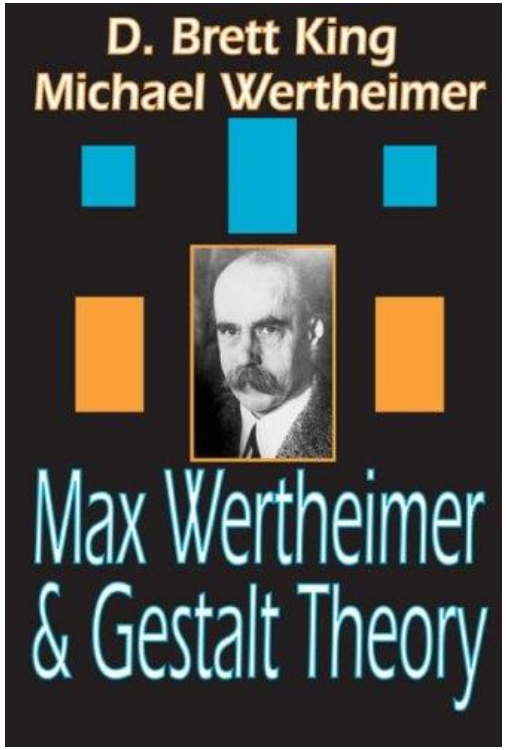
German: *Gestalt* - "form" or "whole"

Berlin School, early 20th century

Kurt Koffka, Max Wertheimer, and Wolfgang Köhler

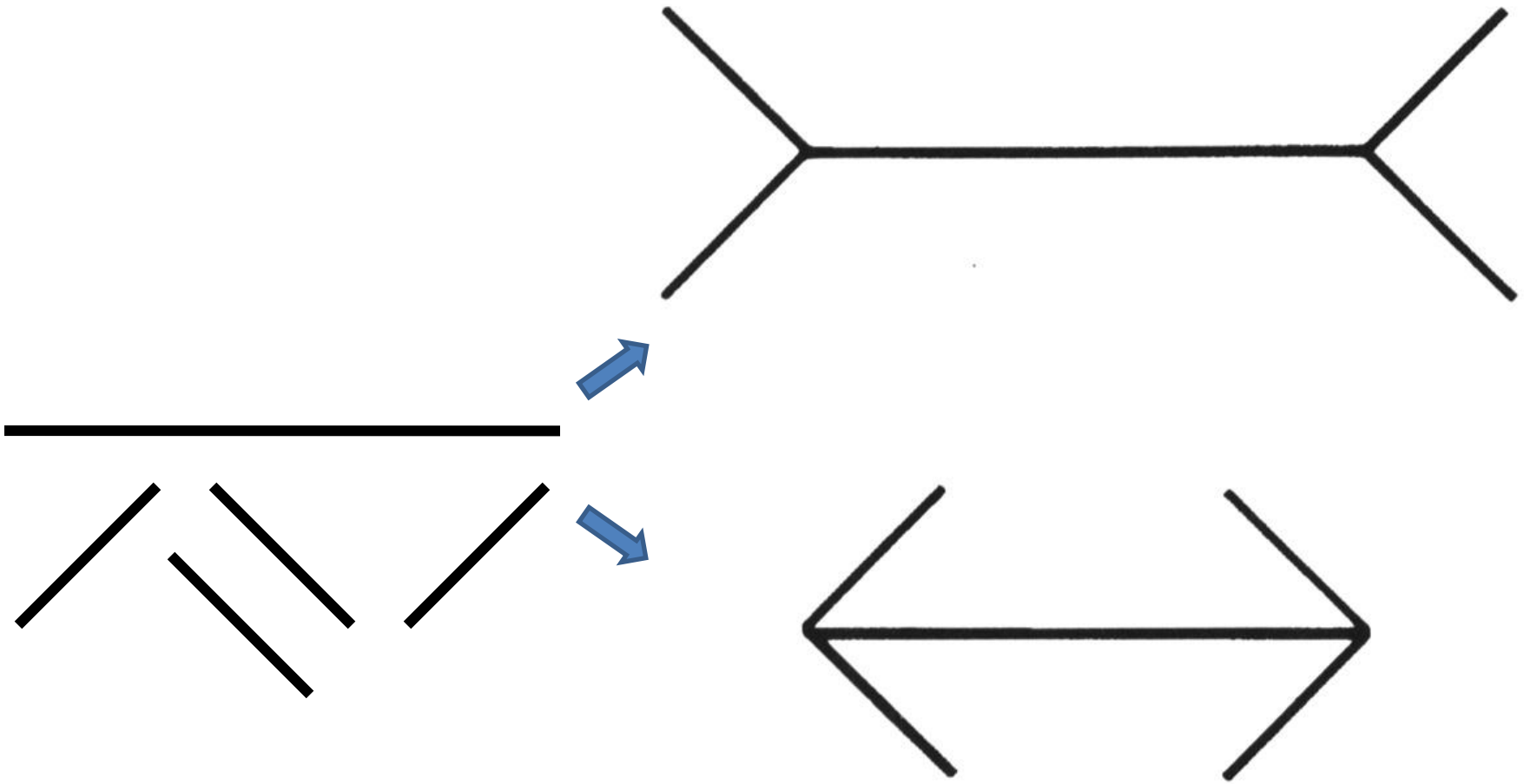
View of brain:

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



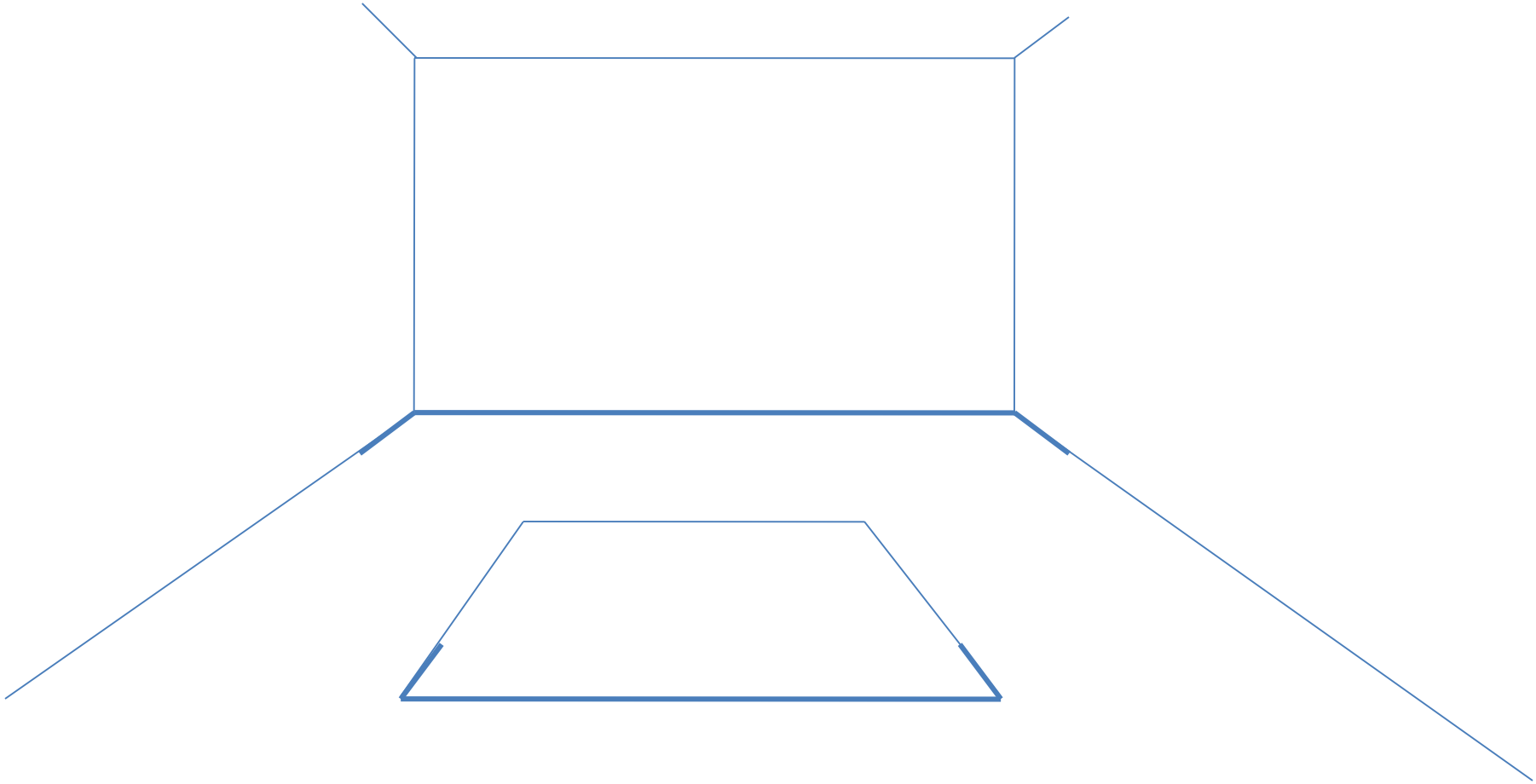

Slide from S. Saverese

# Gestaltism

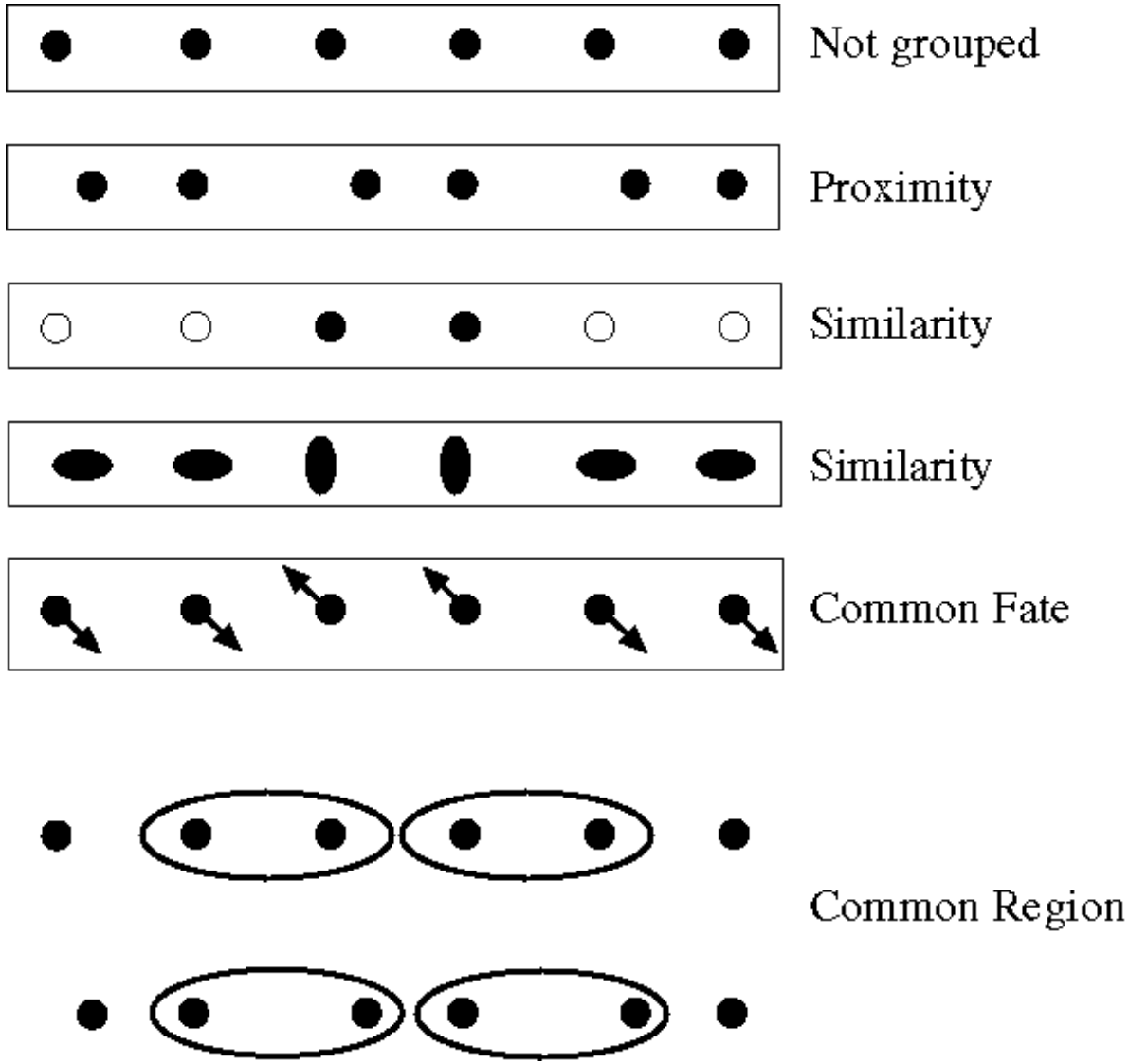


The Muller-Lyer illusion

# We perceive the interpretation, not the senses

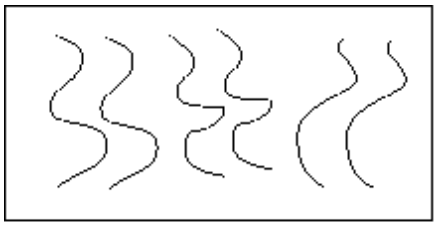


# Principles of perceptual organization

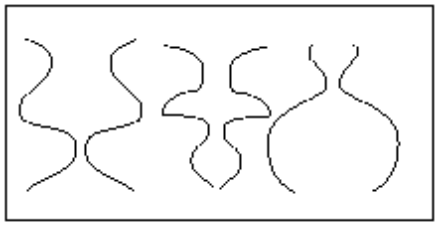



From Steve Lehar: The Constructive Aspect of Visual Perception

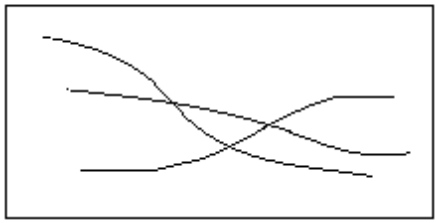
# Principles of perceptual organization



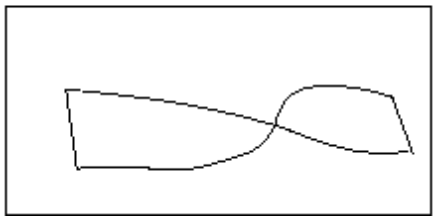
Parallelism



Symmetry

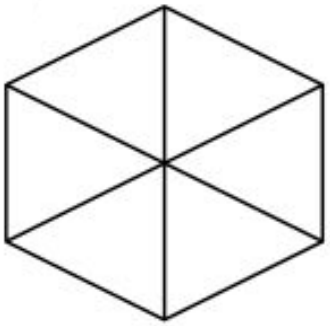


Continuity

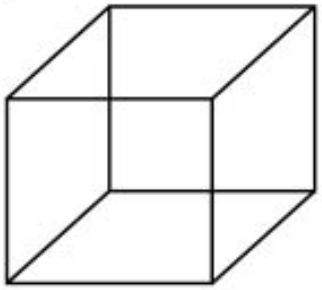


Closure

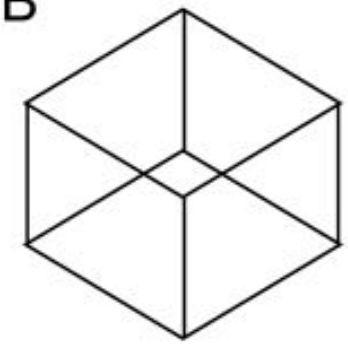
# Gestaltists do not believe in coincidence



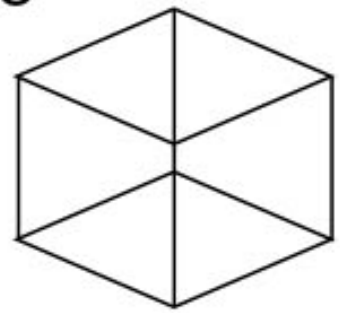
A



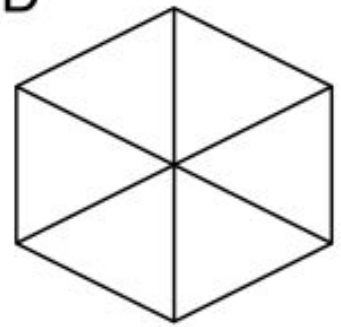
B



C

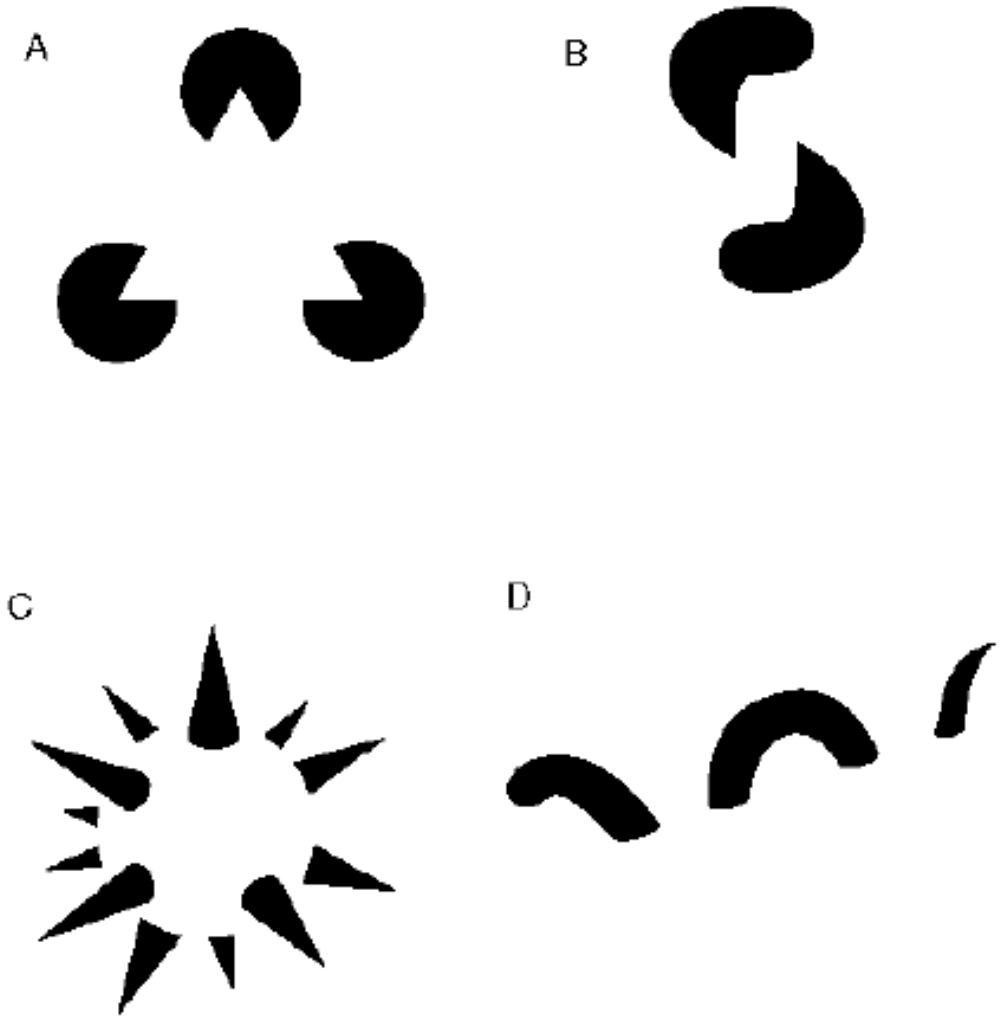


D



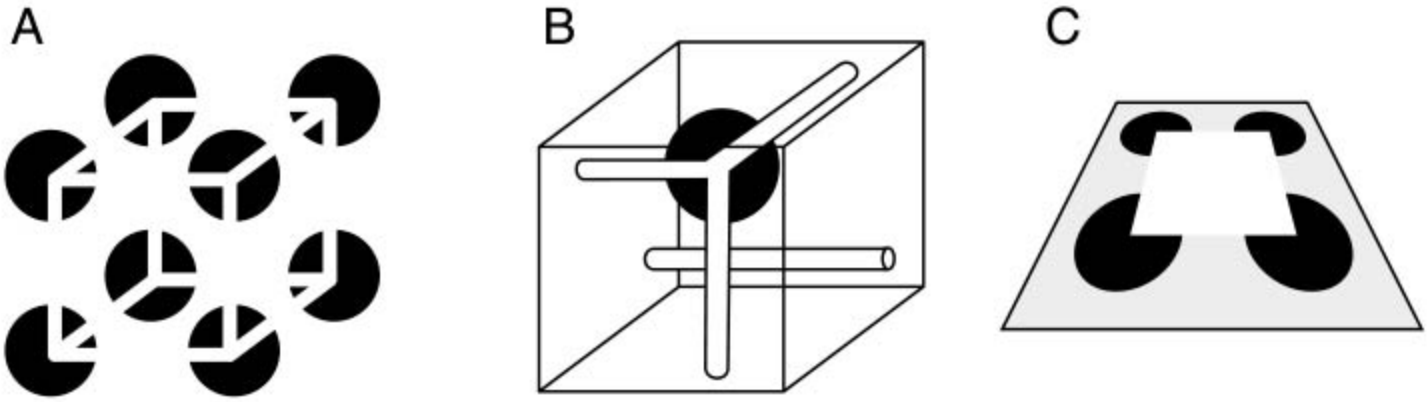
# Emergence

# Grouping by invisible completion




From Steve Lehar: The Constructive Aspect of Visual Perception

# Grouping involves global interpretation




From Steve Lehar: The Constructive Aspect of Visual Perception

# Grouping involves global interpretation

A

B

From Steve Lehar: The Constructive Aspect of Visual Perception

# Gestalt cues

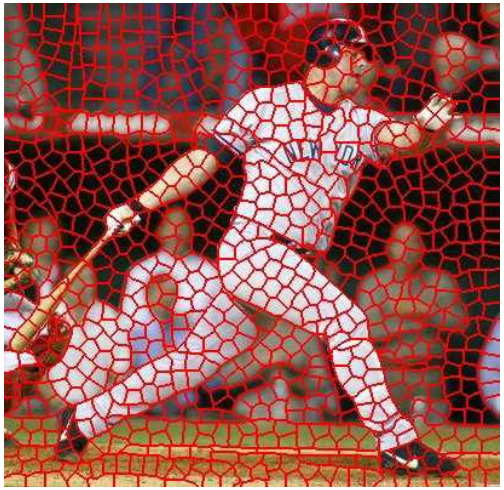
- Good intuition and basic principles for grouping
- Basis for many ideas in segmentation and occlusion reasoning
- Some (e.g., symmetry) are difficult to implement in practice

# Image segmentation

Goal: Group pixels into meaningful or perceptually similar regions

# Segmentation for efficiency: “superpixels”

[Felzenszwalb and Huttenlocher 2004]

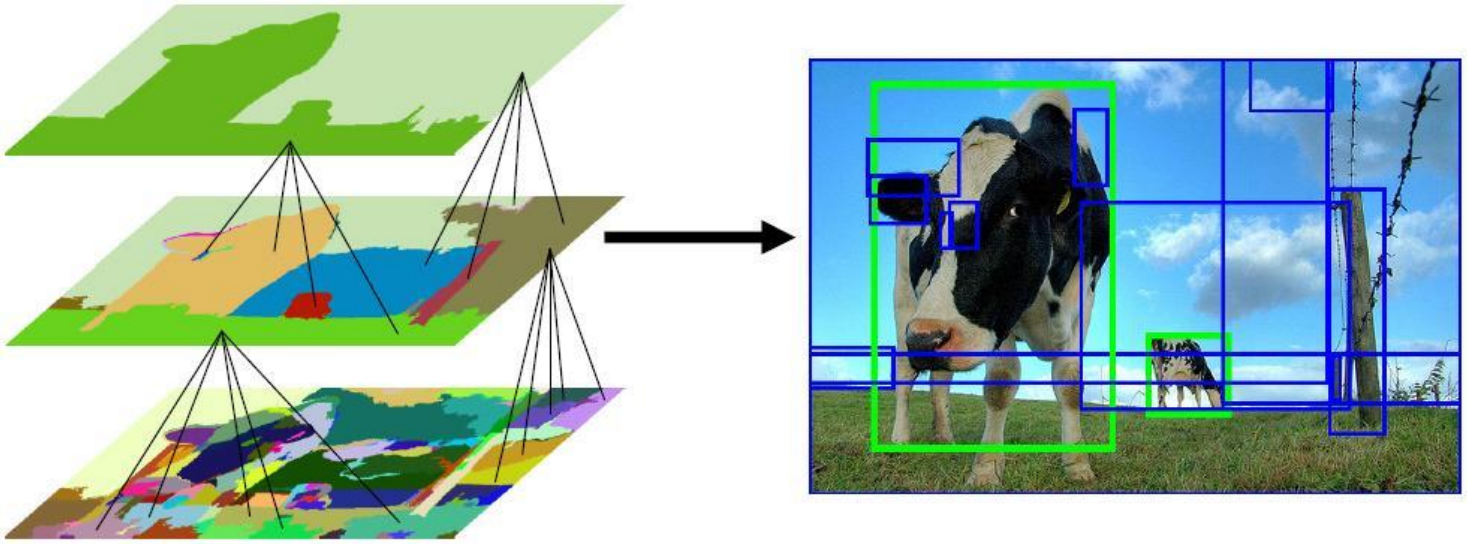


[Shi and Malik 2001]

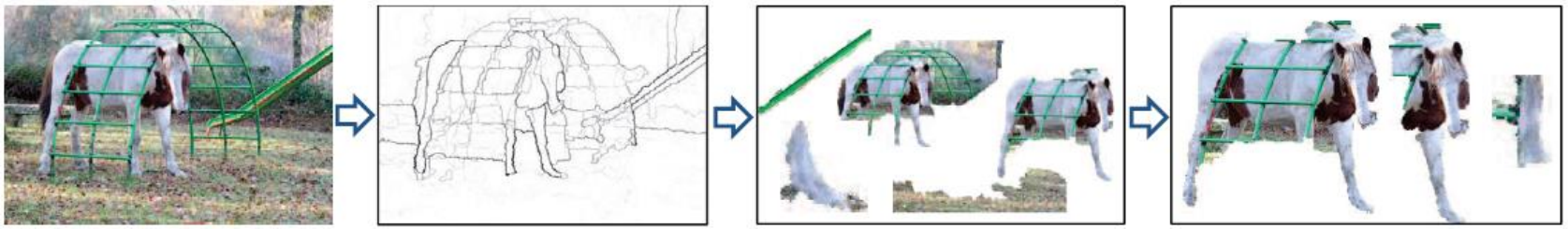
[Hoiem et al. 2005, Mori 2005]

# Segmentation for feature support

# Segmentation for object proposals



"Selective Search" [Sande, Uijlings et al. ICCV 2011, IJCV 2013]




[Endres Hoiem ECCV 2010, IJCV 2014]

- Object proposals

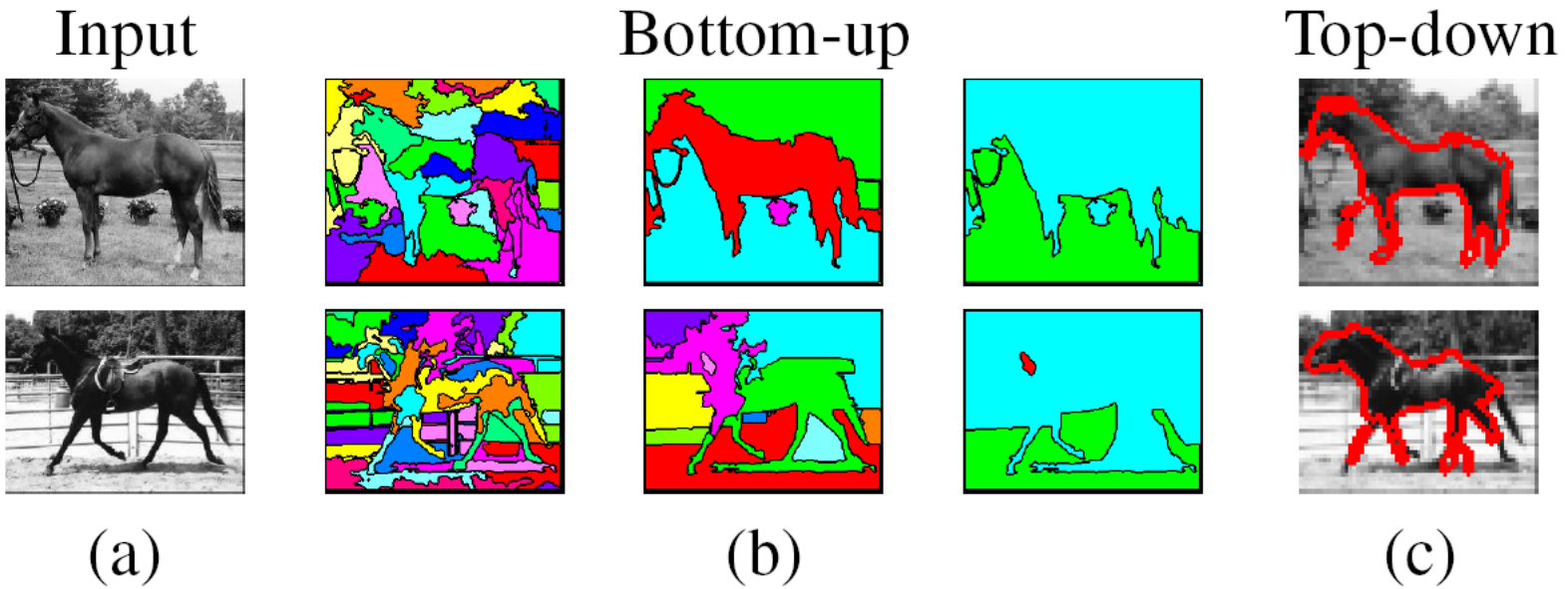
- Superpixels, proposals, multiple segmentations

# Segmentation as a result

Rother et al. 2004

# Major processes for segmentation

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

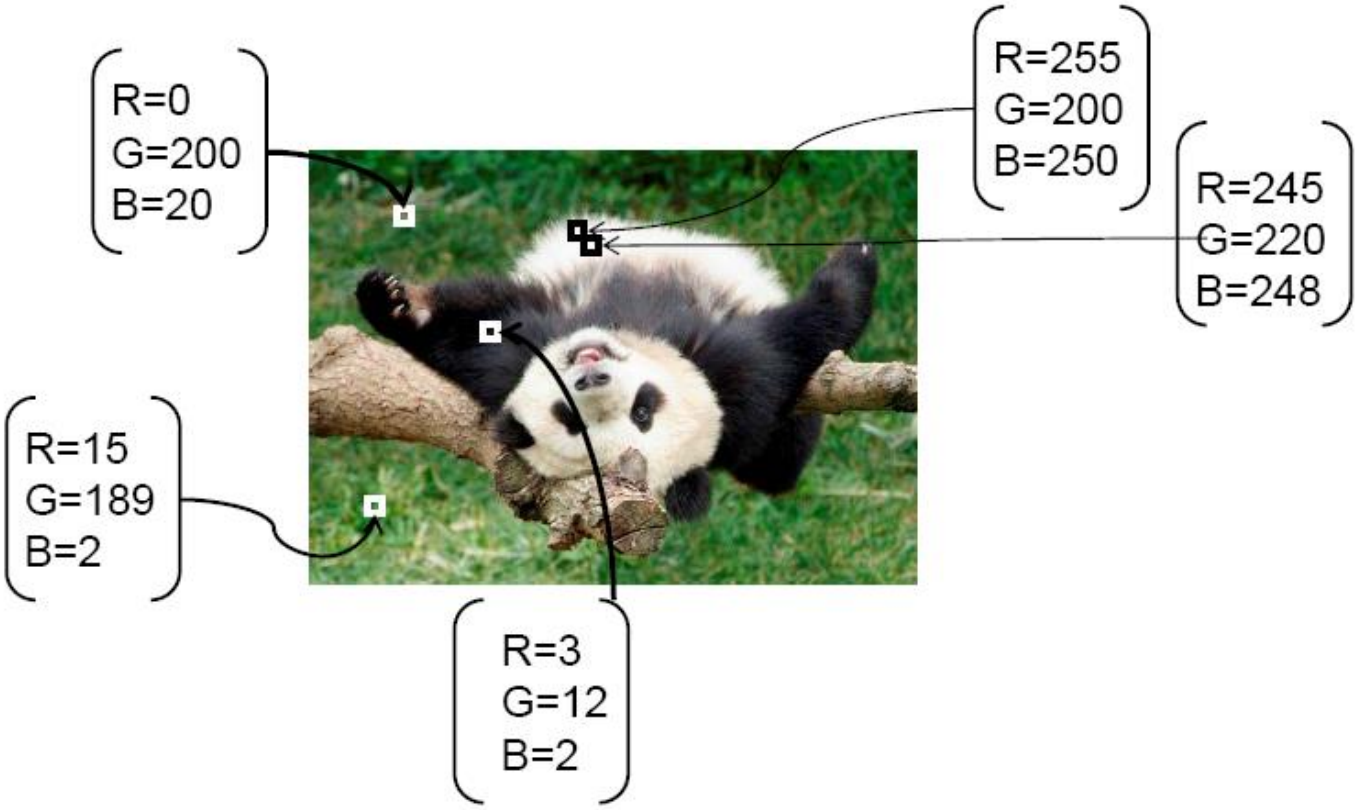



[Levin and Weiss 2006]

# Segmentation using clustering

- Kmeans
- Mean-shift

# Feature Space




Source: K. Grauman

# K-means clustering using intensity alone and color alone

Image

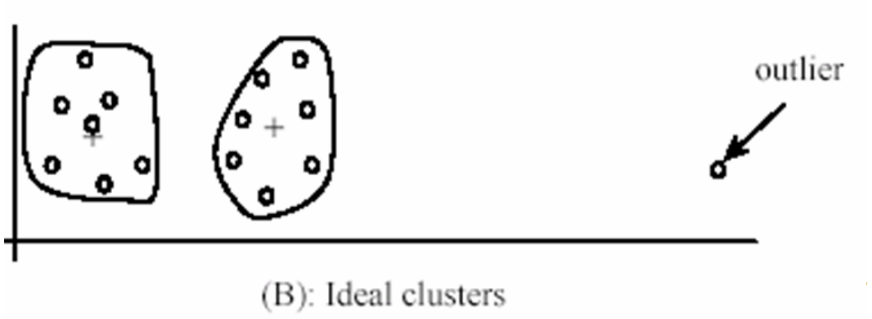
Clusters on intensity

Clusters on color

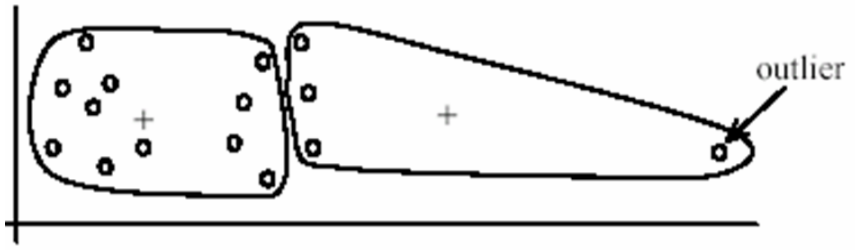
# K-Means pros and cons

- Pros
  - Simple and fast
  - Easy to implement

- Cons
  - Need to choose K
  - Sensitive to outliers



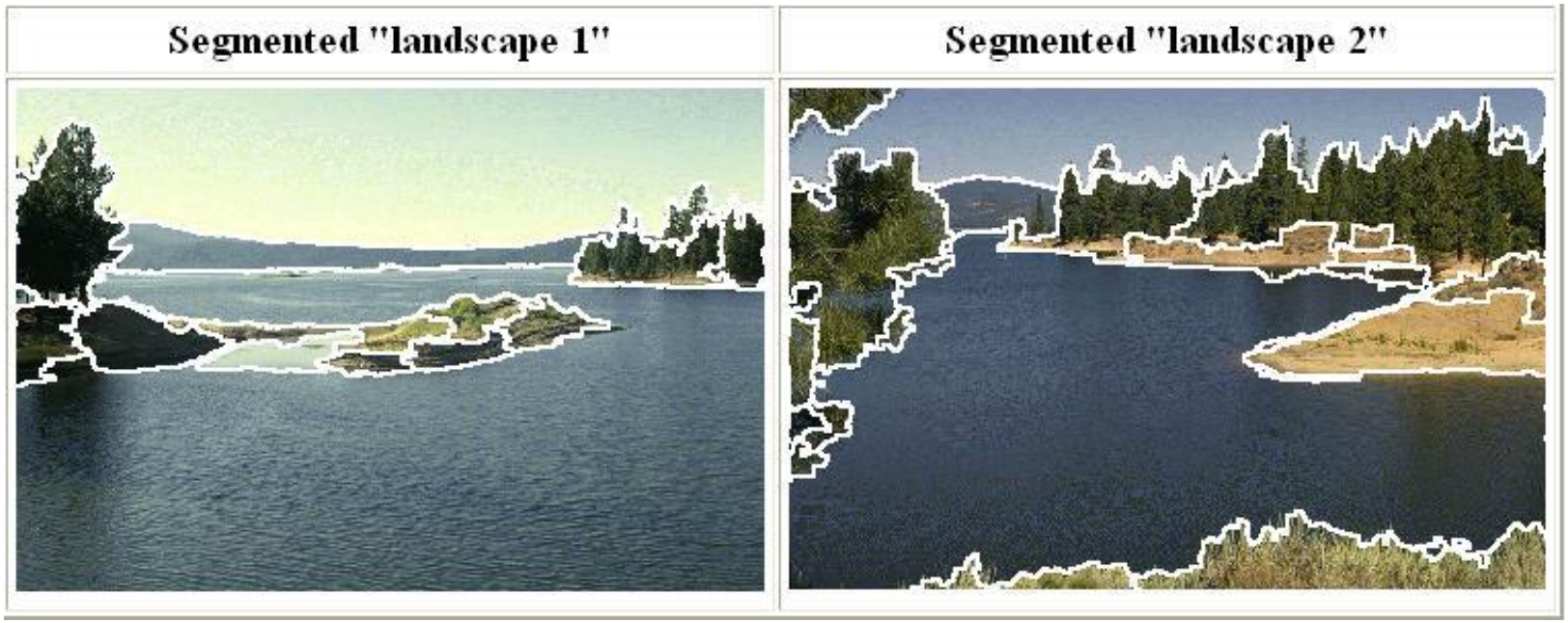

- Usage
  - Rarely used for pixel segmentation



# Mean shift segmentation

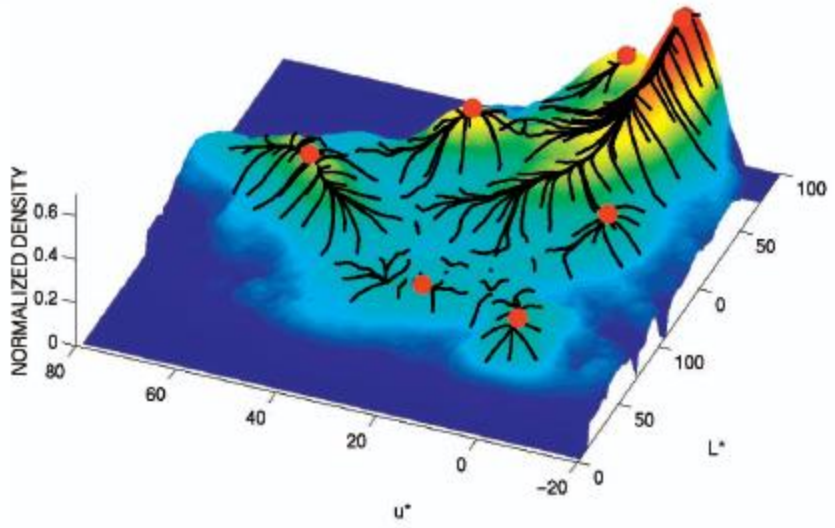
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

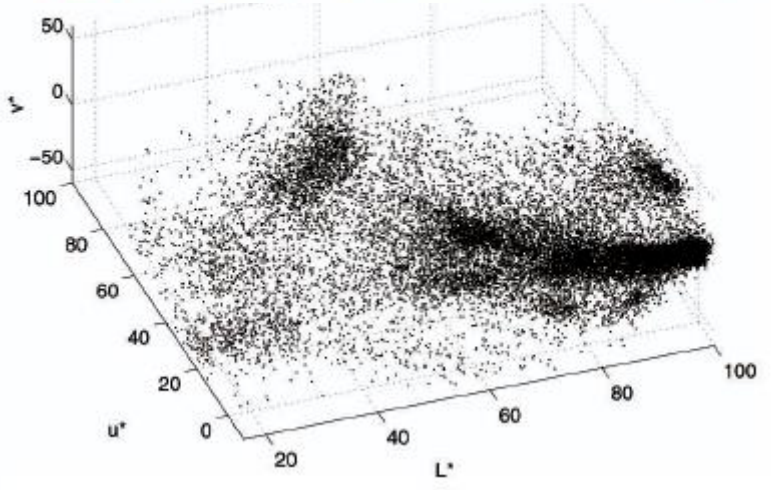
- Versatile technique for clustering-based segmentation

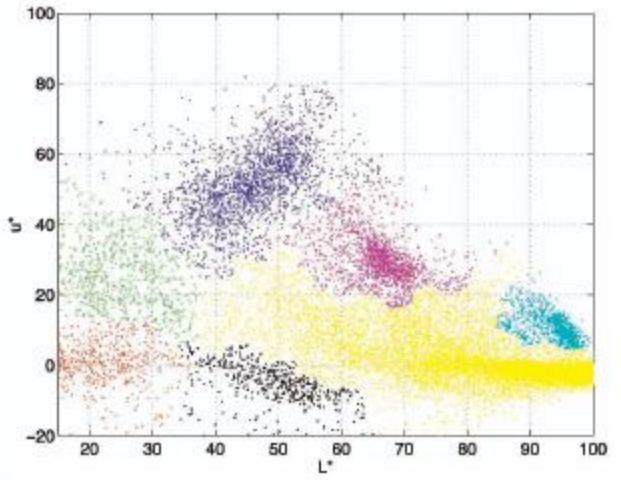


# Mean shift algorithm

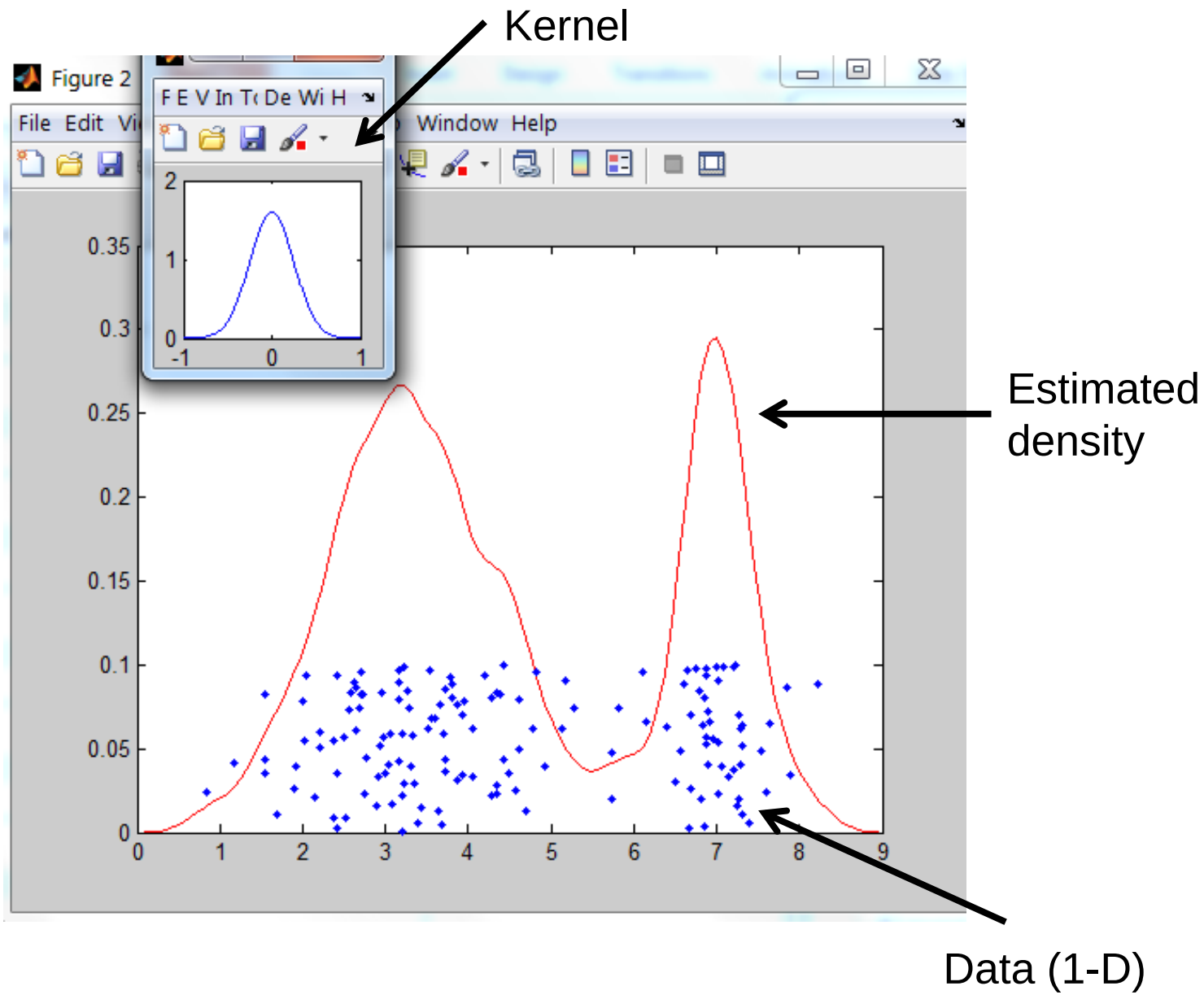
- Try to find *modes* of this non-parametric density



# Kernel density estimation



# Kernel density estimation

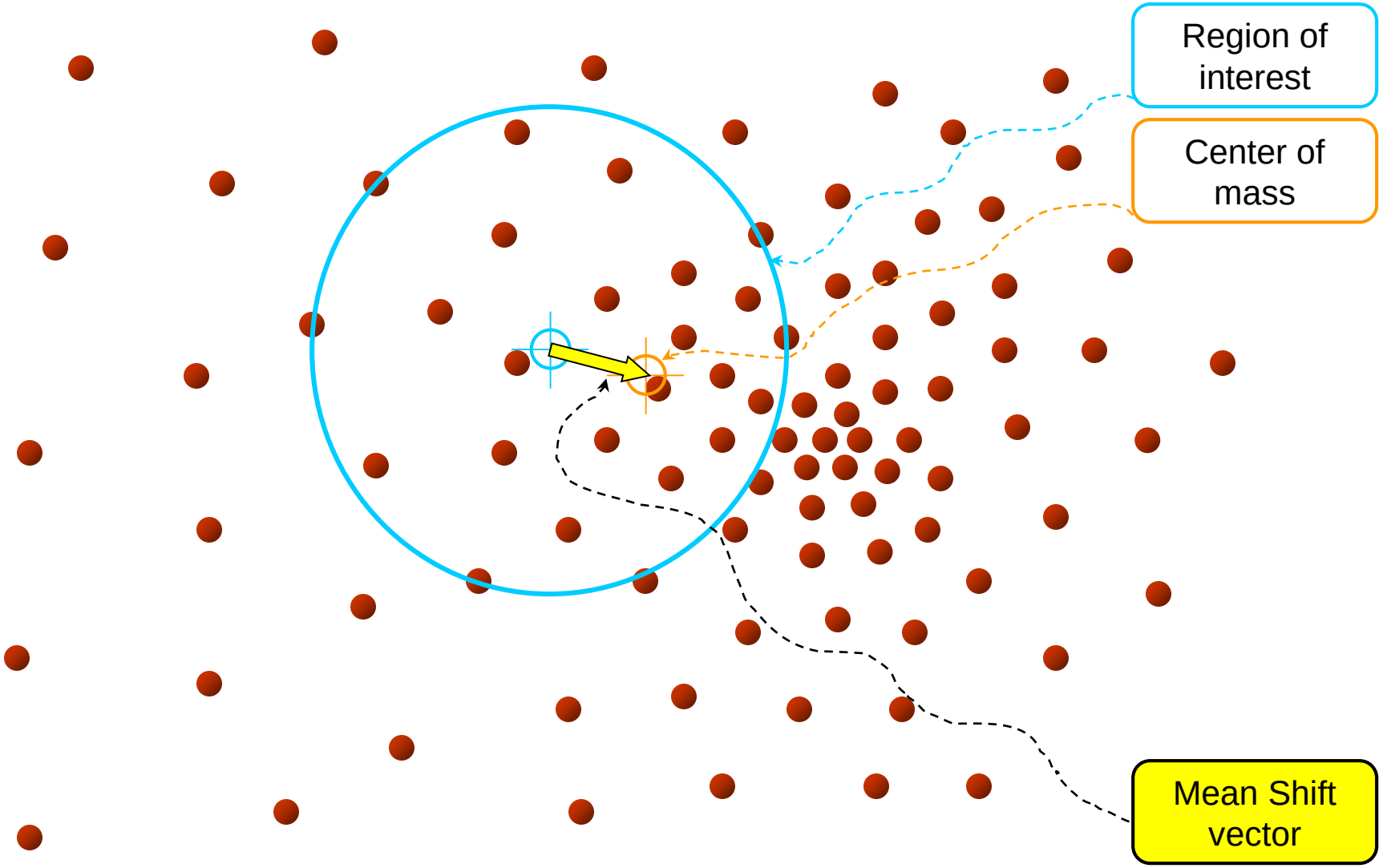
Kernel density estimation function

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

Gaussian kernel

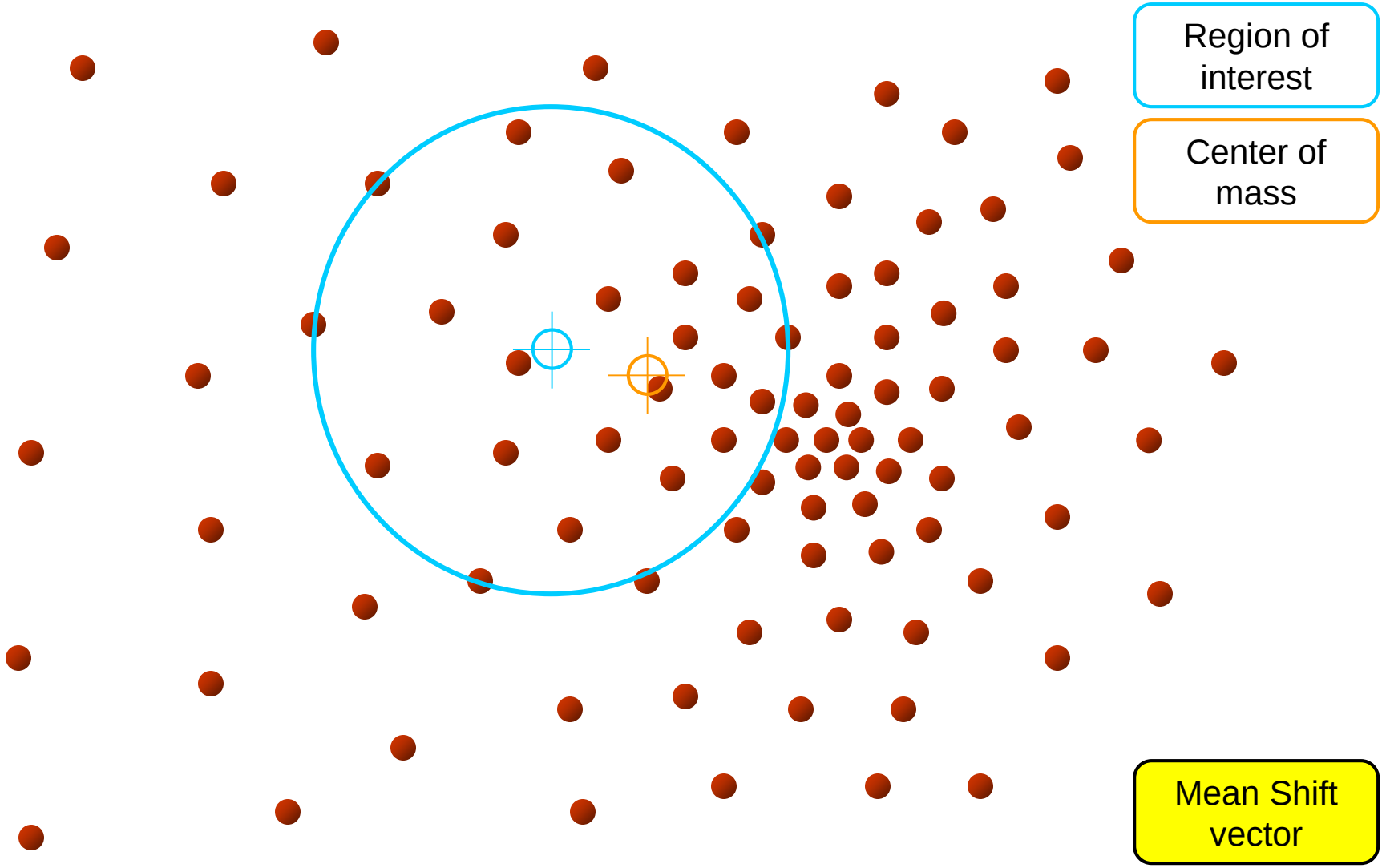
$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-x_i)^2}{2h^2}}.$$

# Mean shift



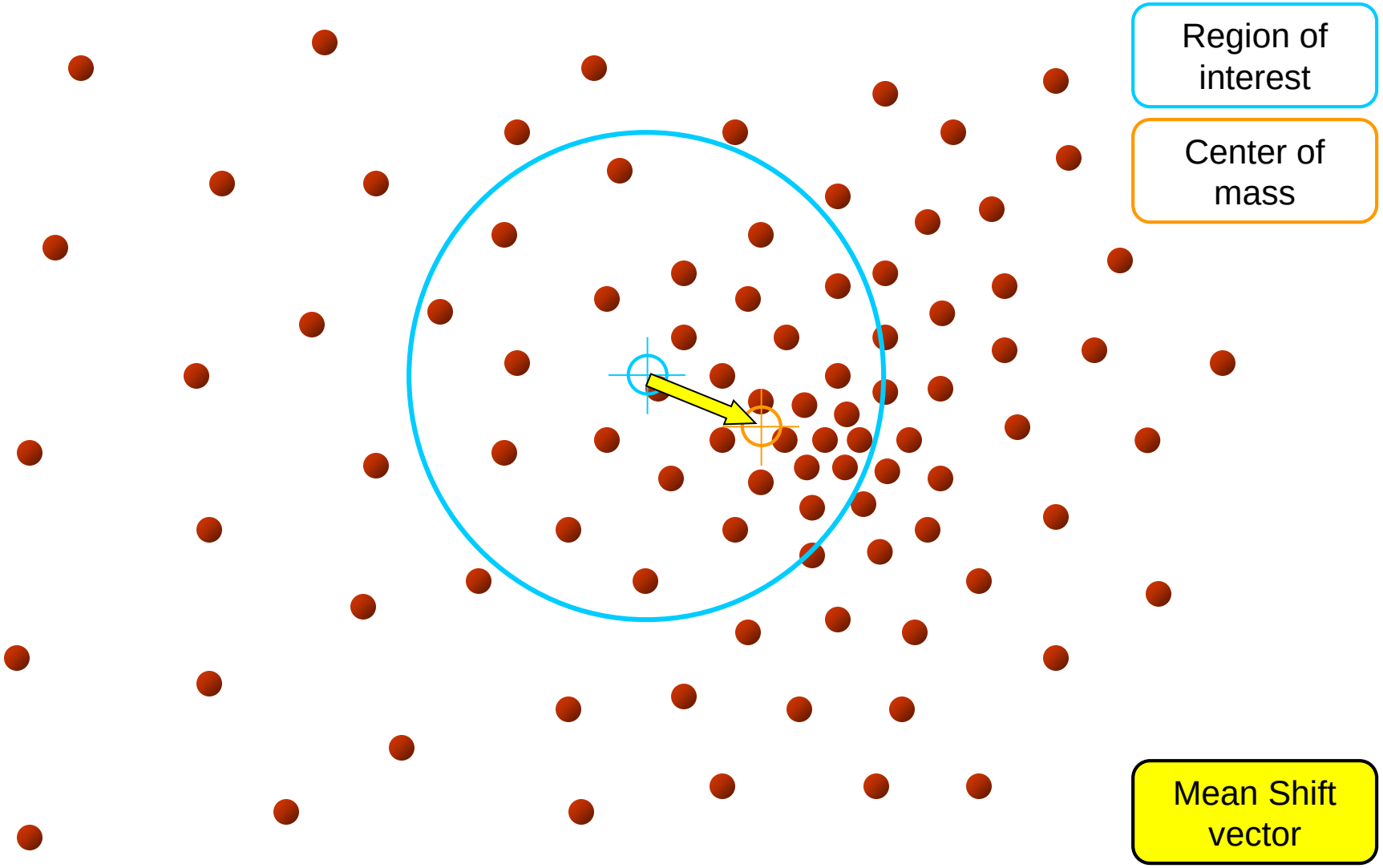

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



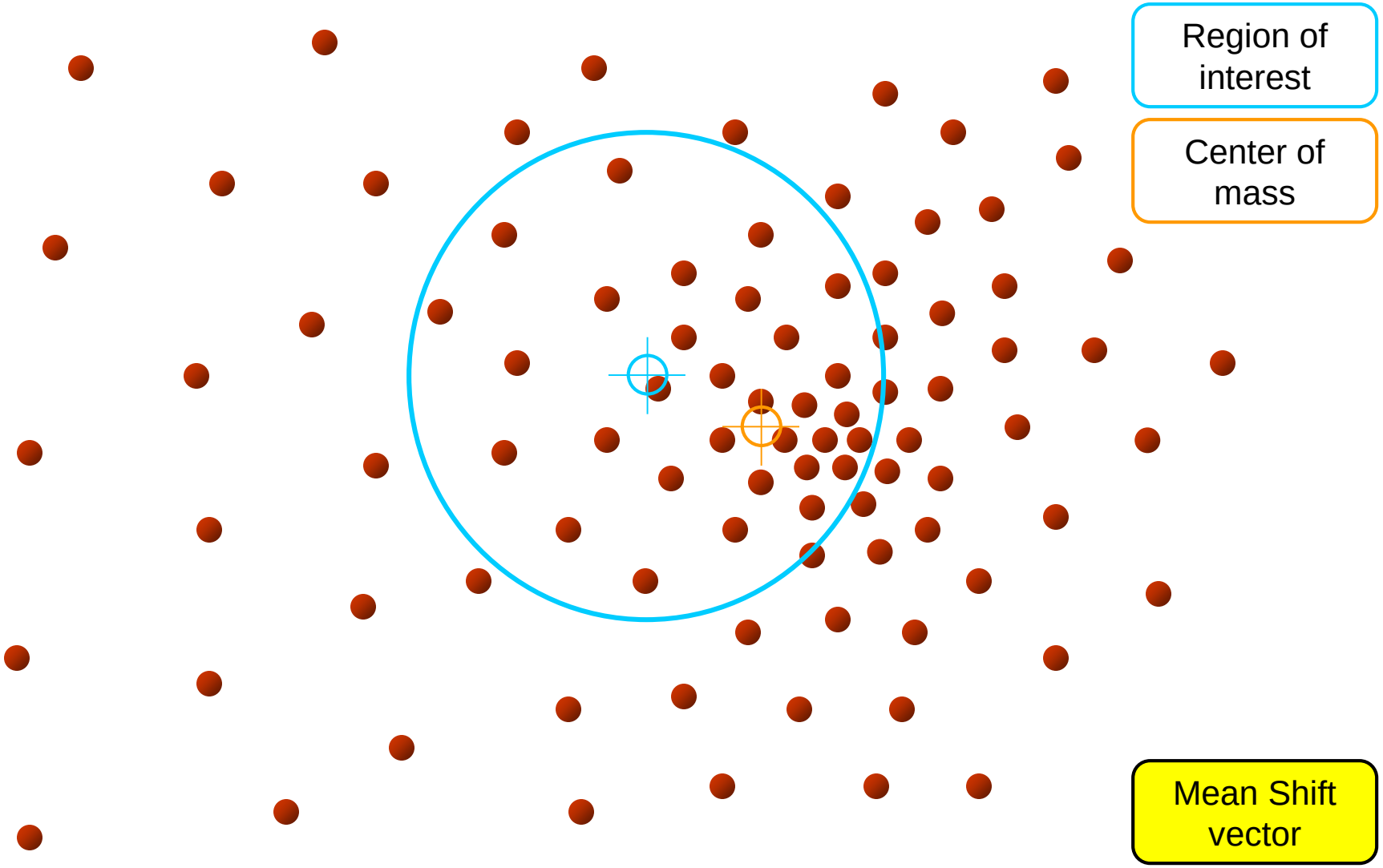

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



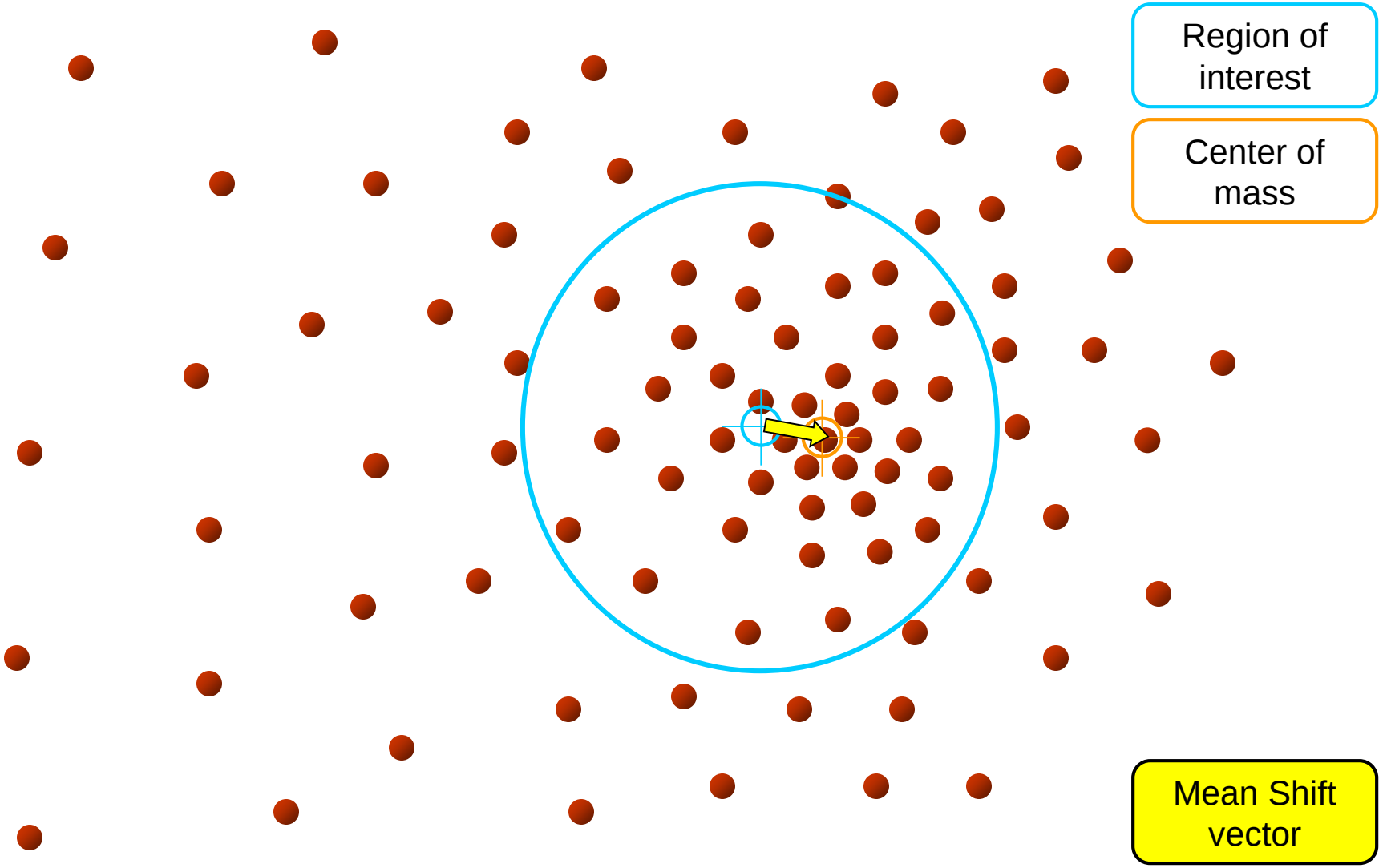

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



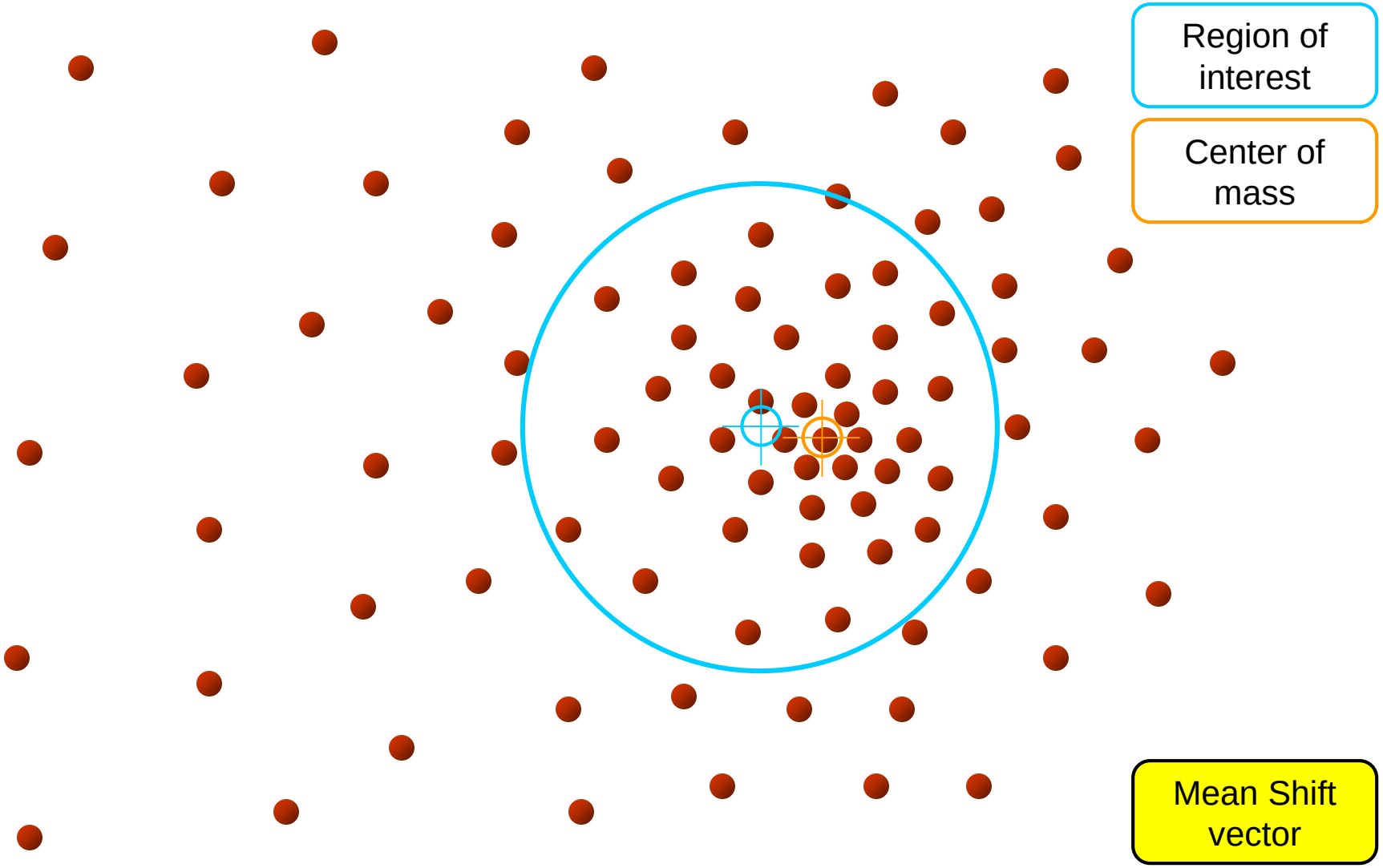

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



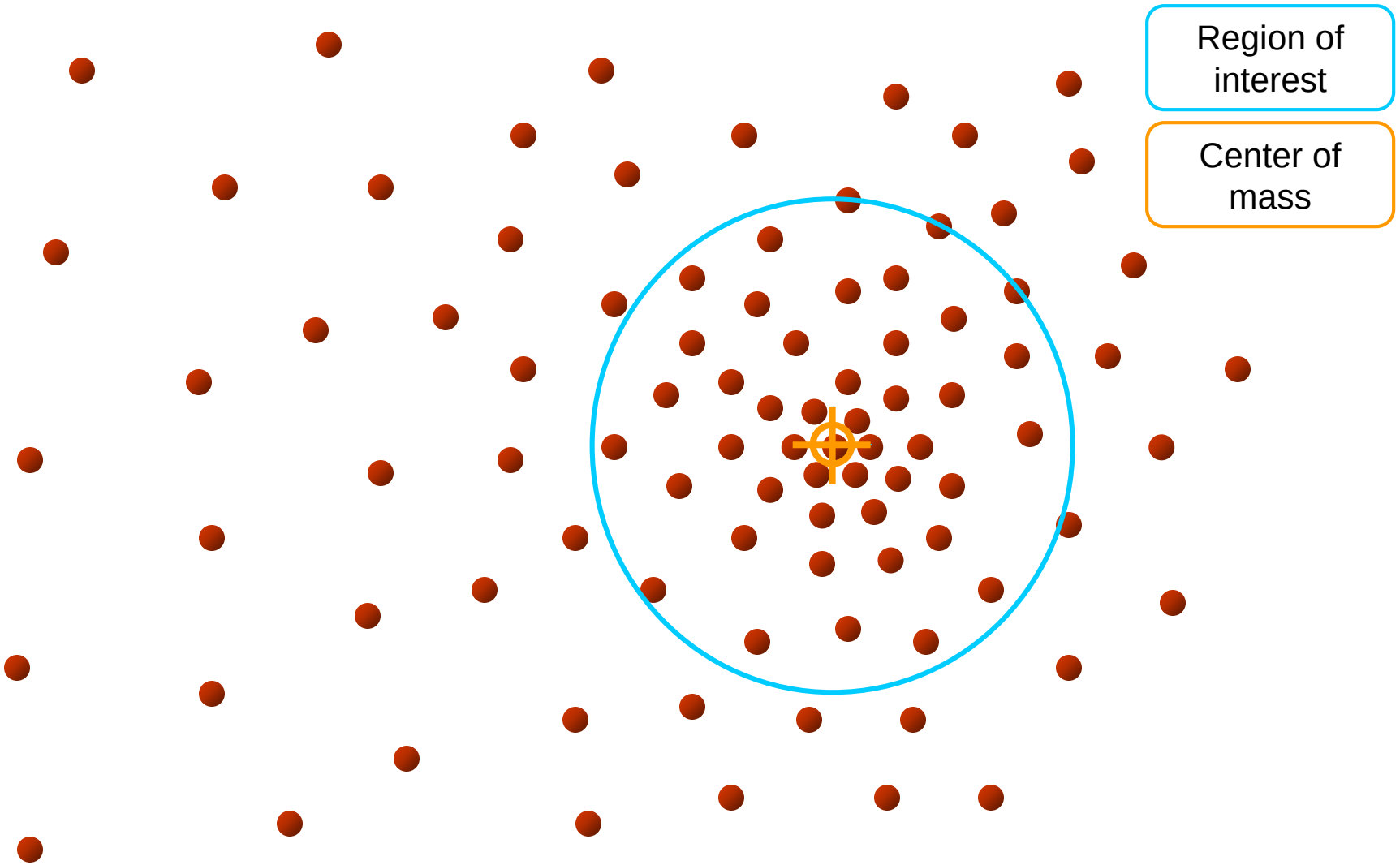

Slide by Y. Ukrainitz & B. Sarel

# Mean shift




Slide by Y. Ukrainitz & B. Sarel

# Mean shift




Slide by Y. Ukrainitz & B. Sarel

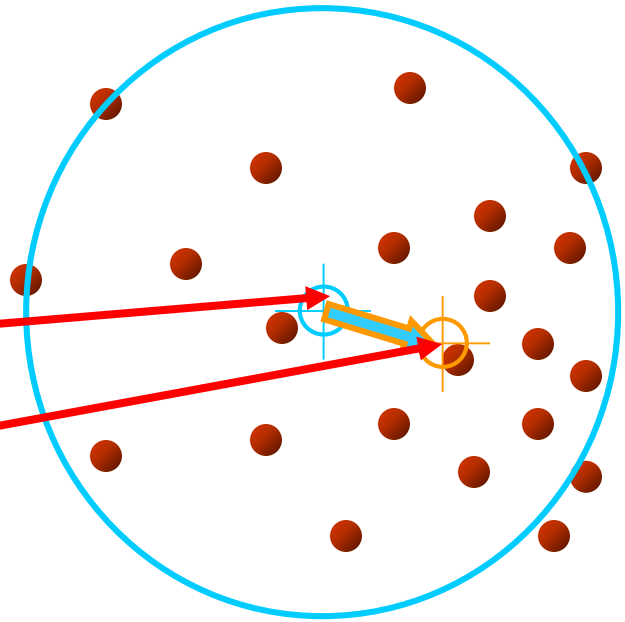
# Computing the Mean Shift

Simple Mean Shift procedure:

- Compute mean shift vector

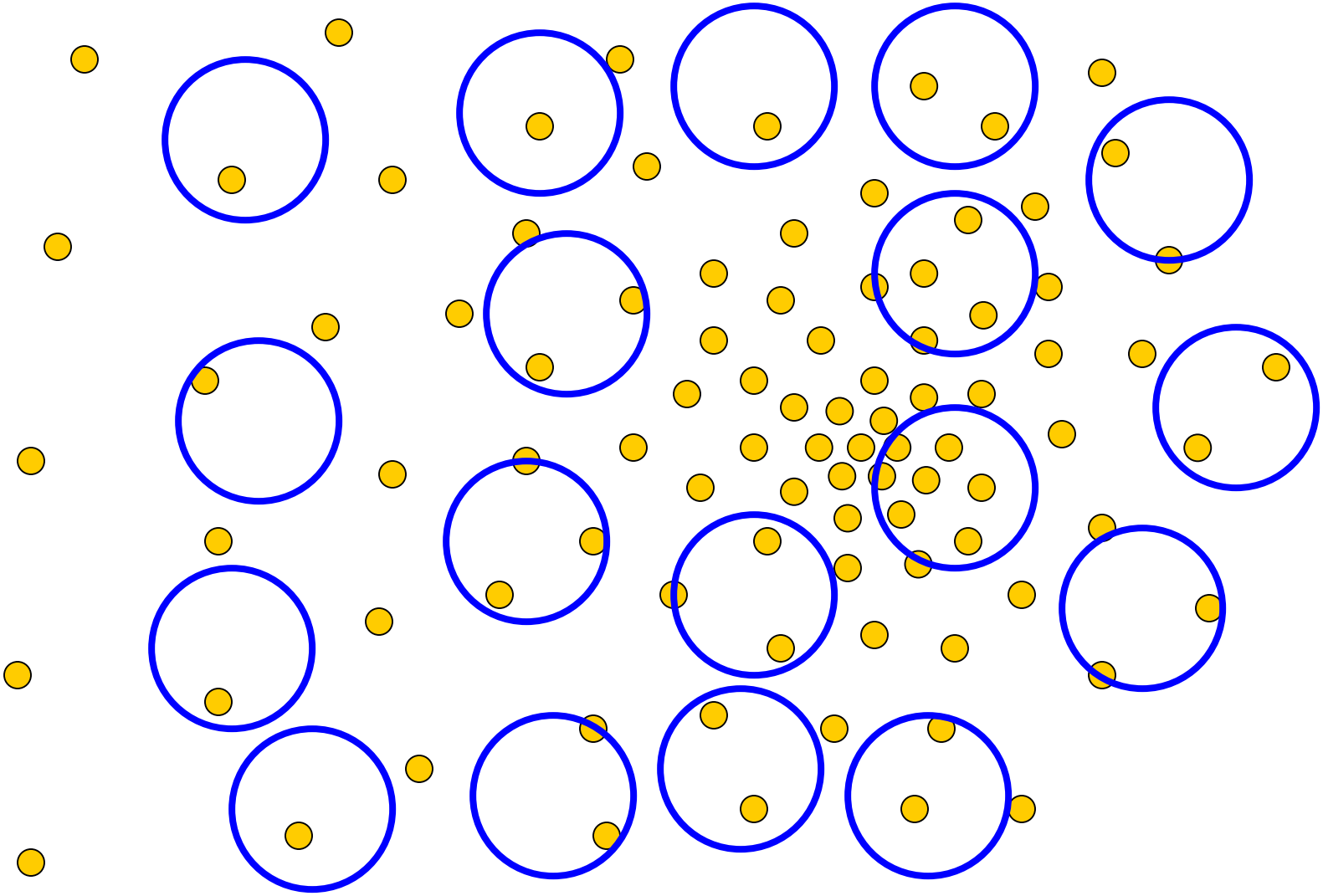
- Translate the Kernel window by **m(x)**

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



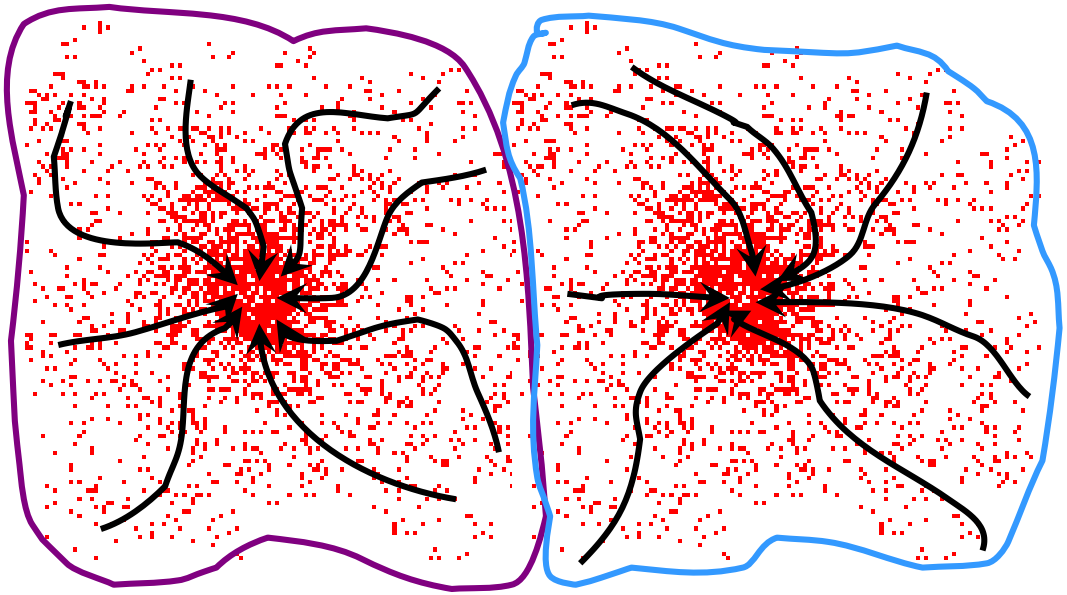
Slide by Y. Ukrainitz & B. Sarel

# Real Modality Analysis



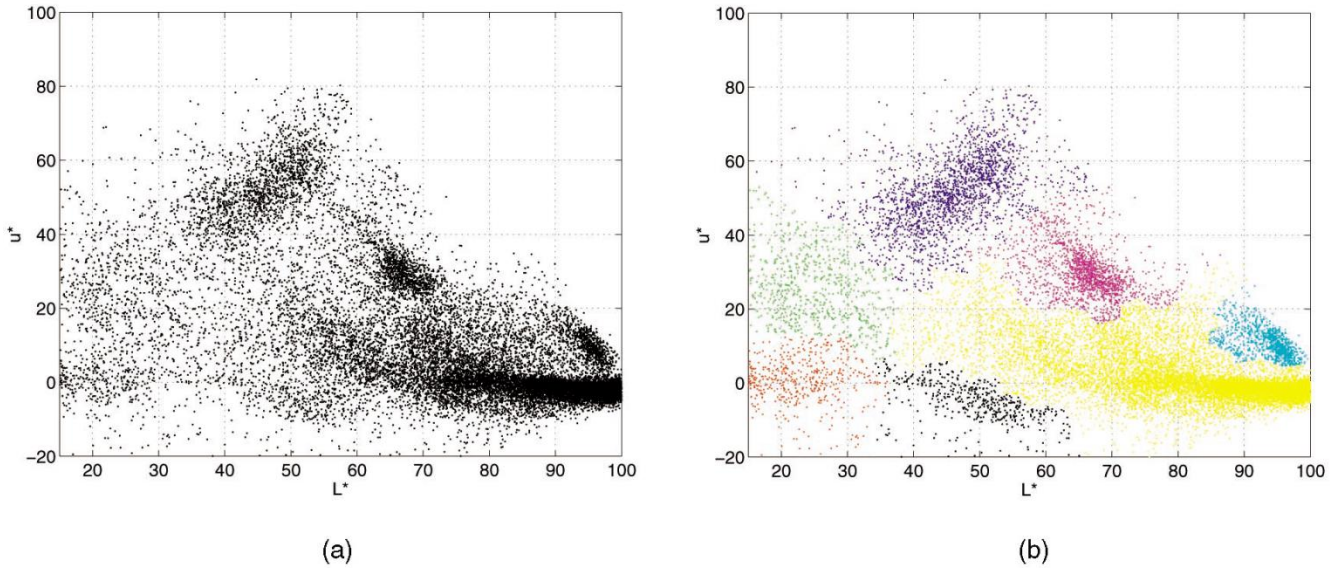
# Attraction basin

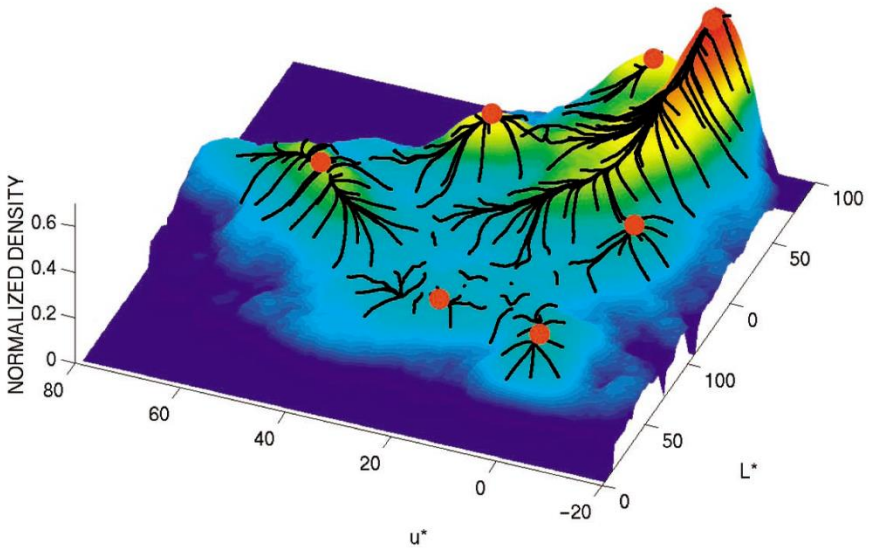
- Attraction basin: the region for which all trajectories lead to the same mode
- Cluster: all data points in the attraction basin of a mode



Slide by Y. Ukrainitz & B. Sarel

# Attraction basin



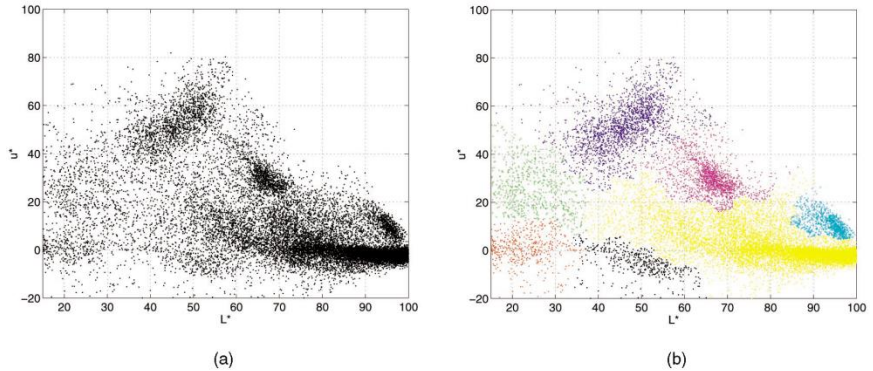



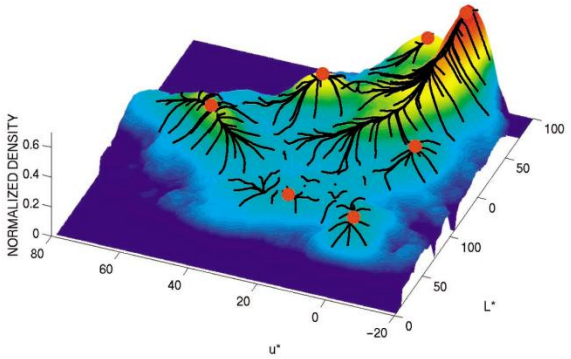
# Mean shift clustering

- 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

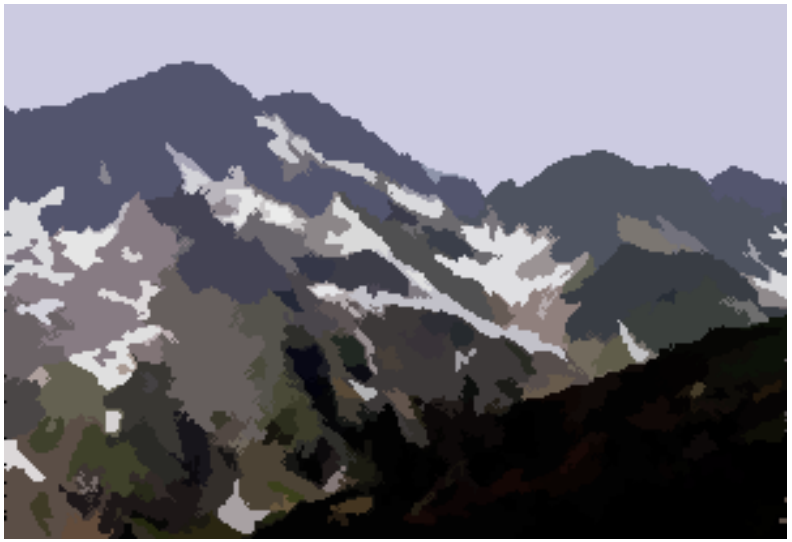
# Segmentation by Mean Shift

- Compute features for each pixel (color, gradients, texture, etc); also store each pixel's position
- 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 modes that are within width of $K_f$ and $K_s$



# Mean shift segmentation results



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




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

# Mean-shift: other issues

- Speedups
  - Binned estimation – replace points within some “bin” by point at center with mass
  - Fast search of neighbors – e.g., k-d tree or approximate NN
  - Update all windows 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-purpose segmentation
  - Flexible in number and shape of regions
  - Robust to outliers
  - General mode-finding algorithm (useful for other problems such as finding most common surface normals)
- 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
    - D. Comaniciu, V. Ramesh, P. Meer: *Real-Time Tracking of Non-Rigid Objects using Mean Shift*, *Best Paper Award*, IEEE Conf. Computer Vision and Pattern Recognition (CVPR'00), Hilton Head Island, South Carolina, Vol. 2, 142-149, 2000

# Mean-shift reading

- Nicely written mean-shift explanation (with math)

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

  - Includes .m code for mean-shift clustering

- Mean-shift paper by Comaniciu and Meer

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

- Adaptive mean shift in higher dimensions

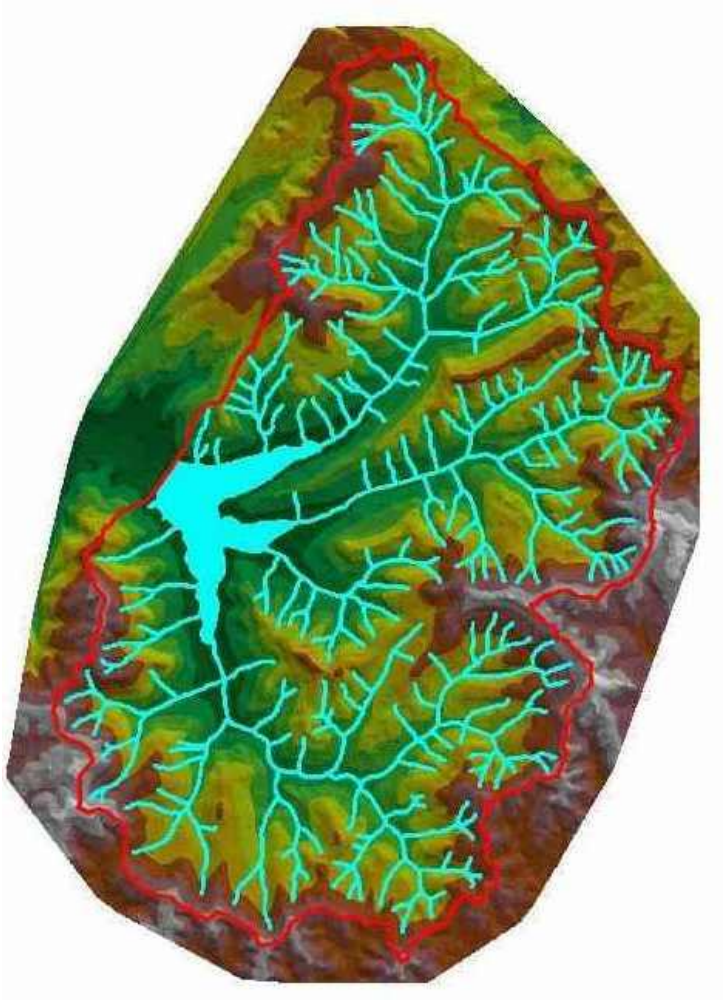
*http://mis.hevra.haifa.ac.il/~ishimshoni/papers/chap9.pdf*

# Superpixel algorithms

- Goal is to divide the image into a large number of regions, such that each regions lie within object boundaries

- Examples
  - Watershed
  - Felzenszwalb and Huttenlocher graph-based
  - Turbopixels
  - SLIC

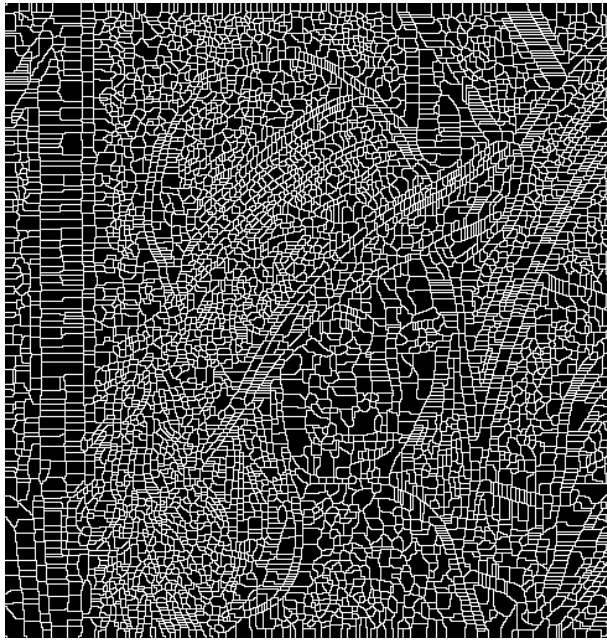
# Watershed algorithm



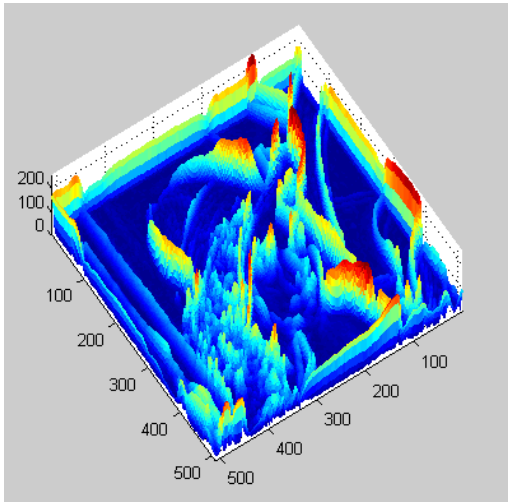
# Watershed segmentation

Image

Gradient



Watershed boundaries



# Meyer's watershed segmentation

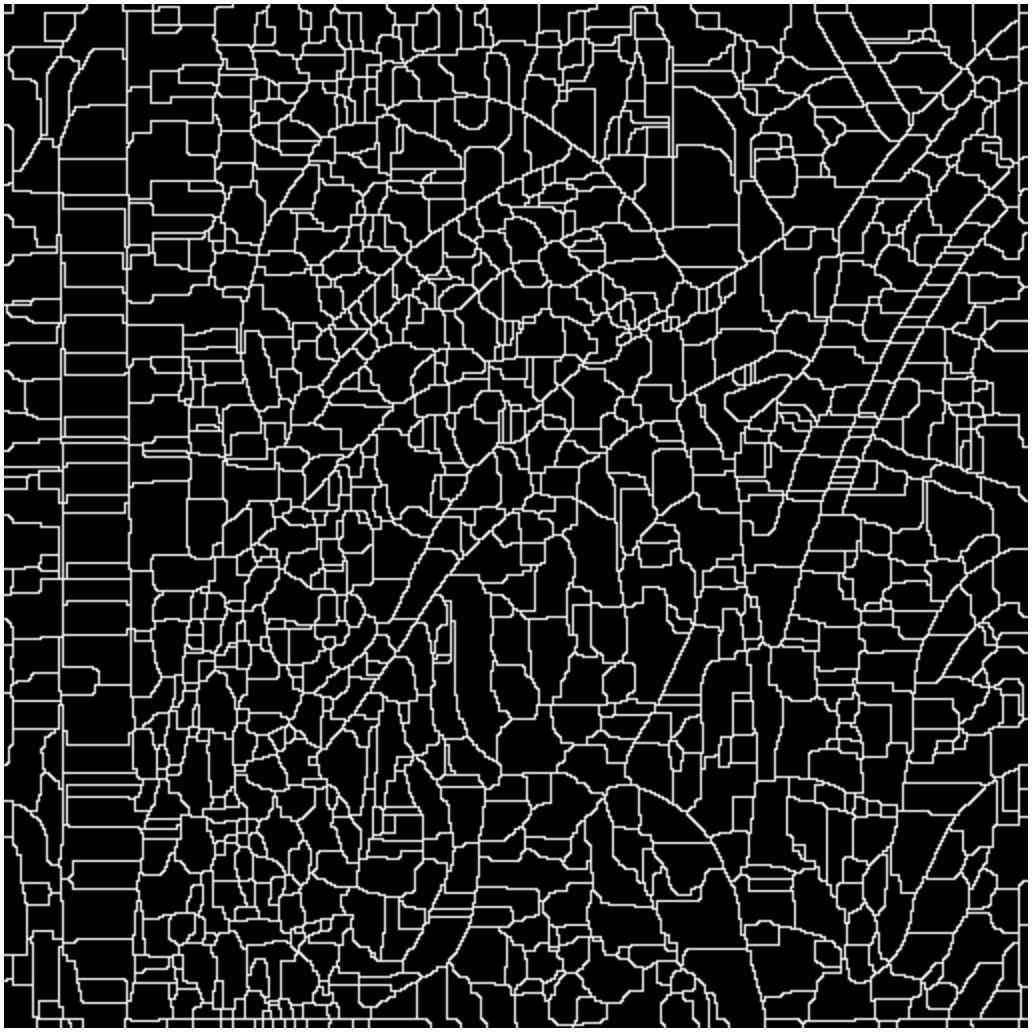
1. Choose local minima as region seeds
2. Add neighbors to priority queue, sorted by value
3. Take top priority pixel from queue
    1. If all labeled neighbors have same label, assign that label to pixel
    2. Add all non-marked neighbors to queue
4. Repeat step 3 until finished (all remaining pixels in queue are on the boundary)

Matlab: seg = watershed(bnd_im)

Meyer 1991

# 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 (w/o non-max suppression)
  - Canny (w/o non-max suppression)
  - Etc.

# Watershed pros and cons

- Pros
  - Fast (< 1 sec for 512x512 image)
  - Preserves boundaries
- Cons
  - Only as good as the soft boundaries (which may be slow to compute)
  - Not easy to get variety of regions for multiple segmentations
- Usage
  - Good algorithm for superpixels, hierarchical segmentation

# Felzenszwalb and Huttenlocher: Graph-Based Segmentation

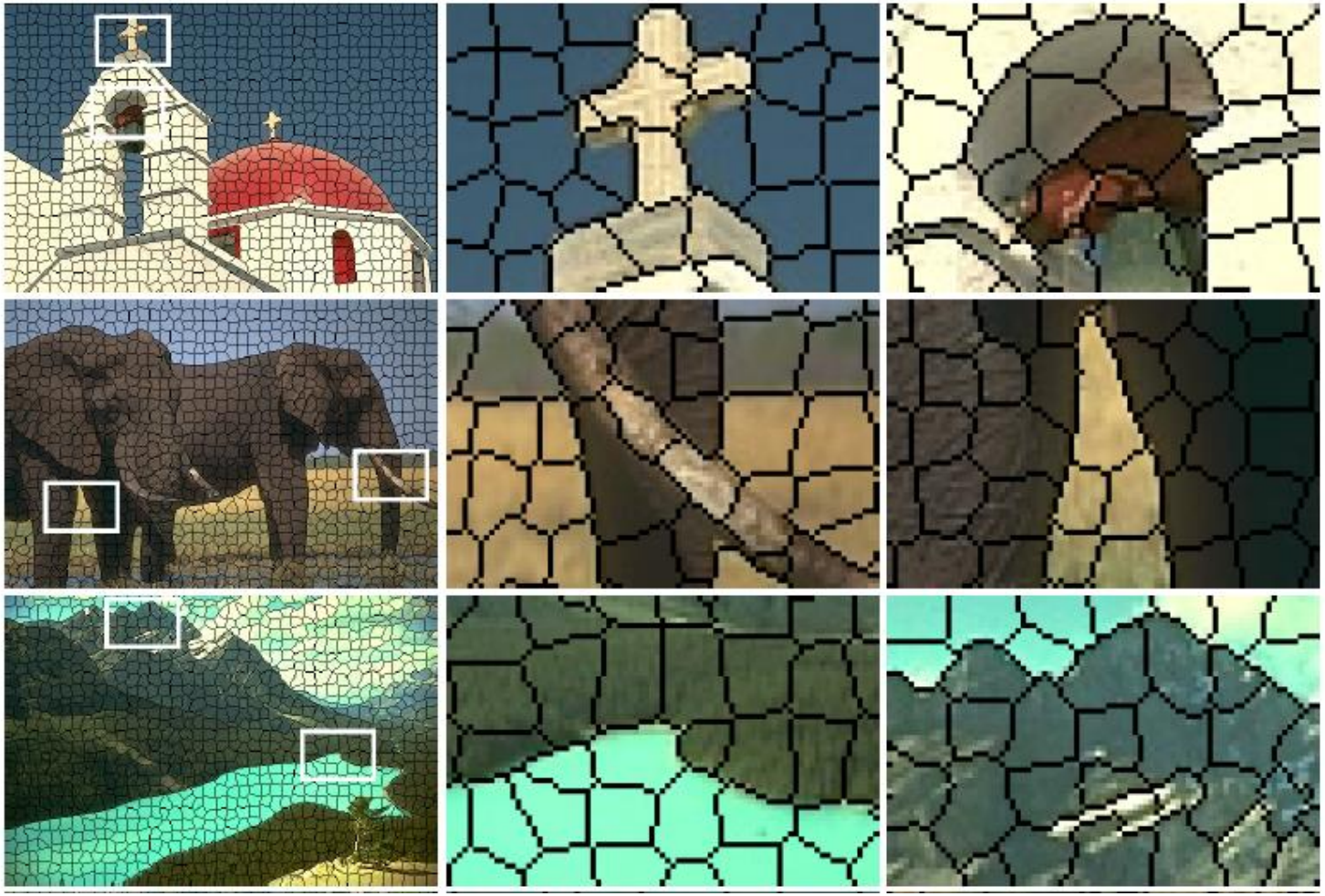
http://www.cs.brown.edu/~pff/segment/

+ Good for thin regions
+ Fast
+ Easy to control coarseness of segmentations
+ Can include both large and small regions
- Often creates regions with strange shapes
- Sometimes makes very large errors

# Turbo Pixels: Levinstein et al. 2009

http://www.cs.toronto.edu/~kyros/pubs/09.pami.turbopixels.pdf

Tries to preserve boundaries like watershed but to produce more regular regions



# SLIC (Achanta et al. PAMI 2012)

http://infoscience.epfl.ch/record/177415/files/Superpixel_PAMI2011-2.pdf

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

# Choices in segmentation algorithms

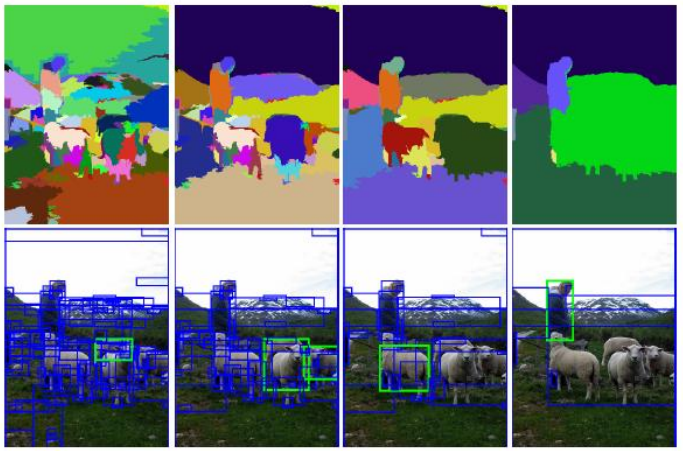
- Oversegmentation
  - Watershed + Pb ← my favorite
  - Felzenszwalb and Huttenlocher 2004 ← my favorite
    http://www.cs.brown.edu/~pff/segment/
  - SLIC ← good recent option
  - Turbopixels
  - Mean-shift

- Larger regions
  - Hierarchical segmentation (e.g., from Pb) ← my favorite
  - Normalized cuts
  - Mean-shift
  - Seed + graph cuts (discussed later)

# Multiple segmentations

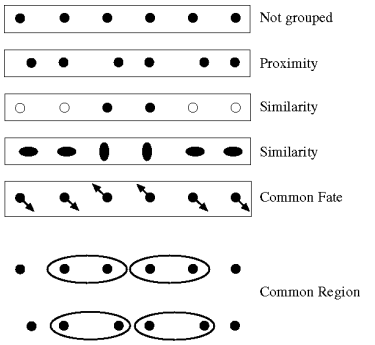
- When creating regions for pixel classification or object detection, don't commit to one partitioning

- Strategies:
  - Hierarchical segmentation
    - Occlusion boundaries hierarchy: Hoiem et al. IJCV 2011 (uses trained classifier to merge)
    - Pb+watershed hierarchy: Arbeleaz et al. CVPR 2009
    - Selective search: FH + agglomerative clustering
  - Vary segmentation parameters
    - E.g., multiple graph-based segmentations or mean-shift segmentations
  - Region proposals
    - Propose seed superpixel, try to segment out object that contains it (Endres Hoiem ECCV 2010, Carreira Sminchisescu CVPR 2010)



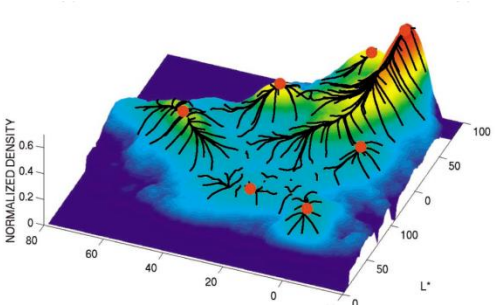
# Things to remember

- Gestalt cues and principles of organization

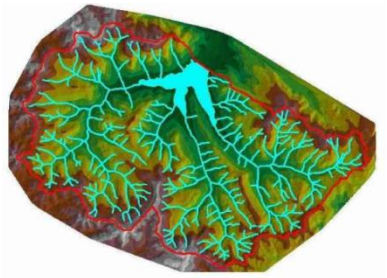



- Uses of segmentation
  - Efficiency
  - Better features
  - Propose object regions
  - Want the segmented object

- 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



# Next class: EM algorithm

- Make sure to bring something to take notes (will include a long derivation)