Lecture 13
Segmentation and Scene understanding

- Introduction
- Mean-shift
- Graph-based segmentation
- Top-down segmentation

Segmentation

- Compact representation for image data in terms of a set of components

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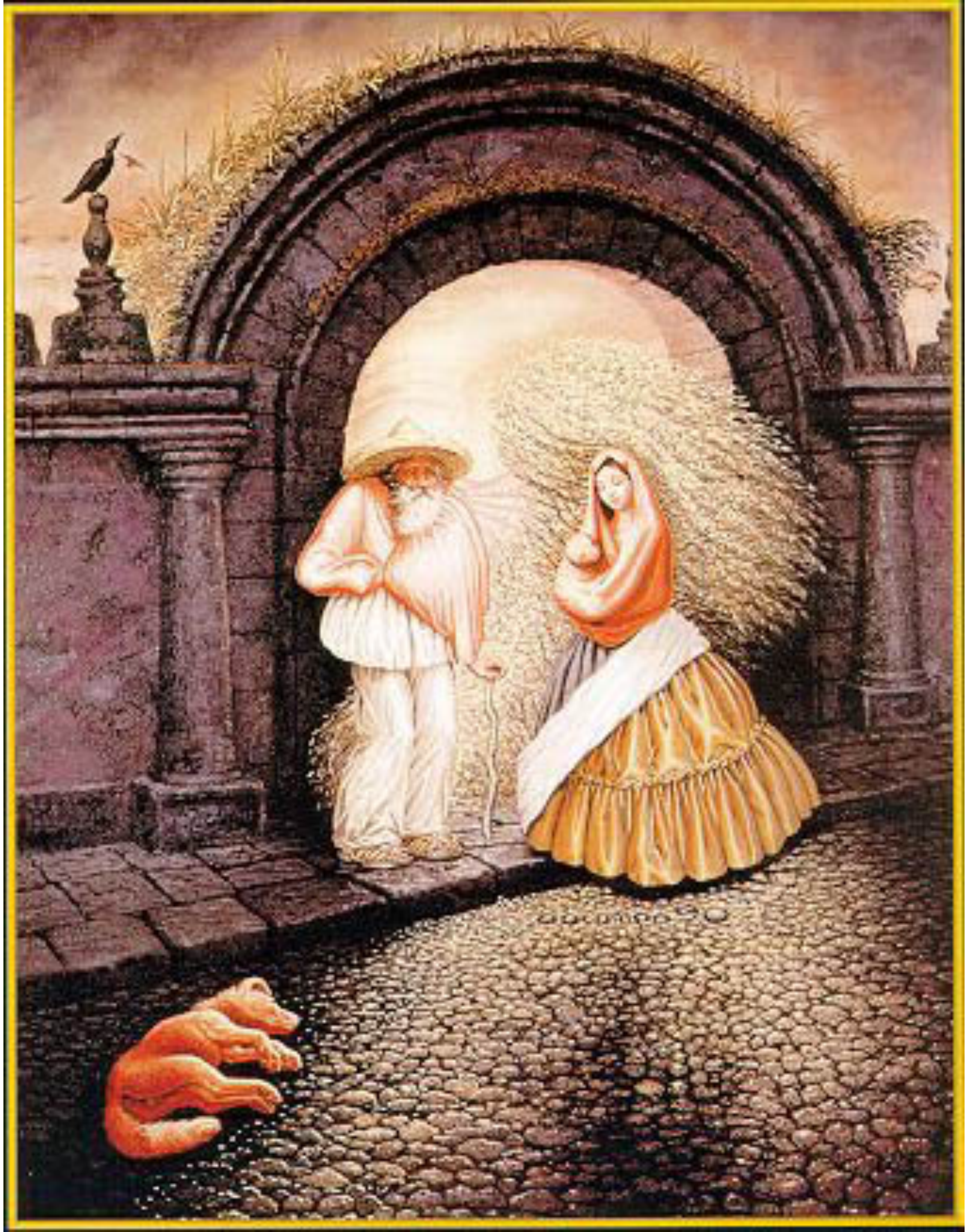
- Components share common properties

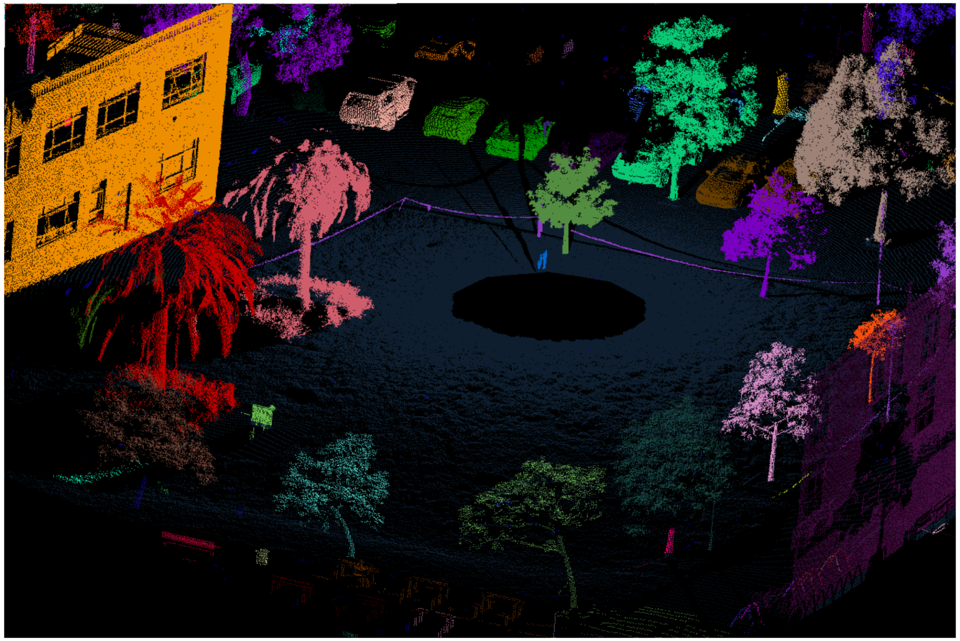
Segmentation

- Compact representation for image data in terms of a set of components
- Components share common properties
- Properties can be defined at different level of abstractions



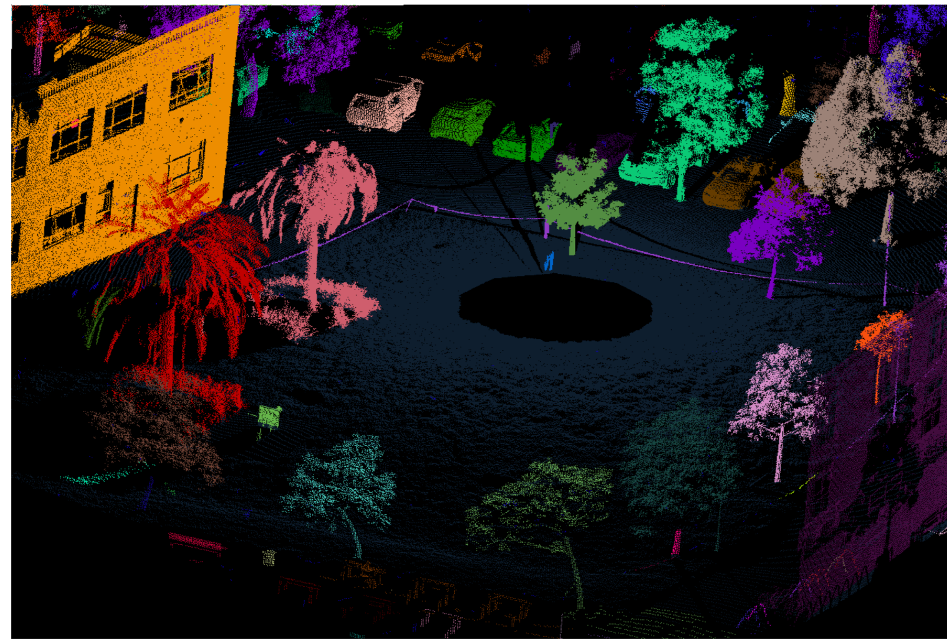
Segmentation

Segmentation



Douillard, et al. ICRA 2011

Segmentation



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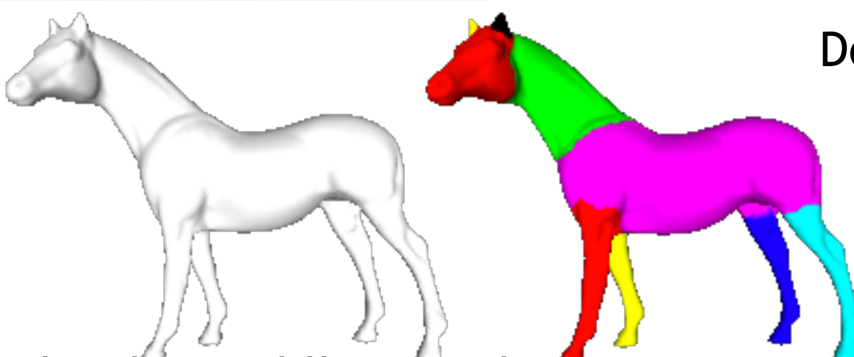


http://www-rech.telecom-lille1.eu/shrec2012-segmentation/

General ideas

- Bottom up segmentation
  - tokens belong together because they are locally coherent

General ideas

- Bottom up segmentation
  - tokens belong together because they are locally coherent

- Top down segmentation
  - tokens belong together because they lie on the same visual entity (object, scene…)

Why Segmentation?

- Segments are building blocks of other vision tasks.
- Complexity
- Boundary

Basic ideas of grouping in human vision

- Gestalt properties
- Figure-ground discrimination
- Emergence

Gestalt psychology or **gestaltism**

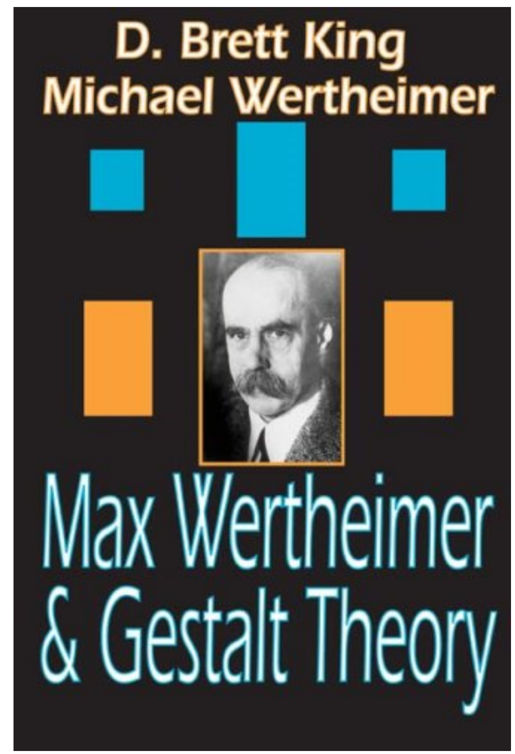
German: *Gestalt* - "form" or "whole”

Berlin School , early 20th century, Carl Stumpf

Kurt Koffka, Max Wertheimer, and Wolfgang Köhler

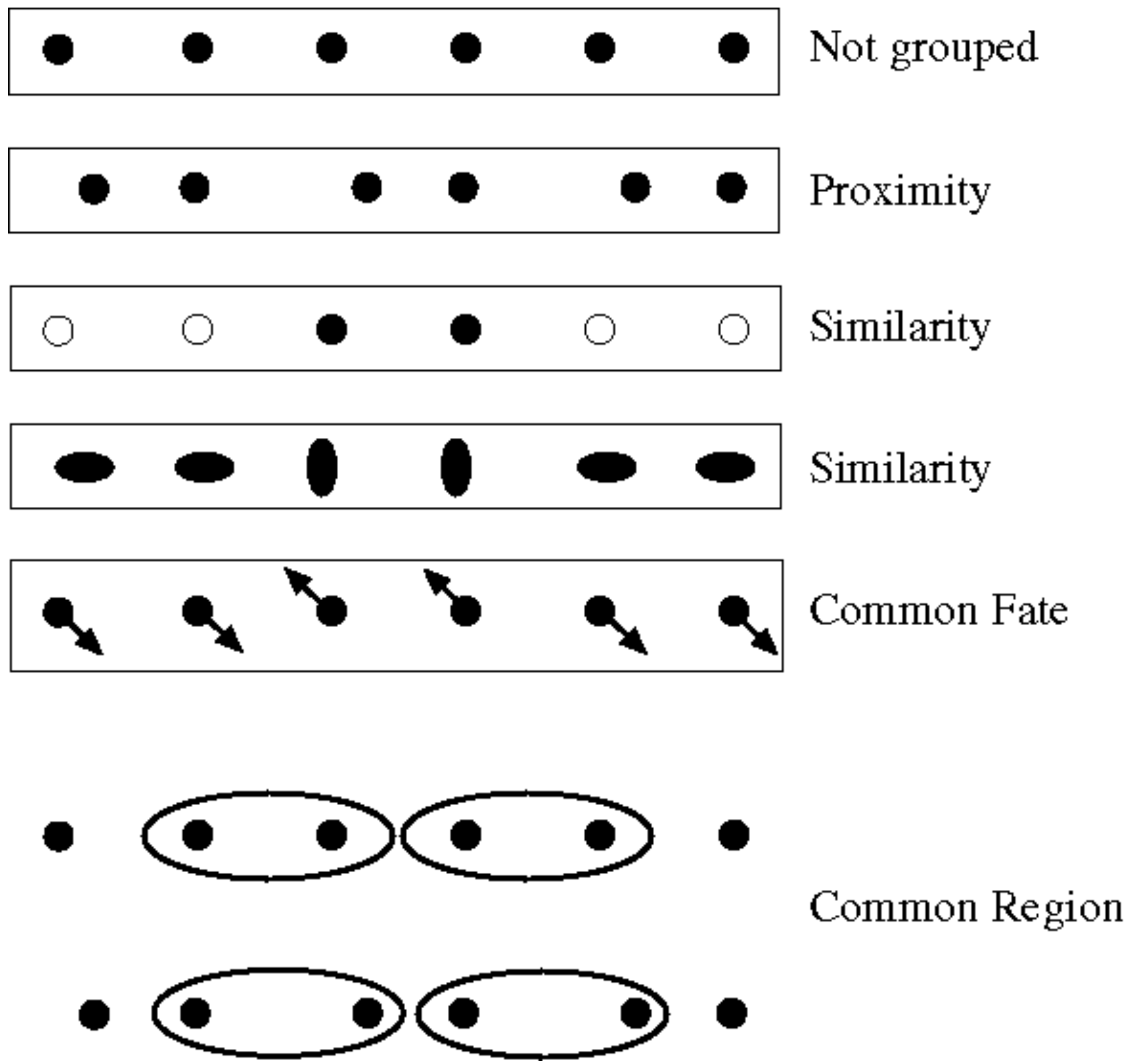
Advocate brain is holistic

Whole is greater than the sum of its parts.



Gestalt properties

–A series of factors affect whether elements should be grouped together



Gestalt properties

Grouping
by occlusions

Gestalt properties

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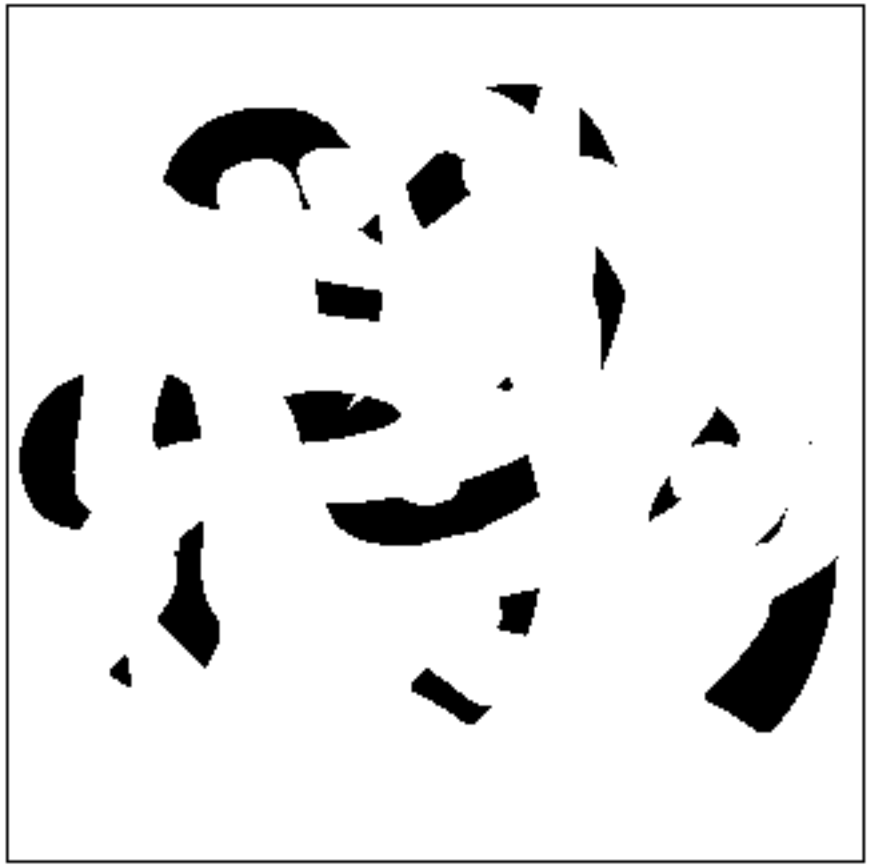


Gestalt properties

Grouping
by invisible
completions

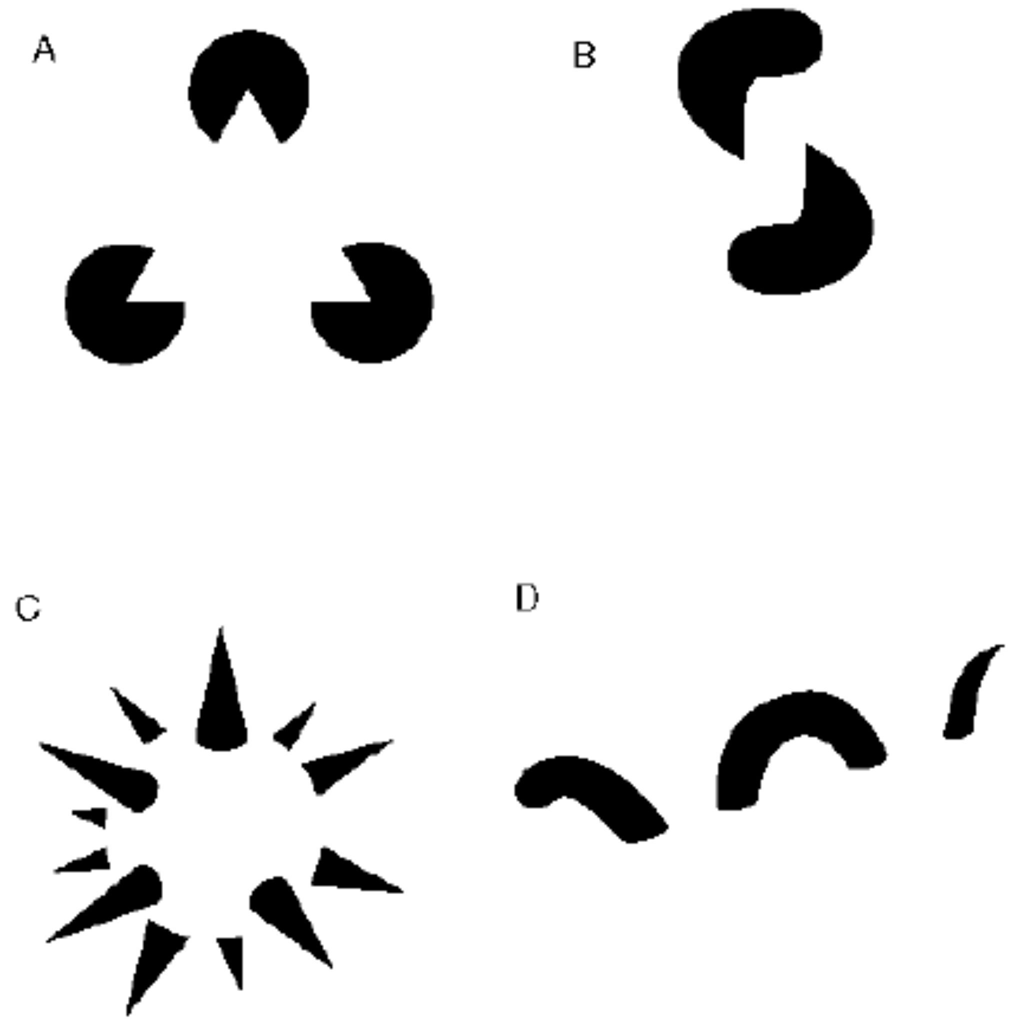
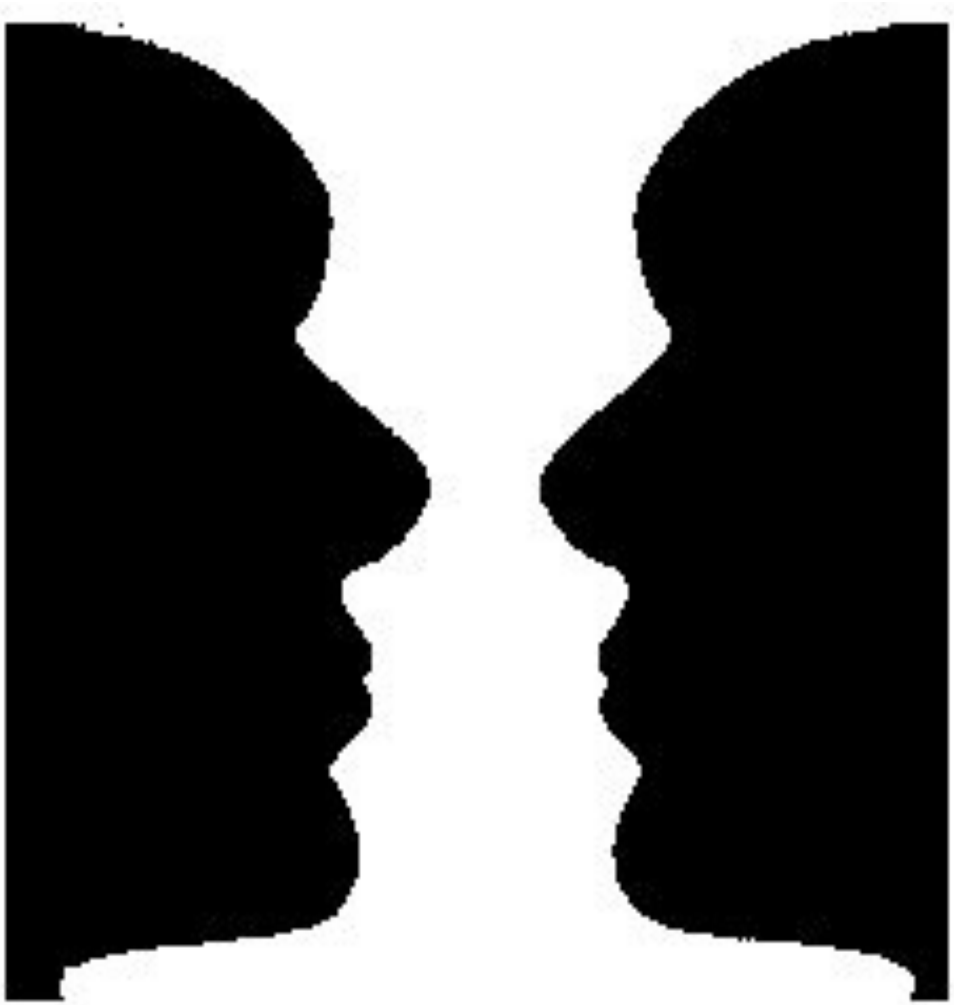


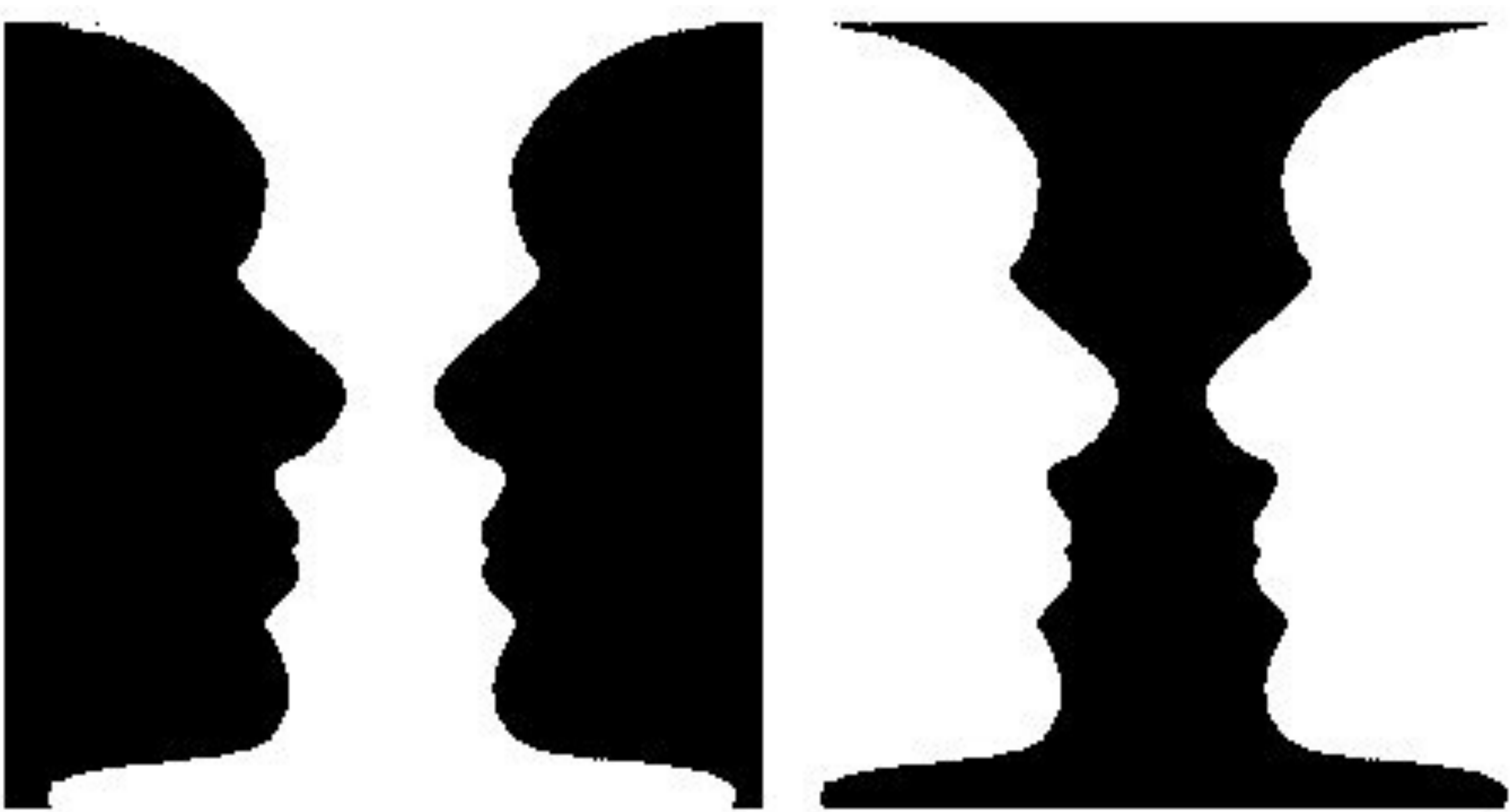
Figure-ground discrimination



–Grouping can be seen in terms of allocating some elements to a figure, some to ground

–Can be based on local bottom-up cues or high level recognition

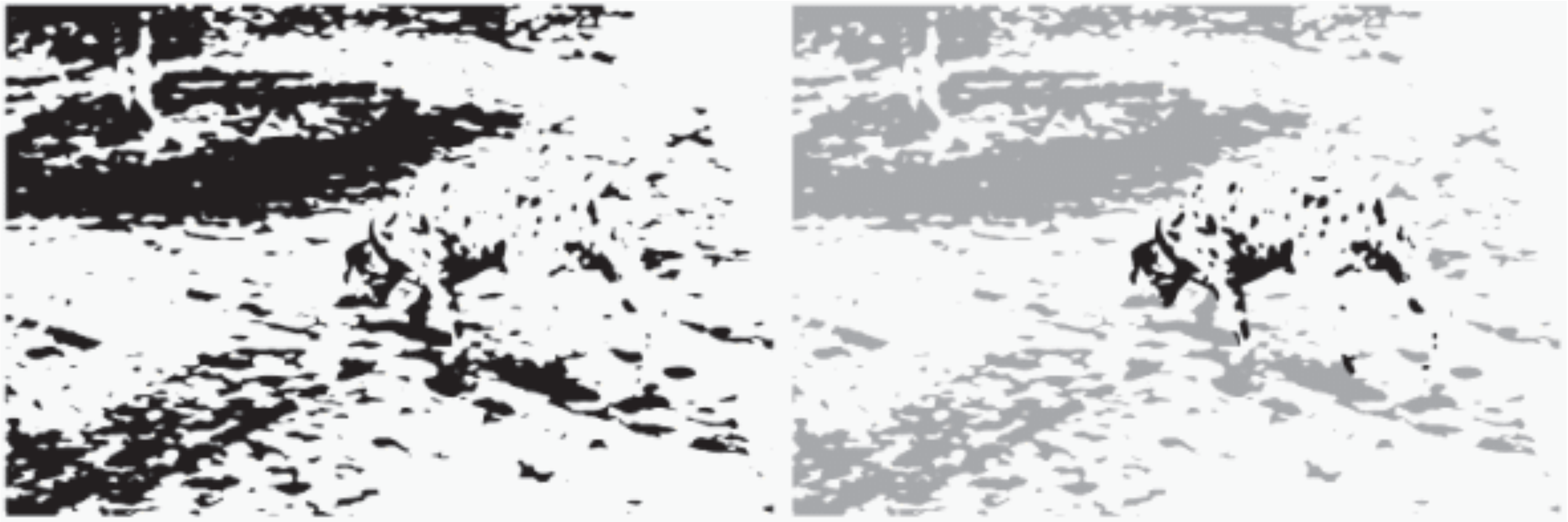
Figure-ground discrimination



Emergence

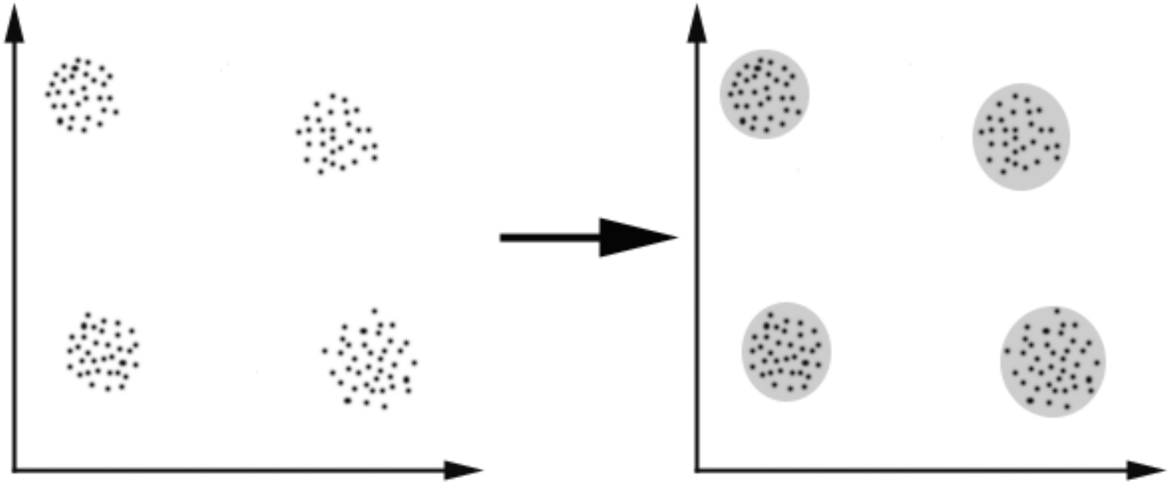
Emergence

- aggregate information from meaningless pieces, and to perceive a meaningful whole.



How would you do it?

Clustering



Segmentation as clustering

Cluster together tokens that share similar visual characteristics

- **K-means**
- **Mean-shift**

Segmentation as clustering

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- **K-means** } See CS131A, CS 229

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  - **Must specify number of clusters K in advance**
  - **Assumes clusters are spherical**
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Segmentation as clustering

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  - **Slow**
  - **Discovers arbitrary number of clusters**
  - **No a priori assumptions about cluster shapes**

Segmentation as clustering

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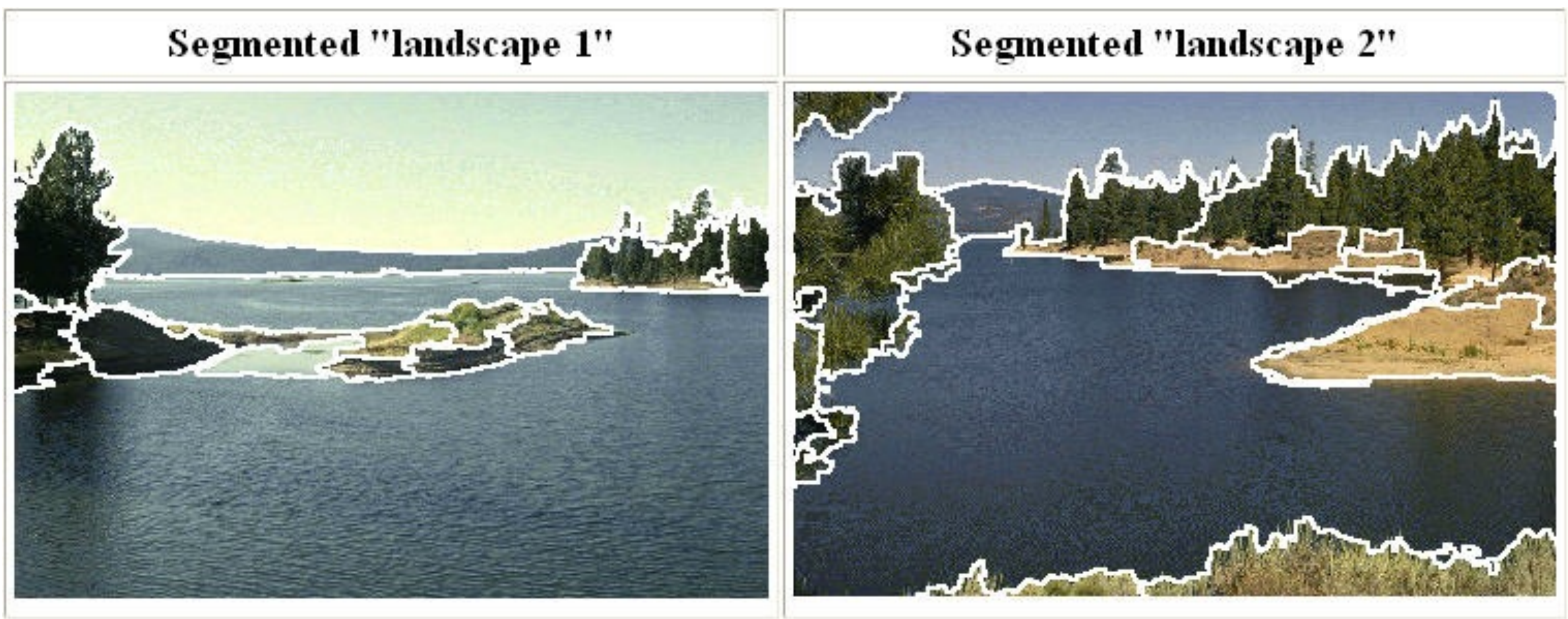
Mean shift segmentation

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

- A versatile technique for clustering-based segmentation



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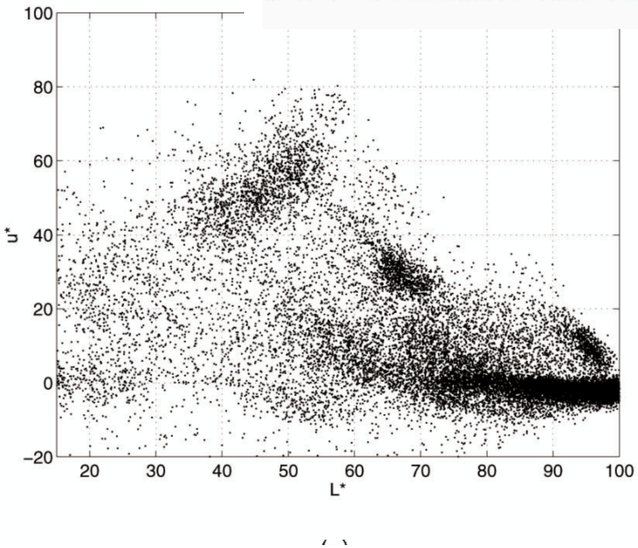

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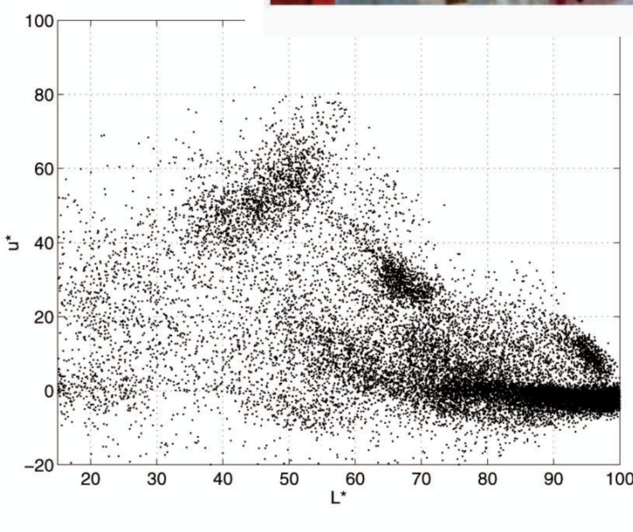

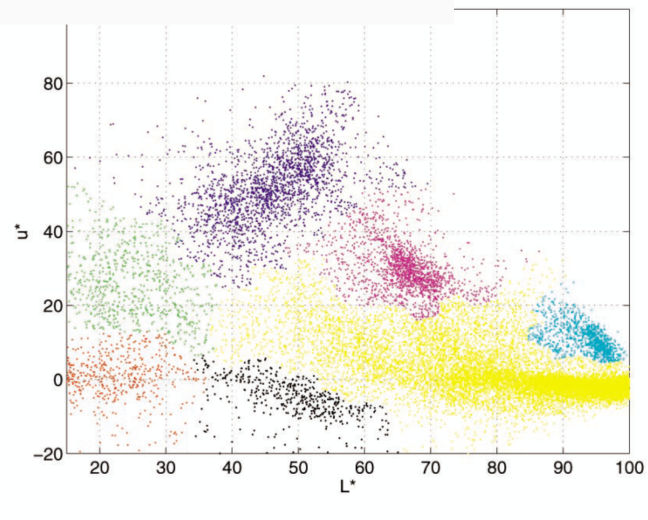

Mean shift algorithm

Fukunaga, Keinosuke; Larry D. Hostetler (January 1975). "The Estimation of the Gradient of a Density Function, with Applications in Pattern Recognition". *IEEE Transactions on Information Theory* (IEEE) **21** (1): 32–40

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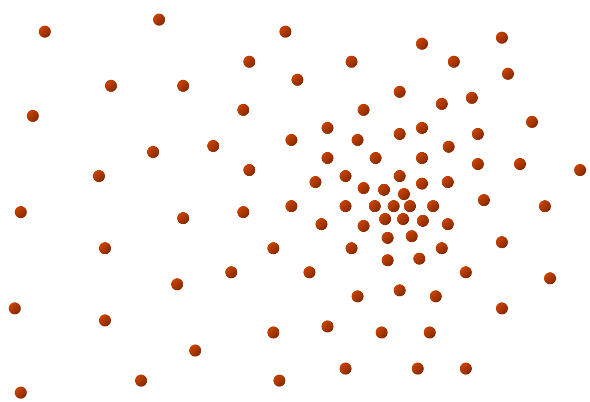

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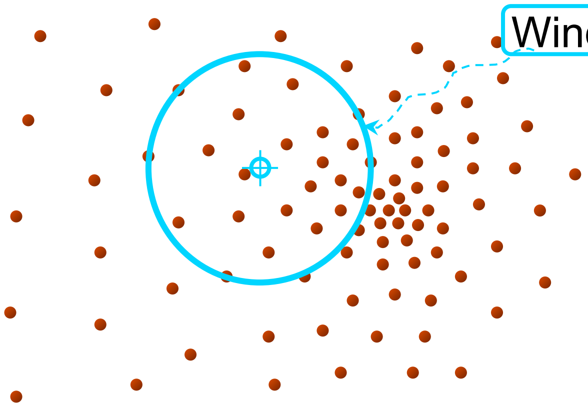

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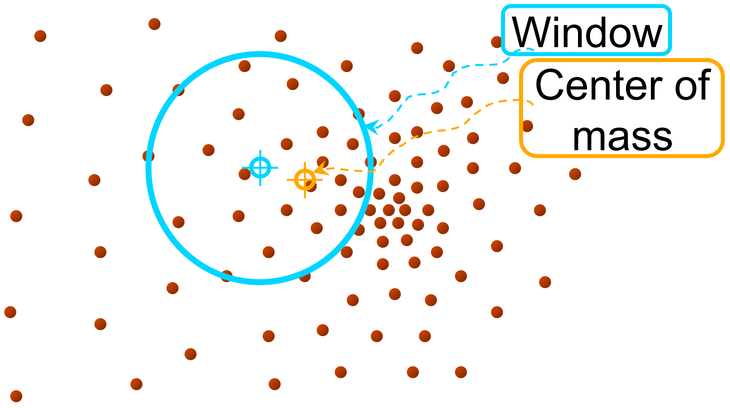

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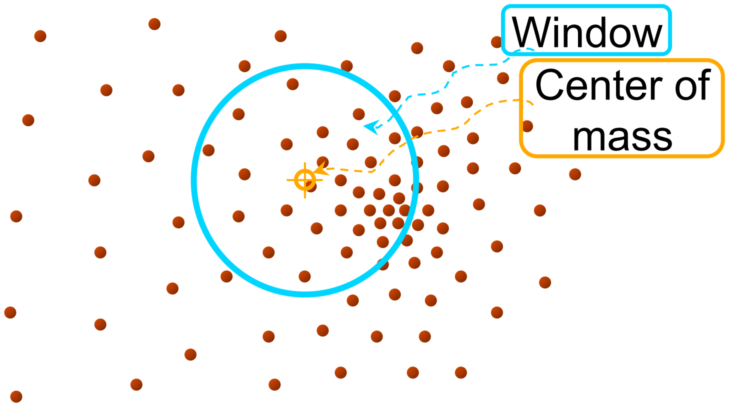

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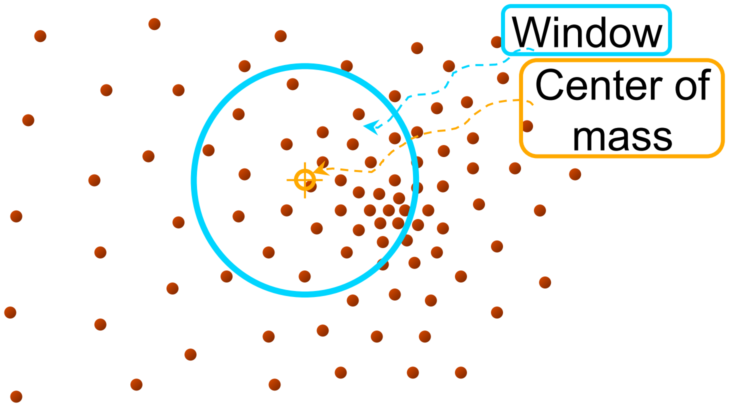

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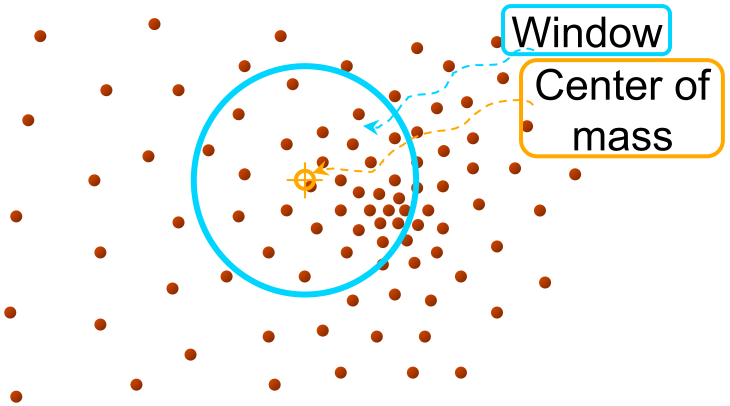
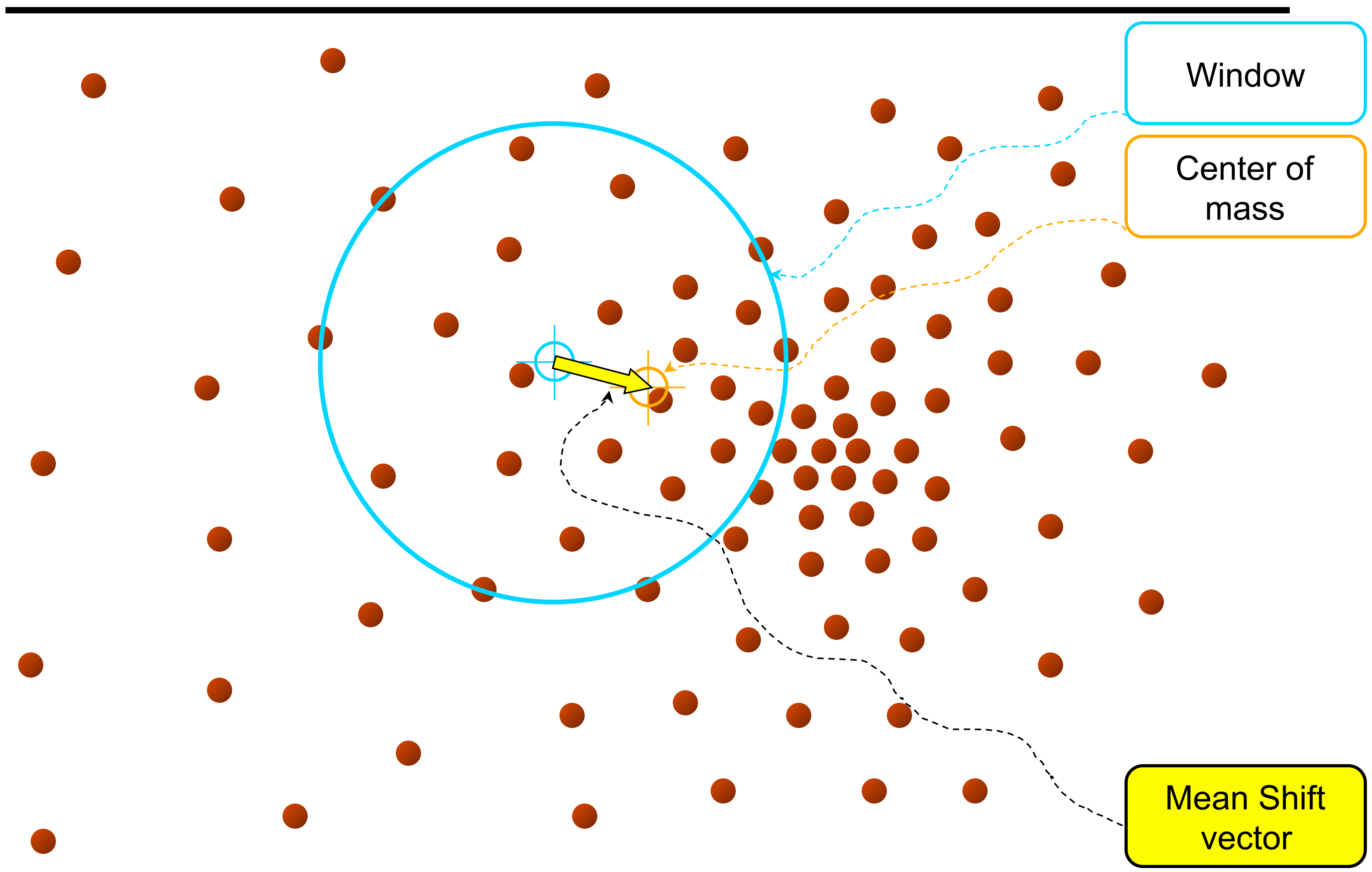
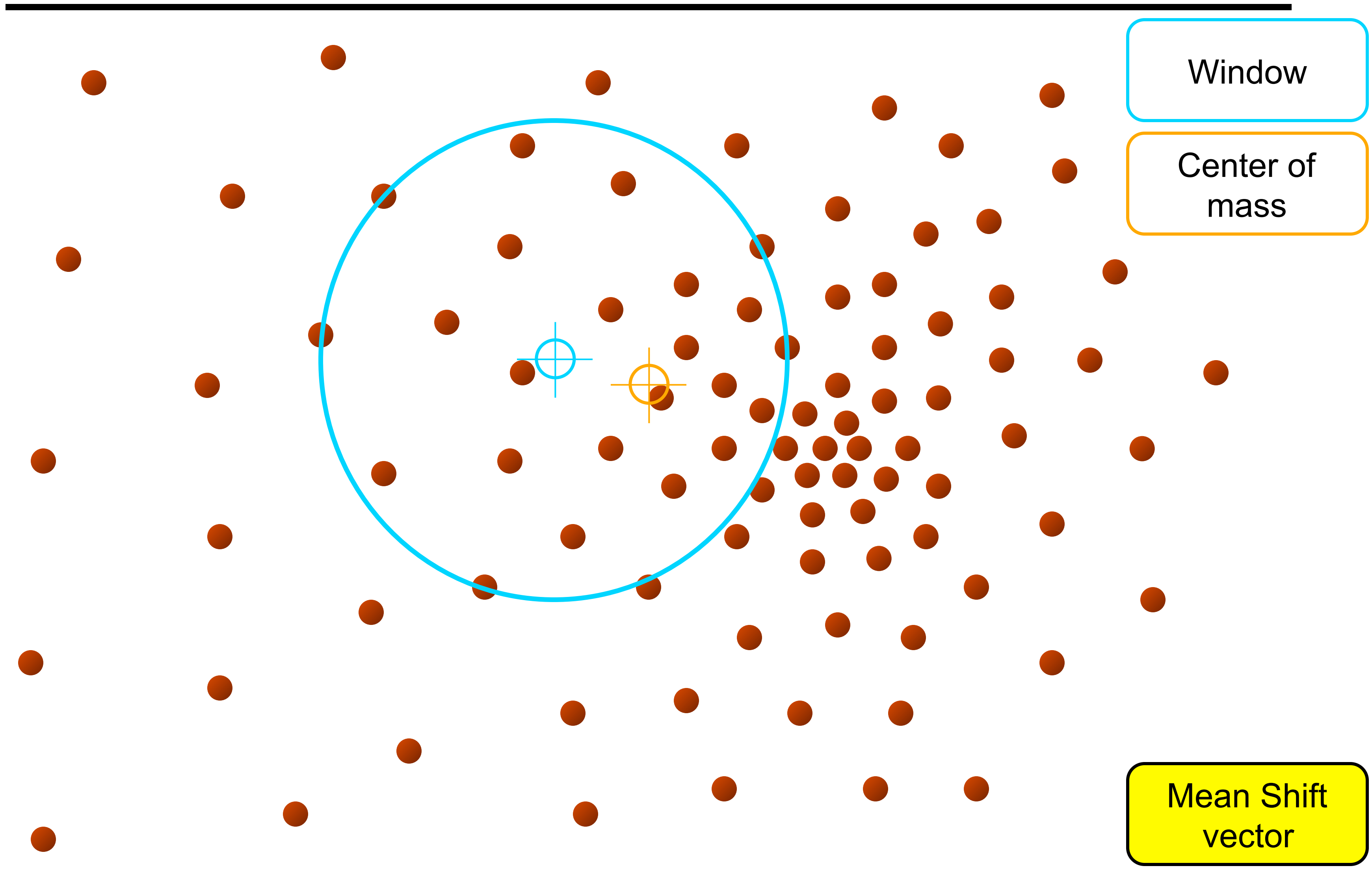


$$m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x)x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$$

$$x \leftarrow m(x)$$



Slide by Y. Ukrainitz & B. Sarel



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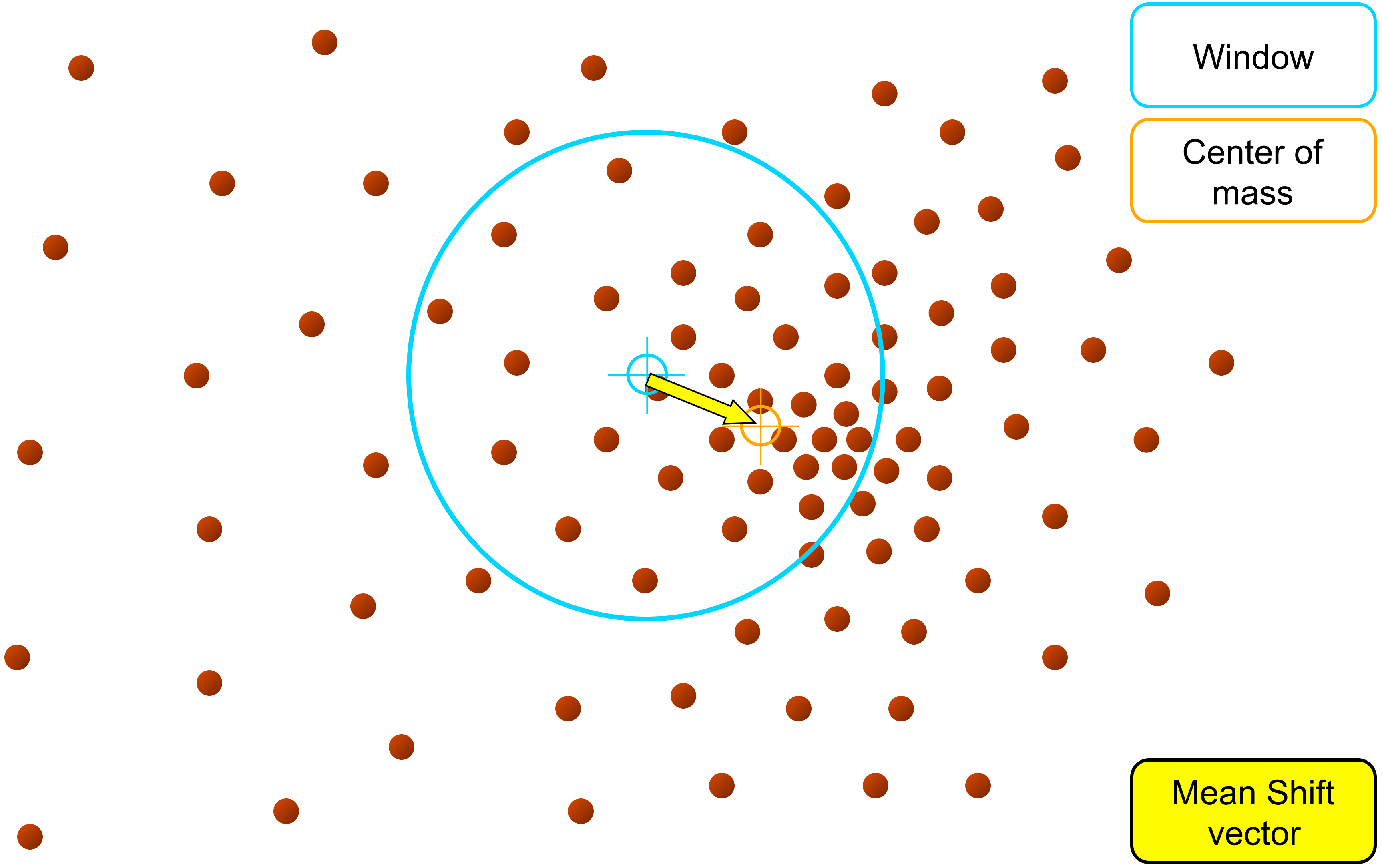

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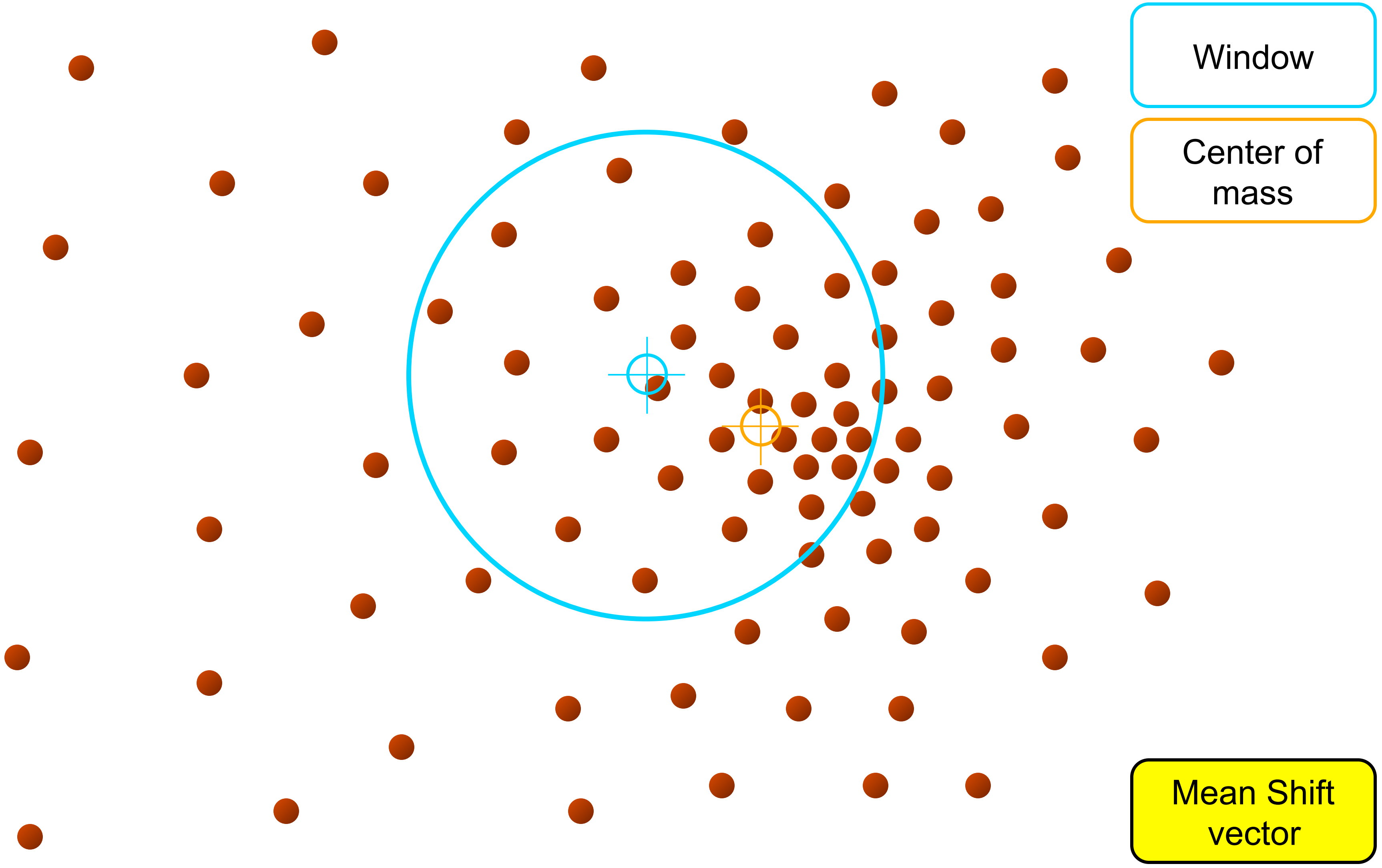

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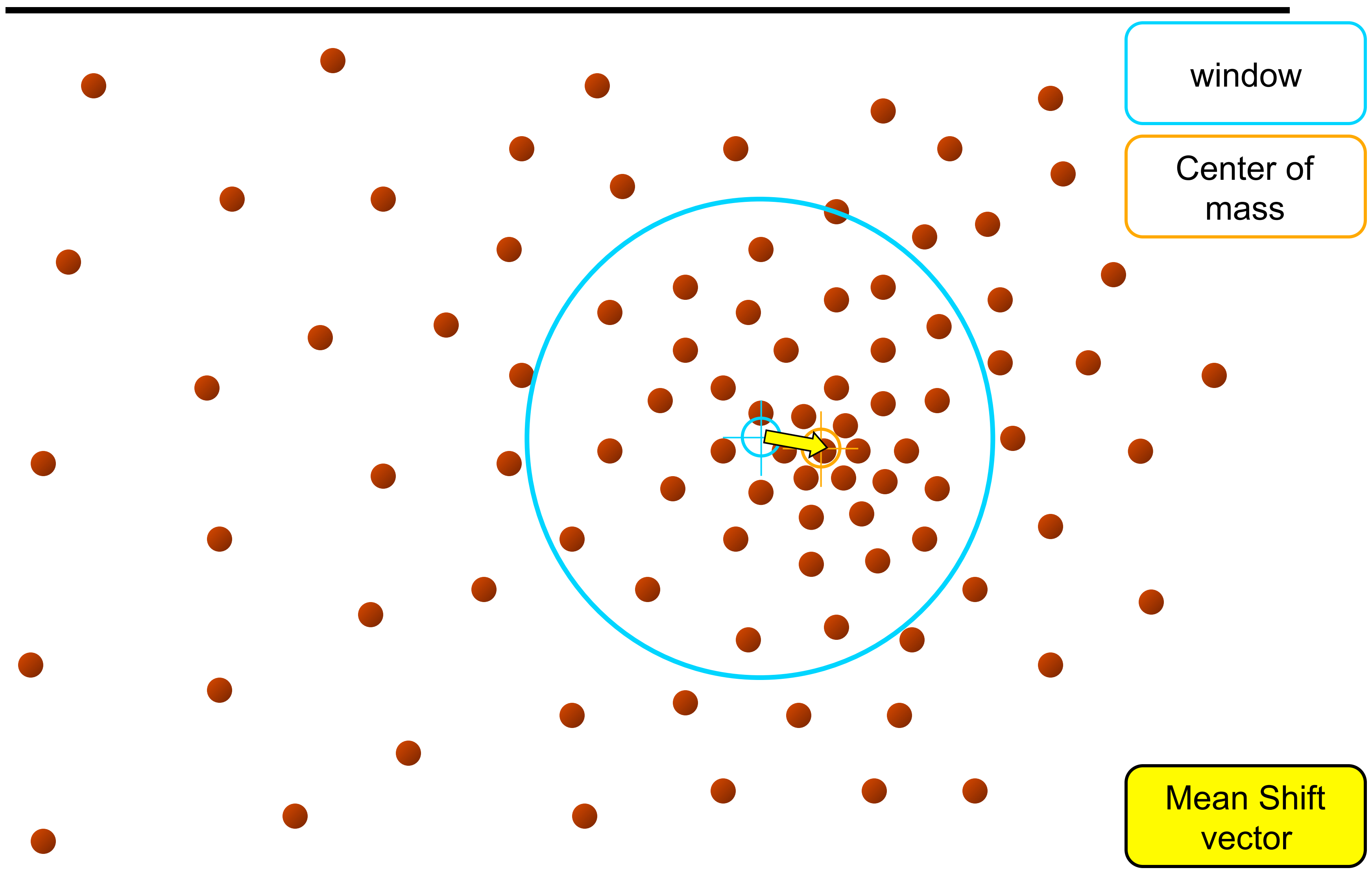

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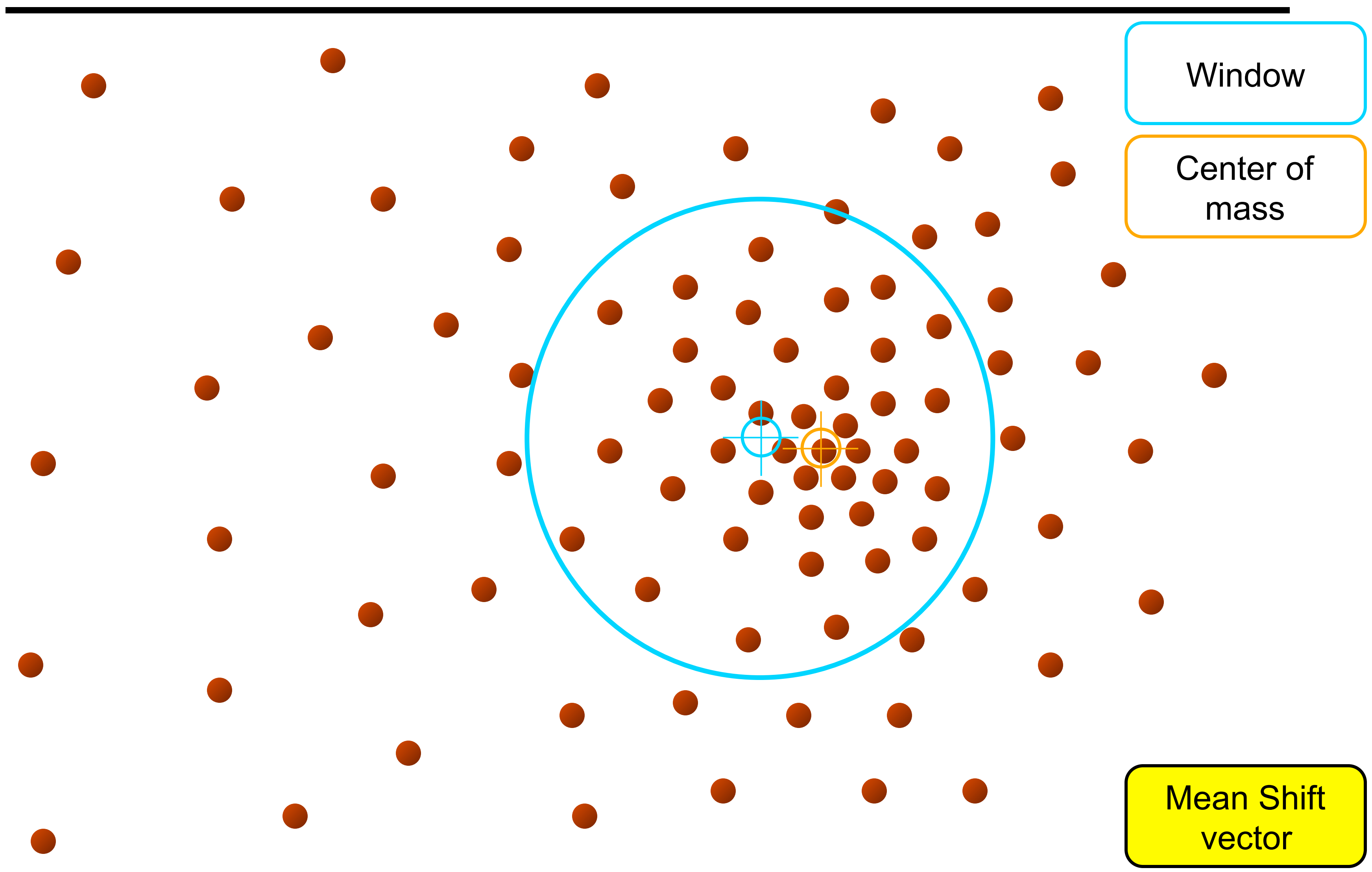

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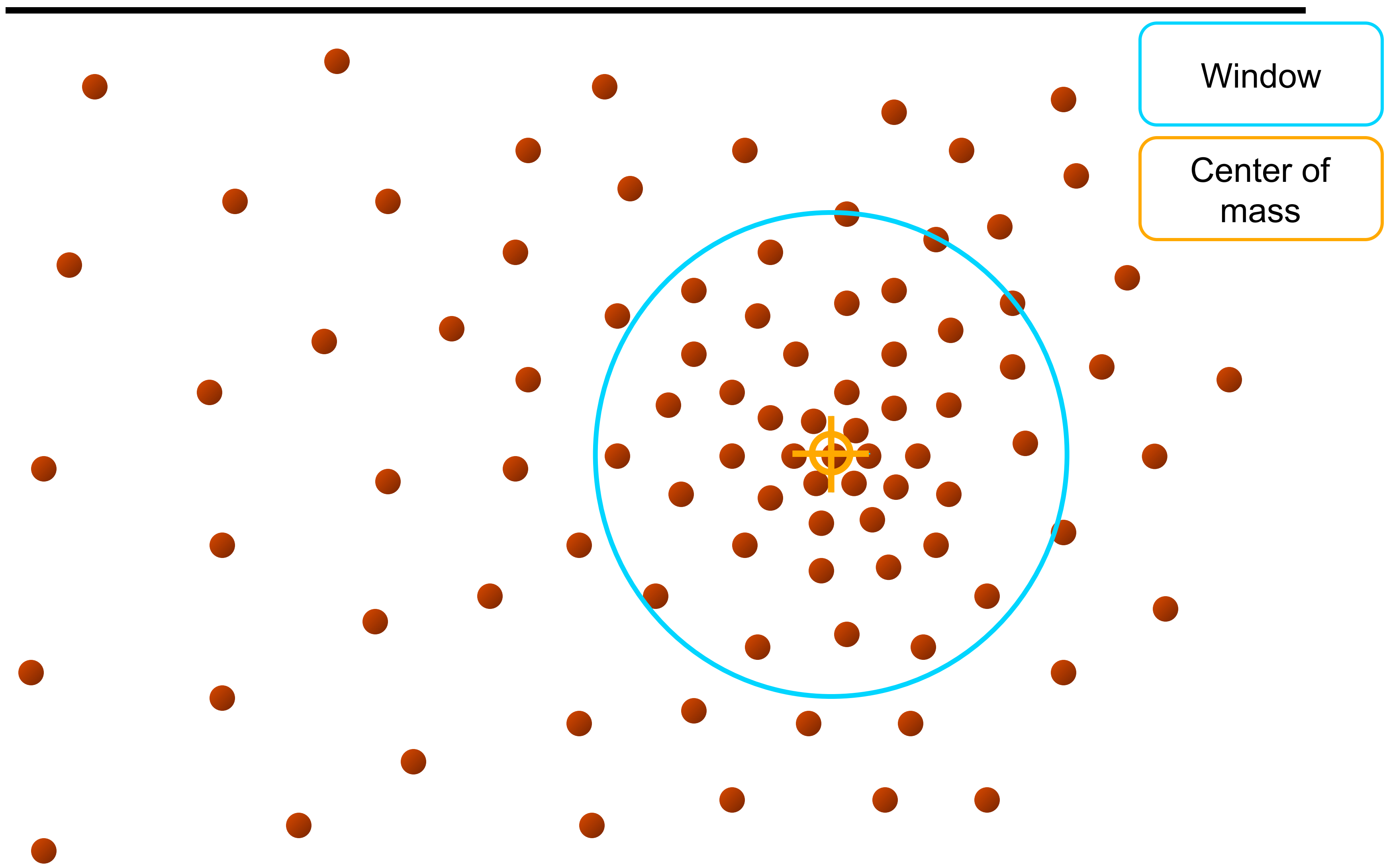

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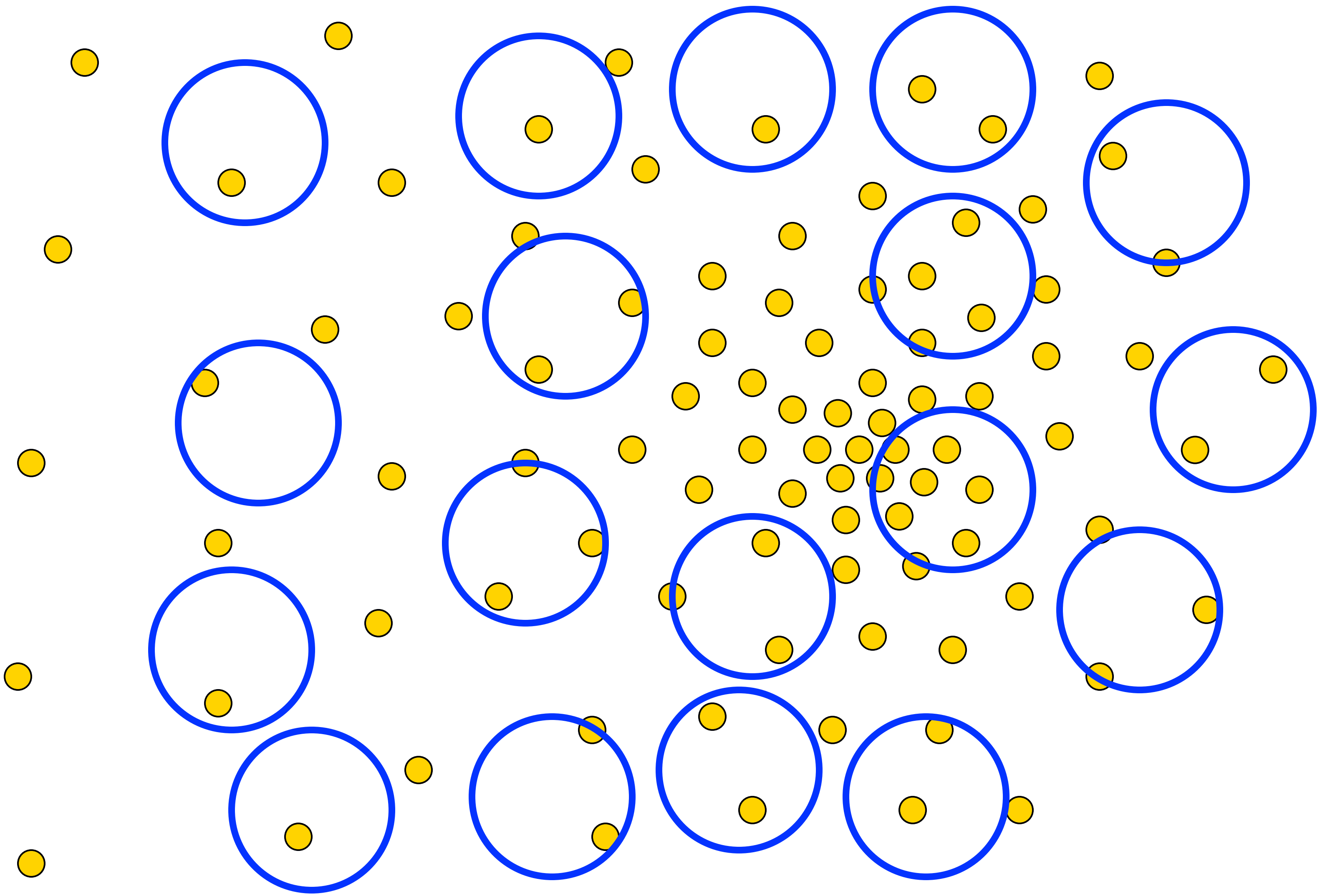
Real Modality Analysis

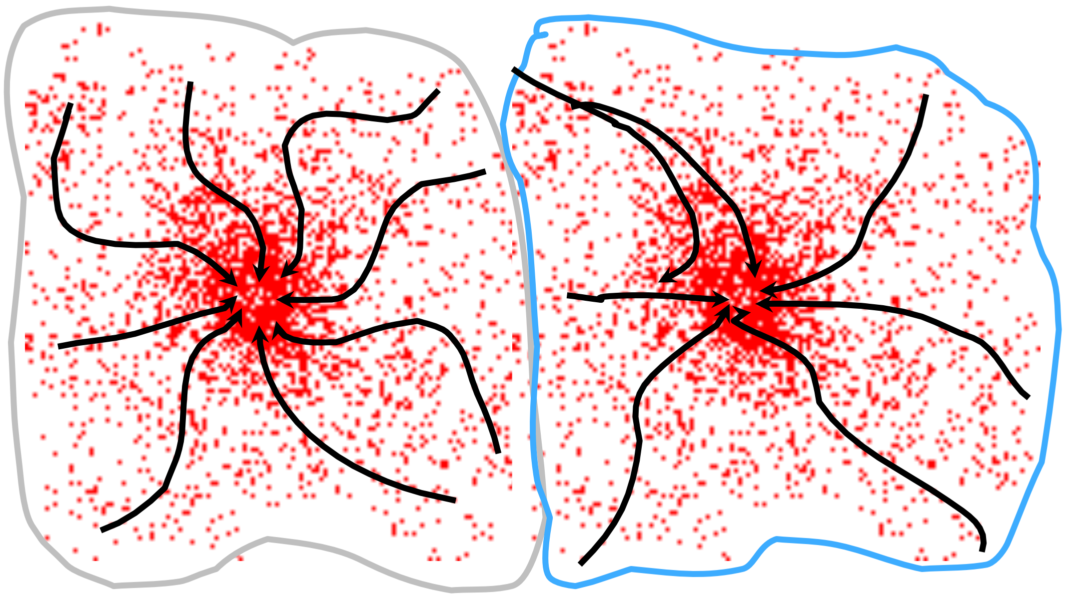


- **Tessellate the space with windows**

- Merge windows that end up near the same “peak” or model

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



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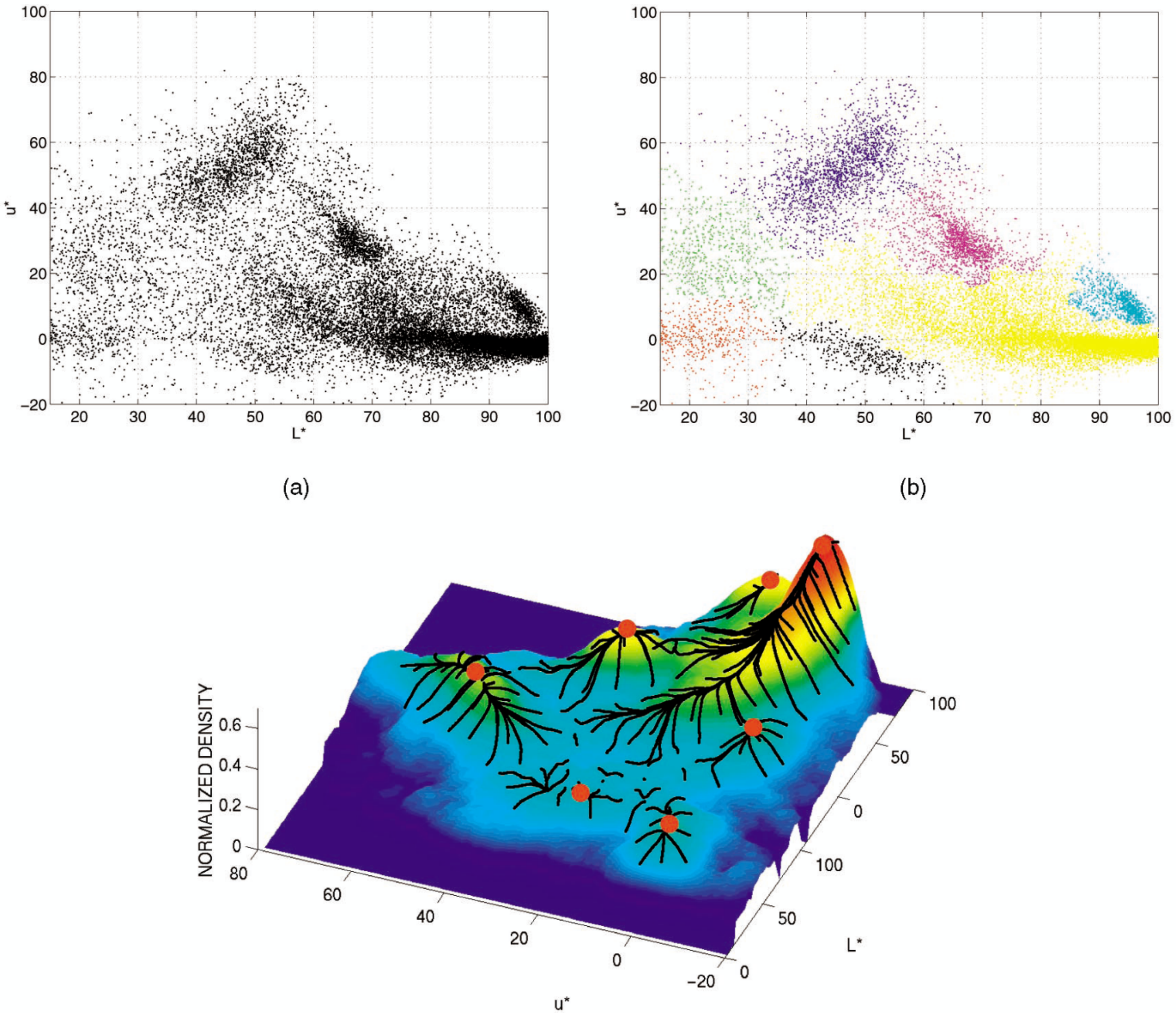

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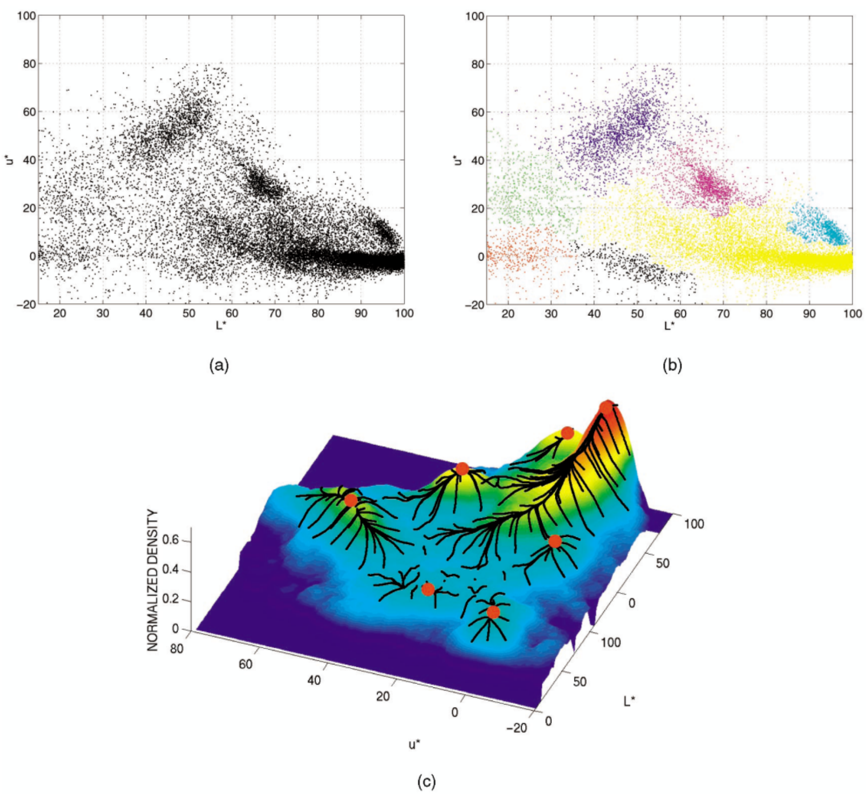
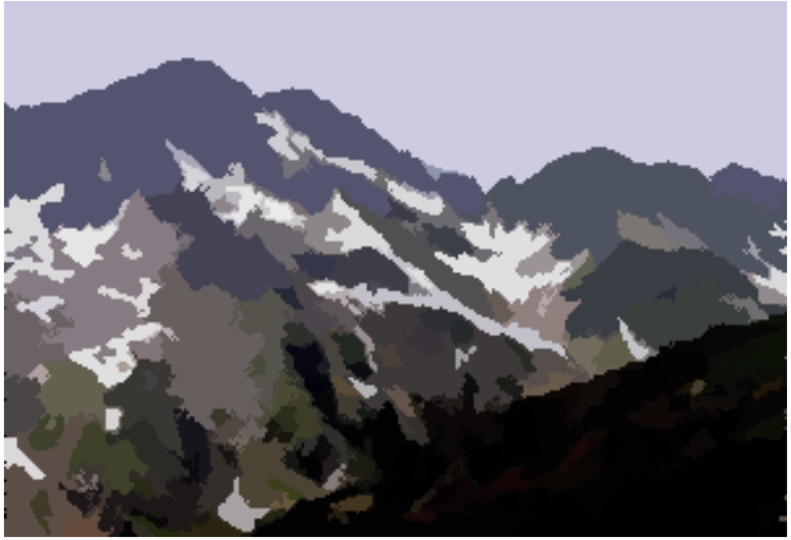
Segmentation by Mean Shift

- Find features (color, gradients, texture, etc)
- Plot points in a joint feature-spatial space, e.g. (u, v, R, G, B)
- Initialize windows at individual pixel locations
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode



Mean shift segmentation results

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

Mean shift pros and cons

- Pros
  - Arbitrary shape of the clusters (not necessarily spherical as in kmeans)
  - Just a small number of parameters
  - Finds variable number of modes
  - Robust to outliers
- Cons
  - Output depends on window size
  - Computationally expensive
  - Does not scale well with dimension of feature space

Lecture 13
Segmentation and Scene understanding

- Introduction
- Mean-shift
- Graph-based segmentation
  - Normalized cut
  - Energy based
- Top-down segmentation

Graph-based segmentation

- Represent features and their relationships using a graph
- Cut the graph to get subgraphs with strong interior links and weaker exterior links
- Cuts correspond to segmentation boundaries

Images as graphs

- Node for every pixel
- Edge between every pair of pixels
- Each edge is weighted by the *affinity* or similarity of the two nodes

Source: S. Seitz

Measuring Affinity

Distance

$$aff(x,y) = \exp\left\{-\left(\frac{1}{2\sigma_d^2}\right)\left(\|x-y\|^2\right)\right\}$$

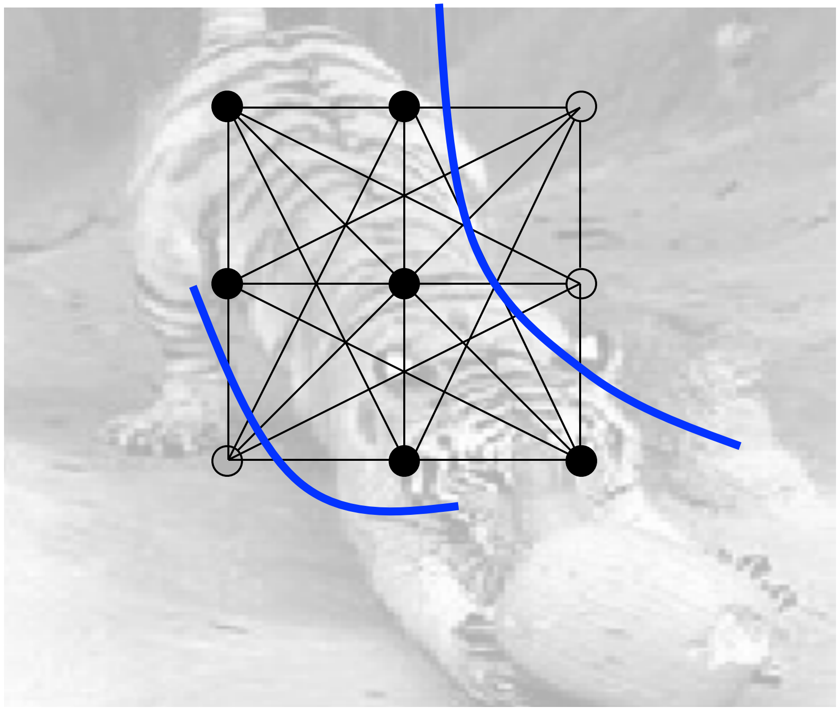
Intensity

$$aff(x,y) = \exp\left\{-\left(\frac{1}{2\sigma_i^2}\right)\left(\|I(x)-I(y)\|^2\right)\right\}$$

Color

$$aff(x,y) = \exp\left\{-\left(\frac{1}{2\sigma_t^2}\right)\left(\|c(x)-c(y)\|^2\right)\right\}$$

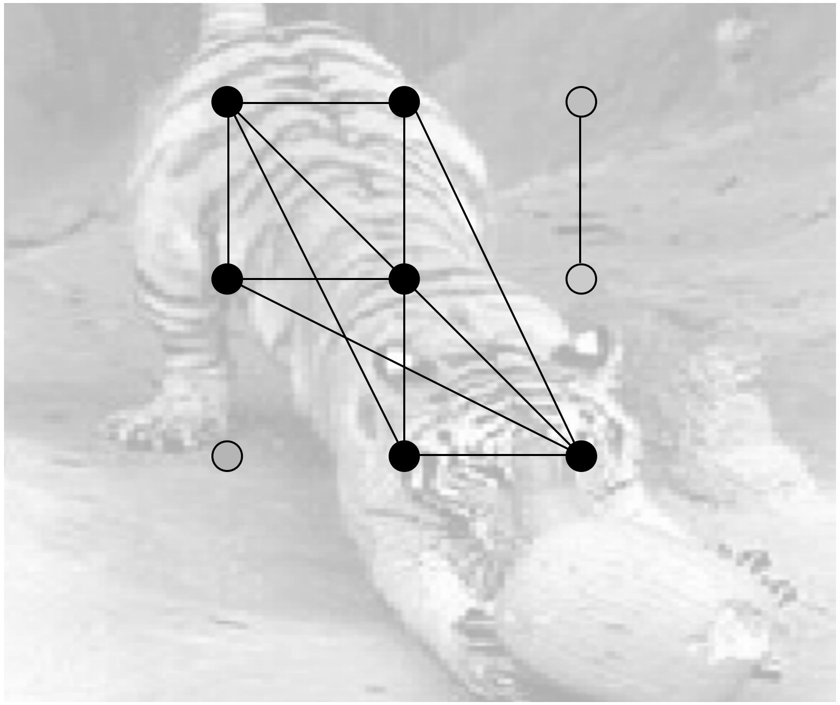
Segmentation by graph partitioning



- Break Graph into sub-graphs
  - Break links (cutting) that have low affinity
    - similar pixels should be in the same sub-graphs
    - dissimilar pixels should be in different sub-graphs

•Sub-graphs represents different image segments

Segmentation by graph partitioning



- Break Graph into sub-graphs
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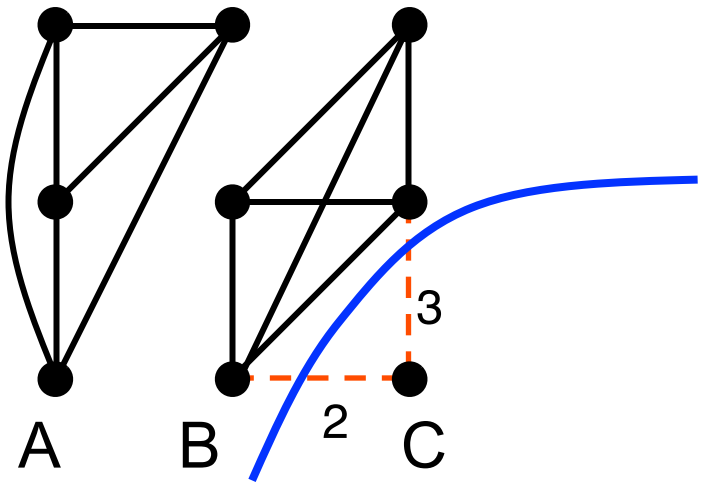
- Sub-graphs represents different image segments
- Graph-cut: technique to cut a graph optimally

Segmentation by graph partitioning

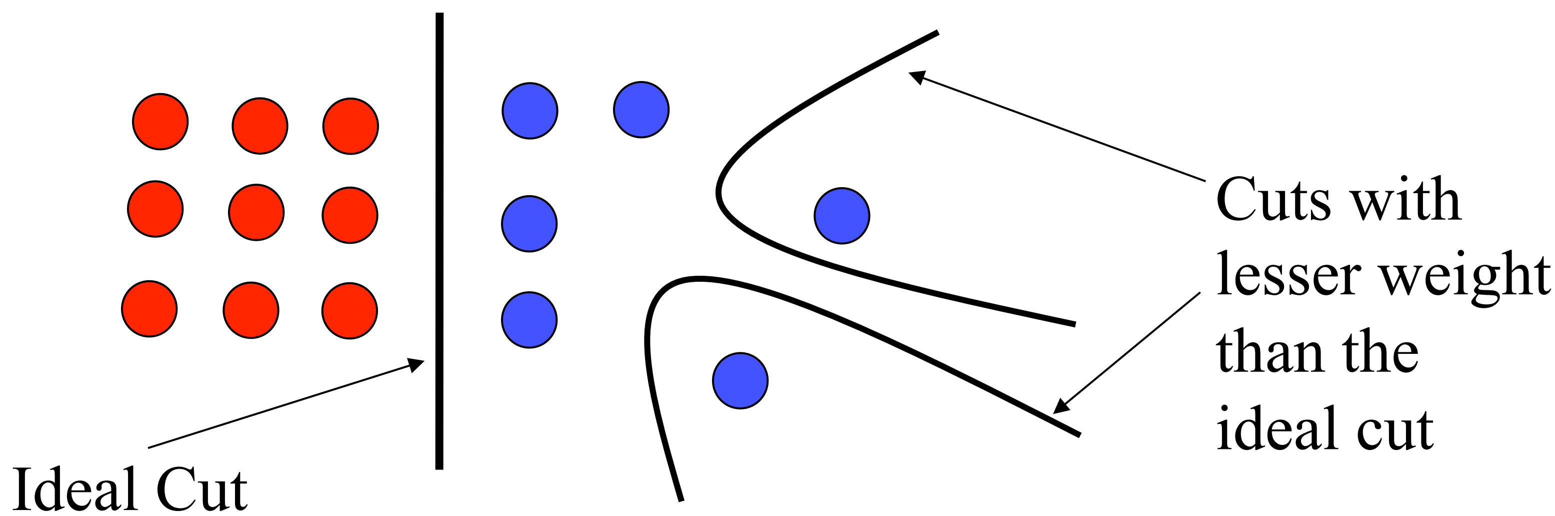


- CUT: Set of edges whose removal makes a graph disconnected
- Cost of a cut: sum of weights of cut edges
- Example: Cost of the blue cut?

Source: S. Seitz

Minimum cut

- We can do segmentation by finding the *minimum cut* in a graph (i.e. cut associated with the min cost)
  - Efficient algorithms exist for doing this
- Drawback: minimum cut tends to cut off very small, isolated components



* Slide from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Normalized cut

J. Shi and J. Malik. Normalized cuts and image segmentation. PAMI 2000

IDEA: normalizing the cut by component size

The *normalized cut* cost is:

$$\frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)}$$

assoc(*A*, *V*) = sum of weights of all edges in V that touch A

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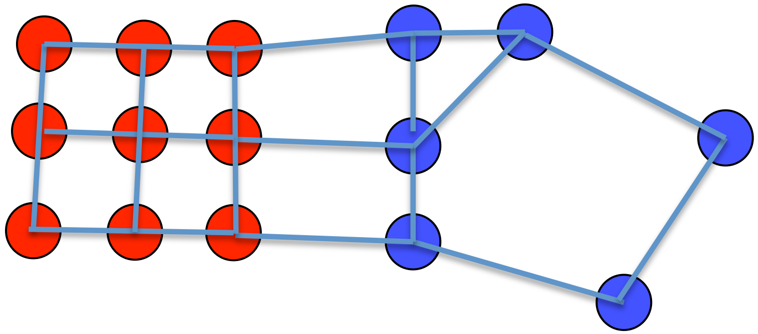

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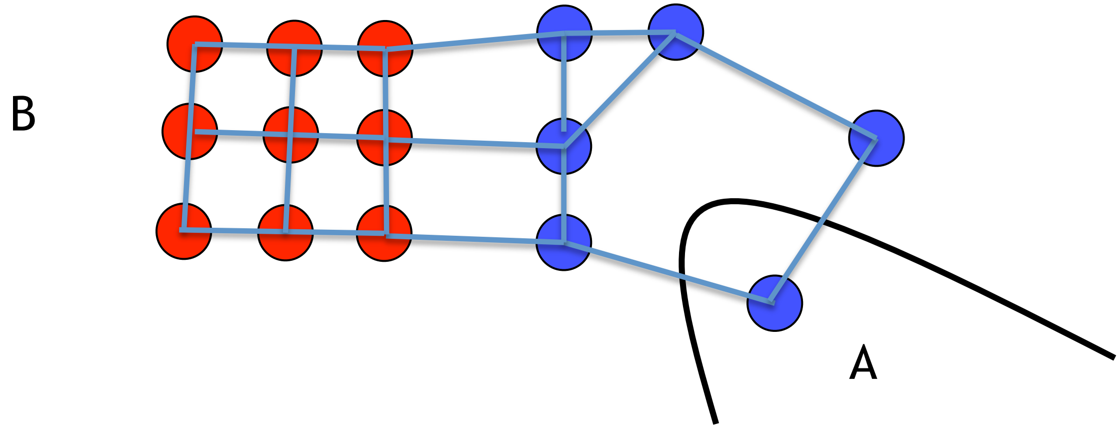

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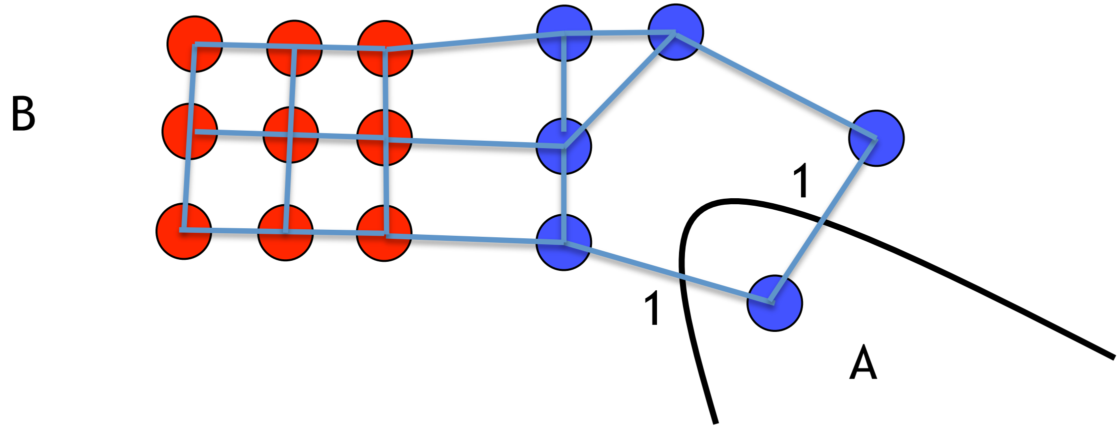

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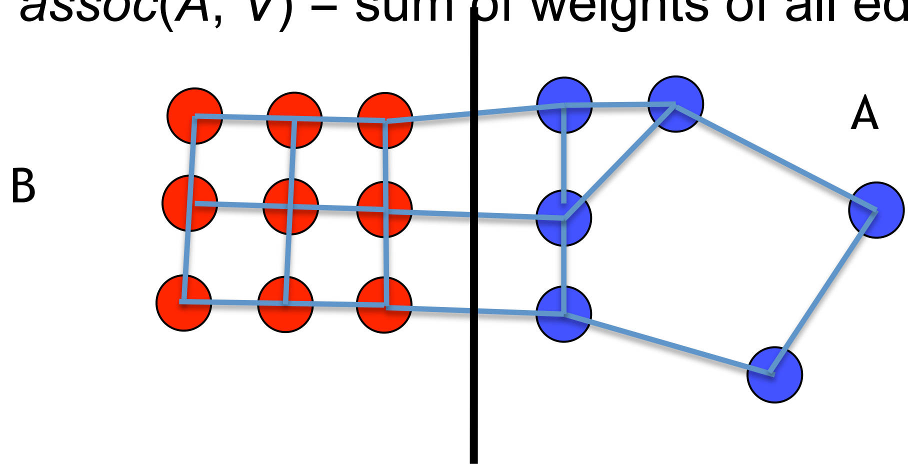

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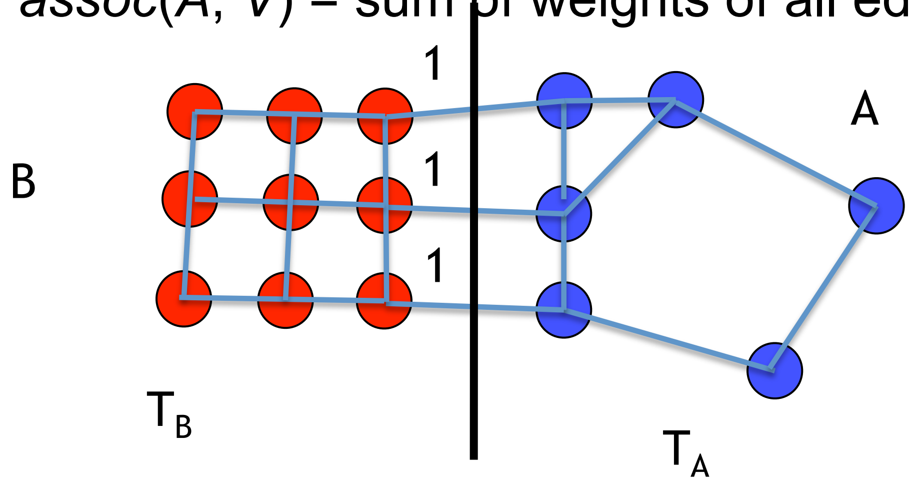

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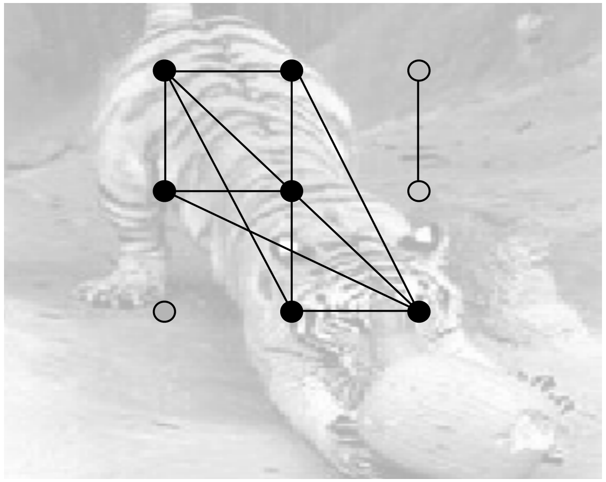
Normalized Cuts

$$G = (V, E, W)$$



$$k = \frac{\sum_{x_i > 0} D_{i,i}}{\sum_i D_{i,i}}$$

$$b = \frac{k}{1-k}$$

$$\min_x \text{ncut}(x, W, D) = \min_y \frac{y^T(W-D)y}{y^T D y}$$

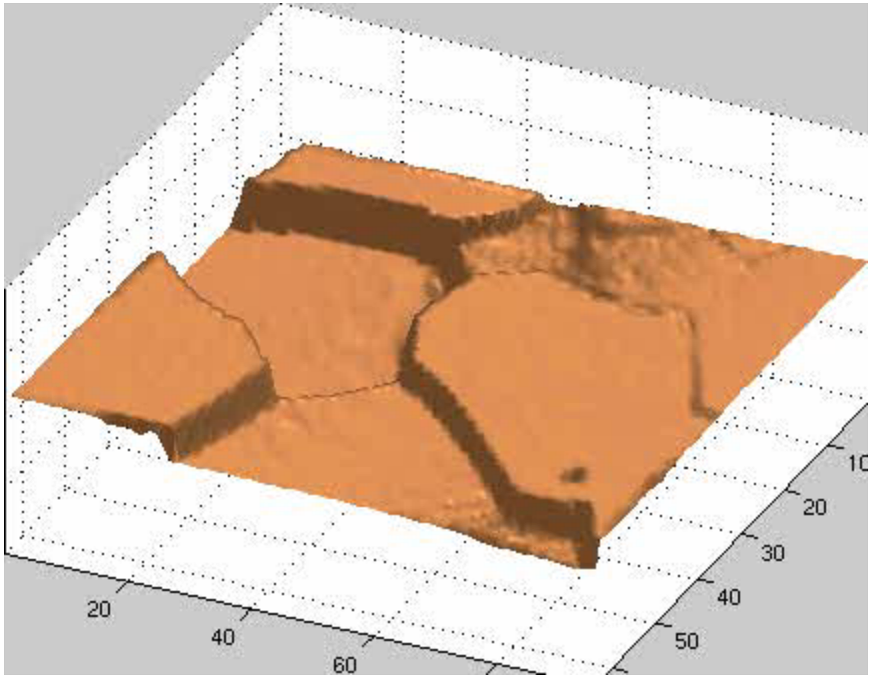
$$y = (1+x) - b(1-x)$$

$$y_i \in \{1, -b\}, \ \ y^T D1 = 0.$$

$$y^T D1 = 0 \text{ and } y^T D y = b1^T D1$$

$$(D - W)y = \lambda D y$$

Interpretation as a Dynamical System

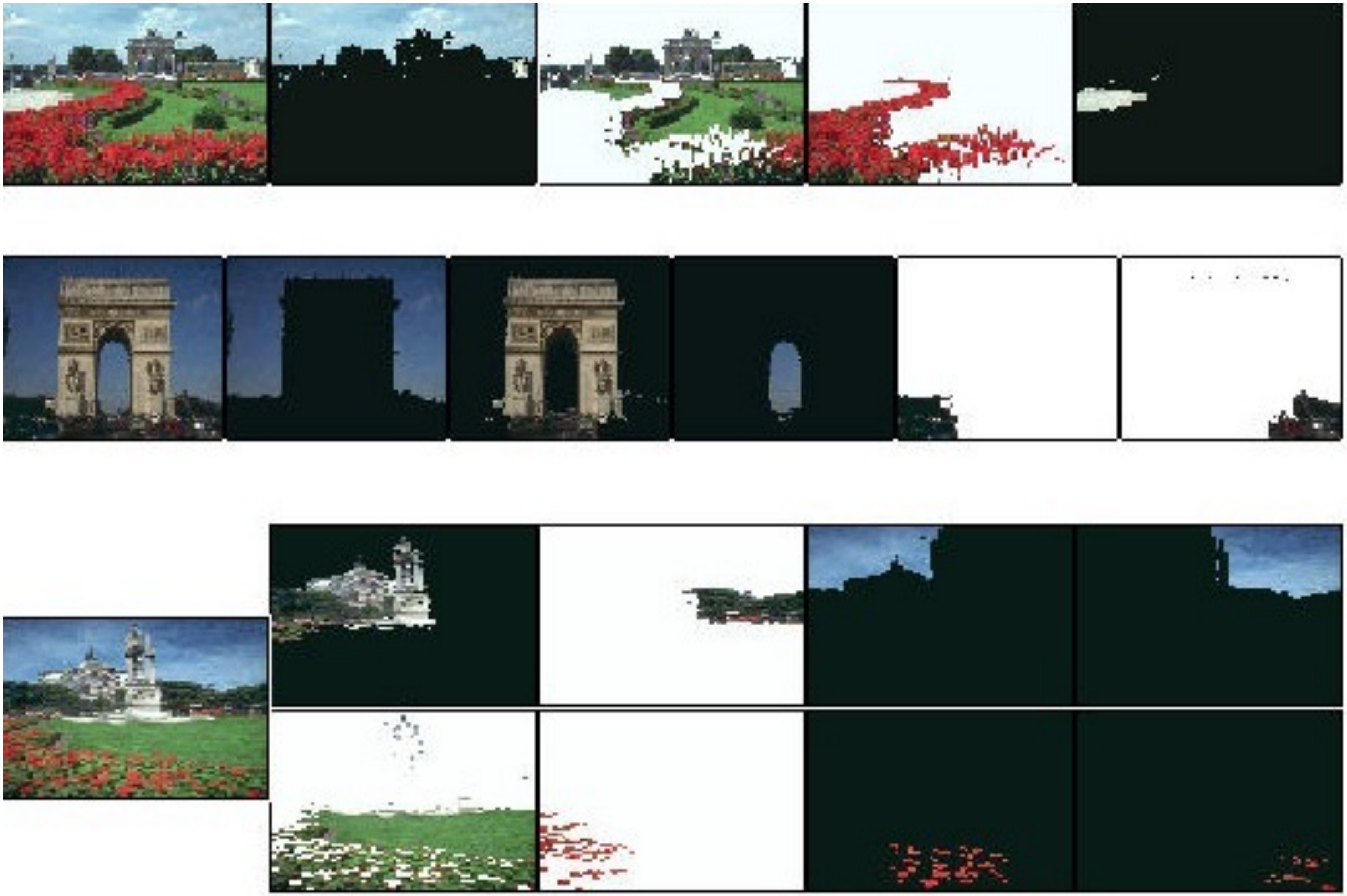


Treat the links as springs and shake the system

- elasticity proportional to cost
- vibration "modes" correspond to segments
  - can compute these by solving an eigenvector problem
  - http://www.cis.upenn.edu/~jshi/papers/pami_ncut.pdf

Courtesy of Noah Snavely

Color Image Segmentation



Normalized cuts: Pro and con

- Pros
  - Generic framework, can be used with many different features and affinity formulations
- Cons
  - High storage requirement and time complexity
  - Bias towards partitioning into equal segments

* Slide from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Lecture 13
Segmentation and Scene understanding

- Introduction
- Mean-shift
- Graph-based segmentation
  - Graph cut
  - Energy based
- Top-down segmentation

Binary segmentation as energy minimization

- Suppose we want to segment an image into foreground and background

User sketches out a few strokes on

foreground and background…

How do we classify the rest of the pixels?

Courtesy of Noah Snavely

Binary segmentation as energy minimization

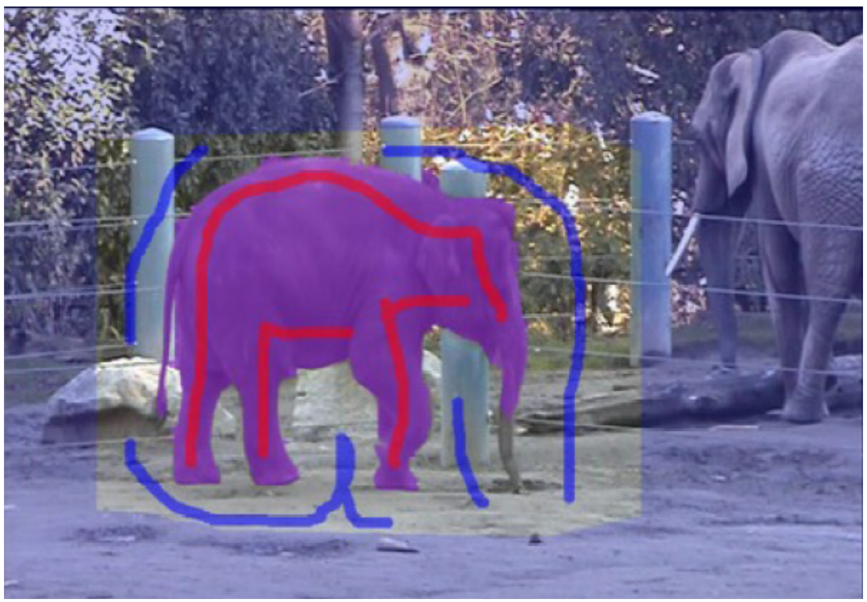
- Define a labeling *L* as an assignment of each pixel with a 0-1 label (background or foreground)
- Problem statement: find the labeling *L* that minimizes

$$E(L) = \underbrace{E_d(L)}_{\text{match cost}} + \lambda \underbrace{E_s(L)}_{\text{smoothness cost}}$$

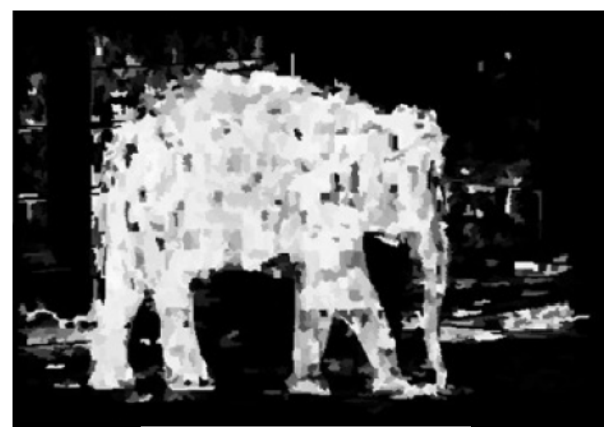
(“how similar is each pixel to the foreground / background?”)

Courtesy of Noah Snavely

$$E(L) = E_d(L) + \lambda E_s(L)$$



$C'(x, y, 0)$



$C'(x, y, 1)$

Courtesy of Noah Snavely

GrabCut

Grabcut [Rother et al., SIGGRAPH 2004]

Courtesy of Noah Snavely

Lecture 13
Segmentation and Scene understanding

- Introduction
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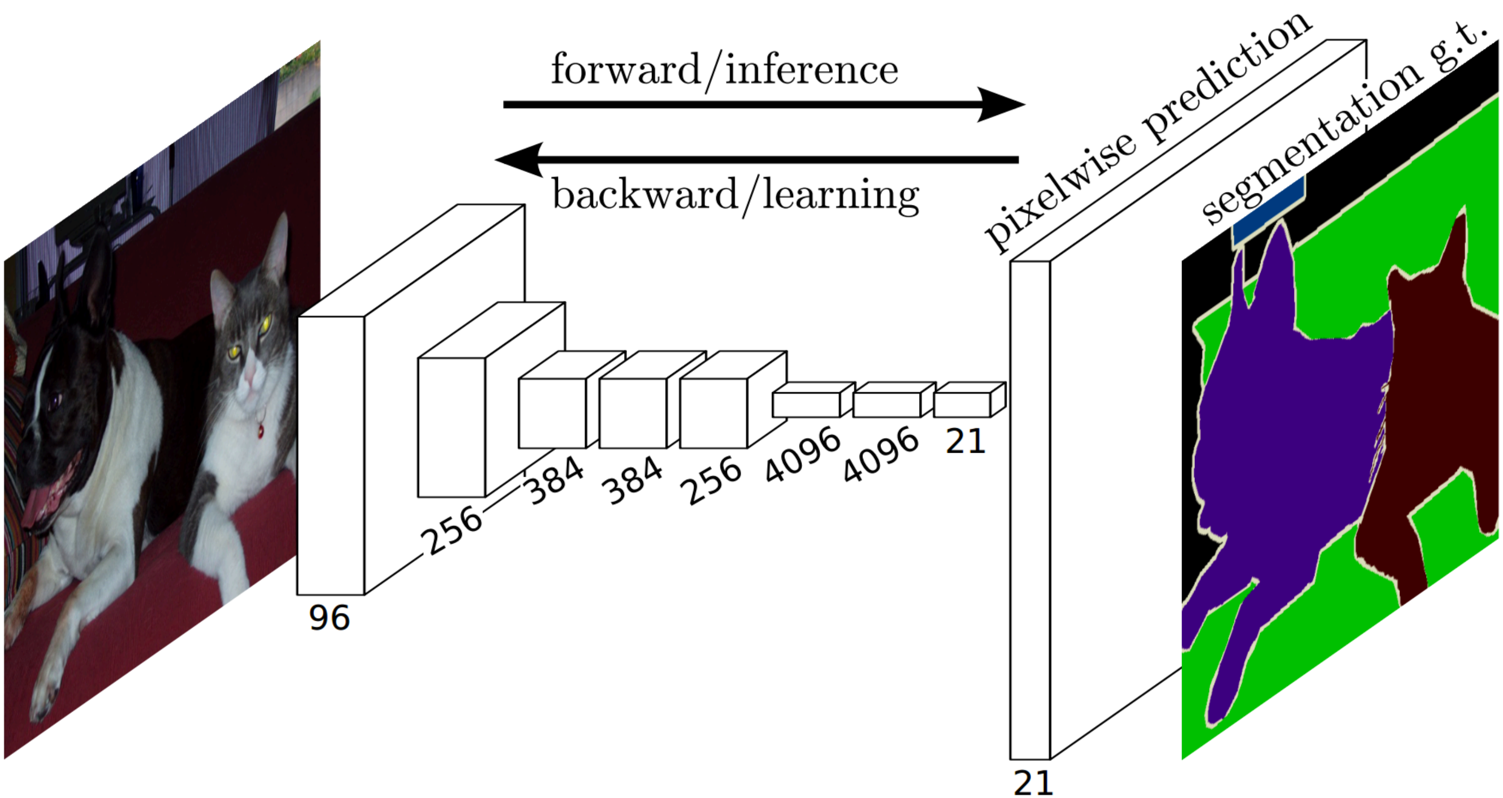
- Top-down segmentation

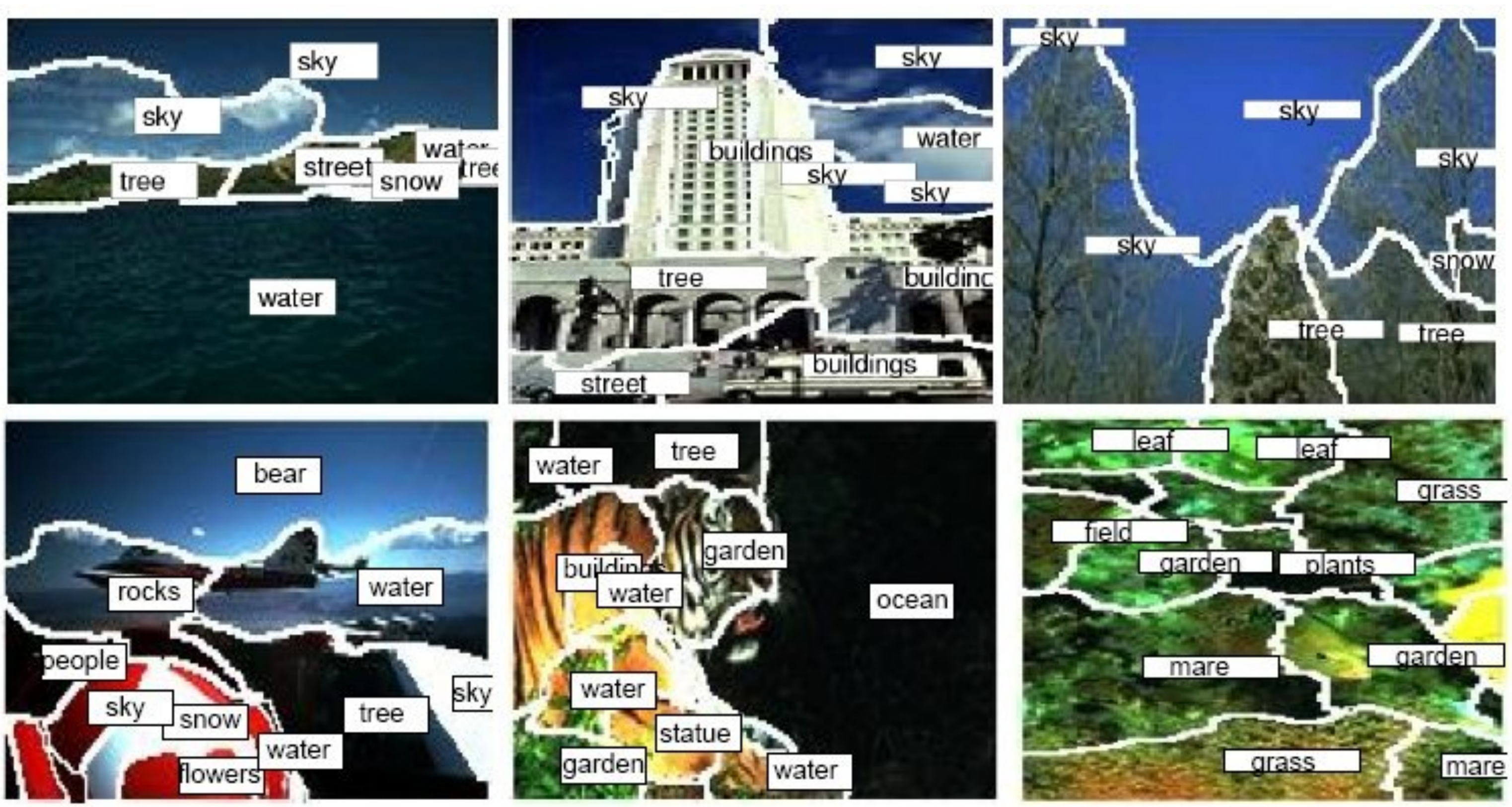
Semantic segmentation



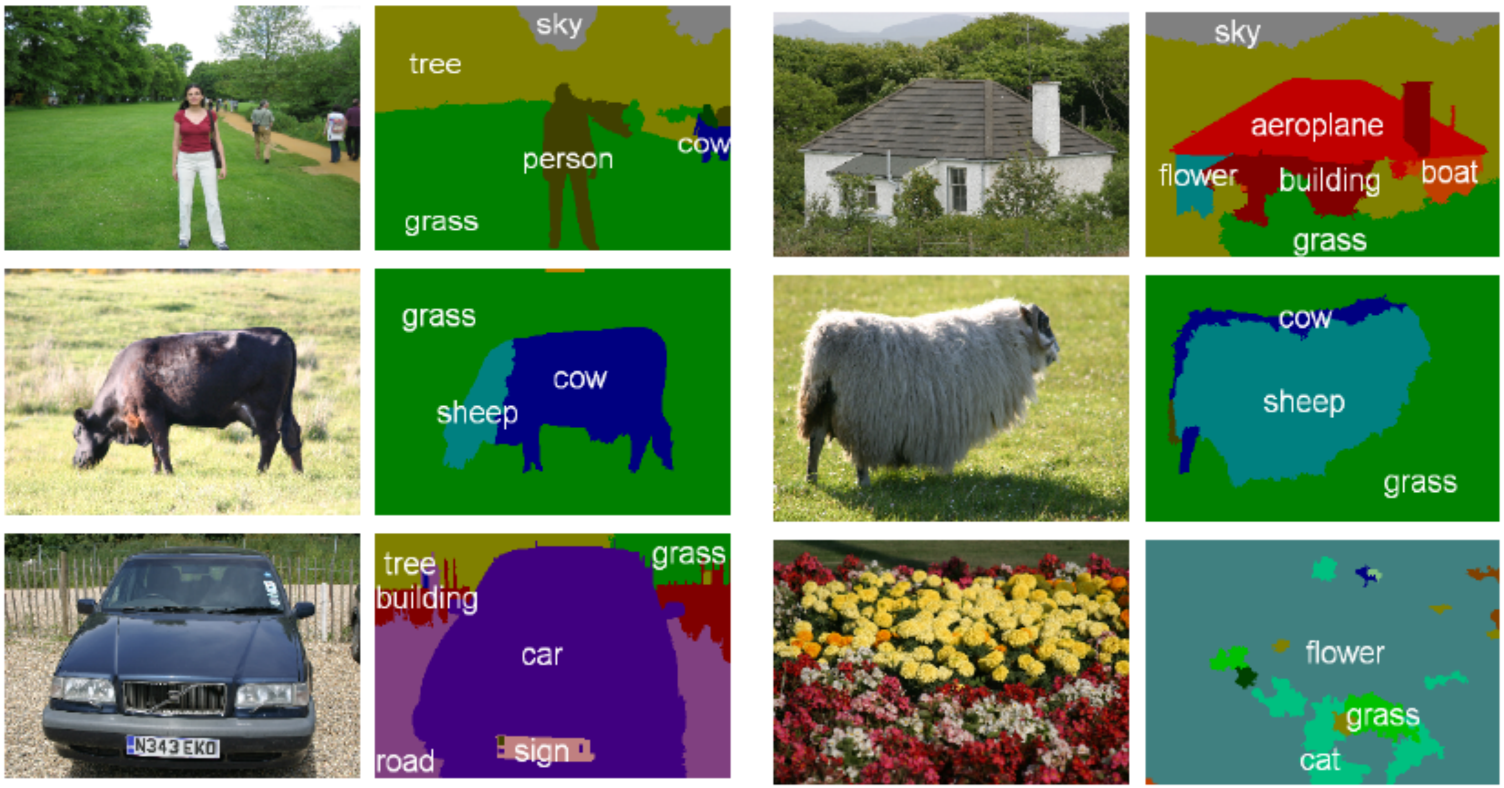
Long, Shelhamer, Darrel (Arxiv)

Semantic segmentation

Object Recognition as Machine Translation, Duygulu, Barnard, **de Freitas**, Forsyth, ECCV02



Semantic segmentation



Ladický, Russell, Kohli, Torr ICCV09