Segmentation I

Goal

Separate image into coherent “regions”

Berkeley segmentation database:

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/

Slide by L. Lazebnik

Applications

"Intelligent scissors"

Foreground / background segmentation

Finding skin-colored regions

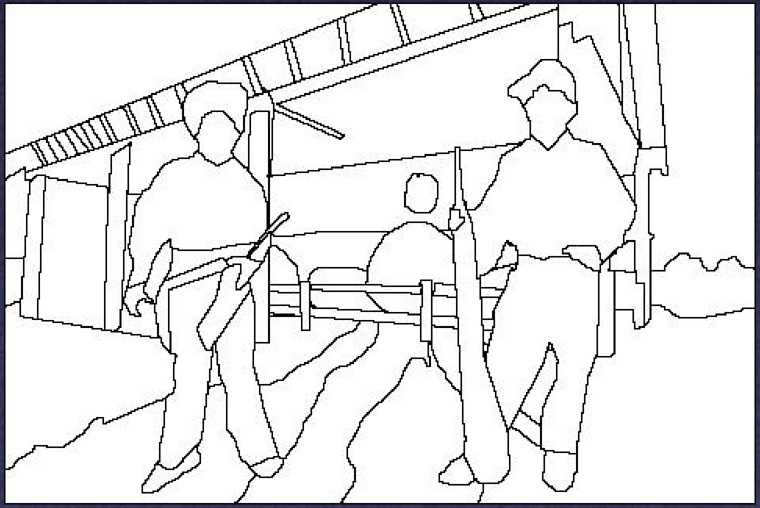
Finding the moving objects

Finding the cars in a video sequence

Semantics

Questions

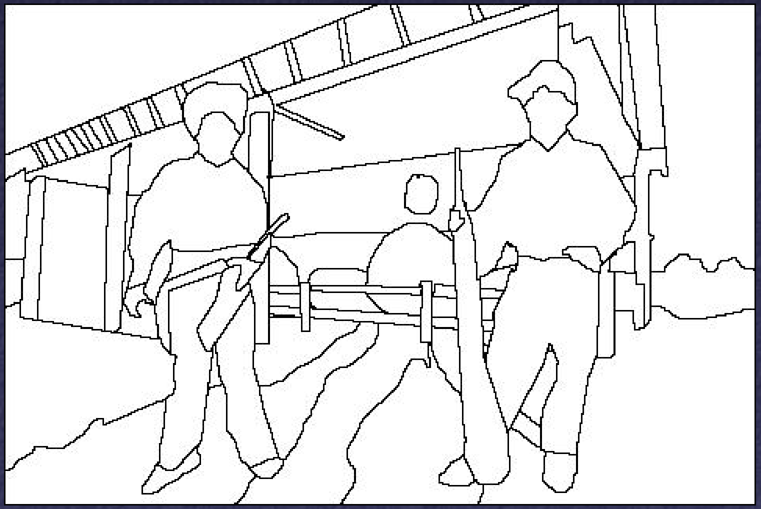
What is coherent?



Questions

What is coherent?

- Spatial proximity?
- Similar color?
- Similar texture?

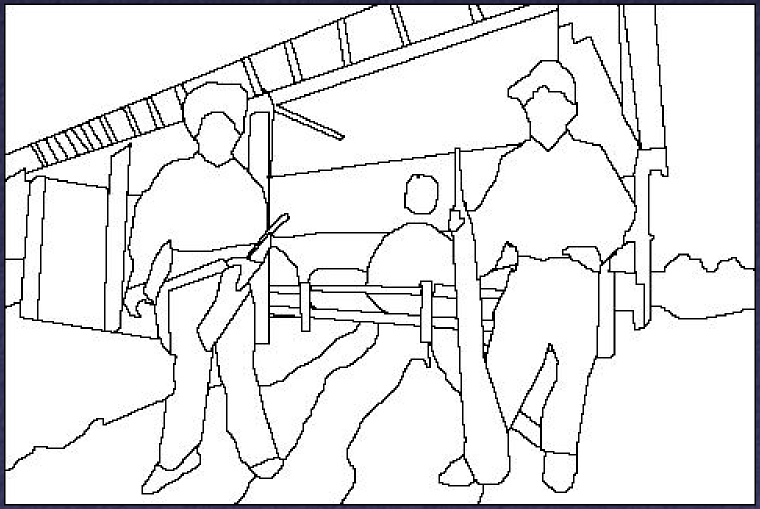


Questions

What is coherent?

- Spatial proximity?
- Similar color?
- Similar texture?

What kinds of regions?



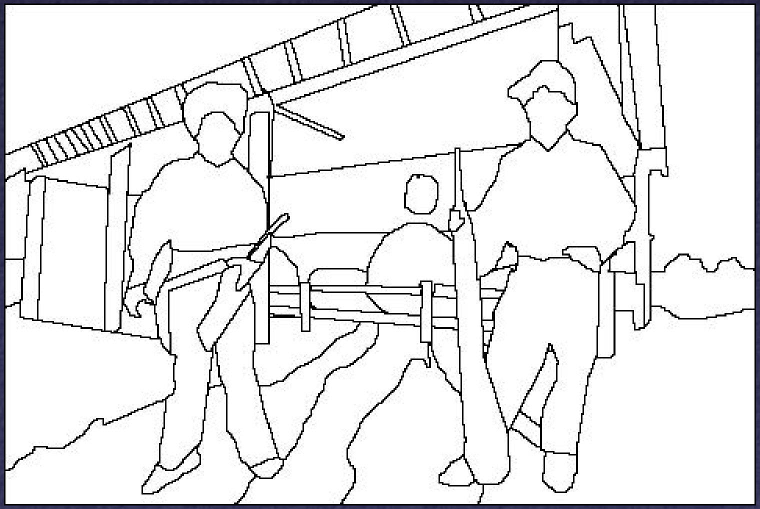
Questions

What is coherent?

- Spatial proximity?
- Similar color?
- Similar texture?

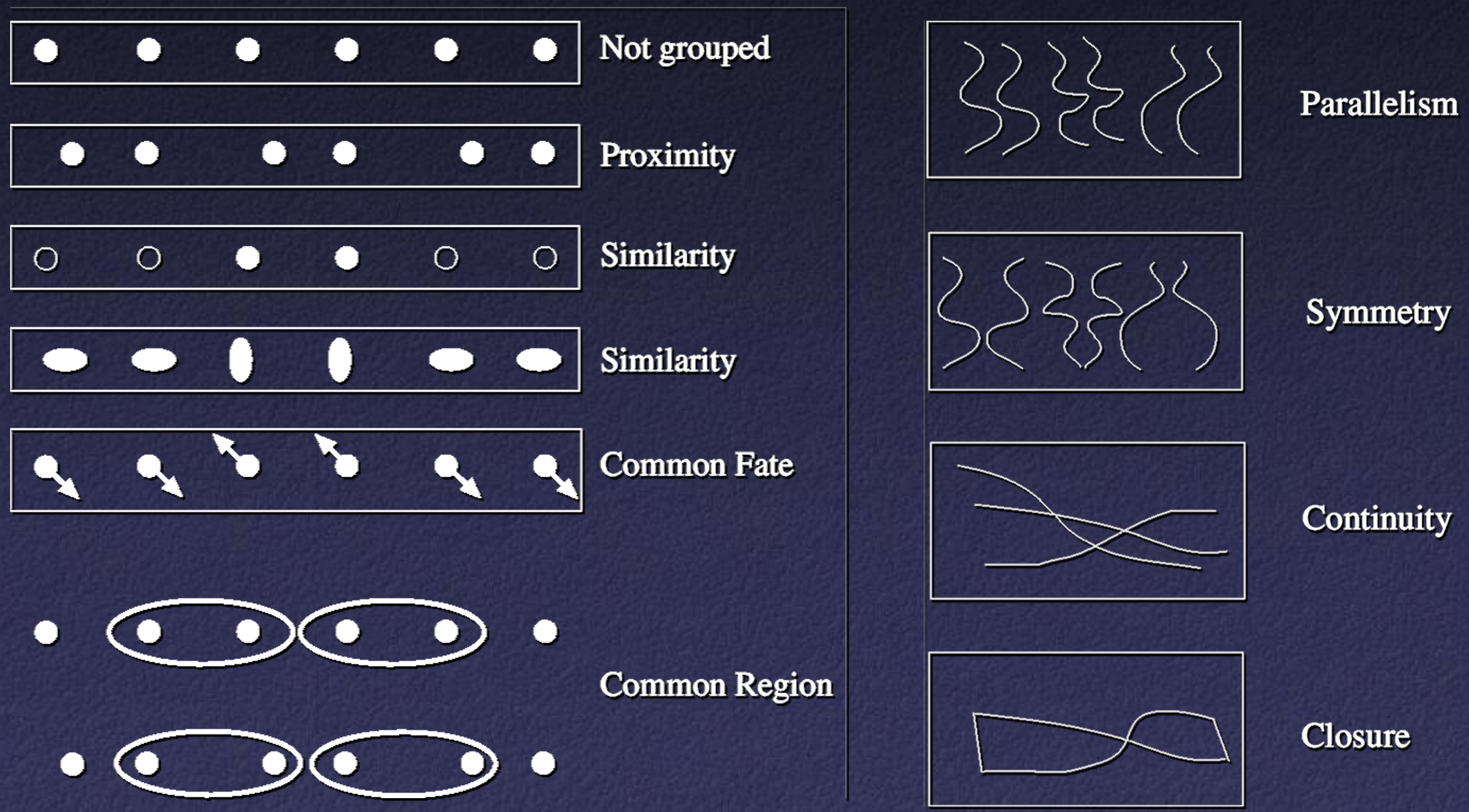
What kinds of regions?

- Nearly convex?
- Smooth boundaries?
- Nearly equal sizes?
- What granularity?



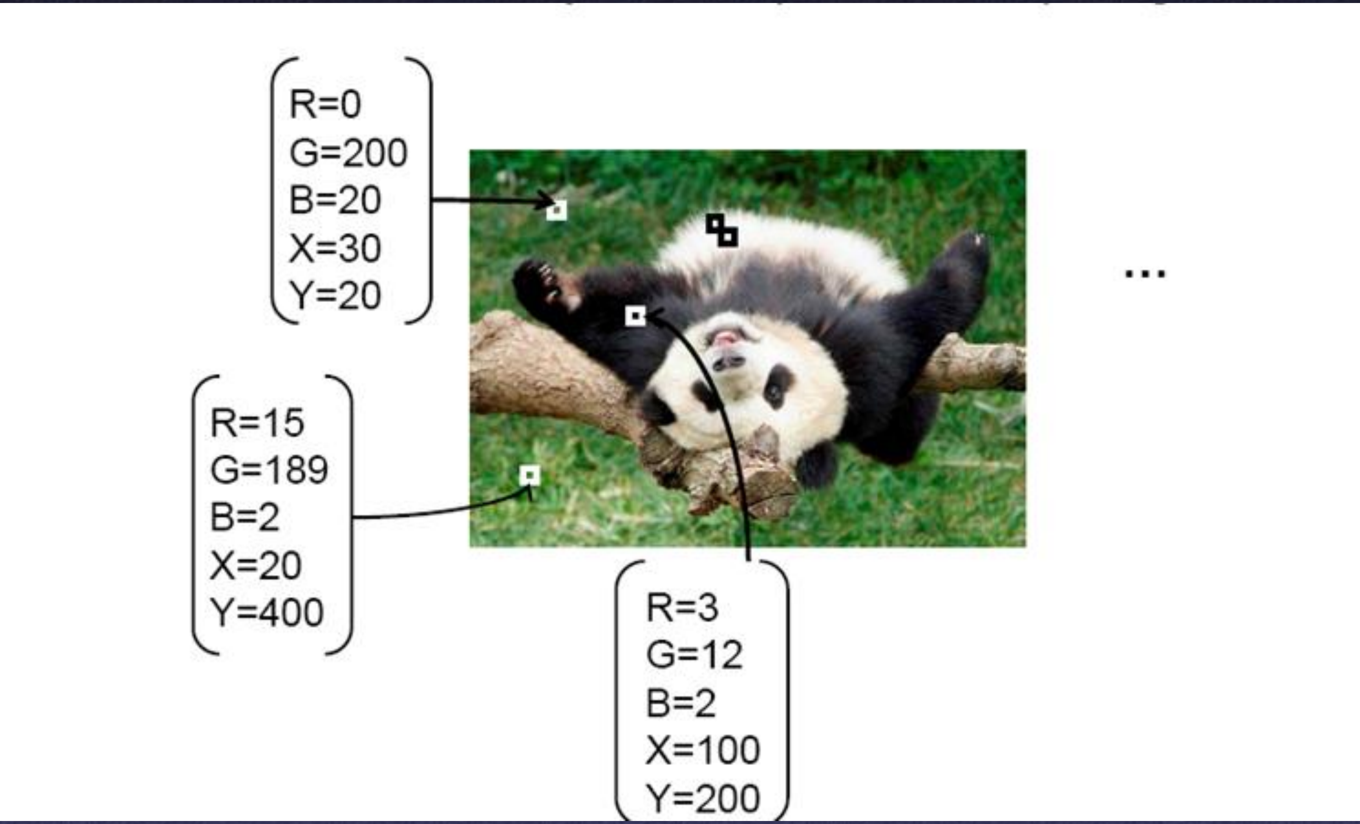
Grouping Cues

Gestault factors:



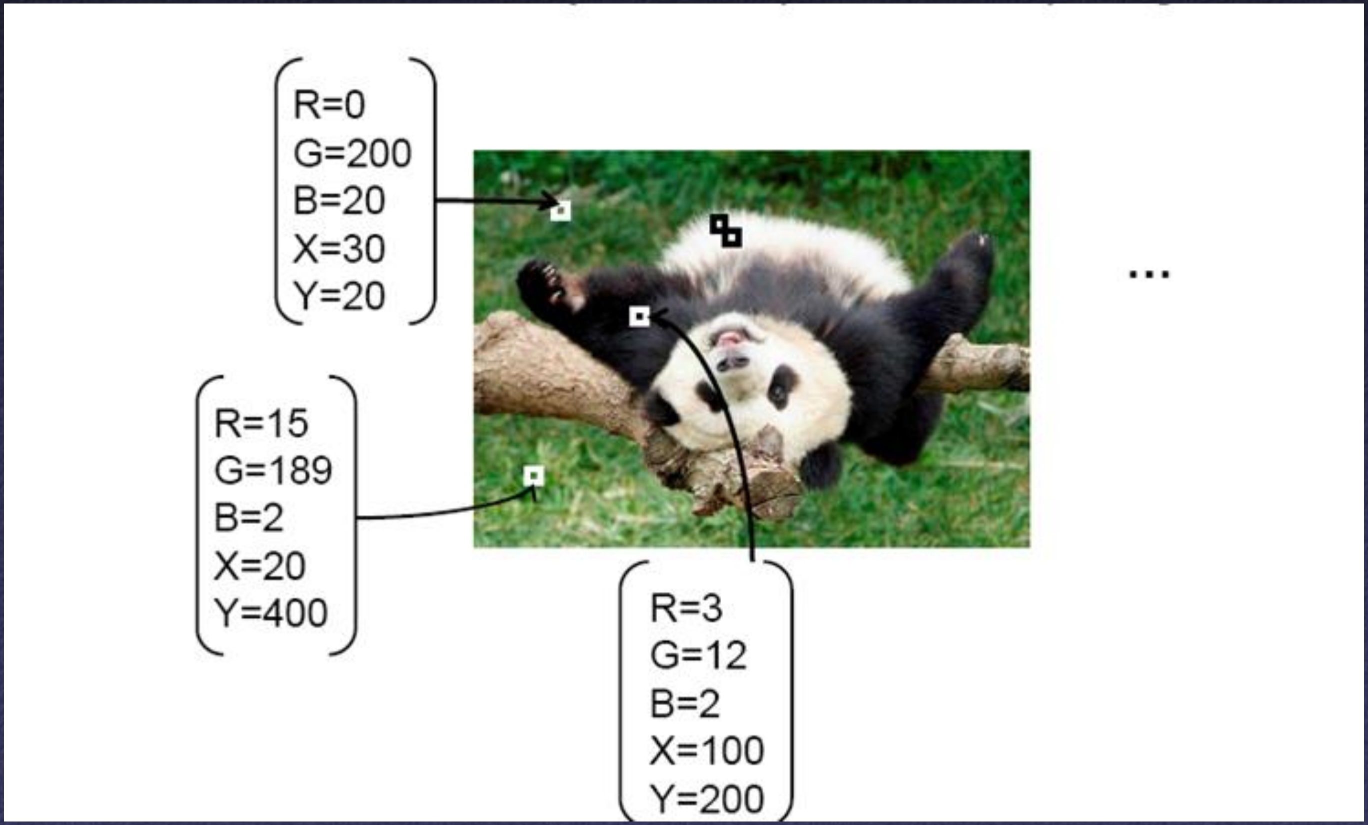
A Typical Segmentation Problem

Partition an image into arbitrarily shaped regions containing pixels with similar colors and positions



Segmentation Algorithms?

What kinds of algorithm(s) can solve this problem?



Some Segmentation Algorithms

Divisive clustering

Hierarchical clustering

K-means clustering

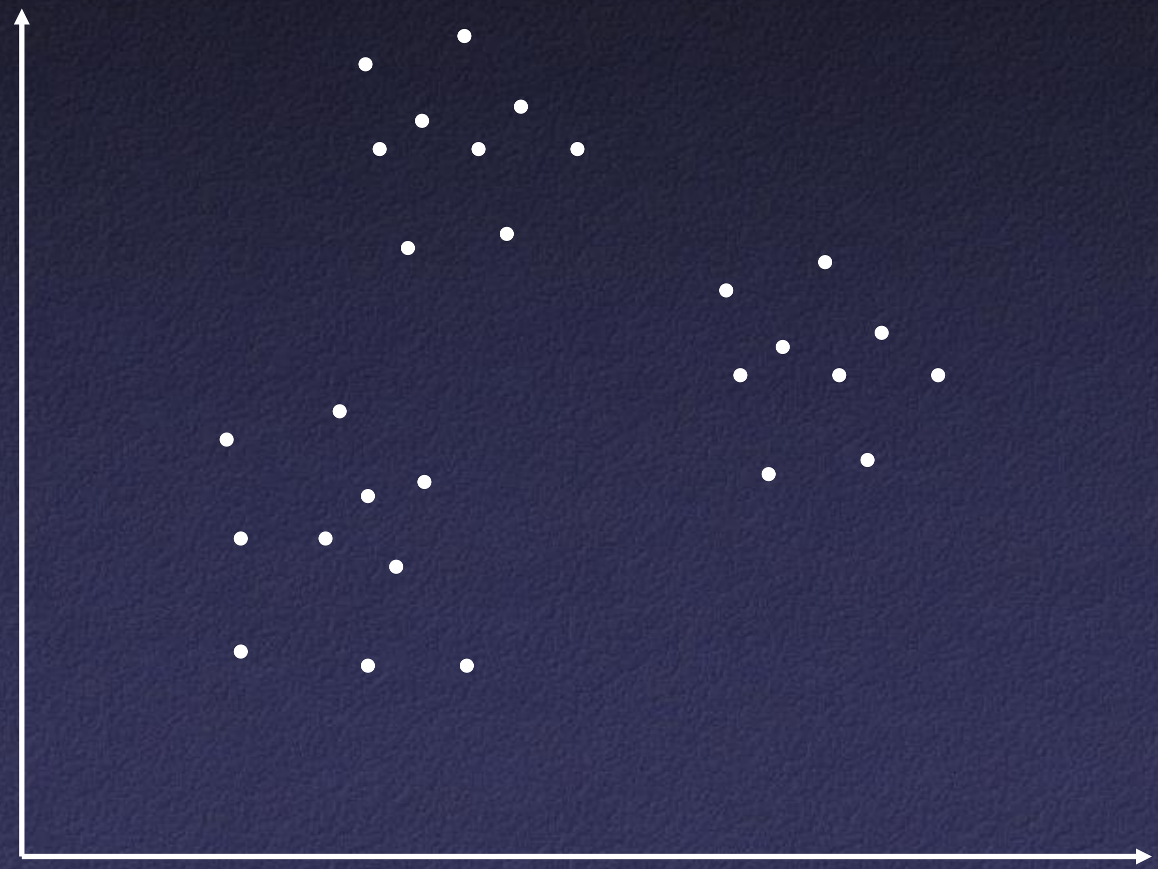
Mean shift clustering

Graph cuts

More next time …

Segmentation as Clustering

Segmentation can be treated as a clustering problem



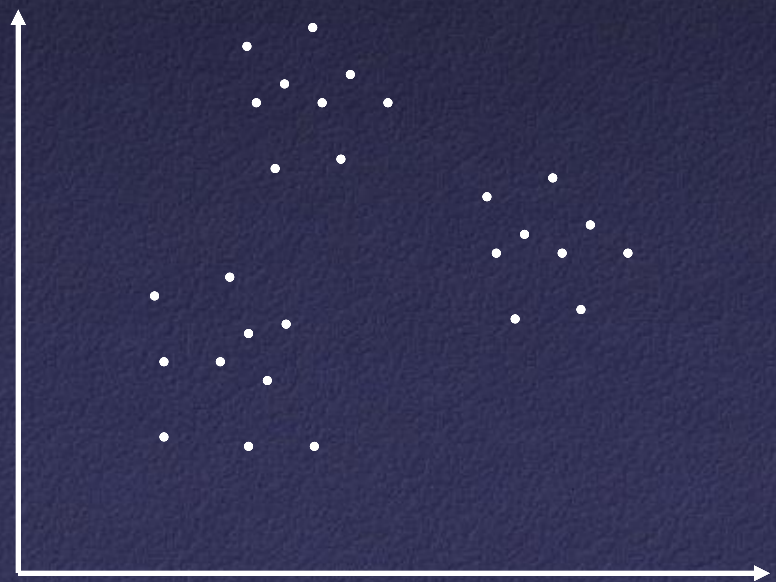
Divisive Clustering

Start with whole image in one cluster

Iterate:

- Find cluster with largest intra-cluster variation
- Split into two pieces that yield largest inter-cluster distance

Stopping criteria?



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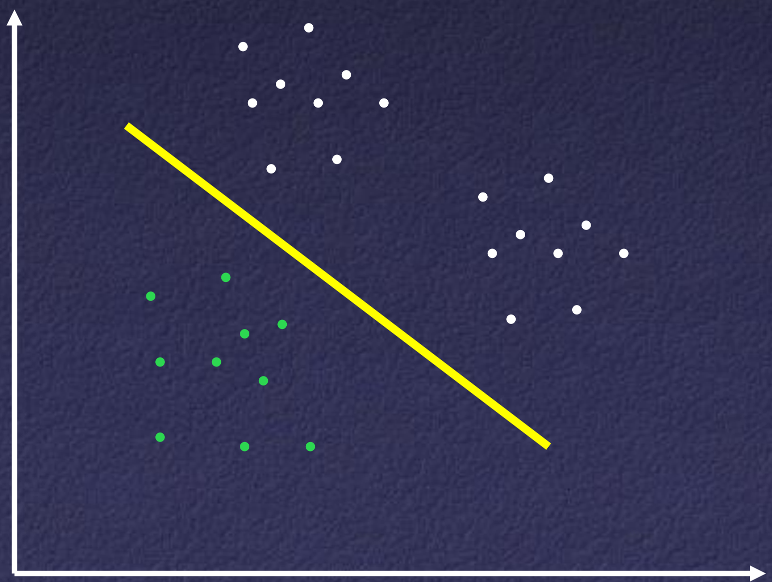

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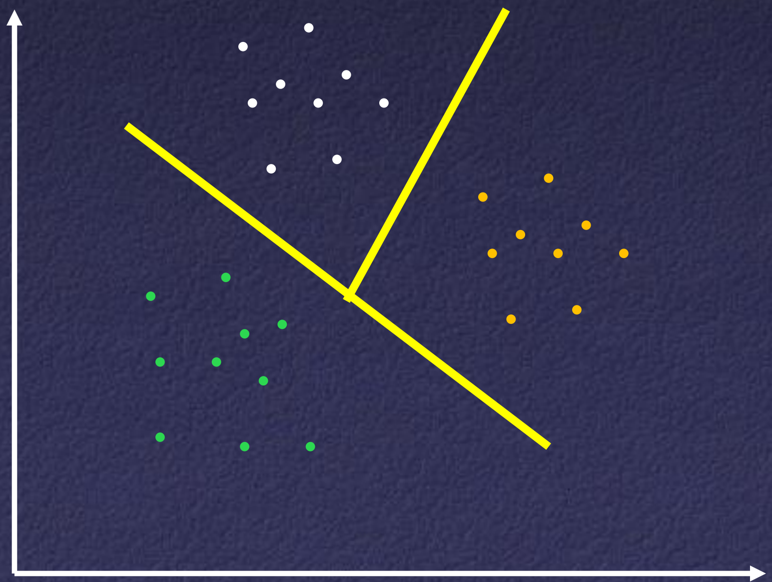


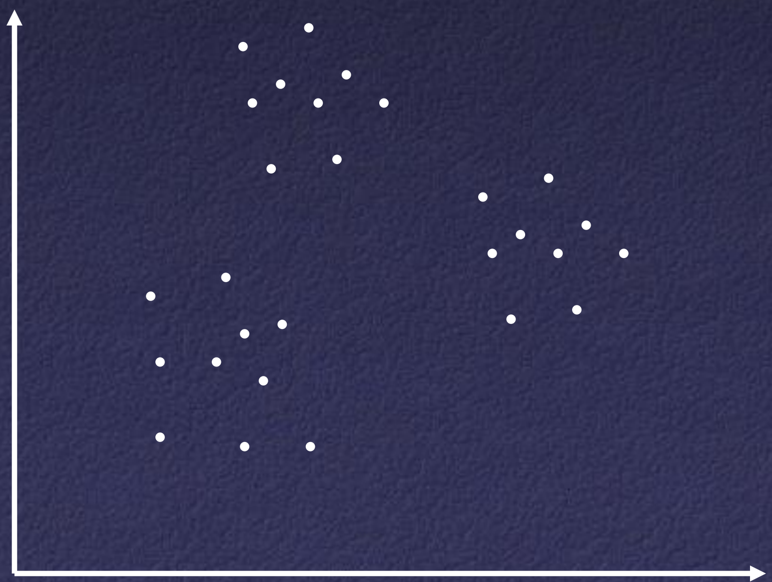
Hierarchical Clustering

Start with each pixel in its own cluster

Iterate:

- Find pair of clusters with smallest inter-cluster distance
- Merge

Stopping criteria?



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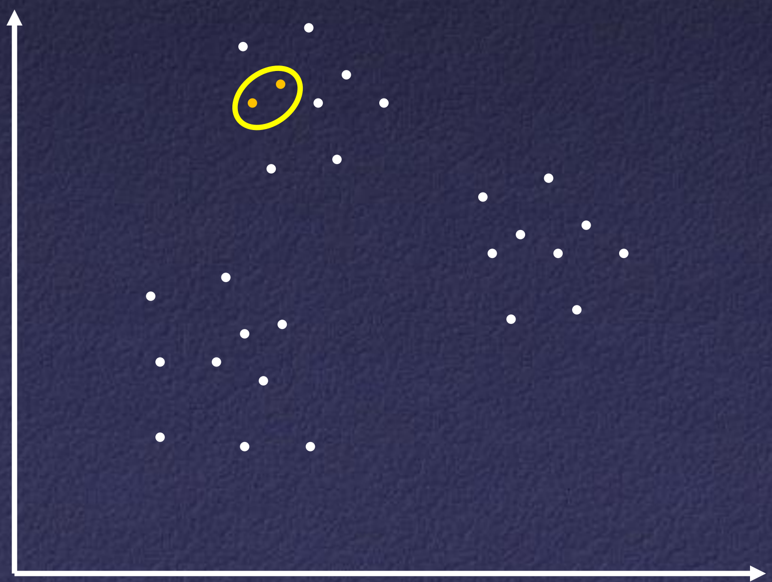

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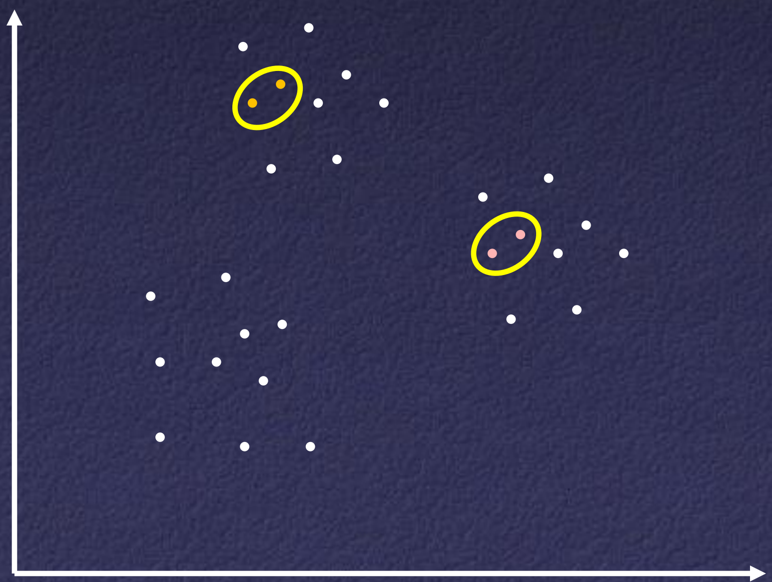

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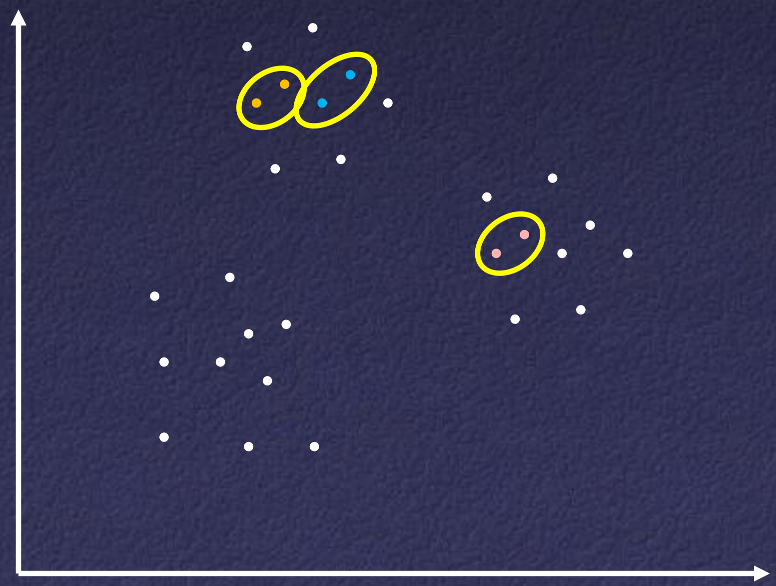

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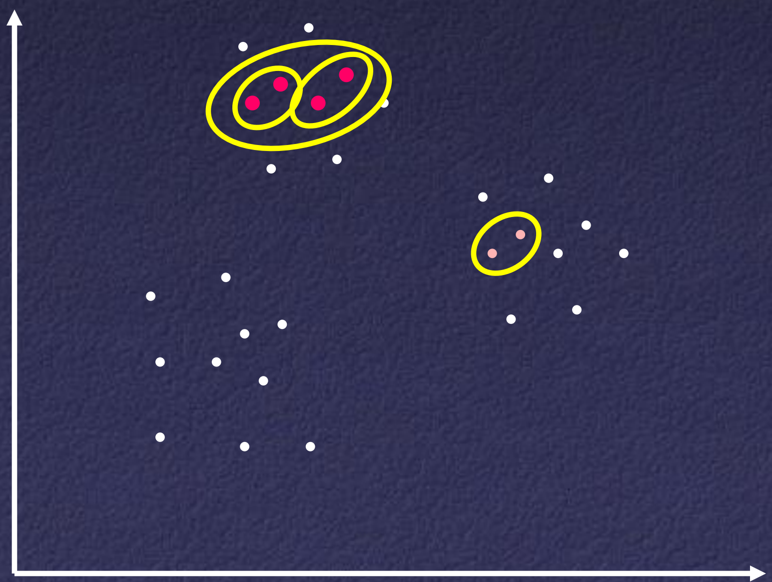

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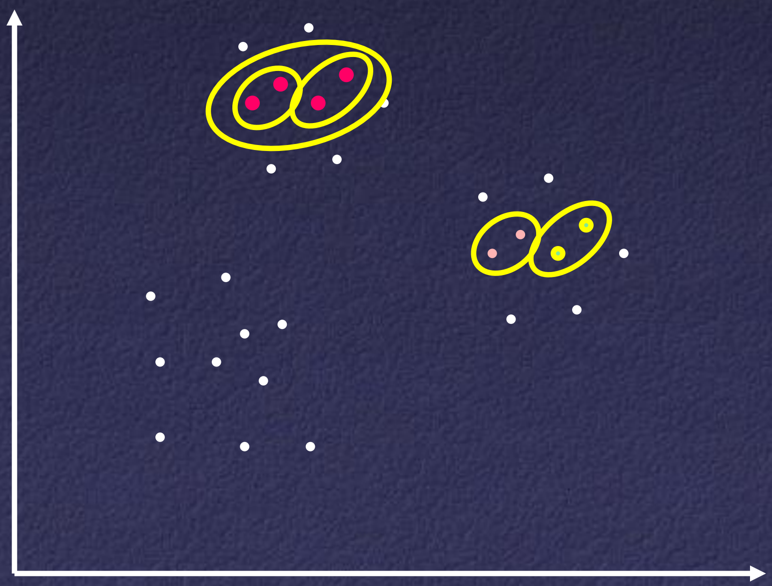

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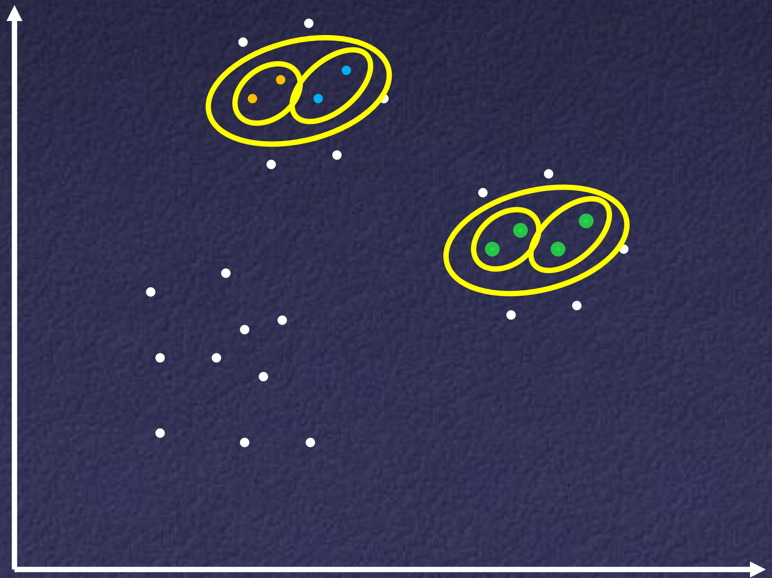

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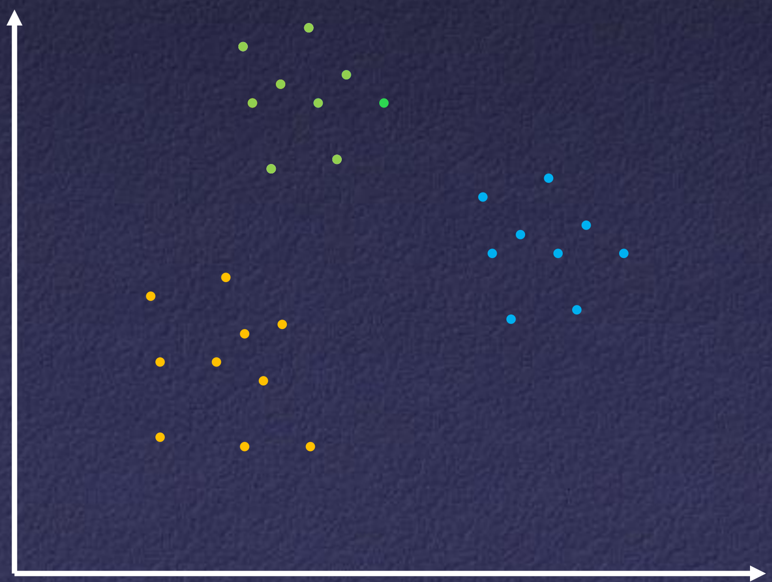
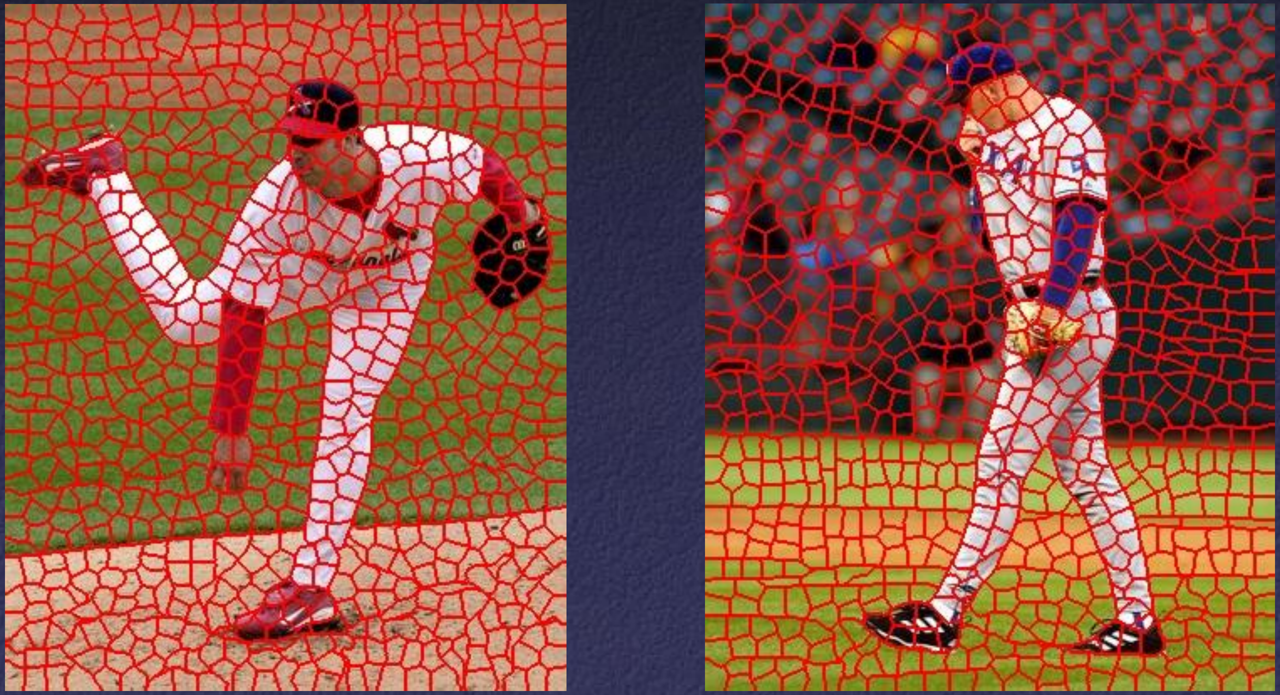


Hierarchical Clustering

Conservative stopping criteria yields “superpixels”, which can be used as starting point for more complex algorithms



Ren et al.

Problems with These Algorithms?

Problems with These Algorithms

Greedy

- Decisions made early in process dictate final result

Making "good" early decisions is hard/expensive

- Many possibilities at each iteration
- Computing "good" merge or split is expensive

Heuristics to speed things up:

- For agglomerative clustering, approximate each cluster by average for distance computations
- For divisive clustering, use summary (histogram) of a region to compute split

Some Segmentation Algorithms

Divisive clustering

Hierarchical clustering

k-means clustering

Mean shift clustering

Graph cuts

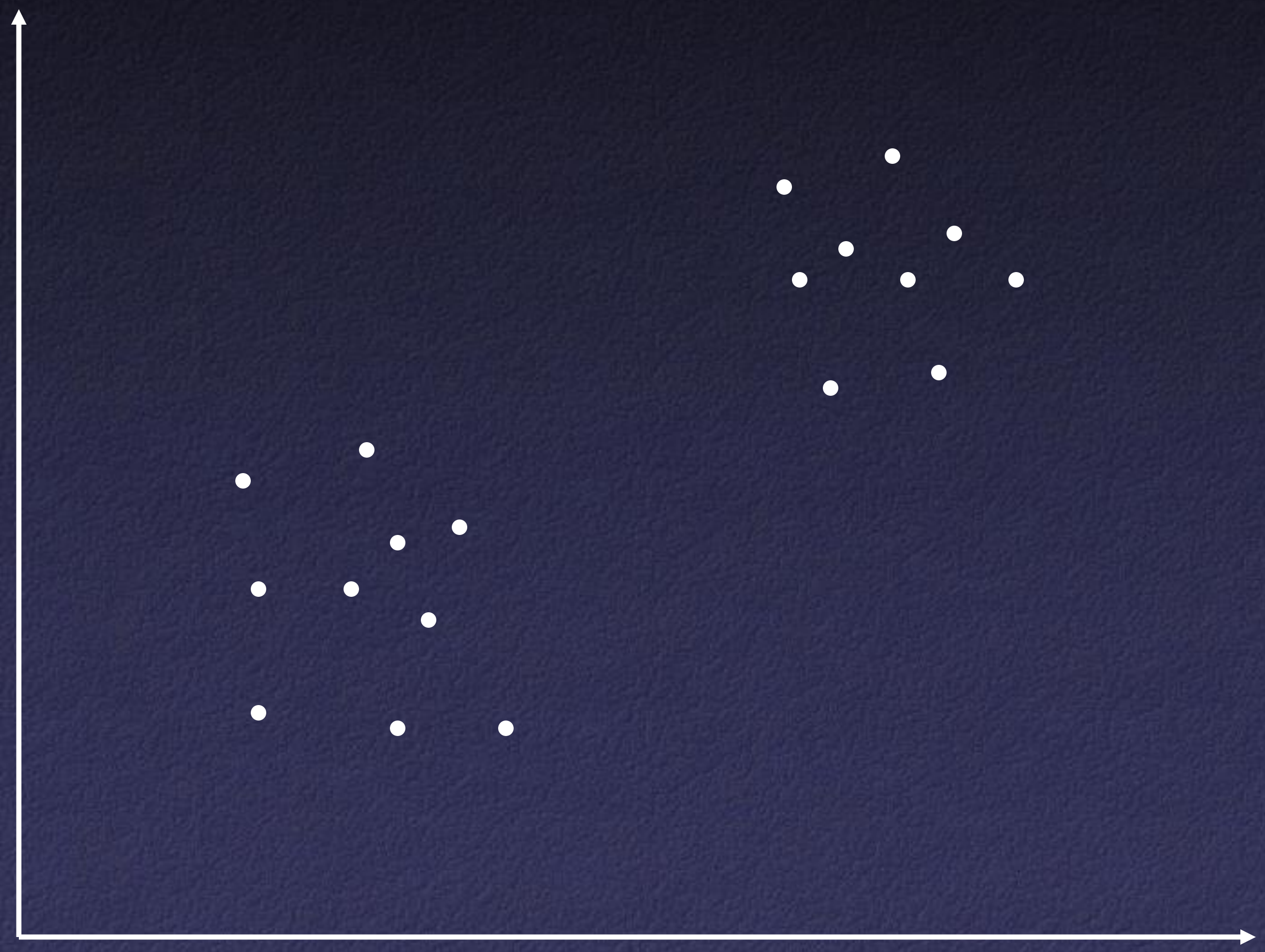
More next time …

k-Means Clustering

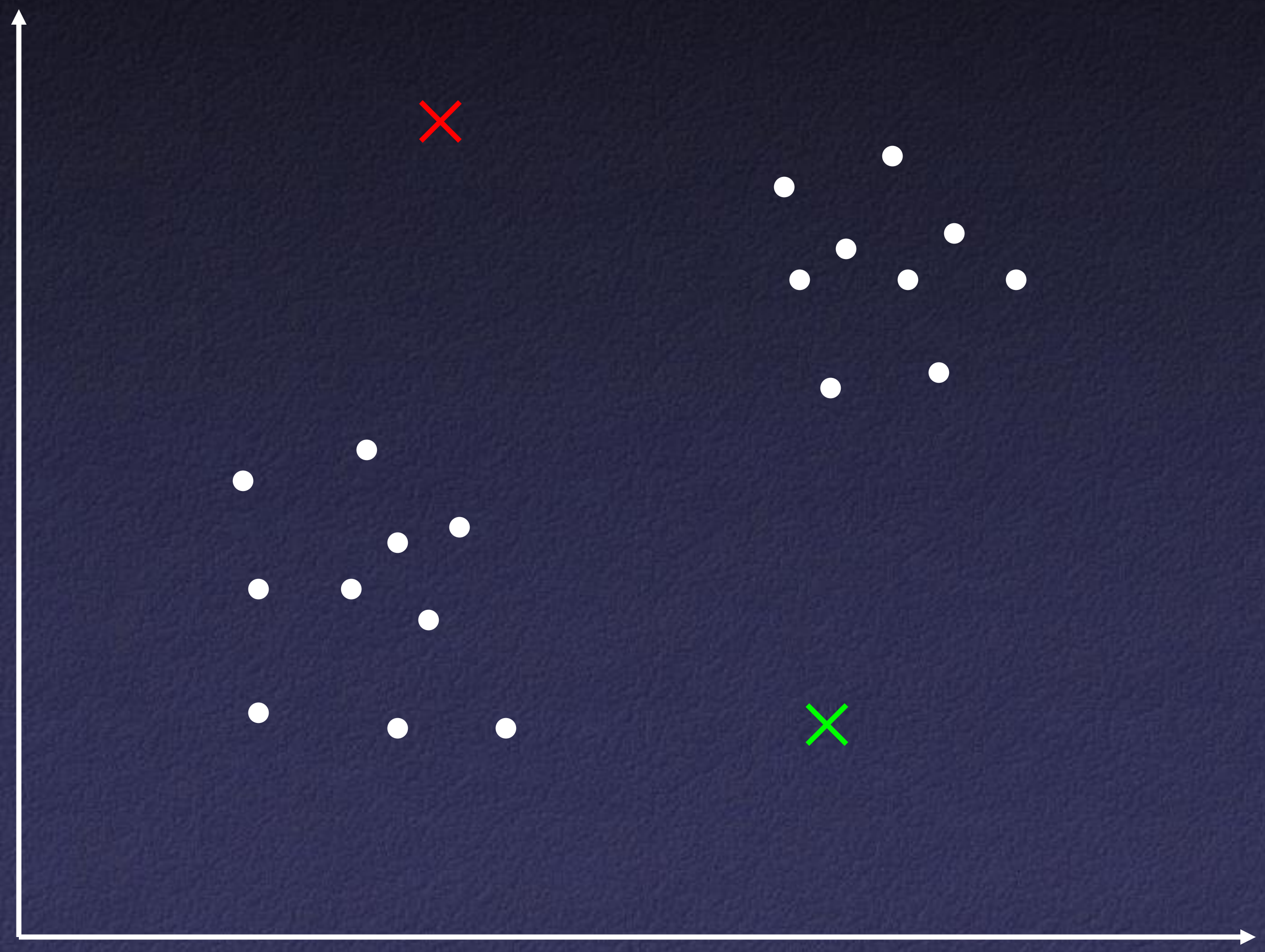
Instead of merging or splitting, start out with the clusters and move them around

1. Pick number of clusters *k*
2. Randomly scatter *k* "cluster centers" in color space
3. Repeat:
   a. Assign each data point to its closest cluster center
   b. Move each cluster center to the mean of the points assigned to it

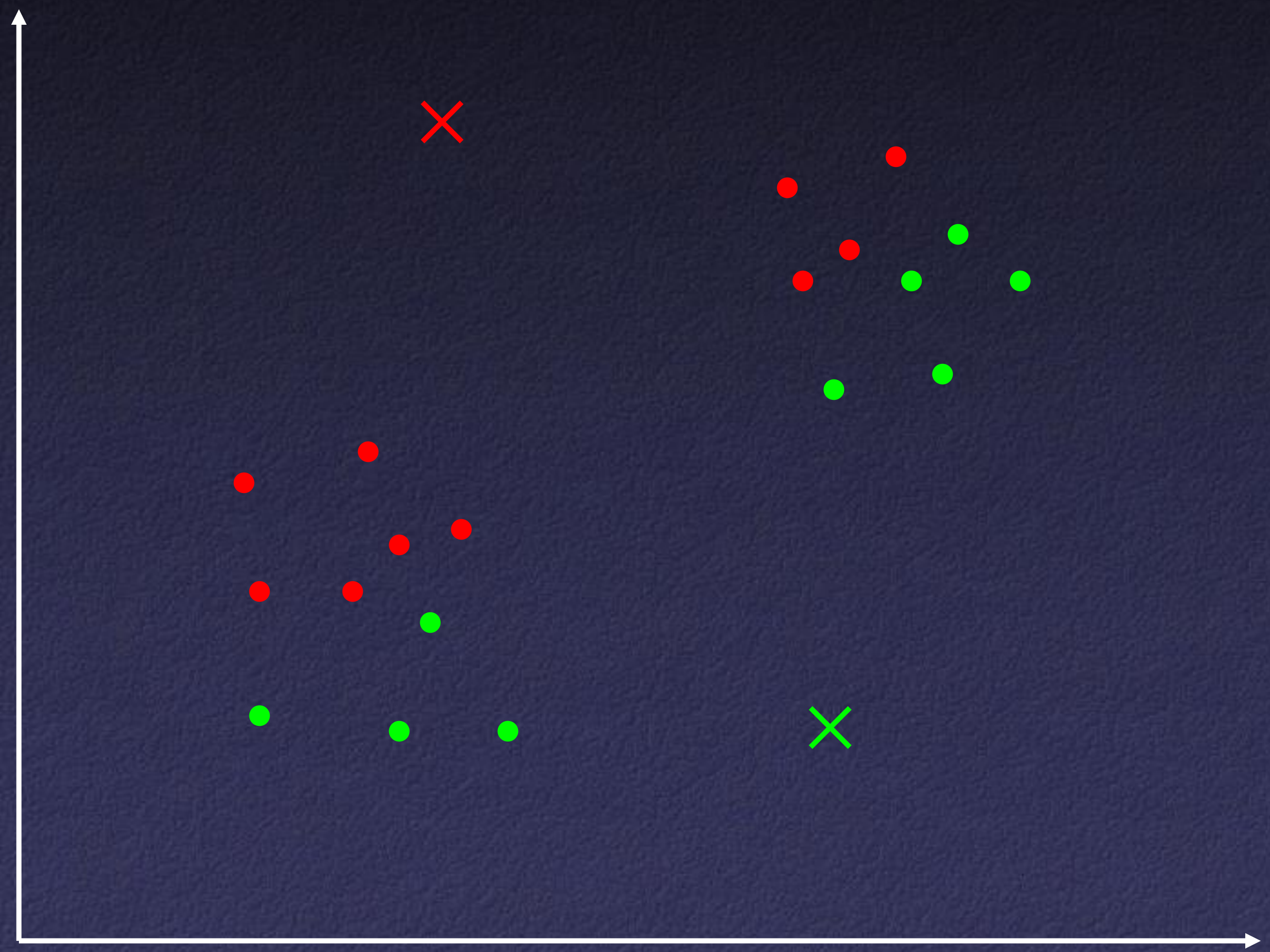
k-Means Clustering



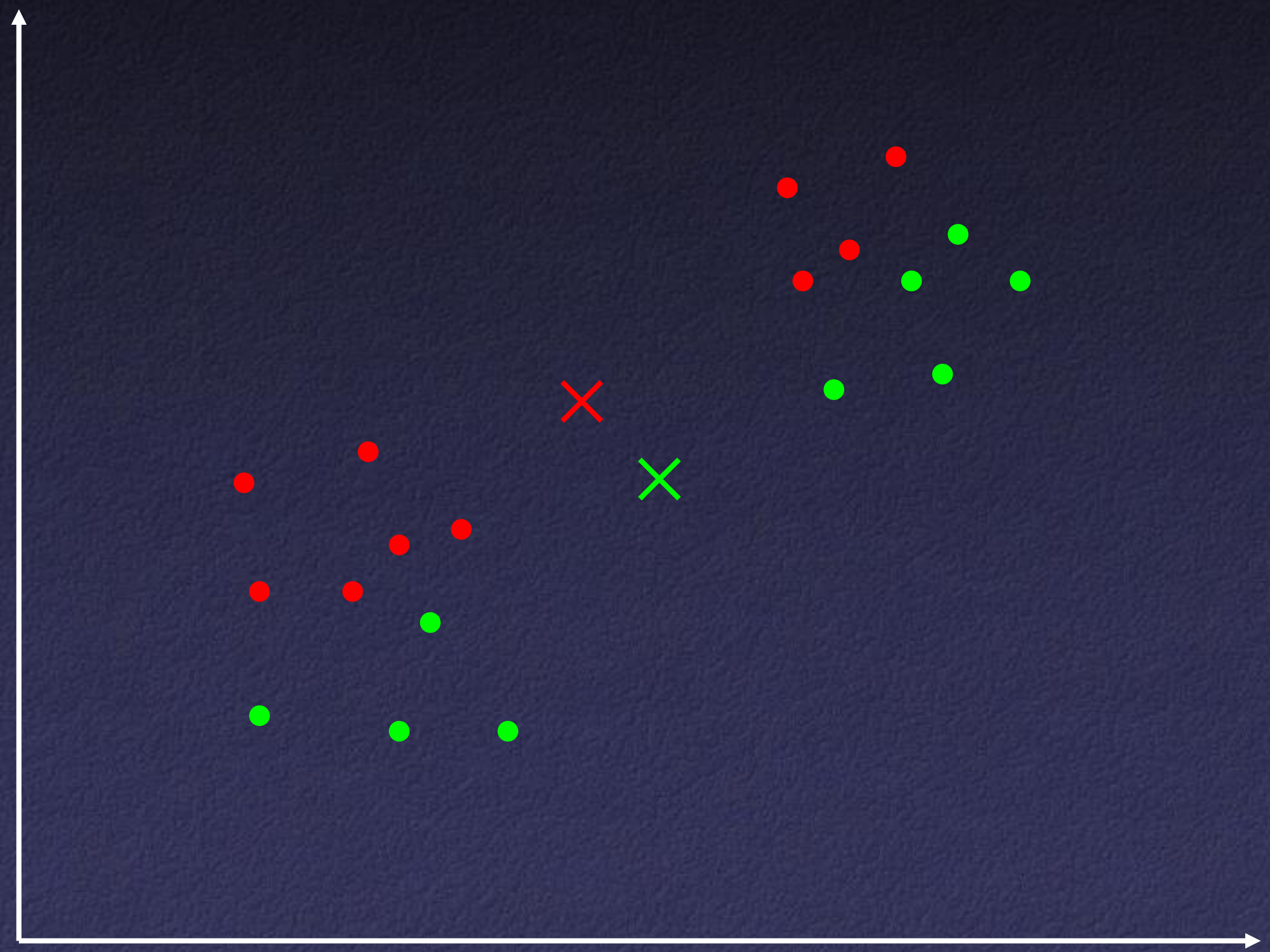
k-Means Clustering



k-Means Clustering



k-Means Clustering



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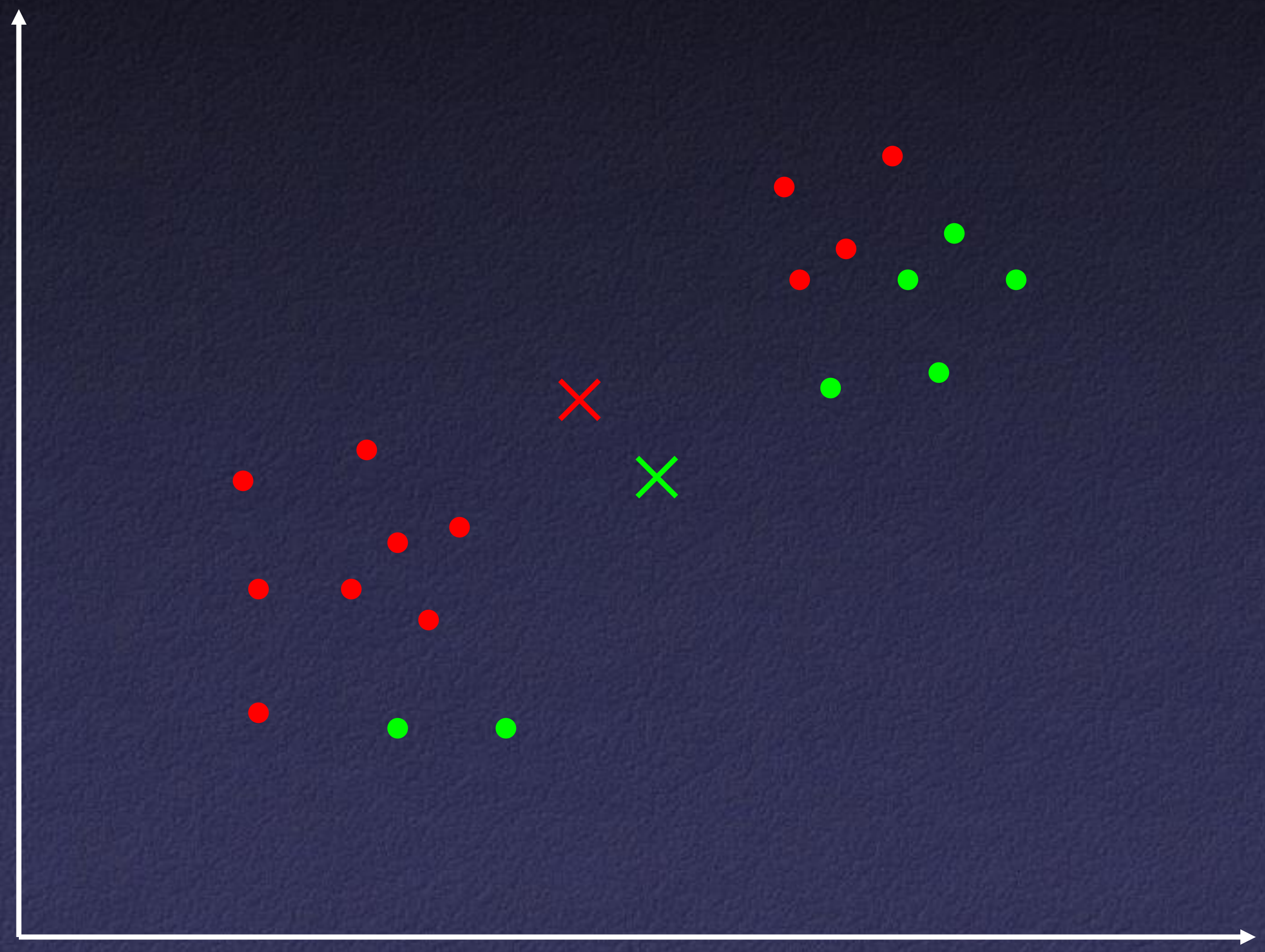

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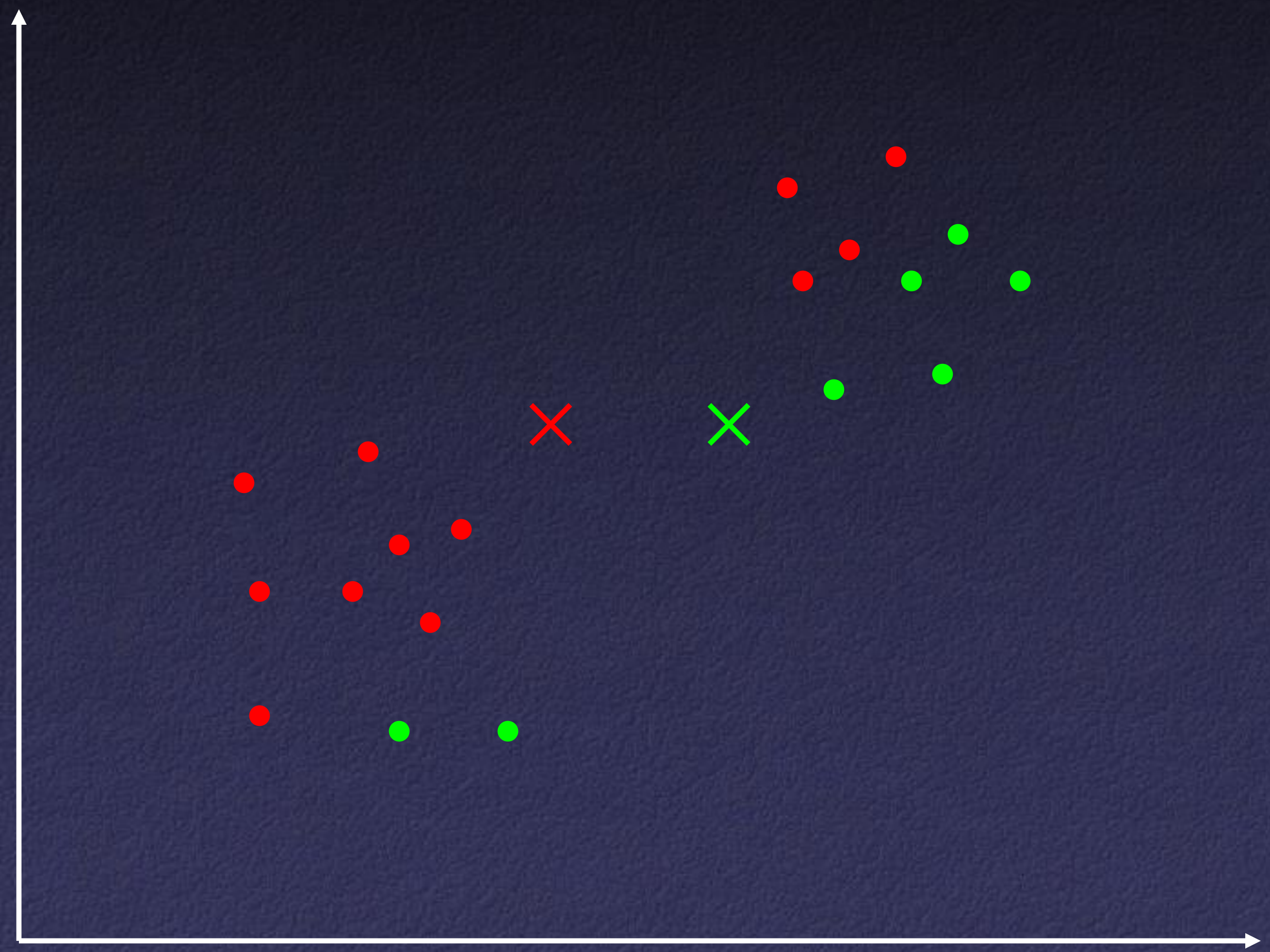

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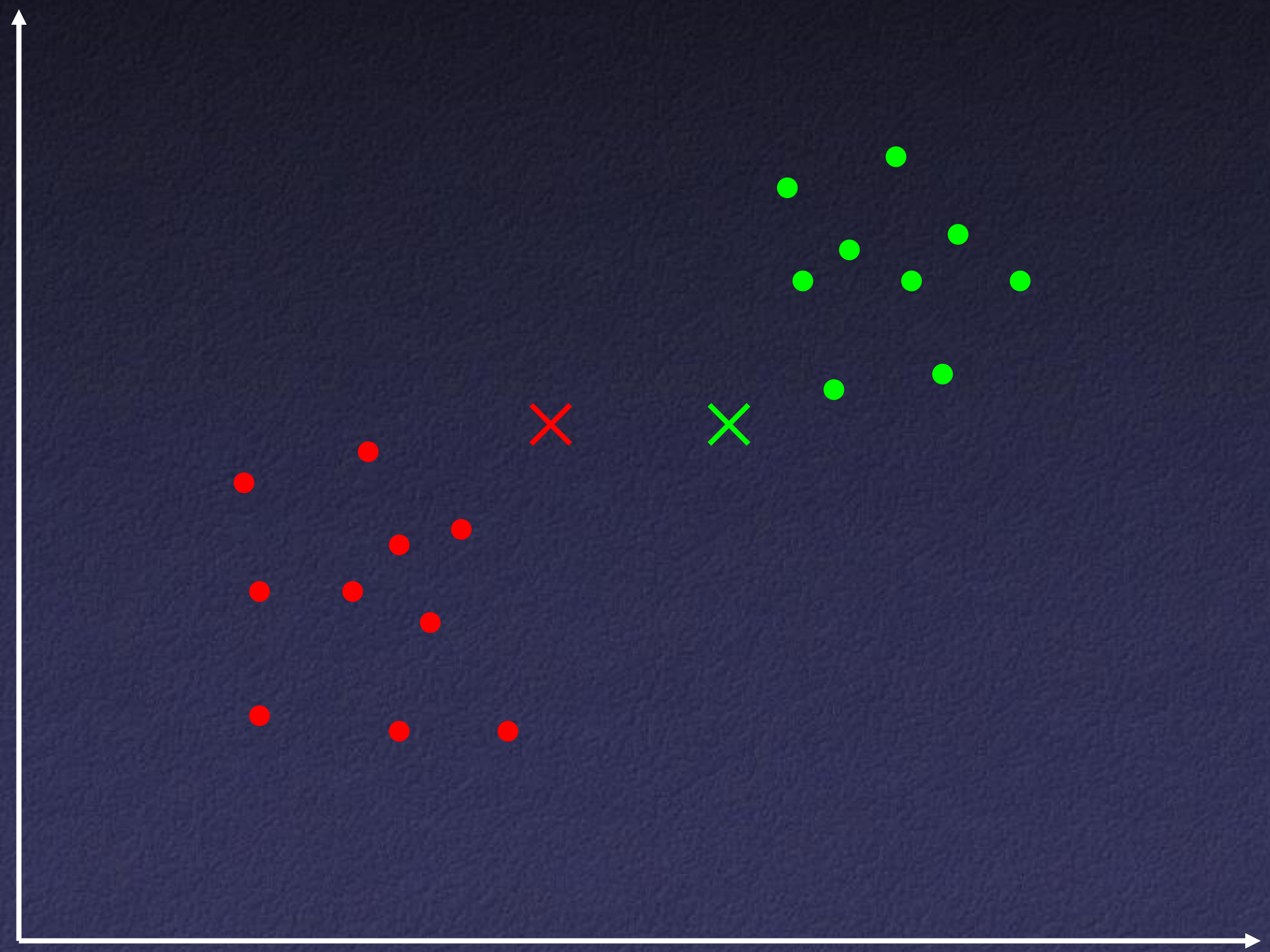

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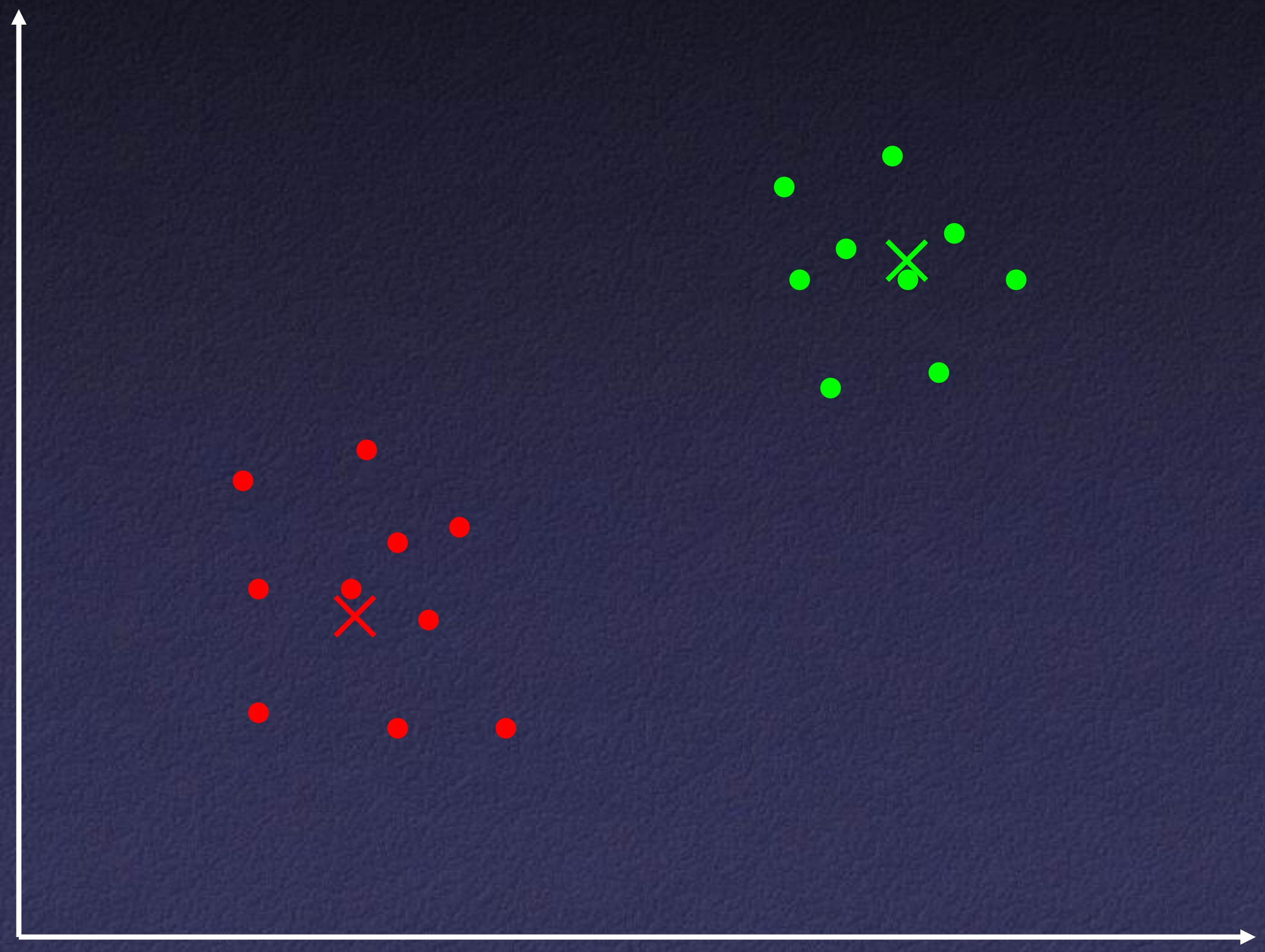
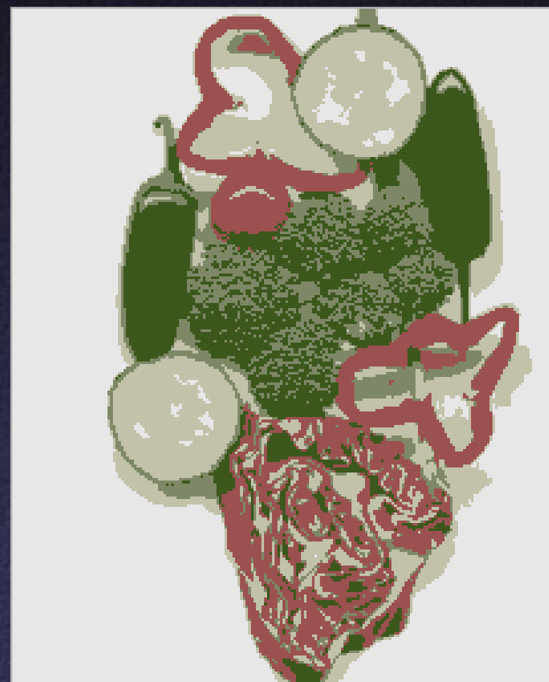


Results of k-Means Clustering

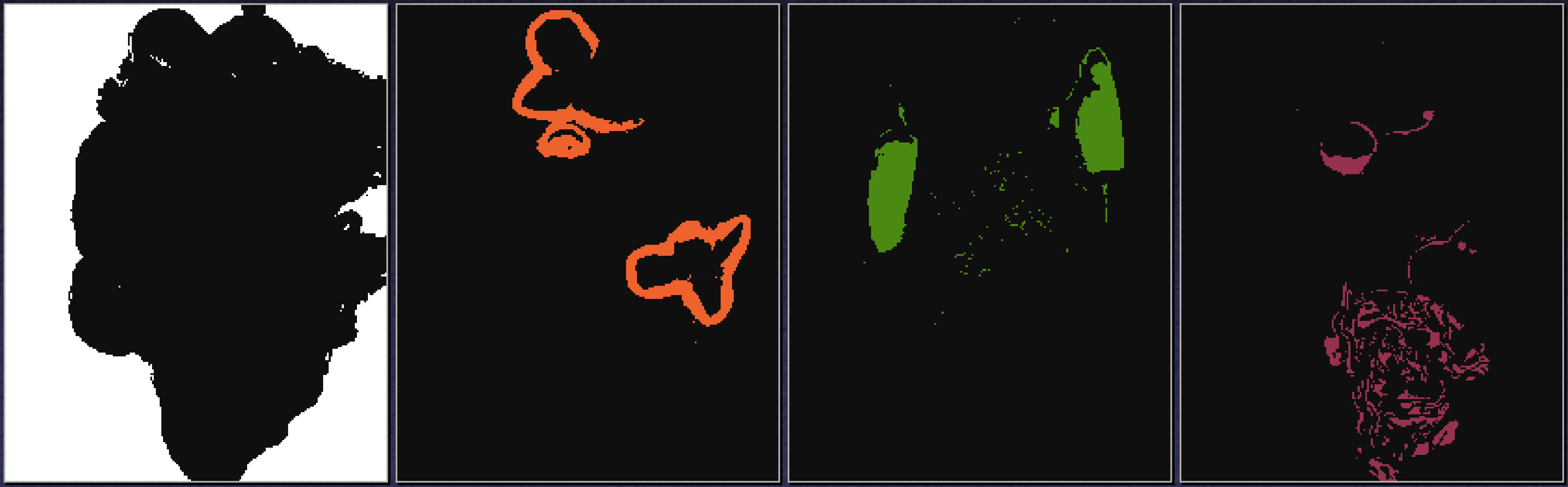
Original Image



k-means, $k=5$

k-means, $k=11$

Results of k-Means Clustering



Sample clusters with *k*-means clustering based on color

k-Means Pros and Cons?

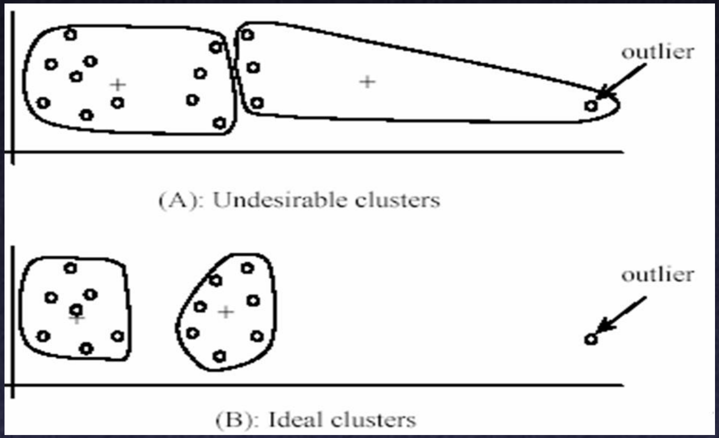
k-Means Pros and Cons

Pros

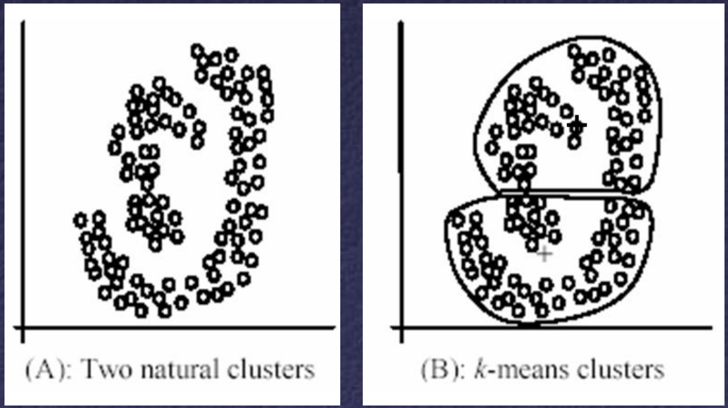
- Very simple method

Cons

- Need to pick K
- Converges to a local minimum
- Sensitive to initialization
- Sensitive to outliers
- Only finds "spherical" clusters



Sensitive to outliers



Spherical clusters

Some Segmentation Algorithms

Divisive clustering

Hierarchical clustering

k-means clustering

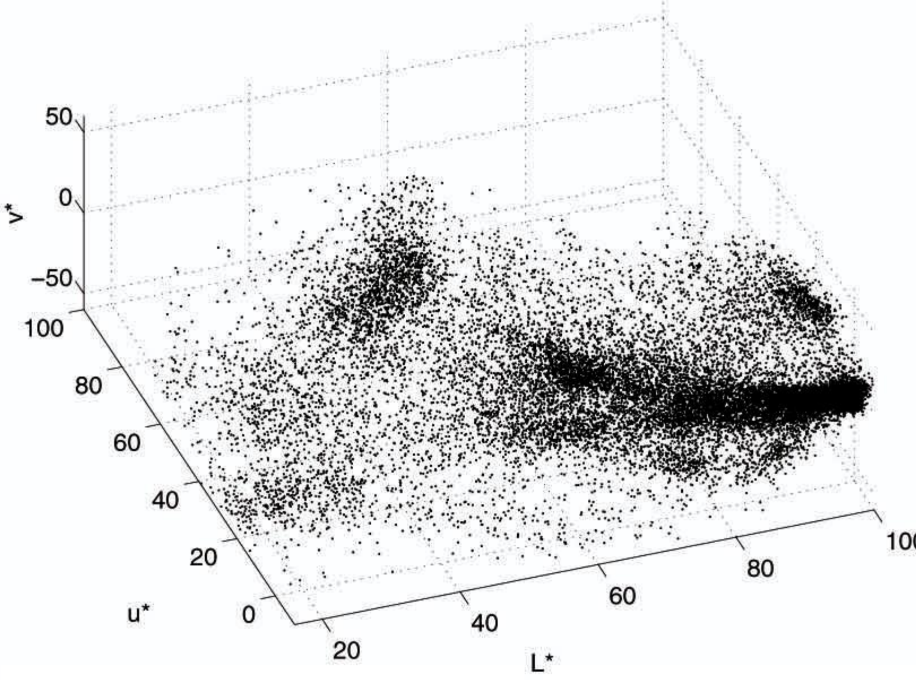
Mean shift clustering ←

Graph cuts

More next time …

Mean Shift Clustering

Seek *modes* (peaks) of density in feature space



Image

Feature space
(color values)

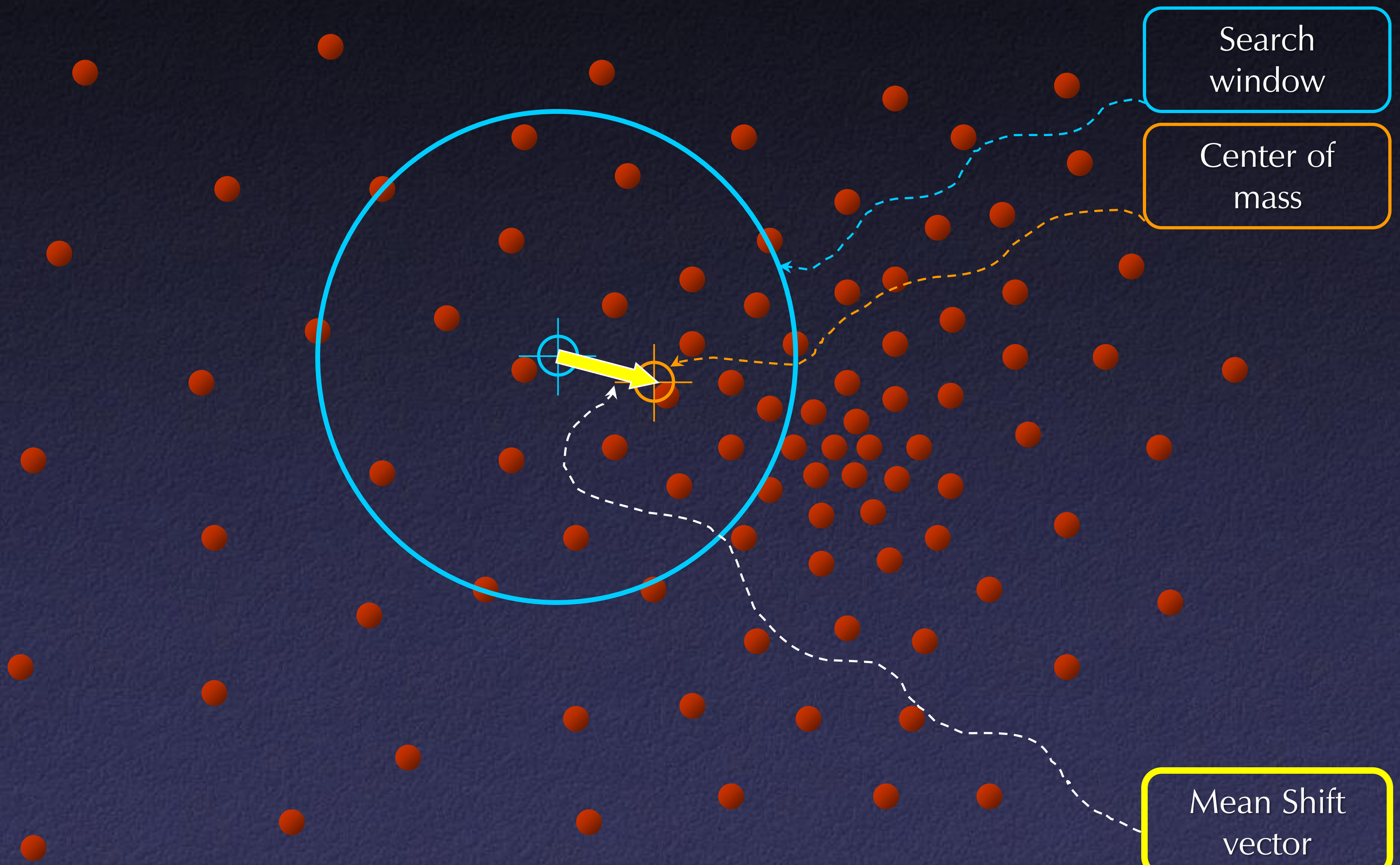
Slide by Y. Ukrainitz & B. Sarel

Mean Shift Clustering

Algorithm:

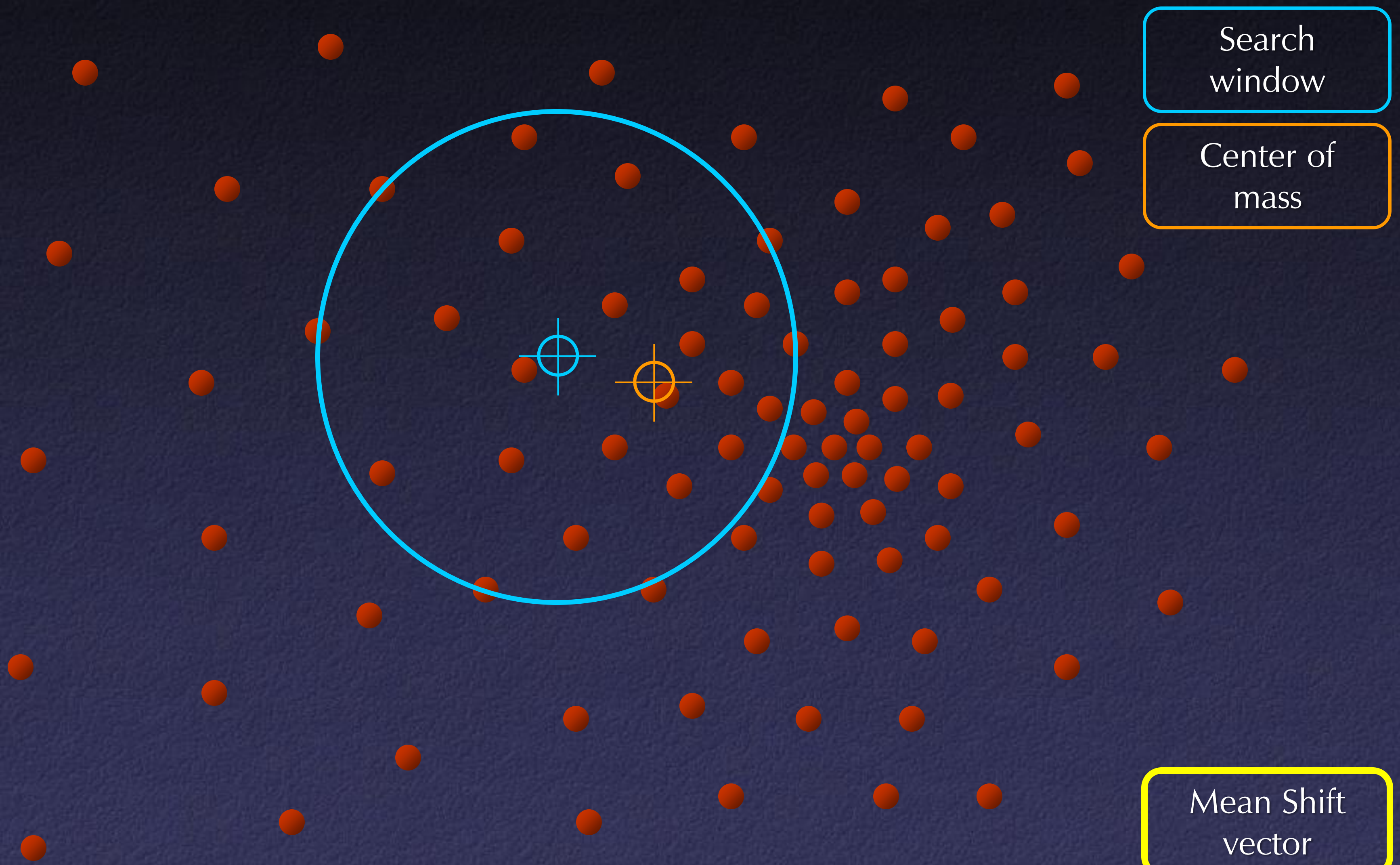
- Initialize windows at individual feature points
- Perform mean shift for each window until convergence
- Merge windows that end up near the same “peak” or mode

Mean Shift Clustering



Slide by Y. Ukrainitz & B. Sarel

Mean Shift Clustering



Slide by Y. Ukrainitz & B. Sarel

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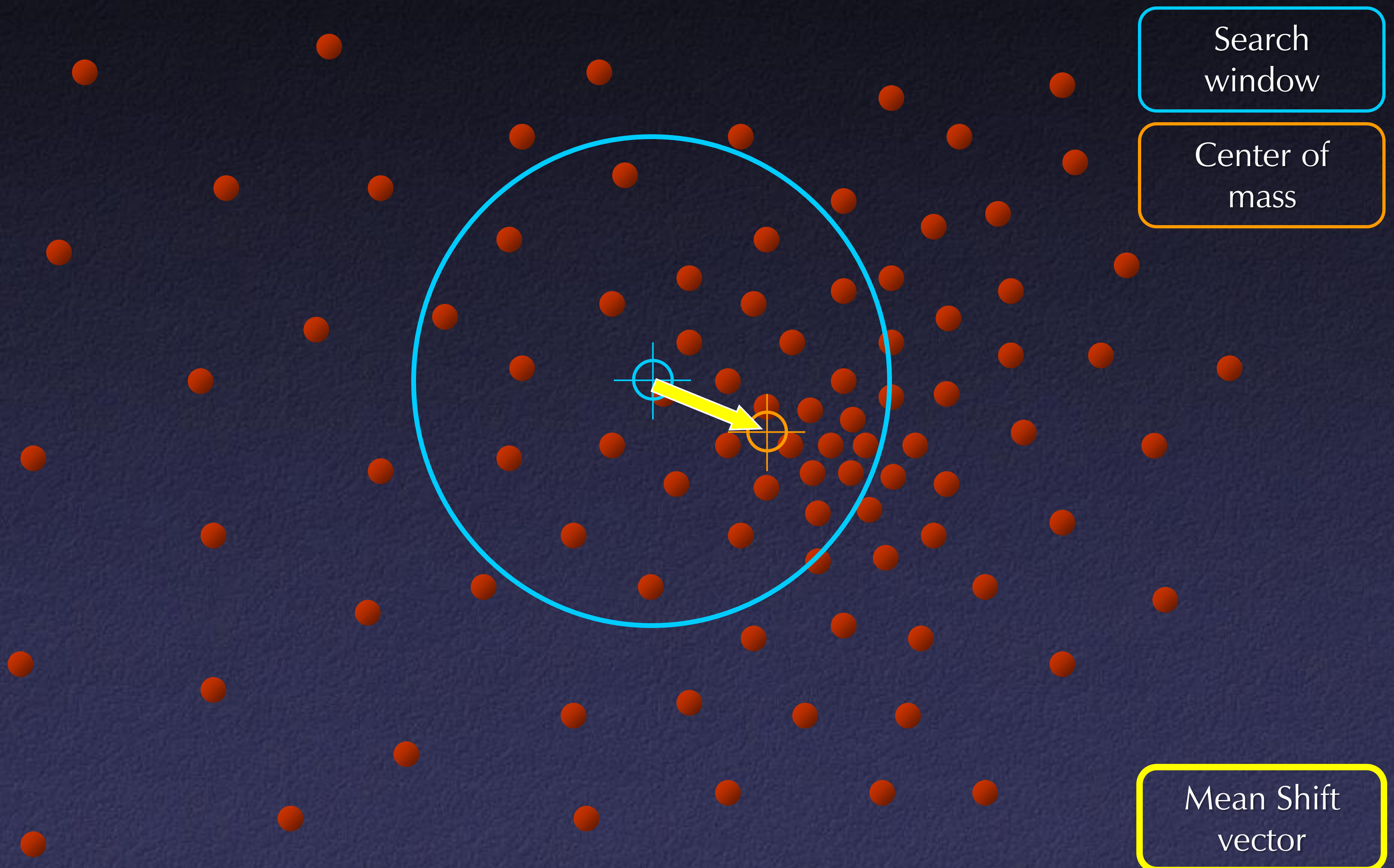

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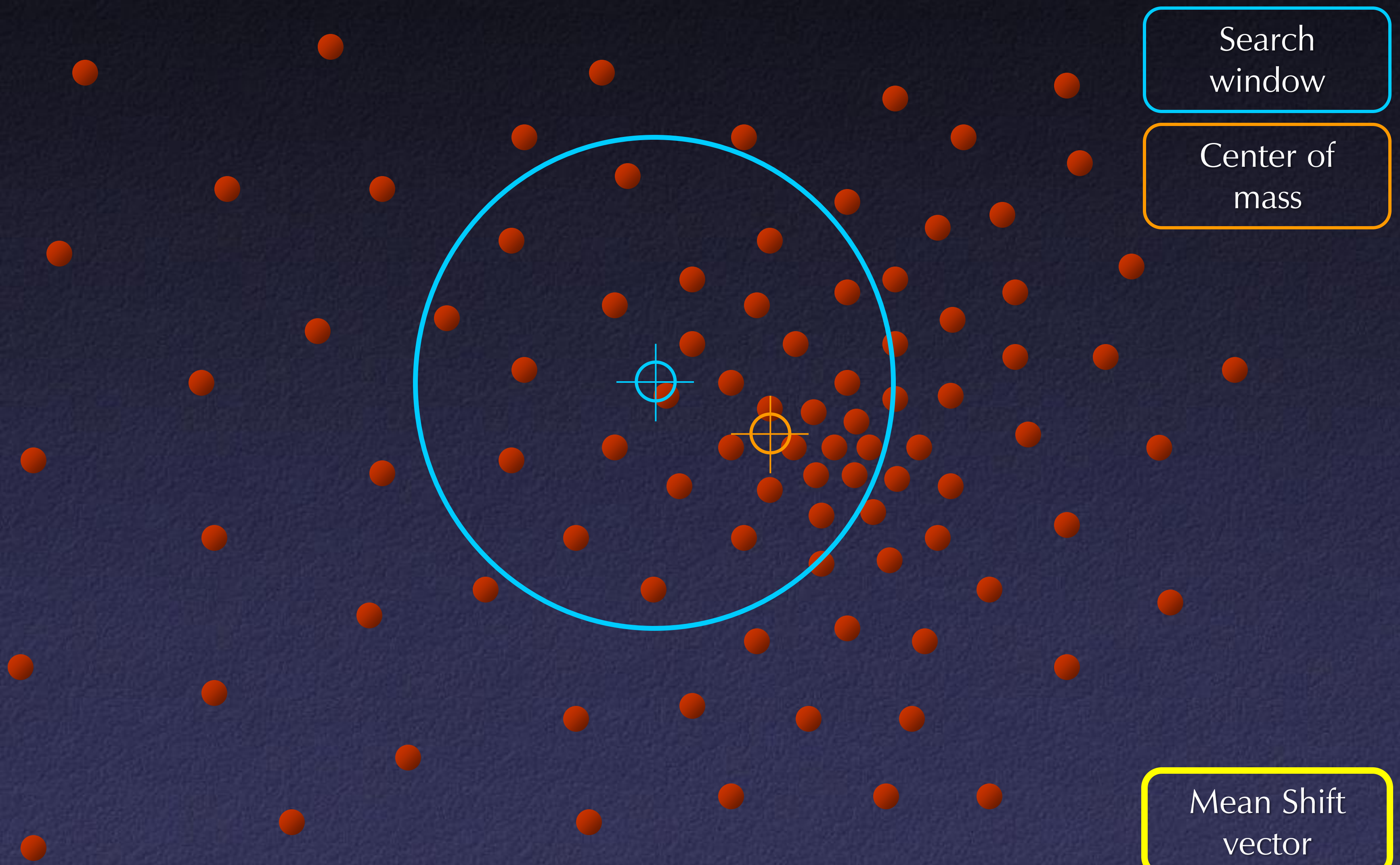

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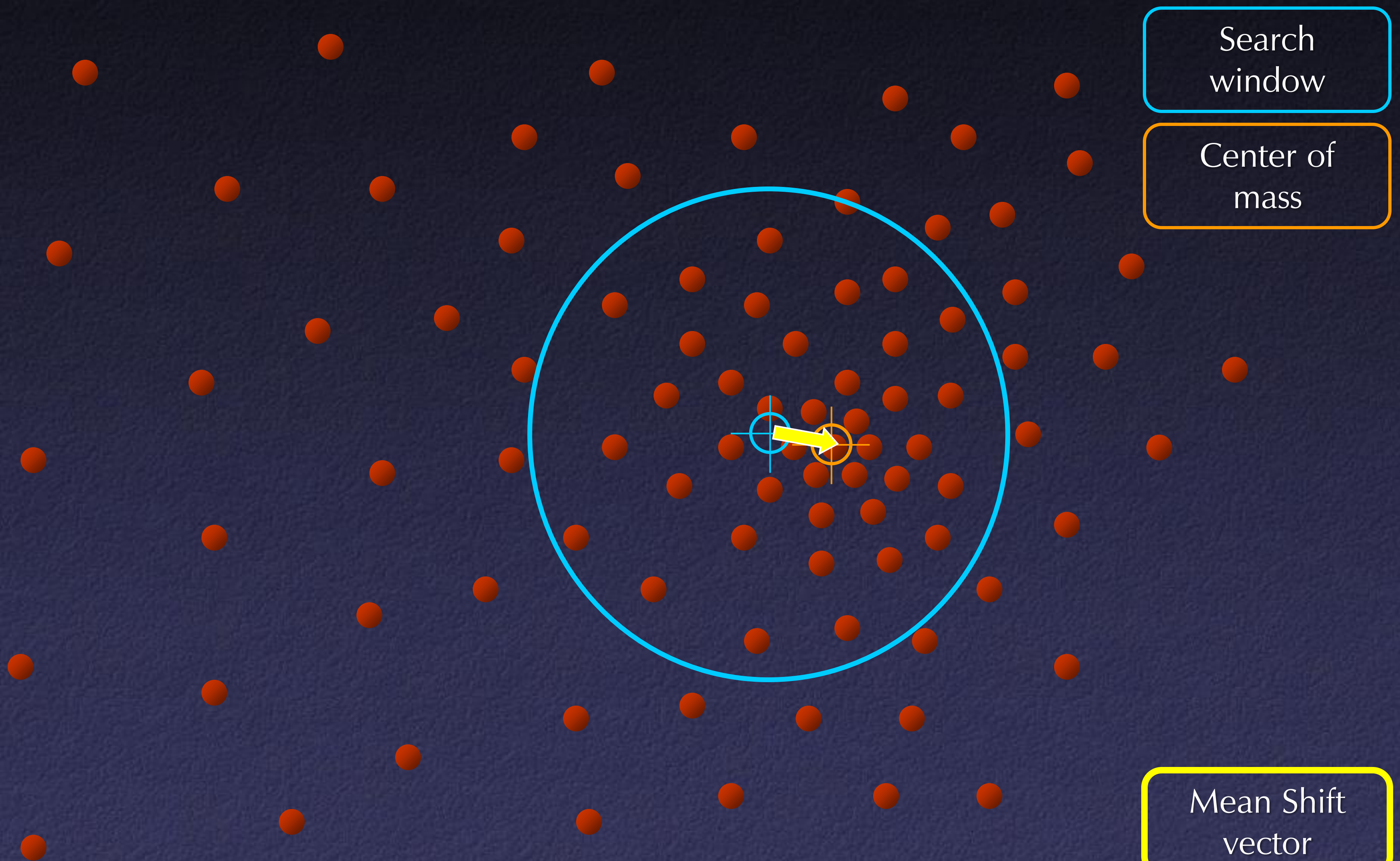

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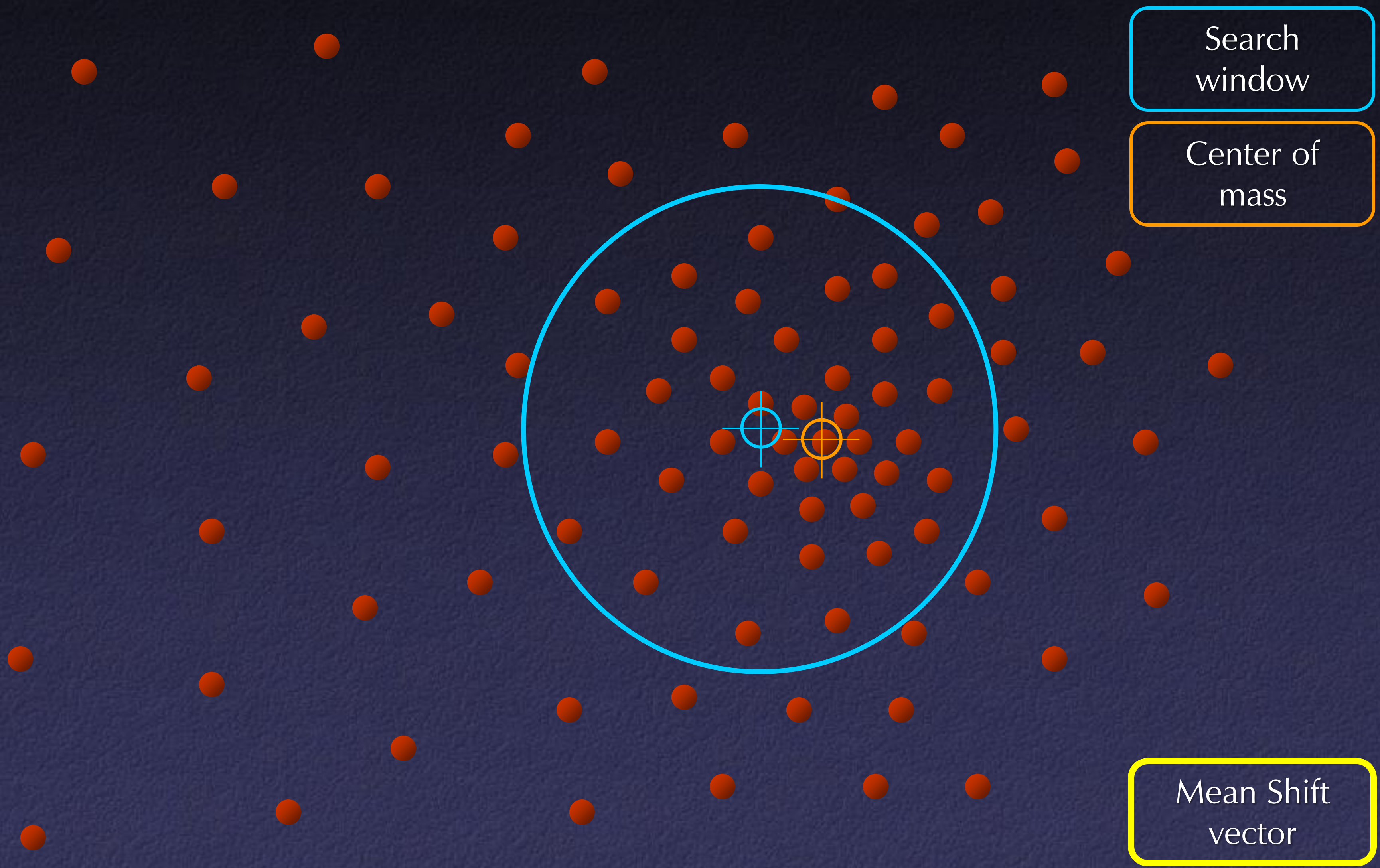

Slide by Y. Ukrainitz & B. Sarel

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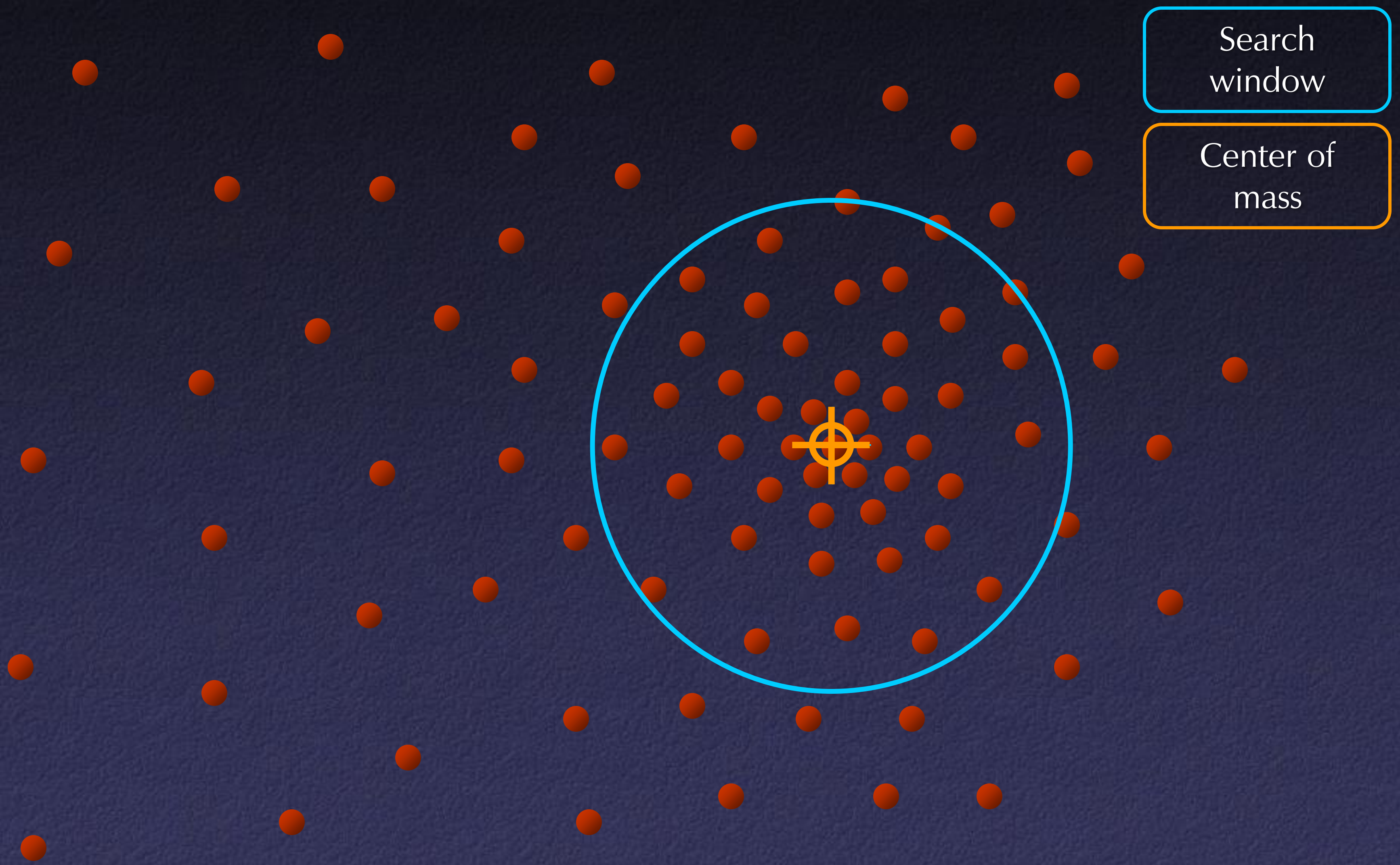

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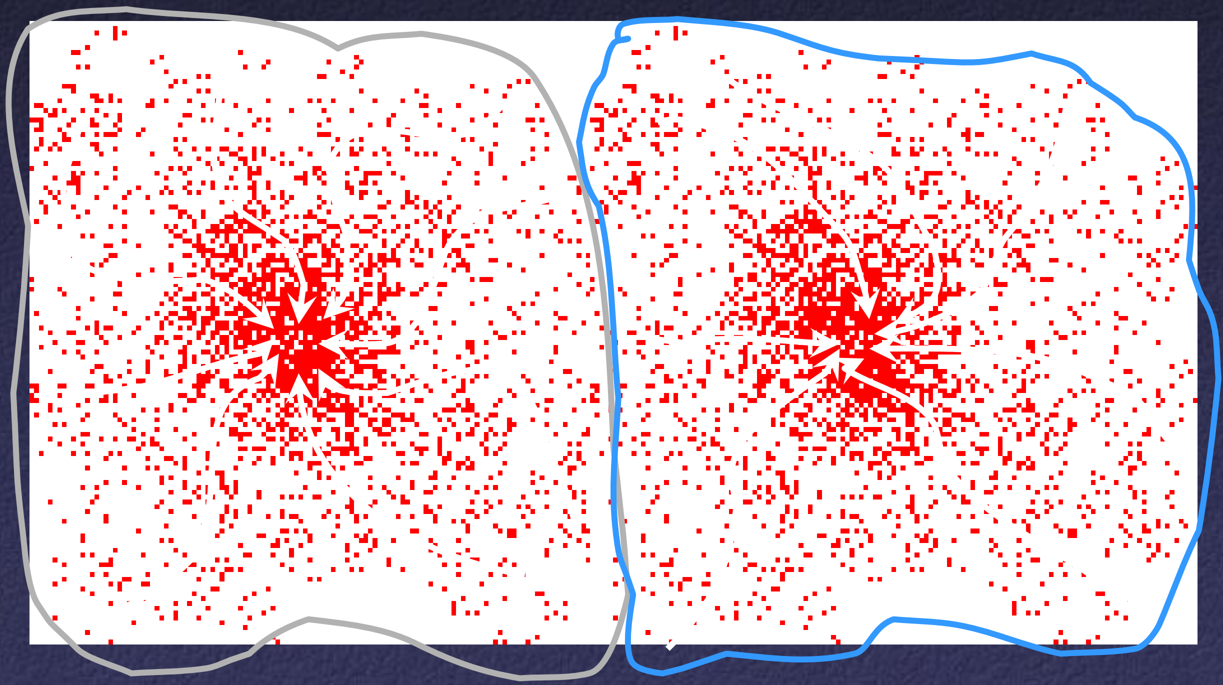
Mean Shift Clustering

Cluster all data points in the attraction basin of a mode

- Separate segment for each mode
- Assign points to segments based on which mode is at the end of their mean shift trajectories



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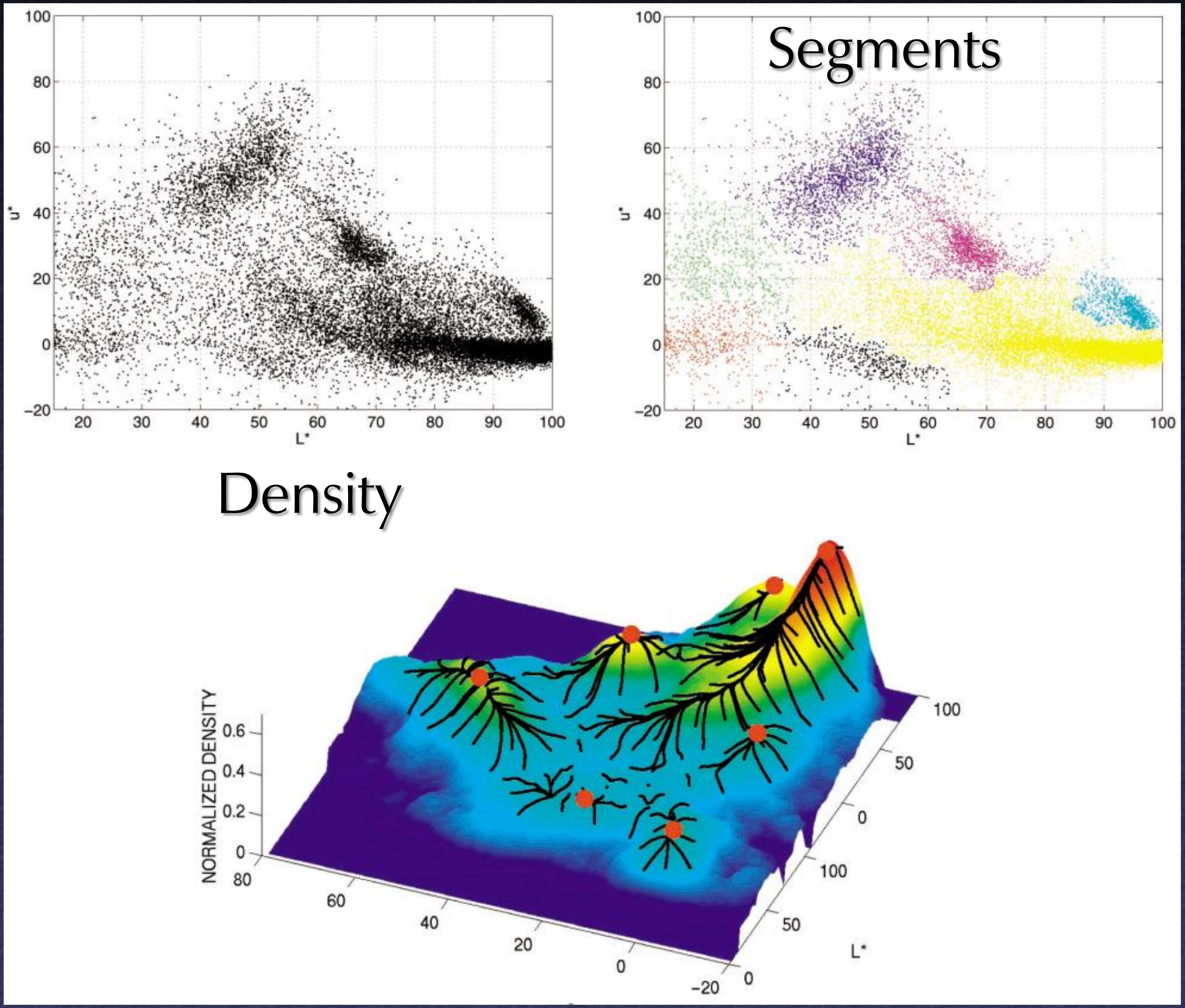
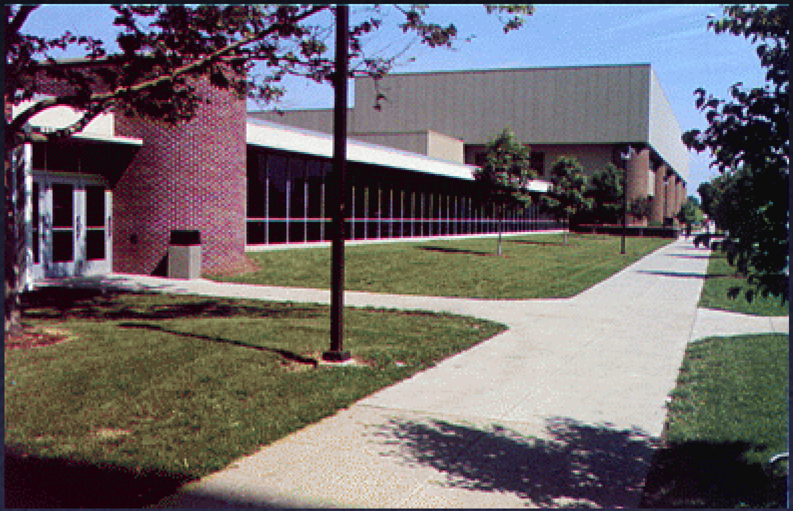
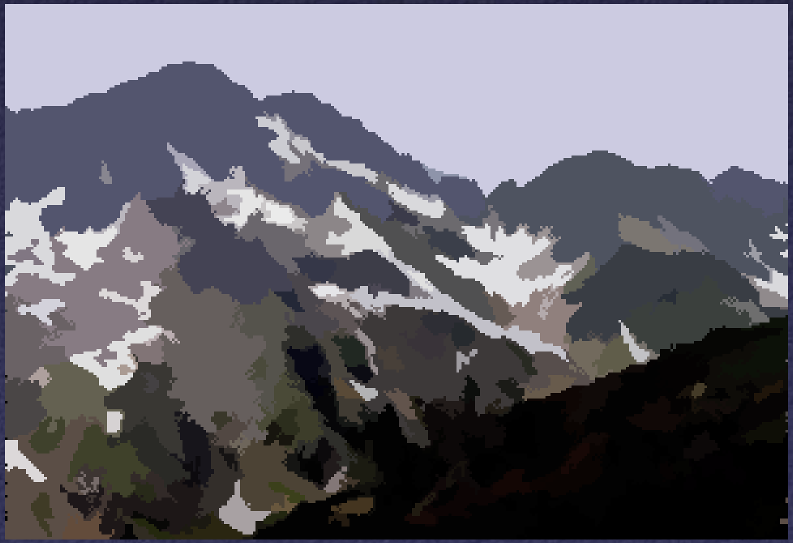
Mean Shift Clustering



Slide by Y. Ukrainitz & B. Sarel

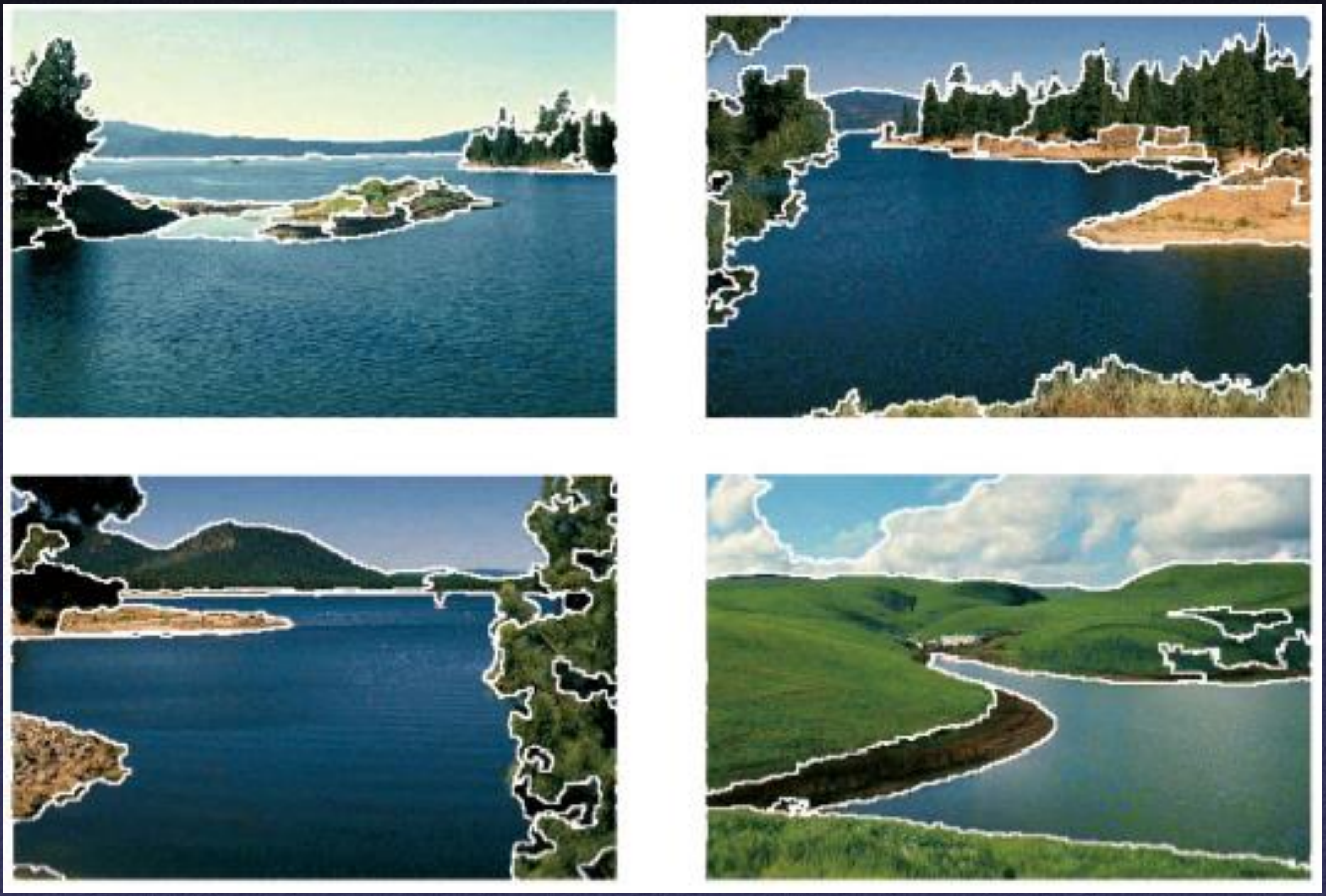
Mean Shift Results



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

Mean Shift Results



Mean Shift Pros and Cons?

Mean Shift Pros and Cons

Pros

- Finds variable number of modes
- Does not assume spherical clusters
- Just a single parameter (window size)
- Robust to outliers

Cons

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

Slide by Kristen Grauman

Some Segmentation Algorithms

Divisive clustering

Hierarchical clustering

k-means clustering

Mean shift clustering

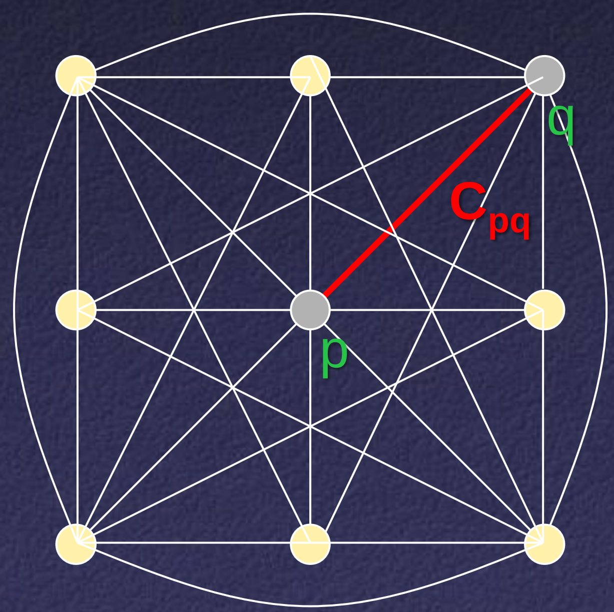
Graph cuts ←

More next time …

Graph Cuts

Create weighted graph:

- Nodes = pixels in image
- Edge between pairs of pixels
- Edge weight = similarity (intensity, color, texture, etc.)

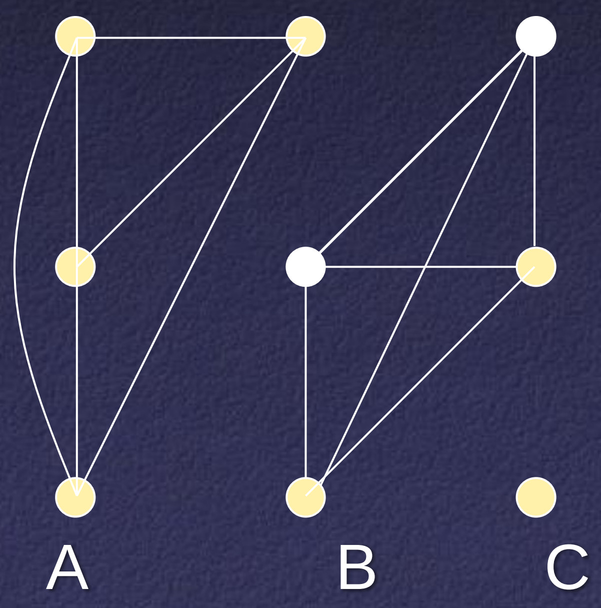


Slide by S. Seitz]

Graph Cuts

Intuition: partition graph into disconnected segments by removing edges that have low cost (low similarity)

- Similar pixels should be in the same segments
- Dissimilar pixels should be in different segments

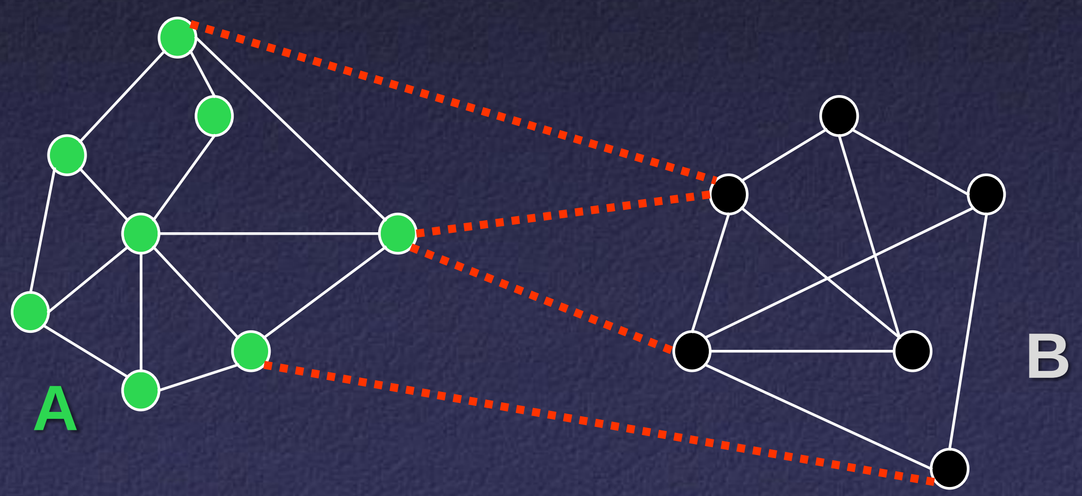


Example by S. Seitz

Graph Cuts

Graph cut

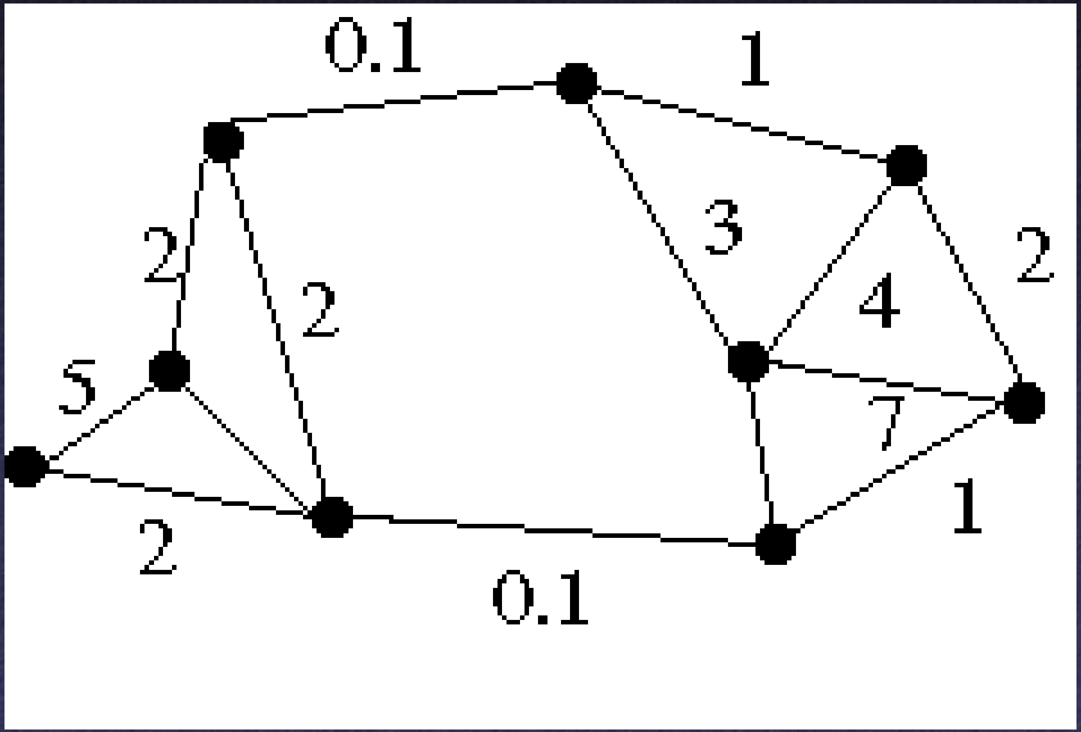
- Set of links whose removal makes a graph disconnected
- Partitions the graph (defines a segmentation)
- Cut cost = sum of costs of all edges in set



Example by S. Seitz

Graph Cuts

Can define arbitrary similarity function between pixels



Example by L. Lazebnik

Graph Cuts

Simple similarity function:

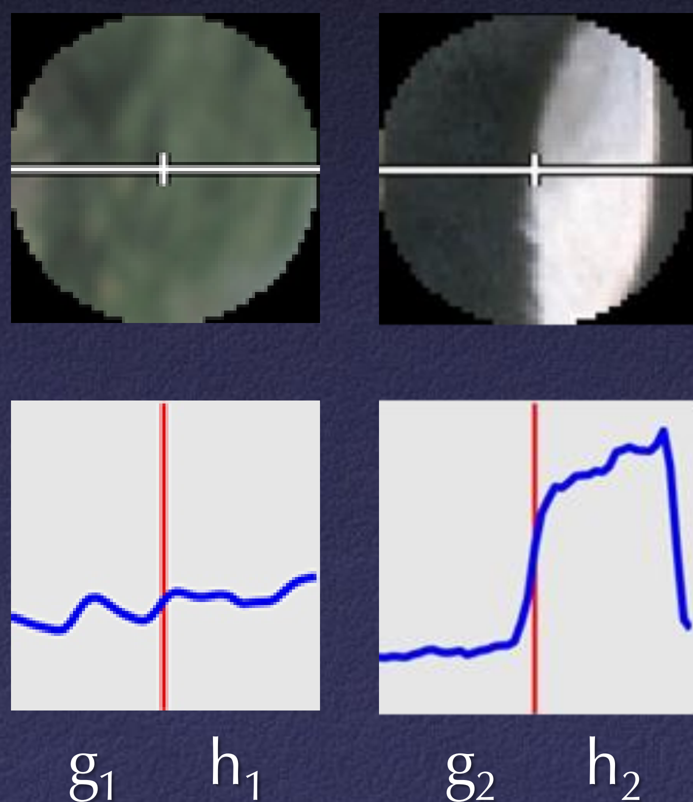
- Suppose we represent each pixel by a feature vector **x**, and define a distance function appropriate for this feature representation
- Then we can convert the distance between two feature vectors into an affinity with the help of a generalized Gaussian kernel:

$$\exp\left(-\frac{1}{2\sigma^2}\operatorname{dist}(\mathbf{x}_i, \mathbf{x}_j)^2\right)$$

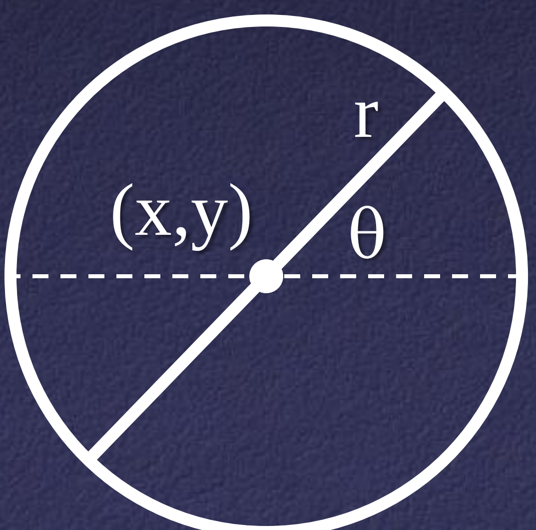
Graph Cuts

More sophisticated similarity functions:

- Difference of histograms built from properties of pixels in optimizally oriented hemi-circles



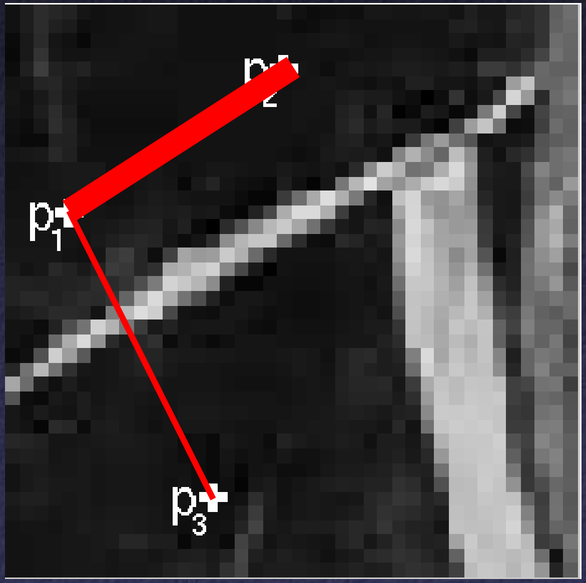
$$\chi^2(g,h) = \frac{1}{2}\sum_i \frac{(g_i - h_i)^2}{g_i + h_i}$$



Graph Cuts

More sophisticated similarity functions:

- Similarity based on intervening contours

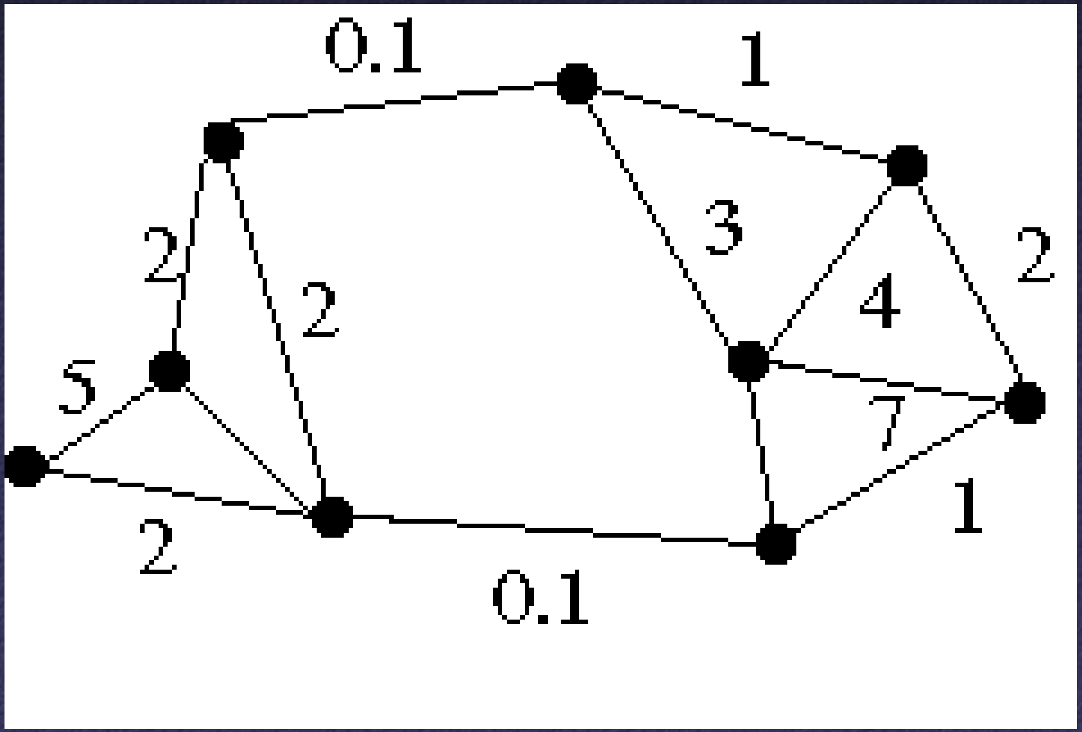


W(p1,p2) >>W(p1,p3) as p1 and p2 are more likely to belong to the same region than are p1 and p3, which are separated by a strong boundary.

Graph Cuts

Now, need to find best cut. How?

- Want to partition nodes based on similarities

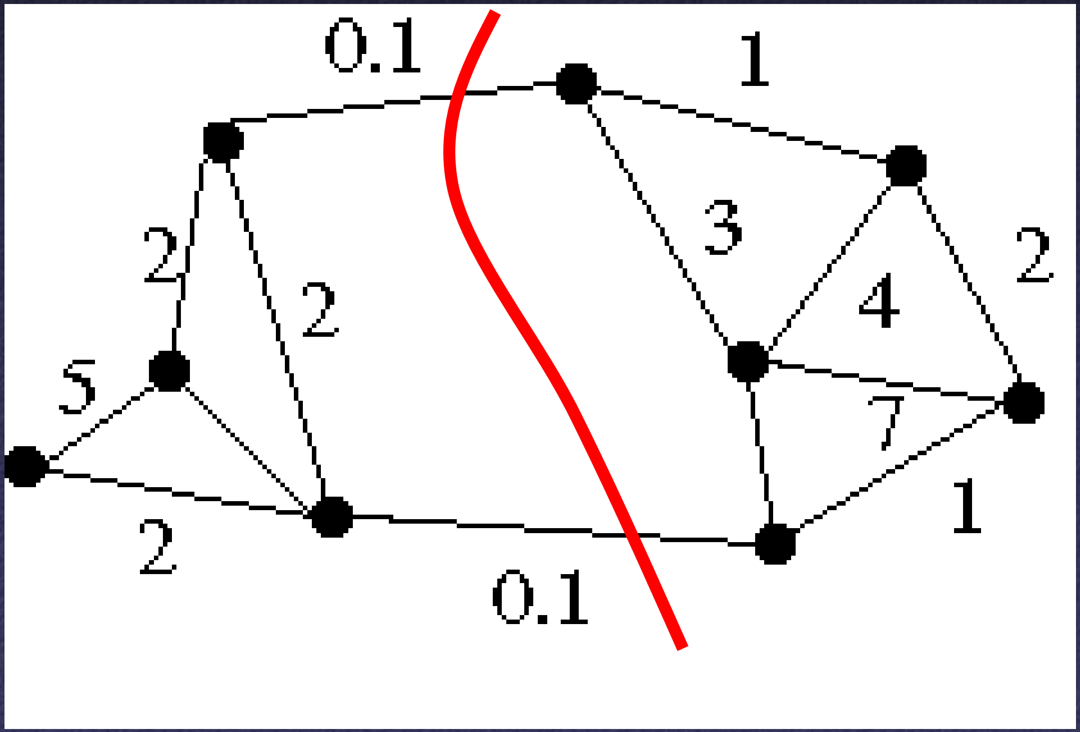


Example by L. Lazebnik

Graph Cuts

Min-cut

- Find cut with minimum cost
- Fast (polynomial-time) algorithm

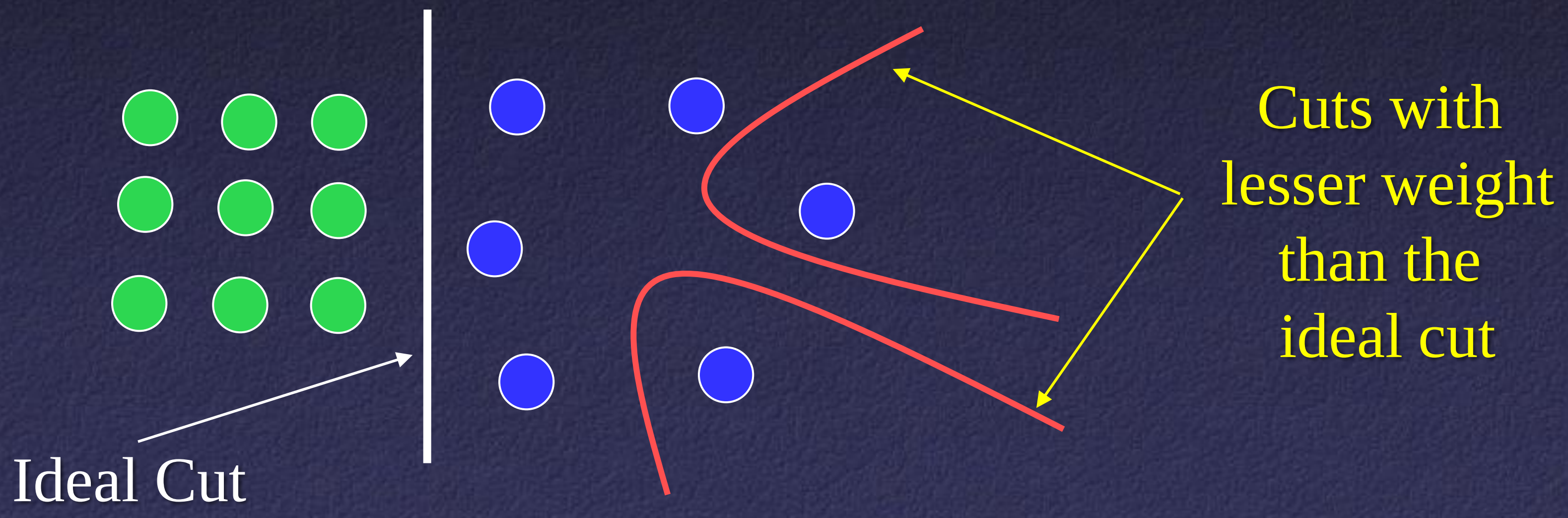


Example by L. Lazebnik

Graph Cuts

Min-cut

- Find cut with minimum cost
- Fast (polynomial-time) algorithm
- Not always the best choice



Example by L. Lazebnik

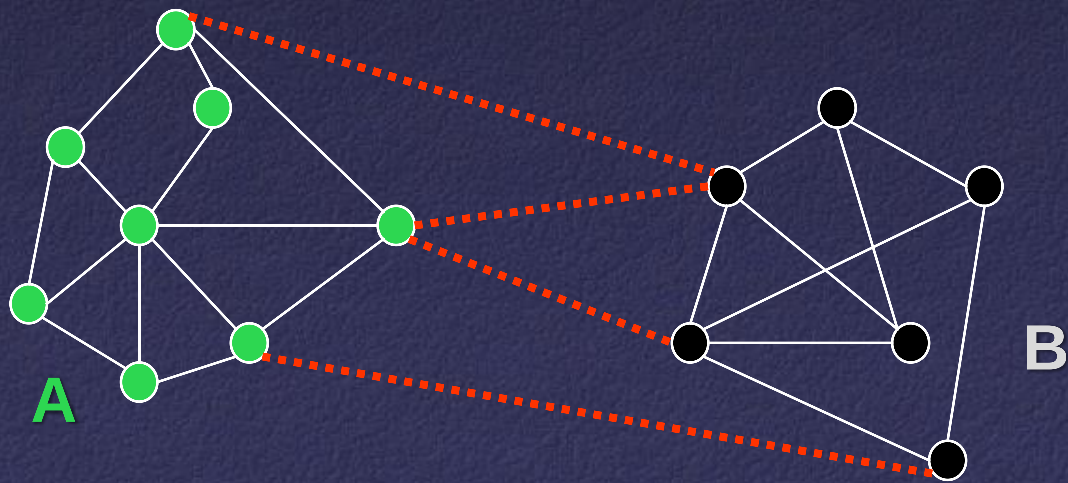
Graph Cuts

Normalized Cut

- Find minimum cut "normalized by segment size"

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

$w(A, B)$ = sum of weights of all edges between A and B

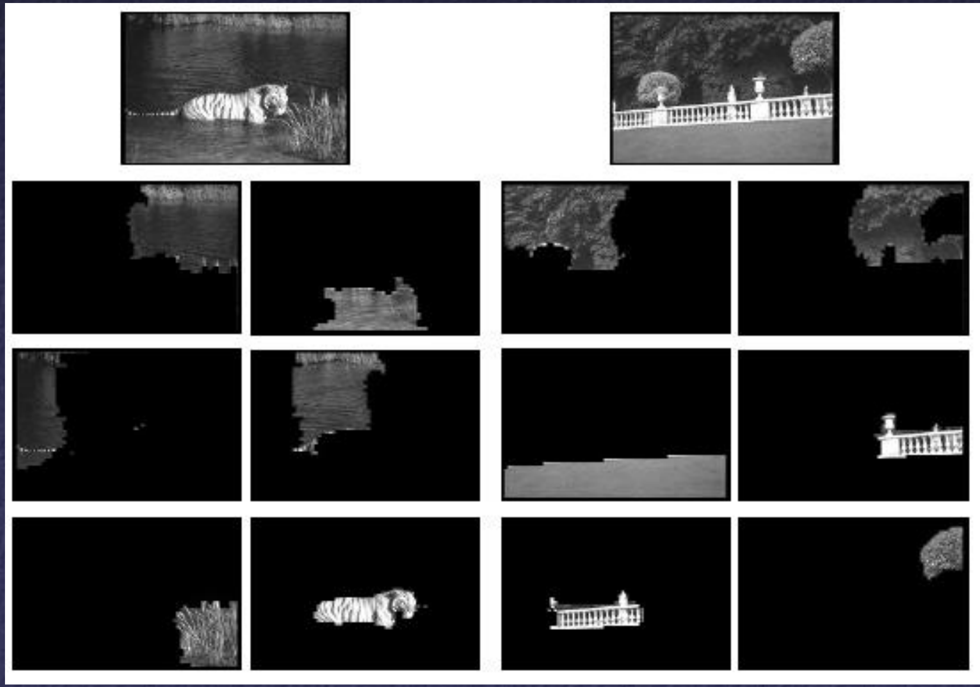


Slide by S. Seitz

Graph Cuts

Normalized Cut

- No polynomial-time algorithm to find optimal cut
- Can use an approximation based on eigen-analysis of the graph adjacency matrix



Graph Cuts

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

Graph Cuts

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Graph Cuts Pros and Cons

Pros

- Generic framework, can be used with many different features and affinity formulations
- Fast and practical for interactive foreground-background segmentation

Cons

- High storage requirement and time complexity for automatic segmentation

Summary

Segmentation:

- Partitioning image into coherent regions

Algorithms:

- Divisive and hierarchical clustering
- k-means clustering
- Mean shift clustering
- Graph cuts
- More next time …

Applications

- Image processing, object recognition, interactive image editing, etc.