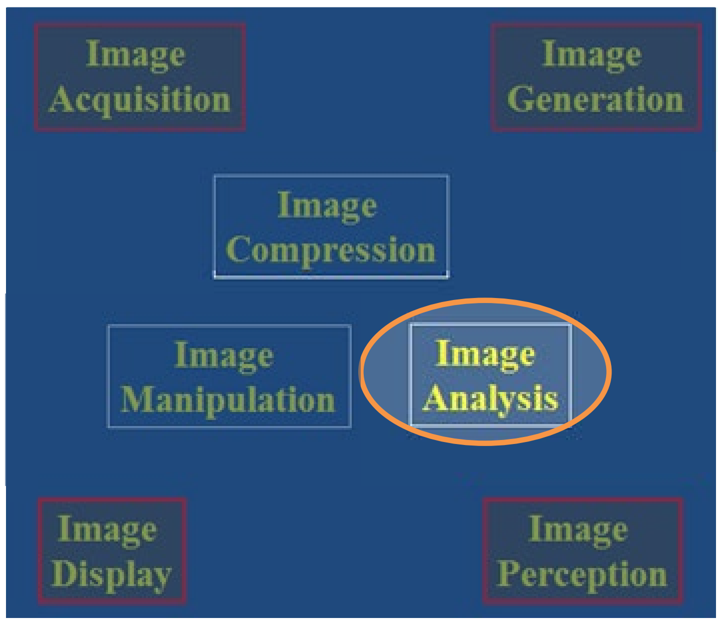
Digital Image Processing

Segmentation



DRAFT

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Material in this presentation is largely based on/derived from presentations by: Sventlana Lazebnik, and Noah Snavely

Lecture Objectives

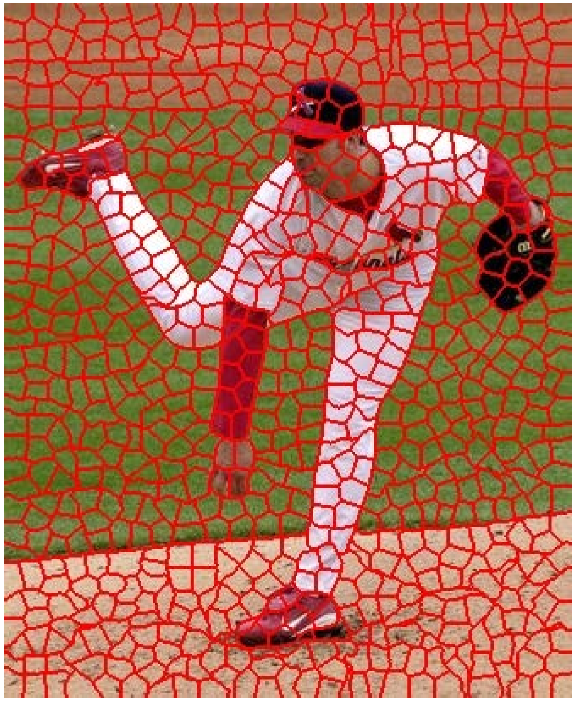
- Previously
  - Image Manipulation and Enhancement
    - Filtering
    - Interpolation
    - Warping
    - Morphing
  - Image Compression
  - Image Analysis
    - Edge Detection
    - Smart Scissors
    - Stereo Image Processing
- Today
  - Segmentation

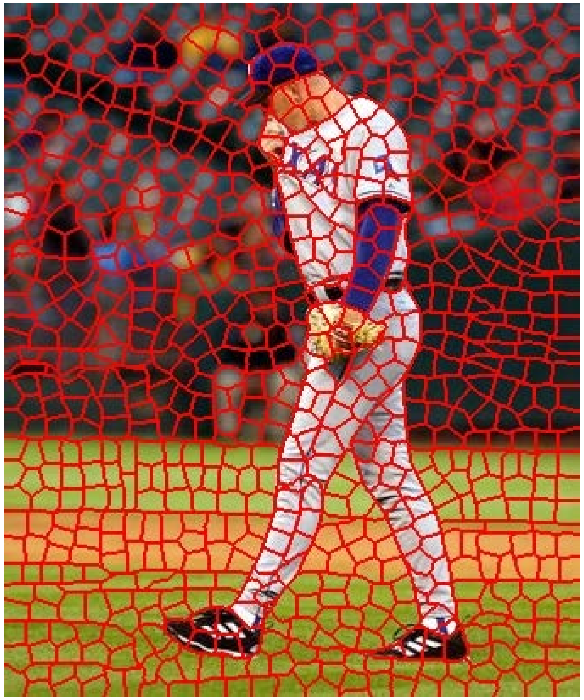
Segmentation Relation

- Segmentation methods touch on and use many previous topics
  - Representation Methods
  - Manipulation Methods
  - Human Perception and Psychology

Segmentation Goals

- Group similar looking pixels together for efficiency of additional processing
  - Superpixels
    - *Learning a classification model for segmentation*, Ren and Malik, ICCV 2003.





Segmentation Goals

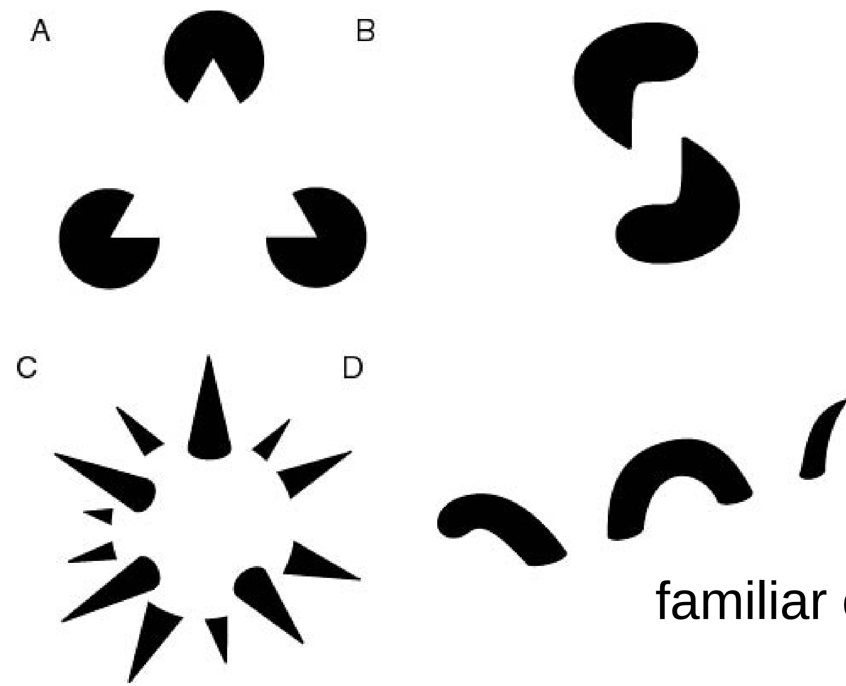
- Separate image into coherent objects
  - Berkeley segmentation database
    - http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

image segmentation

Gestalt Psychology

- Human minds ‘group’ things
  - Our perception is affected by this behavior

subjective contours



occlusion

familiar configuration

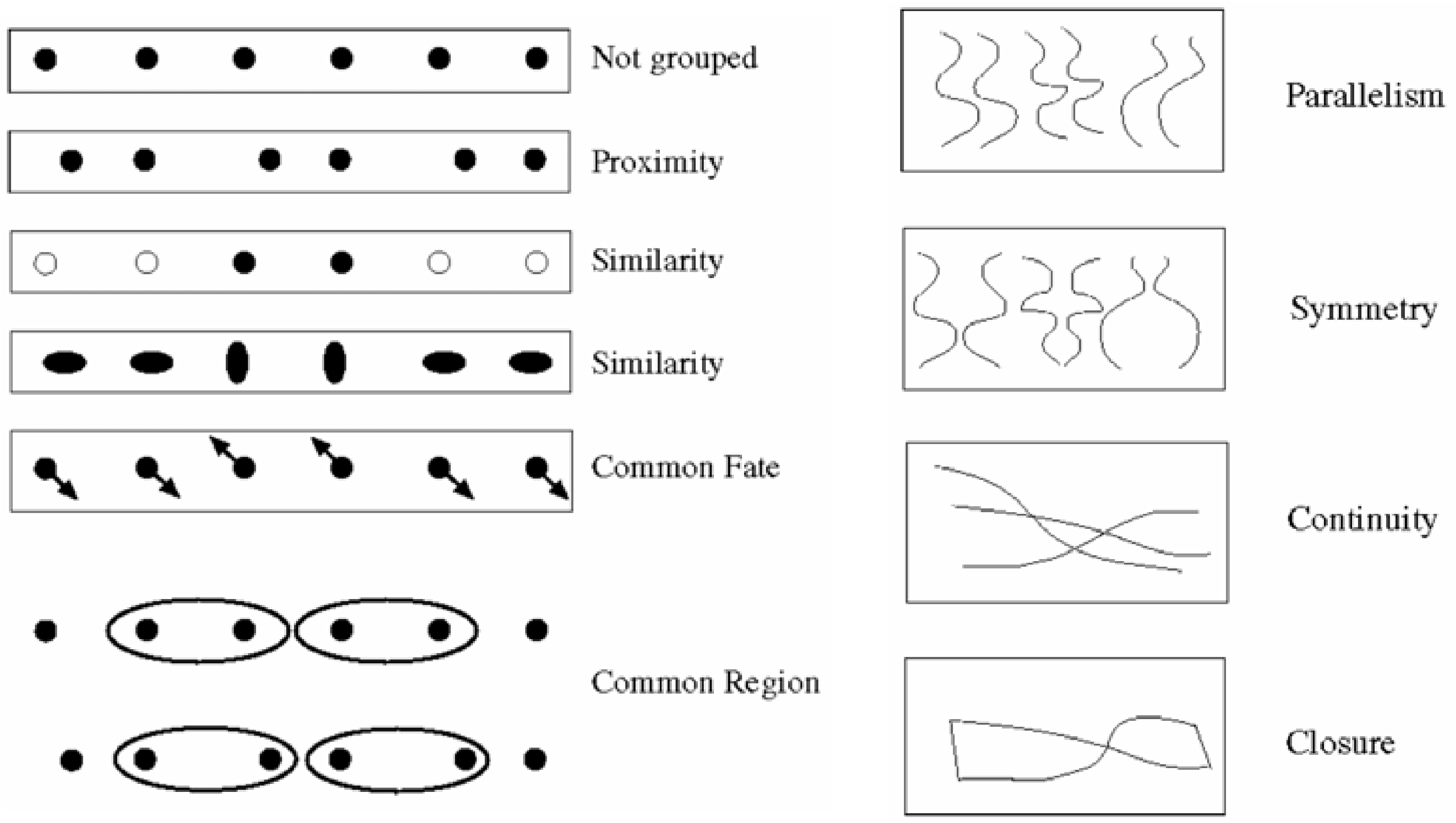
http://en.wikipedia.org/wiki/Gestalt_psychology

Emergence

- Find the dog

http://en.wikipedia.org/wiki/Gestalt_psychology

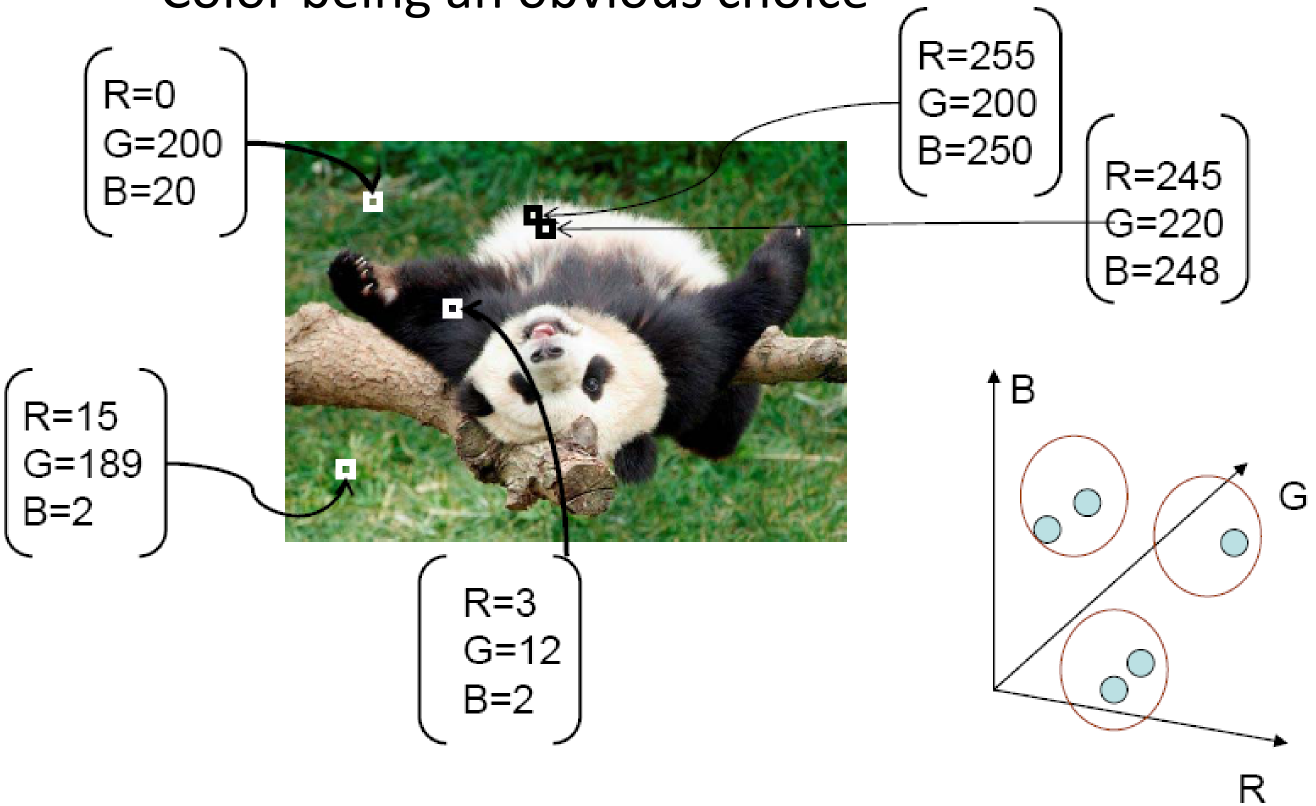
Gestalt Factors



These factors are intuitively obvious to humans
BUT are difficult to code into a computer

Segmentation via Clustering

- Concept:
  - Cluster similar pixels/features together
    - Color being an obvious choice



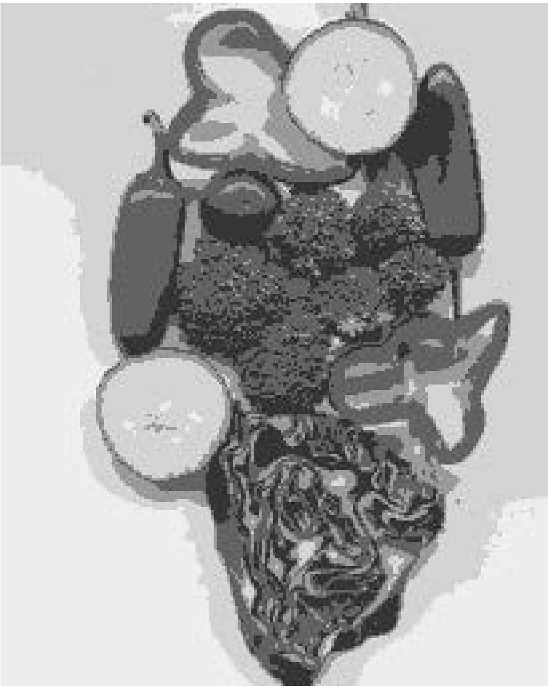
source: K. Grauman

K-Means Clustering

- K-means clustering is based on the intensity or color of pixels
  - Essentially is a vector quantization of the image attributes (intensity or color)
    - Notice the clusters need not be spatially localized

Image

Intensity-based clusters

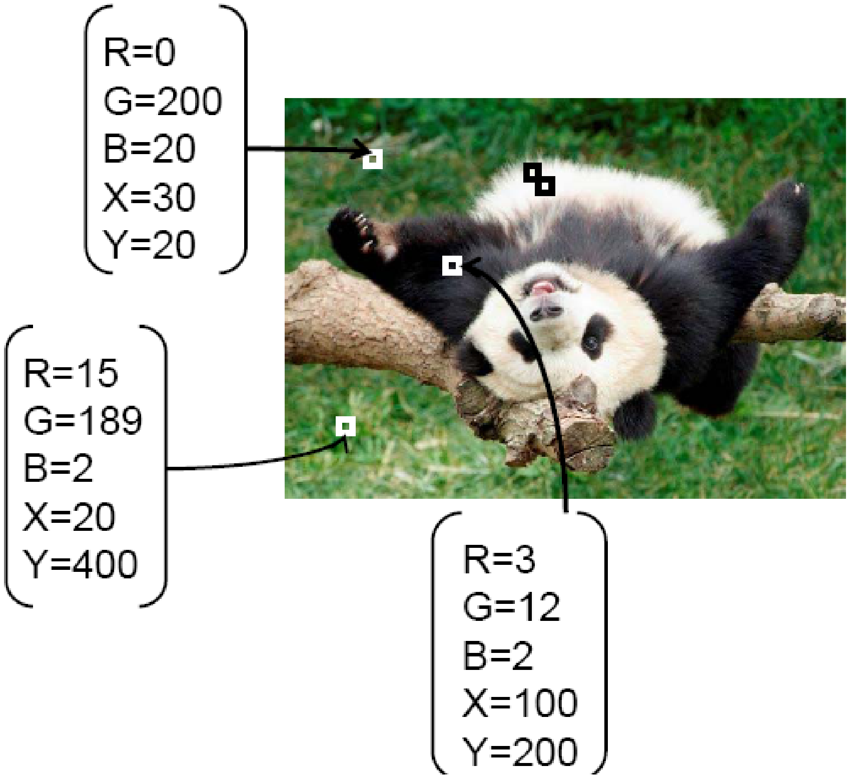


Color-based clusters

source: S. Lazebnik

Segmentation via Clustering

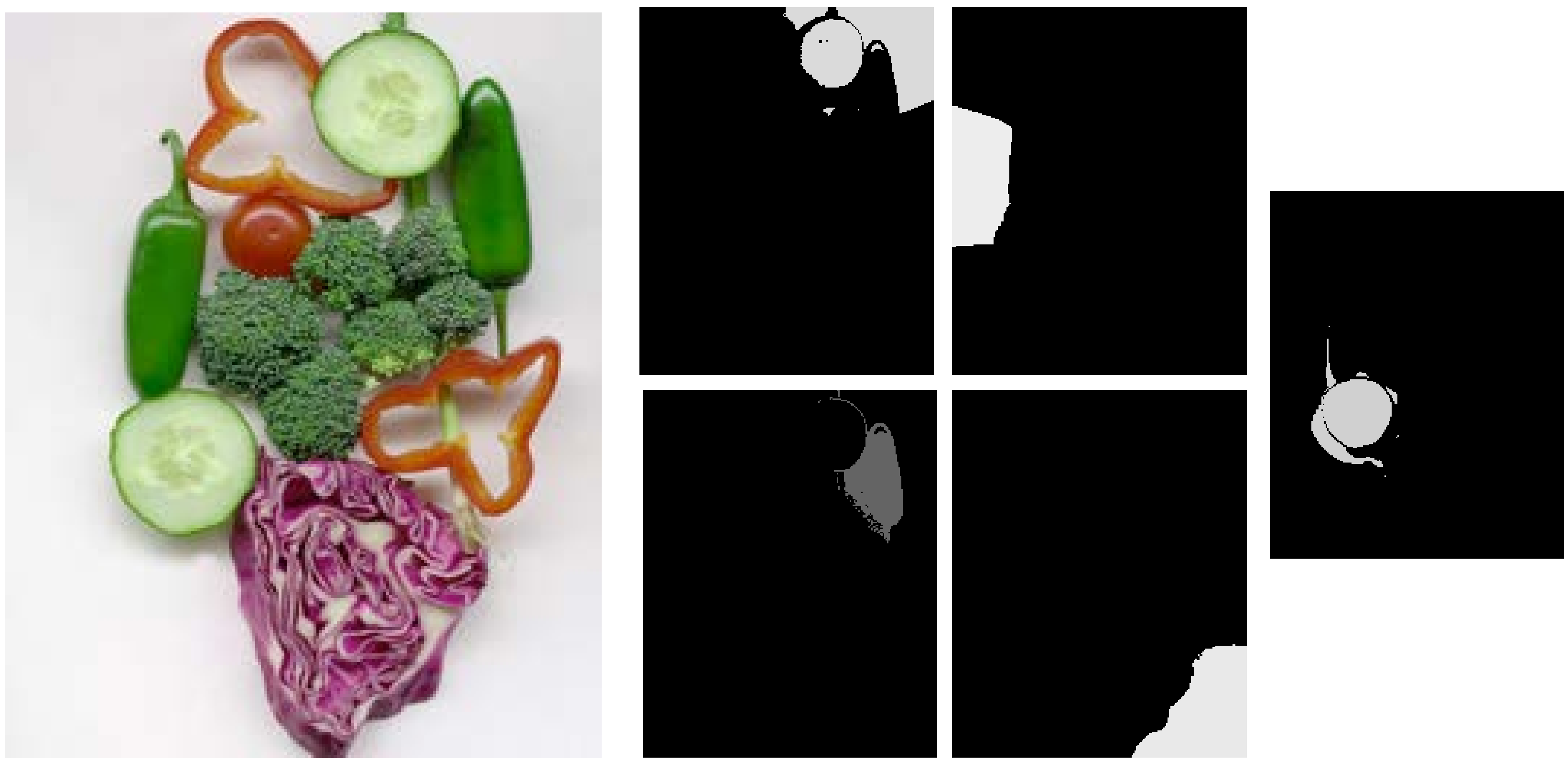
- Cluster similar pixels/features together
  - Color **PLUS LOCATION**



source: K. Grauman

Cluster Color AND Location

- Clustering based on (r, g, b, x, y) values leads to greater spatial coherence



source: S. Lazebnik

Summary: K-means Segmentation

- Good
  - Simple
  - Converges to local minimum of the error function

- Bad
  - Uses lots of memory
  - Human picks K
  - Sensitive to initialization
  - Sensitive to outliers
  - Only finds ‘sphere-like’ clusters

source: S. Lazebnik

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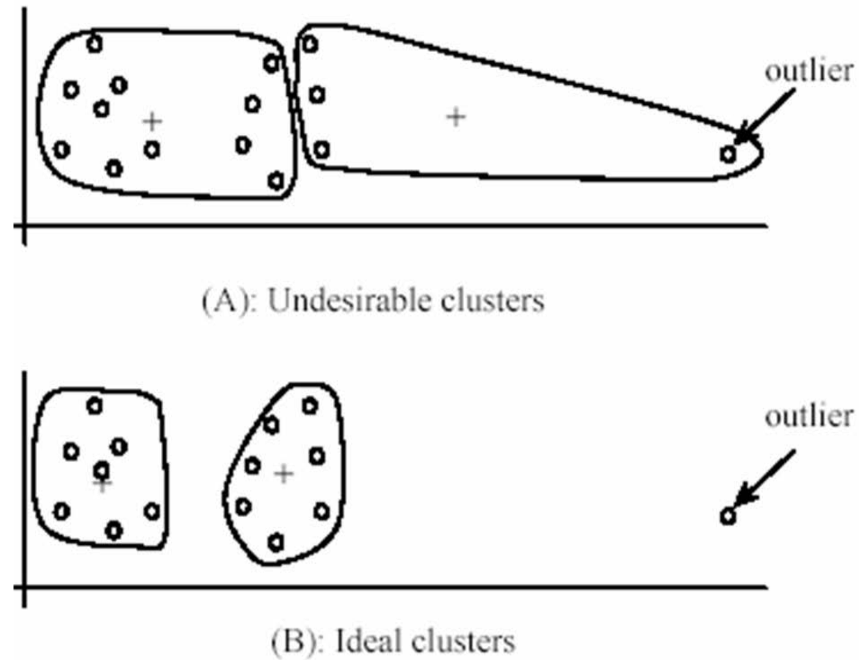


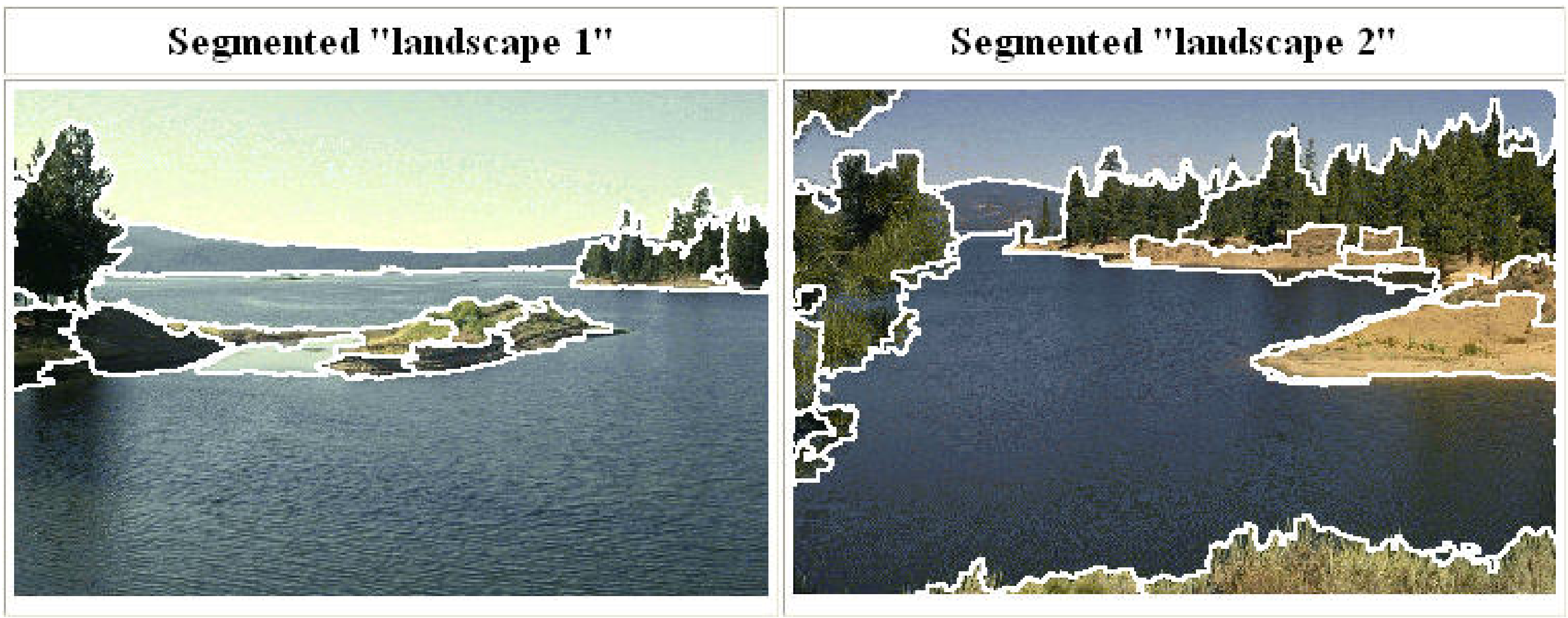
source: S. Lazebnik

Questions So Far?

- Questions on K-Means Segmentation?

Mean Shift Clustering

- An advanced and versatile method of clustering-based segmentation



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

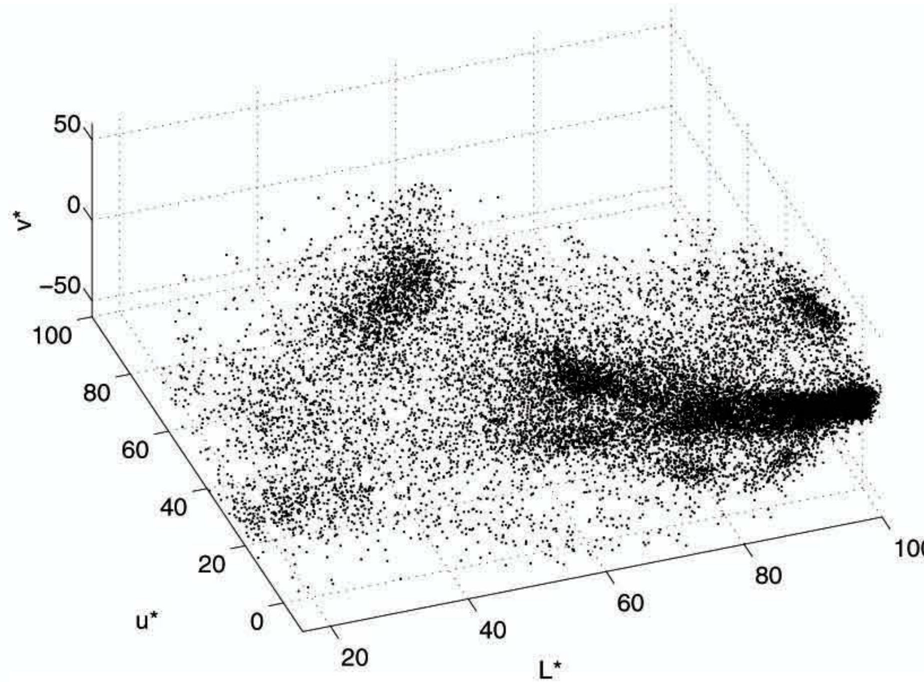
Mean Shift: A Robust Approach toward Feature Space Analysis, D. Comaniciu and P. Meer, PAMI 2002.

Mean Shift Algorithm

- Seeks ***modes*** or local maxima of density in the feature space

image

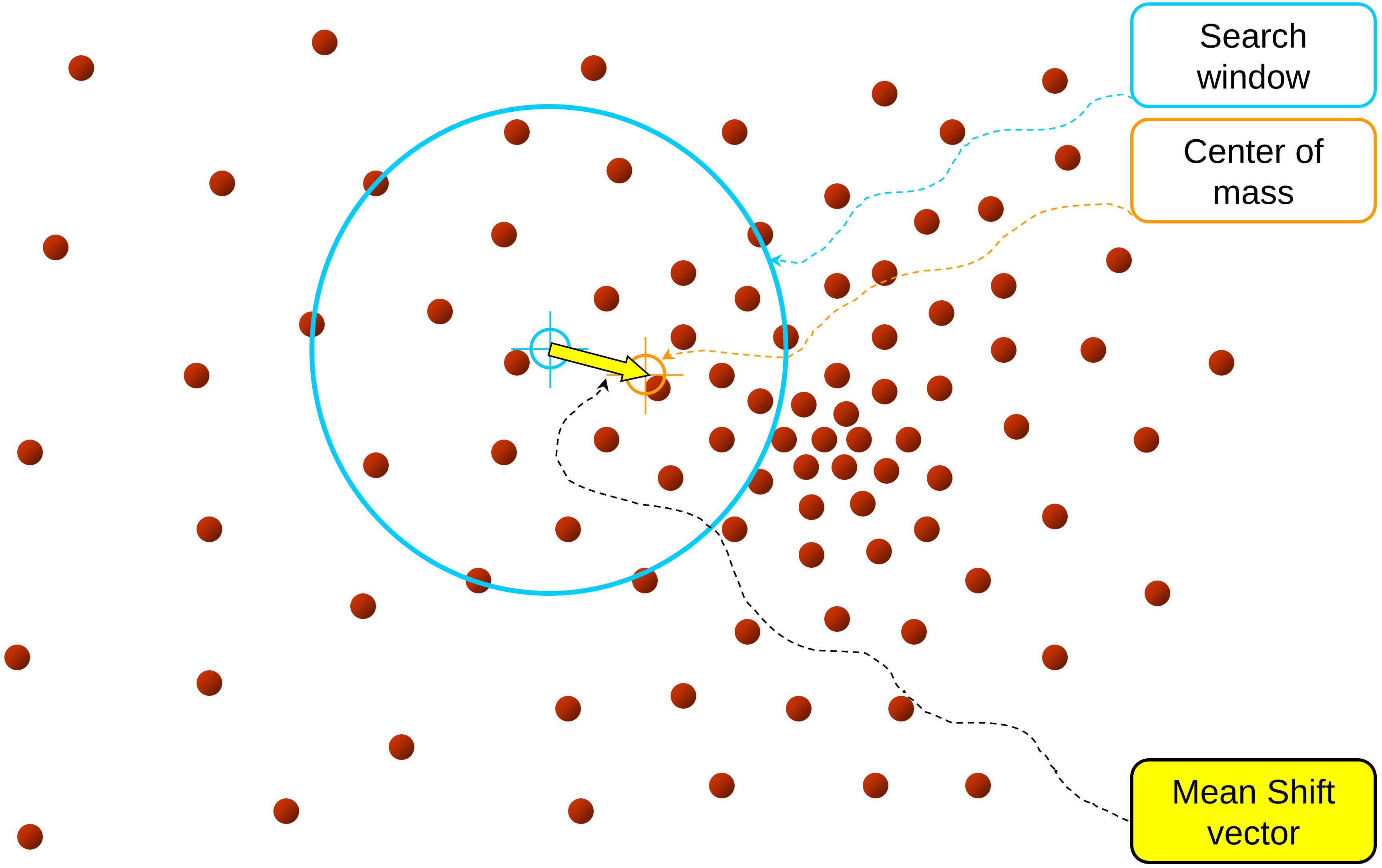
Feature space (L*u*v* color values)



L = luminance
u and v are spatial coordinates

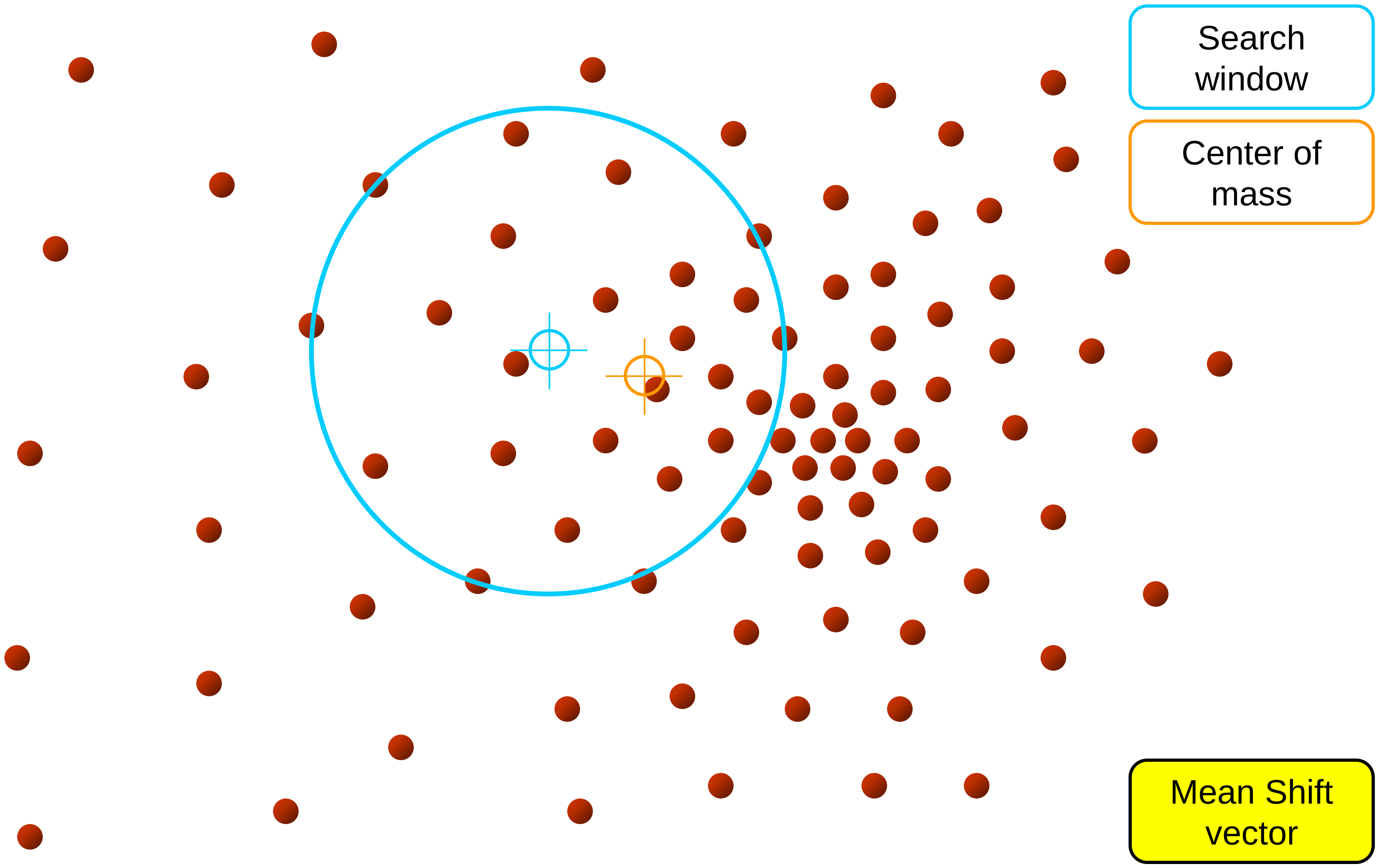
source: S. Lazebnik

Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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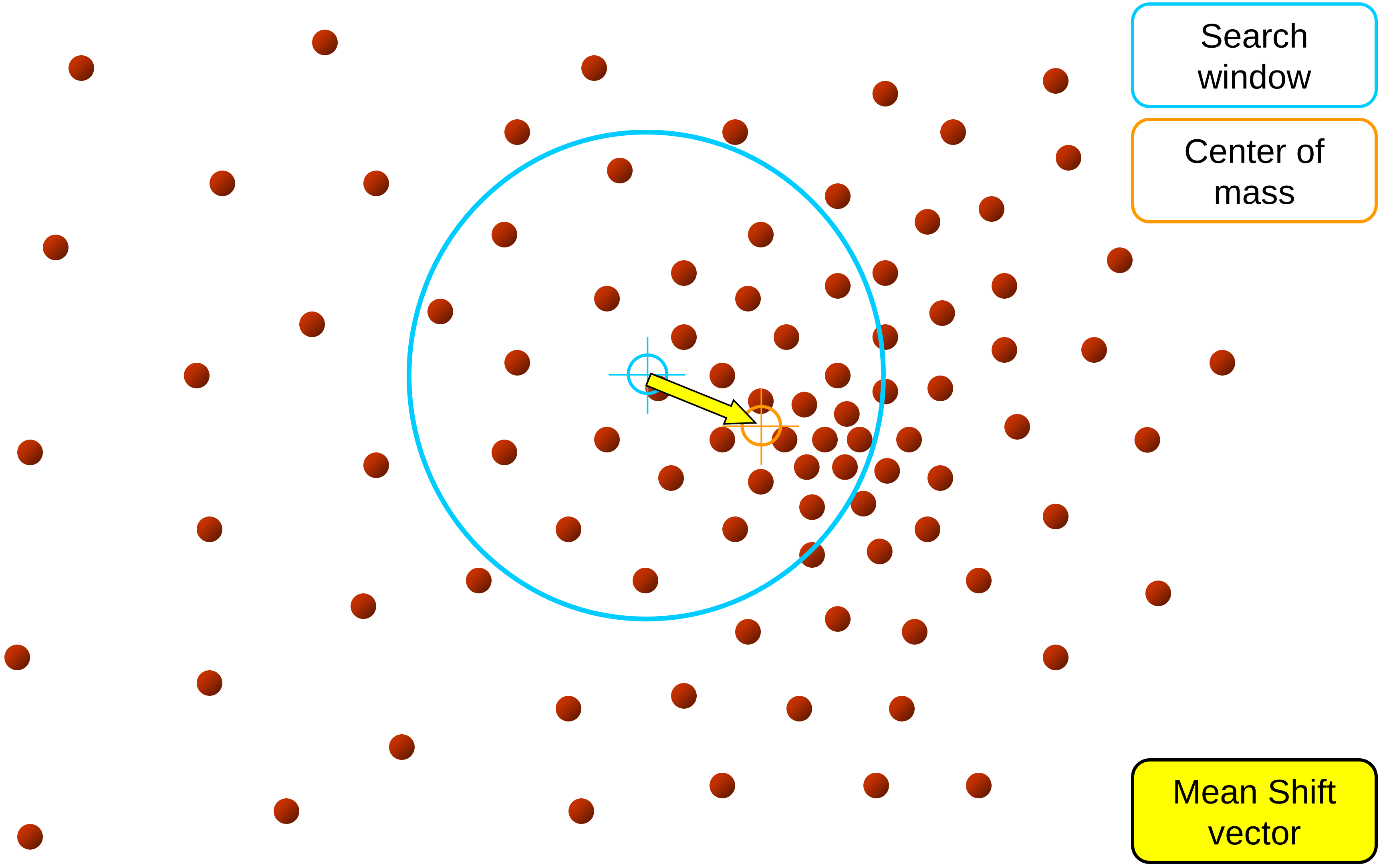

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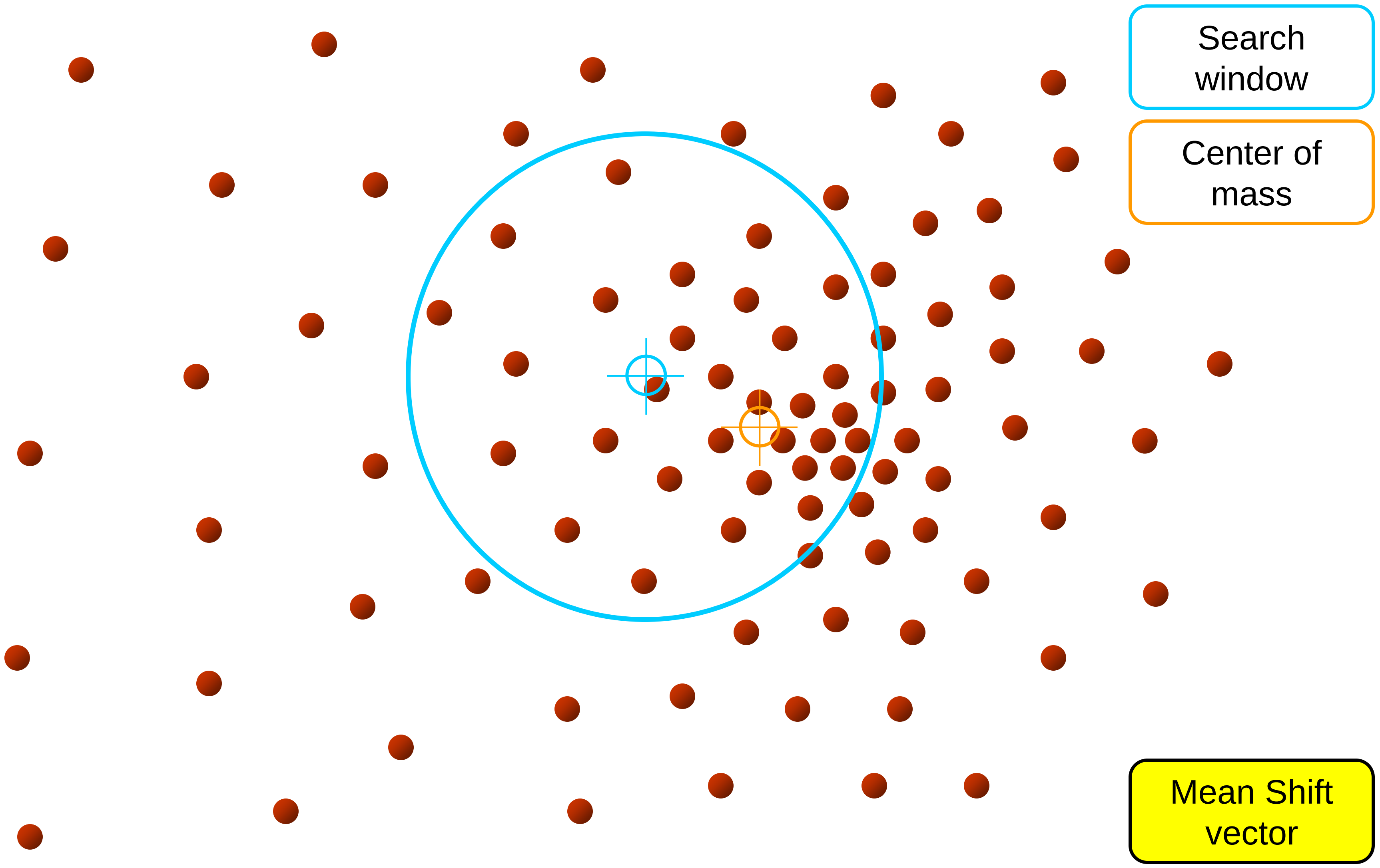
Mean shift



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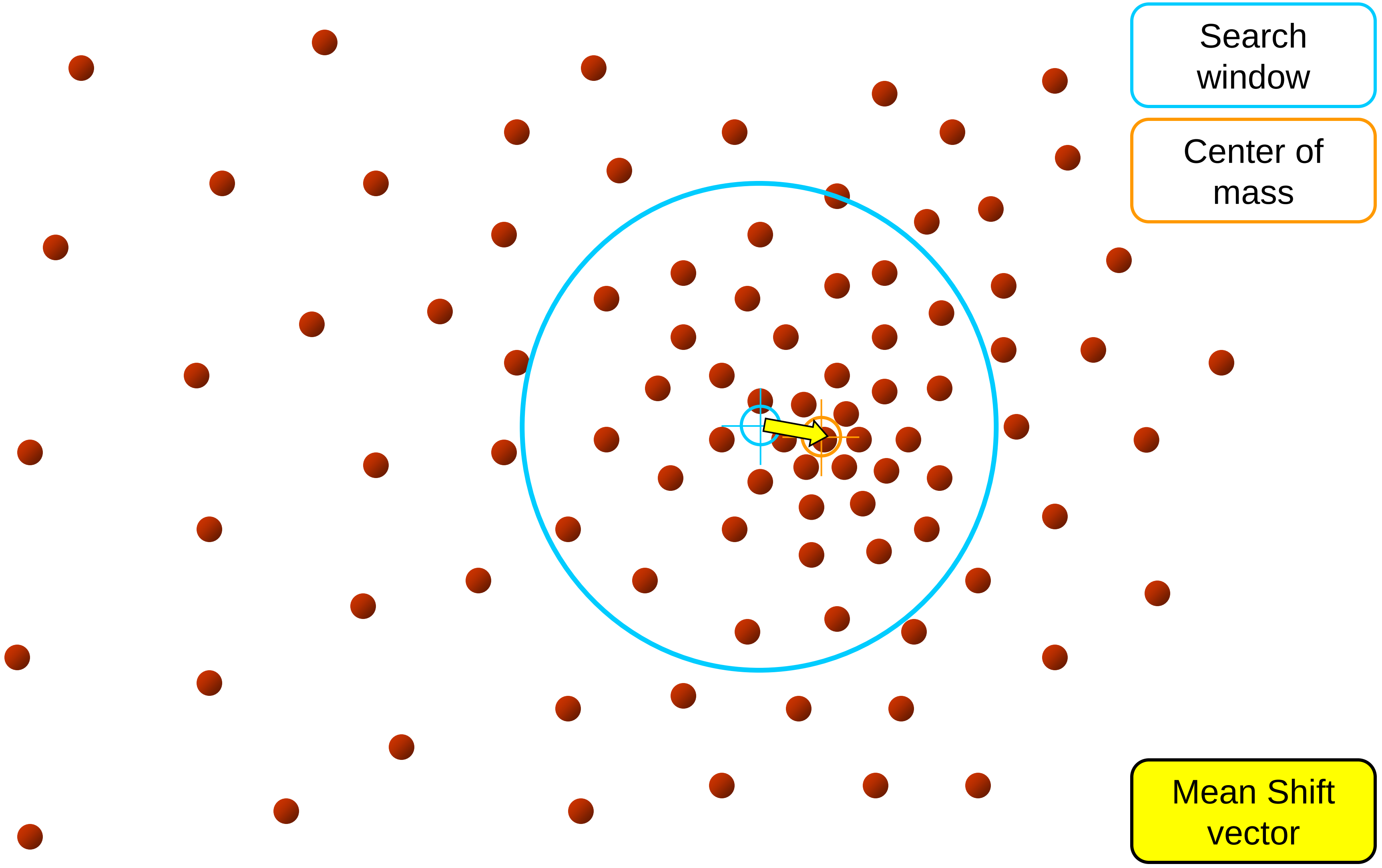
Mean shift



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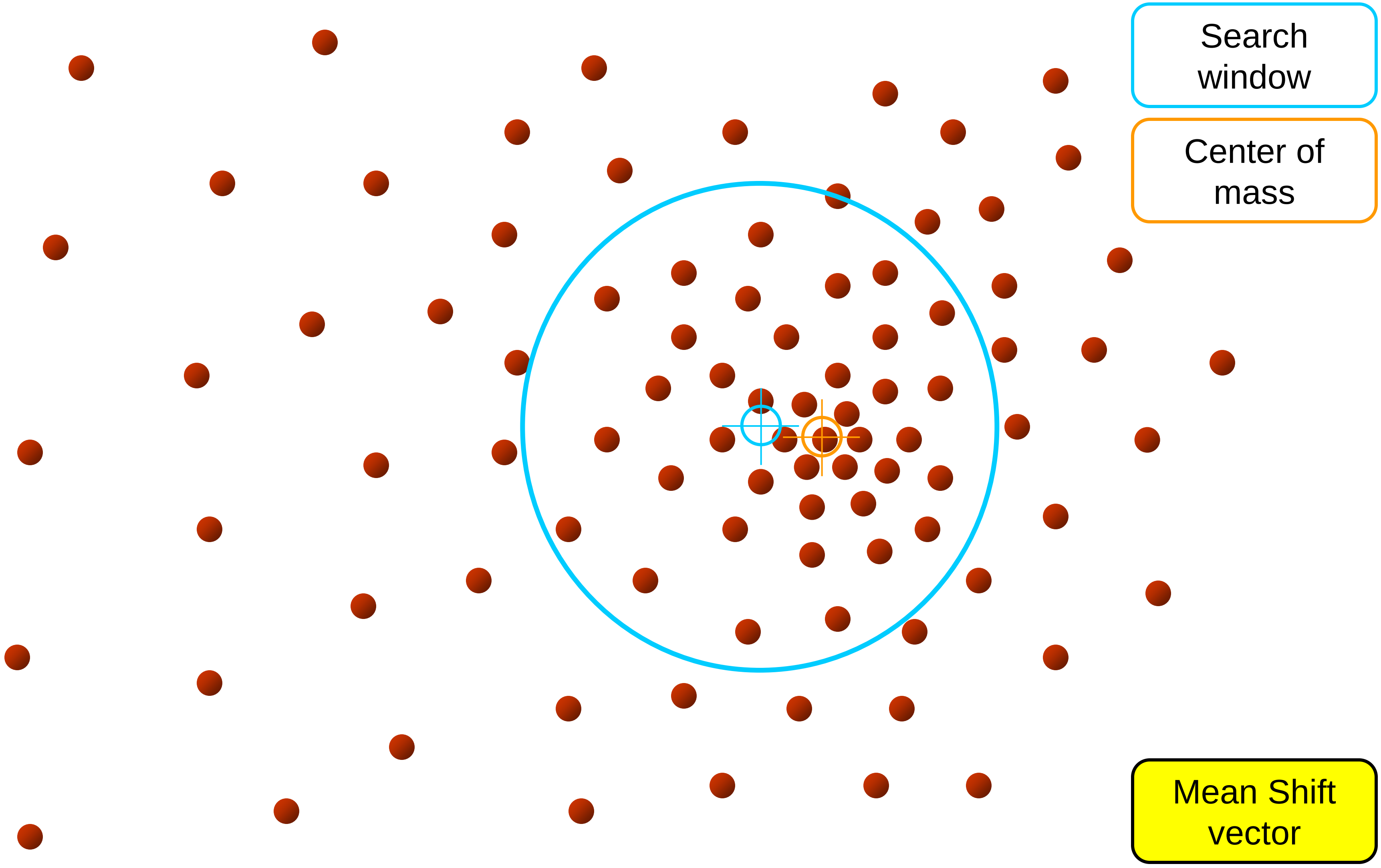

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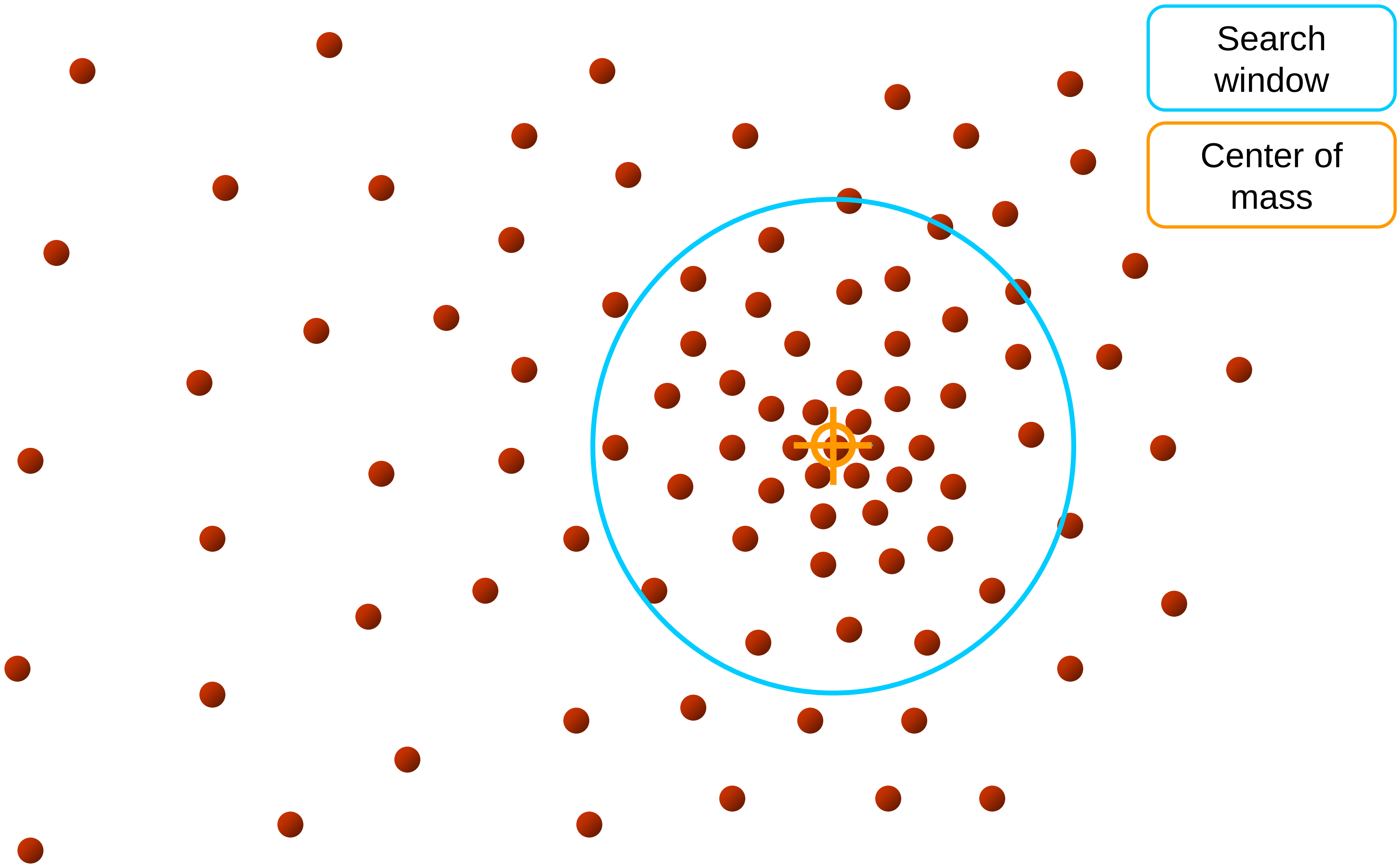
Mean shift



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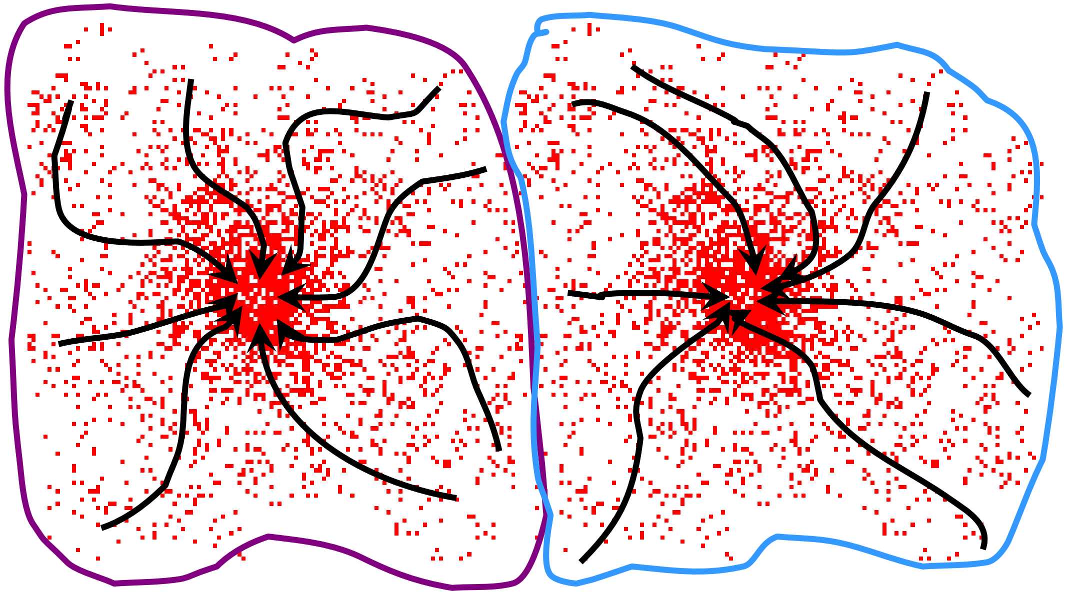
Mean Shift Clustering

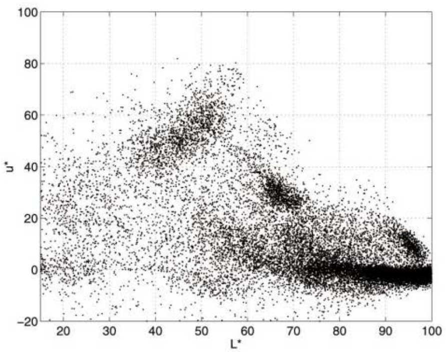
- Define Cluster as
  - all data points in the attraction basin of a mode
- Define Attraction Basin as
  - the region for which all trajectories lead to the same mode



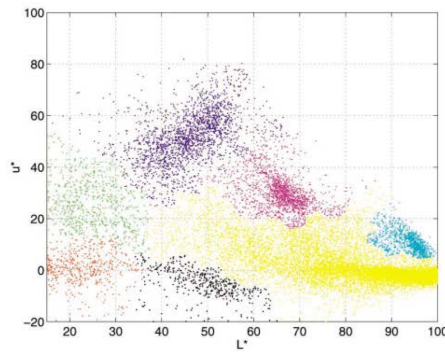
Slide by Y. Ukrainitz & B. Sarel

Mean Shift Clustering / Segmentation

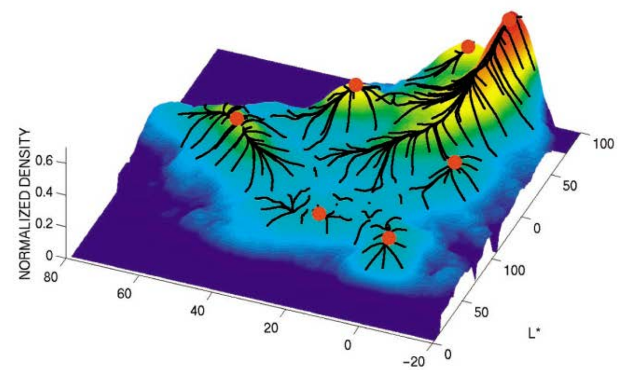
- Find Features (color, gradients, texture…)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end near the same ‘peak’ or mode



(a)

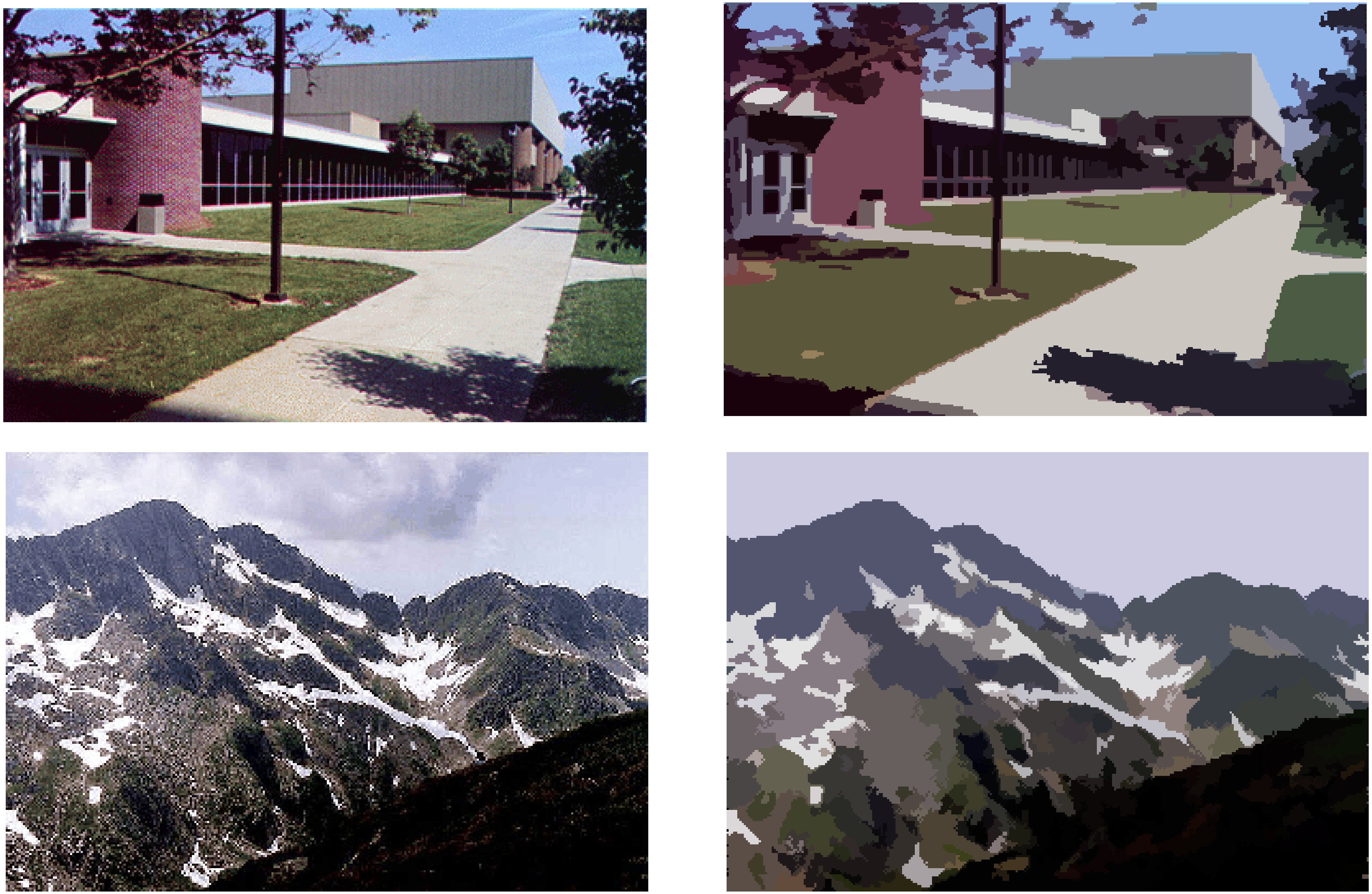


(b)



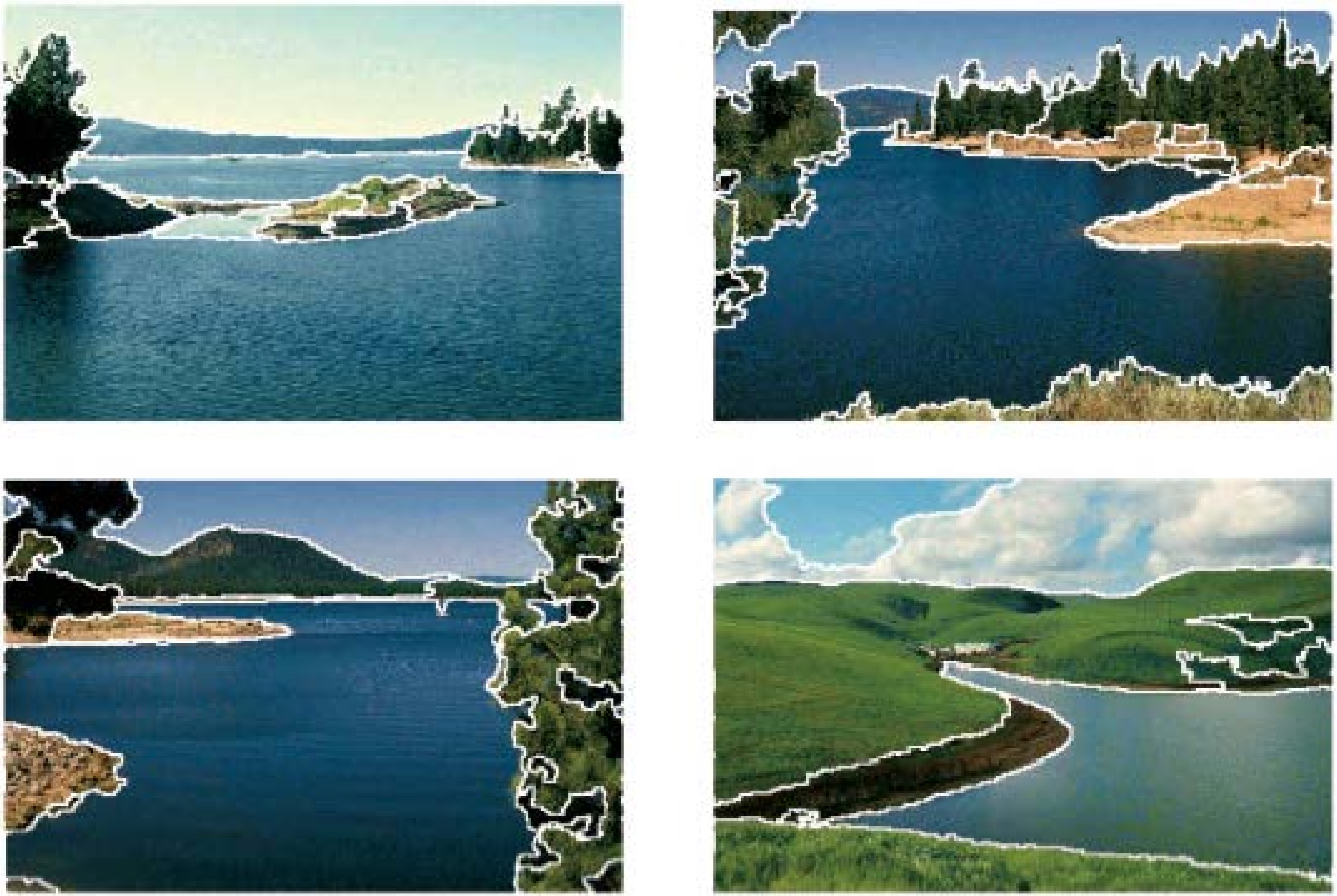
source: S. Lazebnik

Example: Mean Shift Results



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

Mean Shift Results *(c1)*



Mean Shift Results *(c2)*

Summary: Mean Shift

- Good
  - Does not assume spherical clusters
  - Takes a single parameter (window size)
  - Finds variable number of nodes
  - Robust outliers

- Bad
  - Output depends on window size
  - Computationally expensive
  - Does not scale well with dimension of feature space

Questions So Far?

- Questions on Mean Shift Clustering/Segmentation?

More Questions?

- Beyond D2L
  - Examples and information can be found online at:
    - *http://docdingle.com/teaching/cs.html*

    - *Continue to more stuff as needed*

Extra Reference Stuff Follows

Credits

- Much of the content derived/based on slides for use with the book:
  - *Digital Image Processing,* Gonzalez and Woods

- Some layout and presentation style derived/based on presentations by
  - Donald House, Texas A&M University, 1999
  - Sventlana Lazebnik, UNC, 2010
  - Noah Snavely, Cornell University, 2012
  - Xin Li, WVU, 2014
  - George Wolberg, City College of New York, 2015
  - Yao Wang and Zhu Liu, NYU-Poly, 2015