Image Segmentation

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Image segmentation

Goal: Group pixels into meaningful or perceptually similar regions

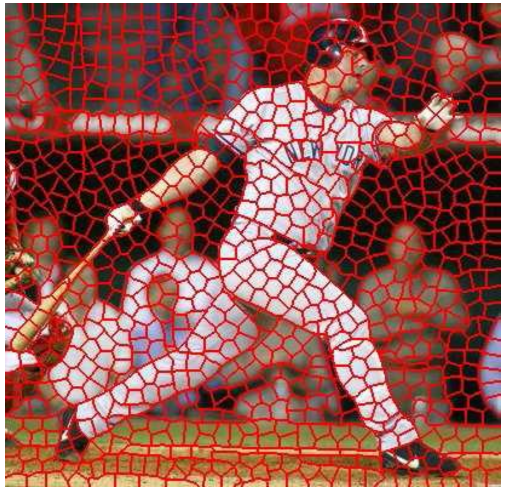
Applications of Segmentation

- Object proposals

- Superpixels, proposals, multiple segmentations

Segmentation for efficiency: “superpixels”

[Felzenszwalb and Huttenlocher 2004]

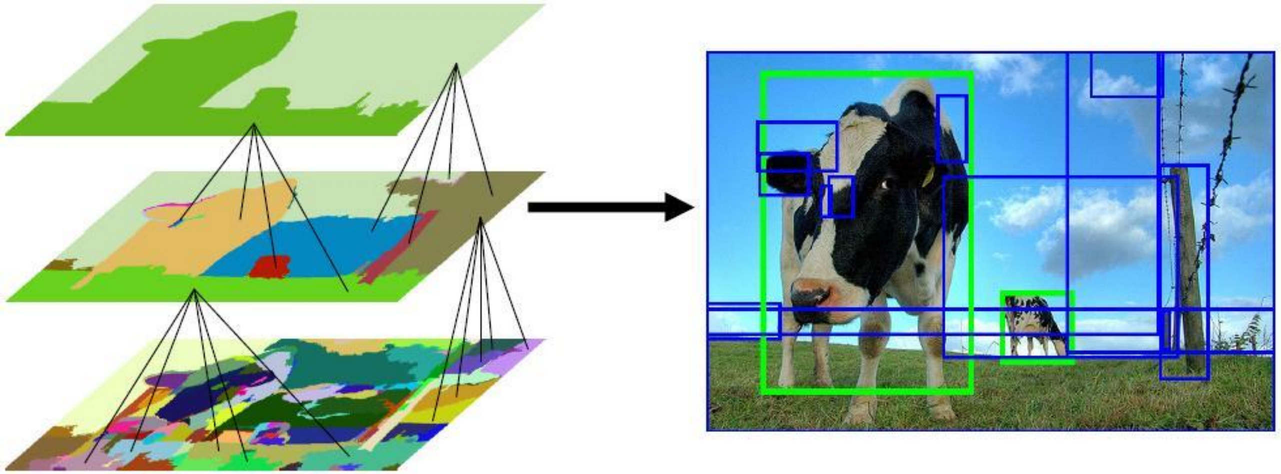


[Shi and Malik 2001]

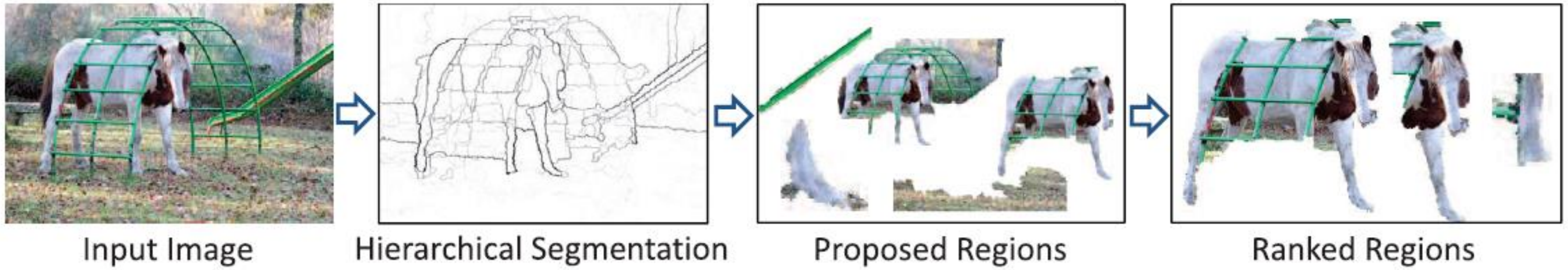
[Hoiem et al. 2005, Mori 2005]

Segmentation for feature support

Segmentation for object proposals



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

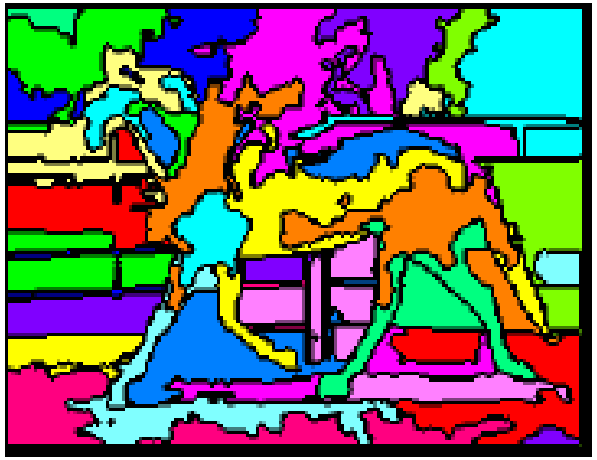


[Endres Hoiem ECCV 2010, IJCV 2014]

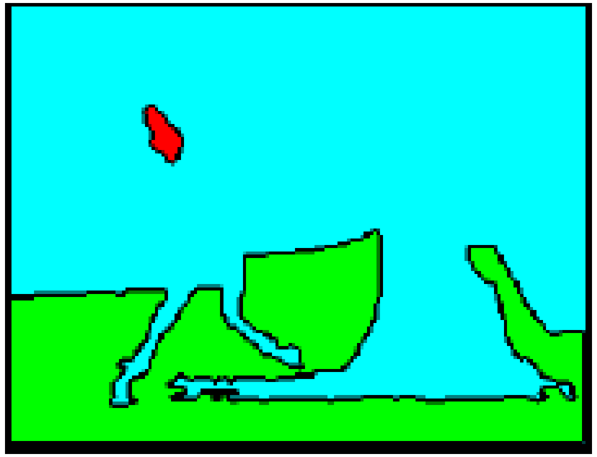
Segmentation as a result

Rother et al. 2004

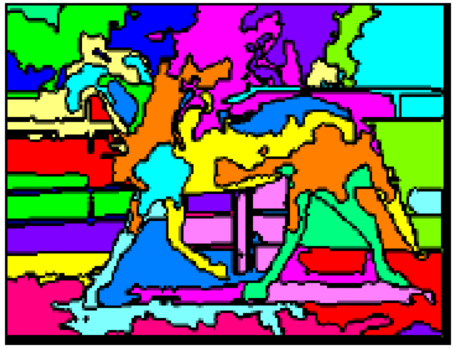
Types of segmentations

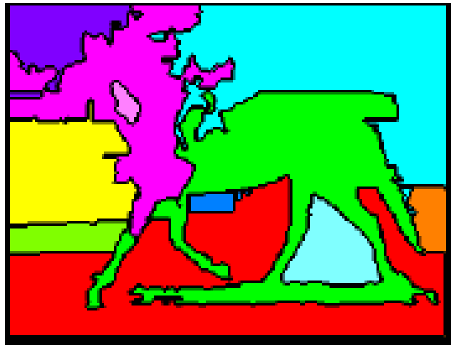


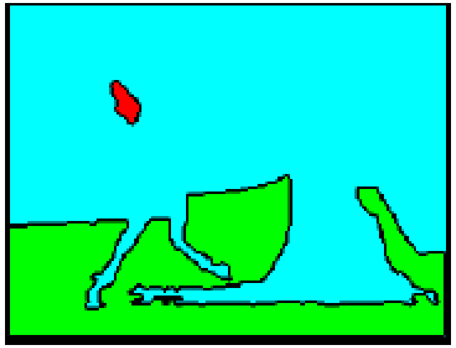
Oversegmentation



Undersegmentation



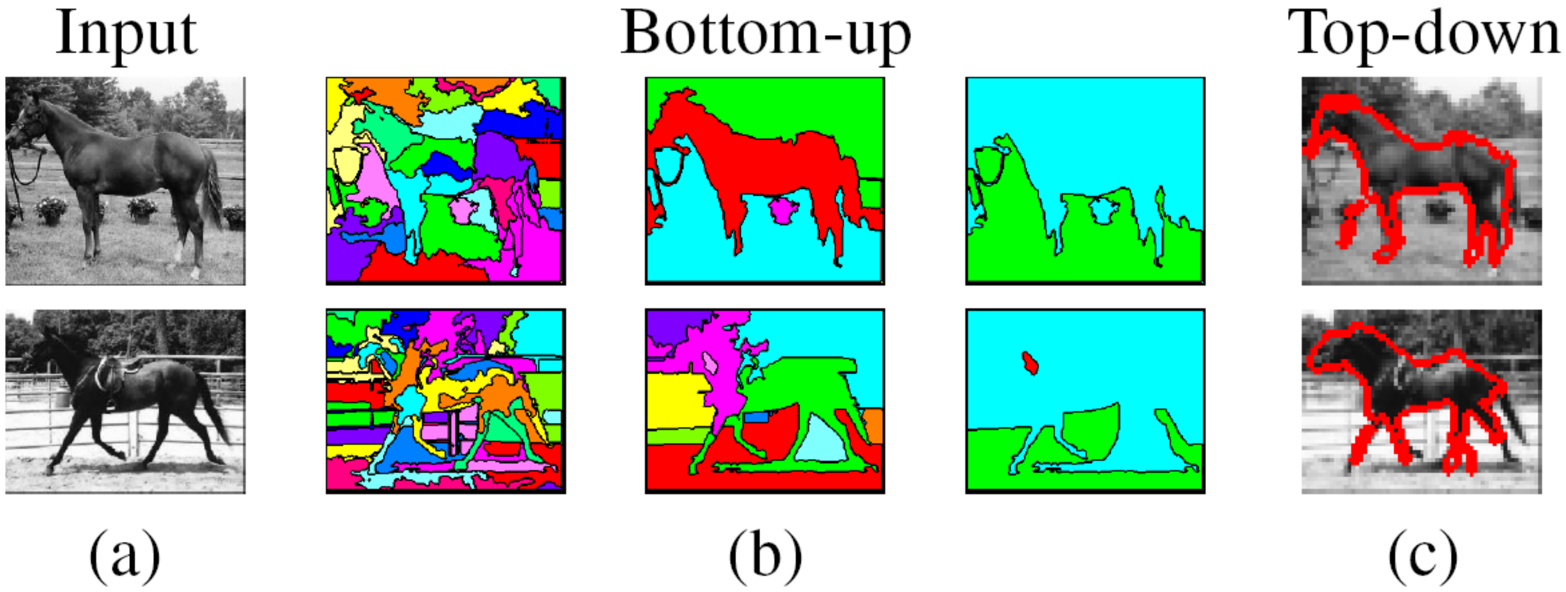




Multiple Segmentations

Major processes for segmentation

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



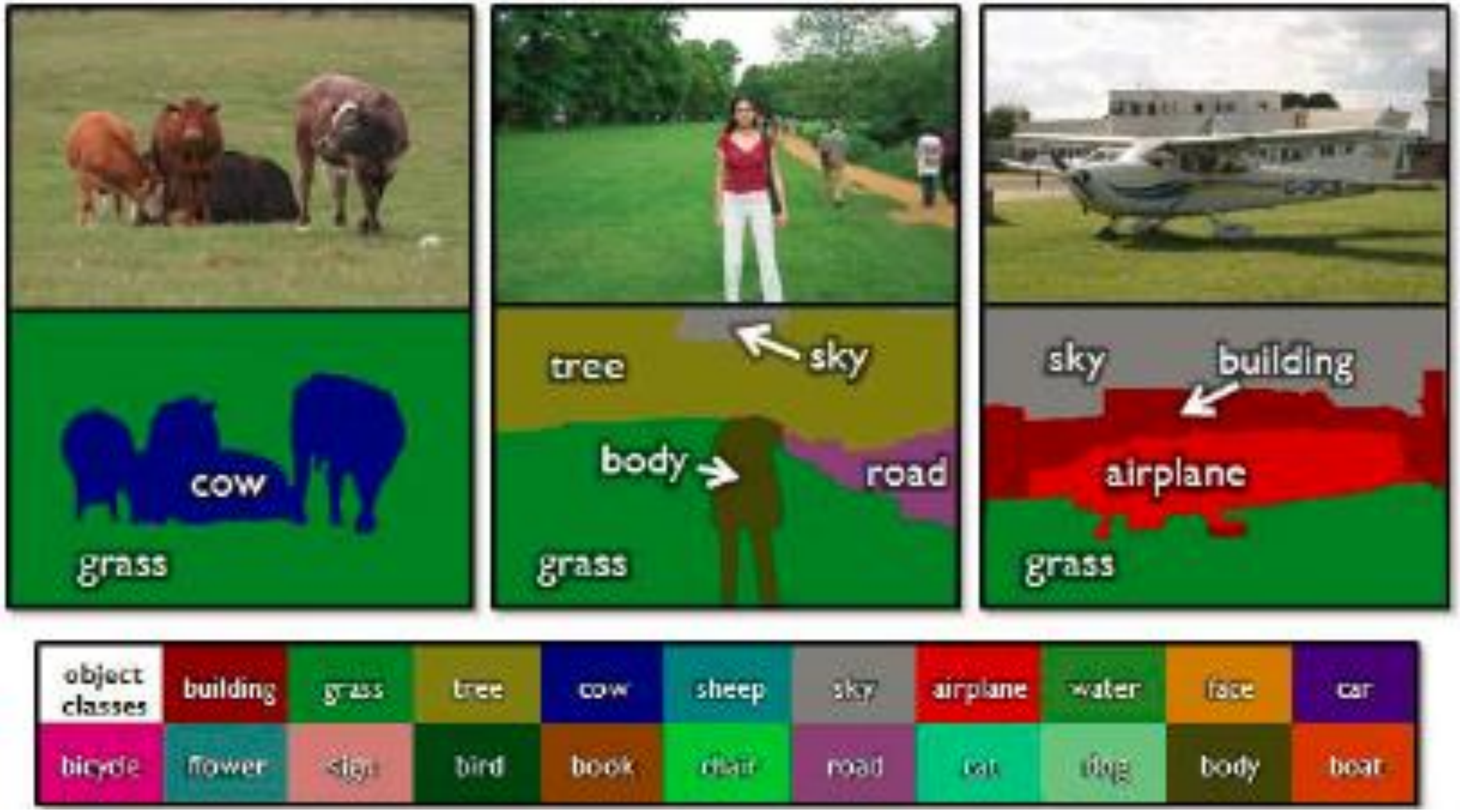
[Levin and Weiss 2006]

Segmentation

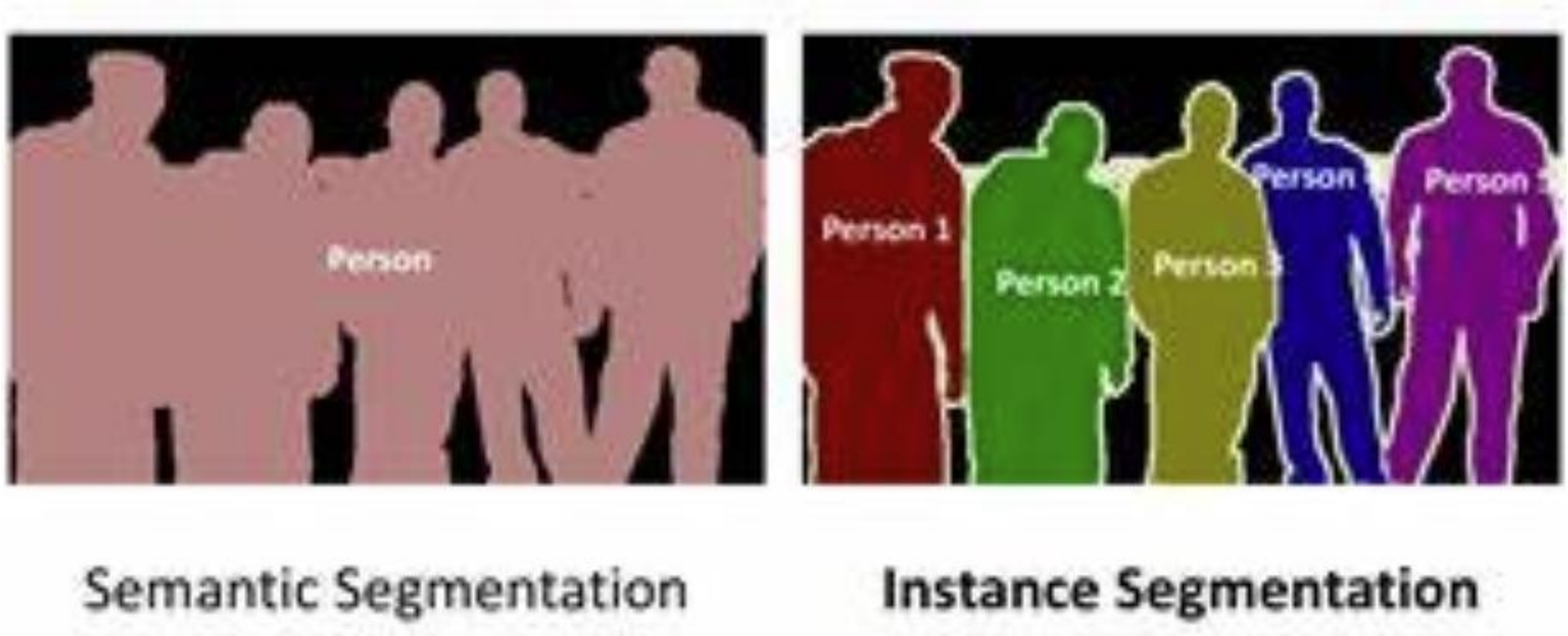
- Image segmentation (unsupervised)
- Semantic segmentation
- Instance segmentation
- Panoptic segmentation
- Amodal segmentation

Semantic Segmentation

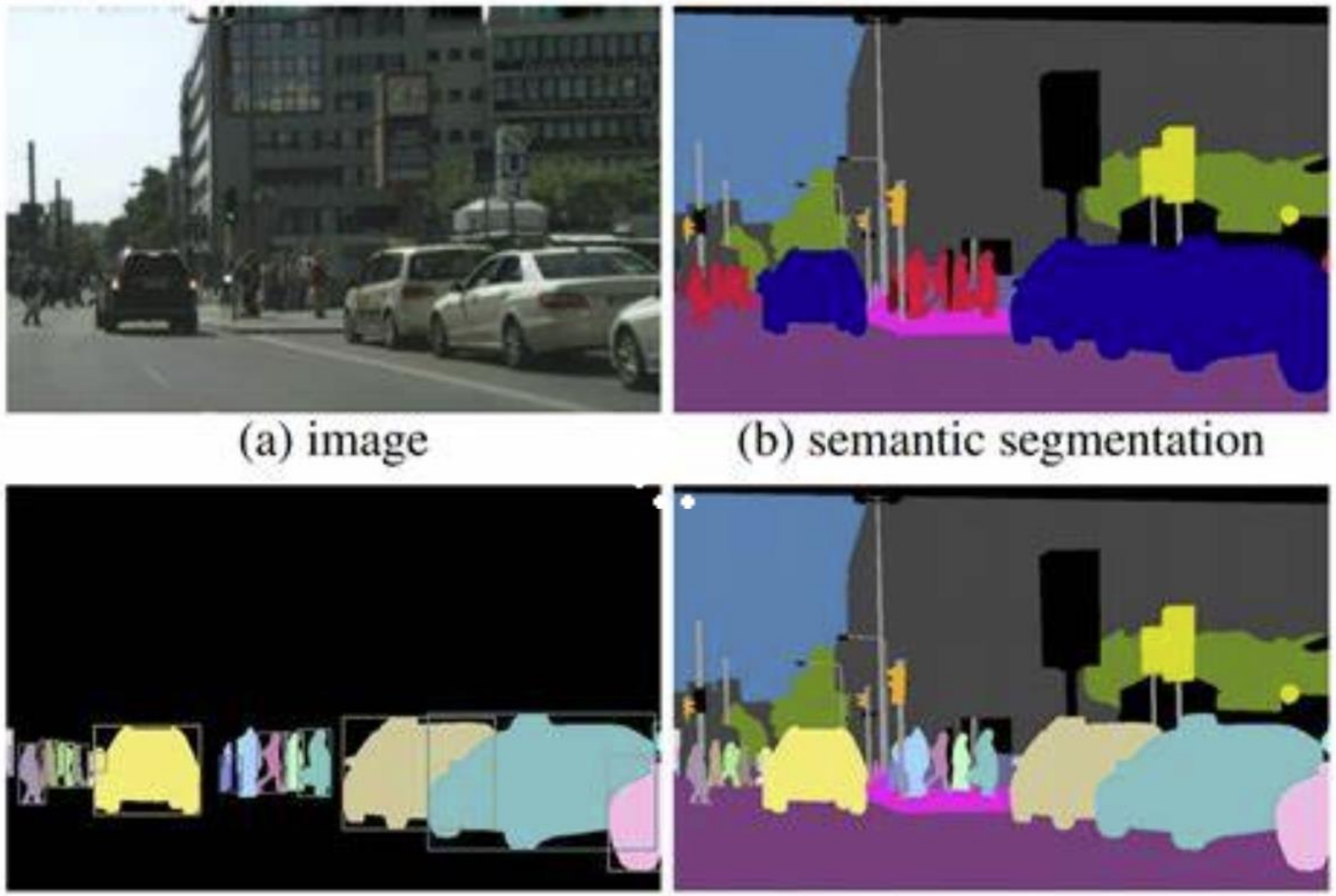
- Segmenting images based on its semantic notion



Instance segmentation



Panoptic segmentation

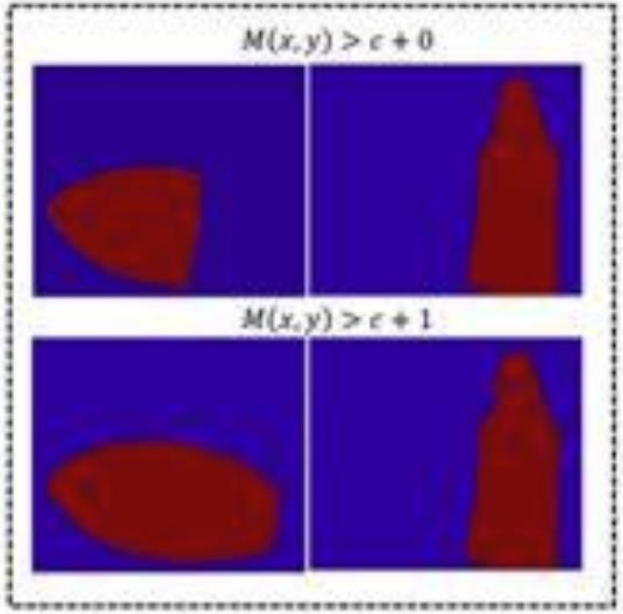


(a) image (b) semantic segmentation

(c) instance segmentation (d) panoptic segmentation

Amodal segmentation

(e)

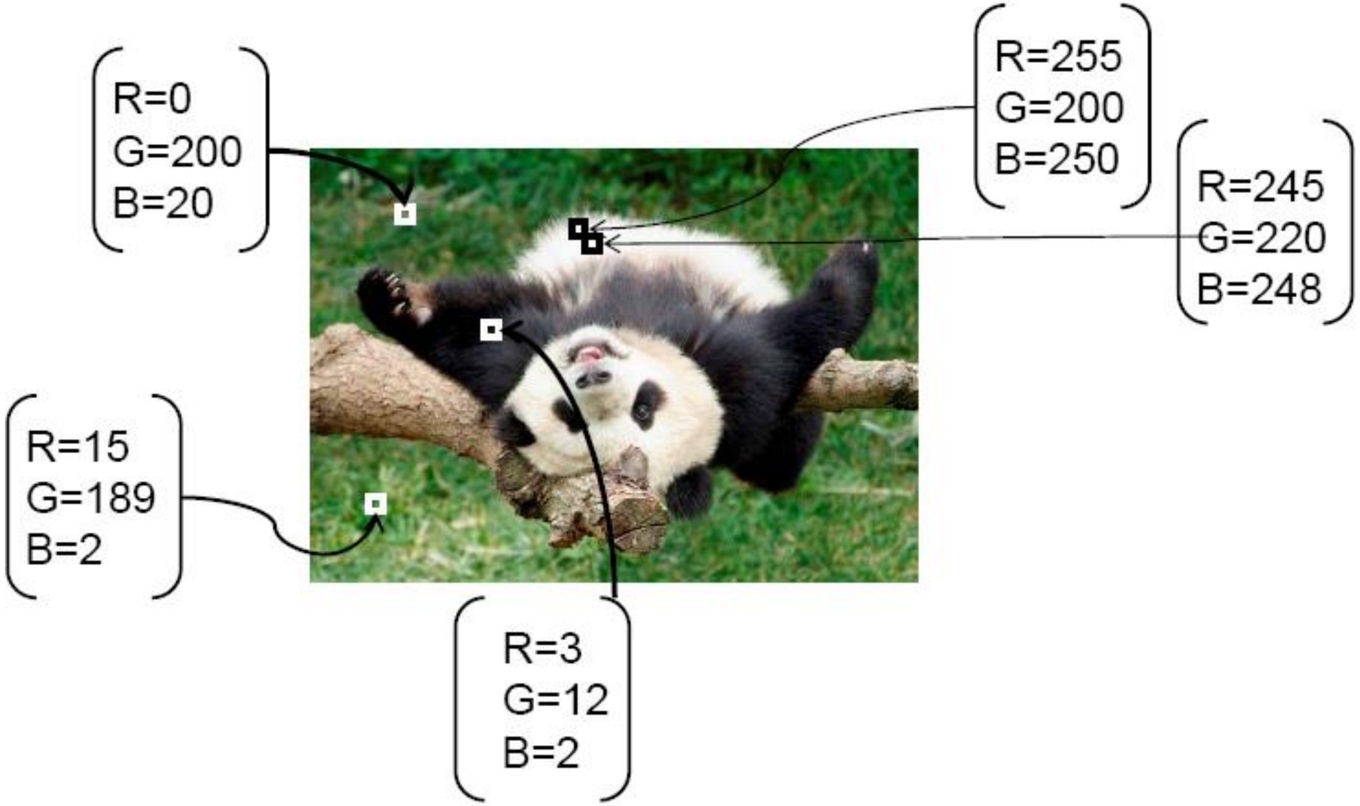


(d)

Segmentation using clustering

- Kmeans
- Mean-shift

Feature Space



Source: K. Grauman

K-means clustering using intensity alone and color alone

Image

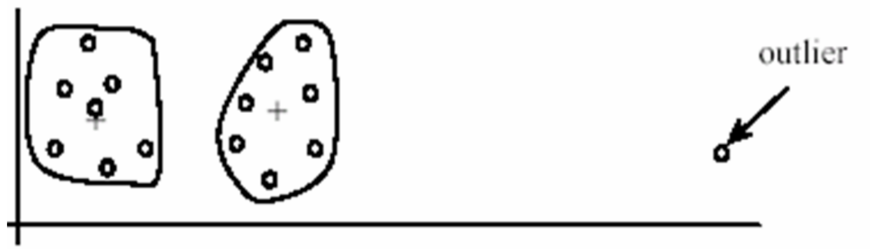
Clusters on intensity

Clusters on color

K-Means pros and cons

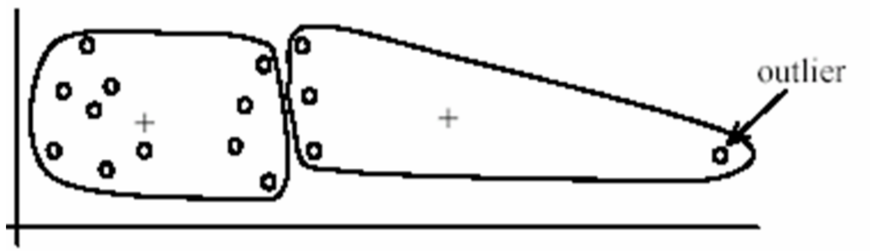
- Pros
  - Simple and fast
  - Easy to implement

- Cons
  - Need to choose K
  - Sensitive to outliers



(B): Ideal clusters

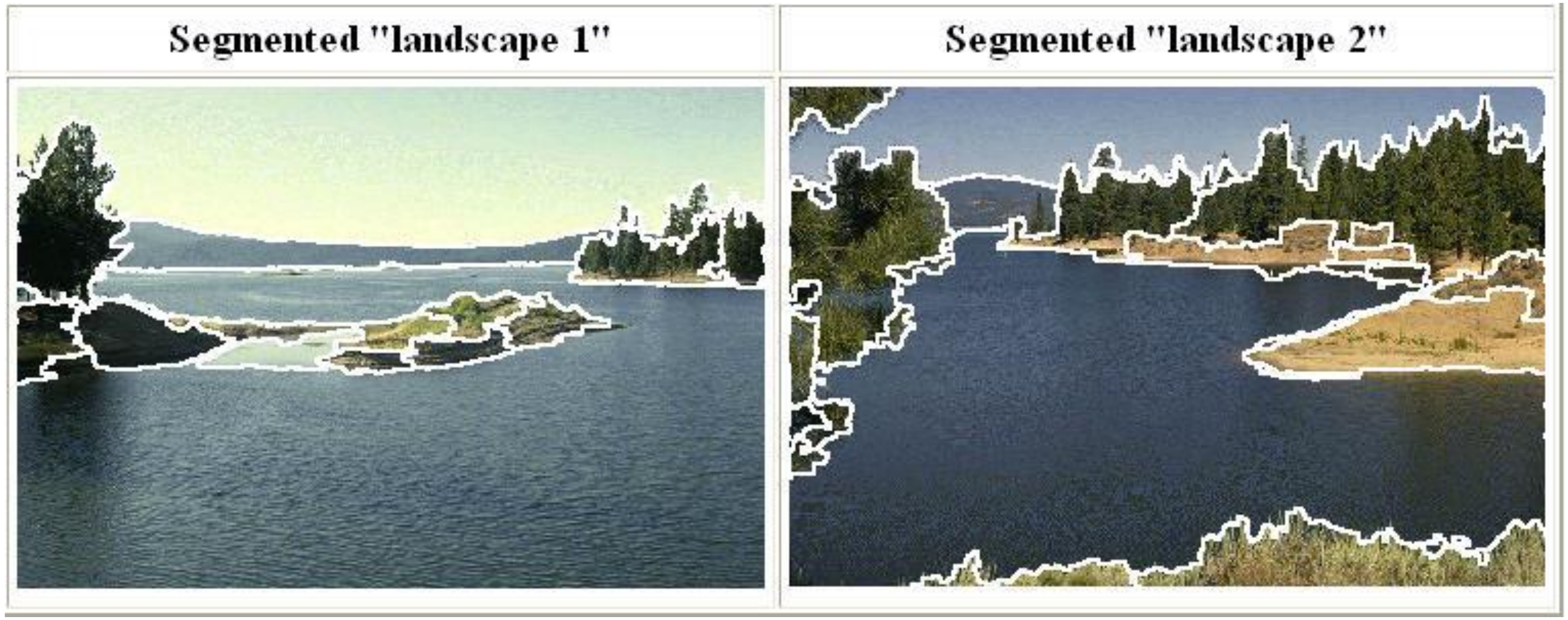
- Usage
  - Rarely used for pixel segmentation



Mean shift segmentation

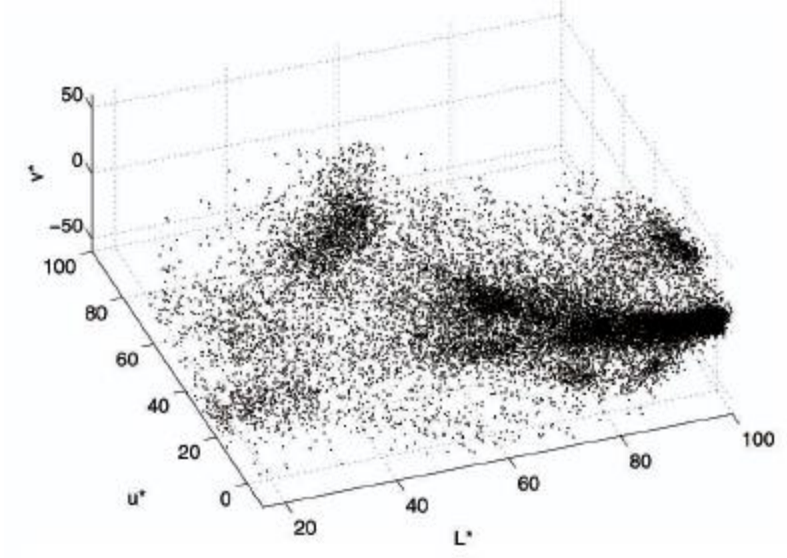
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

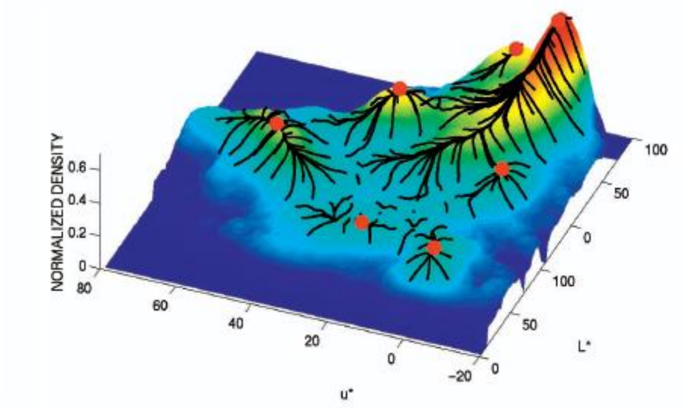
- Versatile technique for clustering-based segmentation

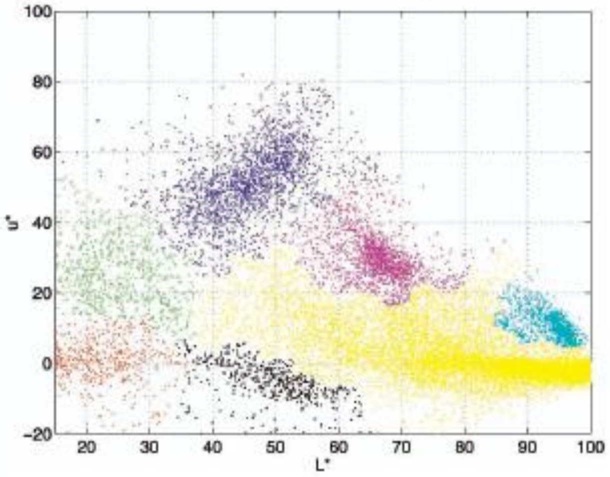


Mean shift algorithm

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







Kernel density estimation

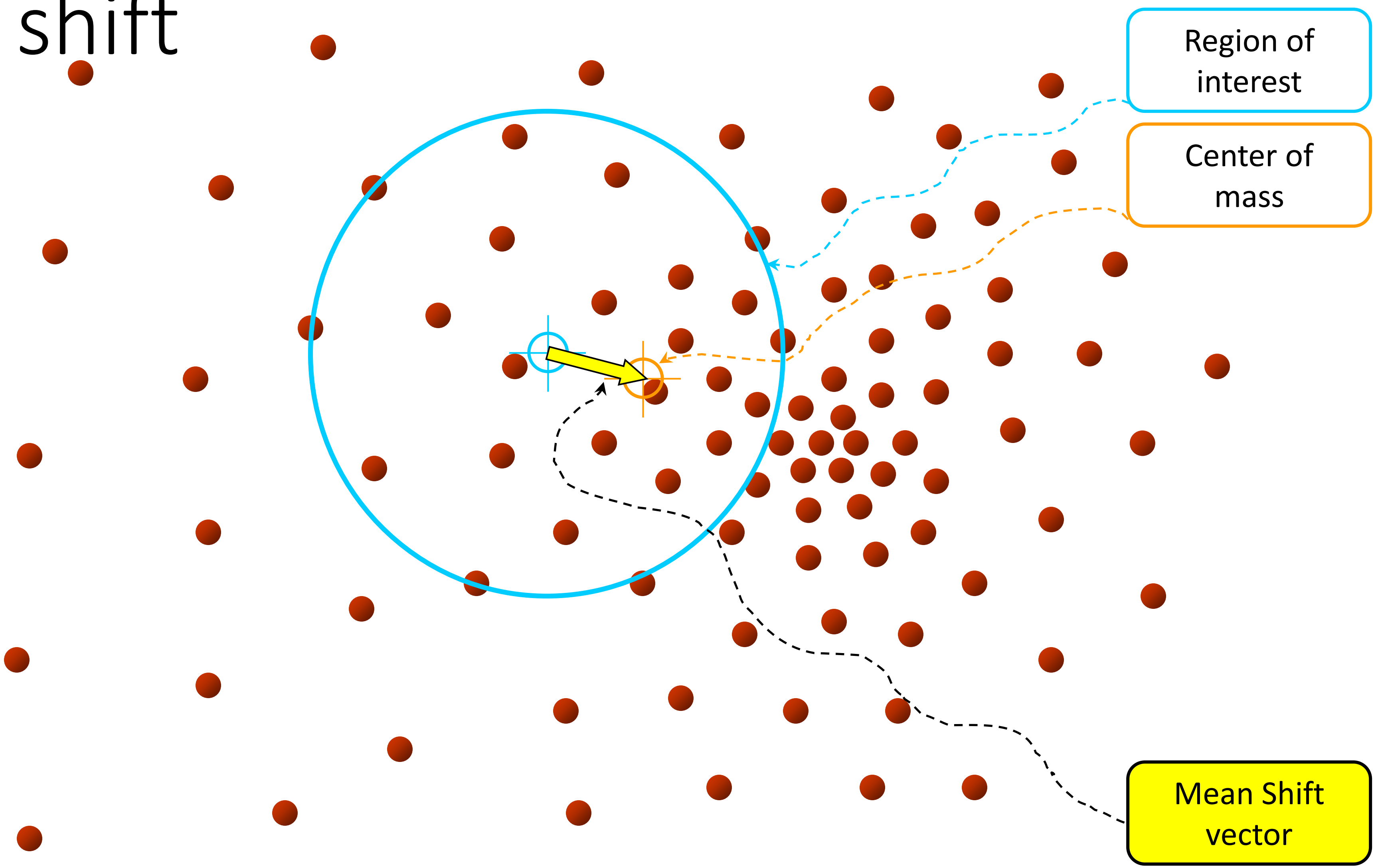
Kernel density estimation function

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

Gaussian kernel

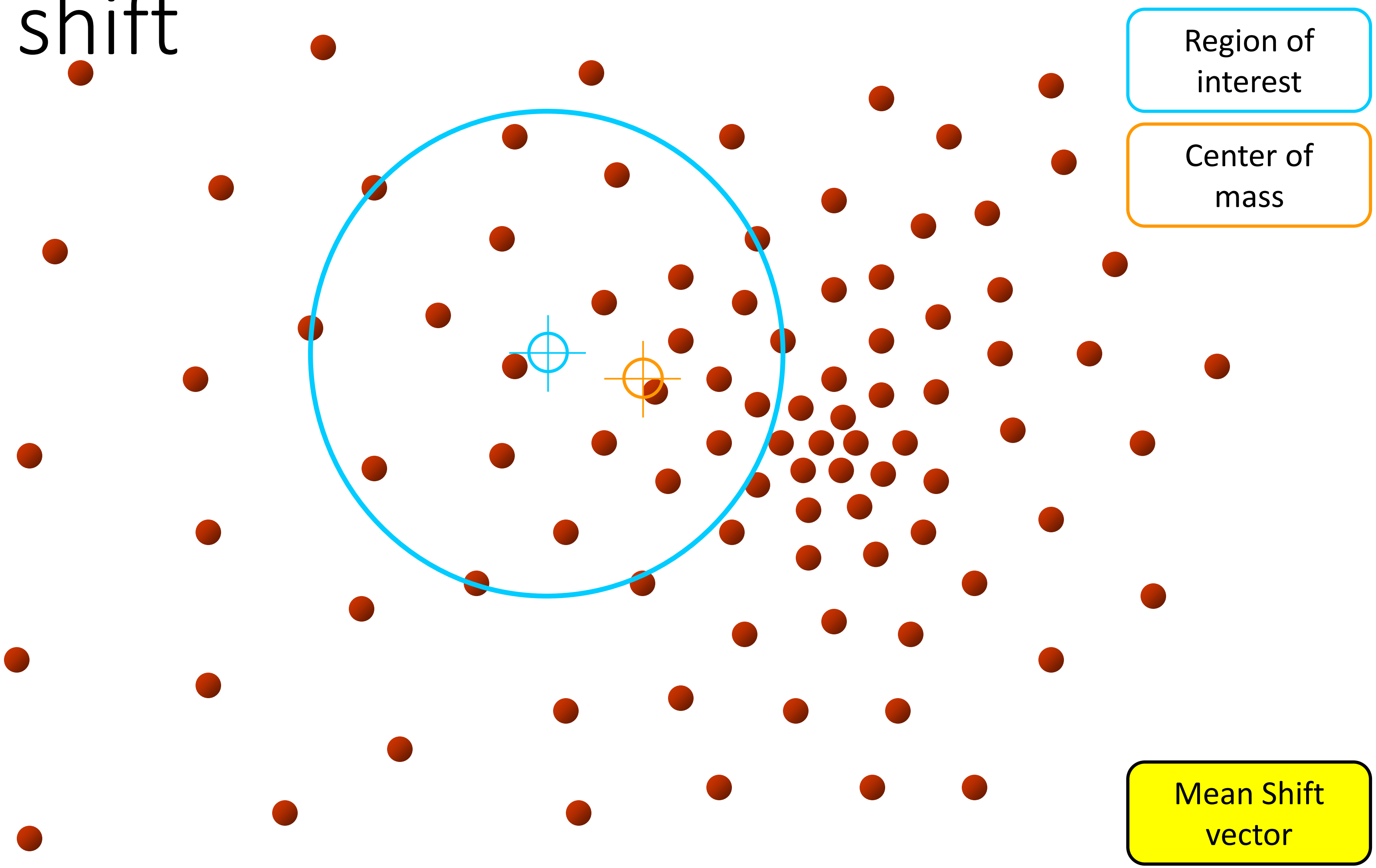
$$K\left(\frac{x - x_i}{h}\right) = \frac{1}{\sqrt{2\pi}}\, e^{-\frac{(x-x_i)^2}{2h^2}}.$$

Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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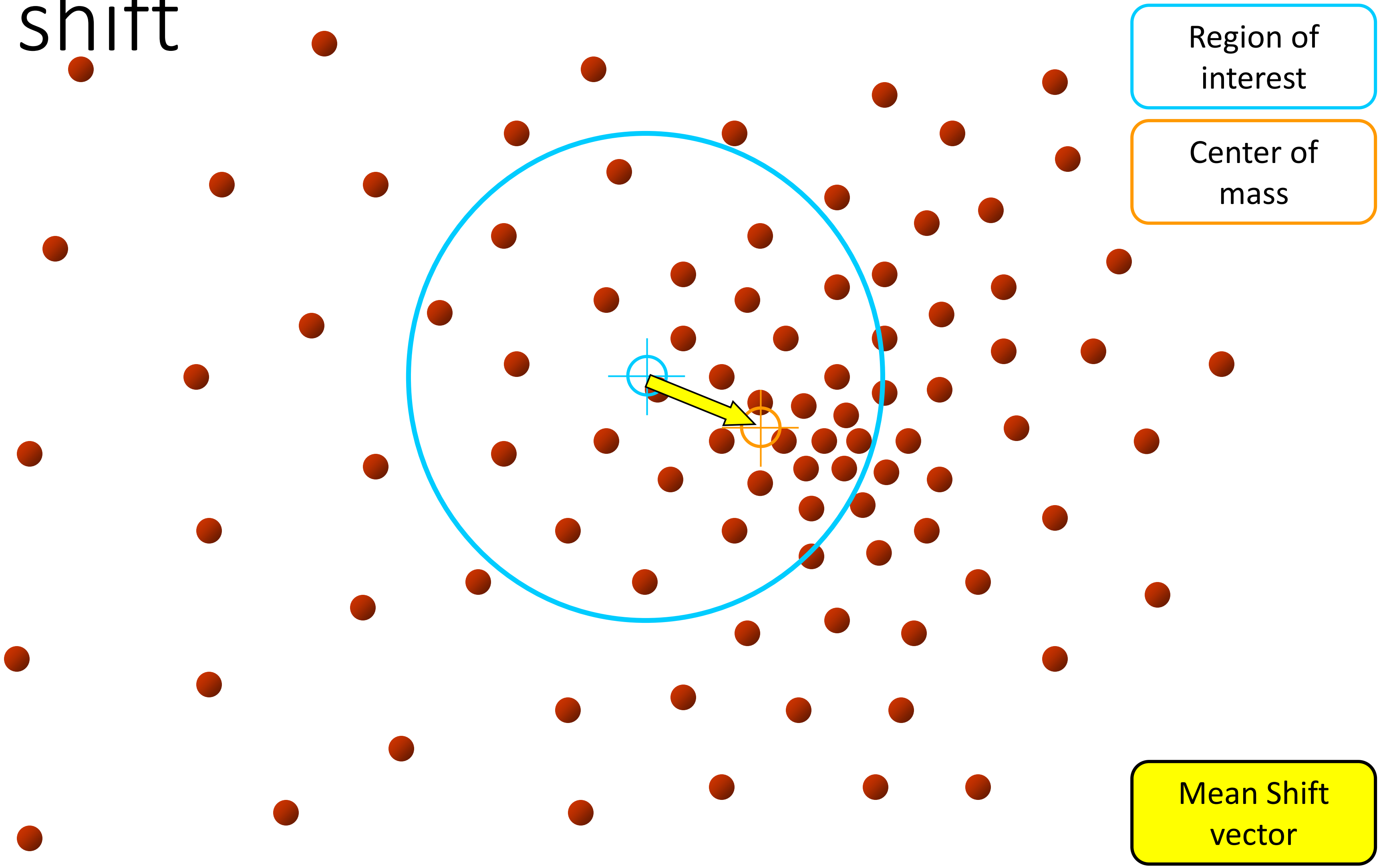
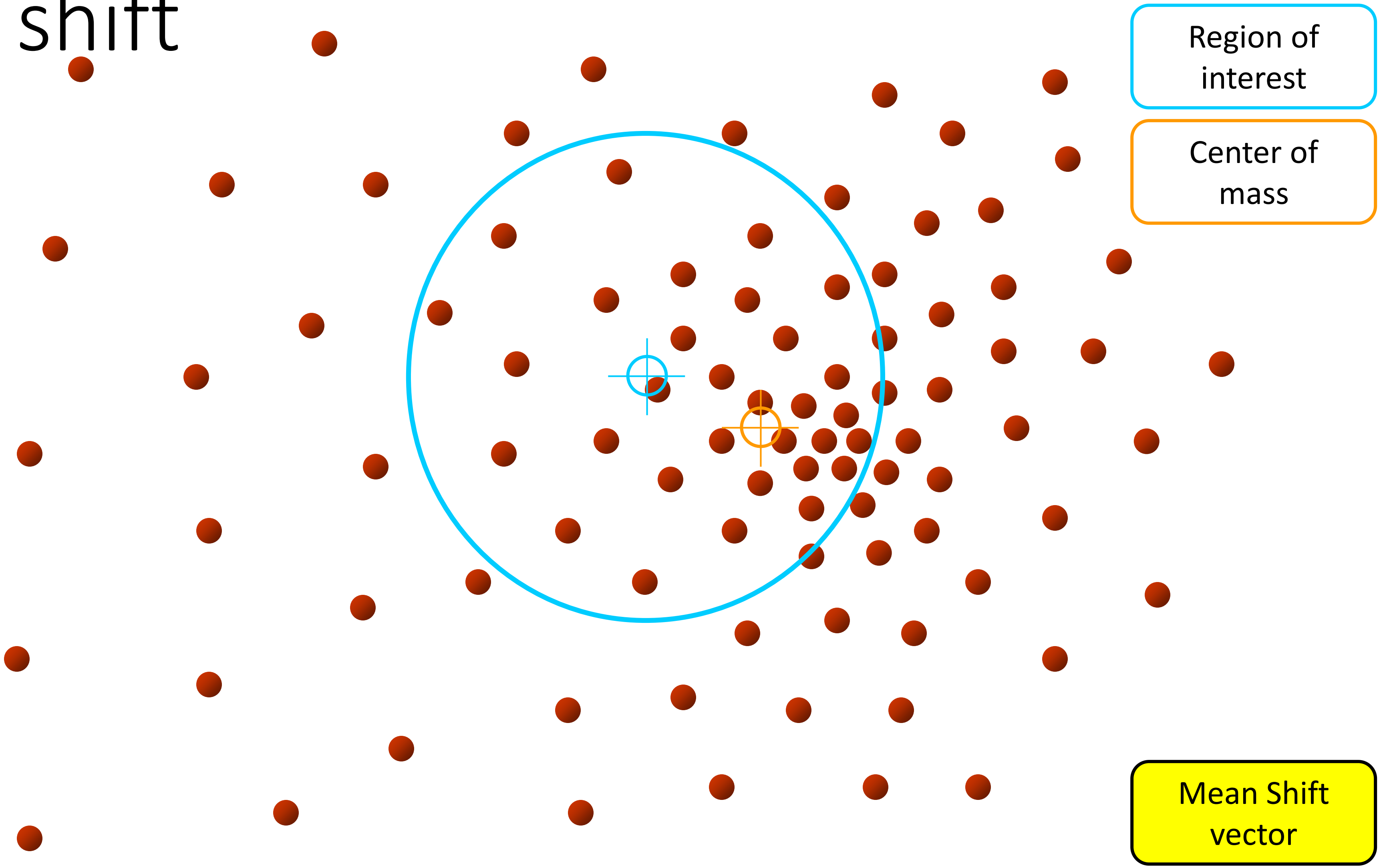
Mean shift



Mean shift



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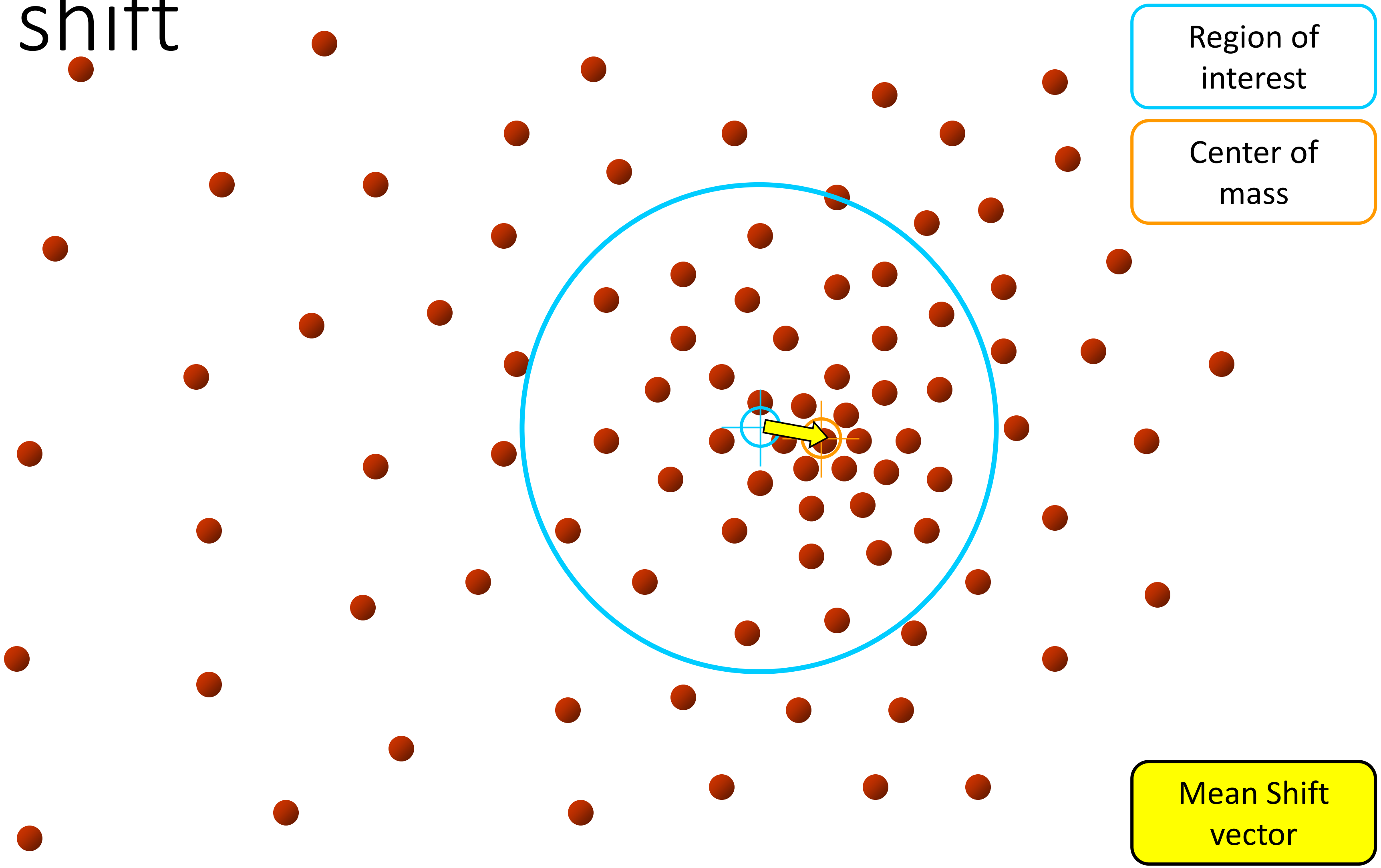
Mean shift



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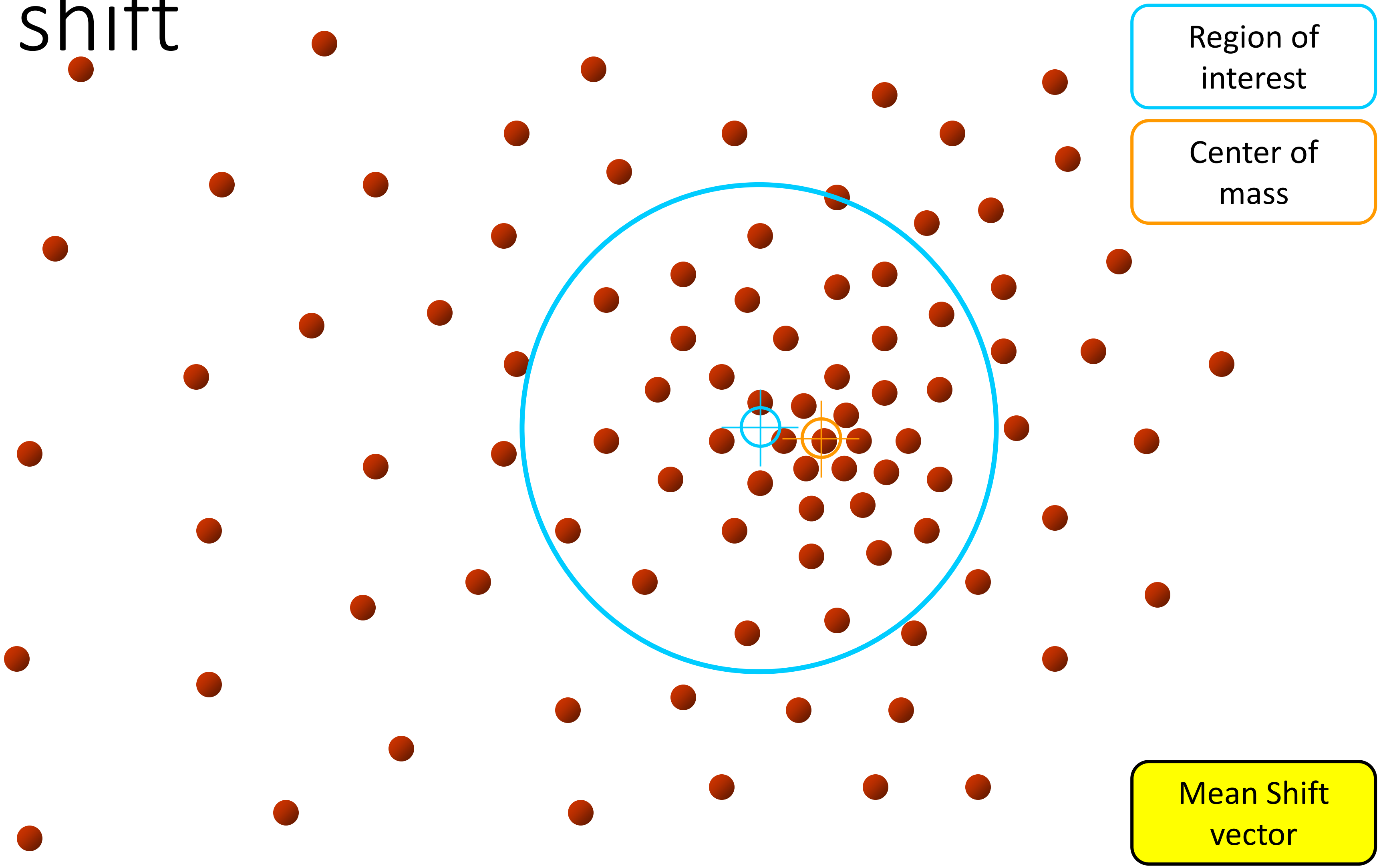
Mean shift



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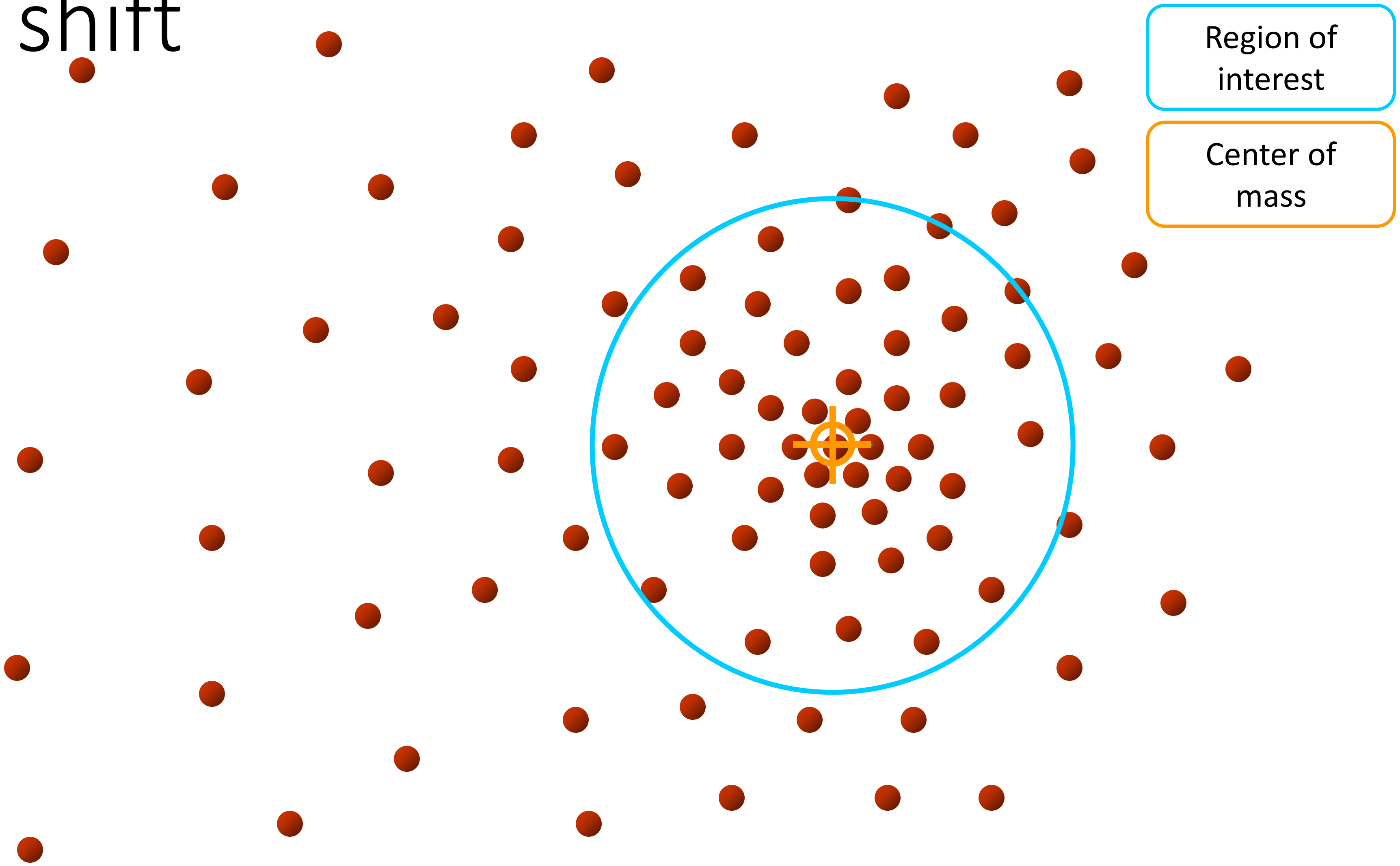
Mean shift



Slide by Y. Ukrainitz & B. Sarel

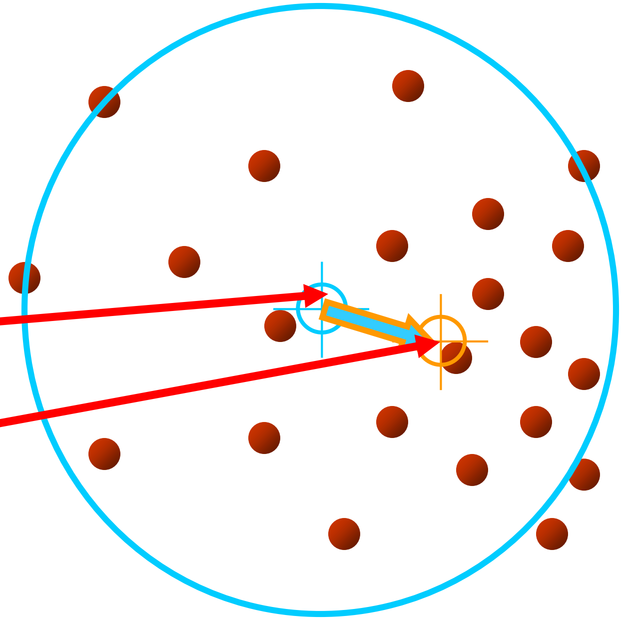
Computing the Mean Shift

Simple Mean Shift procedure:

- Compute mean shift vector

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

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



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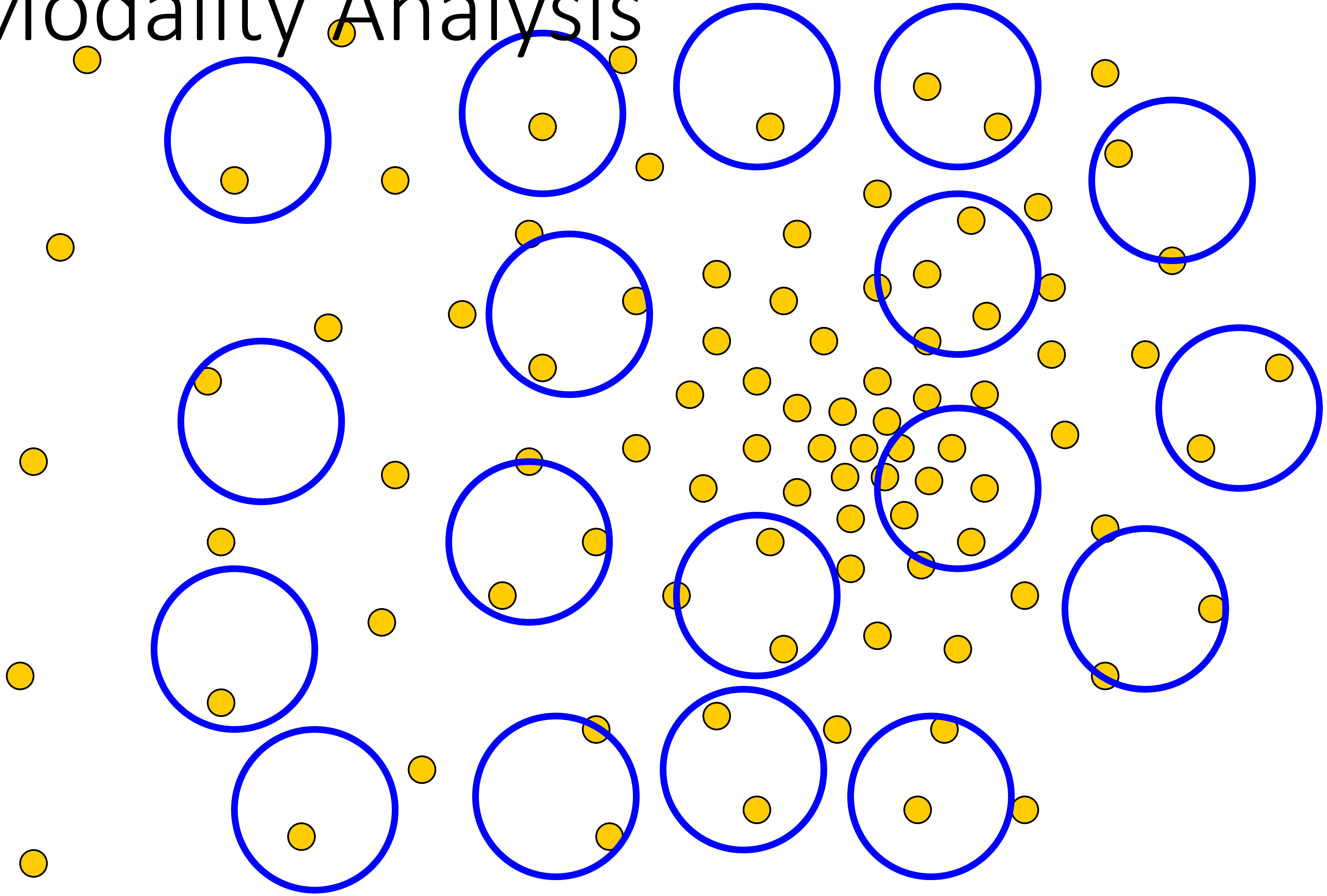
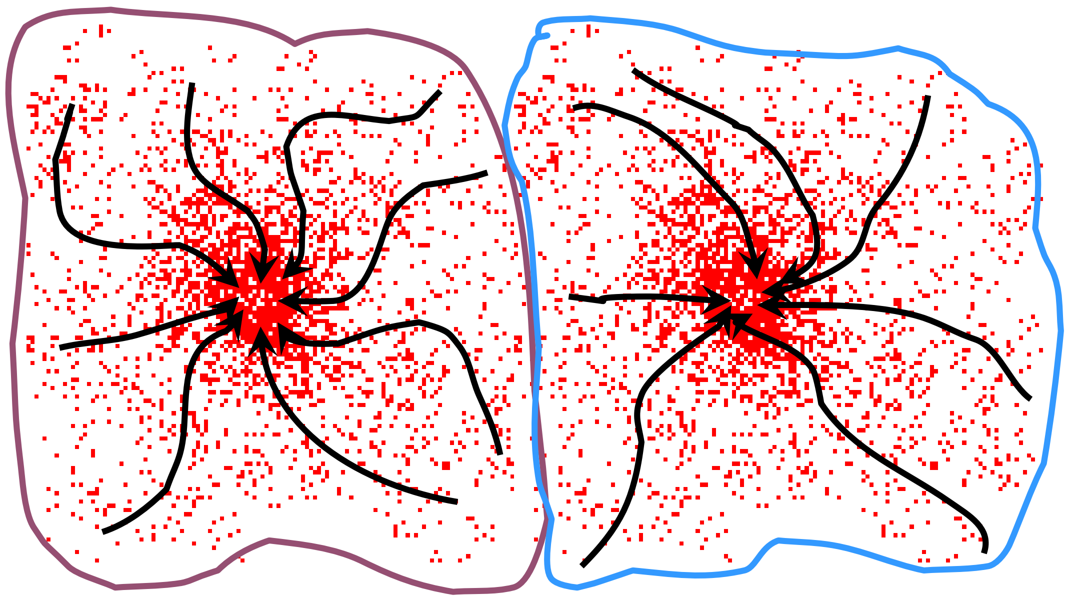
Real Modality Analysis



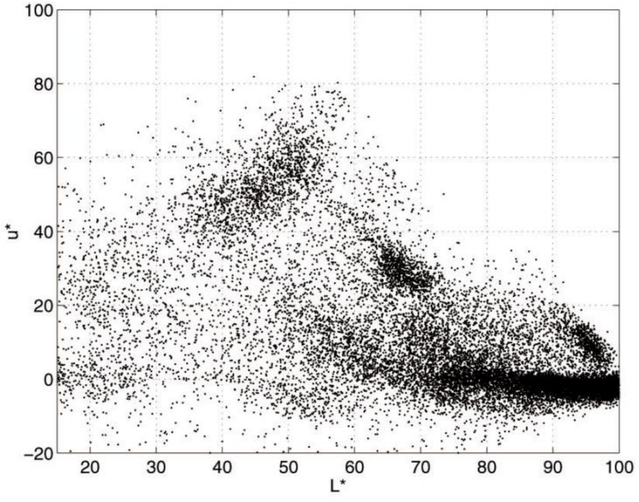
Attraction basin

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

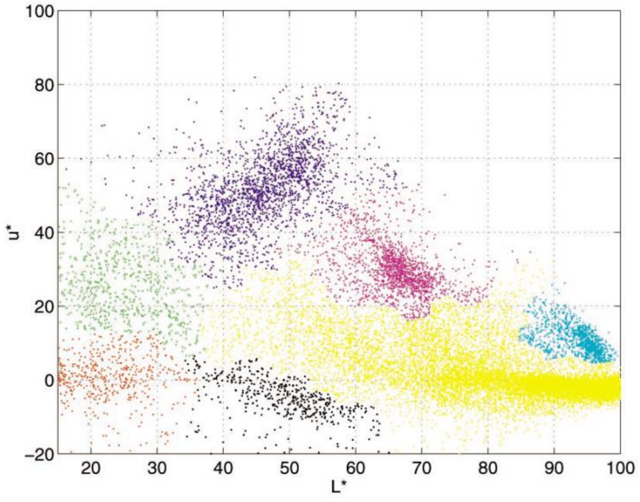


Slide by Y. Ukrainitz & B. Sarel

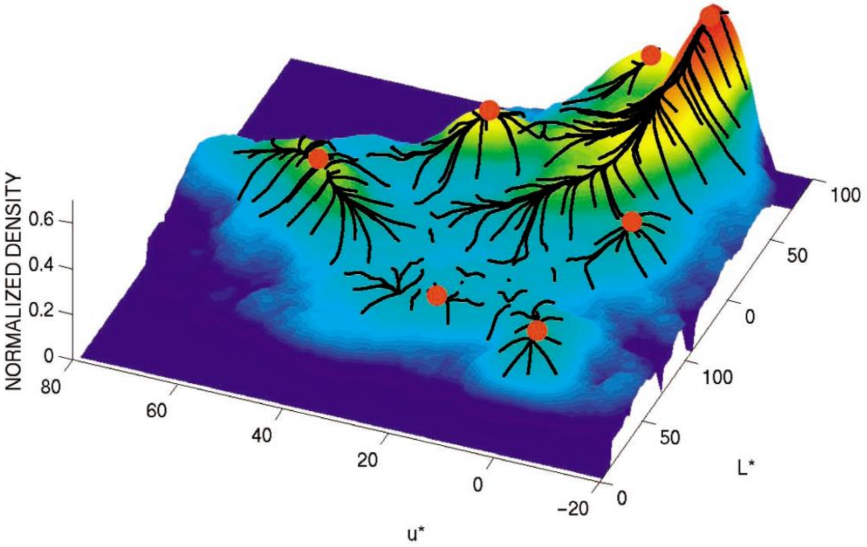
Attraction basin



(a)



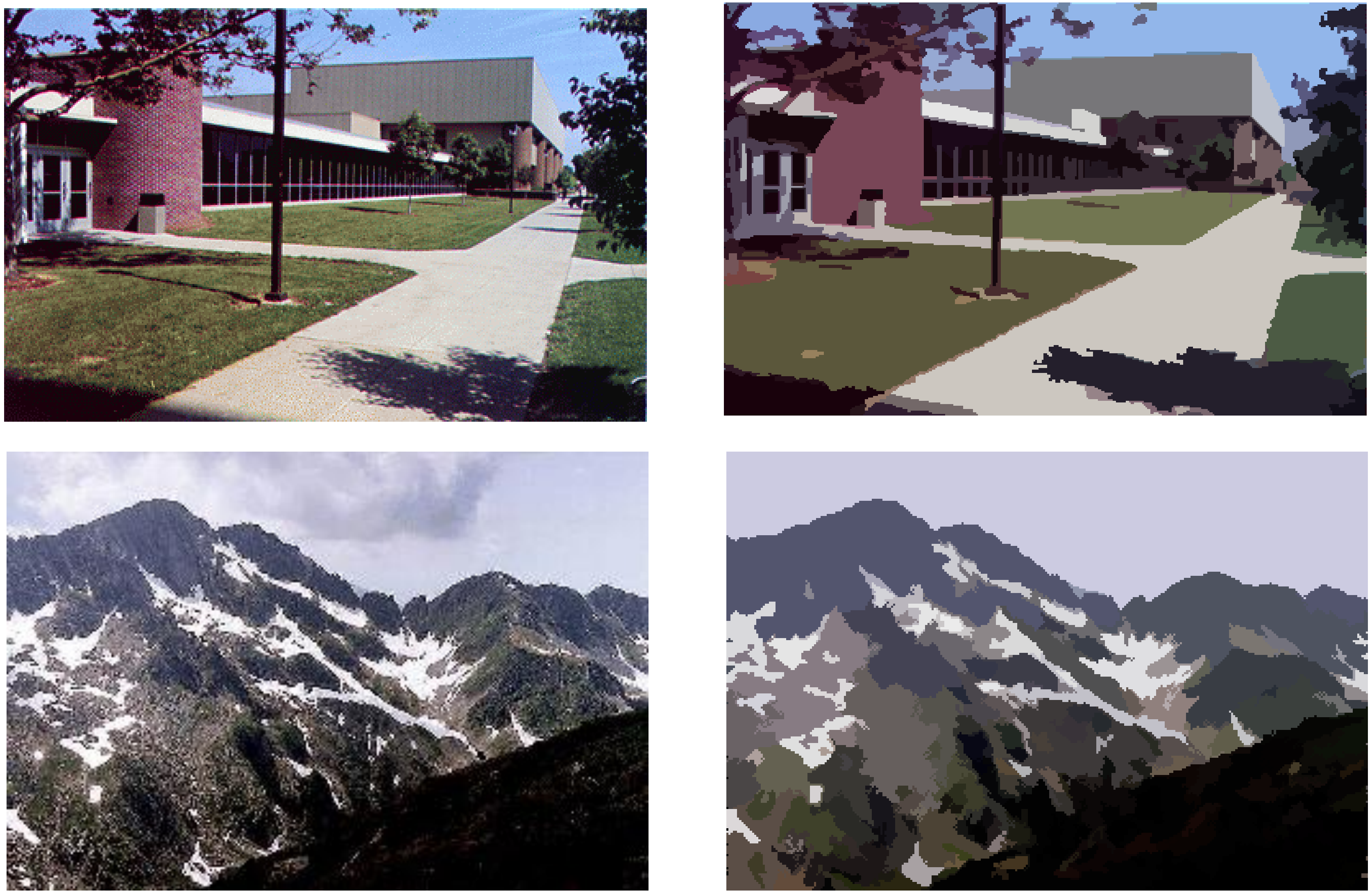
(b)



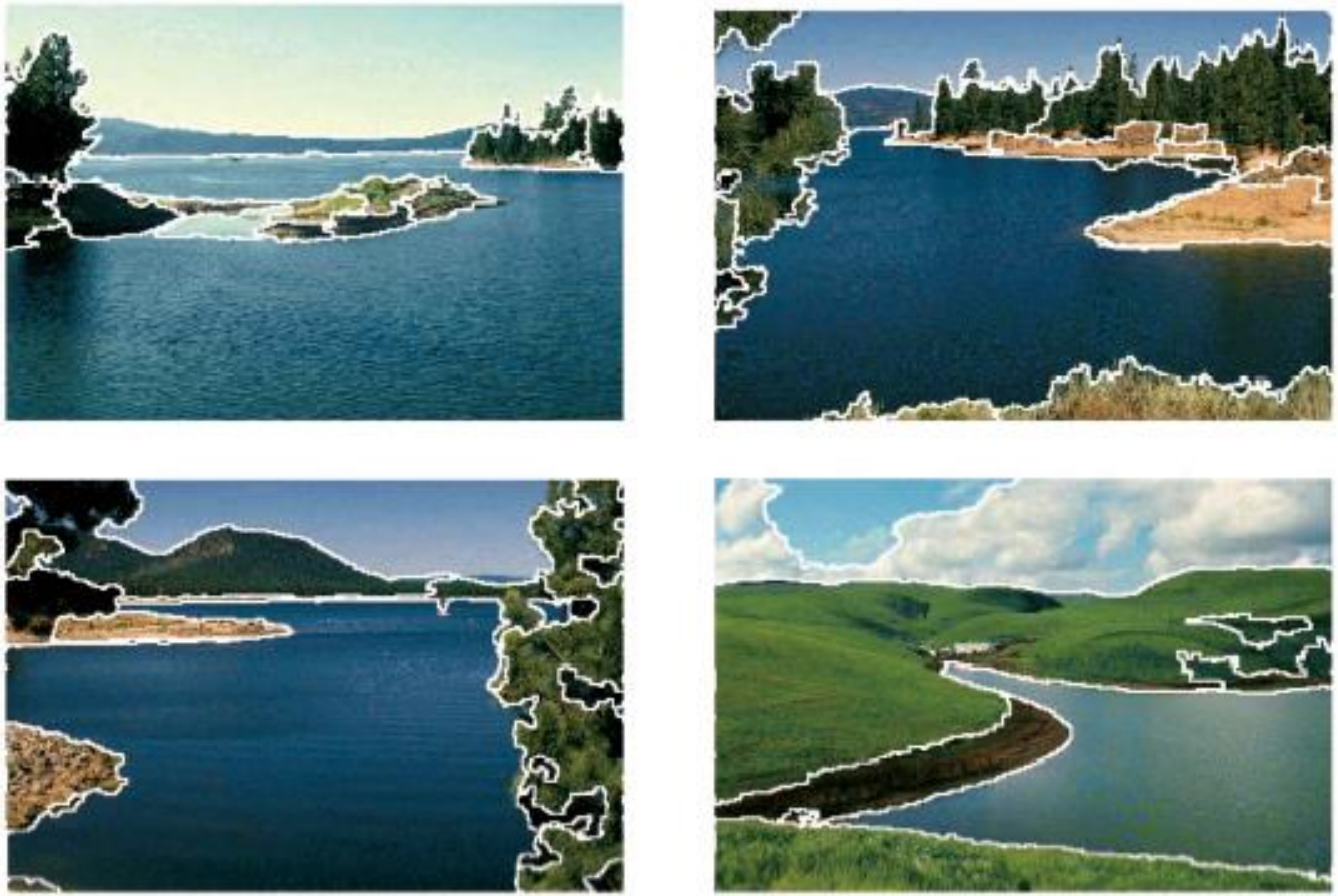
Mean shift clustering

- 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

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