Grouping and Segmentation

Vinay P. Namboodiri

- Slide credits to Derek Hoiem and Kirsten Grauman

Overview

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

Gestalt grouping

Gestalt psychology or **gestaltism**

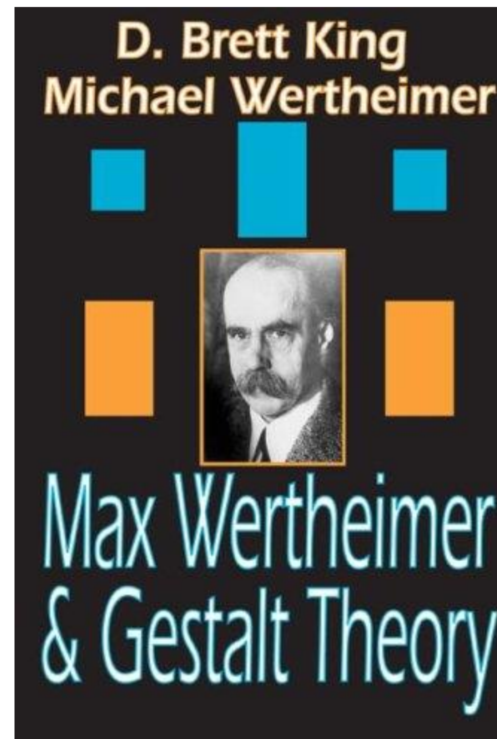
German: *Gestalt* - "form" or "whole”

Berlin School, early 20th century

Kurt Koffka, Max Wertheimer, and Wolfgang Köhler

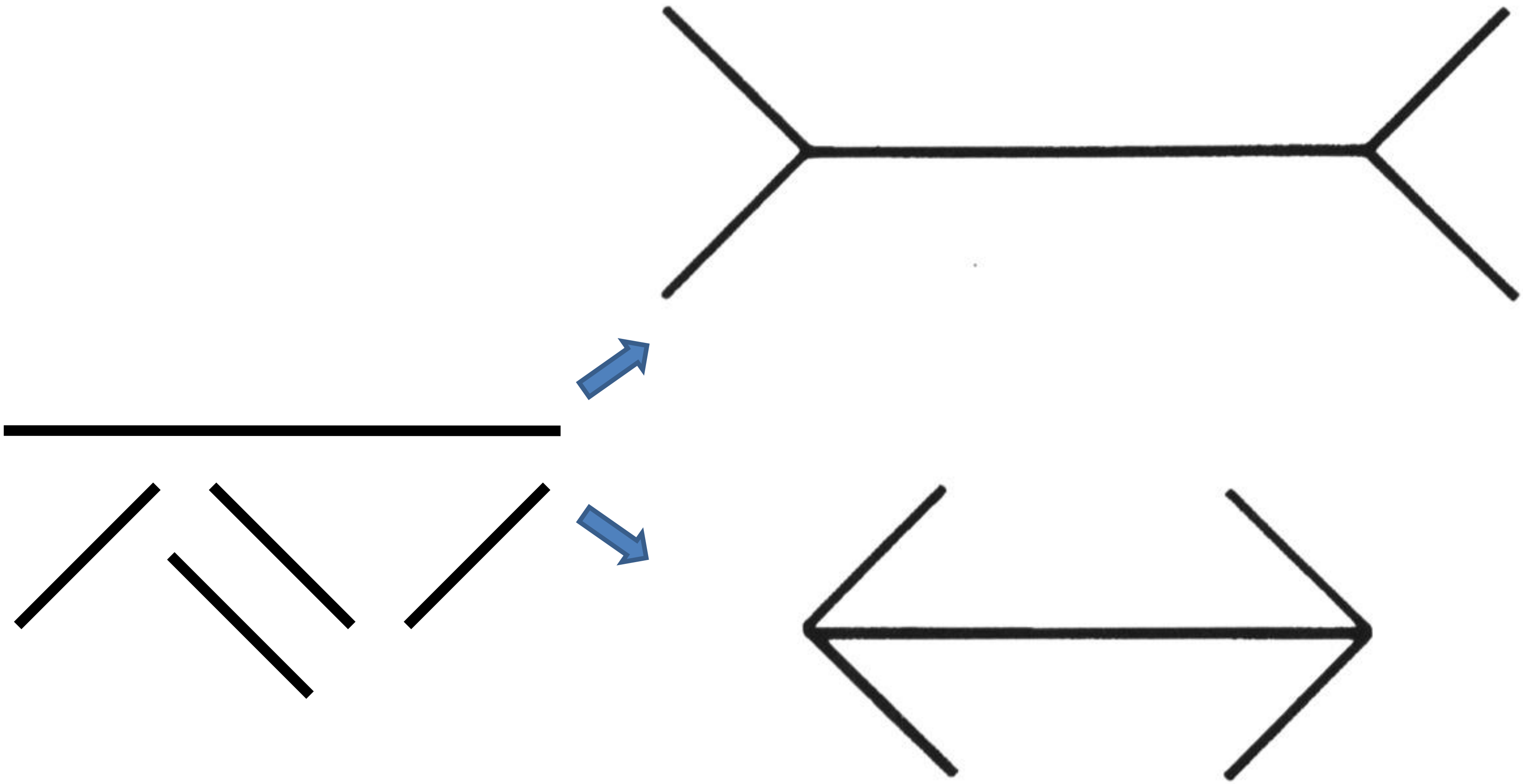
View of brain:

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



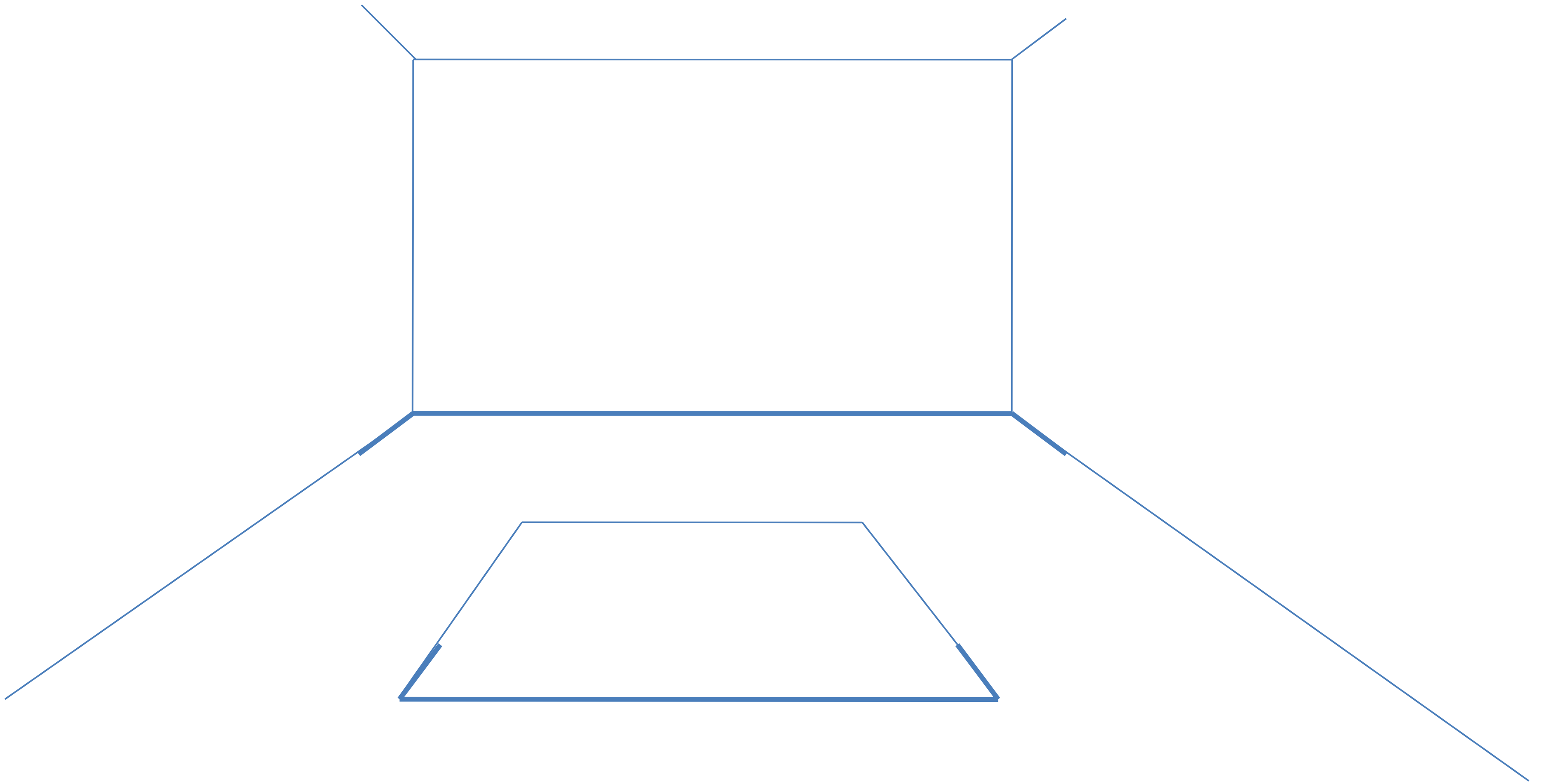
Slide from S. Saverese

Gestaltism

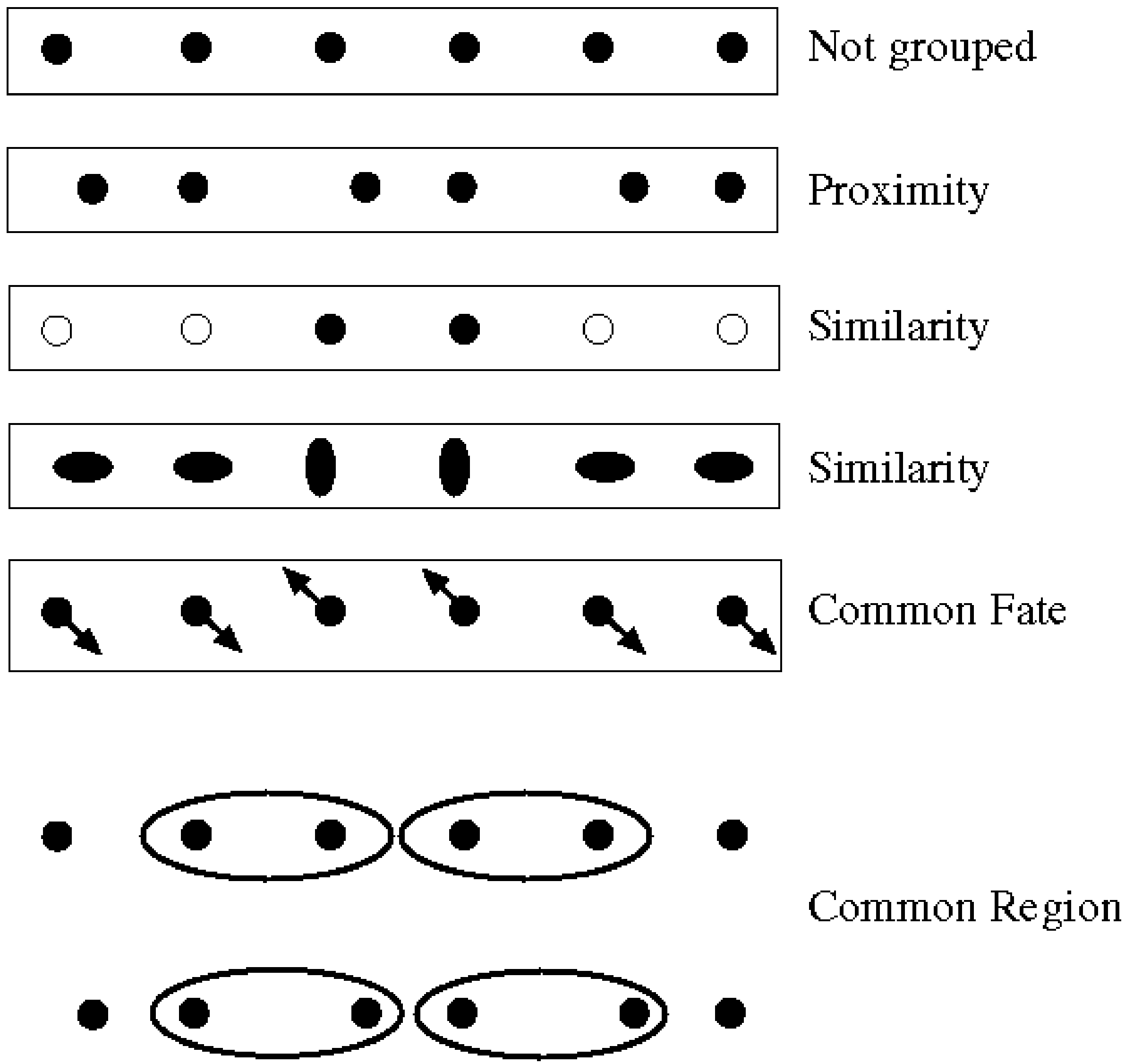


The Muller-Lyer illusion

We perceive the interpretation, not the senses

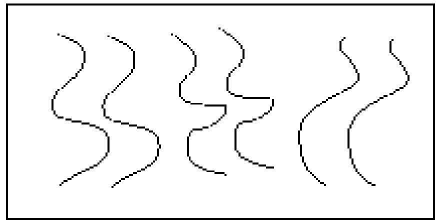


Principles of perceptual organization

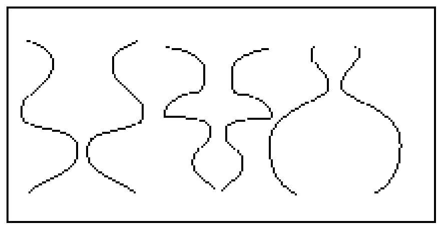


From Steve Lehar: The Constructive Aspect of Visual Perception

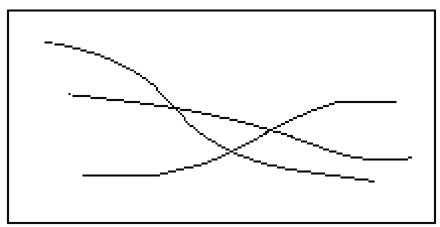
Principles of perceptual organization



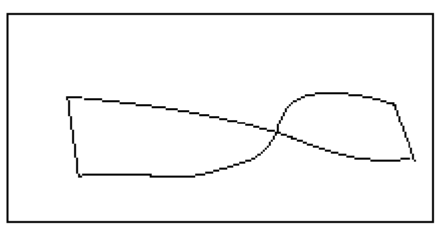
Parallelism



Symmetry

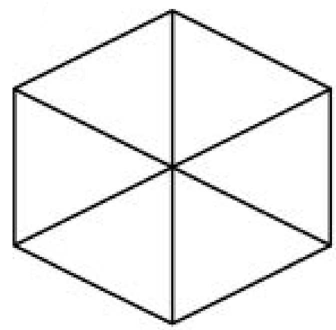


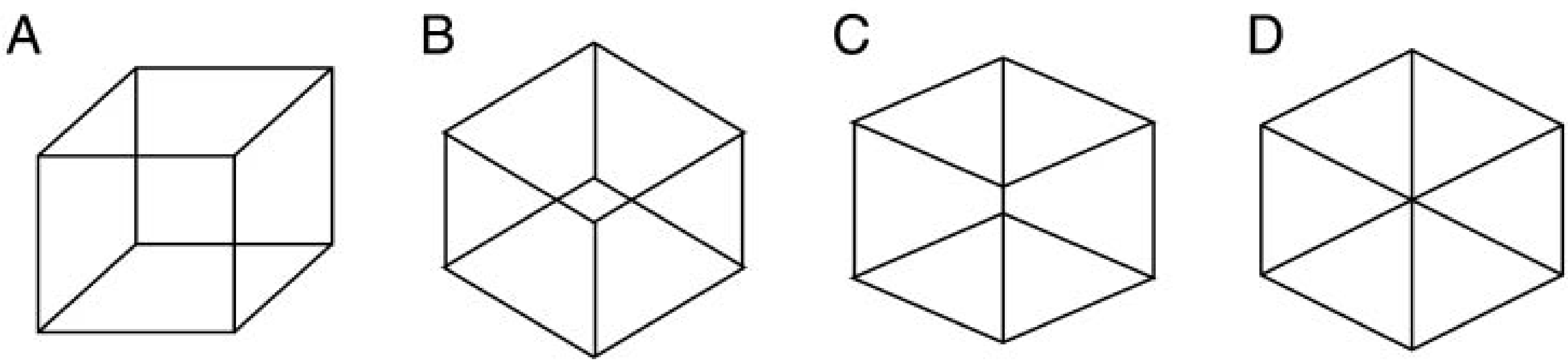
Continuity



Closure

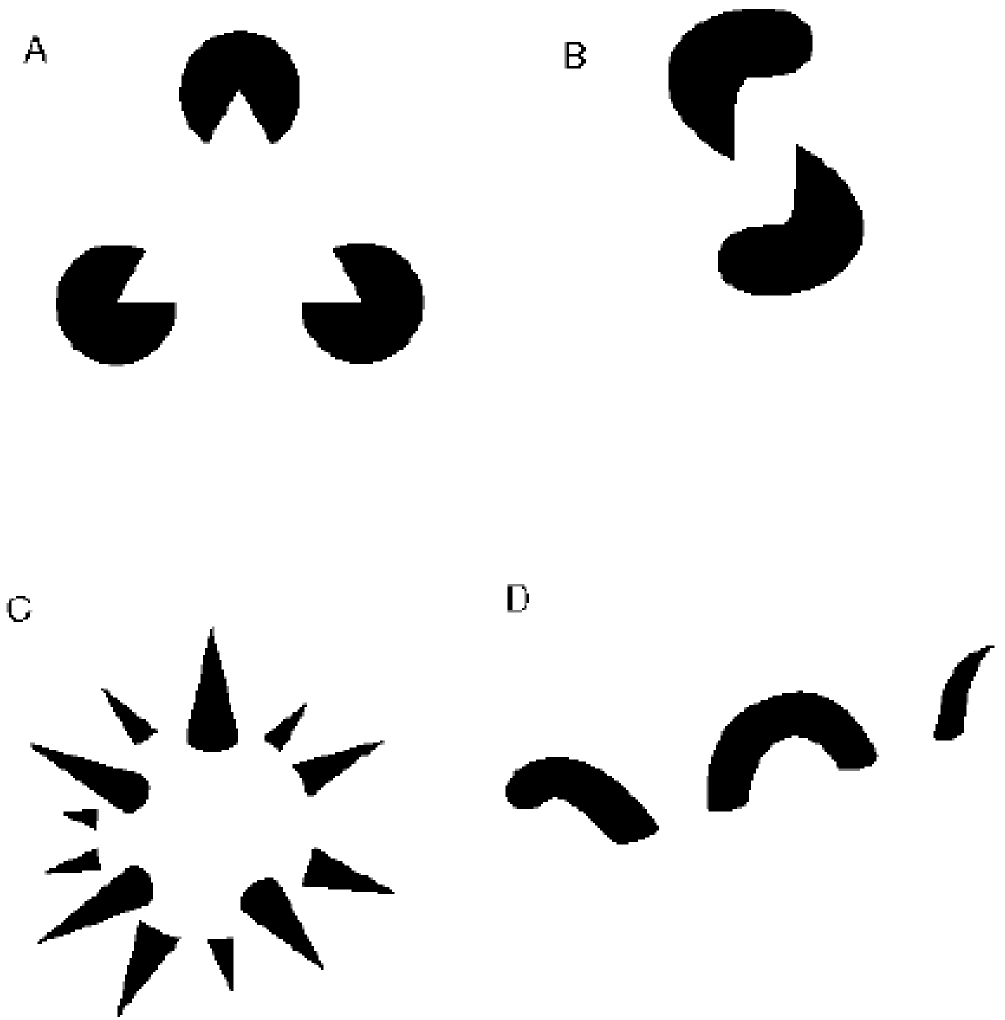
Gestaltists do not believe in coincidence





Emergence

Grouping by invisible completion



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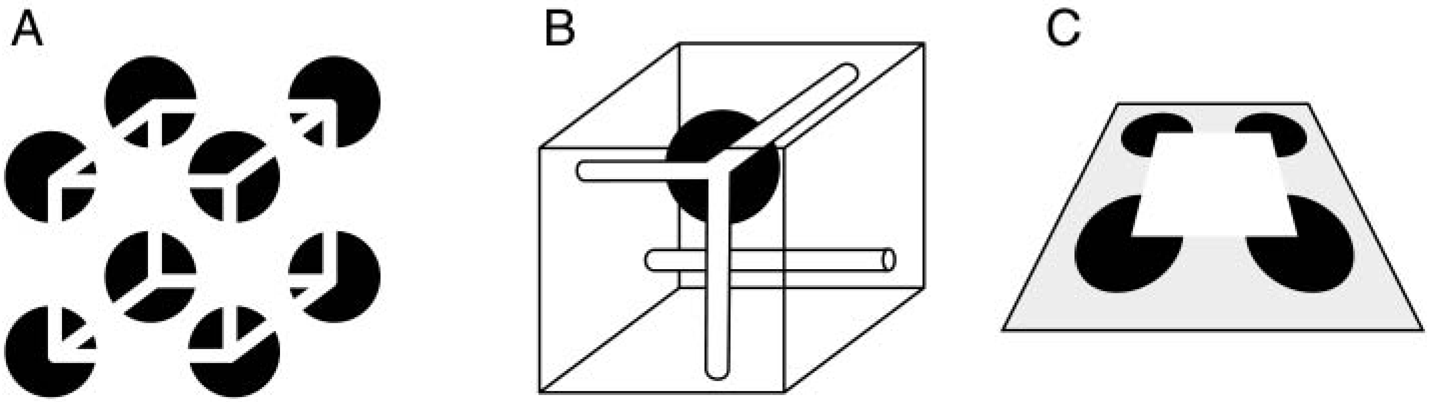
Grouping involves global interpretation



From Steve Lehar: The Constructive Aspect of Visual Perception

Grouping involves global interpretation

A

B

From Steve Lehar: The Constructive Aspect of Visual Perception

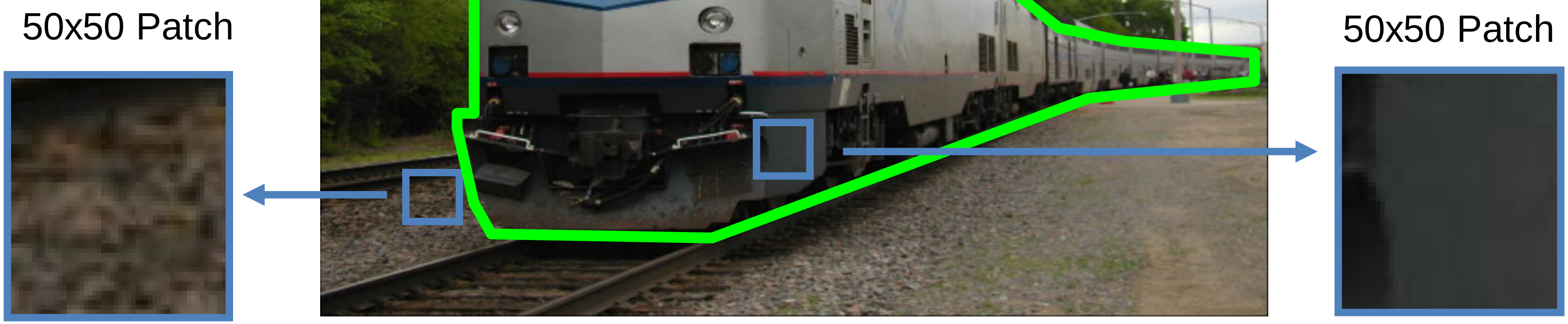
Gestalt cues

- 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

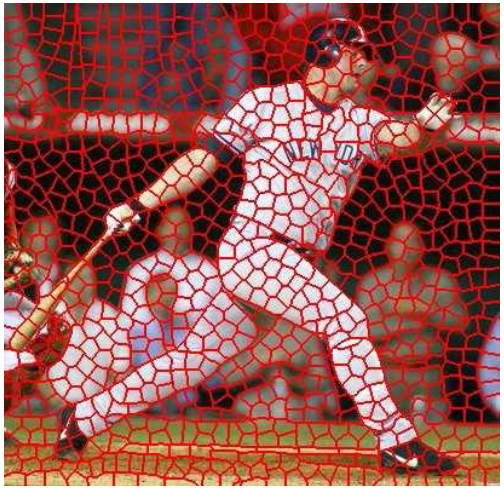
Goal: Group pixels into meaningful or perceptually similar regions

Segmentation for feature support



Segmentation for efficiency

[Felzenszwalb and Huttenlocher 2004]



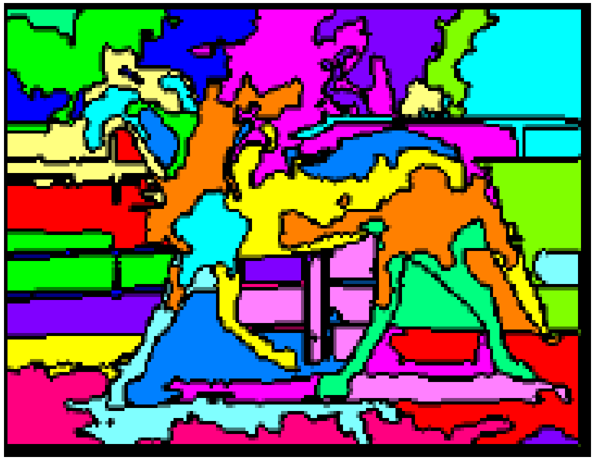
[Shi and Malik 2001]

[Hoiem et al. 2005, Mori 2005]

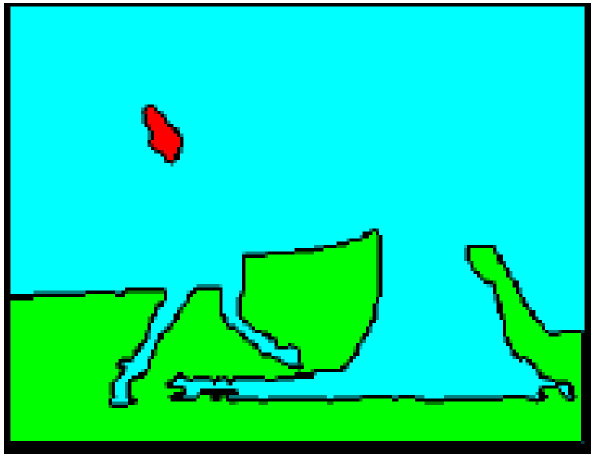
Segmentation as a result

Rother et al. 2004

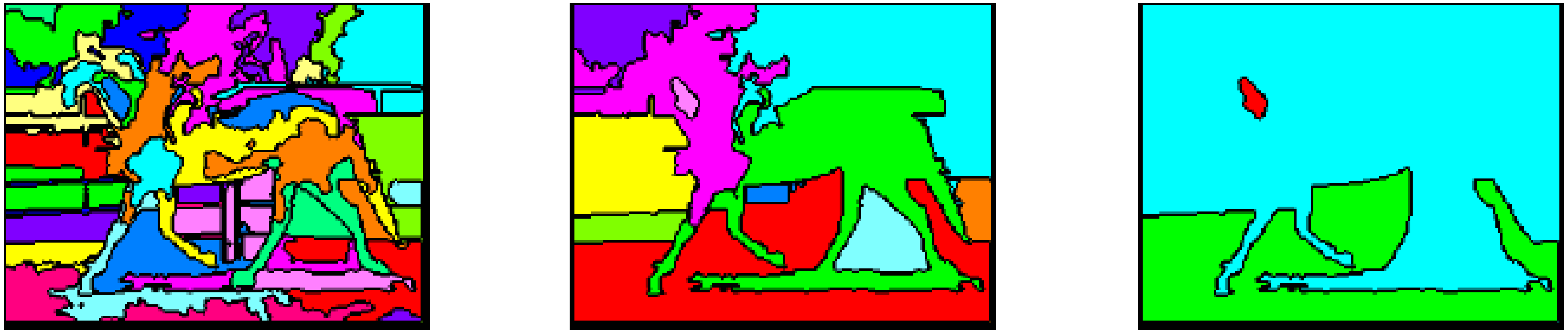
Types of segmentations



Oversegmentation



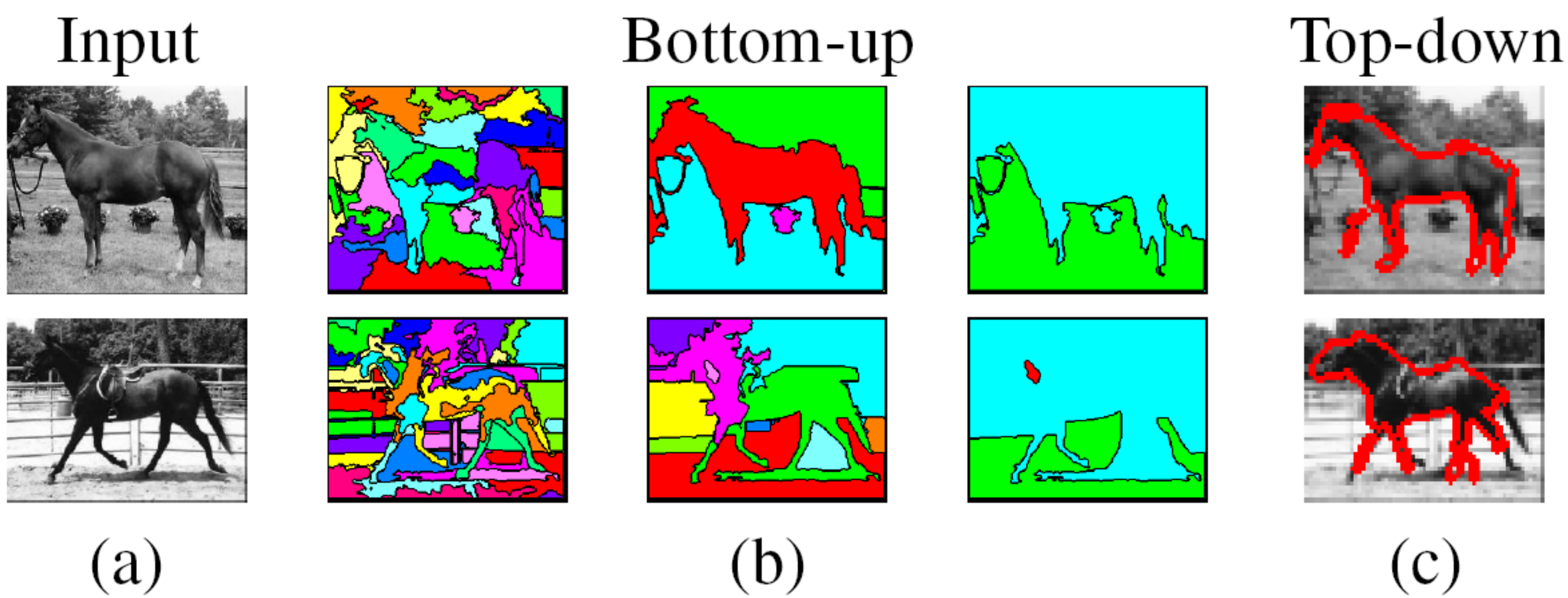
Undersegmentation



Multiple Segmentations

Major processes for segmentation

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

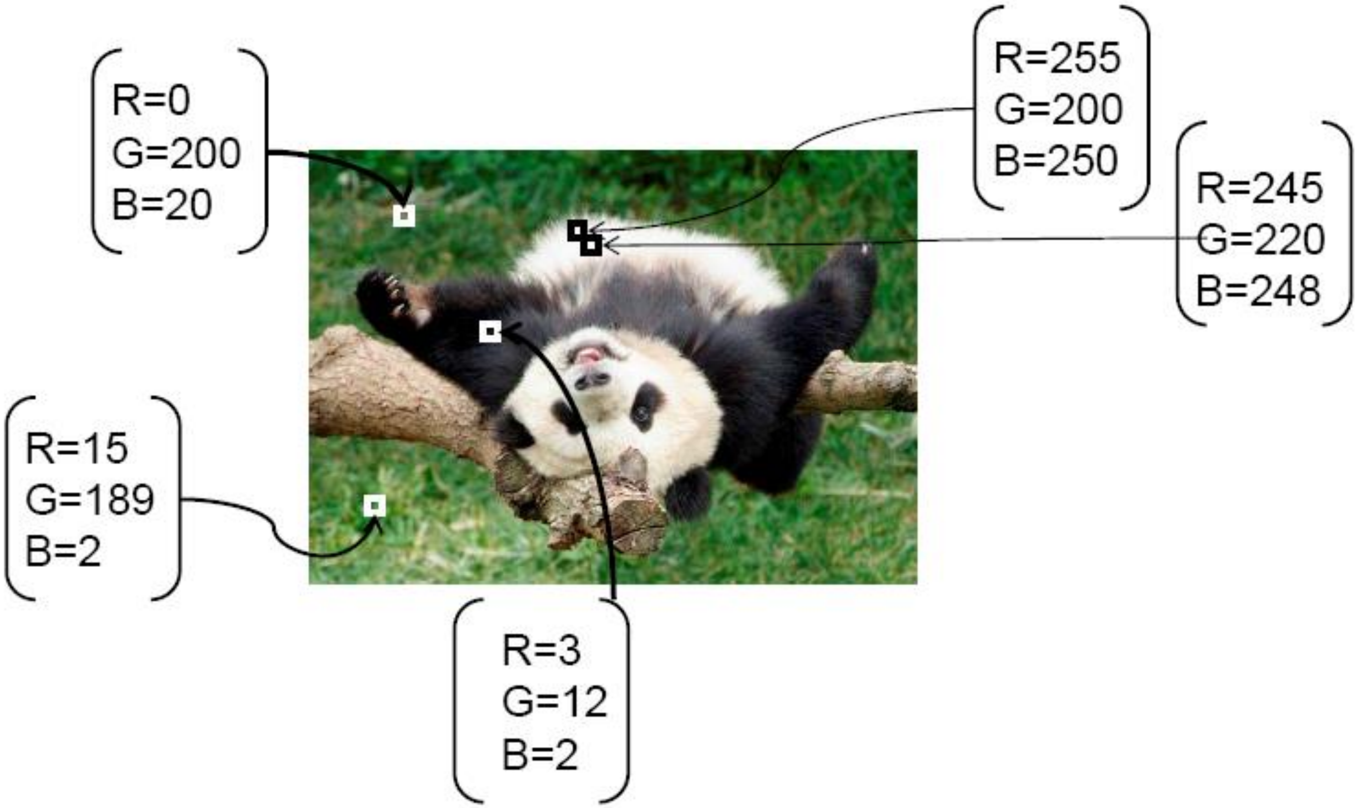


[Levin and Weiss 2006]

Segmentation using clustering

- Kmeans
- Mean-shift

Feature Space



Source: K. Grauman

K-means clustering using intensity alone and color alone

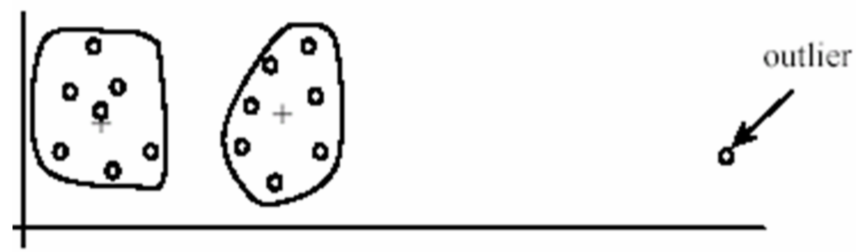
Image

Clusters on intensity

Clusters on color

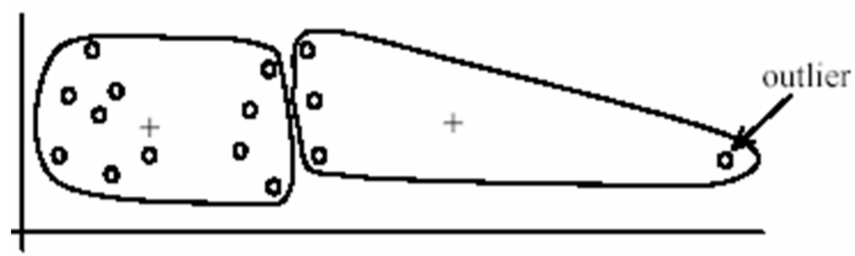
K-Means pros and cons

- Pros
  - Simple and fast
  - Easy to implement
- Cons
  - Need to choose K
  - Sensitive to outliers



(B): Ideal clusters

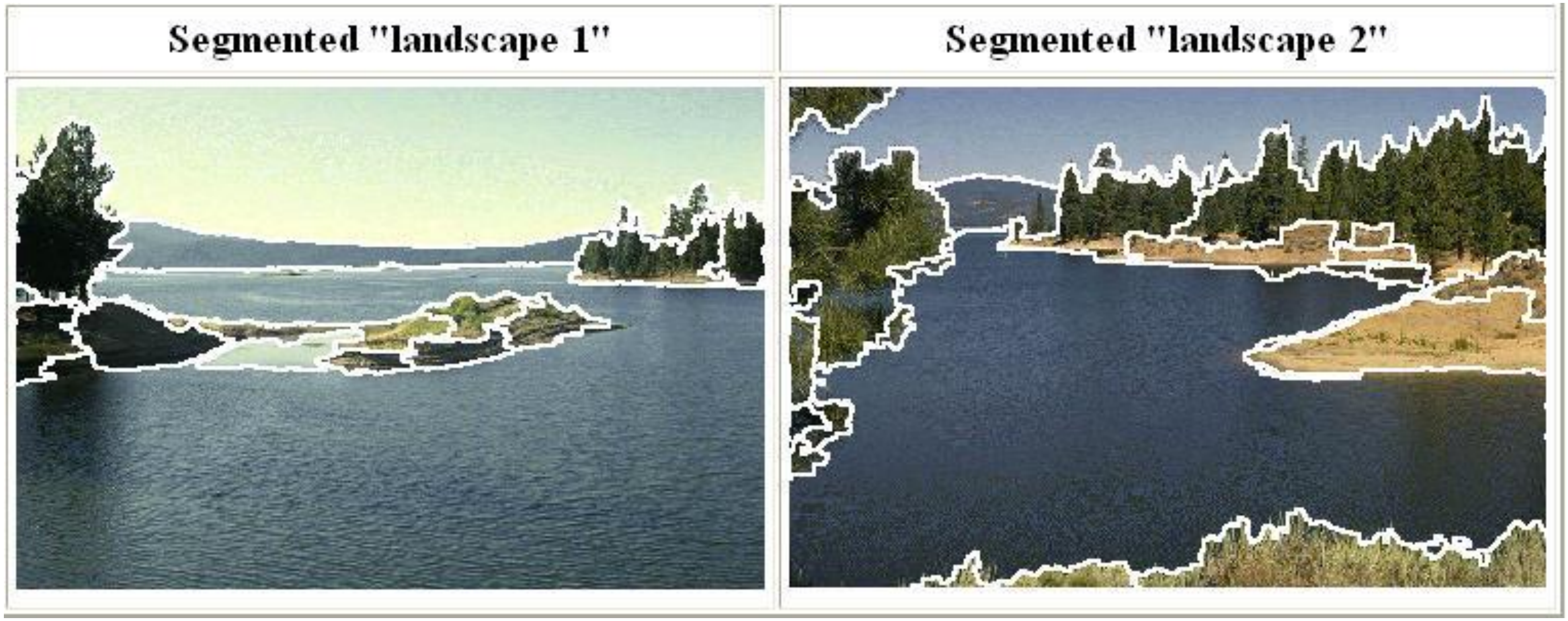
- Usage
  - Rarely used for pixel segmentation



Mean shift segmentation

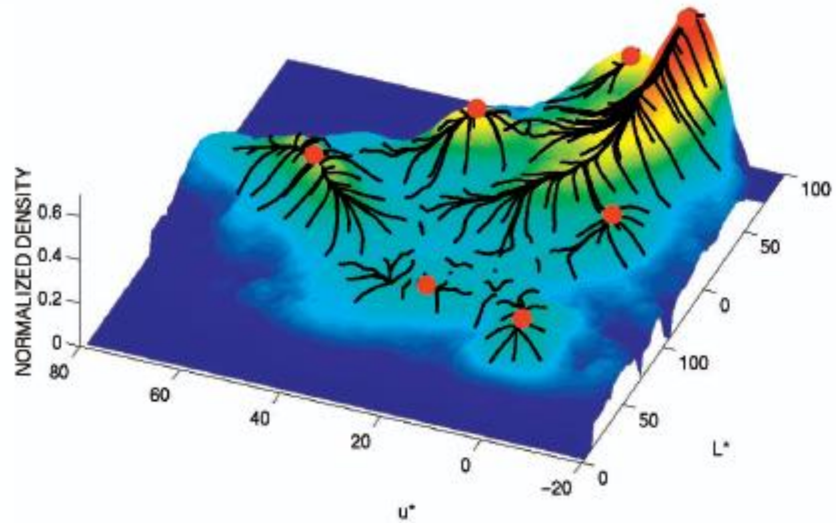
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

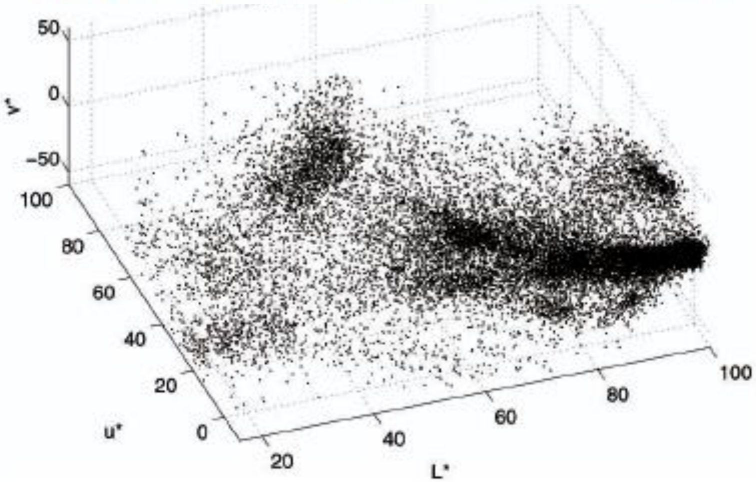
- Versatile technique for clustering-based segmentation

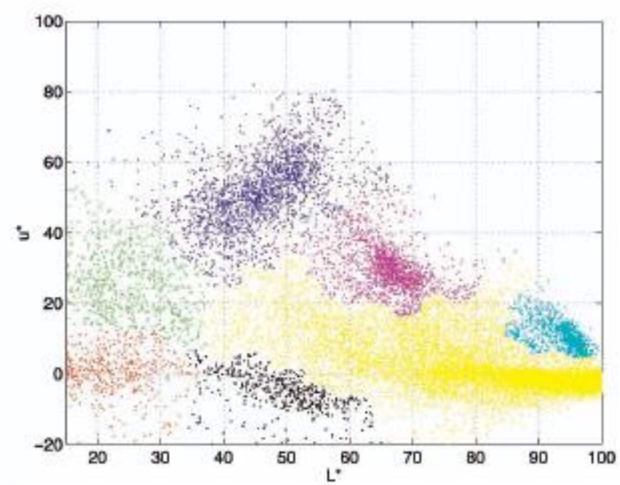


Mean shift algorithm

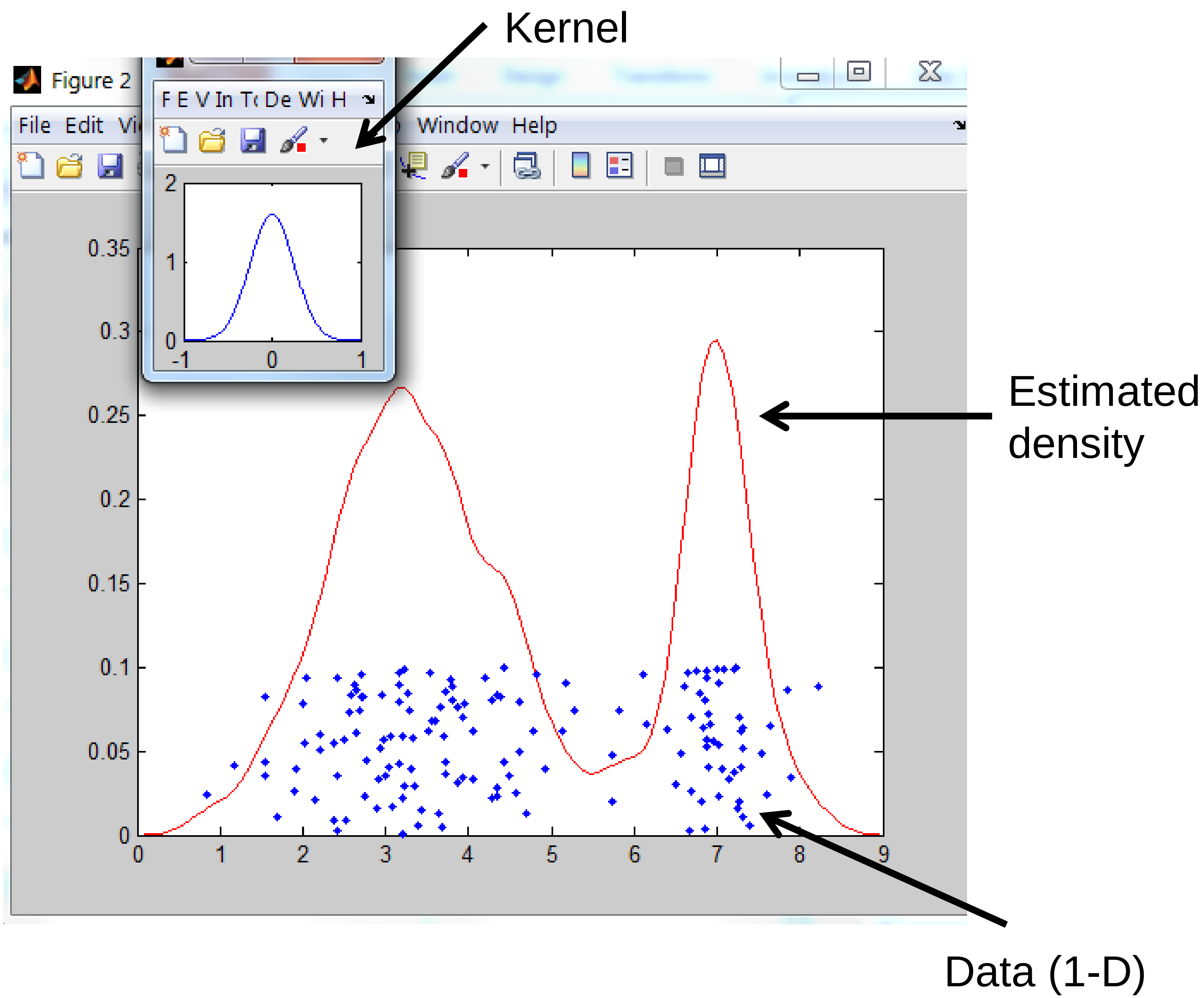
- Try to find *modes* of this non-parametric density







Kernel density estimation



Kernel density estimation

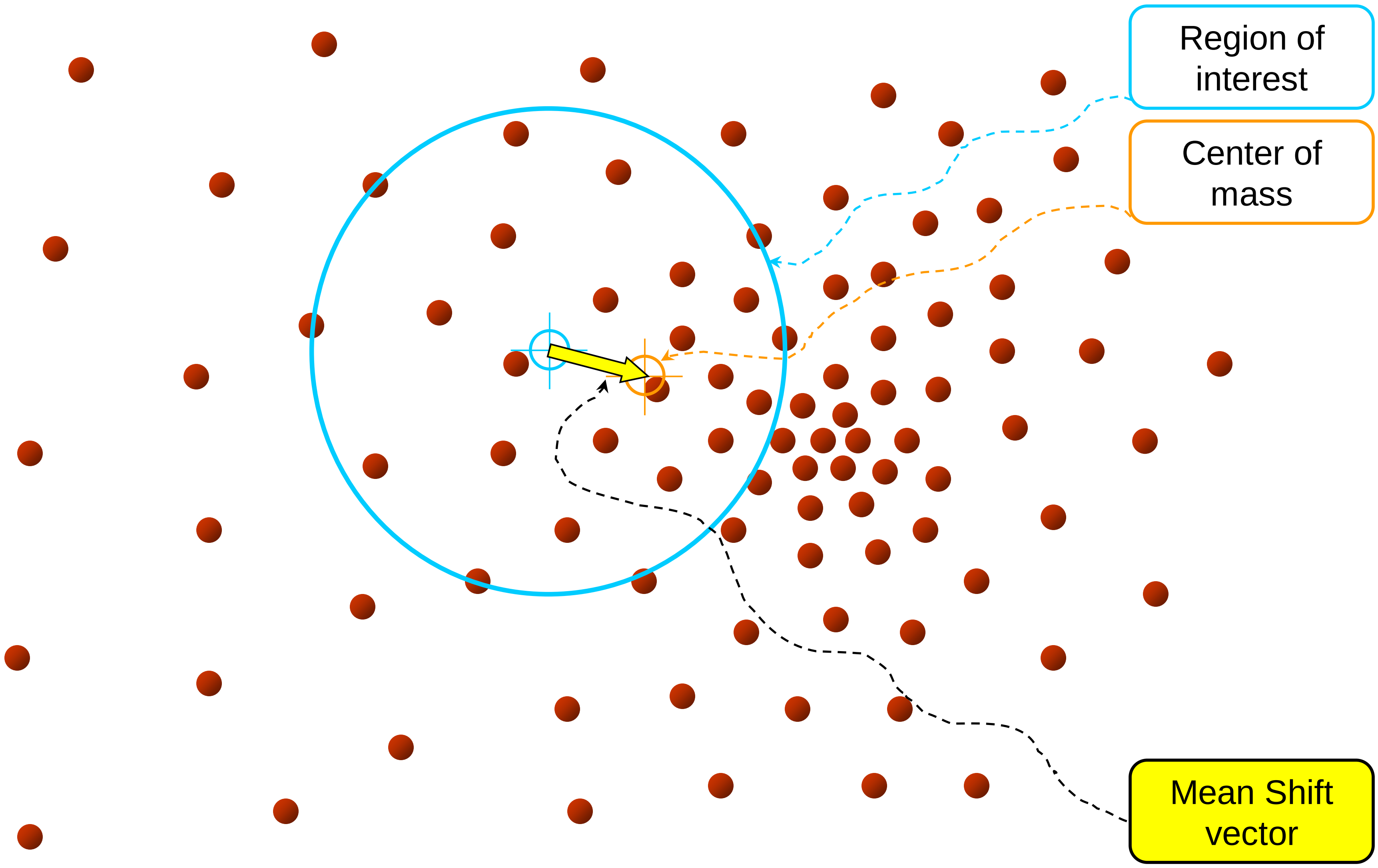
Kernel density estimation function

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

Gaussian kernel

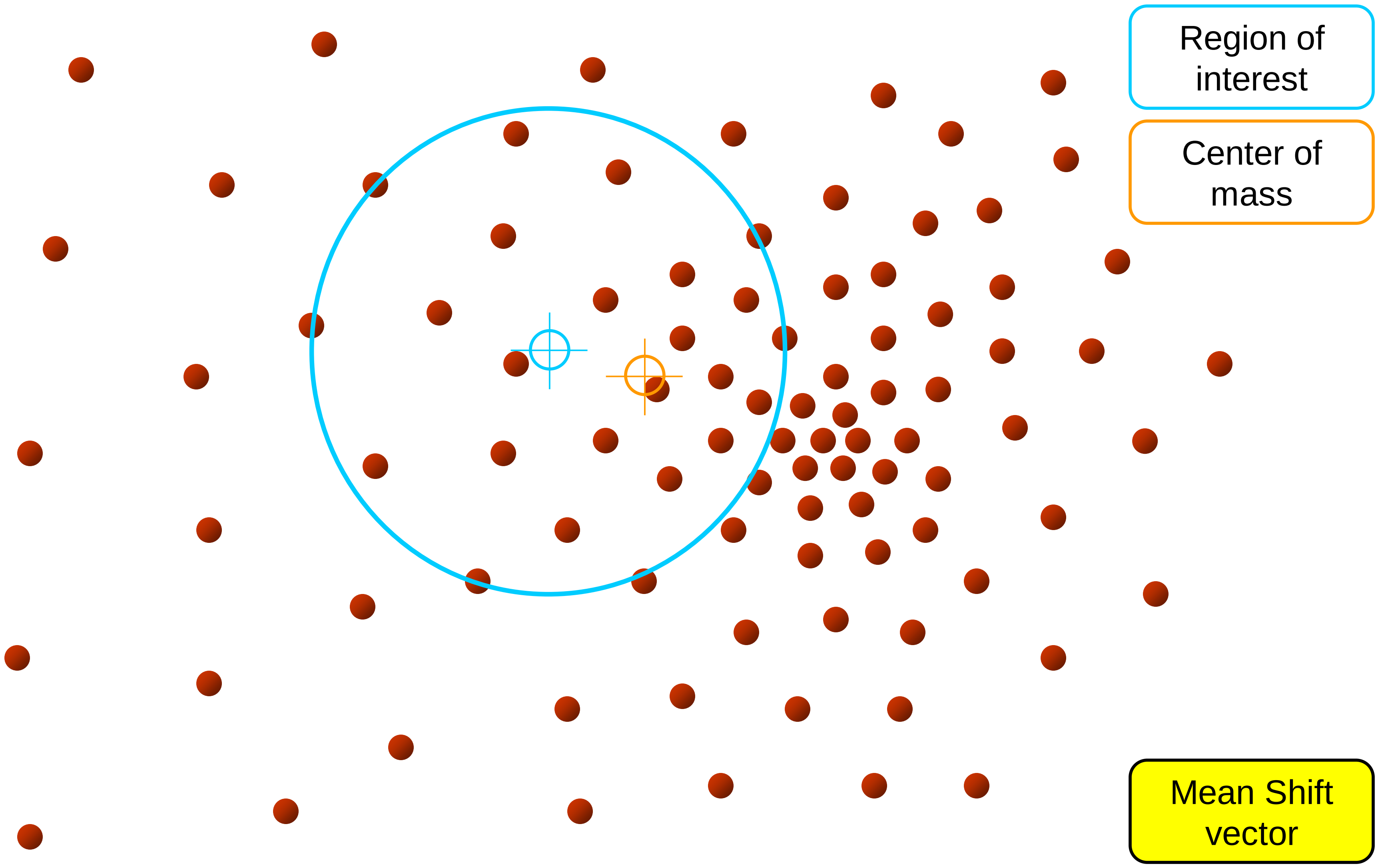
$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x-x_i)^2}{2h^2}}.$$

Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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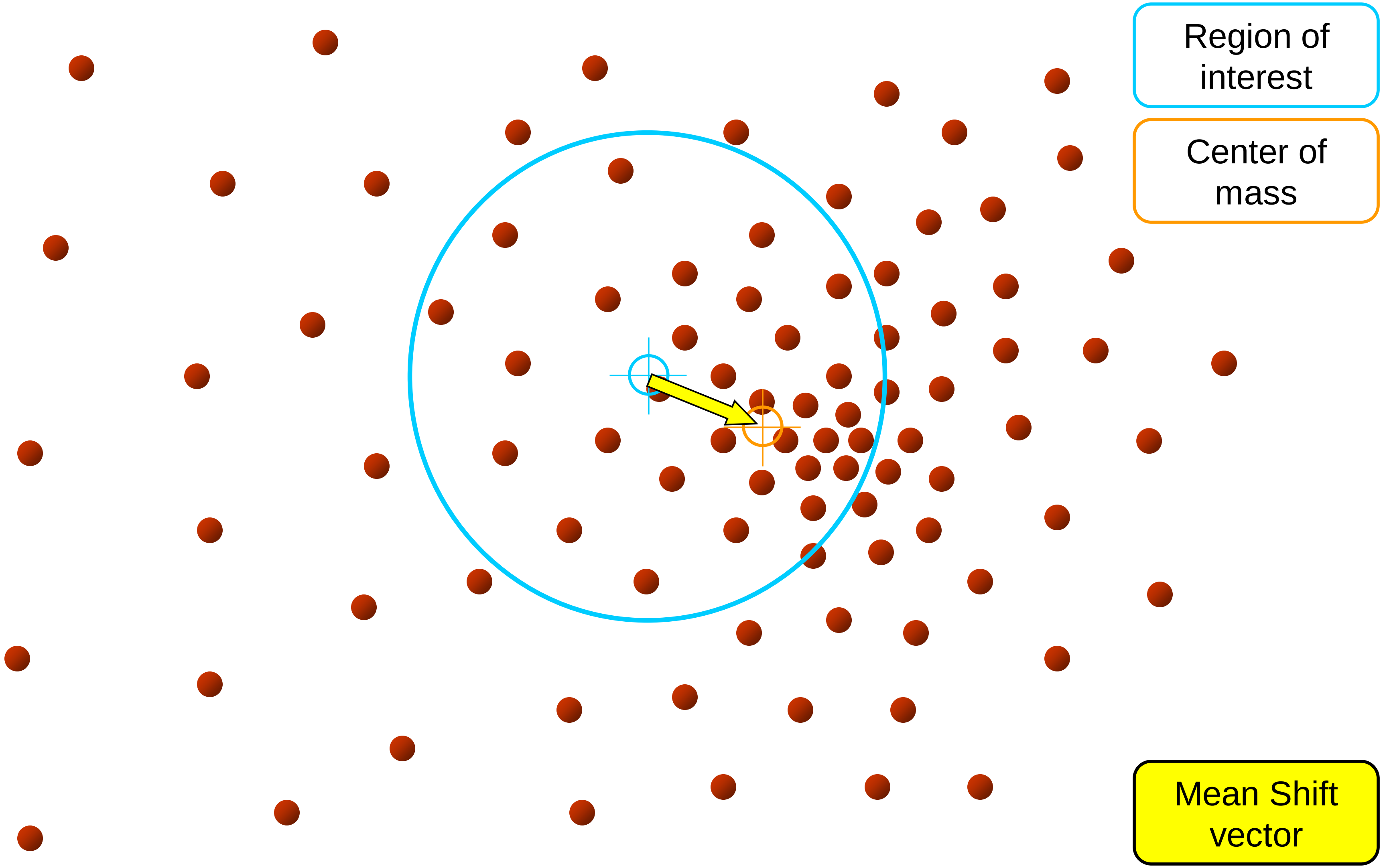
Mean shift



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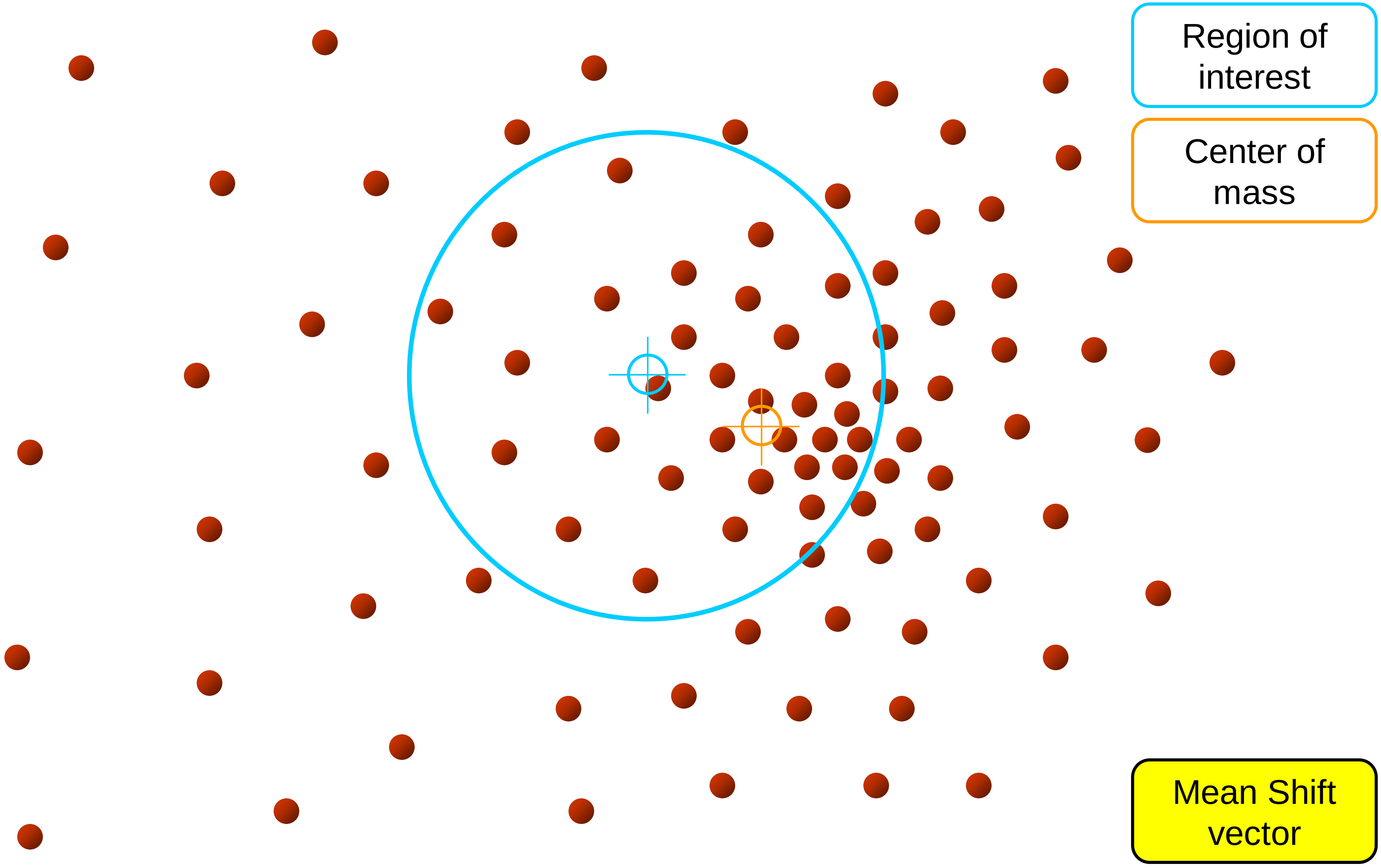
Mean shift



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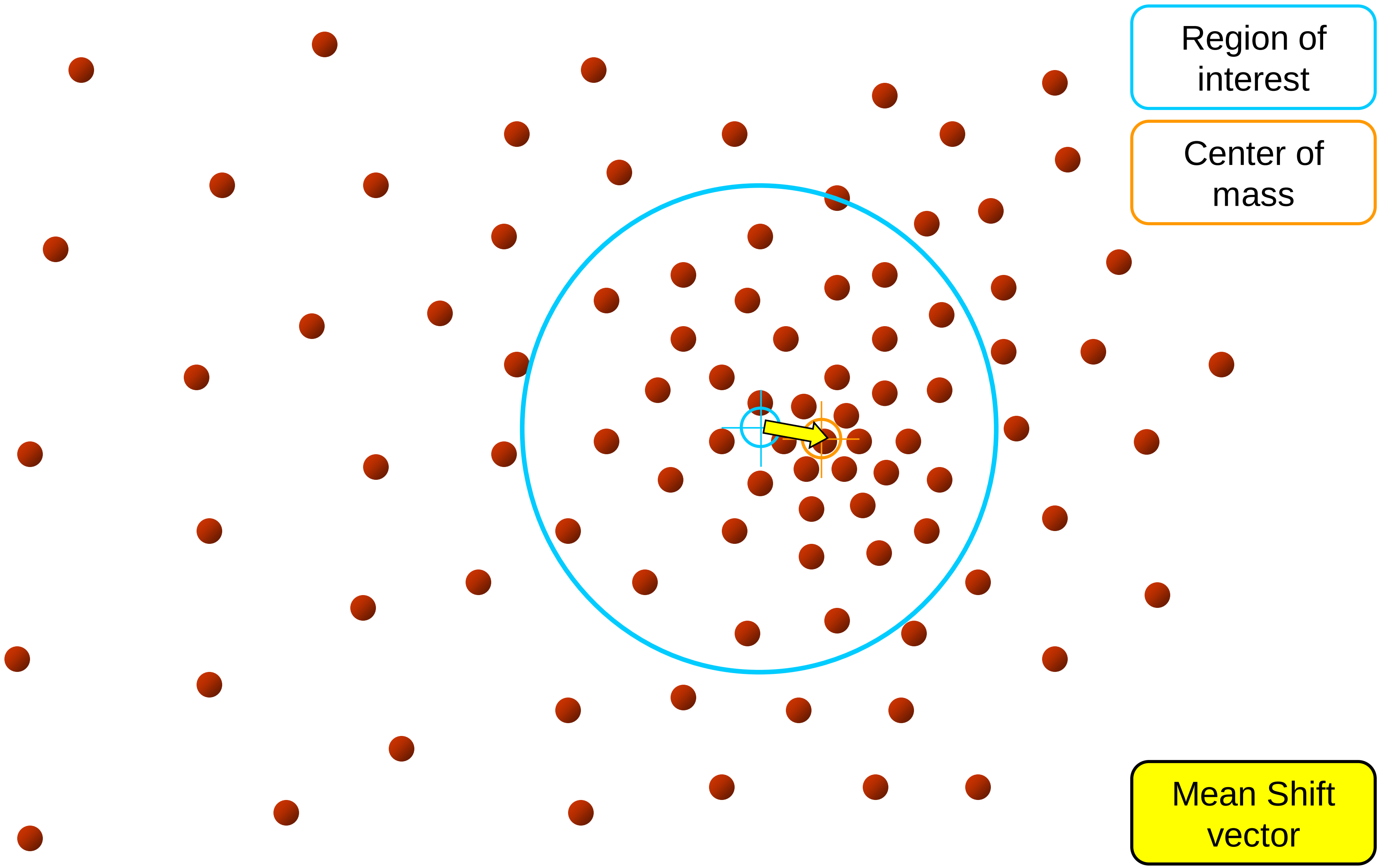
Mean shift



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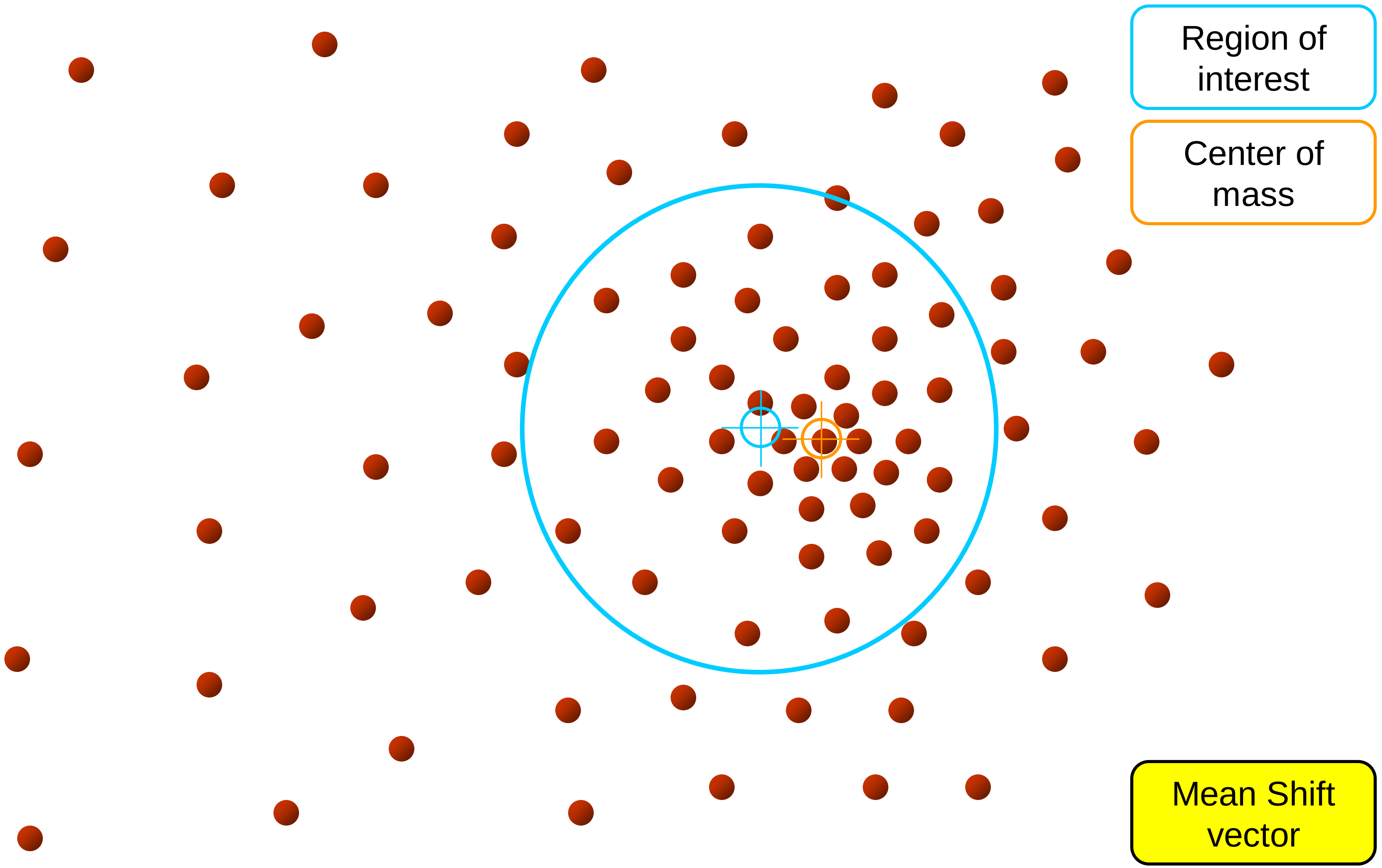
Mean shift



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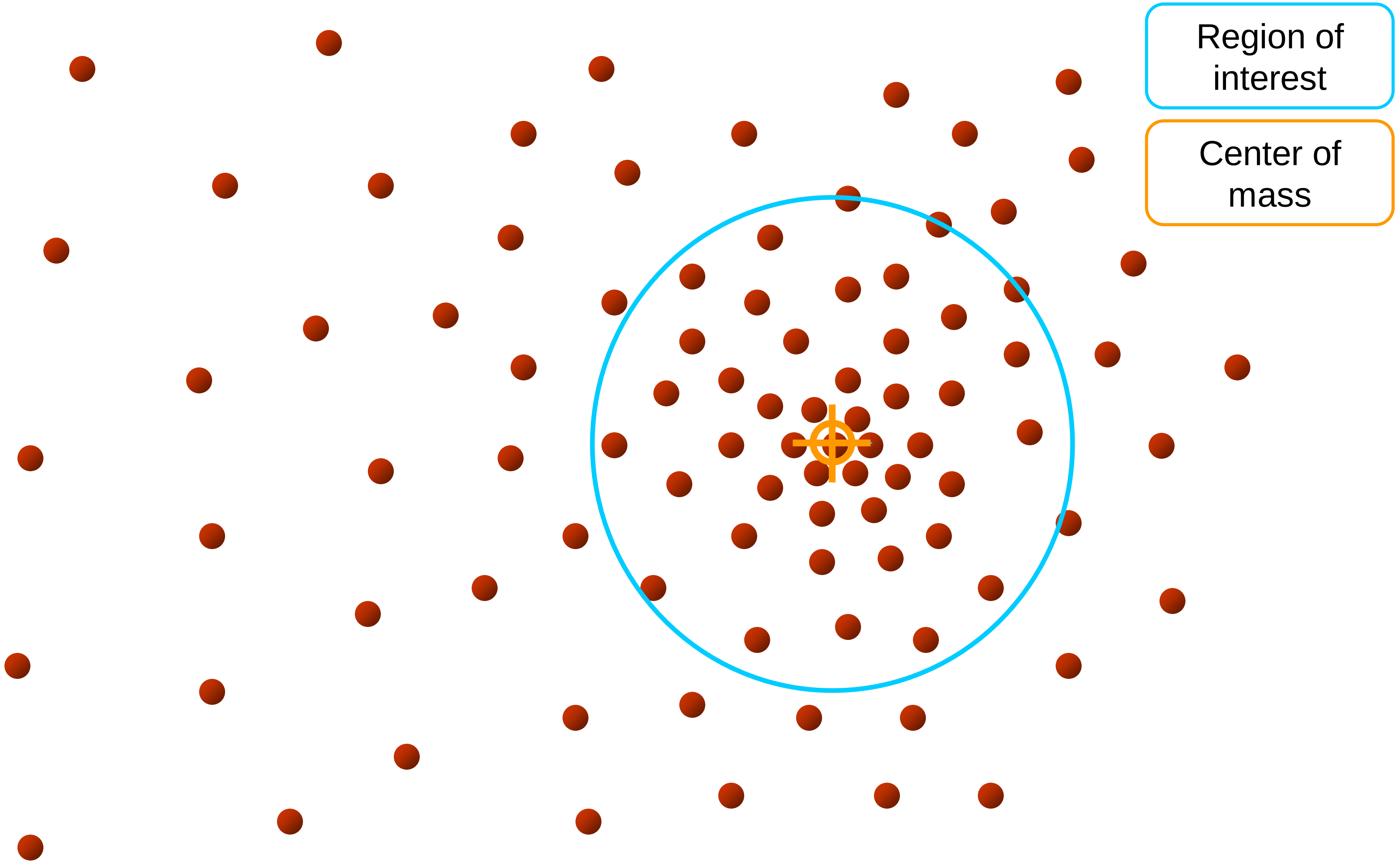
Mean shift



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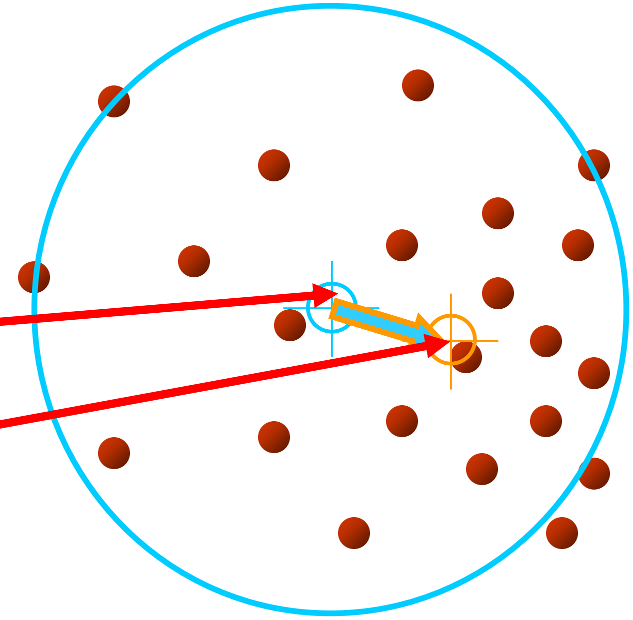
Computing the Mean Shift

Simple Mean Shift procedure:

- Compute mean shift vector

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

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



$g(\mathbf{x}) = -k'(\mathbf{x})$

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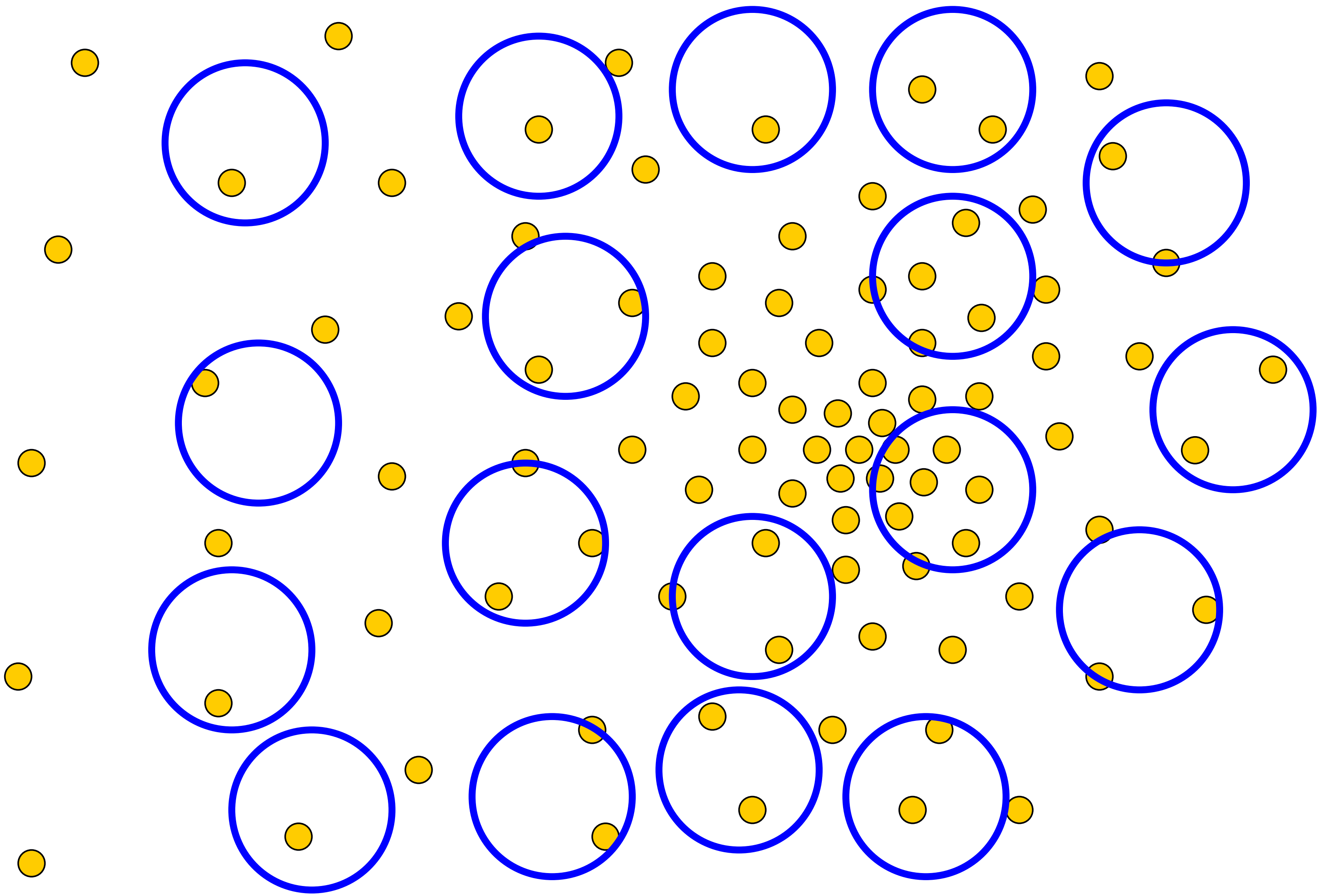
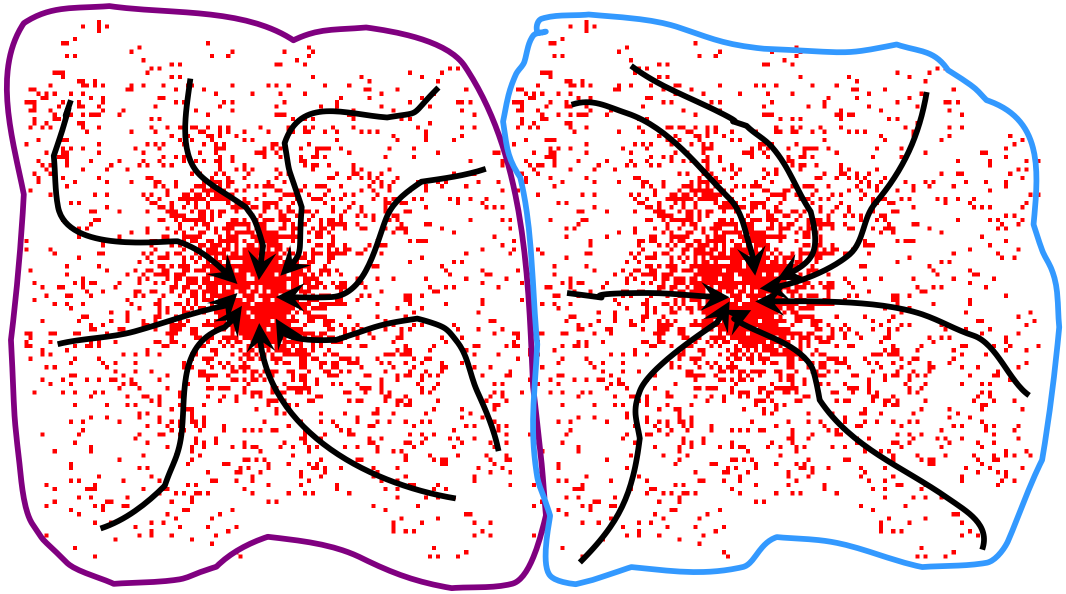
Real Modality Analysis



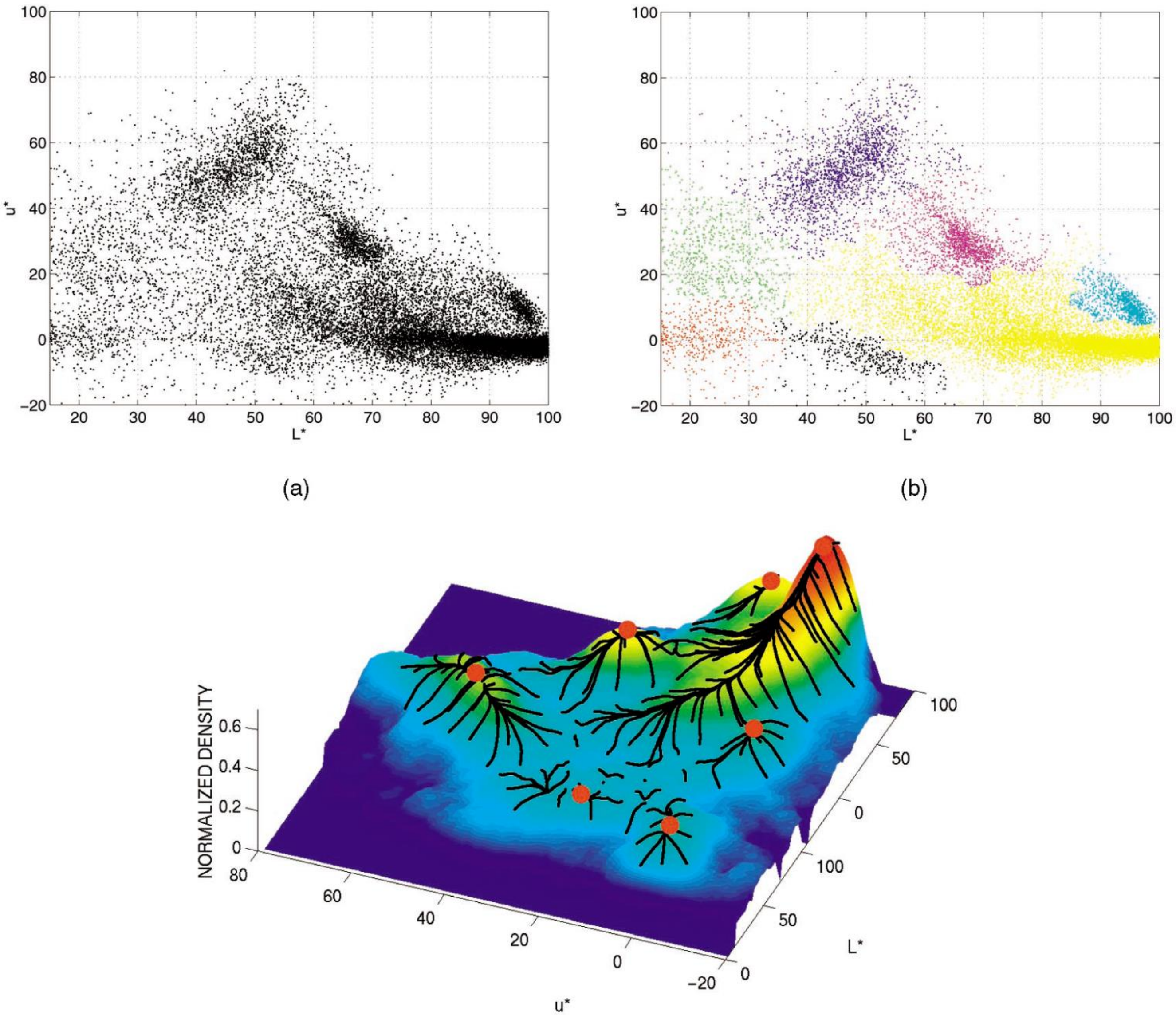
Attraction basin

- 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

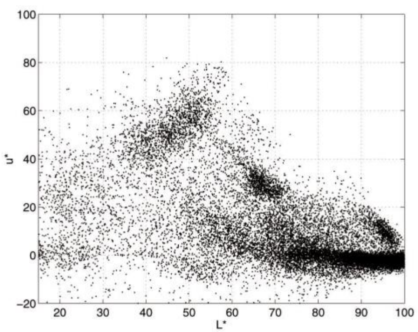


Mean shift clustering

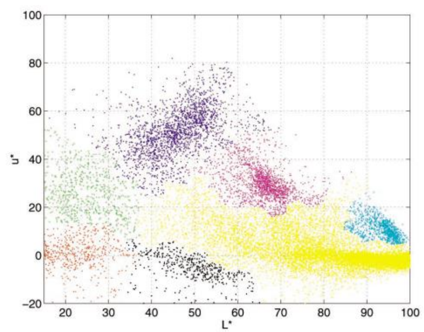
- The mean shift algorithm seeks *modes* of the given set of points
  1. Choose kernel and bandwidth
  2. For each point:
     a) Center a window on that point
     b) Compute the mean of the data in the search window
     c) Center the search window at the new mean location
     d) Repeat (b,c) until convergence
  3. Assign points that lead to nearby modes to the same cluster

Segmentation by Mean Shift

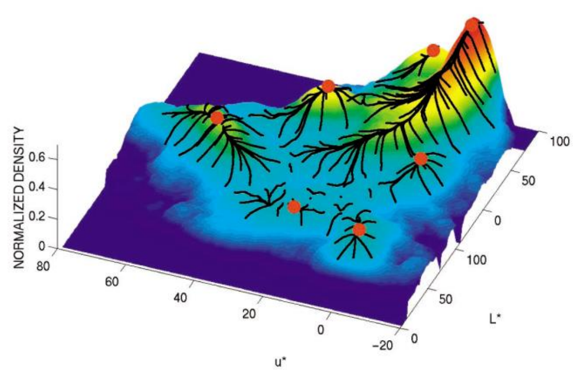
- Compute features for each pixel (color, gradients, texture, etc); also store each pixel's position
- Set kernel size for features K_f and position K_s
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge modes that are within width of K_f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



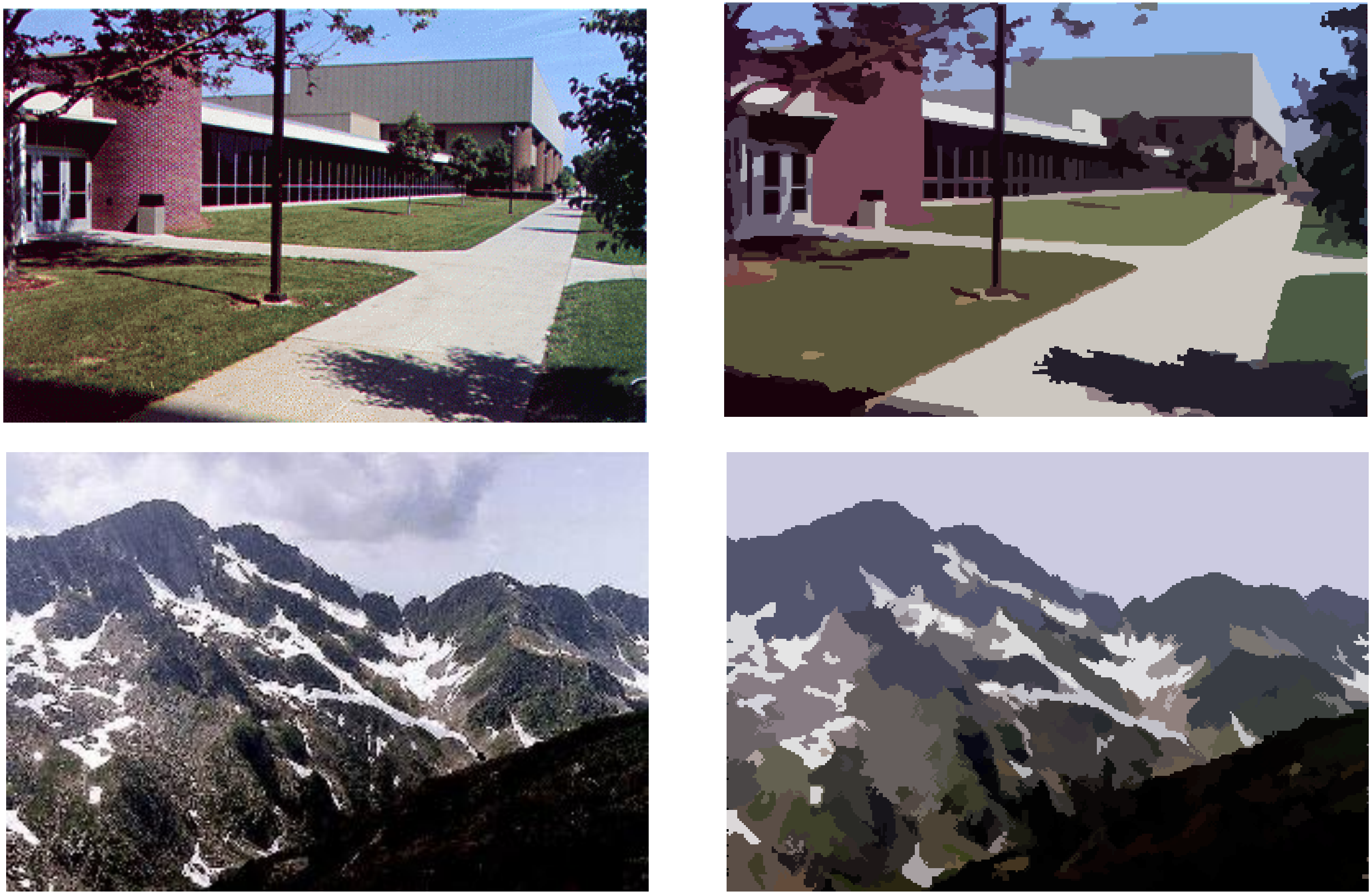
(a)



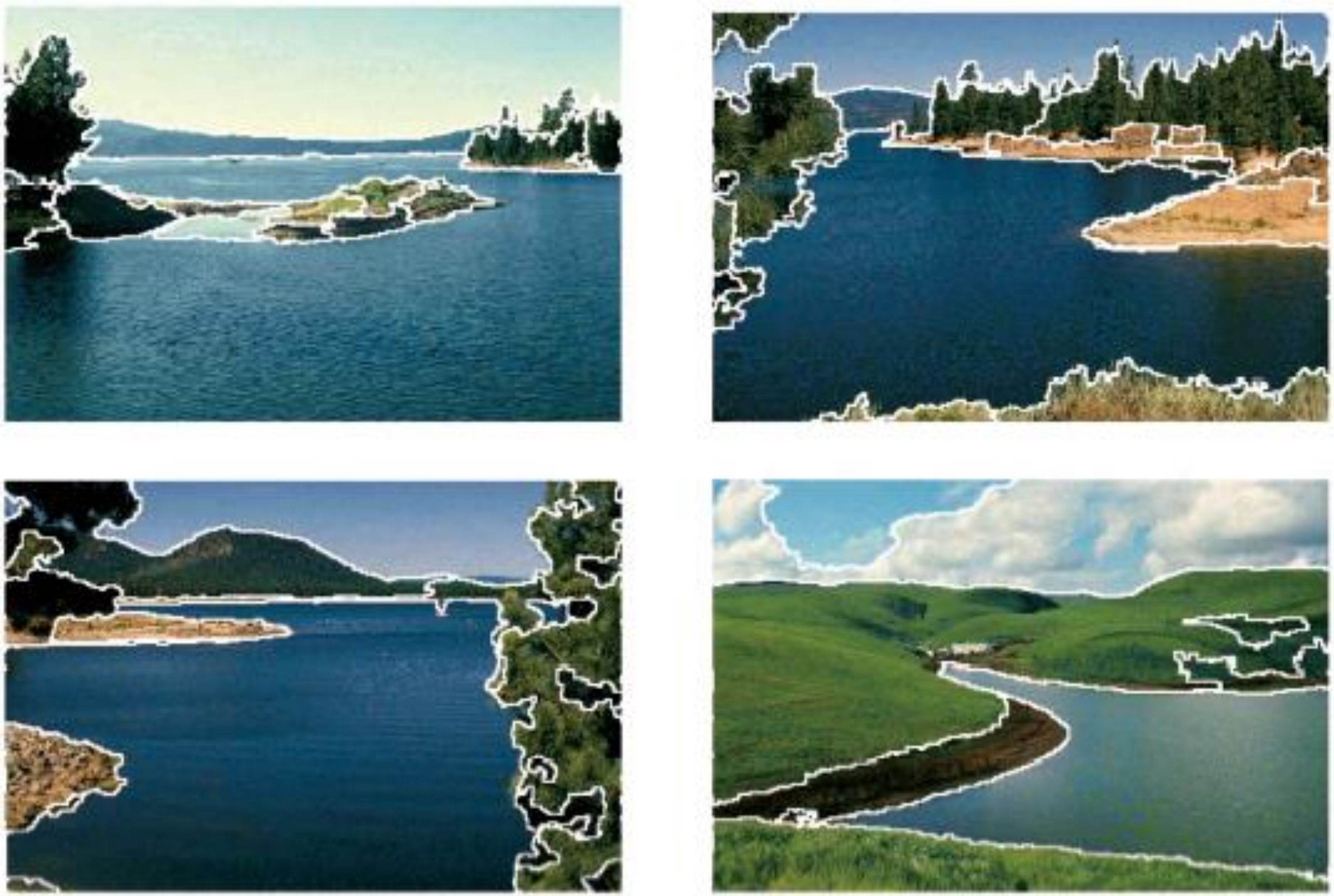
(b)



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

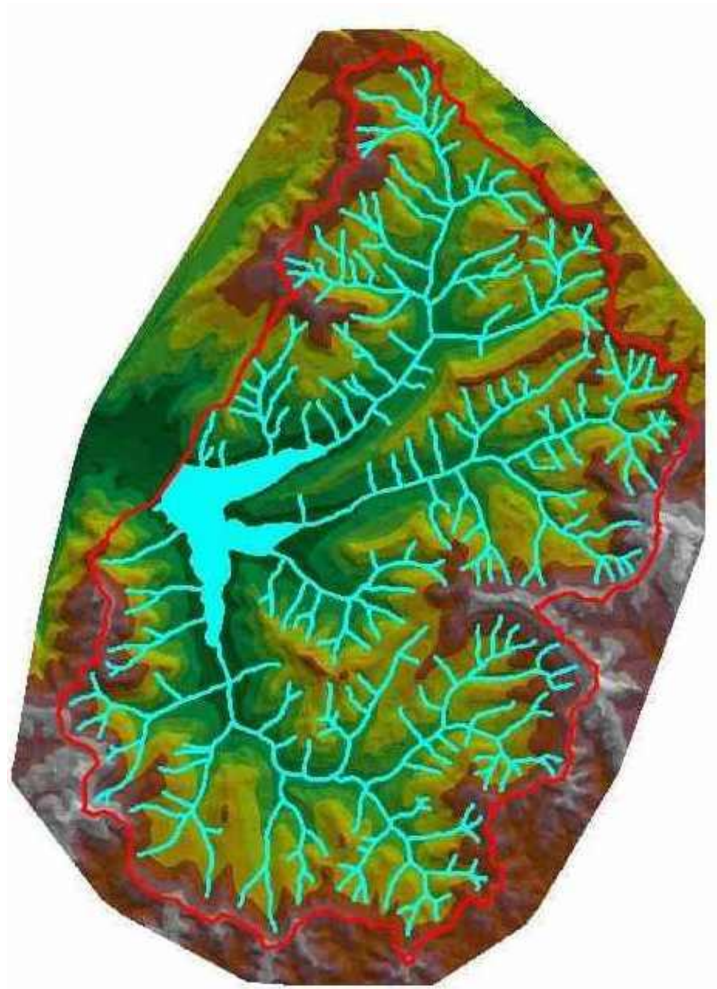
- Lots of theoretical support

  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
- 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

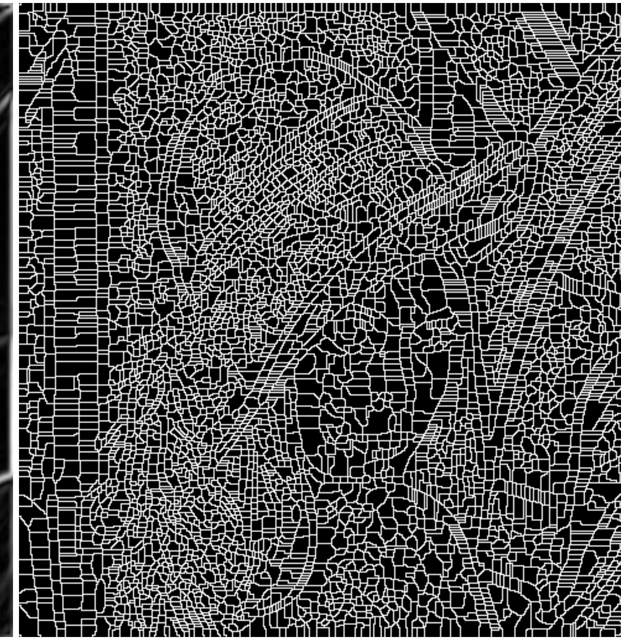
Watershed algorithm



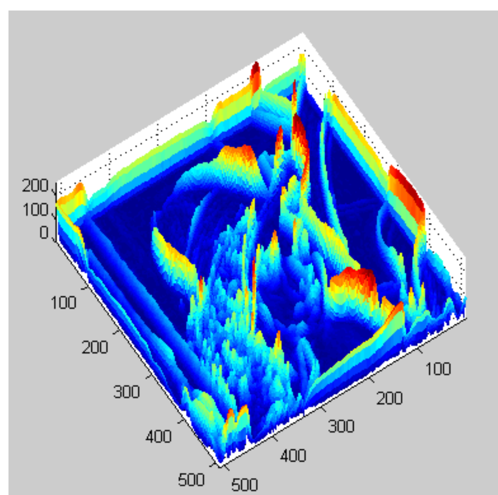
Watershed segmentation

Image

Gradient



Watershed boundaries



Meyer's watershed segmentation

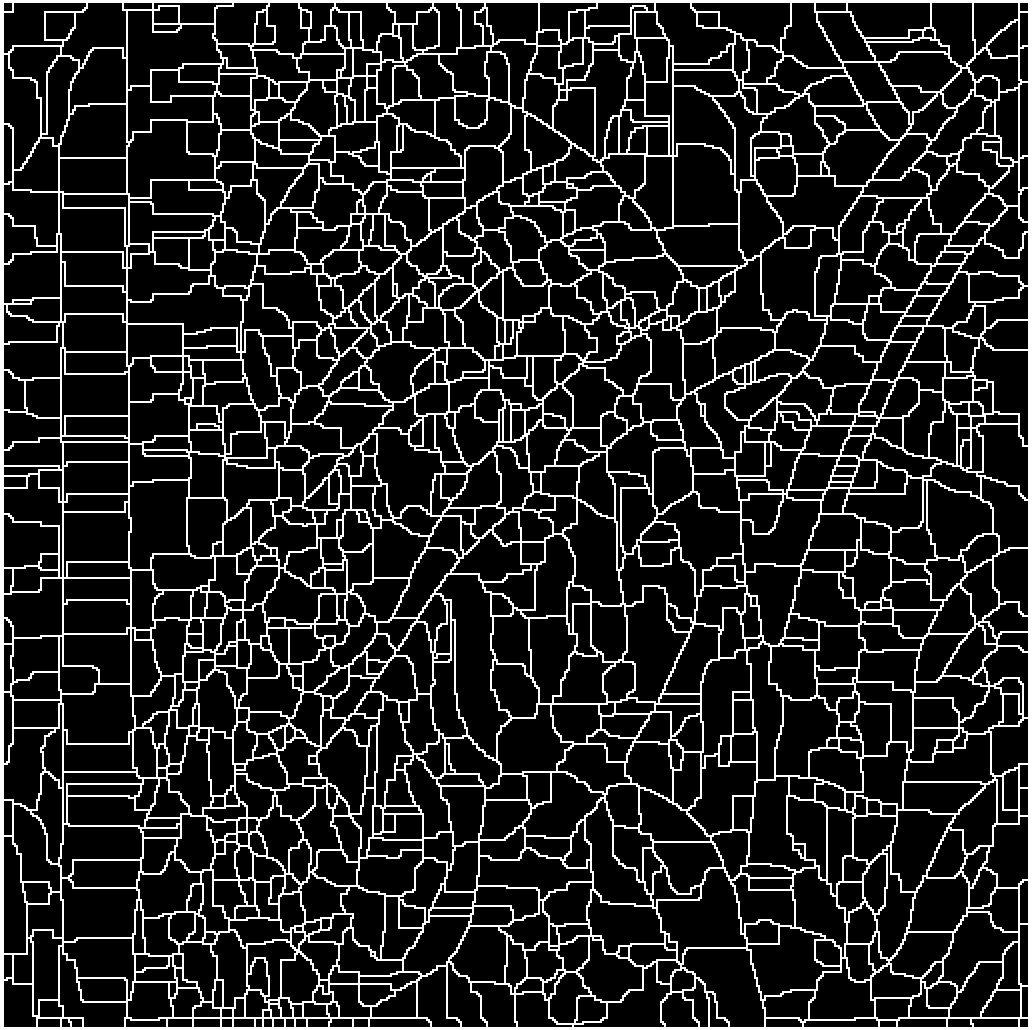
1. Choose local minima as region seeds
2. Add neighbors to priority queue, sorted by value
3. Take top priority pixel from queue
   1. If all labeled neighbors have same label, assign that label to pixel
   2. Add all non-marked neighbors to queue
4. Repeat step 3 until finished (all remaining pixels 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
  - Not easy to get variety of regions for multiple segmentations
- Usage
  - Preferred algorithm for hierarchical segmentation

Choices in segmentation algorithms

- Oversegmentation
  - Watershed + Pb
  - Felzenszwalb and Huttenlocher
    http://www.cs.brown.edu/~pff/segment/
  - Turbopixels
  - Mean-shift

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

Felzenszwalb and Huttenlocher: Graph-Based Segmentation

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

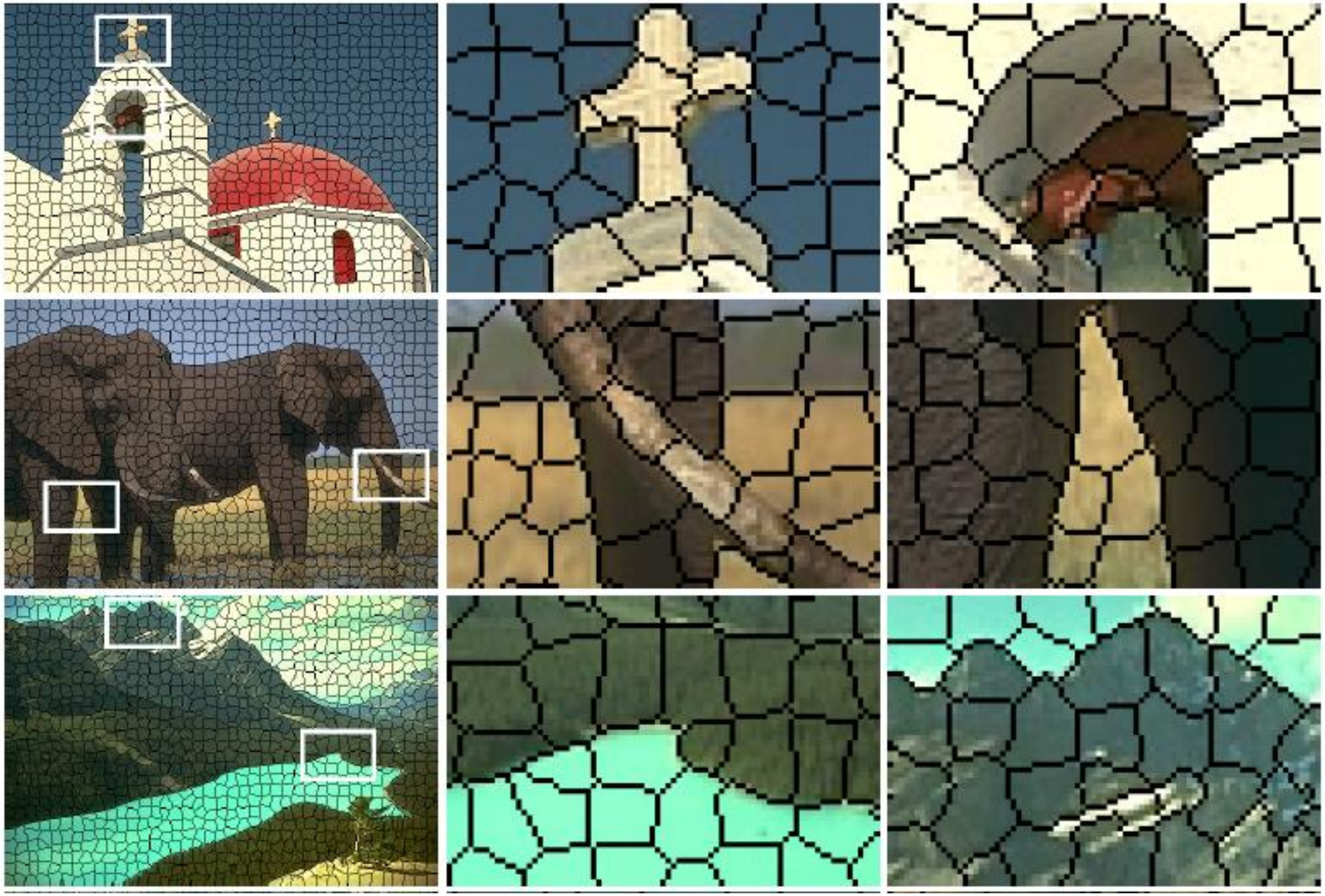



+ Good for thin regions
+ Fast
+ Easy to control coarseness of segmentations
+ Can include both large and small regions
 - Often creates regions with strange shapes
 - Sometimes makes very large errors

Turbo Pixels: Levinstein et al. 2009

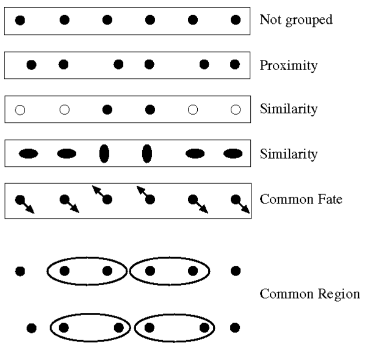
http://www.cs.toronto.edu/~kyros/pubs/09.pami.turbopixels.pdf

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



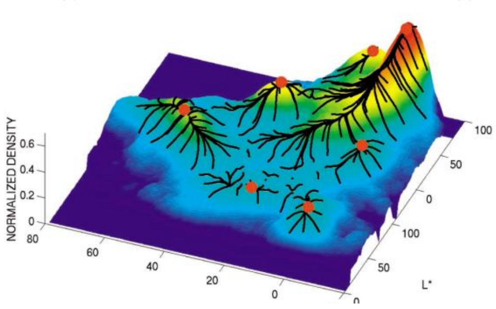
Things to remember

- 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