Outline

- What are grouping problems in vision?
- Inspiration from human perception
  – Gestalt properties
- Bottom-up segmentation via clustering
  – Algorithms:
    - Mode finding and mean shift: k-means, mean-shift
    - Graph-based: normalized cuts
  – Features: color, texture, …
    - Quantization for texture summaries

Grouping in vision

- Goals:
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image or video parts

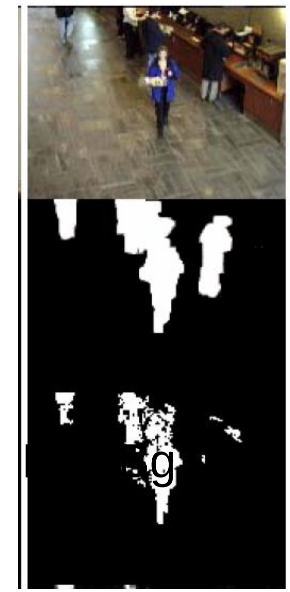
Examples of grouping in vision

[Figure by J. Shi]

Determine image regions

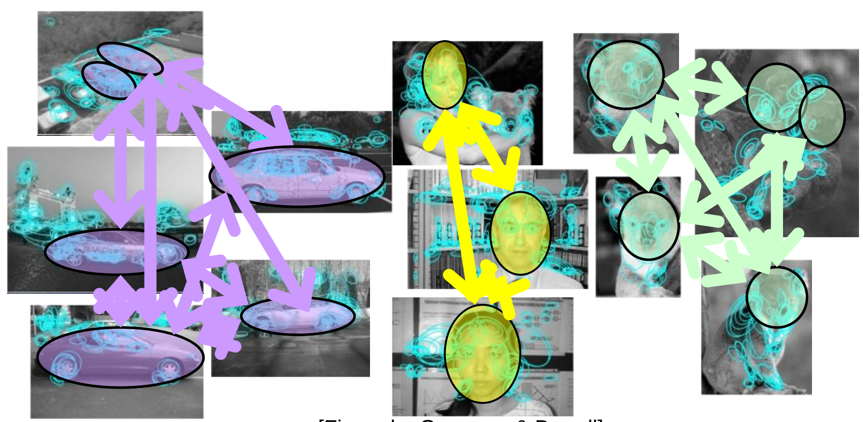
[http://poseidon.csd.auth.gr/LAB_RESEARCH/Latest/imgs/SpeakDepVidIndex_img2.jpg]

Group video frames into shots



[Figure by Wang & Suter]

Figure-ground



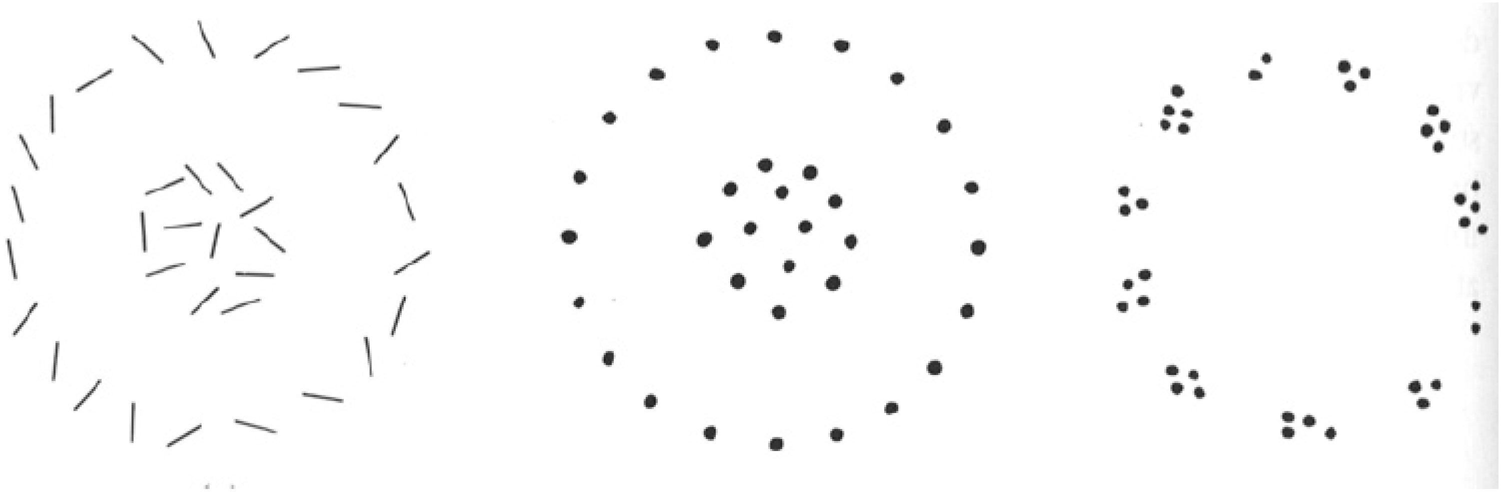
[Figure by Grauman & Darrell]

Object-level grouping

Slide credit: Kristen Grauman

Grouping in vision

- Goals:
  - Gather features that belong together
  - Obtain an intermediate representation that compactly describes key image (video) parts
- Top down vs. bottom up segmentation
  - Top down: pixels belong together because they are from the same object
  - Bottom up: pixels belong together because they look similar
- Hard to measure success
  - What is interesting depends on the app.



What are meta-cues for grouping?

A Few General Principles

Gestalt

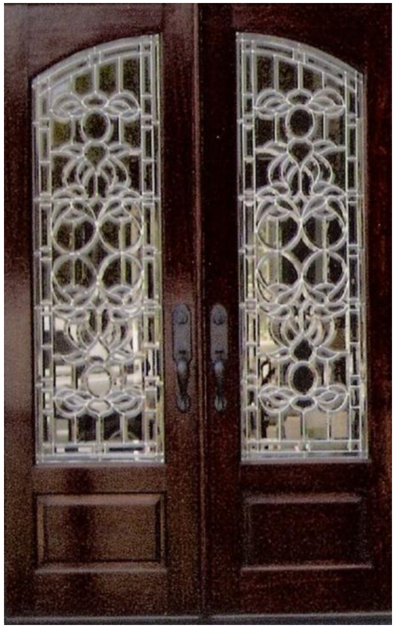
- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)

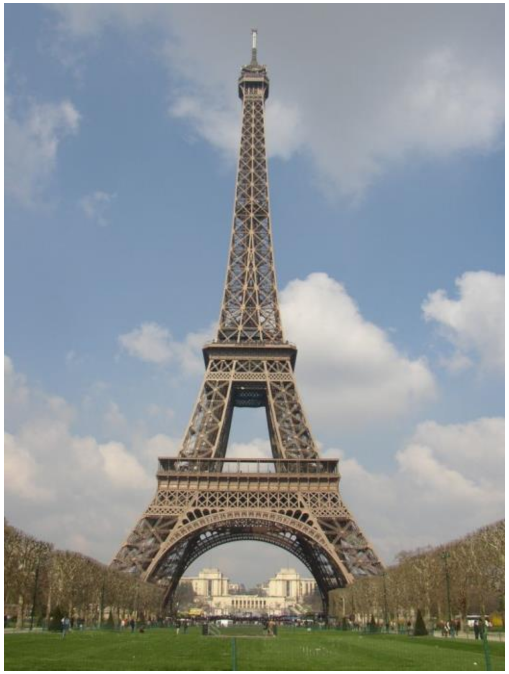
Similarity

Slide credit: Kristen Grauman

http://chicagoist.com/attachments/chicagoist_alicia/GEESE.jpg, http://wwwdelivery.superstock.com/WI/223/1532/PreviewComp/SuperStock_1532R-0831.jpg

Symmetry





Slide credit: Kristen Grauman

http://seedmagazine.com/news/2006/10/beauty_is_in_the_processingtim.php

Common fate

Image credit: Arthus-Bertrand (via F. Durand)

Proximity

Slide credit: Kristen Grauman

http://www.capital.edu/Resources/Images/outside6_035.jpg

Gestalt

- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)
- Inspiring observations/explanations; challenge remains how to best map to algorithms.

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The goals of segmentation

Separate image into coherent "objects"

image human segmentation

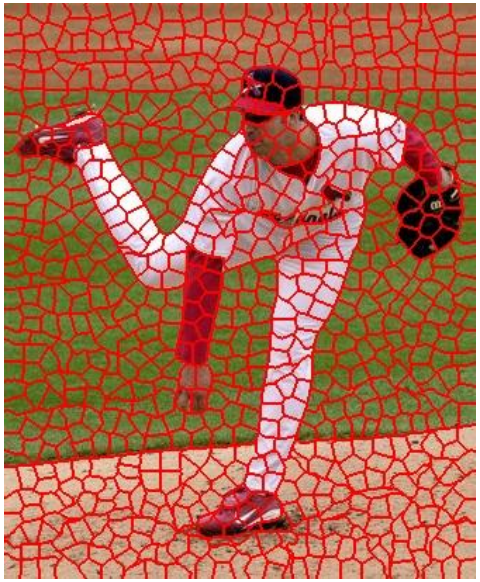
Source: Lana Lazebnik

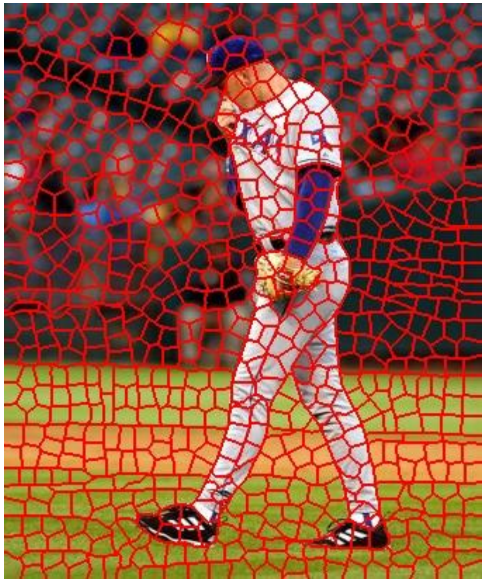
The goals of segmentation

Separate image into coherent “objects”

Group together similar-looking pixels for efficiency of further processing

“superpixels”





X. Ren and J. Malik. **Learning a classification model for segmentation.** ICCV 2003.

Source: Lana Lazebnik

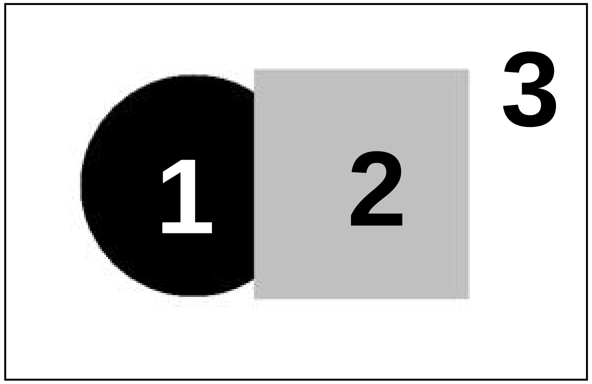
Clustering

- Clustering algorithms:
  - Unsupervised learning
  - Detect patterns in unlabeled data
    - E.g. group emails or search results
    - E.g. find categories of customers
    - E.g. group pixels into regions

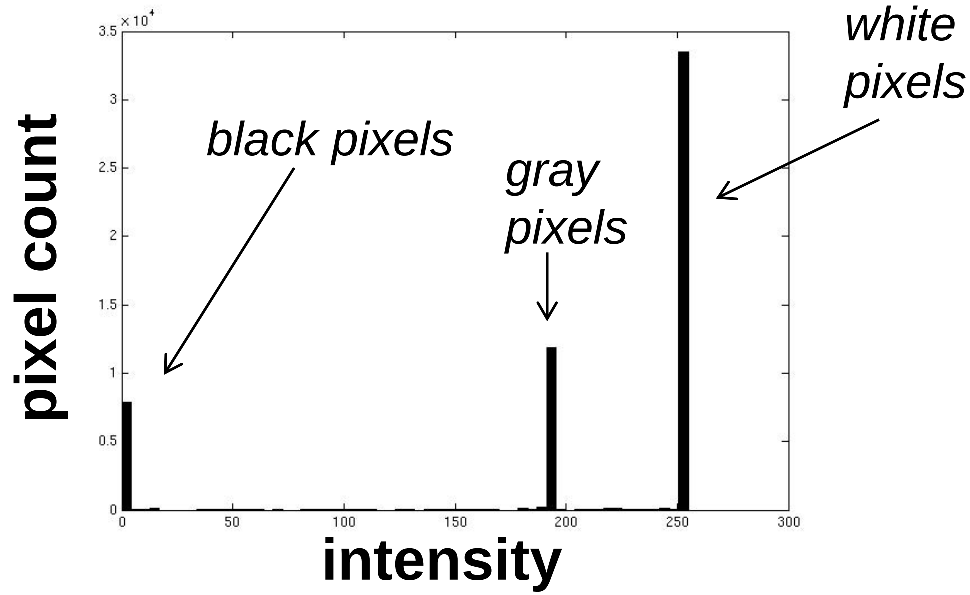
  - Useful when don’t know what you’re looking for
  - Requires data, but no labels

Slide credit: Dan Klein

Image segmentation: toy example

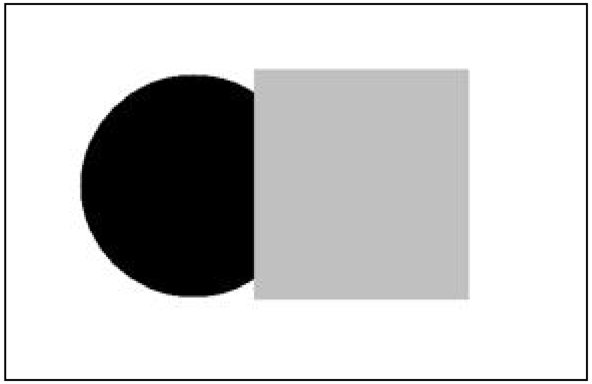


input image

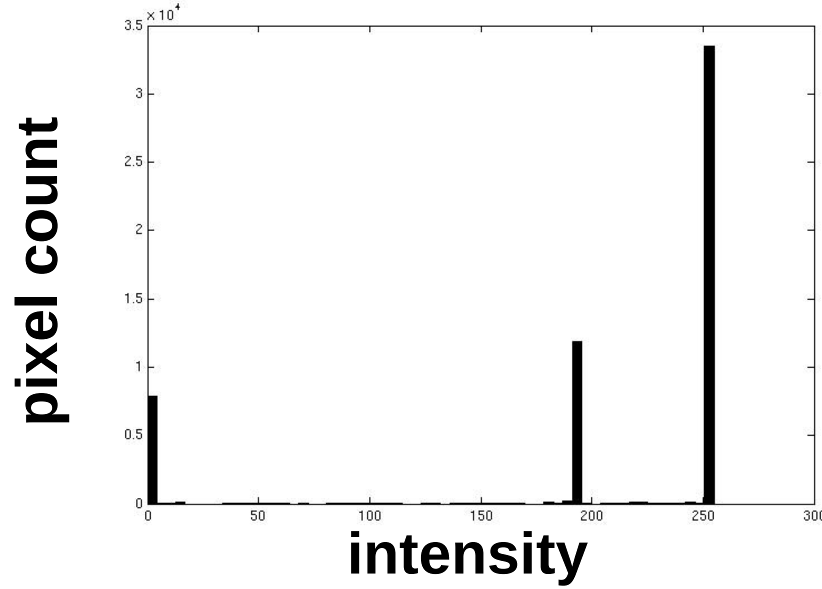


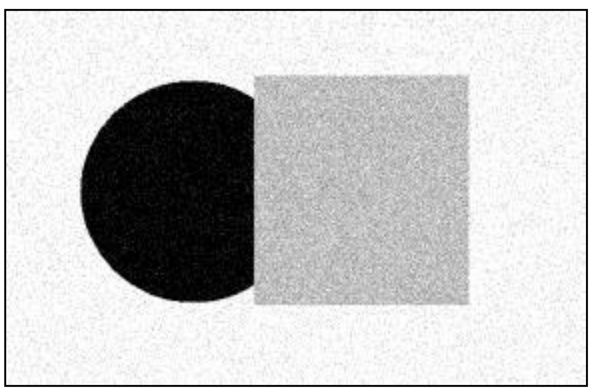
- These intensities define the three groups.
- We could label every pixel in the image according to which of these primary intensities it is.
  - i.e., *segment* the image based on the intensity feature.
- What if the image isn't quite so simple?

Slide credit: Kristen Grauman

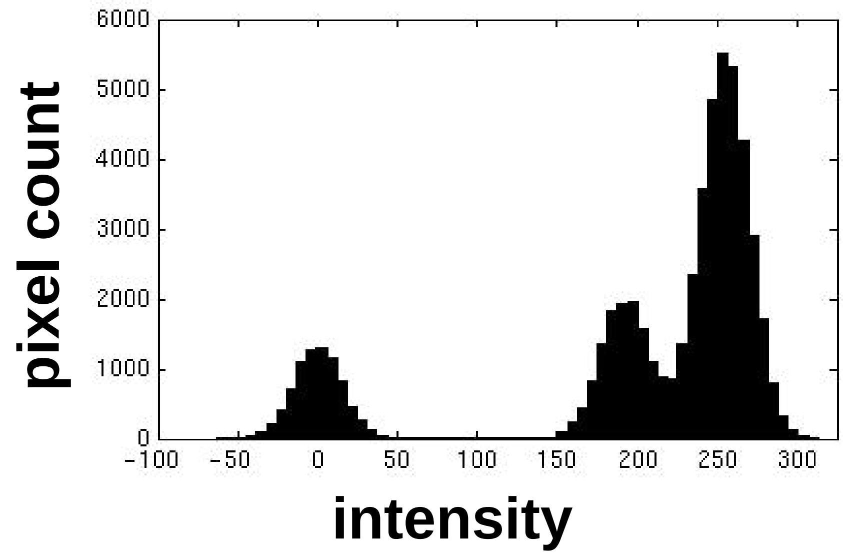


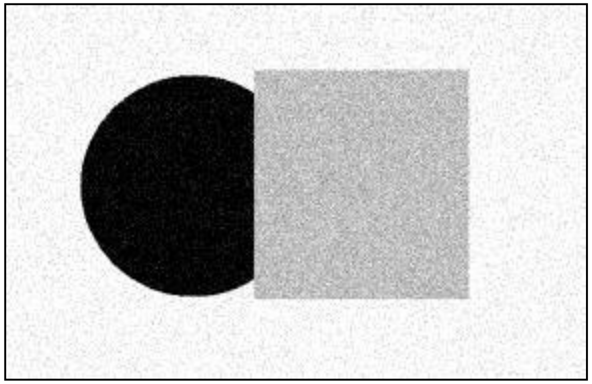
input image



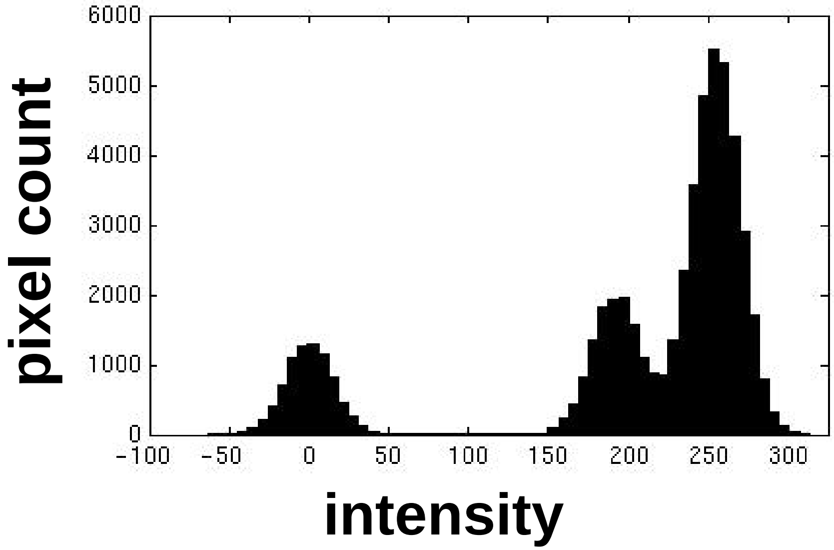


input image



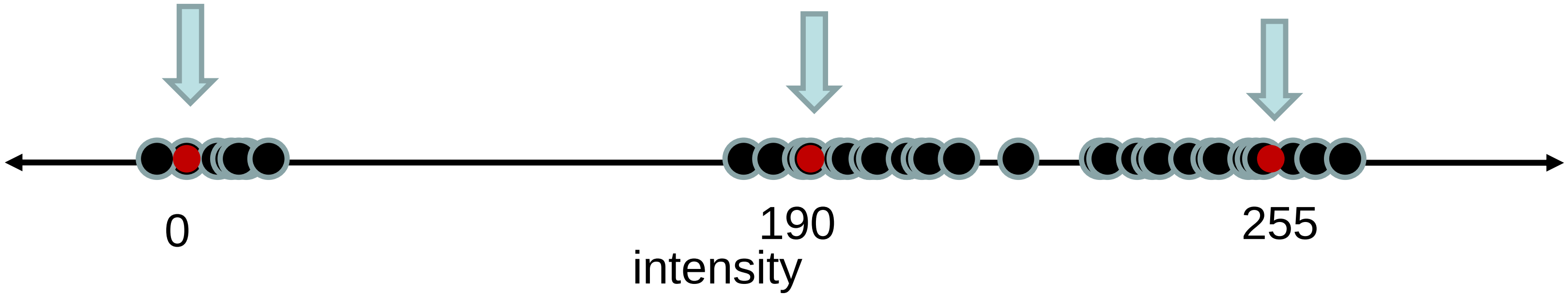


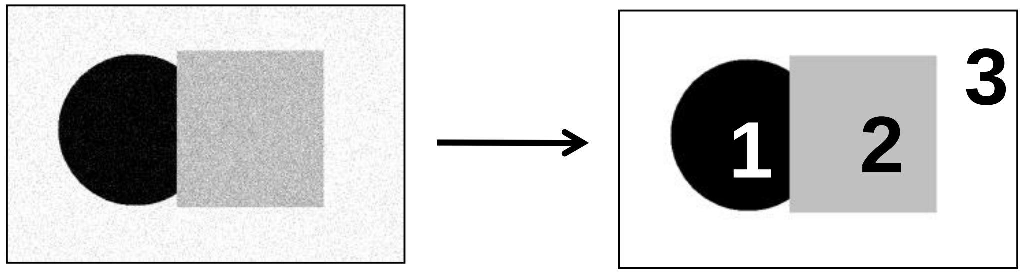
input image



- Now how to determine the three main intensities that define our groups?
- We need to ***cluster.***

Slide credit: Kristen Grauman





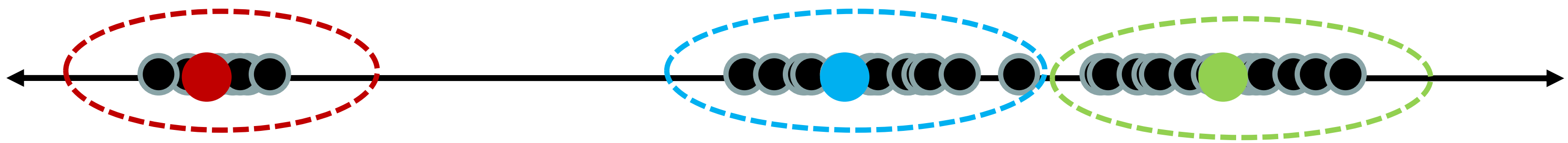
- Goal: choose three "centers" as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize SSD between all points and their nearest cluster center c_i:

$$\sum_{\text{clusters } i} \; \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

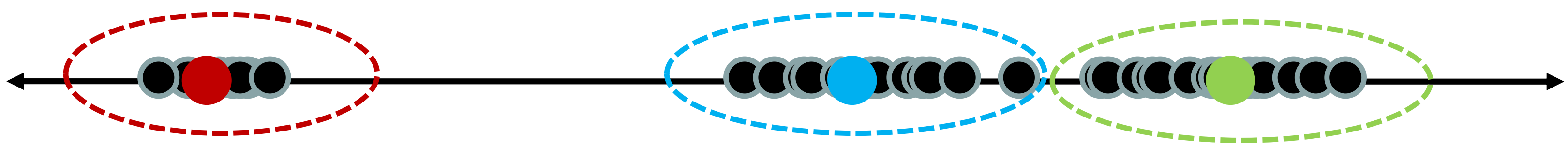
Slide credit: Kristen Grauman

Clustering

- With this objective, it is a “chicken and egg” problem:
  – If we knew the **cluster centers**, we could allocate points to groups by assigning each to its closest center.



  – If we knew the **group memberships**, we could get the centers by computing the mean per group.



Slide credit: Kristen Grauman

K-means clustering

- Basic idea: randomly initialize the *k* cluster centers, and iterate between the two steps we just saw.

  1. Randomly initialize the cluster centers, $c_1, ..., c_K$
  2. Given cluster centers, determine points in each cluster
     - For each point p, find the closest c_i. Put p into cluster i
  3. Given points in each cluster, solve for c_i
     - Set c_i to be the mean of points in cluster i
  4. If c_i have changed, repeat Step 2

Properties

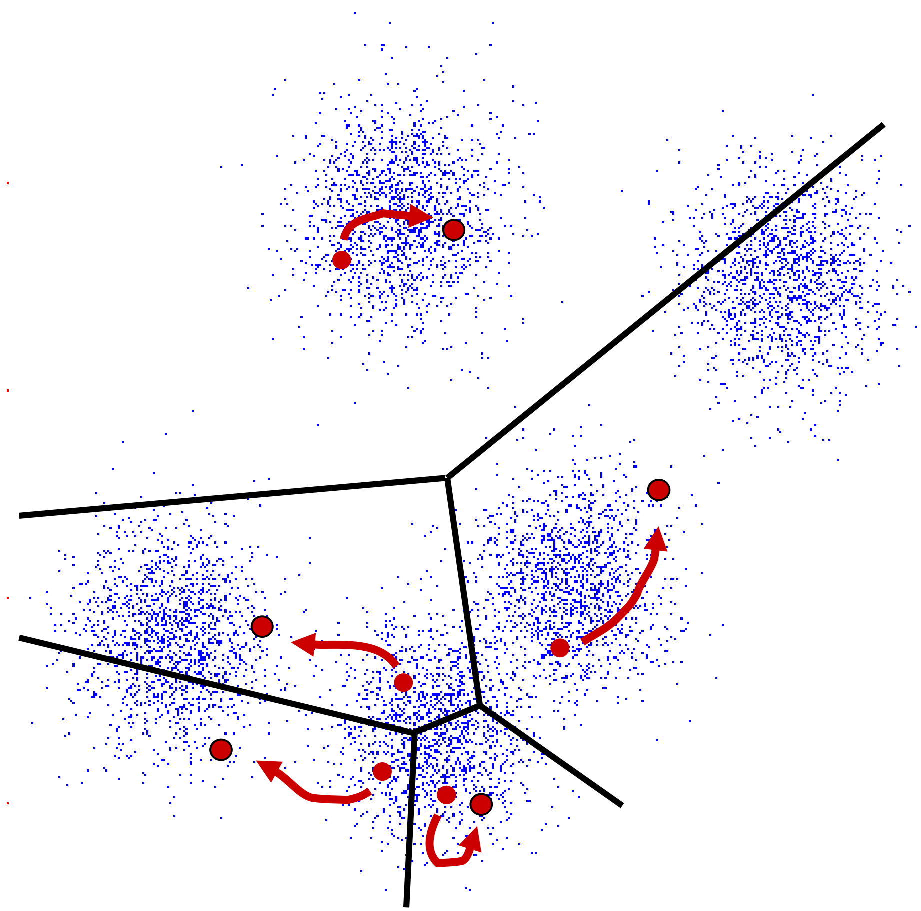
- Will always converge to *some* solution
- Can be a “local minimum”
  - does not always find the global minimum of objective function:

$$\sum_{\text{clusters } i} \quad \sum_{\text{points p in cluster } i} ||p - c_i||^2$$

Source: Steve Seitz

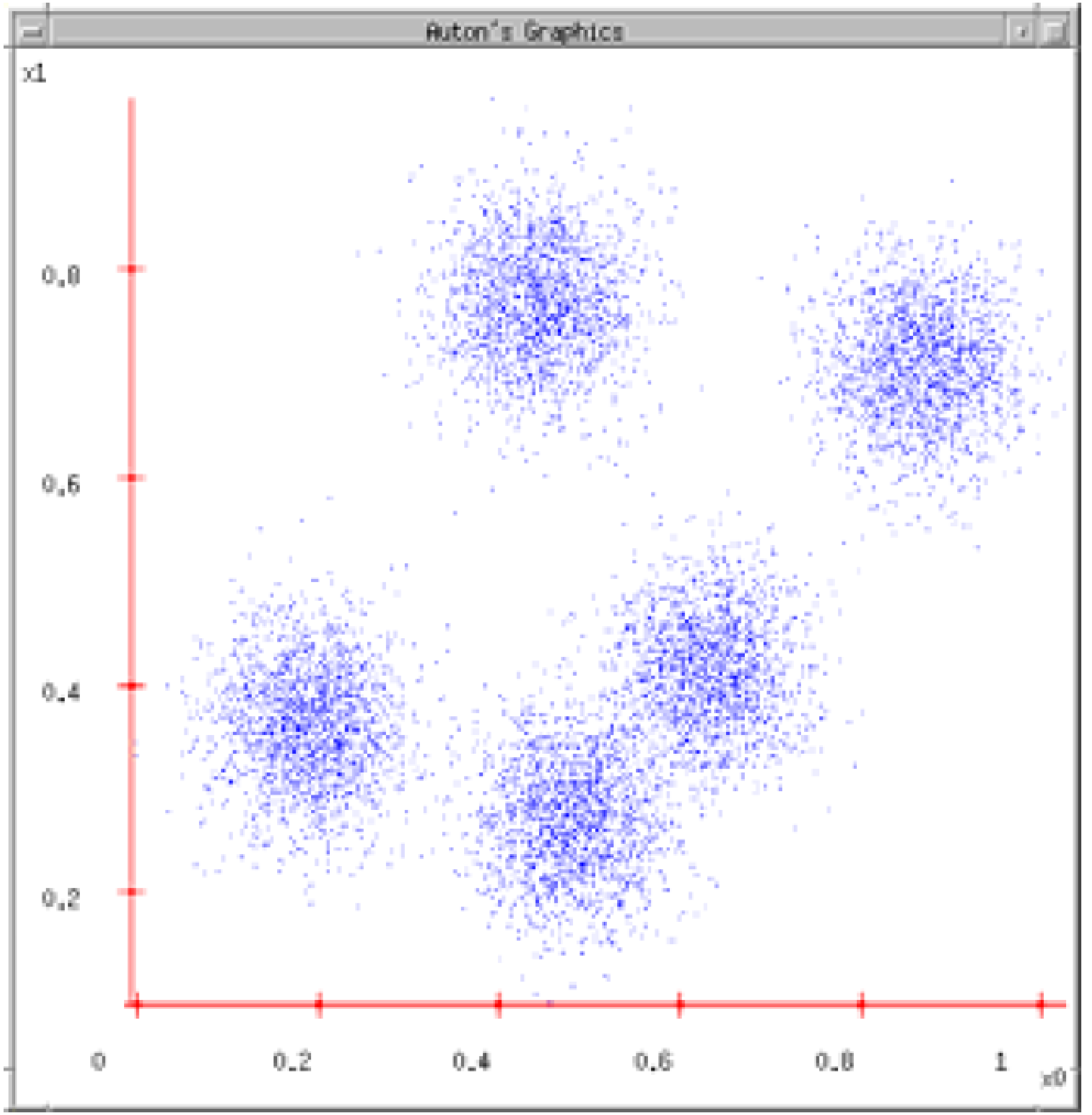
K-Means

- An iterative clustering algorithm
  - Pick K random points as cluster centers (means)
  - Alternate:
    - Assign data instances to closest mean
    - Assign each mean to the average of its assigned points
  - Stop when no points' assignments change



K-means

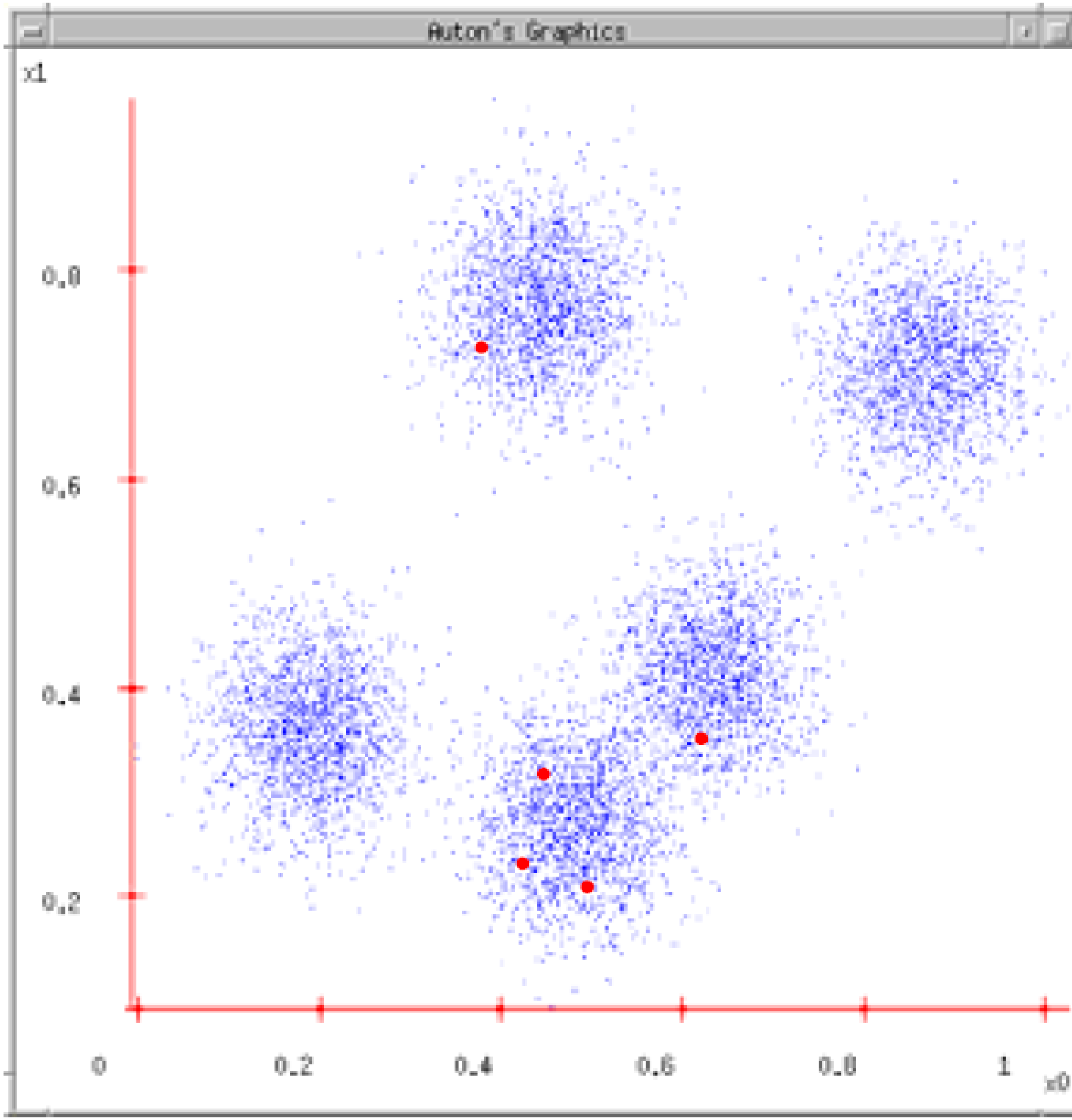
1. Ask user how many clusters they'd like. *(e.g. k=5)*



Slide credit Andrew Moore

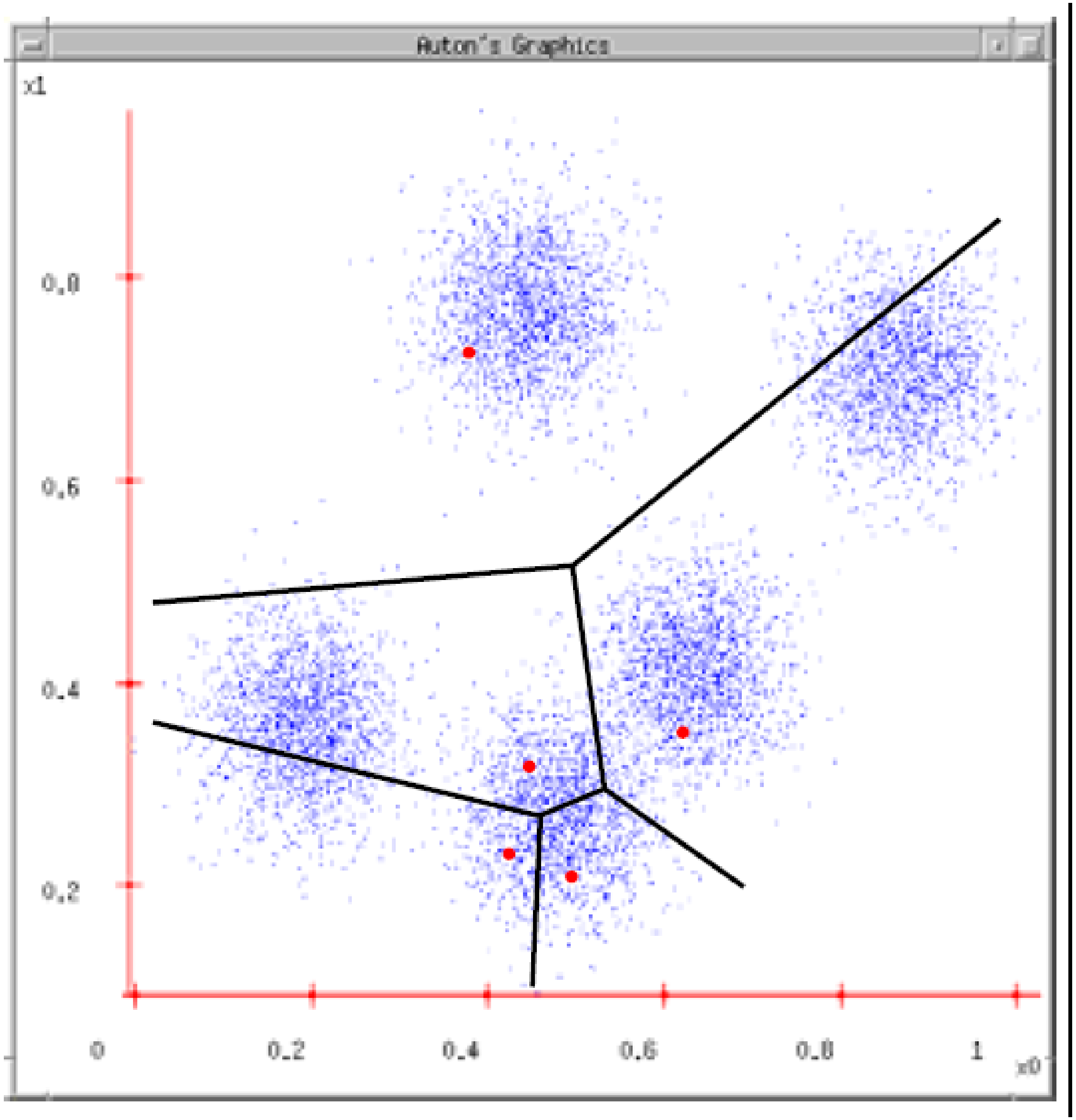
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations



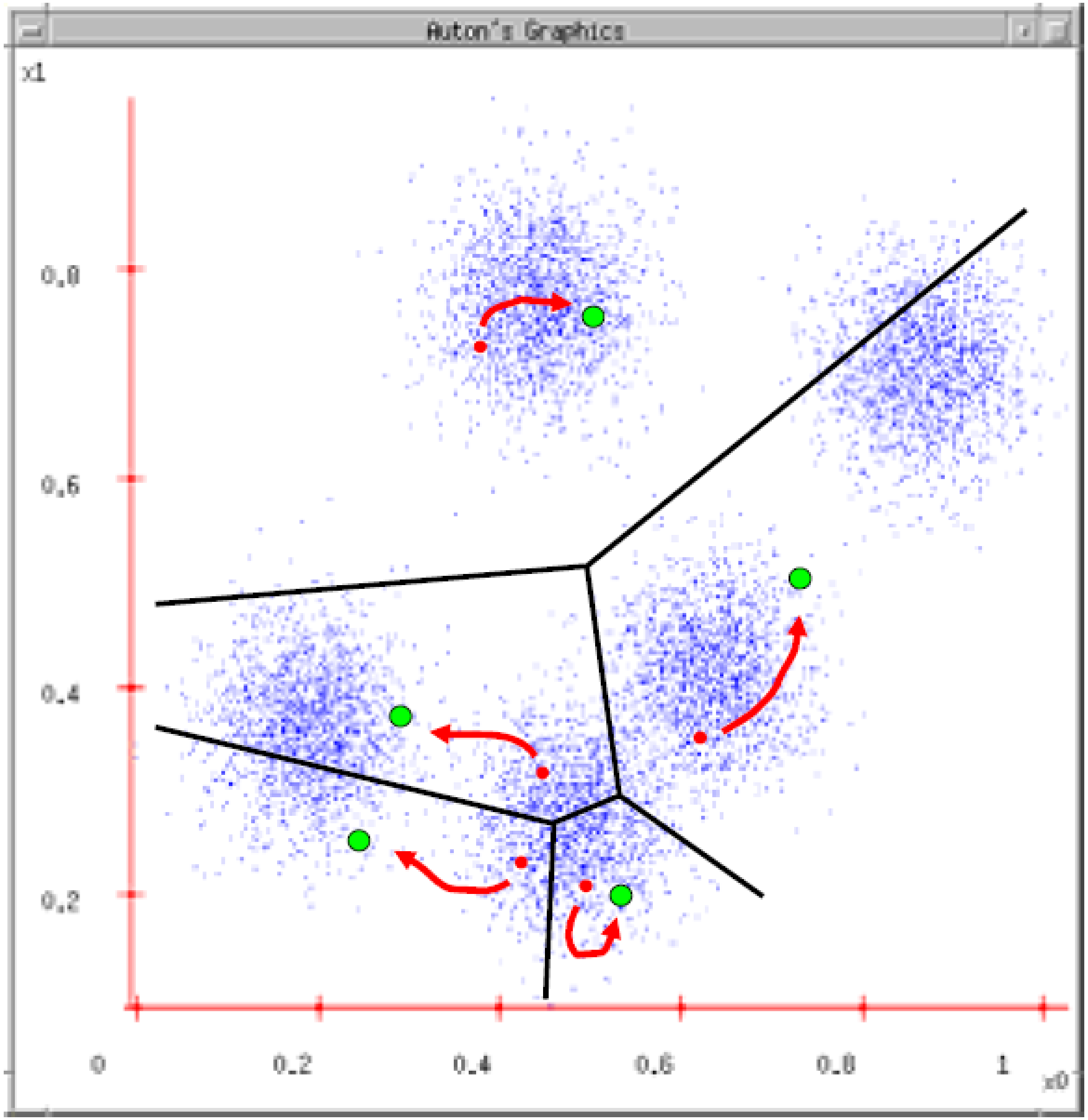
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to. (Thus each Center "owns" a set of datapoints)



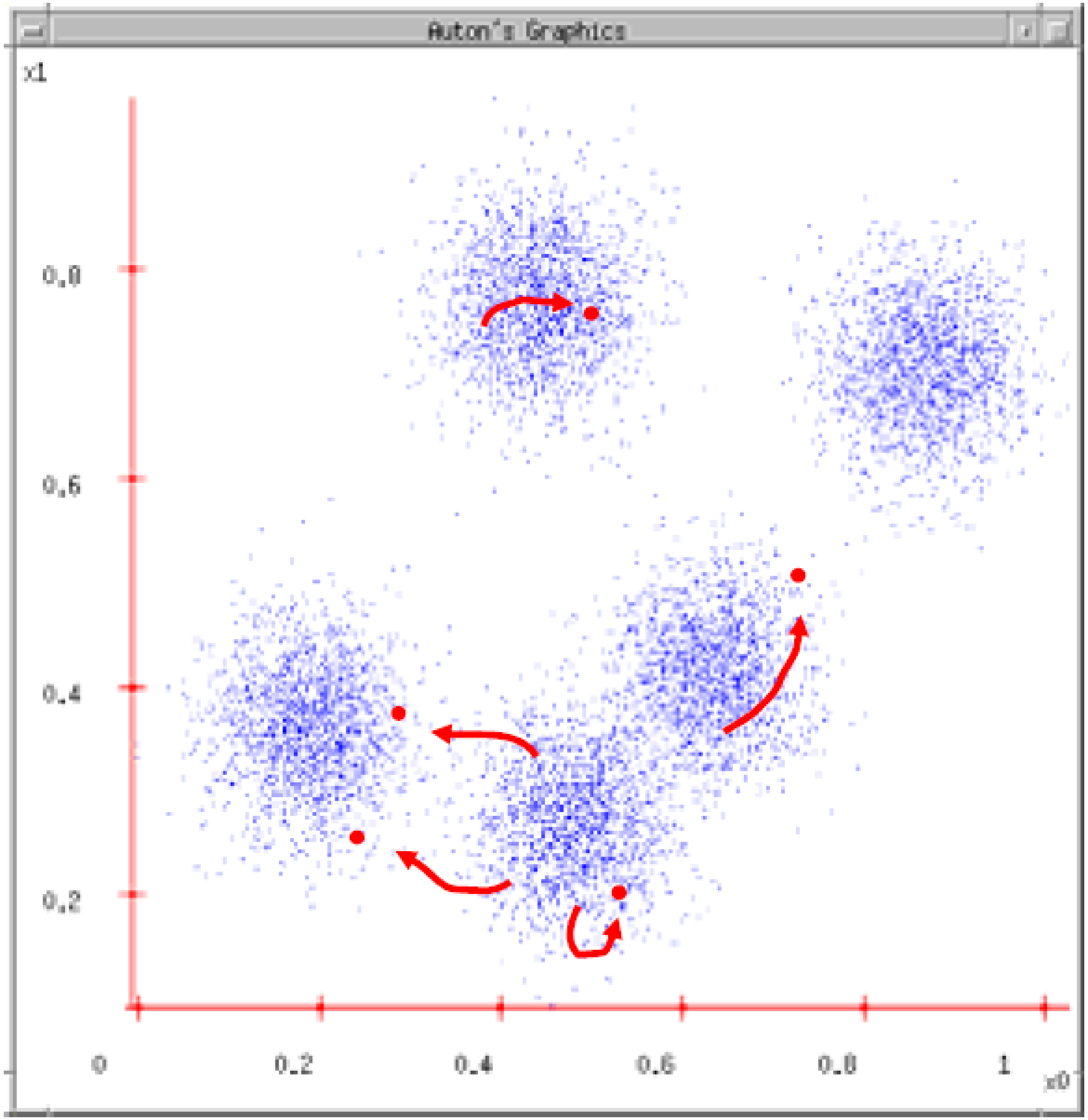
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns



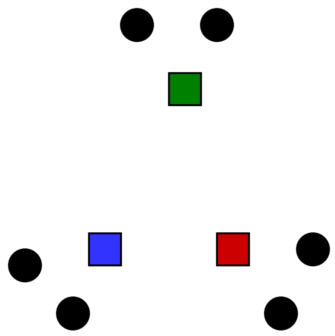
K-means

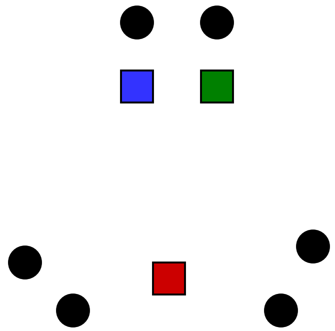
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns…
5. …and jumps there
6. …Repeat until terminated!



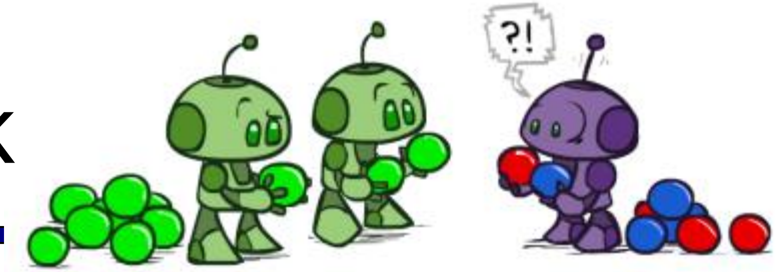
Initialization

- K-means is non-deterministic
  - Requires initial means
  - It does matter what you pick!
  - What can go wrong?
  - Various schemes for preventing this kind of thing

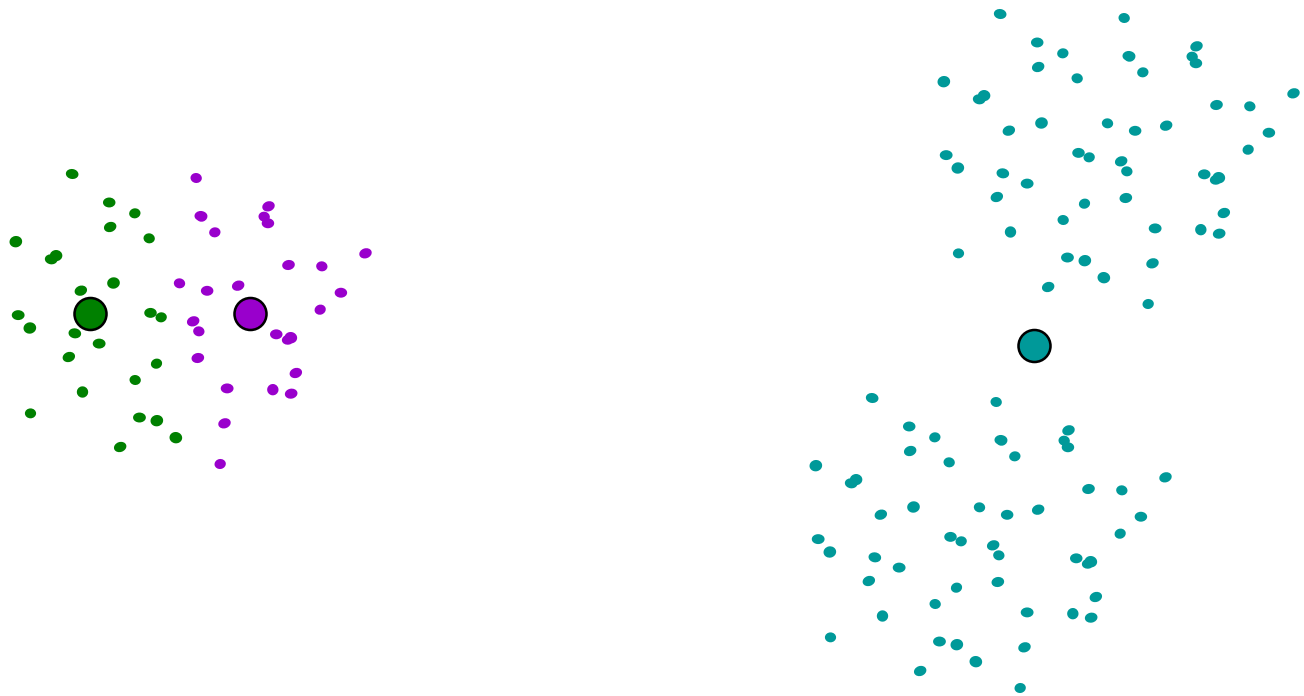




K-Means Getting Stuck



- A local optimum:



Slide credit: Dan Klein

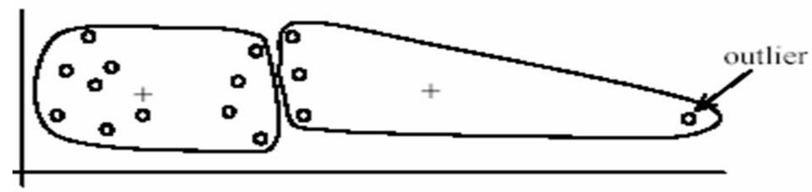
K-means: pros and cons

Pros

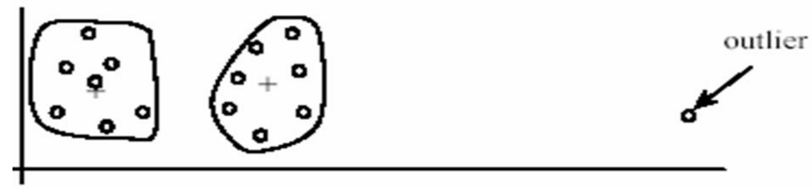
- Simple, fast to compute
- Converges to local minimum of within-cluster squared error

Cons/issues

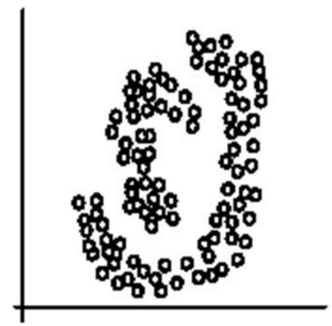
- Setting k?
- Sensitive to initial centers
- Sensitive to outliers
- Detects spherical clusters
- Assuming means can be computed



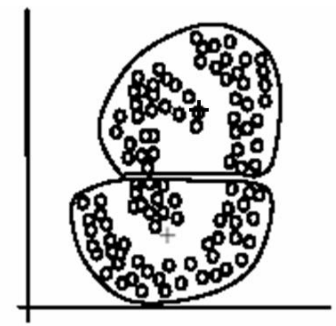
(A): Undesirable clusters



(B): Ideal clusters



(A): Two natural clusters



(B): *k*-means clusters

K-Means Questions

- Will K-means converge?
  - To a global optimum?
- Will it always find the true patterns in the data?
  - If the patterns are very very clear?
- Will it find something interesting?
- How many clusters to pick?
- Do people ever use it?

Slide credit: Dan Klein

Probabilistic clustering

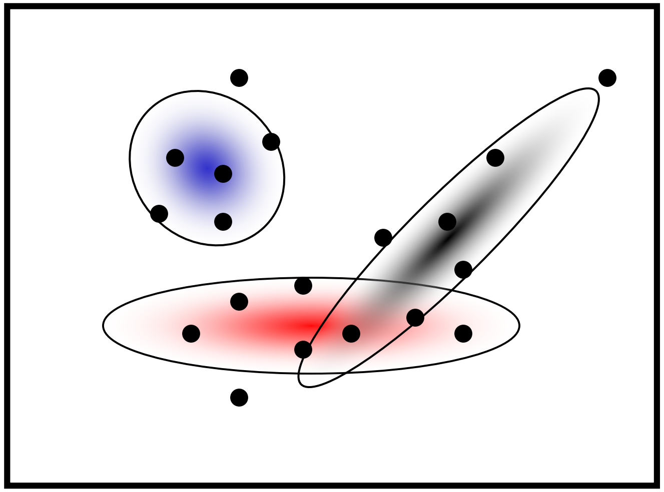
Basic questions

- what's the probability that a point **x** is in cluster m?
- what's the shape of each cluster?

K-means doesn't answer these questions

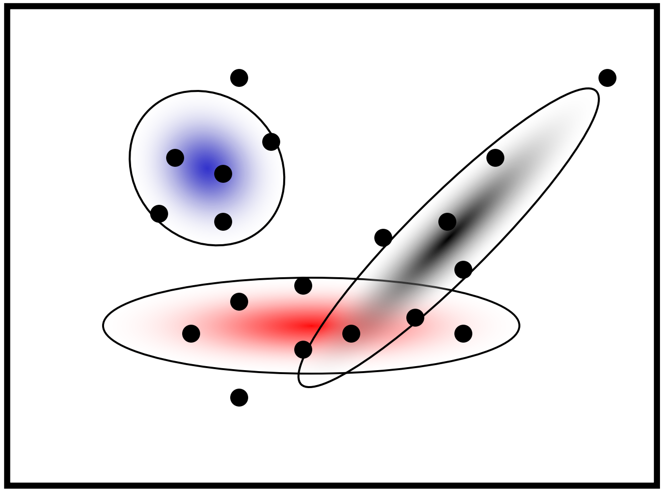
Probabilistic clustering (basic idea)

- Treat each cluster as a Gaussian density function



Slide credit: Steve Seitz

Expectation Maximization (EM)



A probabilistic variant of K-means:

- E step: “soft assignment” of points to clusters
  - estimate probability that a point is in a cluster
- M step: update cluster parameters
  - mean and variance info (covariance matrix)
- maximizes the likelihood of the points given the clusters

Slide credit: Steve Seitz

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity** similarity

Feature space: intensity value (1-d)

Slide credit: Kristen Grauman

K=2

K=3

quantization of the feature space; segmentation label map

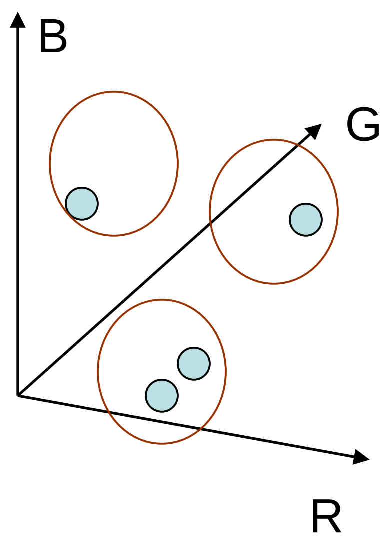
```
img_as_col = double(im(:));
cluster_membs = kmeans(img_as_col, K);

labelim = zeros(size(im));
for i=1:k
   inds = find(cluster_membs==i);
   meanval = mean(img_as_column(inds));
   labelim(inds) = meanval;
end
```

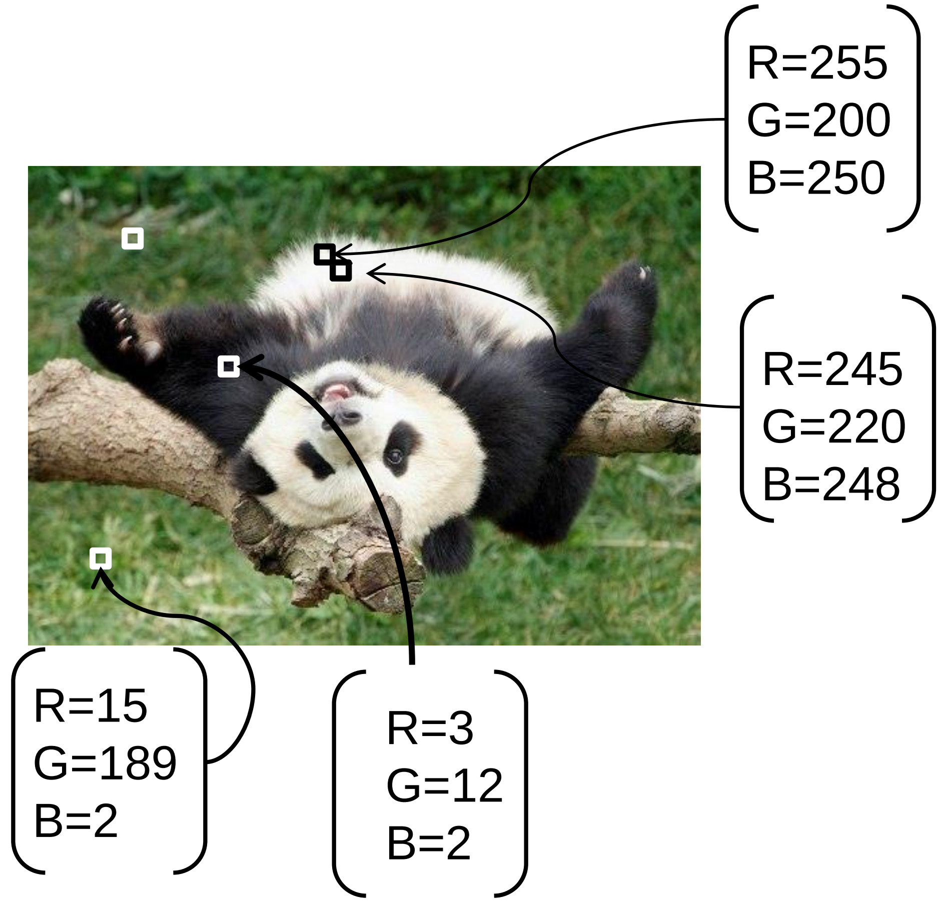
Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **color** similarity





Feature space: color value (3-d)

Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity** similarity

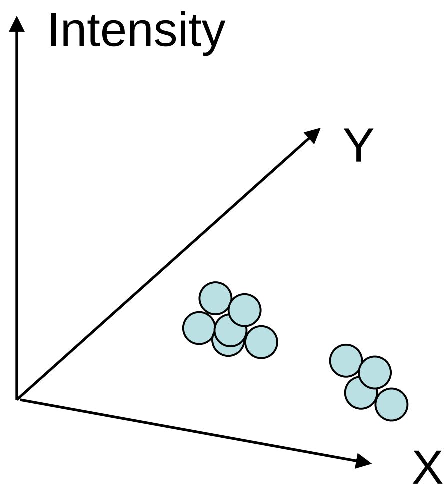
Clusters based on intensity similarity don’t have to be spatially coherent.

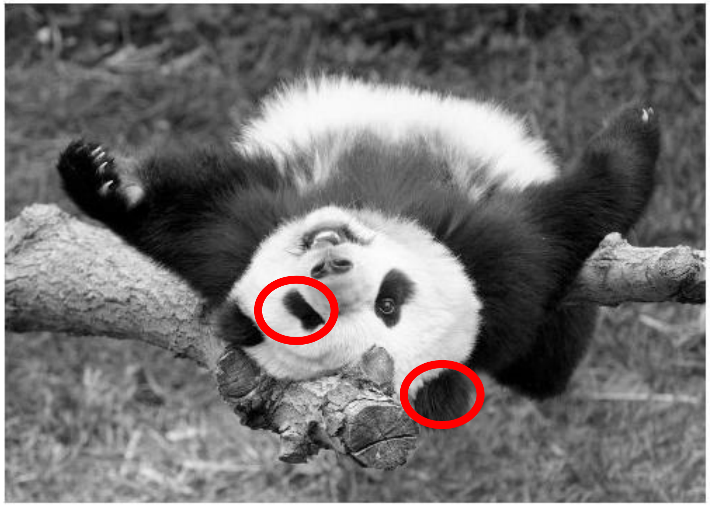
Slide credit: Kristen Grauman

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **intensity+position** similarity





Both regions are black, but if we also include **position (x,y),** then we could group the two into distinct segments; way to encode both similarity & proximity.

Slide credit: Kristen Grauman

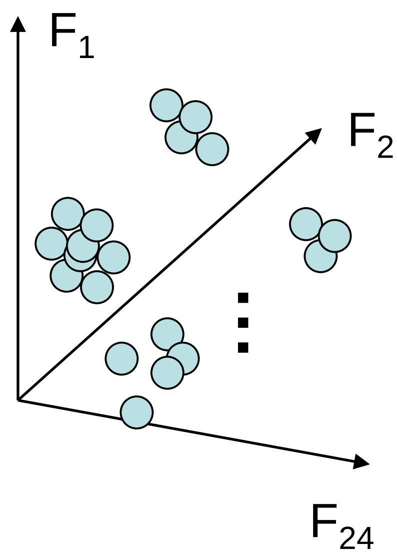
Segmentation as clustering

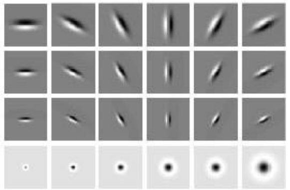
- Color, brightness, position alone are not enough to distinguish all regions…

Segmentation as clustering

Depending on what we choose as the *feature space*, we can group pixels in different ways.

Grouping pixels based on **texture** similarity

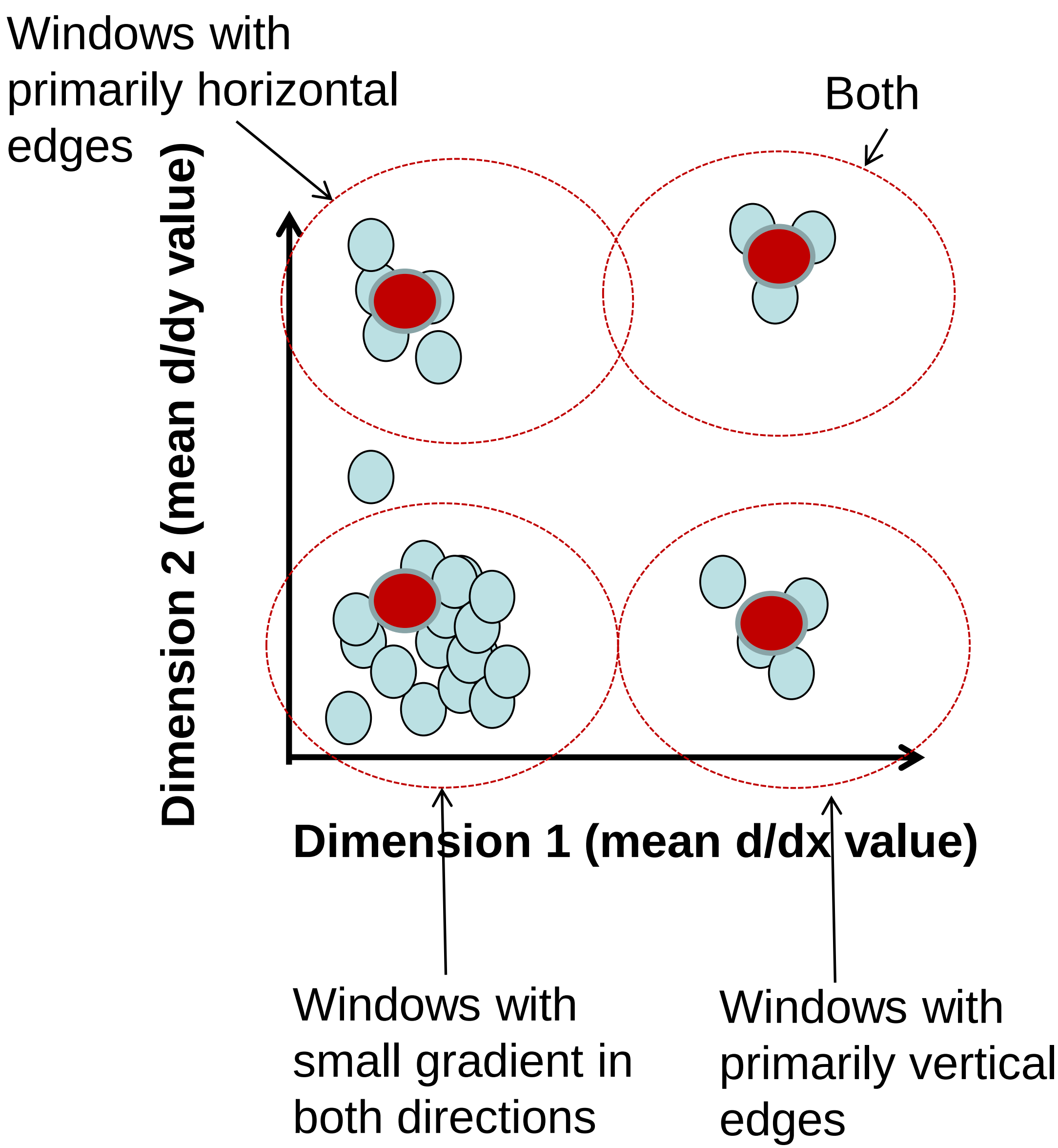


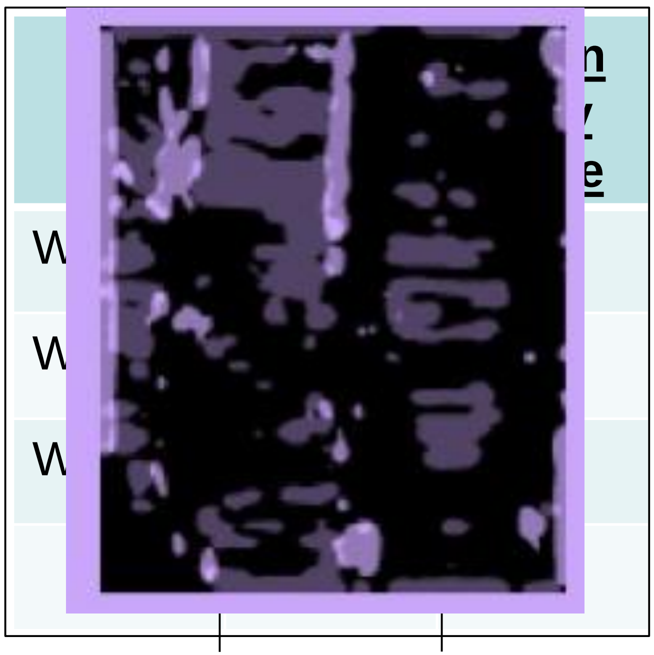


Filter bank of 24 filters

Feature space: filter bank responses (e.g., 24-d)

Recall: texture representation example





⋮

statistics to summarize patterns in small windows

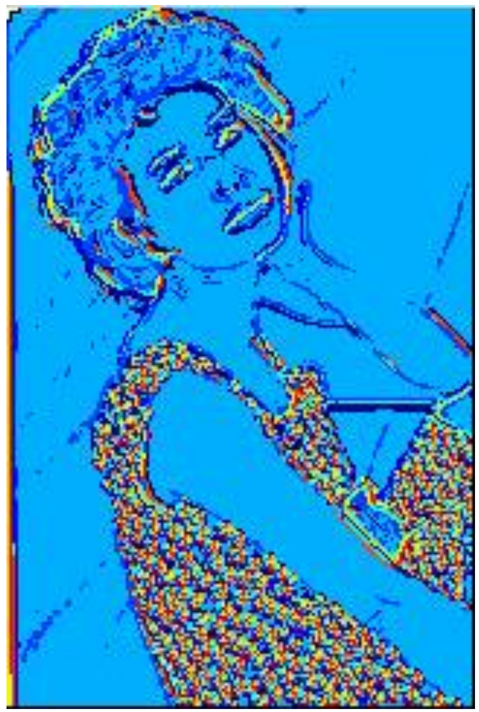
Slide credit: Kristen Grauman

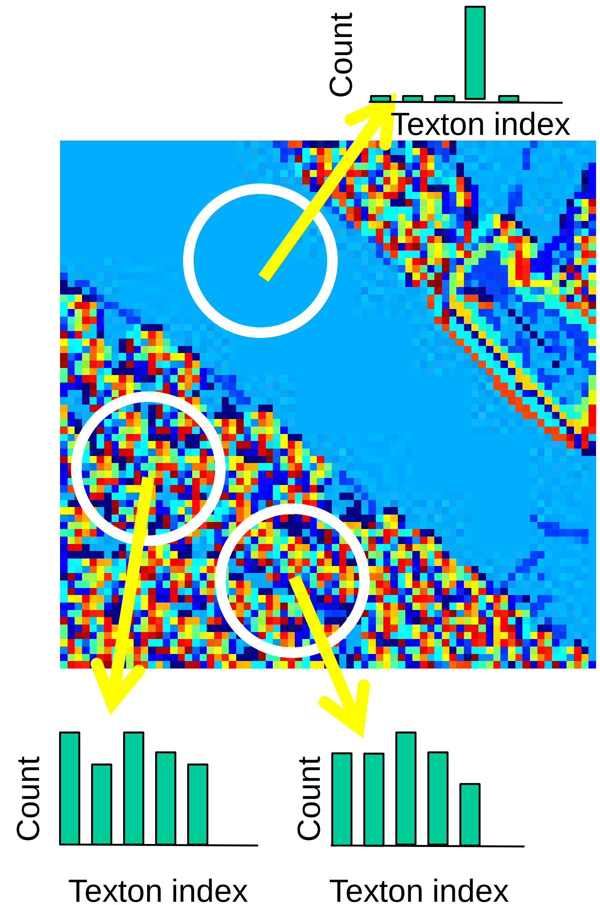
Segmentation with texture features

- Find “textons” by **clustering** vectors of filter bank outputs
- Describe texture in a window based on *texton histogram*

Image

Texton map

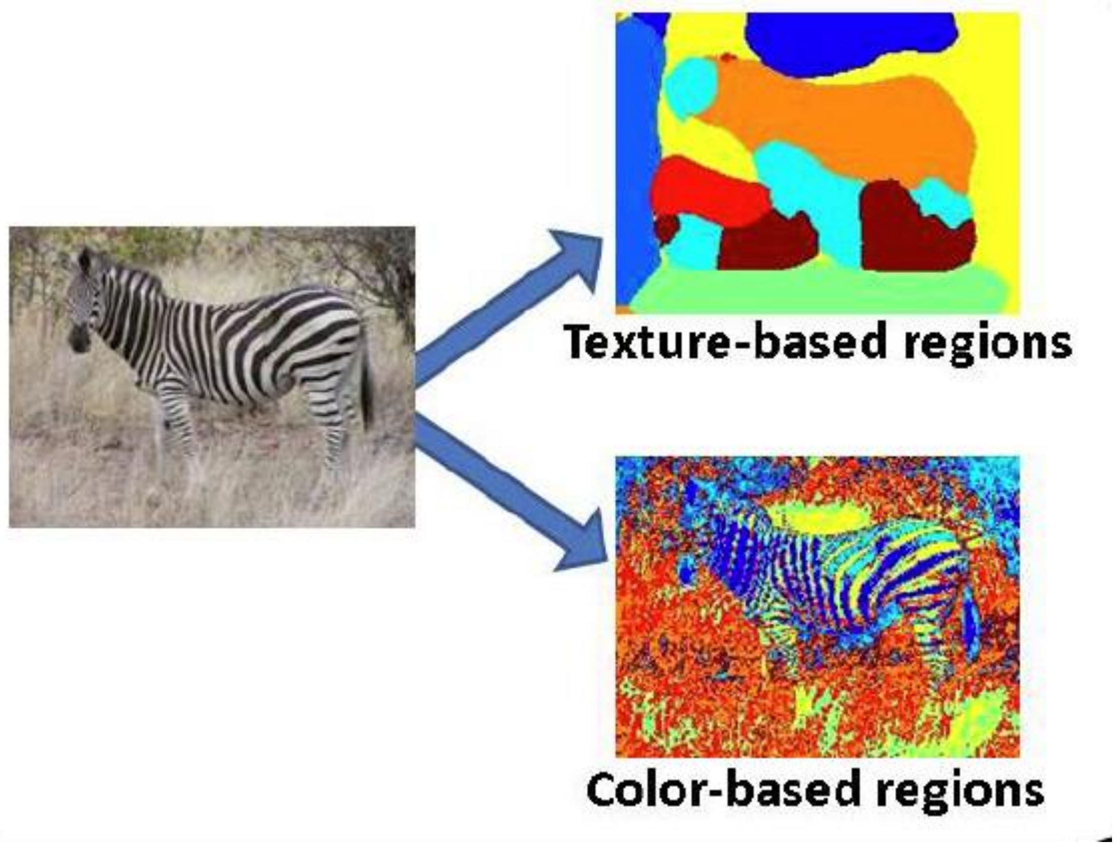




Malik, Belongie, Leung and Shi. IJCV 2001.

Adapted from Lana Lazebnik

Image segmentation example



Slide credit: Kristen Grauman

Pixel properties vs. neighborhood properties

These look very similar in terms of their color distributions (histograms).

How would their *texture* distributions compare?

Slide credit: Kristen Grauman

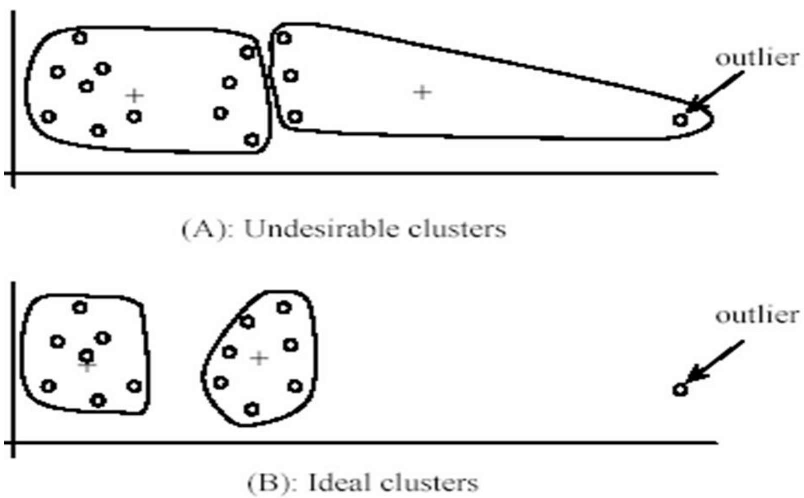
Outline

- What are grouping problems in vision?

- Inspiration from human perception
  – Gestalt properties

- Bottom-up segmentation via clustering
  – Algorithms:
    - Mode finding and mean shift: k-means, mean-shift
    - Graph-based: normalized cuts
  – Features: color, texture, …
    - Quantization for texture summaries

Recall: K-means pros and cons



Pros
- Simple, fast to compute
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Cons/issues
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- Sensitive to initial centers
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- Detects spherical clusters
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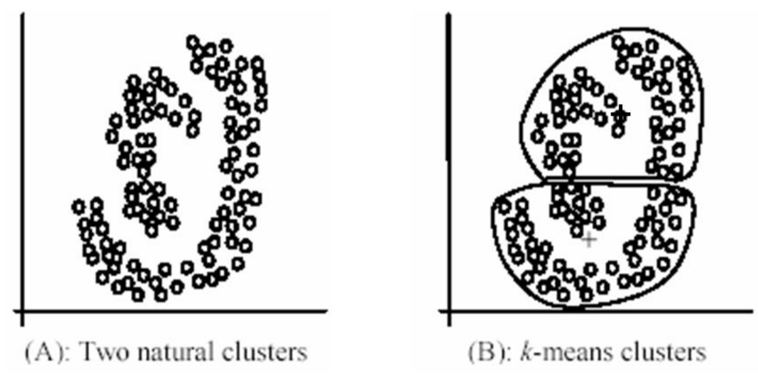
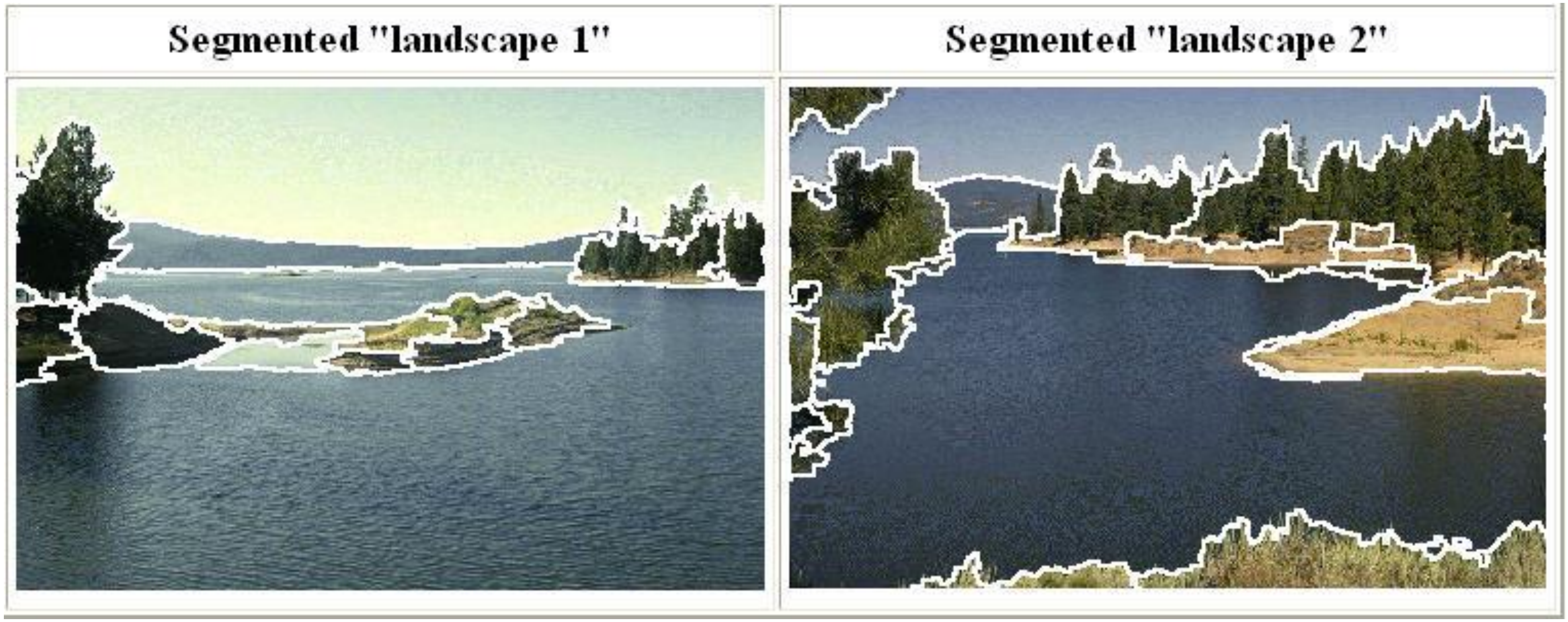


Mean shift clustering and segmentation

- An advanced and versatile technique for clustering-based segmentation



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

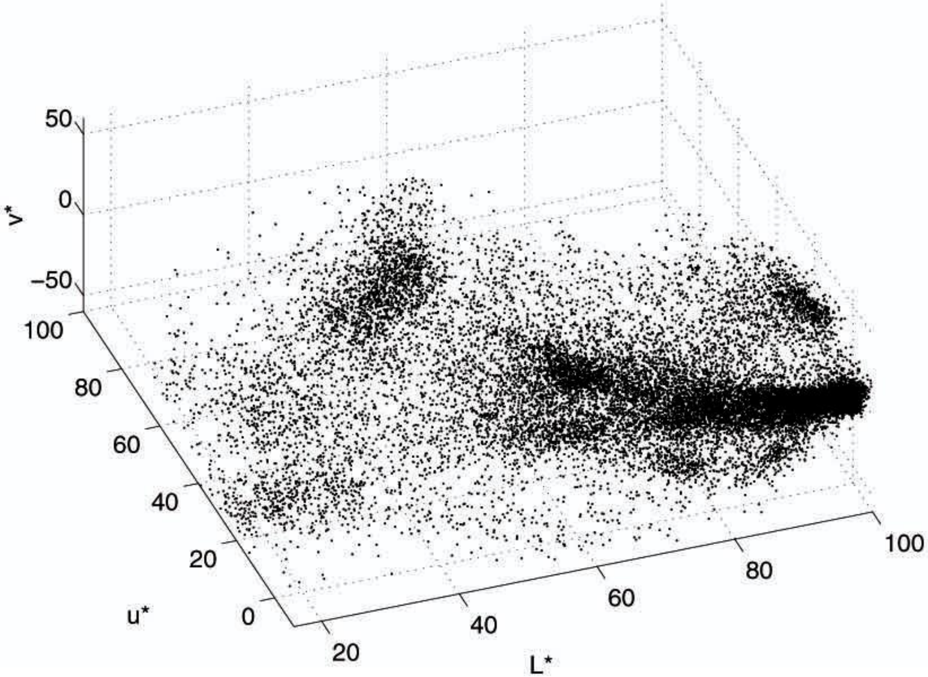
D. Comaniciu and P. Meer, Mean Shift: A Robust Approach toward Feature Space Analysis, PAMI 2002.

Mean shift algorithm

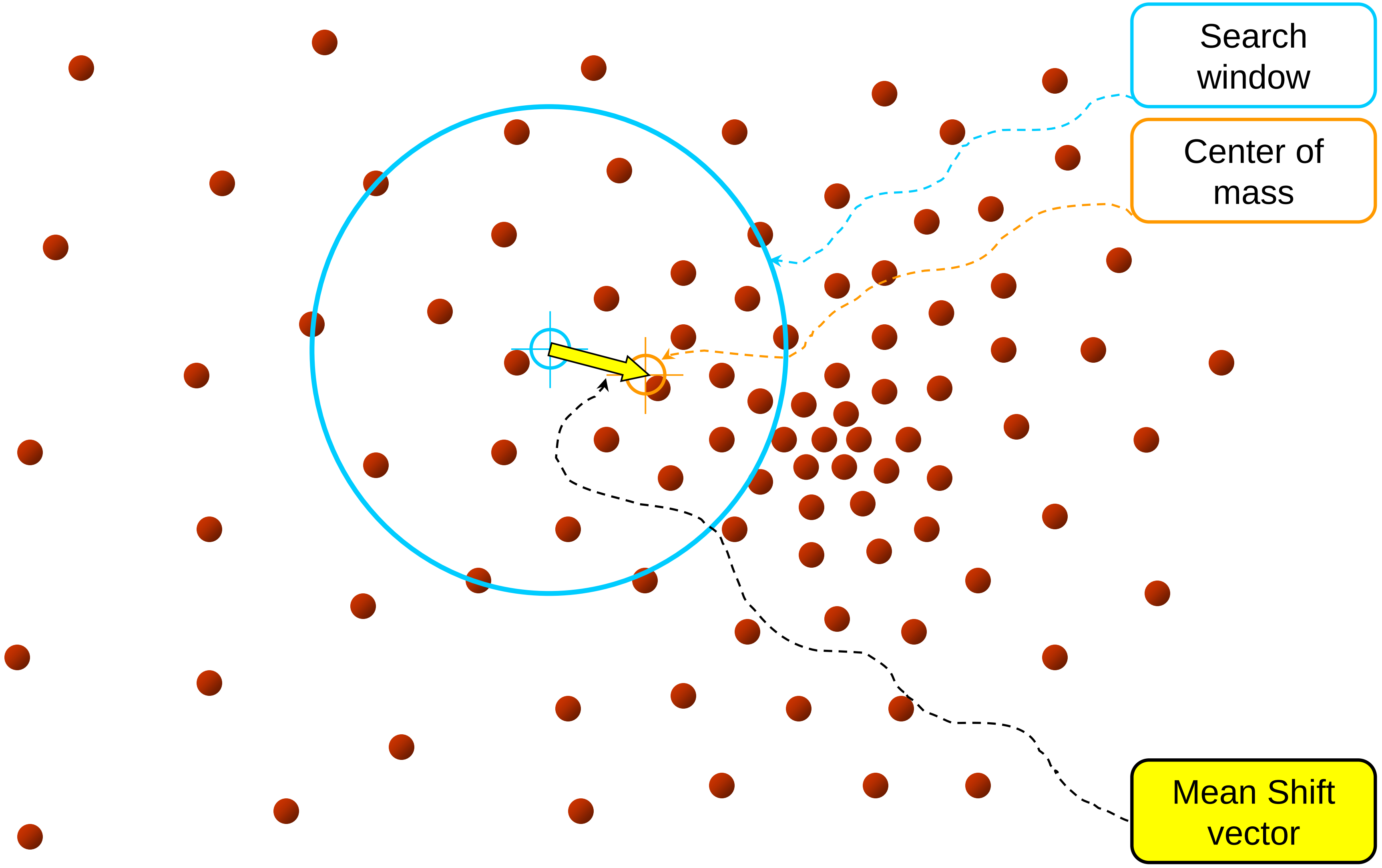
- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

image

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

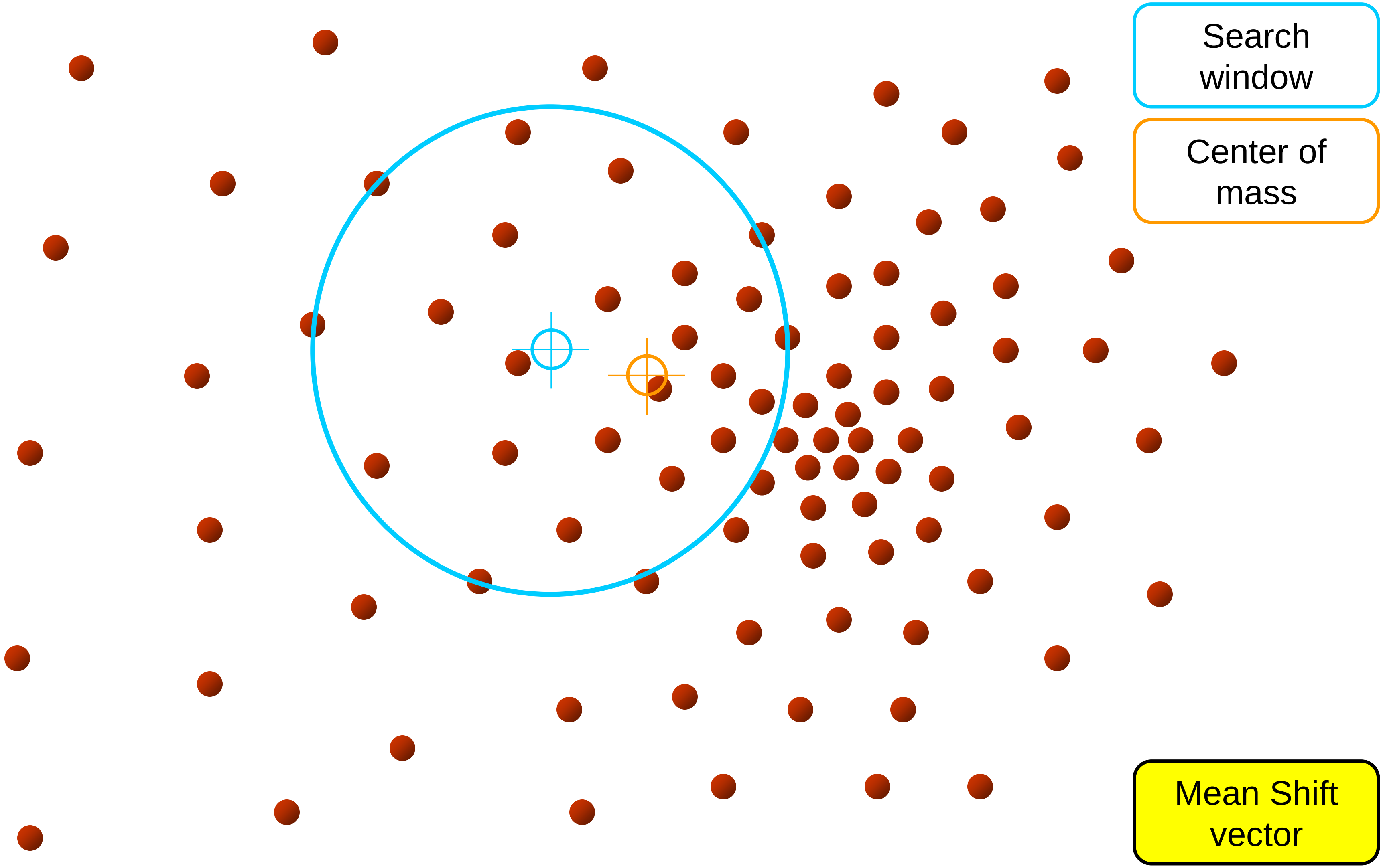


Mean shift



Slide by Y. Ukrainitz & B. Sarel

Mean shift



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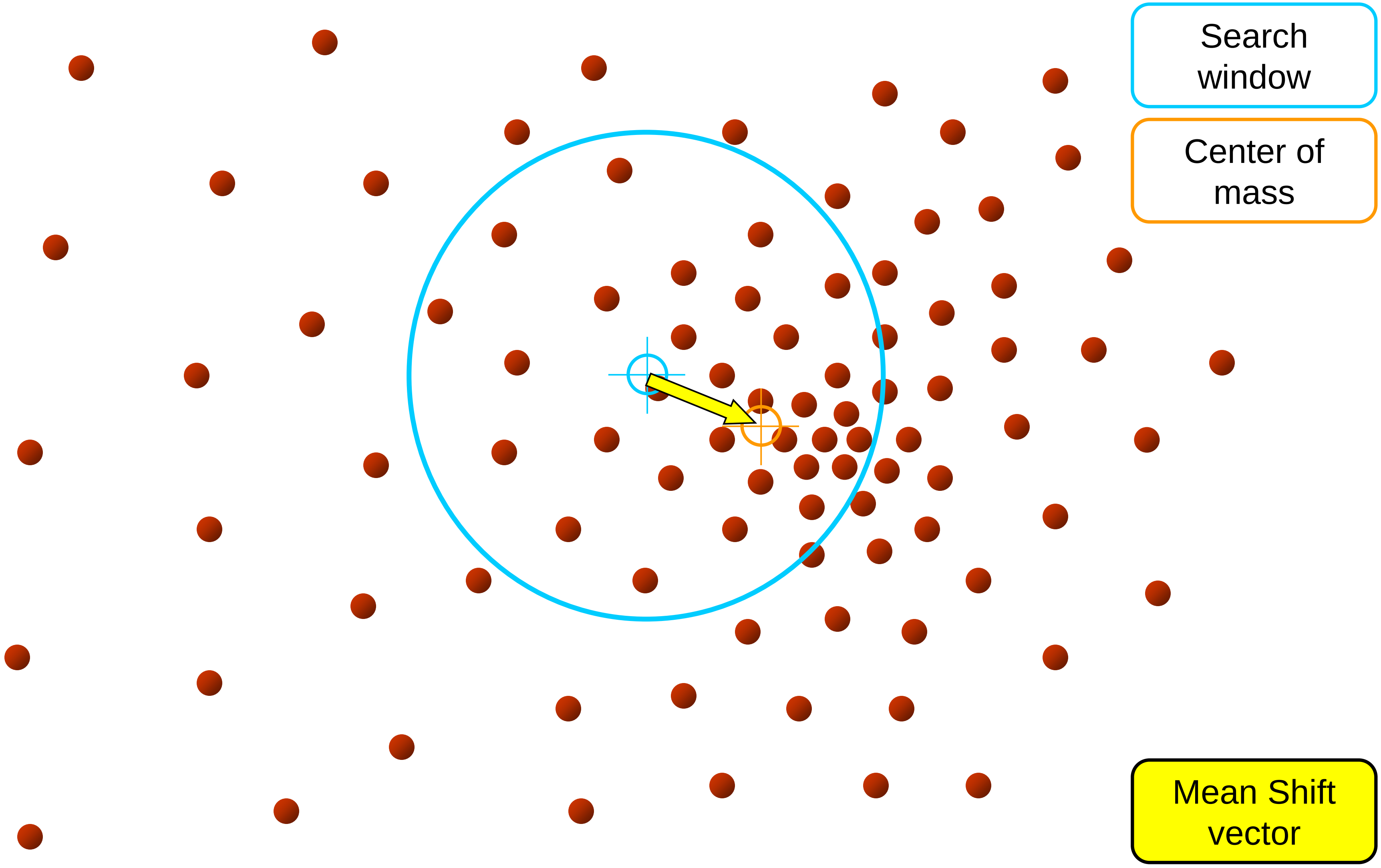
Mean shift



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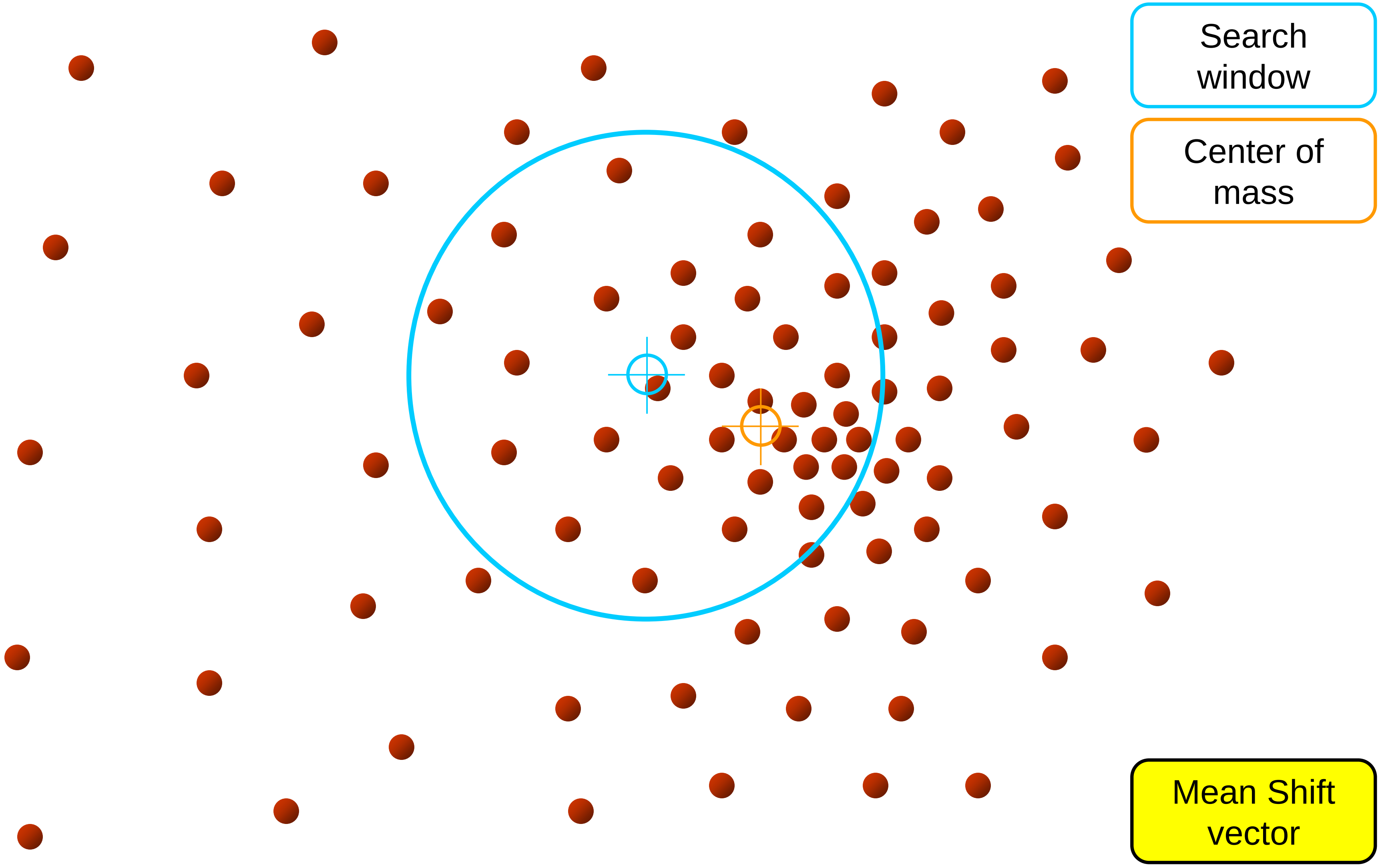
Mean shift



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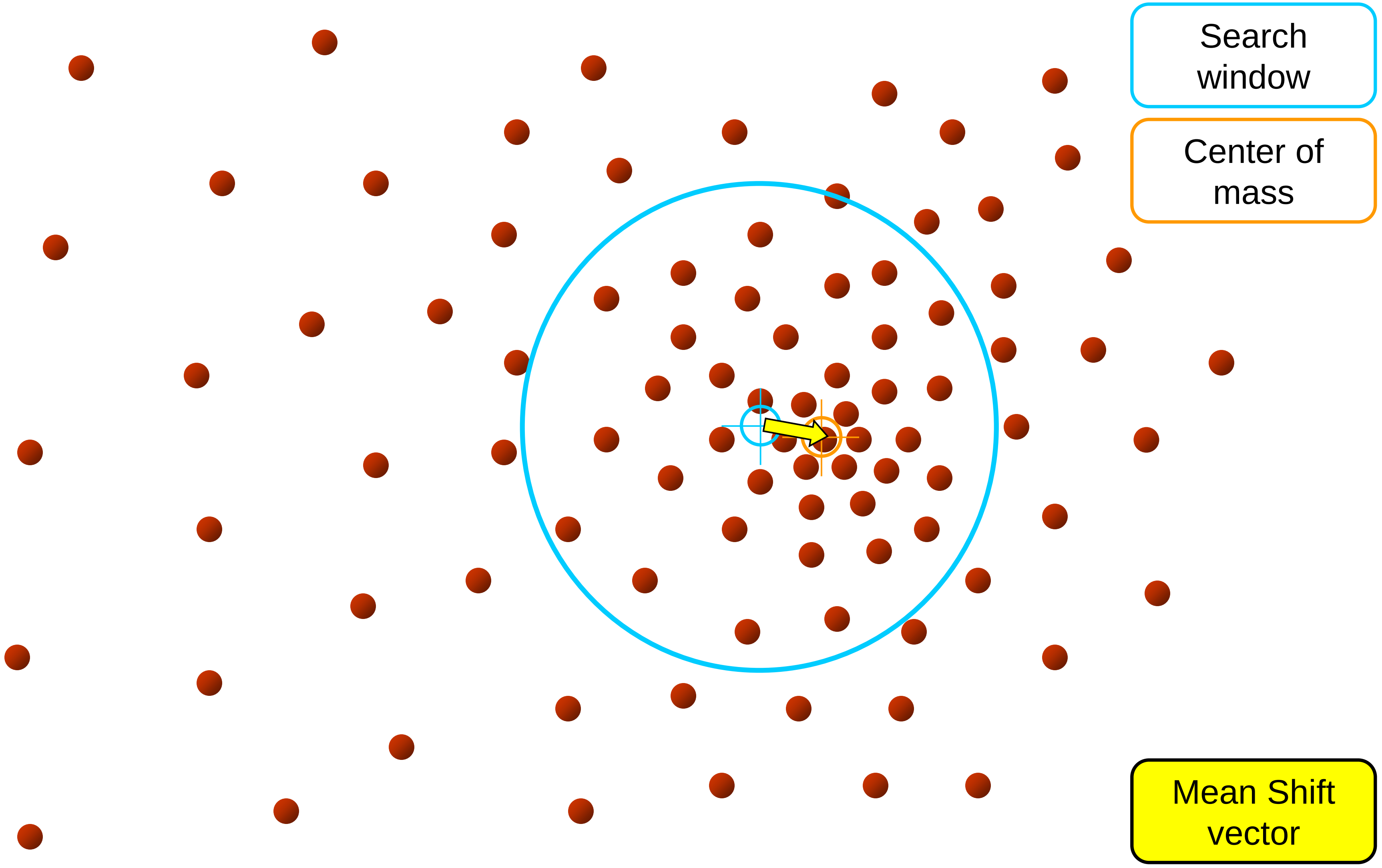
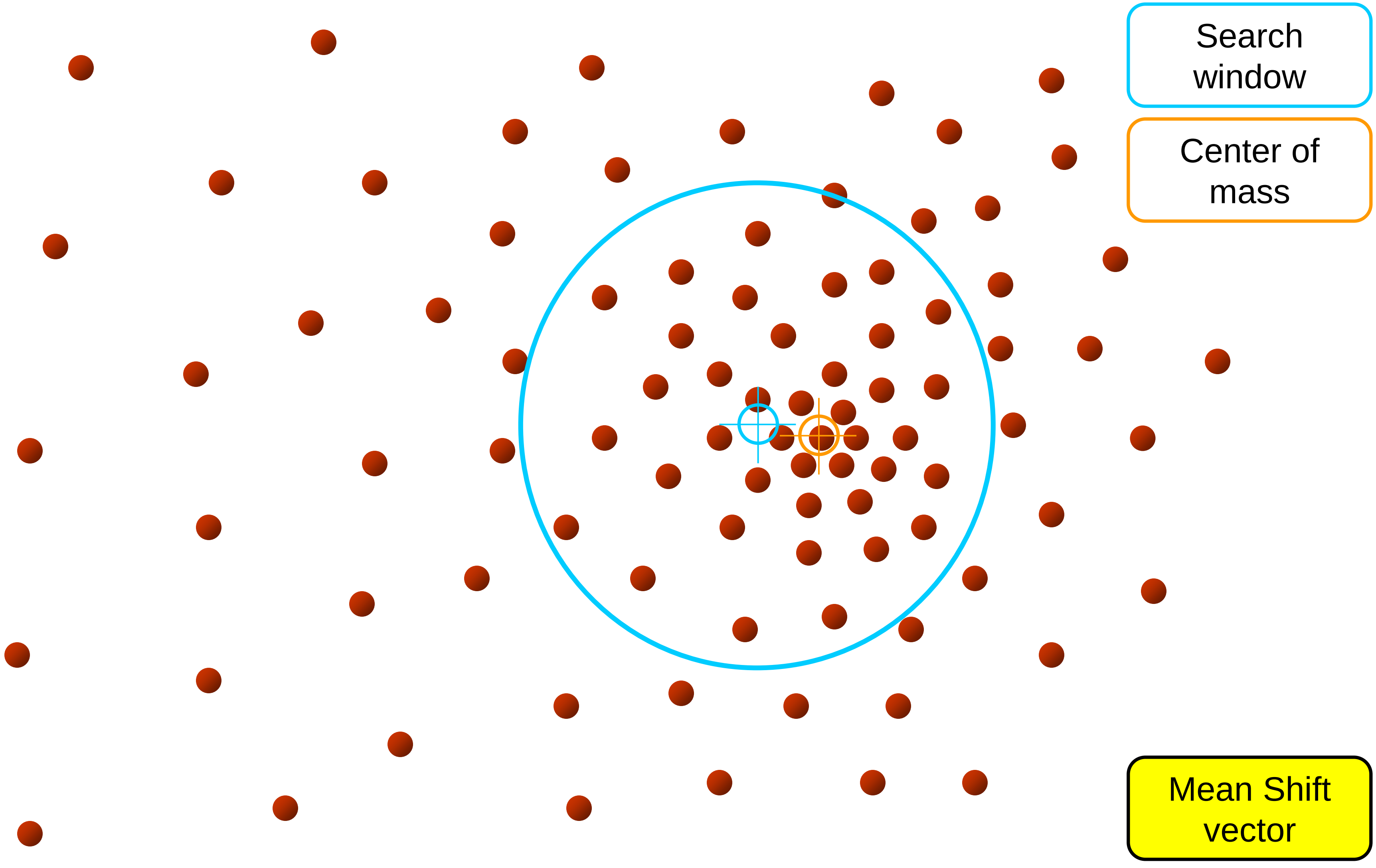
Mean shift



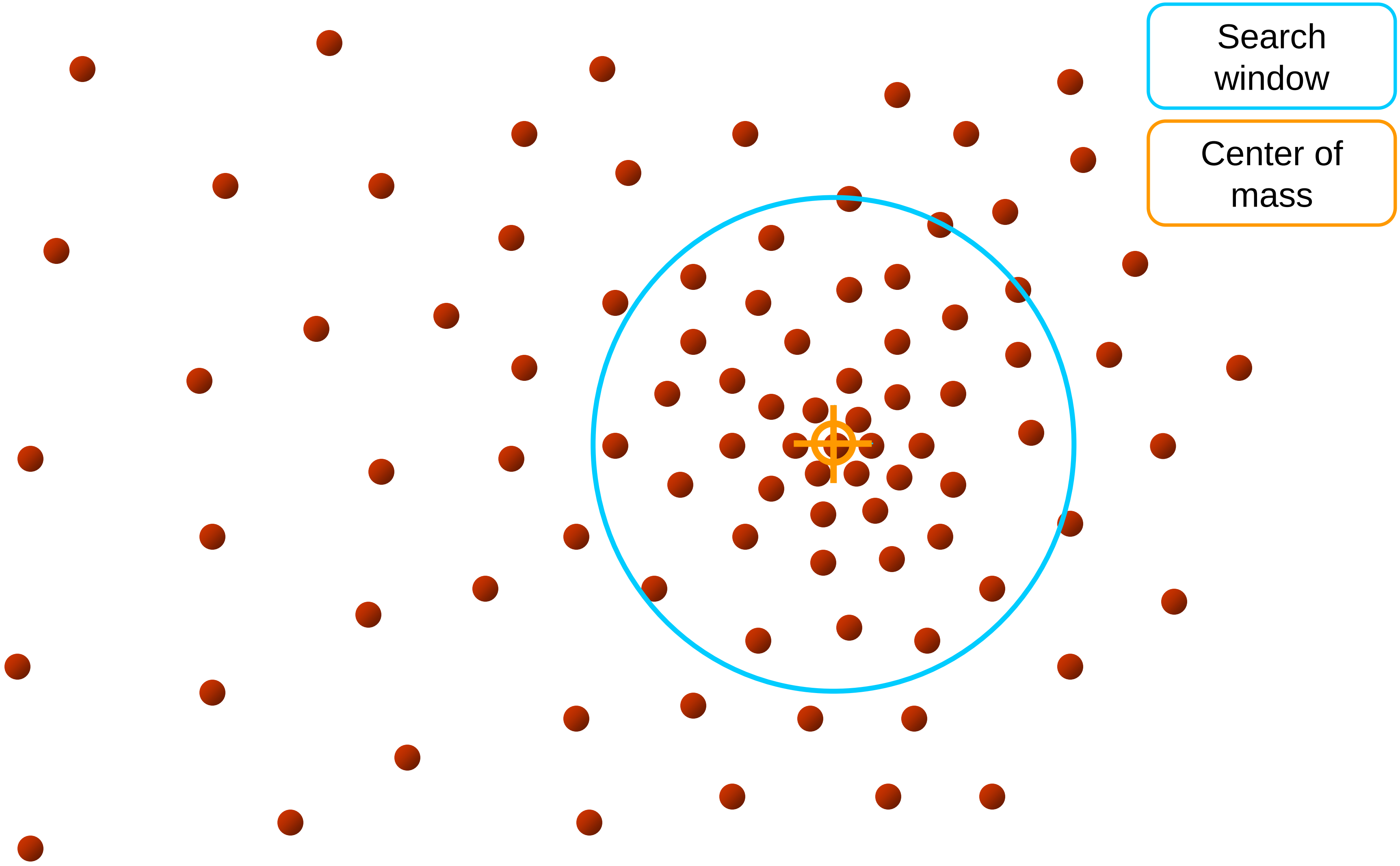
Slide by Y. Ukrainitz & B. Sarel

Mean shift



Slide by Y. Ukrainitz & B. Sarel

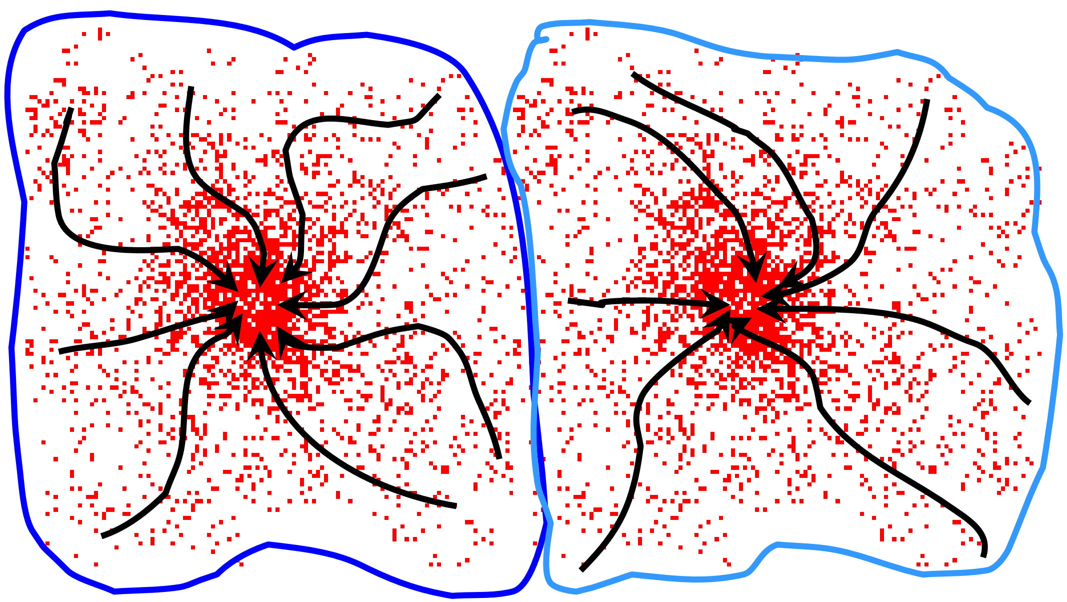
Mean shift



Slide by Y. Ukrainitz & B. Sarel

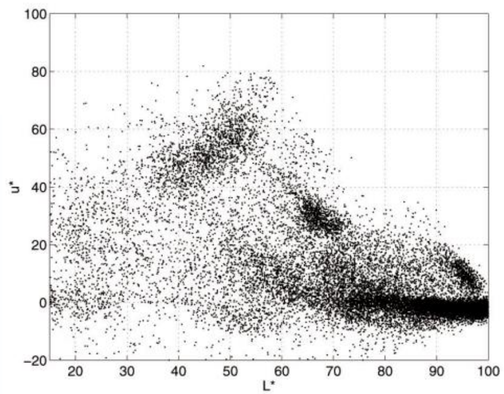
Mean shift clustering

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

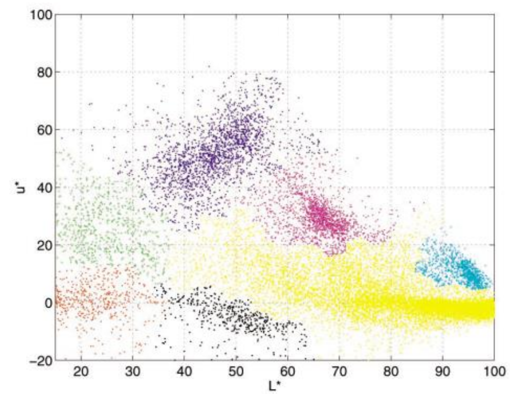


Mean shift clustering/segmentation

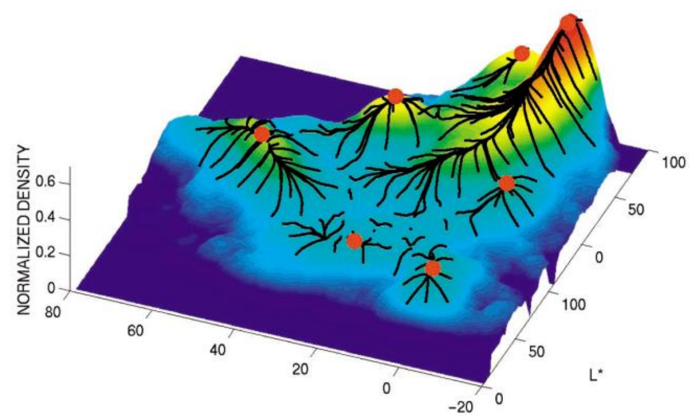
- Find features (color, gradients, texture, etc)
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode



(a)

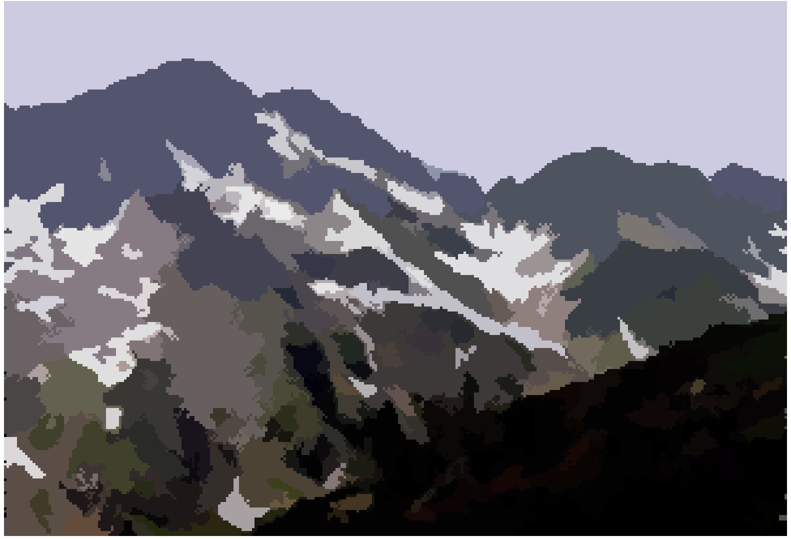


(b)



Mean shift segmentation results



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

Mean shift segmentation results

Mean shift segmentation results

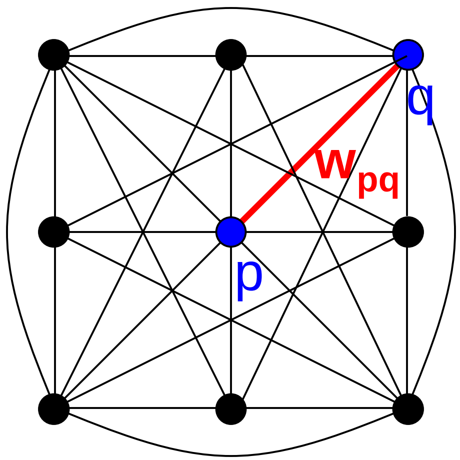
Mean shift

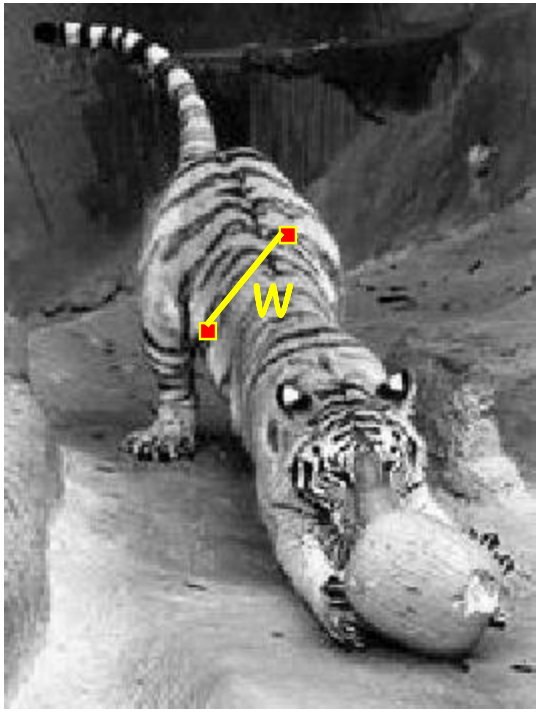
- Pros:
  - Does not assume shape on clusters
  - One parameter choice (window size, aka “bandwidth”)
  - Generic technique
  - Find multiple modes
- Cons:
  - Selection of window size
  - Does not scale well with dimension of feature space

Outline

- What are grouping problems in vision?
- Inspiration from human perception
  - Gestalt properties
- Bottom-up segmentation via clustering
  - Algorithms:
    - Mode finding and mean shift: k-means, mean-shift
    - Graph-based: normalized cuts
  - Features: color, texture, …
    - Quantization for texture summaries

Images as graphs



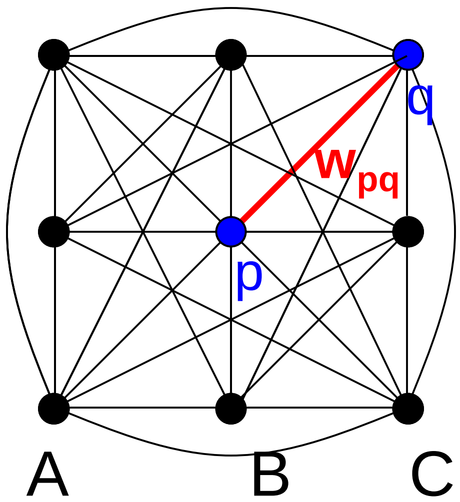


Fully-connected graph

- node (vertex) for every pixel
- link between *every* pair of pixels, **p**,**q**
- affinity weight $\mathbf{w_{pq}}$ for each link (edge)
  - $\mathbf{w_{pq}}$ measures *similarity*
    - » similarity is *inversely proportional* to difference (in color and position…)

Source: Steve Seitz

Segmentation by Graph Cuts



Break Graph into Segments

- Want to delete links that cross **between** segments
- Easiest to break links that have low similarity (low weight)
  - similar pixels should be in the same segments
  - dissimilar pixels should be in different segments

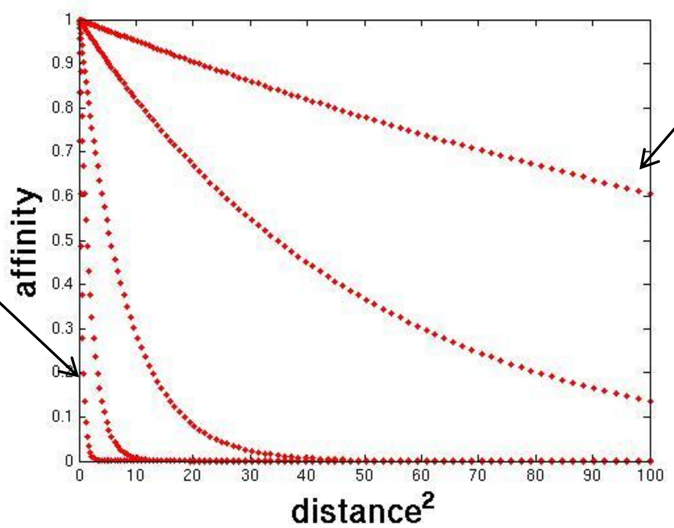
Source: Steve Seitz

Measuring affinity

- One possibility:

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

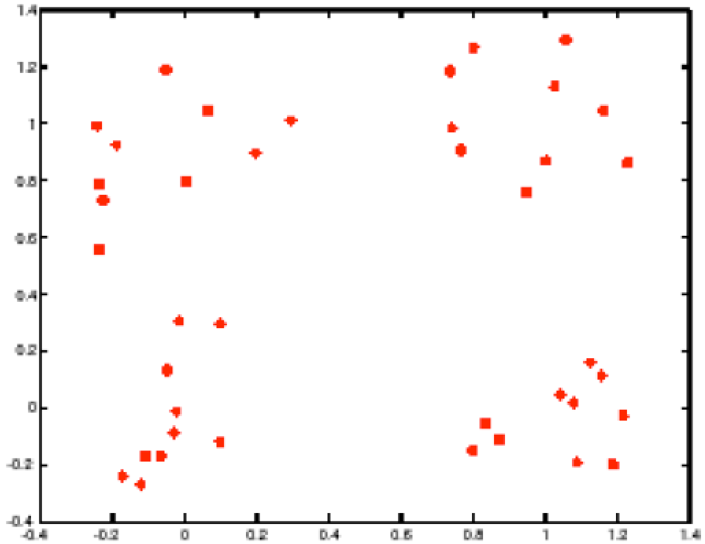
Small sigma:
group only
nearby points



Large sigma:
group distant
points

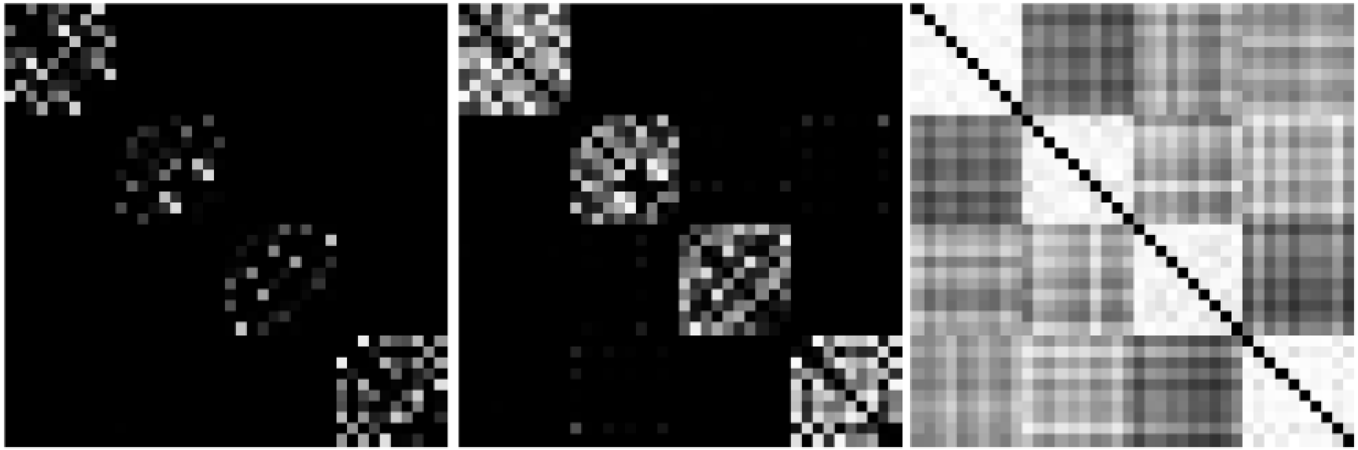
Measuring affinity

Data points



σ=.2

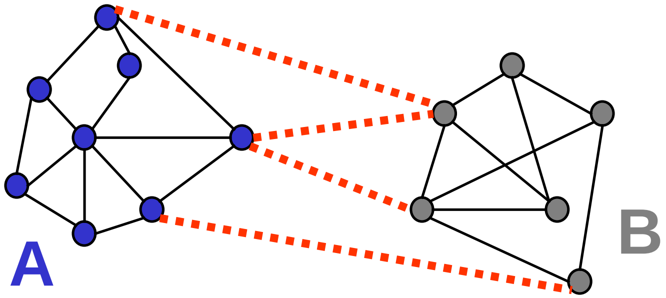
Affinity matrices



σ=.1 σ=.2 σ=1

Slide credit: Kristen Grauman

Cuts in a graph: Min cut



Link Cut

- set of links whose removal makes a graph disconnected
- cost of a cut: $$cut(A,B) = \sum_{p \in A, q \in B} w_{p,q}$$

Find minimum cut

- gives you a segmentation
- fast algorithms exist for doing this

Source: Steve Seitz

Minimum cut

- Problem with minimum cut:

  Weight of cut proportional to number of edges in the cut; tends to produce small, isolated components.

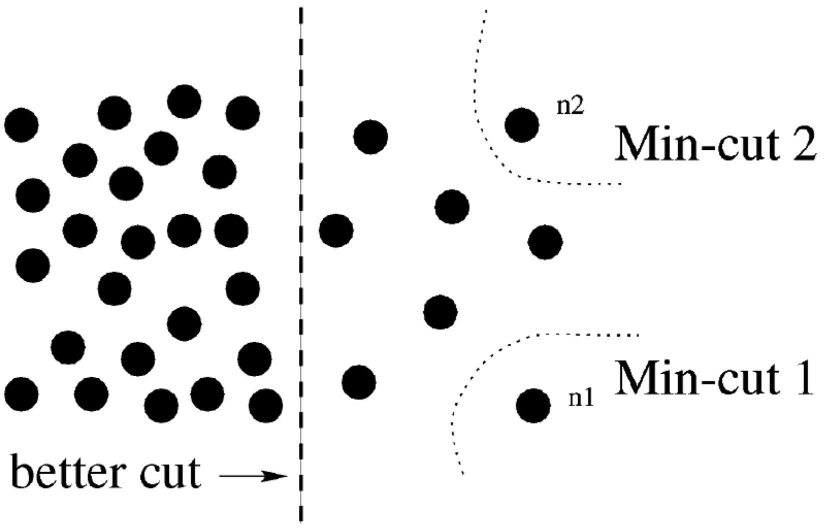
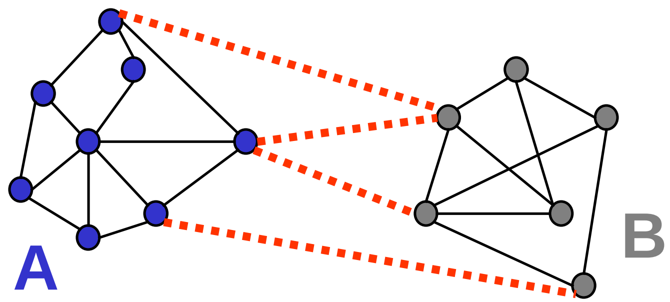


Fig. 1. A case where minimum cut gives a bad partition.

[Shi & Malik, 2000 PAMI]

Cuts in a graph: Normalized cut



Normalized Cut

- fix bias of Min Cut by **normalizing** for size of segments:

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

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

- Ncut value small when we get two clusters with many edges with high weights, and few edges of low weight between them
- Approximate solution for minimizing the Ncut value : generalized eigenvalue problem.

J. Shi and J. Malik, Normalized Cuts and Image Segmentation, CVPR, 1997

Source: Steve Seitz

Example results

Results: Berkeley Segmentation Engine

http://www.cs.berkeley.edu/~fowlkes/BSE/

Normalized cuts: pros and cons

Pros:

- Generic framework, flexible to choice of function that computes weights ("affinities") between nodes
- Does not require model of the data distribution

Cons:

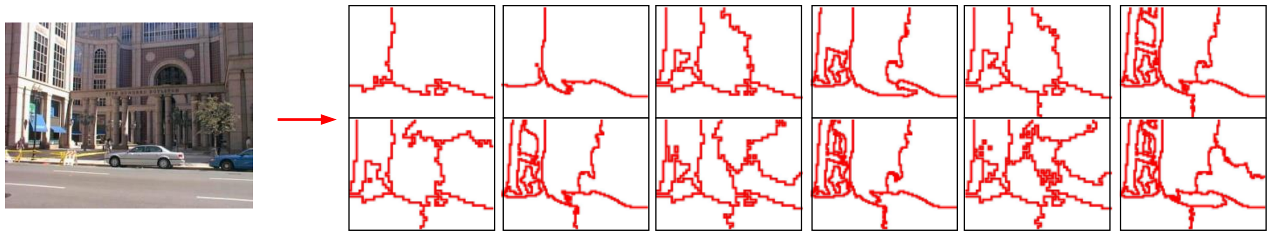
- Time complexity can be high
  - Dense, highly connected graphs → many affinity computations
  - Solving eigenvalue problem
- Preference for balanced partitions

Summary

- Segmentation to find object boundaries or mid-level regions, tokens.
- Bottom-up segmentation via clustering
  - General choices -- features, affinity functions, and clustering algorithms
- Grouping also useful for quantization, can create new feature summaries
  - Texton histograms for texture within local region
- Example clustering methods
  - K-means
  - Mean shift
  - Graph cut, normalized cuts

Segments as primitives for recognition

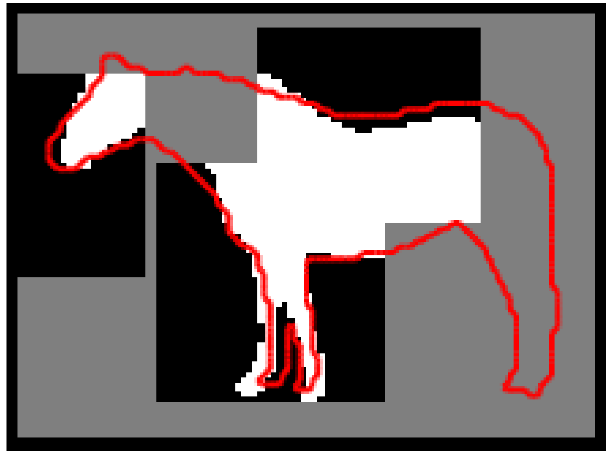
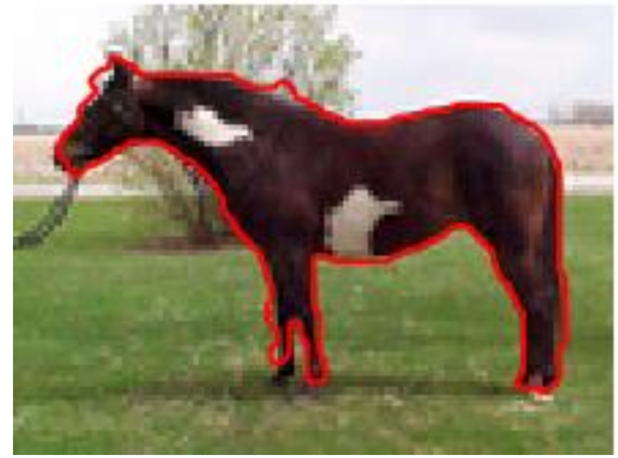
Multiple segmentations



B. Russell et al., [“Using Multiple Segmentations to Discover Objects and their Extent in Image Collections,”]() CVPR 2006

Slide credit: Lana Lazebnik

Top-down segmentation

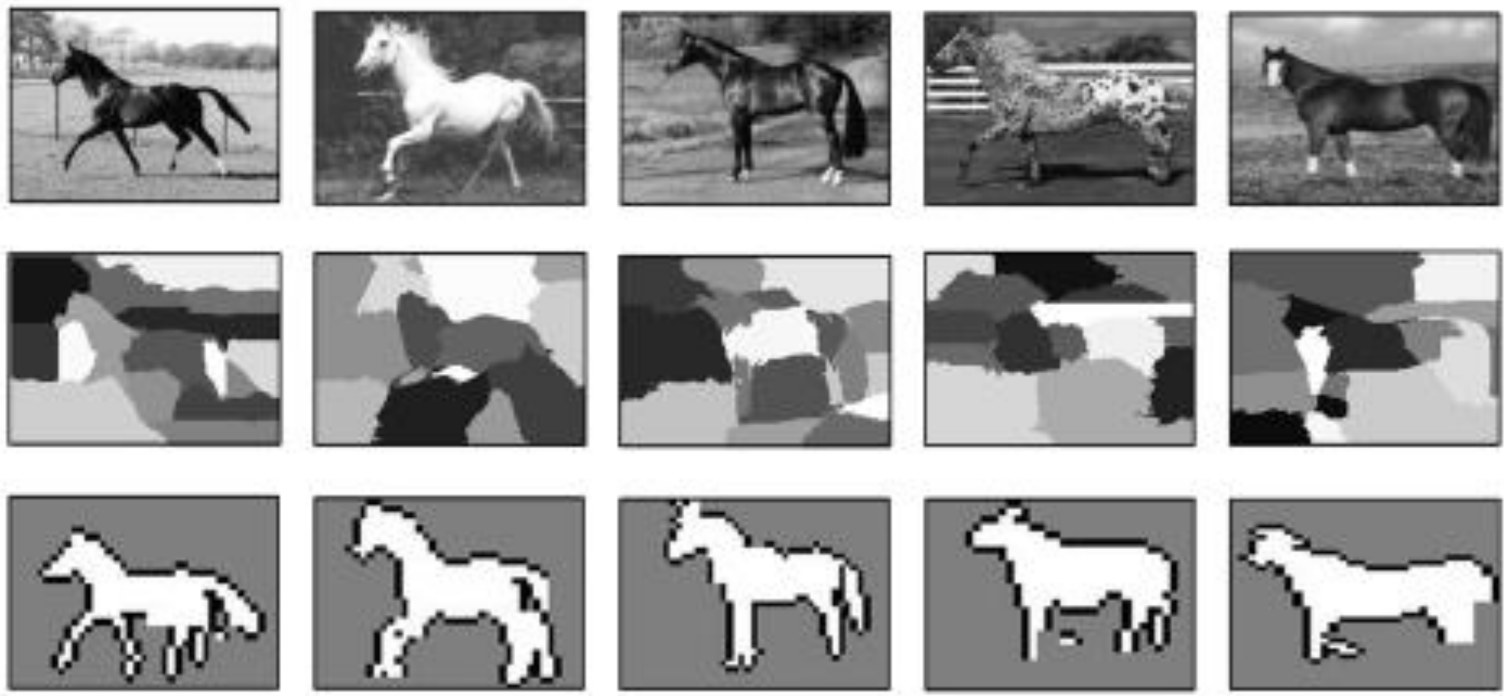




E. Borenstein and S. Ullman, “Class-specific, top-down segmentation,” ECCV 2002

A. Levin and Y. Weiss, “Learning to Combine Bottom-Up and Top-Down Segmentation,” ECCV 2006.

Slide credit: Lana Lazebnik

Top-down segmentation



Normalized cuts

Top-down segmentation

E. Borenstein and S. Ullman, [“Class-specific, top-down segmentation,”]() ECCV 2002

A. Levin and Y. Weiss, [“Learning to Combine Bottom-Up and Top-Down Segmentation,”]() ECCV 2006.

Slide credit: Lana Lazebnik

Motion segmentation


Input sequence

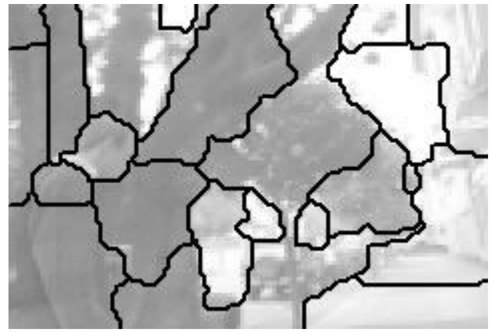


Image Segmentation


Motion Segmentation

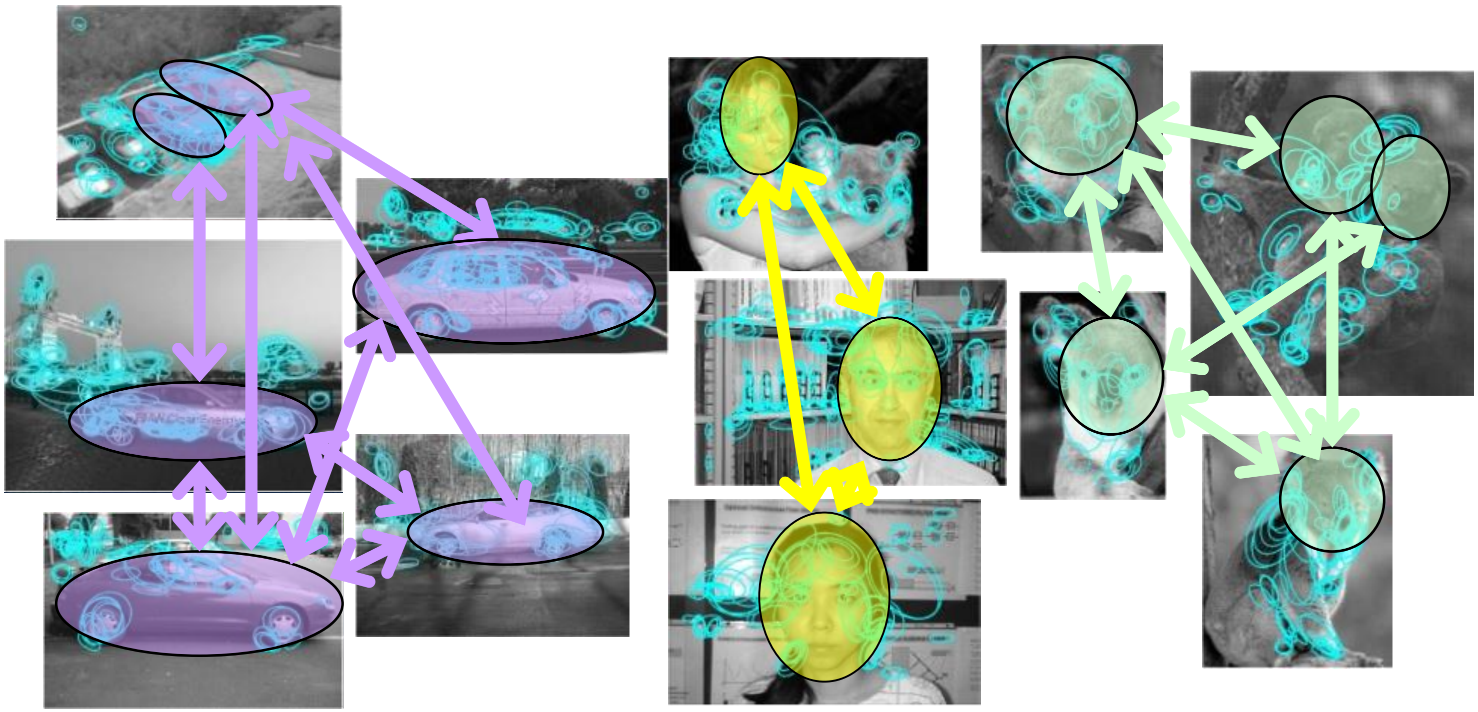

Input sequence


Image Segmentation


Motion Segmentation

A.Barbu, S.C. Zhu. Generalizing Swendsen-Wang to sampling arbitrary posterior probabilities, *IEEE Trans. PAMI,* August 2005.

Image grouping



K. Grauman & T. Darrell, Unsupervised Learning of Categories from Sets of Partially Matching Image Features, CVPR 2006.