# Grouping and Segmentation


CS 554 – Computer Vision

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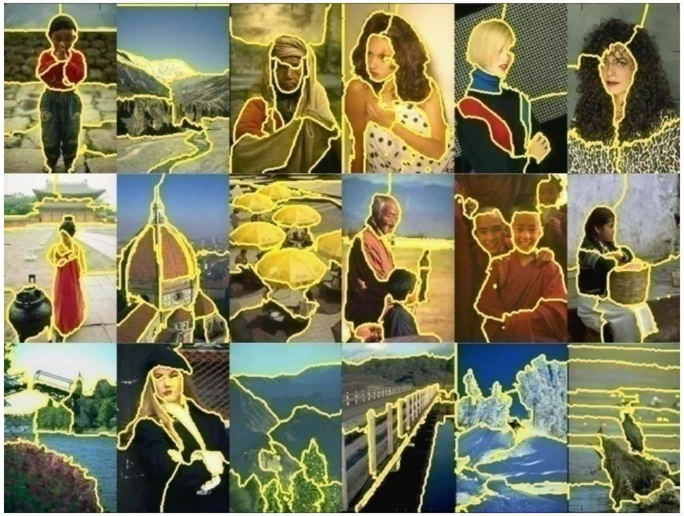
Bilkent University


(Source:Kristen Grauman )

# 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]

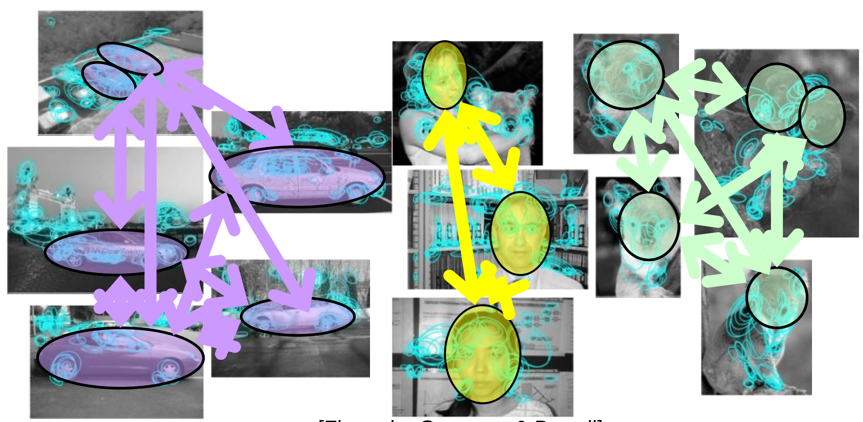
Determine image regions


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

Group video frames into shots

[Figure by Wang & Suter]

Figure-ground



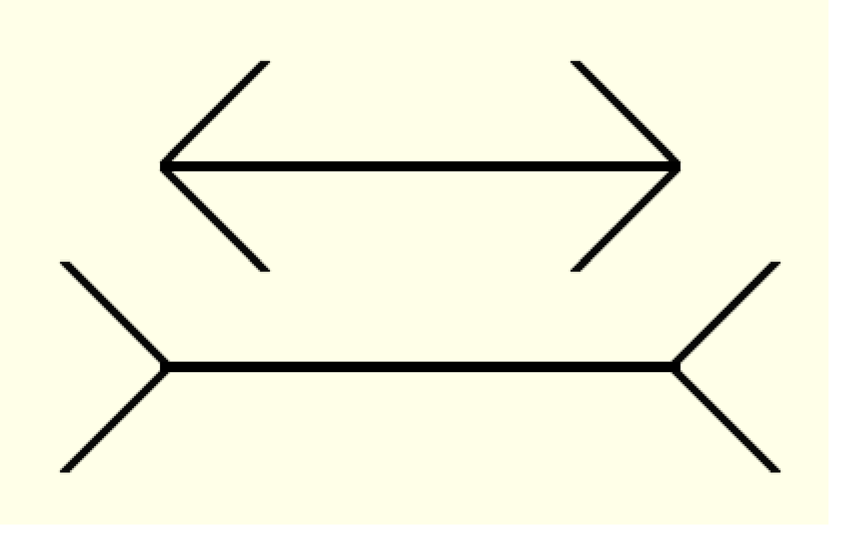
[Figure by Grauman & Darrell]

Object-level grouping

# 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.

# Muller-Lyer illusion



What things should be grouped?
What cues indicate groups?

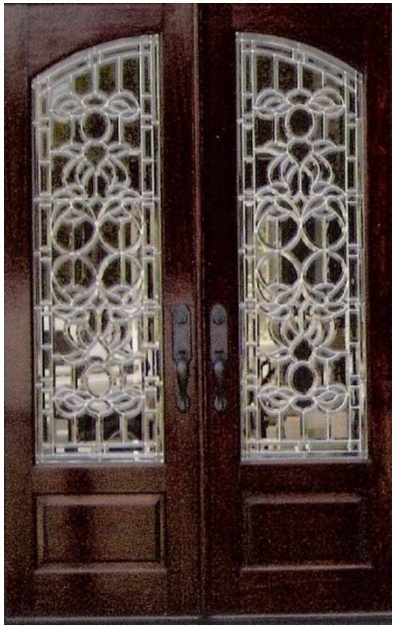
# Gestalt

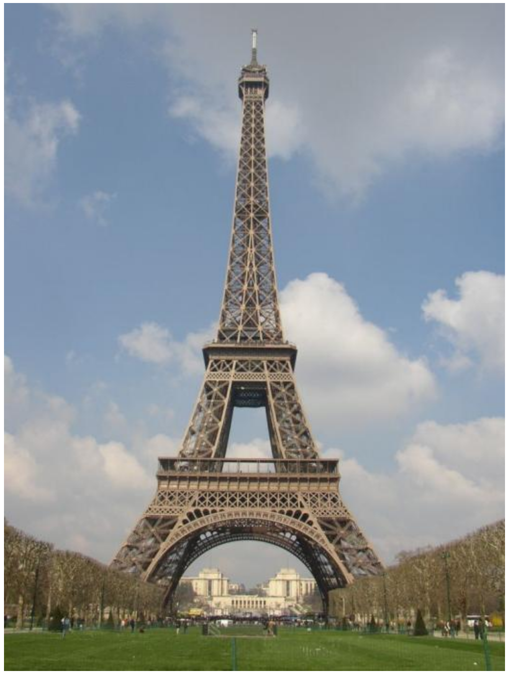
- Gestalt: whole or group
  - Whole is greater than sum of its parts
  - Relationships among parts can yield new properties/features
- Psychologists identified series of factors that predispose set of elements to be grouped (by human visual system)

# Similarity

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

# Symmetry





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

# Common fate


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

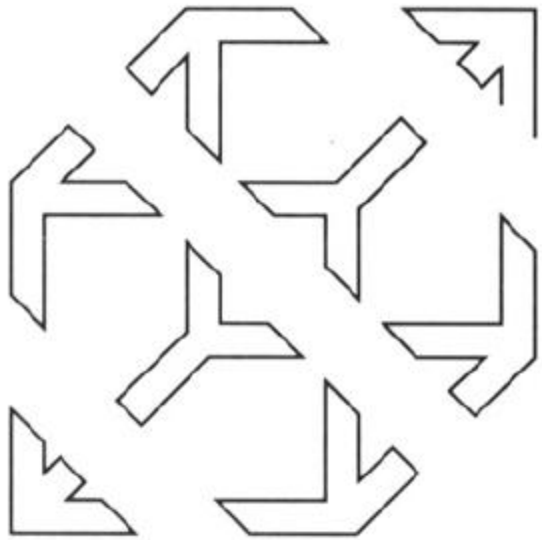
# Proximity

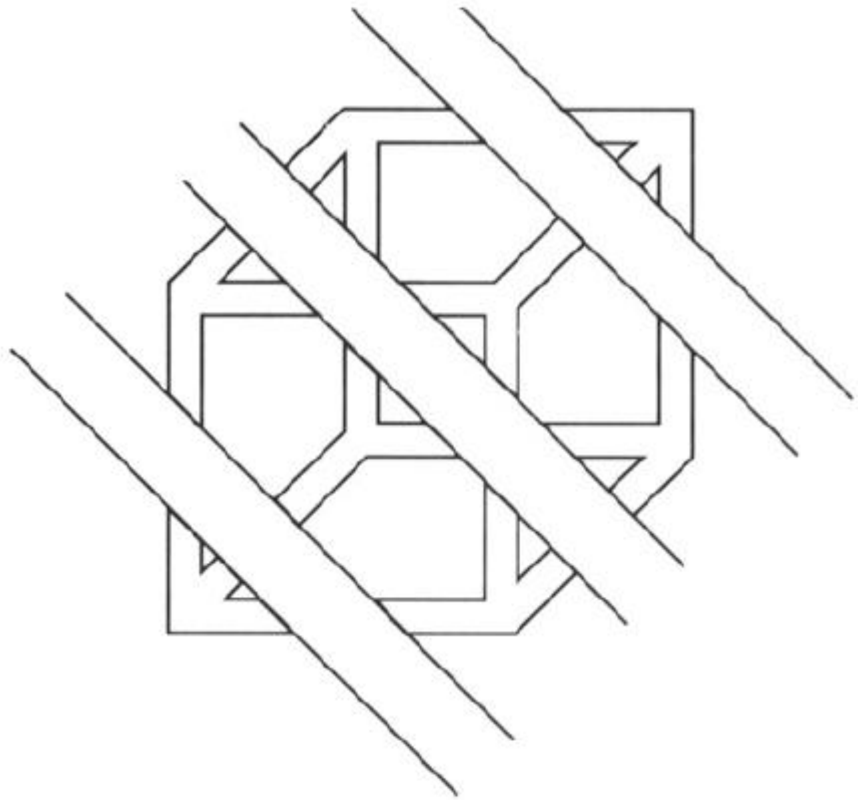
http://www.capital.edu/Resources/Images/outside6_035.jpg

# A "simple" segmentation problem

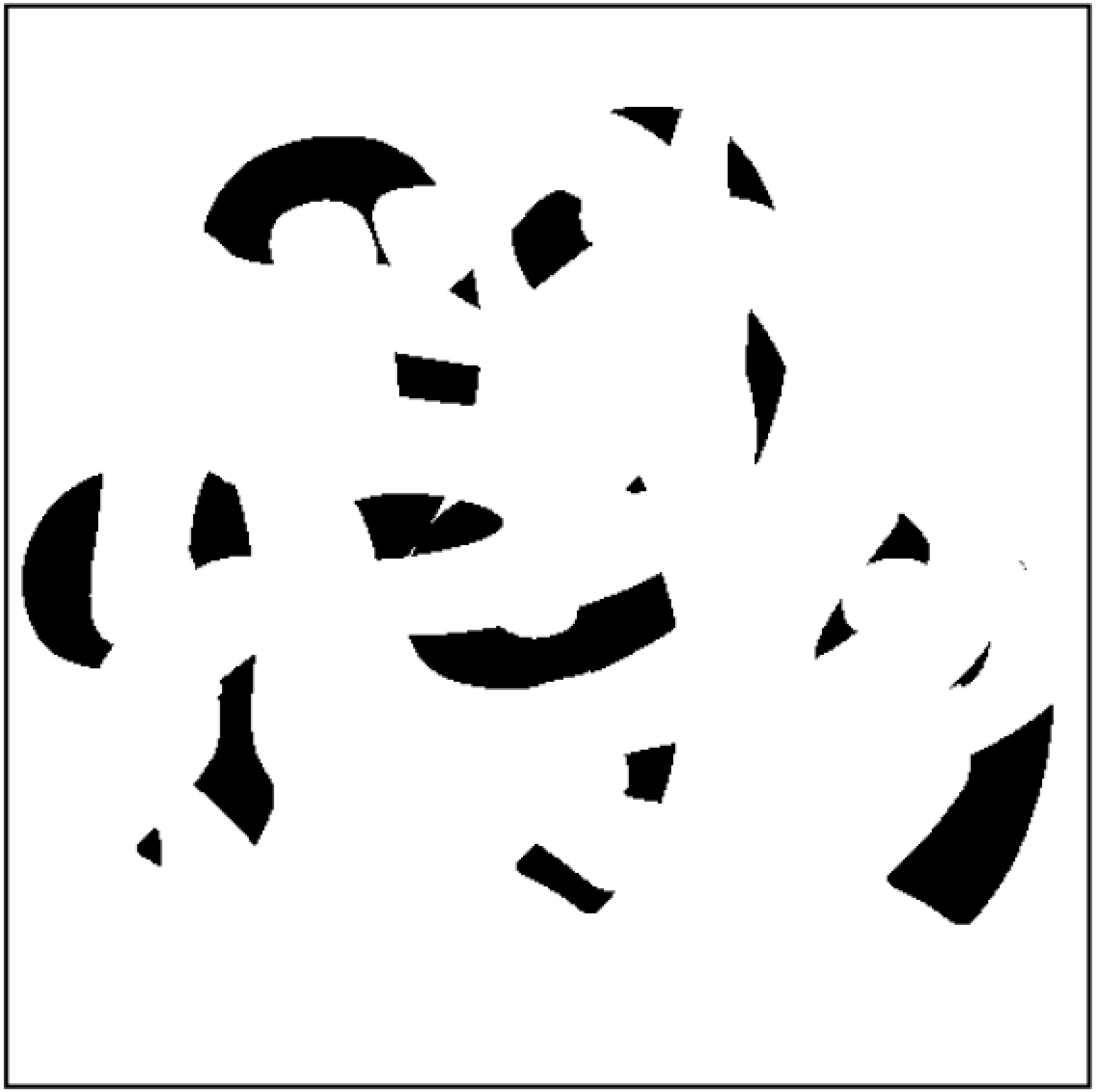
# It can get a lot harder

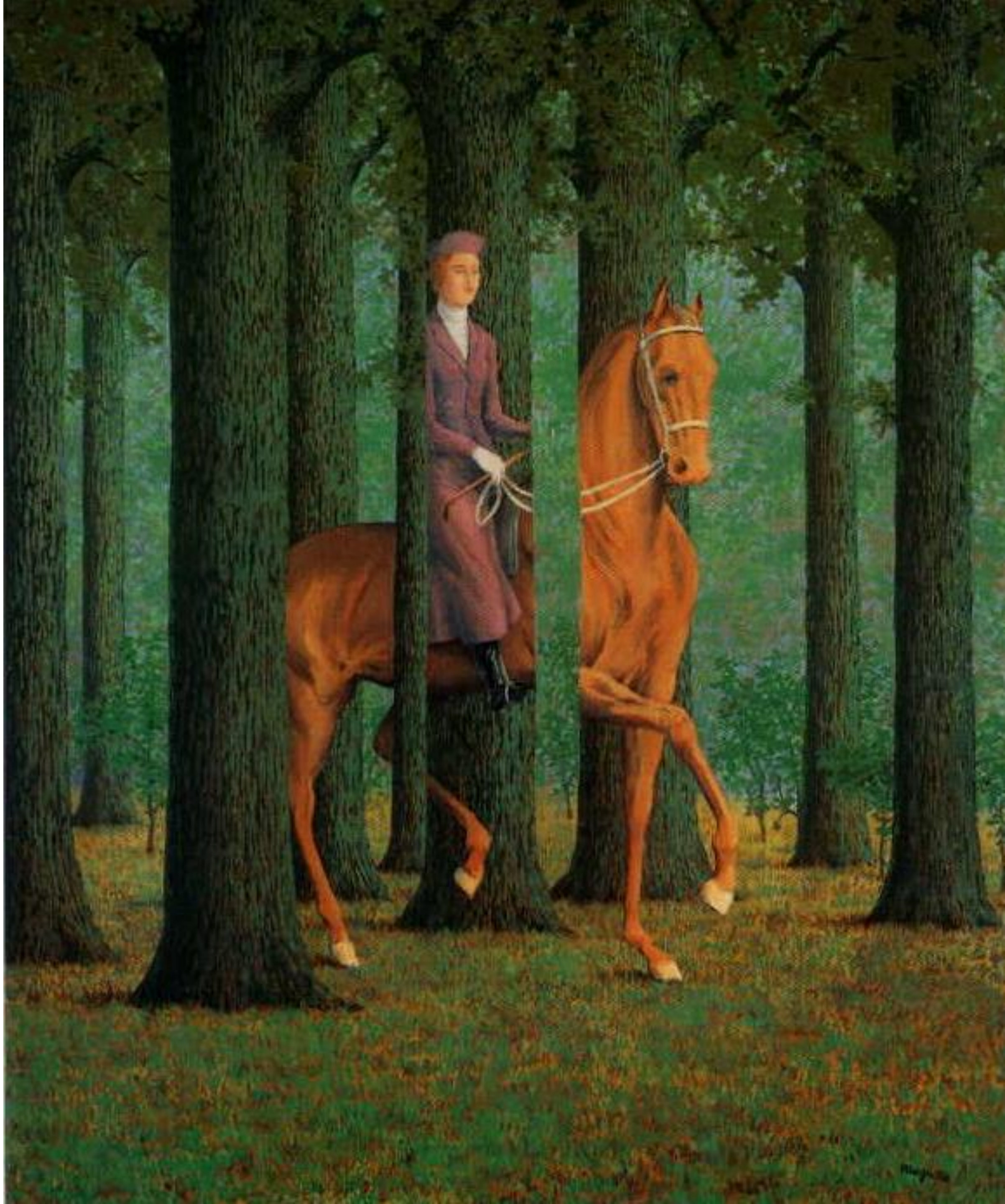
Brady, M. J., & Kersten, D. (2003). Bootstrapped learning of novel objects. J Vis, 3(6), 413-422





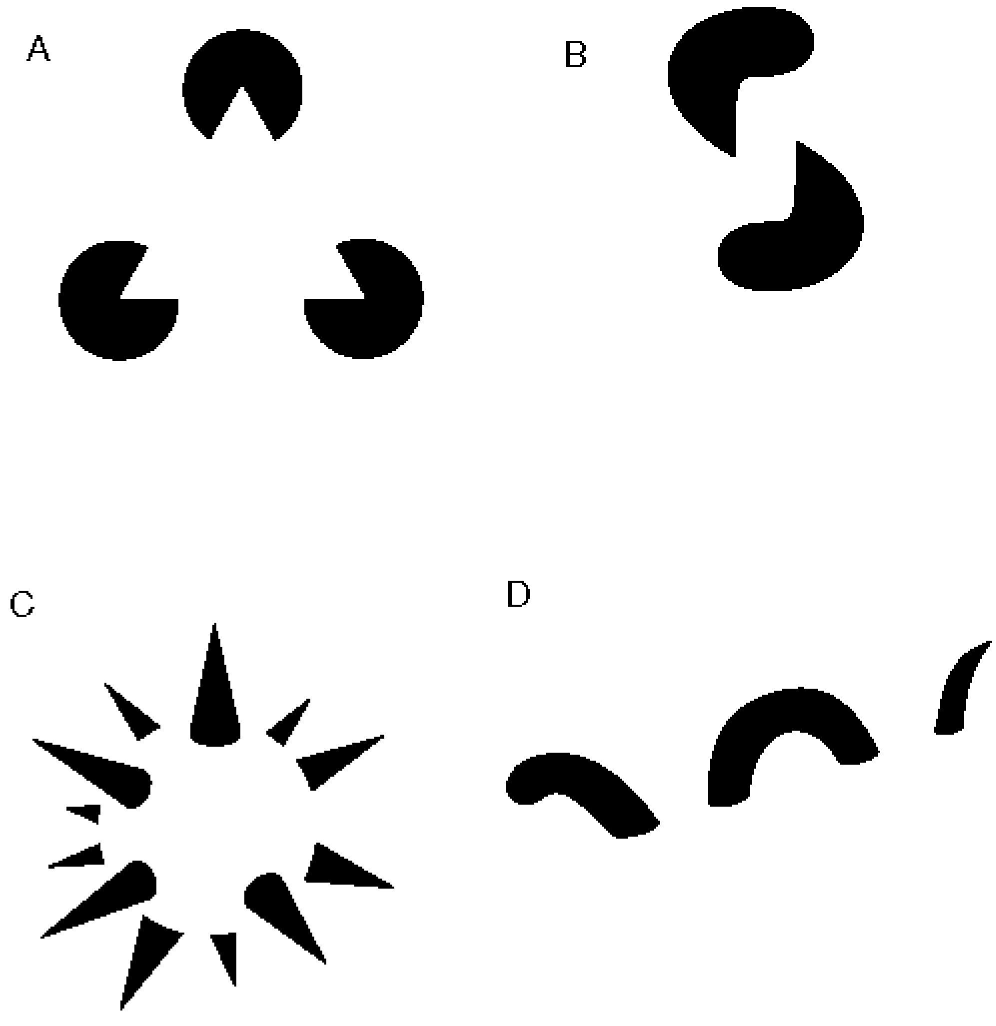
Continuity, explanation by occlusion





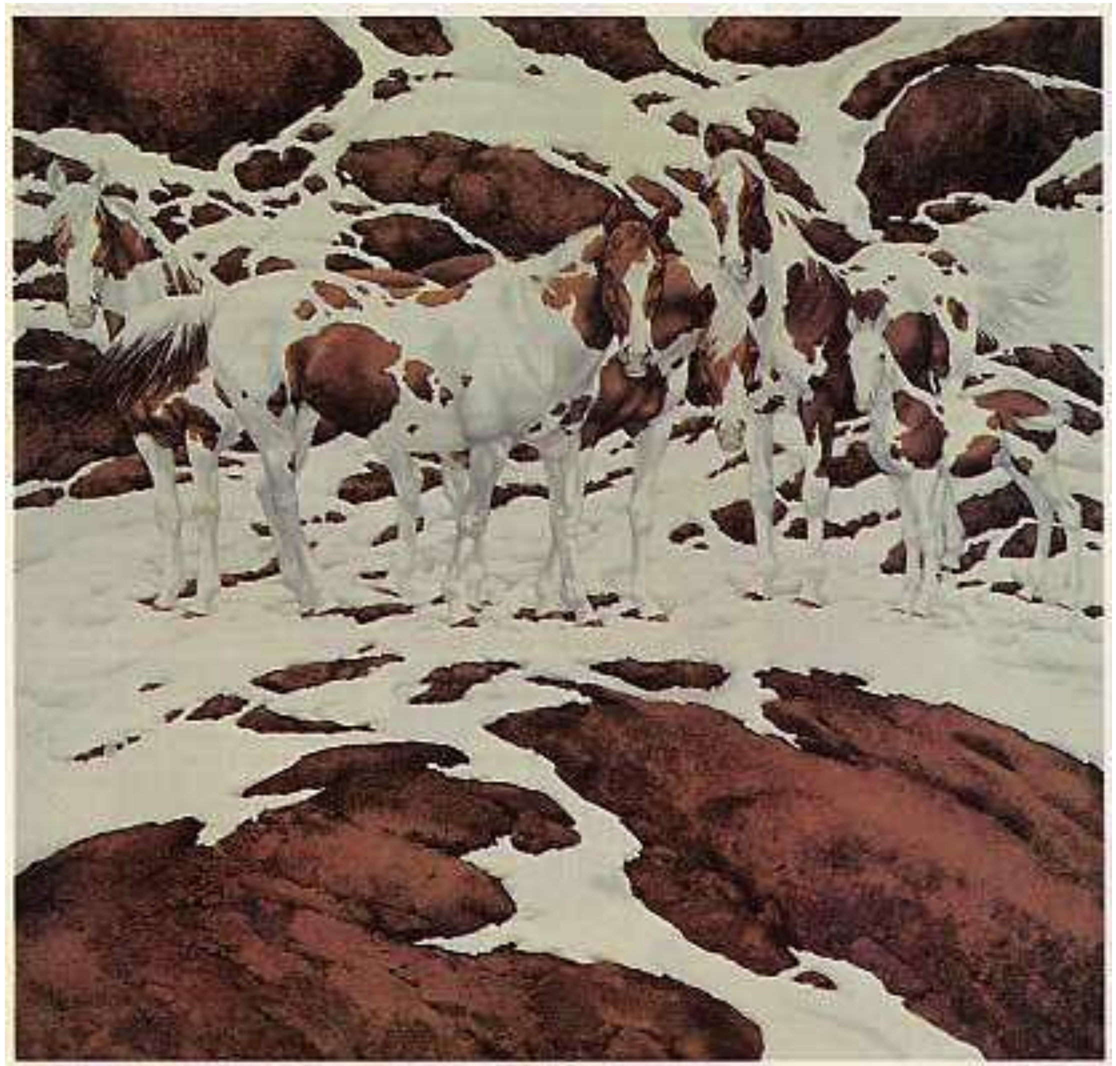
Magritte, 1957

# Groupings by Invisible Completions




* Images from Steve Lehar's Gestalt papers

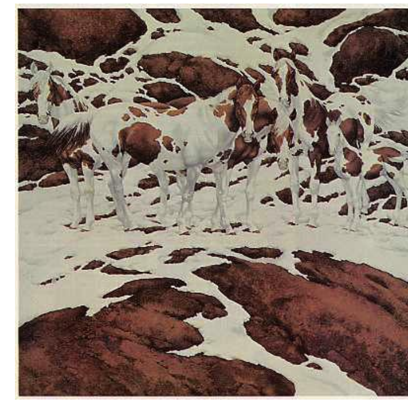
1970s: R. C. James



2000s: Bev Doolittle

# Perceptual organization

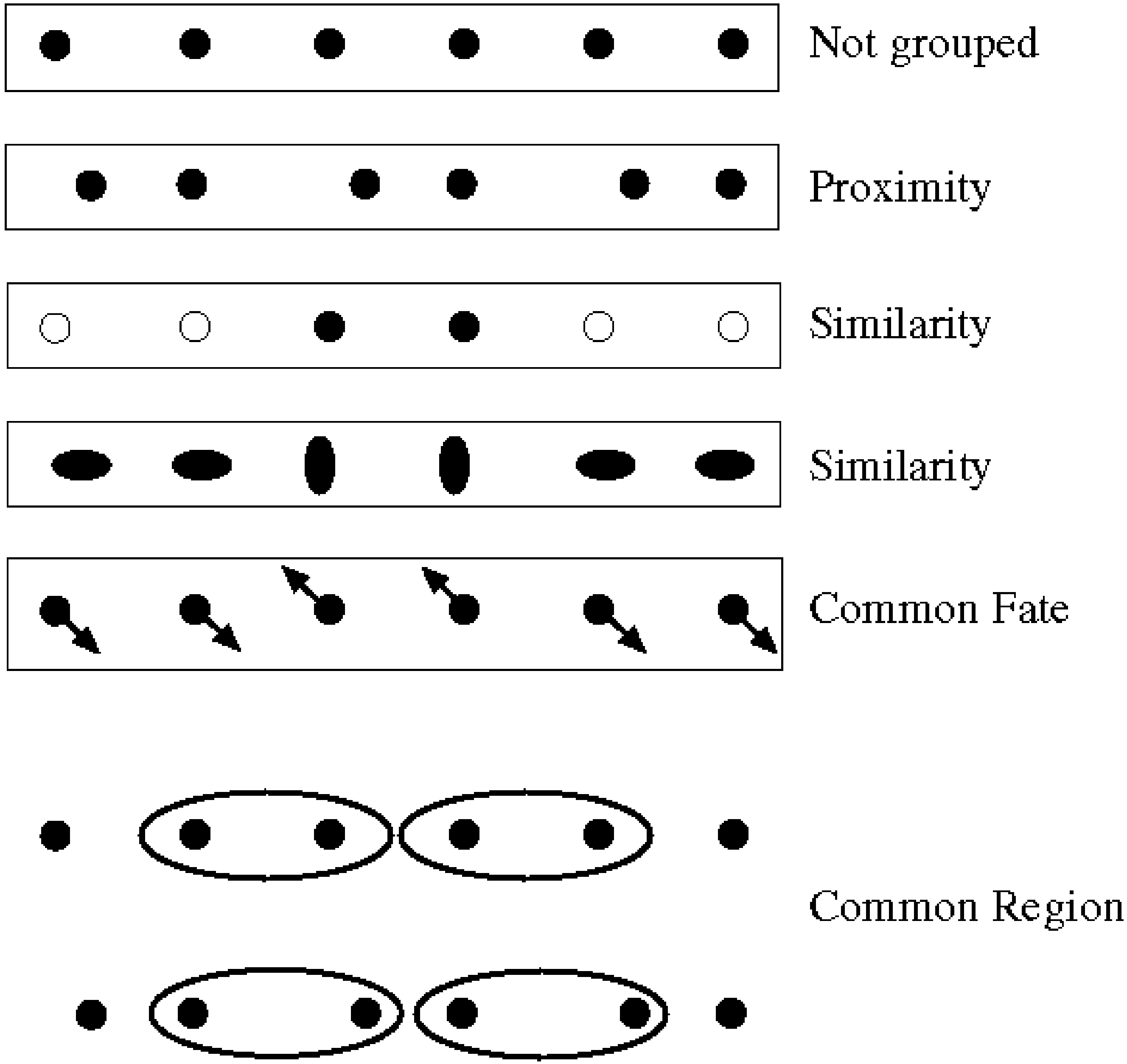
*"…the processes by which the bits and pieces of visual information that are available in the retinal image are structured into the larger units of perceived objects and their interrelations"*

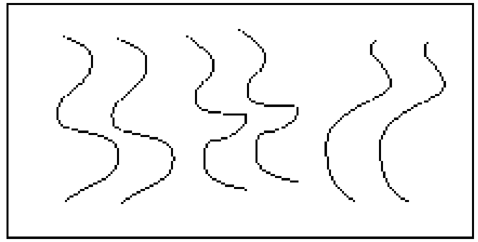


Stephen E. Palmer, *Vision Science, 1999*

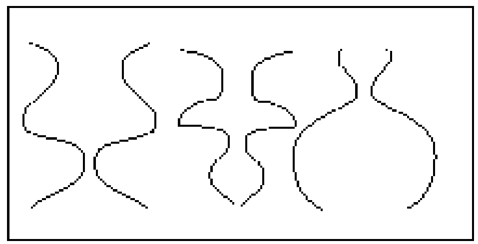
# Gestalt

- 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.

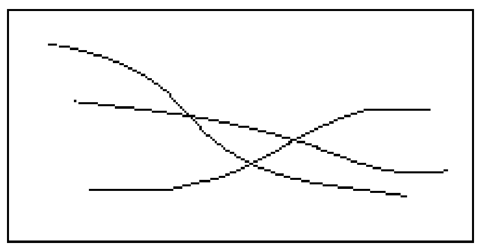

Not grouped
Proximity
Similarity
Similarity
Common Fate
Common Region



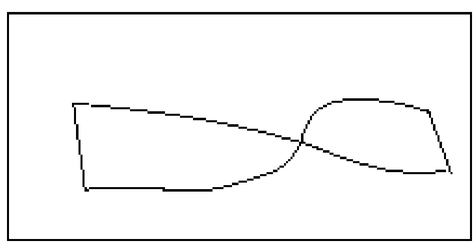
Parallelism



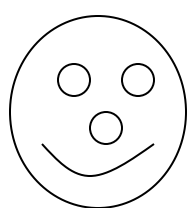
Symmetry



Continuity



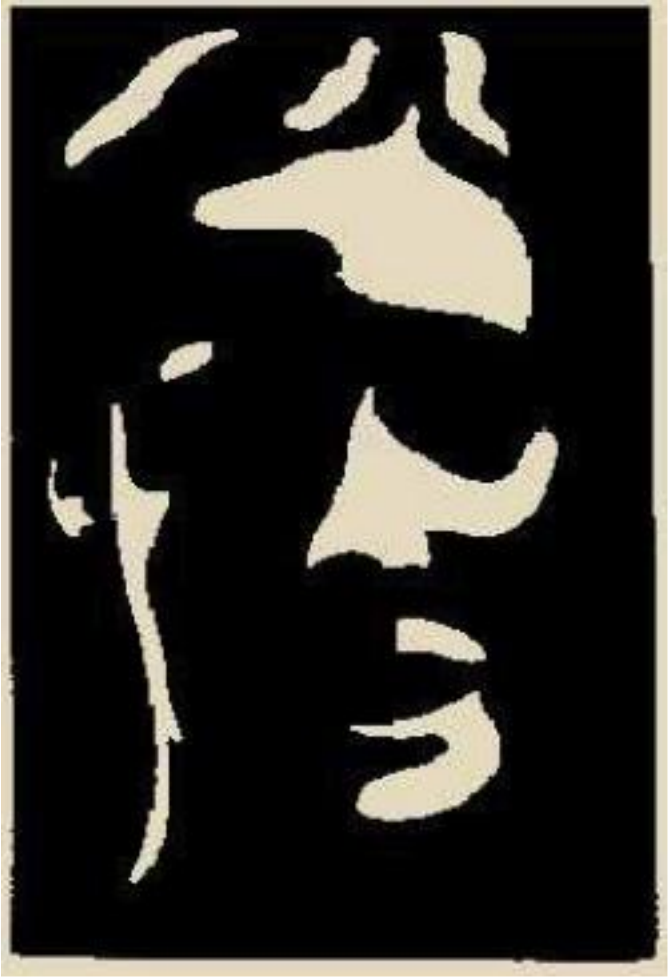
Closure



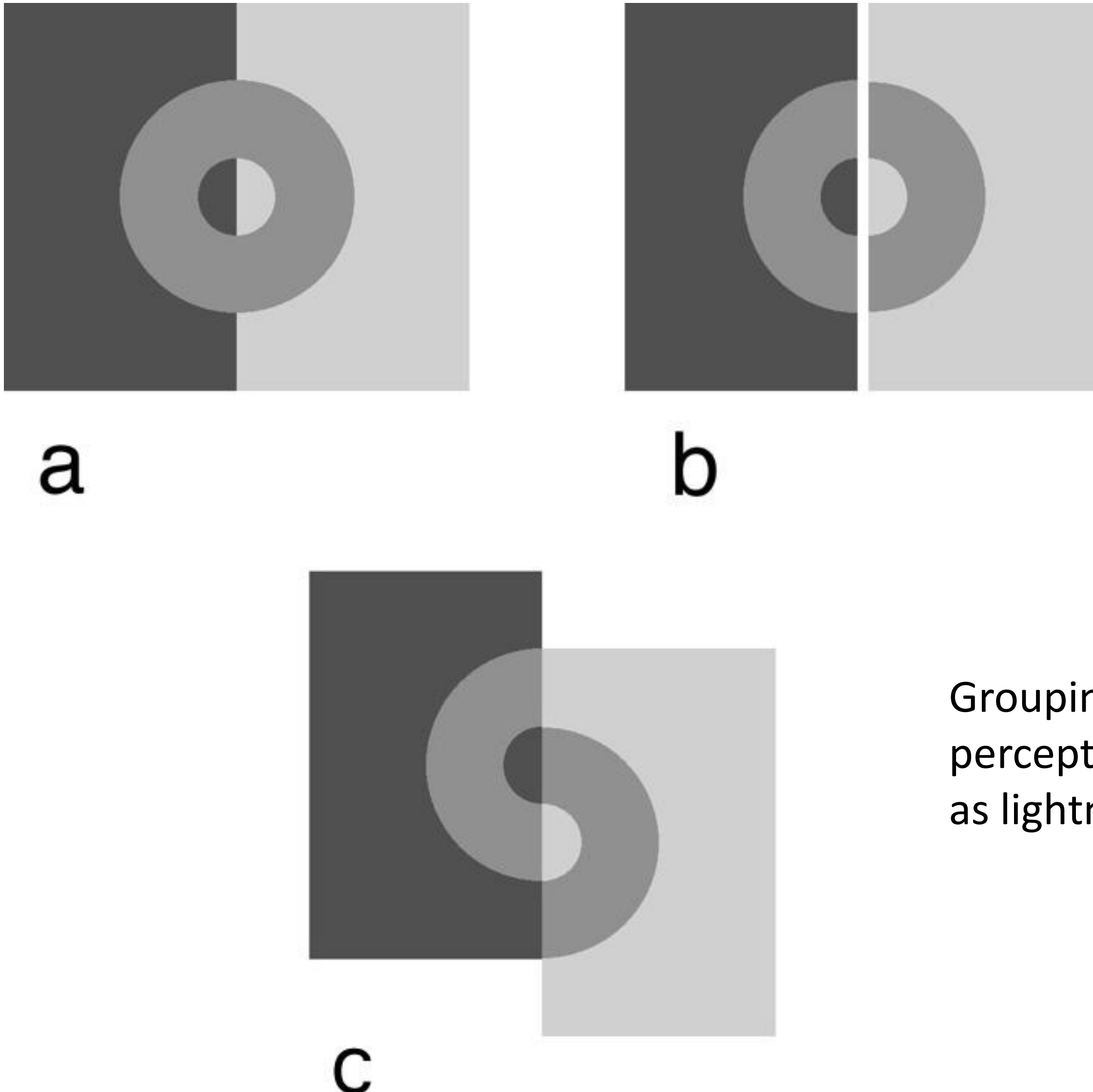
Familiar configuration

# Familiarity

# Familiarity



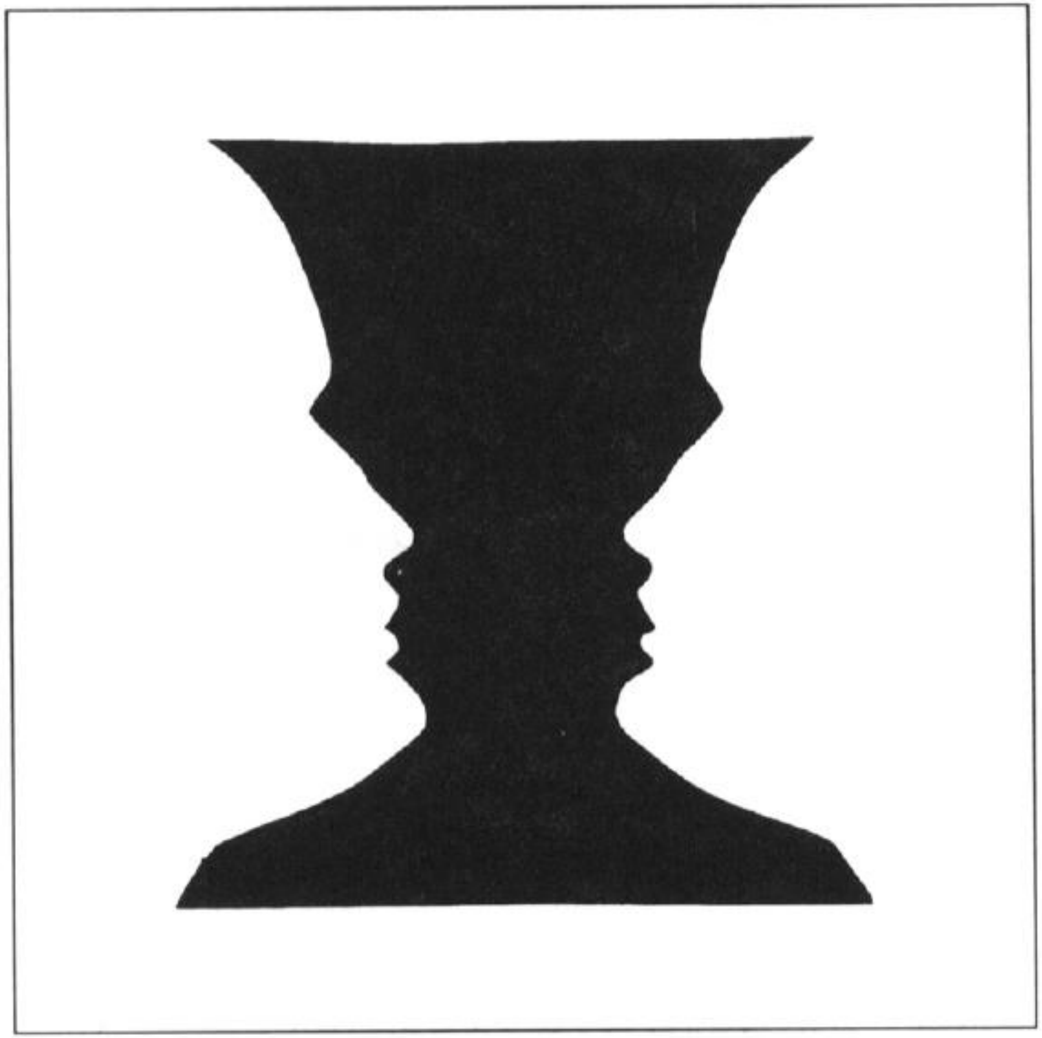
# Influences of grouping



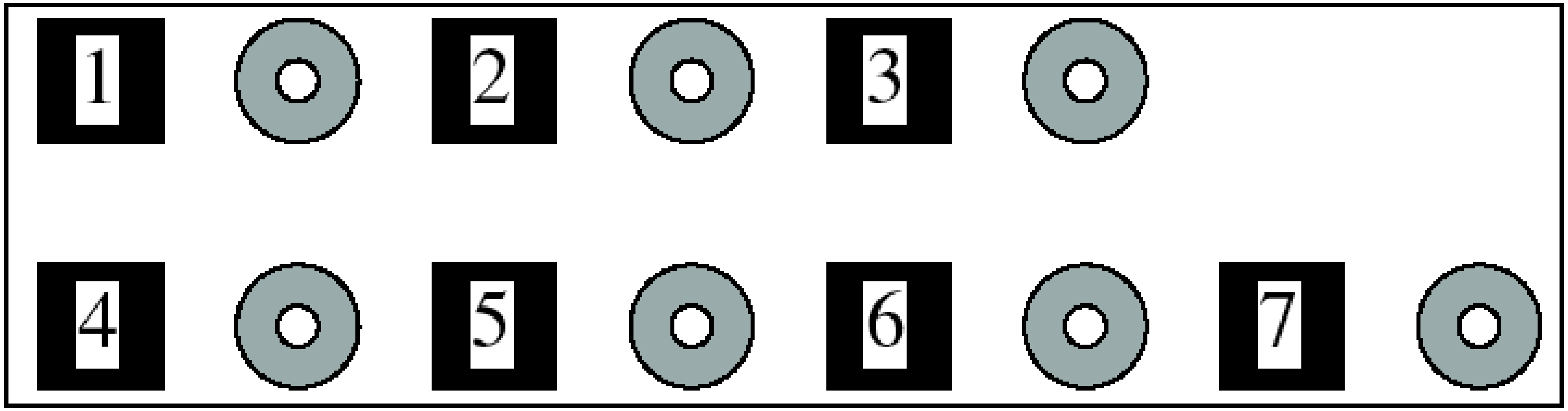

Grouping influences other perceptual mechanisms such as lightness perception

http://web.mit.edu/persci/people/adelson/publications/gazzan.dir/koffka.html

# Figure-ground

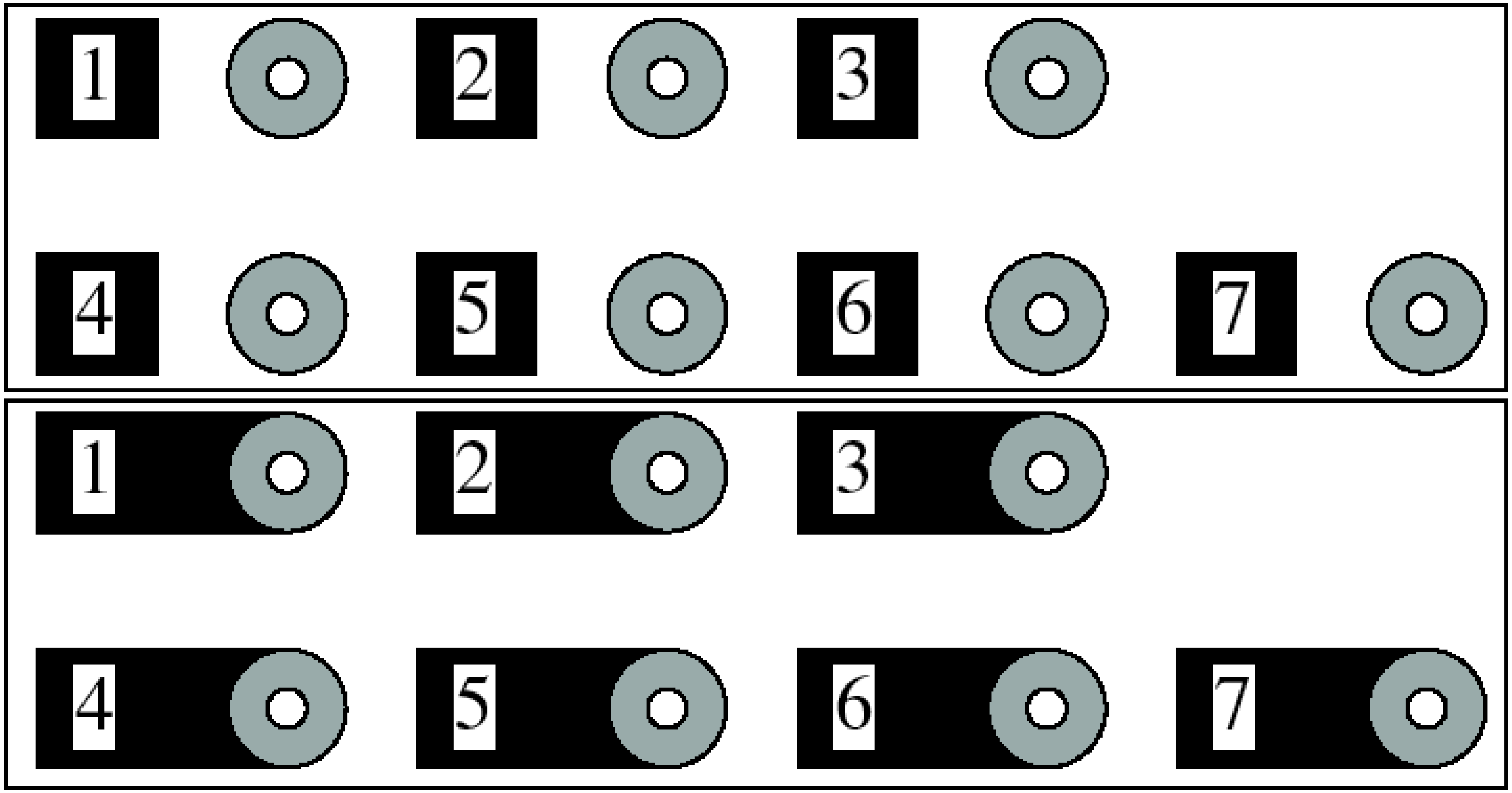


# Grouping phenomena in real life




Forsyth & Ponce, Figure 14.7

# Grouping phenomena in real life




Forsyth & Ponce, Figure 14.7

# The goals of segmentation

- Separate image into coherent “objects”

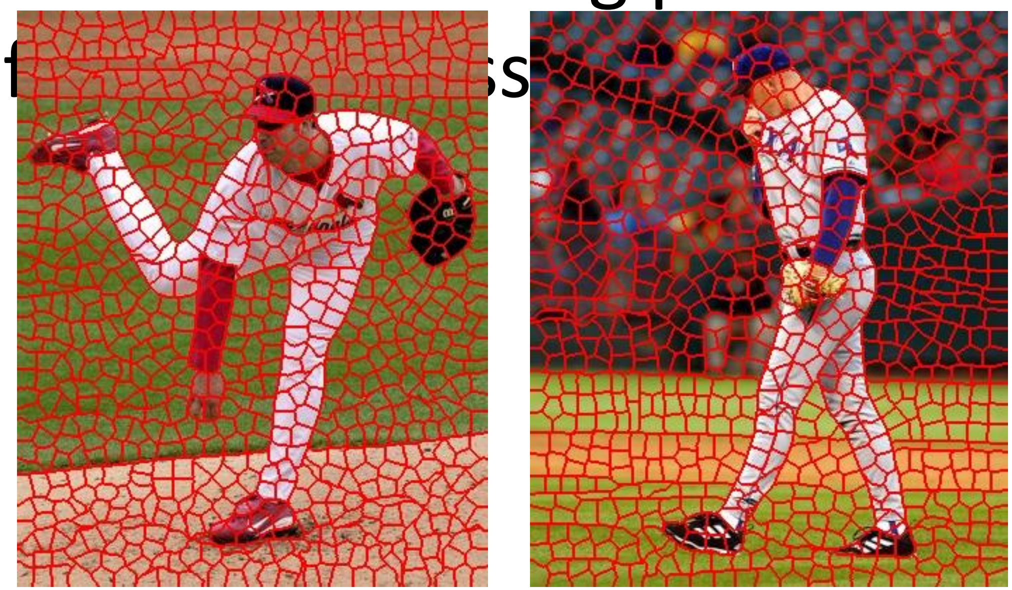

Source: Lana Lazebnik

# The goals of segmentation

- Separate image into coherent “objects”

- Group together similar-looking pixels for efficiency of f … ss

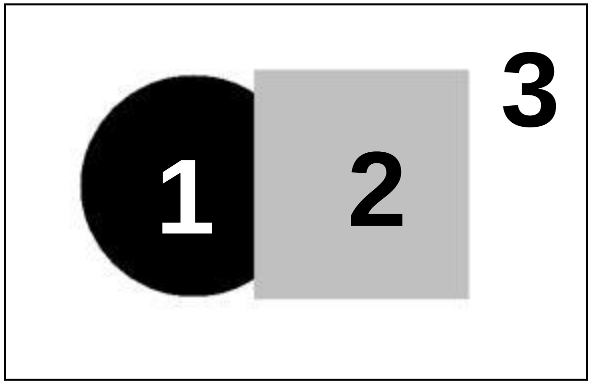
“superpixels”



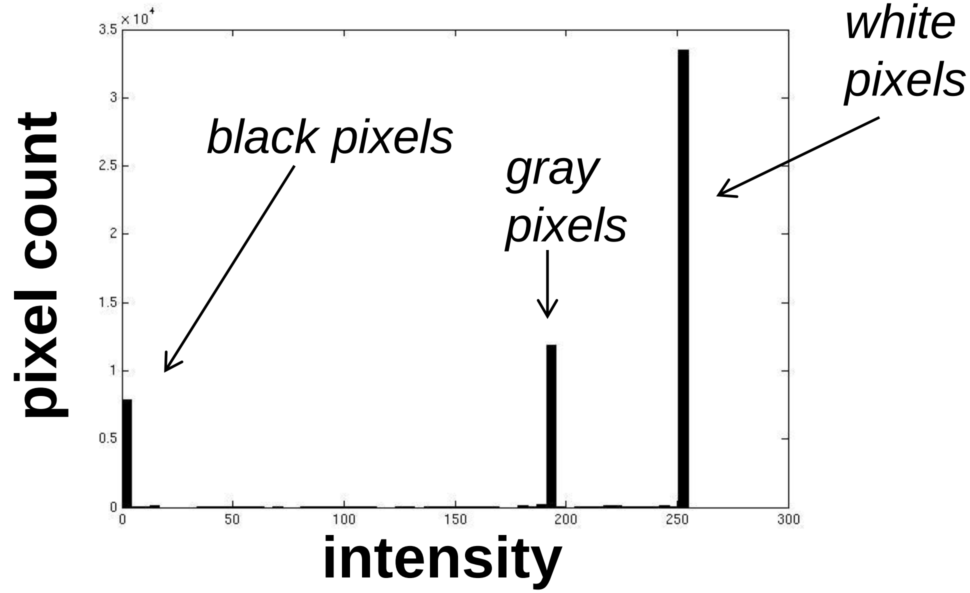
X. Ren and J. Malik. [Learning a classification model for segmentation.]() ICCV 2003.

Source: Lana Lazebnik

# 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?

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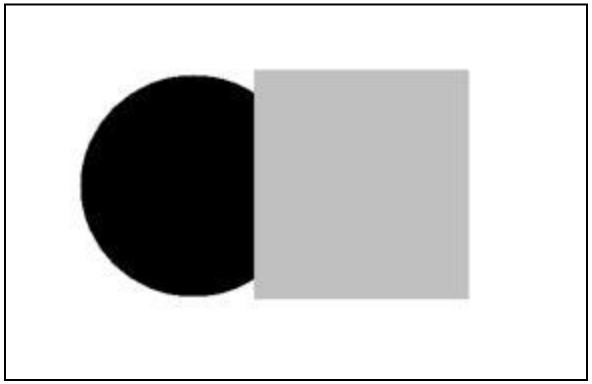
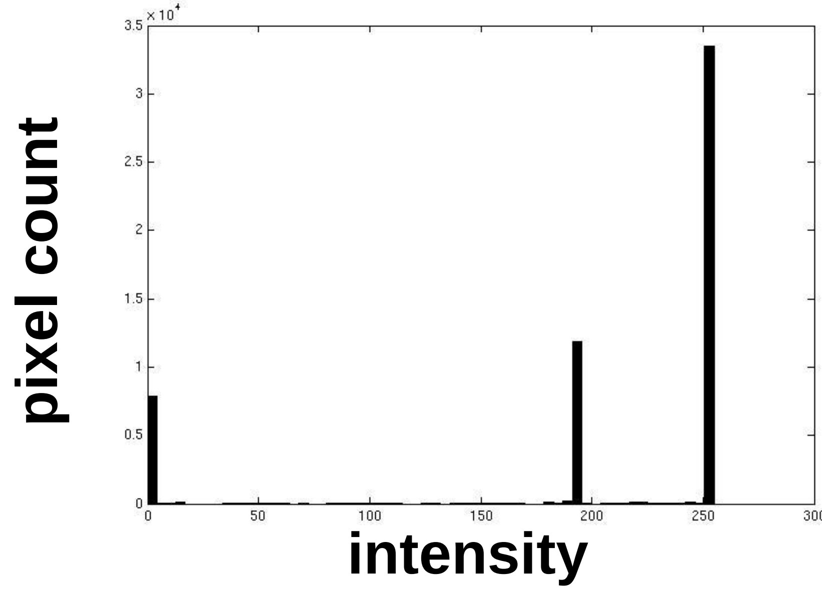
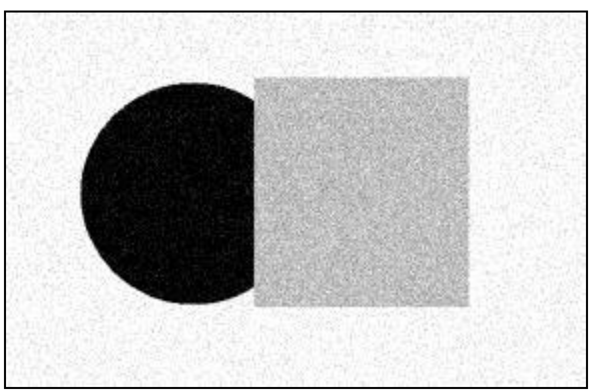
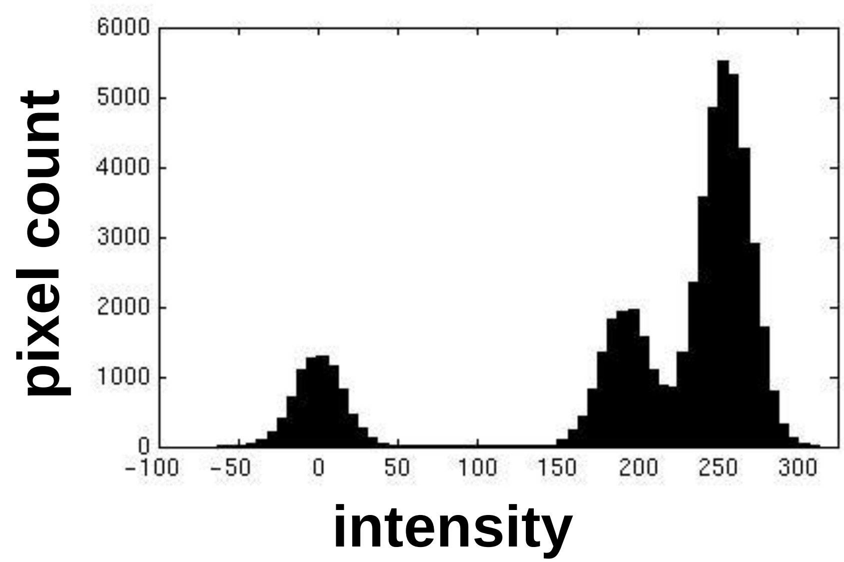


input image



input image

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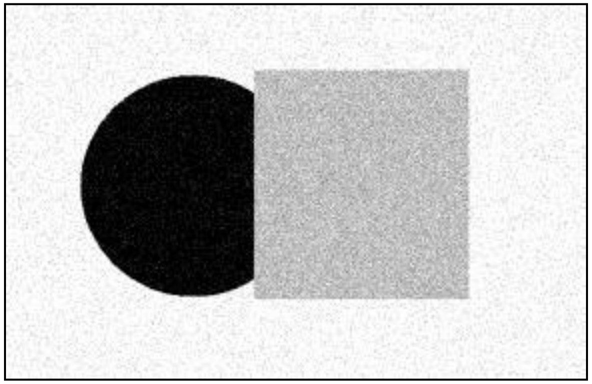
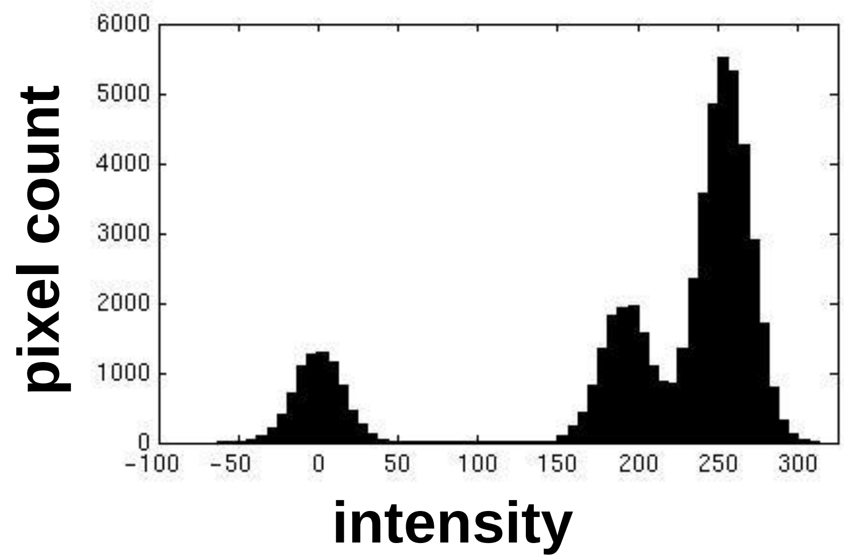
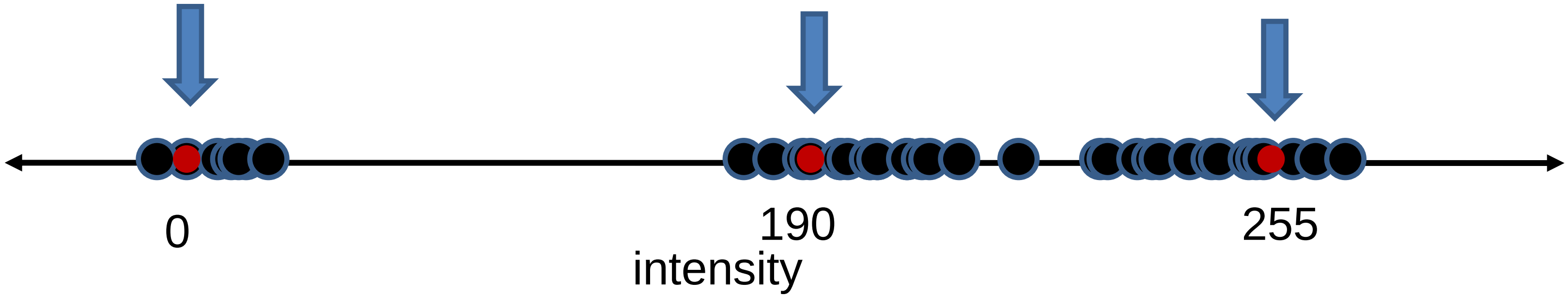
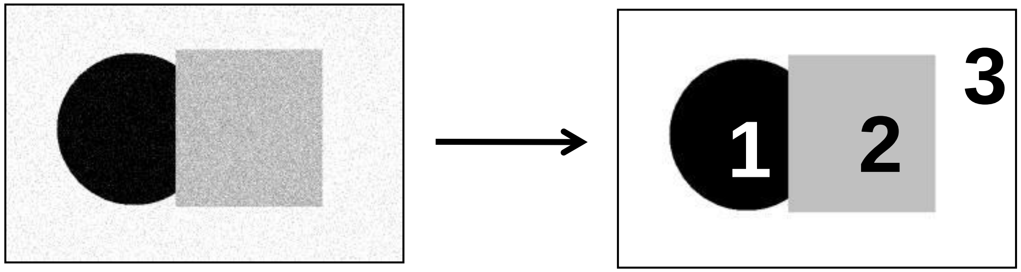


**input image**




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




- 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 $c_i$:

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

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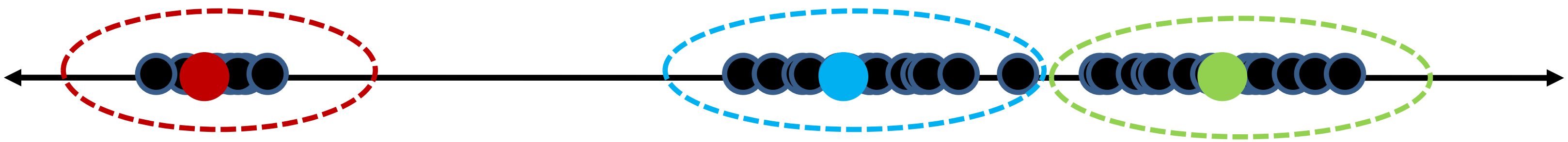
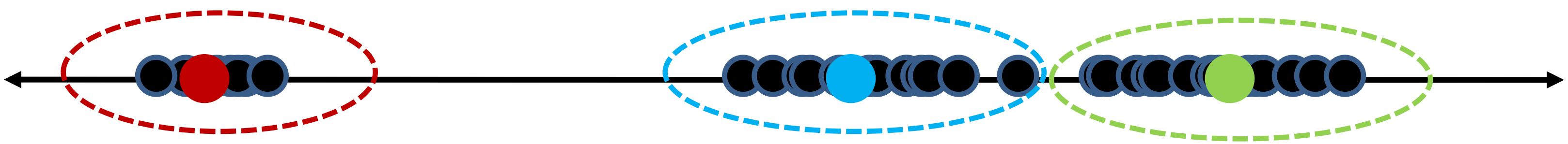
# Clustering

- 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.



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# 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, $c_1, \ldots, c_K$
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

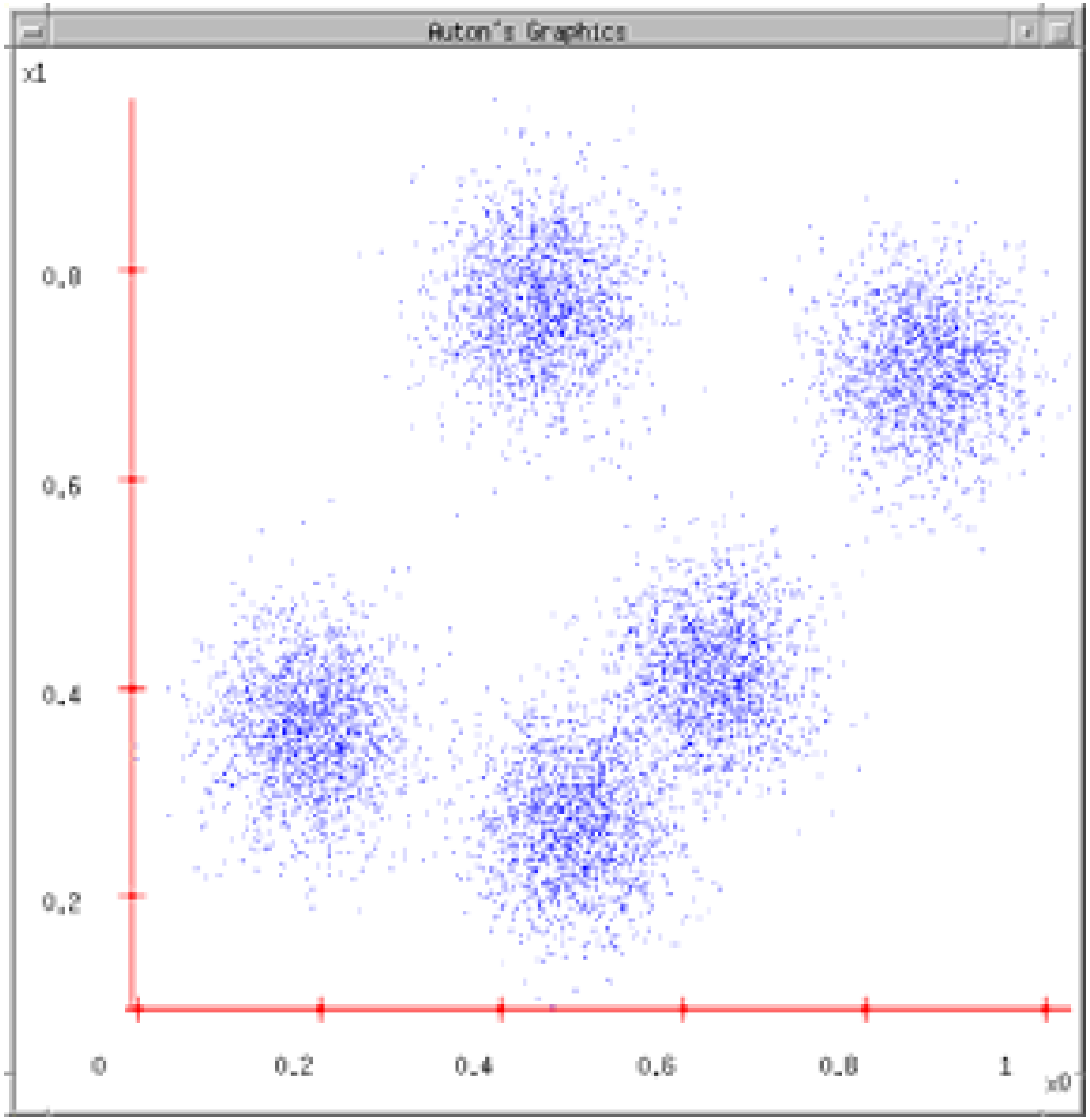
- Will always converge to *some* solution
- Can be a "local minimum"
  - does not always find the global minimum of objective function:

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

**Source: Steve Seitz**

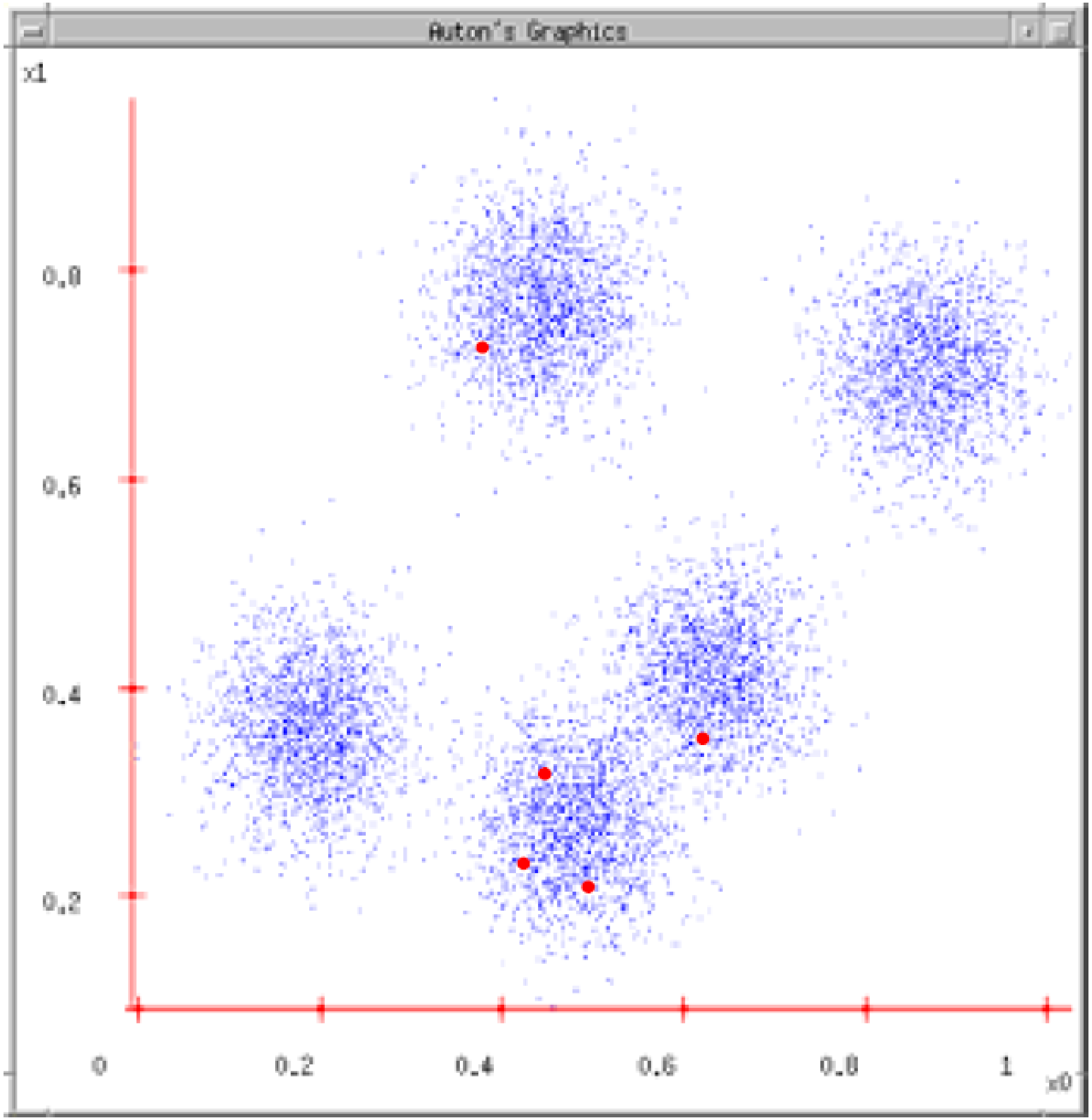
# K-means

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



# K-means

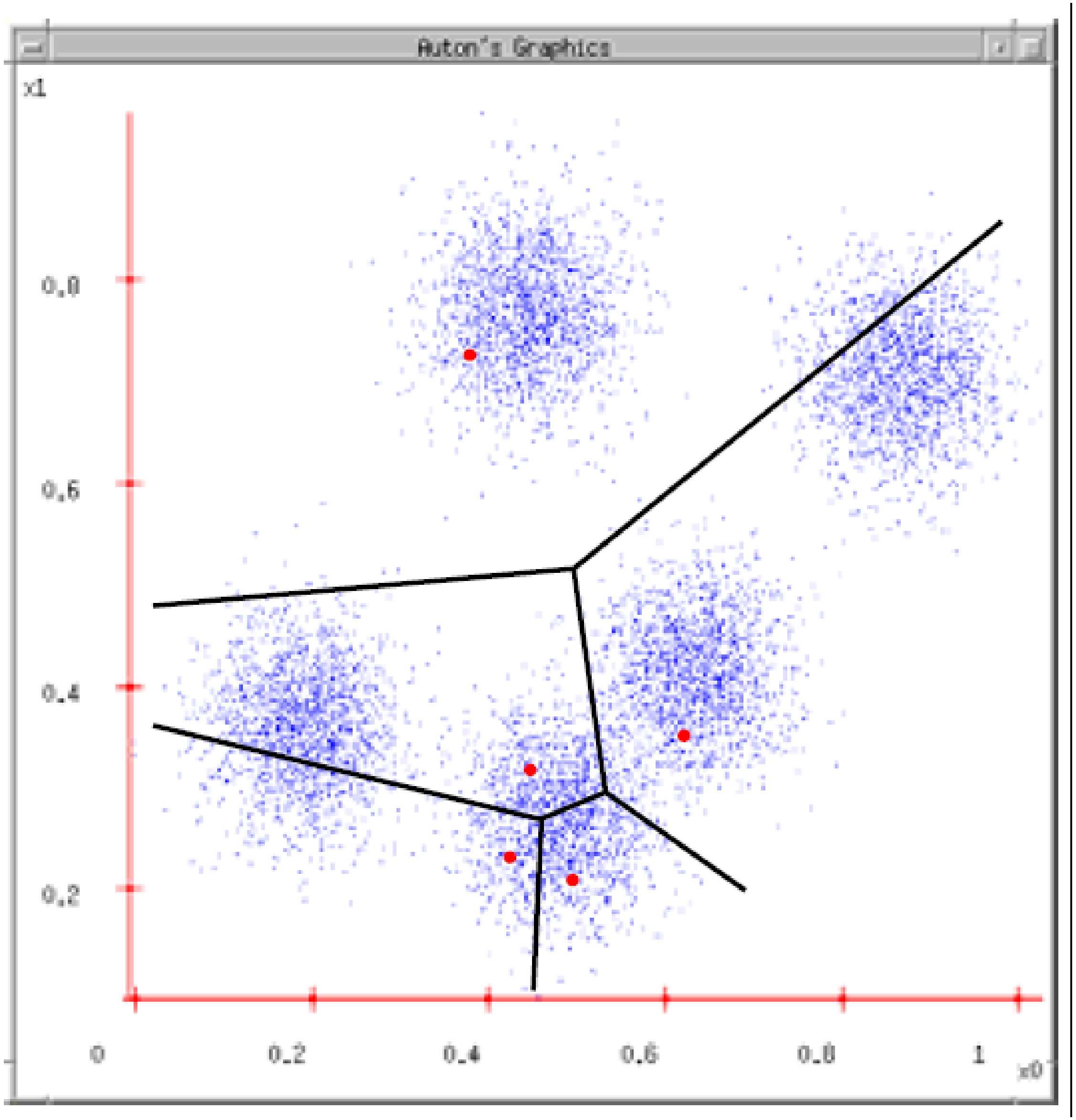
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations




Andrew Moore

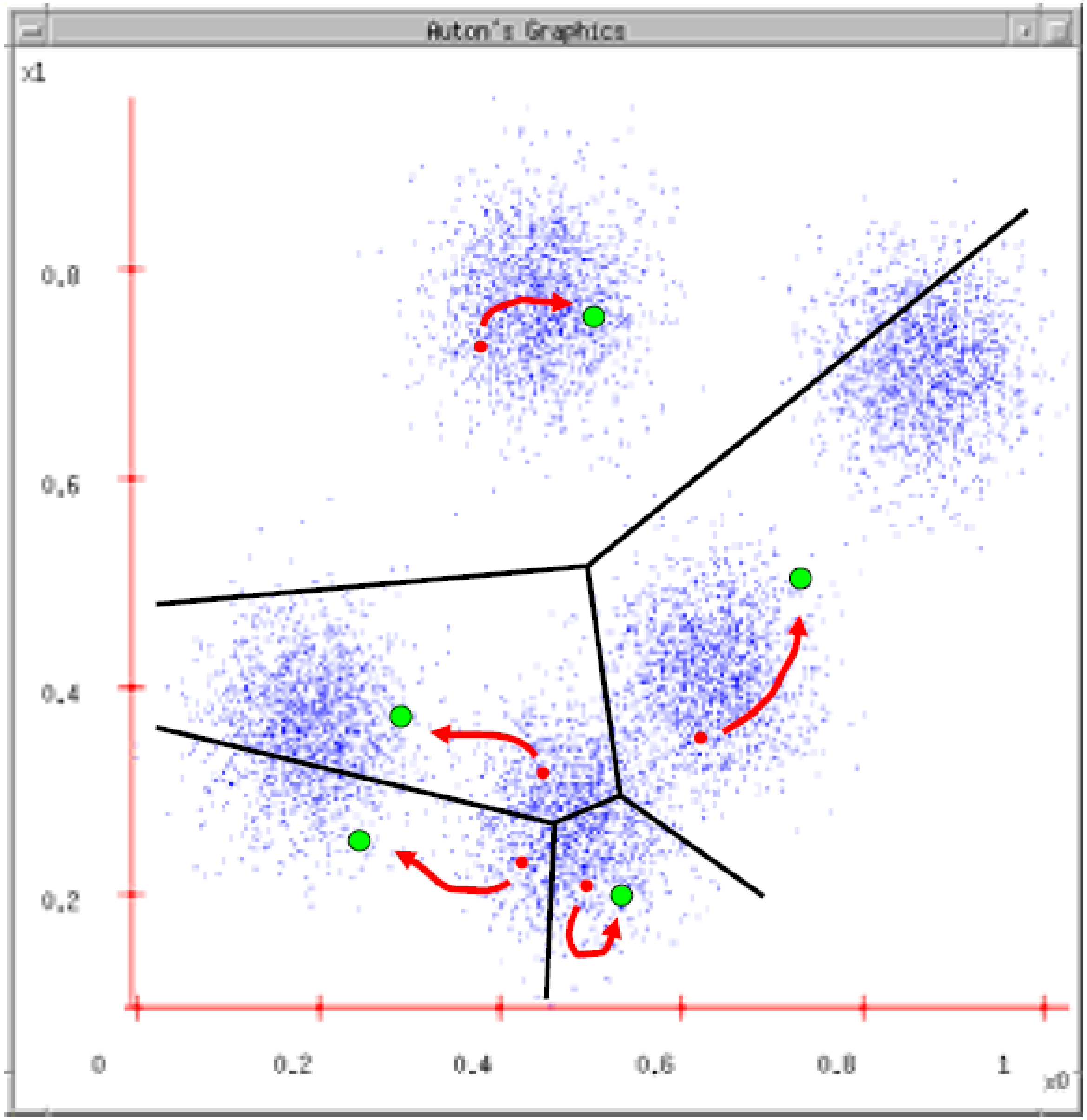
# K-means

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

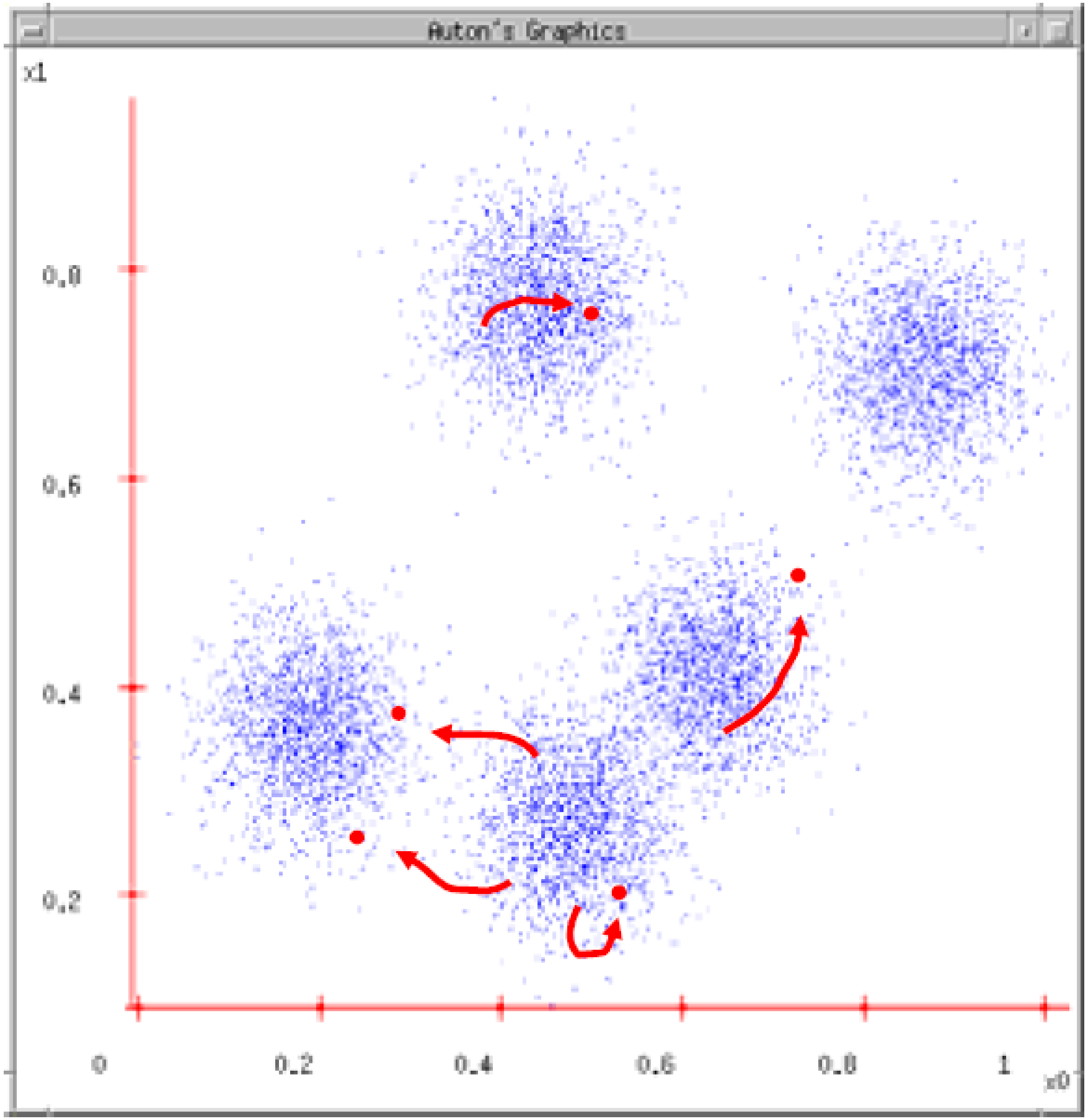
1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns




Andrew Moore

# 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!



# K-means clustering

- Java demo:

http://kovan.ceng.metu.edu.tr/~maya/kmeans/index.html

http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletKM.html

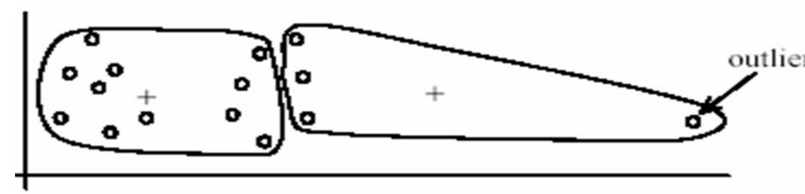
# K-means: pros and cons

## Pros

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

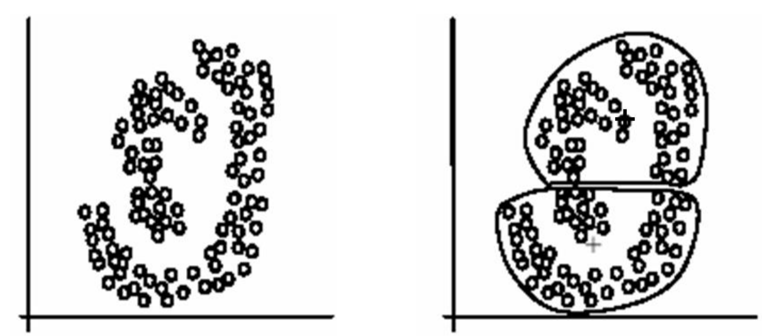
## Cons/issues

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




(A): Undesirable clusters

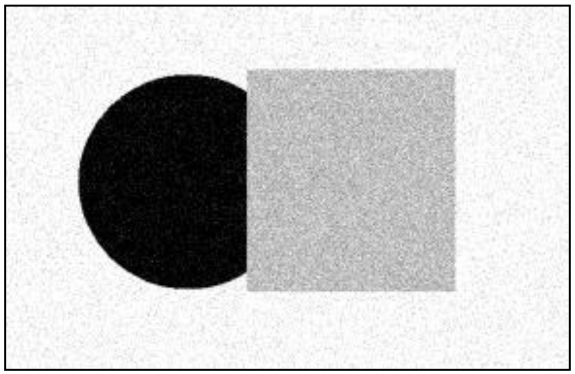

(B): Ideal clusters



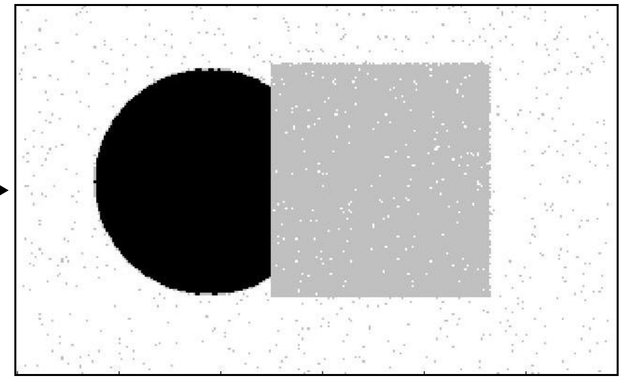
(A): Two natural clusters (B): *k*-means clusters

# An aside: Smoothing out cluster assignments

- Assigning a cluster label per pixel may yield outliers:



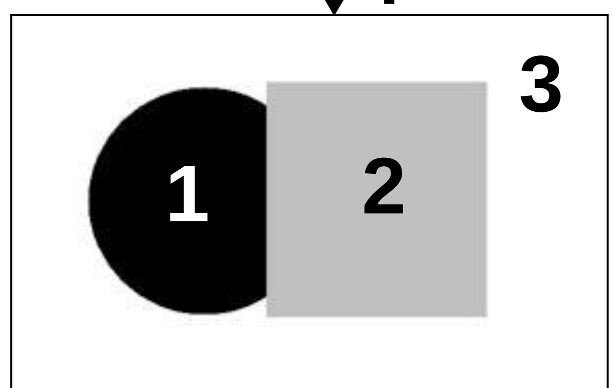
original



labeled by cluster center's intensity

?

- How to ensure they are spatially smooth?



# 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)

K=2

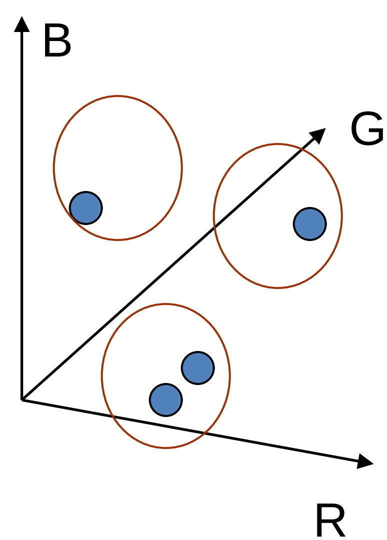
K=3

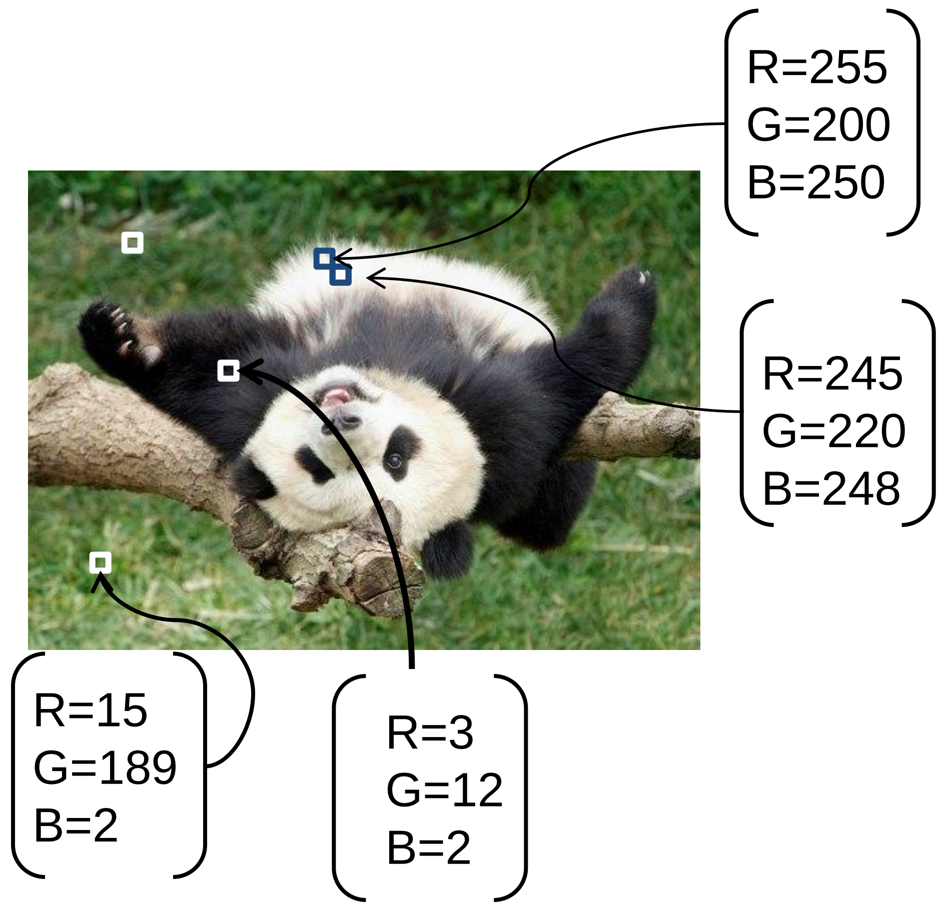
*quantization* of the feature space;
segmentation label map

# 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)

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# 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.

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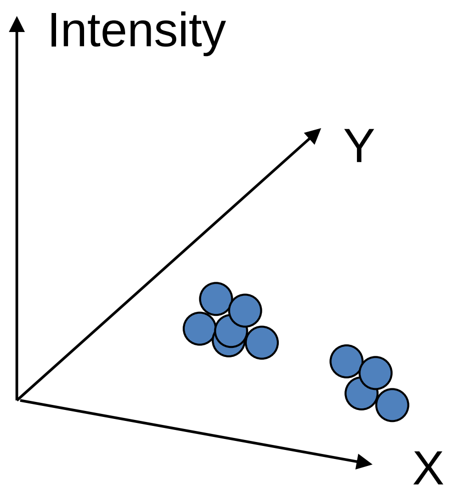
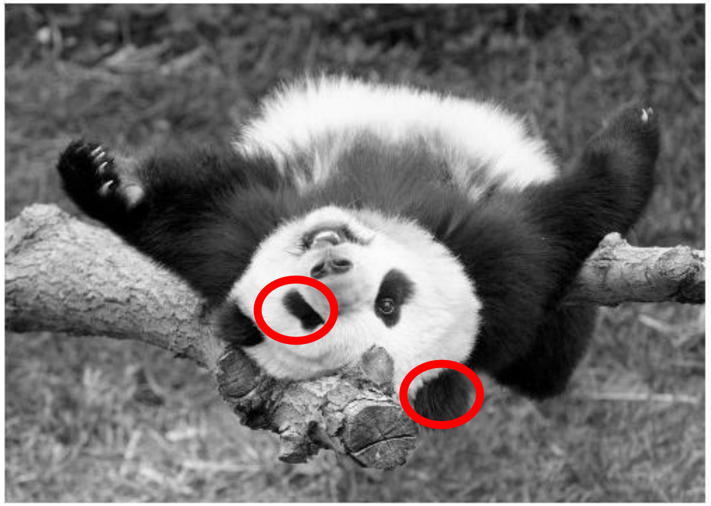
# Segmentation as clustering

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.

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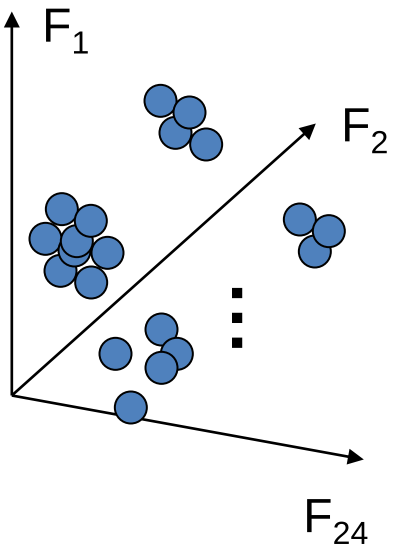
# Segmentation as clustering

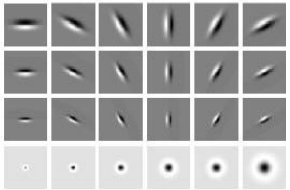
- Color, brightness, position alone are not enough to distinguish all regions…

# 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

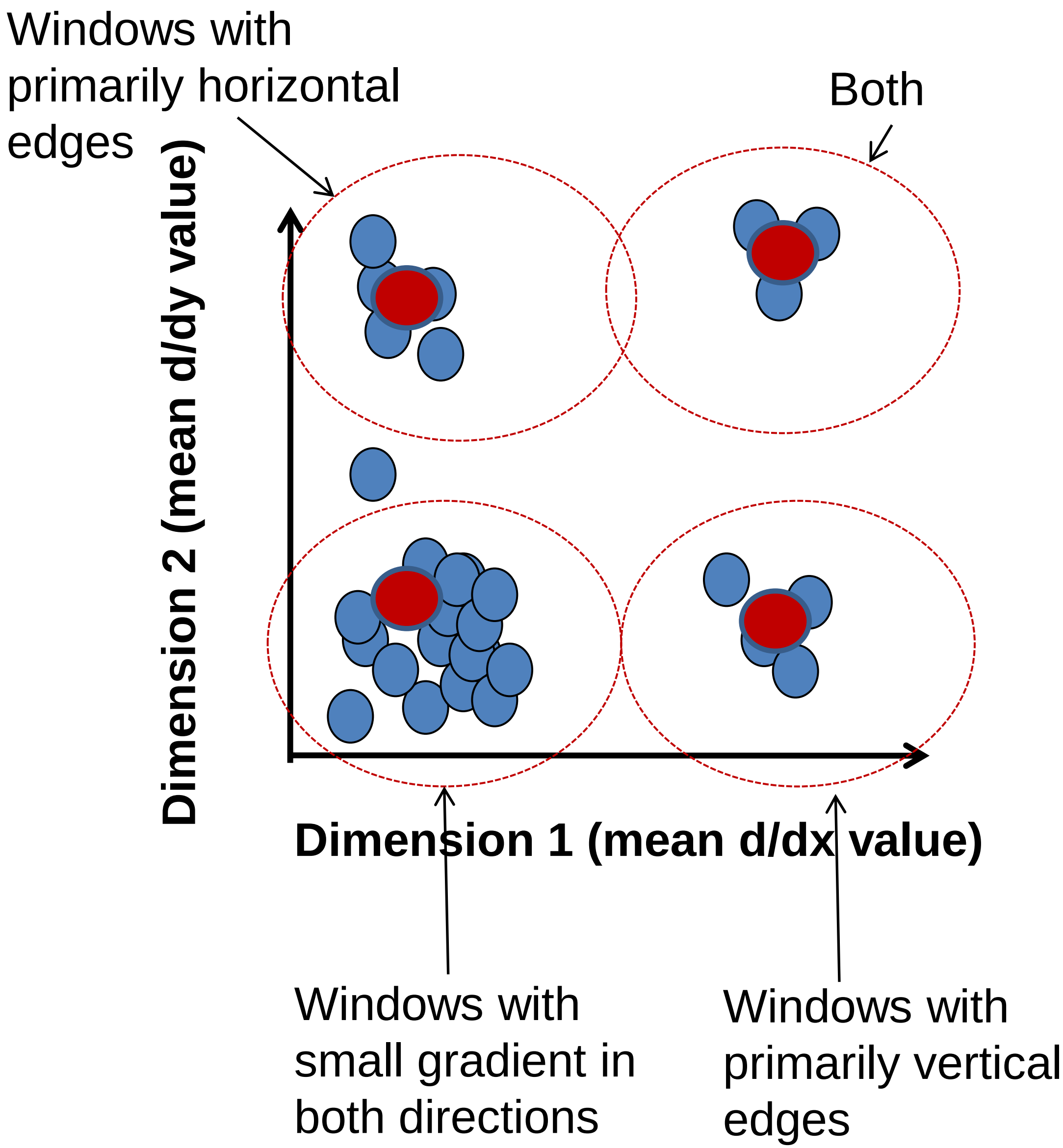


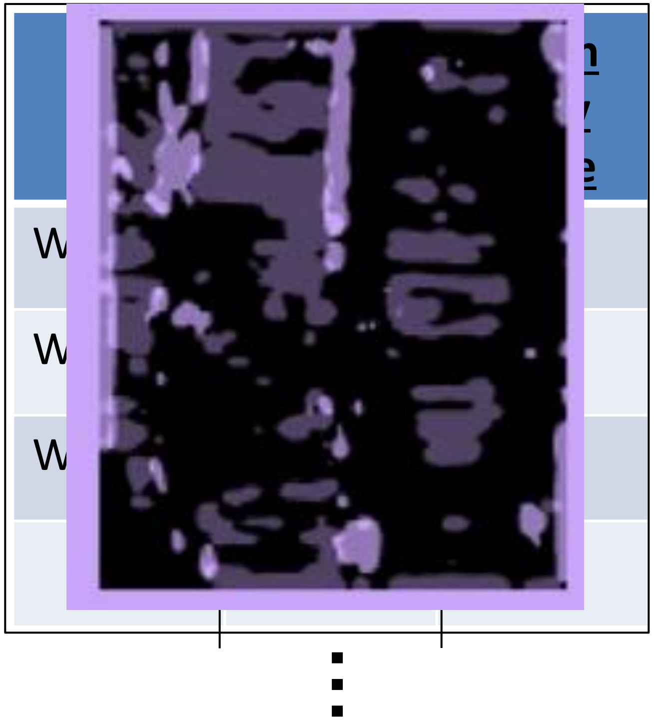



**Filter bank of 24 filters**

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

# Recall: texture representation example



**statistics to summarize patterns in small windows**

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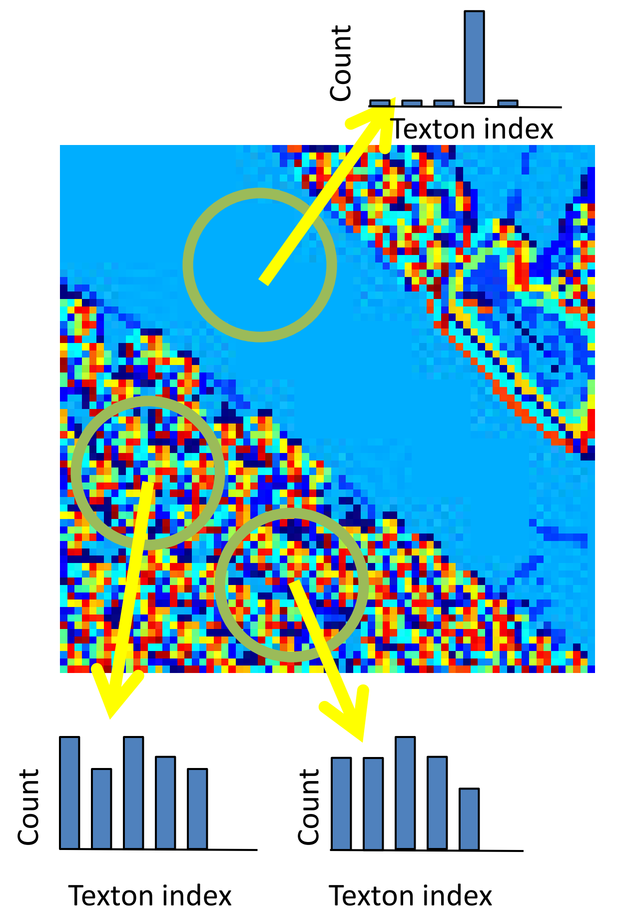
# Segmentation with texture features

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

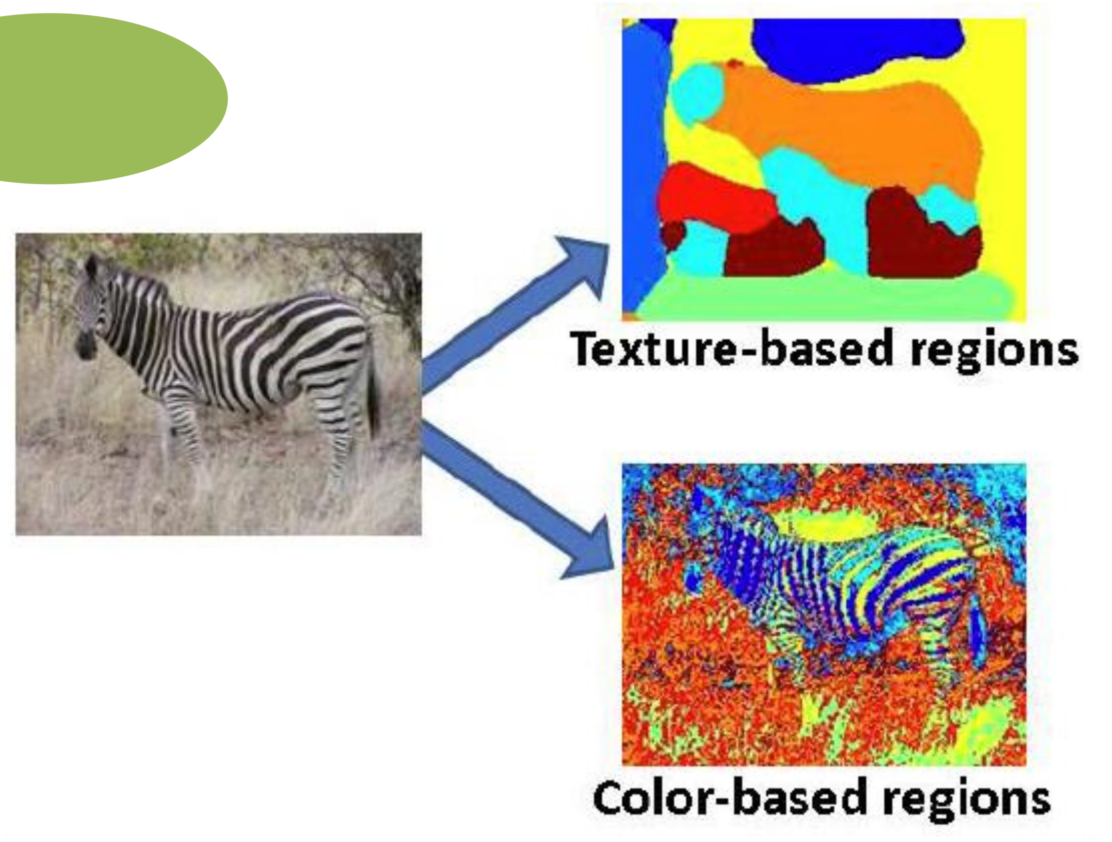





Malik, Belongie, Leung and Shi. IJCV 2001.

Adapted from Lana Lazebnik

# Image segmentation example




Kristen Grauman

# Pixel properties vs. neighborhood properties


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

How would their *texture* distributions compare?

Kristen Grauman

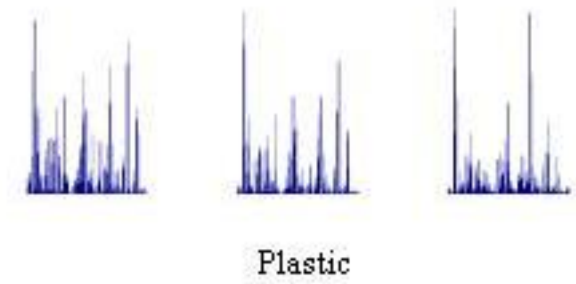
# Material classification example

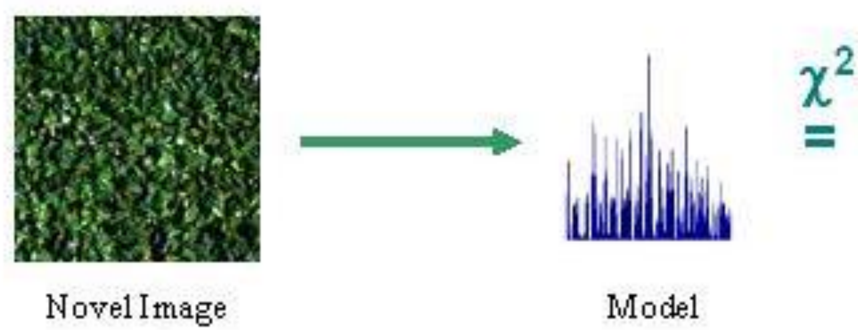
For an image of a single texture, we can classify it according to its global (image-wide) texton histogram.


Figure from Varma & Zisserman, IJCV 2005

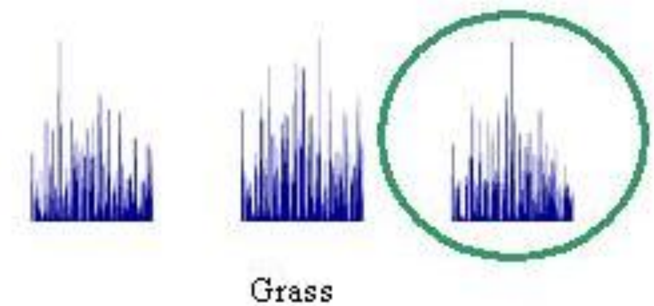
# Material classification example

*Nearest neighbor* classification: label the input according to the nearest known example's label.




$$\chi^2(h_i, h_j) = \frac{1}{2}\sum_{k=1}^{K}\frac{[h_i(k) - h_j(k)]^2}{h_i(k) + h_j(k)}$$




Manik Varma
http://www.robots.ox.ac.uk/~vgg/research/texclass/with.html

# 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

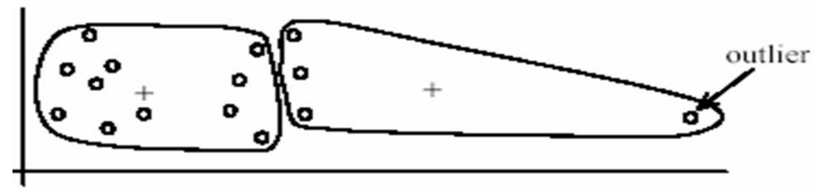
# K-means: pros and cons

**Pros**

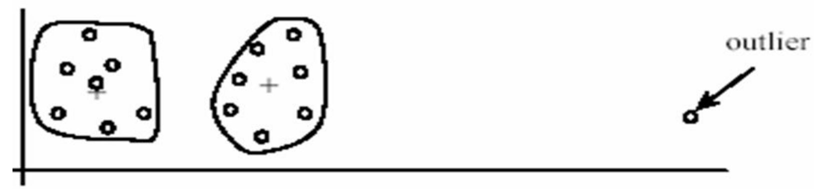
- Simple, fast to compute
- Converges to local minimum of within-cluster squared error

**Cons/issues**

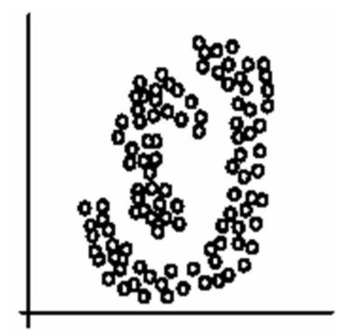
- Setting k?
- Sensitive to initial centers
- Sensitive to outliers
- Detects spherical clusters
- Assuming means can be computed



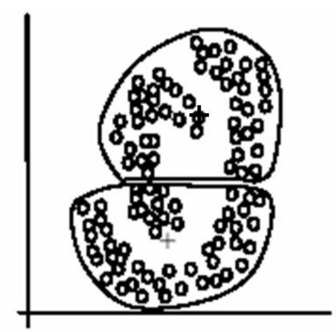

(A): Undesirable clusters




(B): Ideal clusters



(A): Two natural clusters



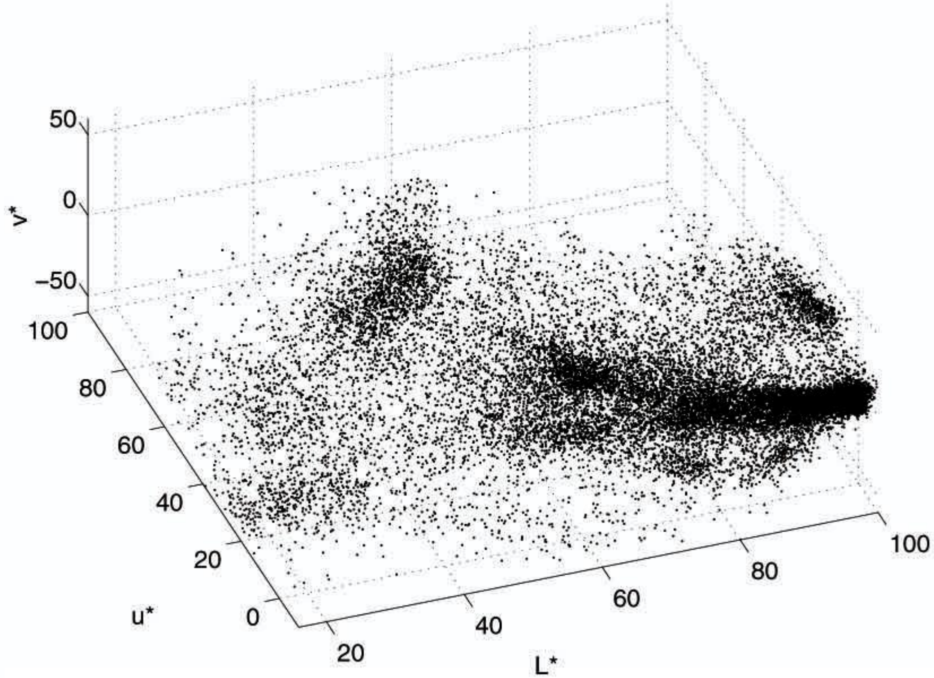
(B): *k*-means clusters

# Mean shift algorithm

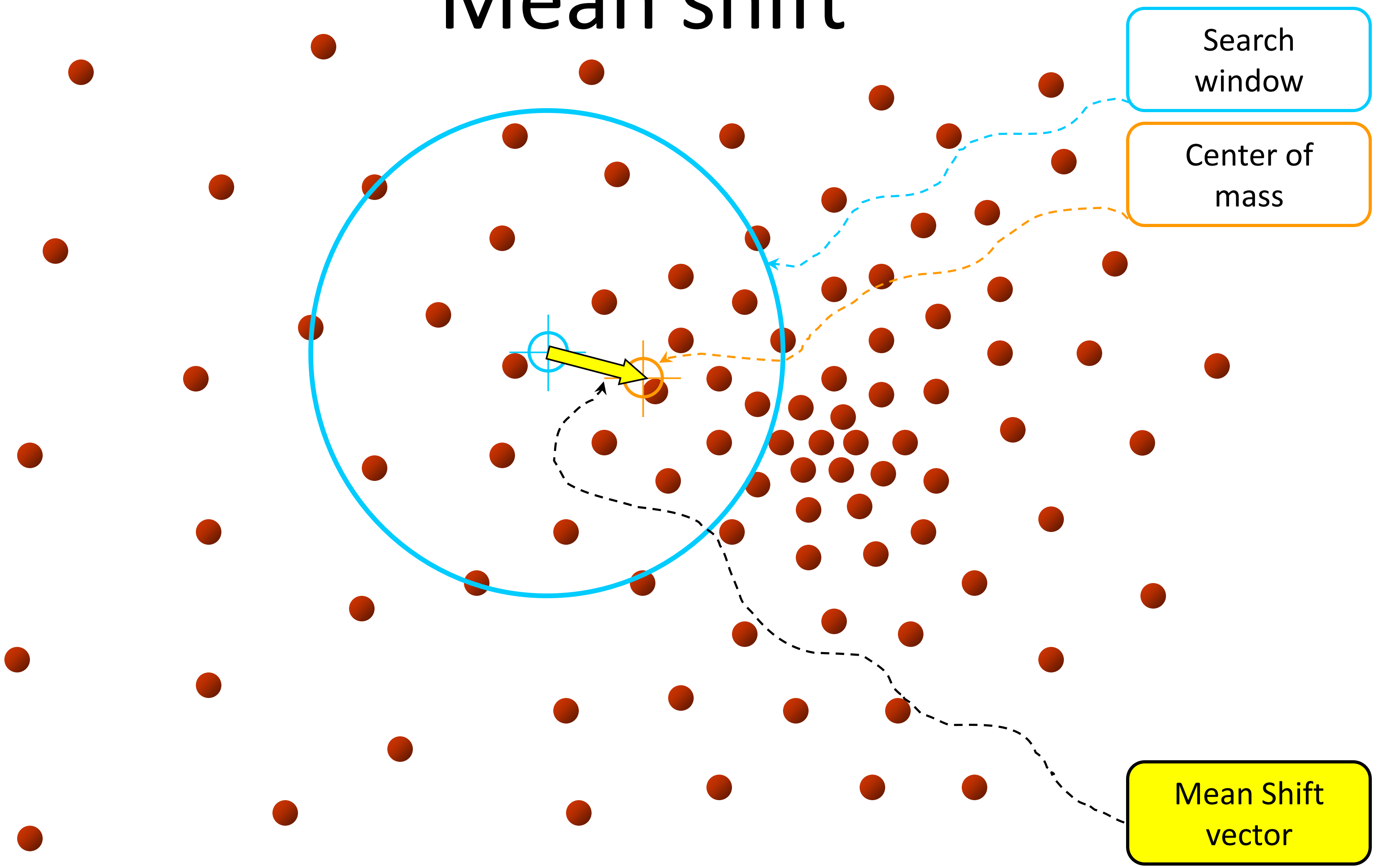
- The mean shift algorithm seeks *modes* or local maxima of density in the feature space

**image**

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

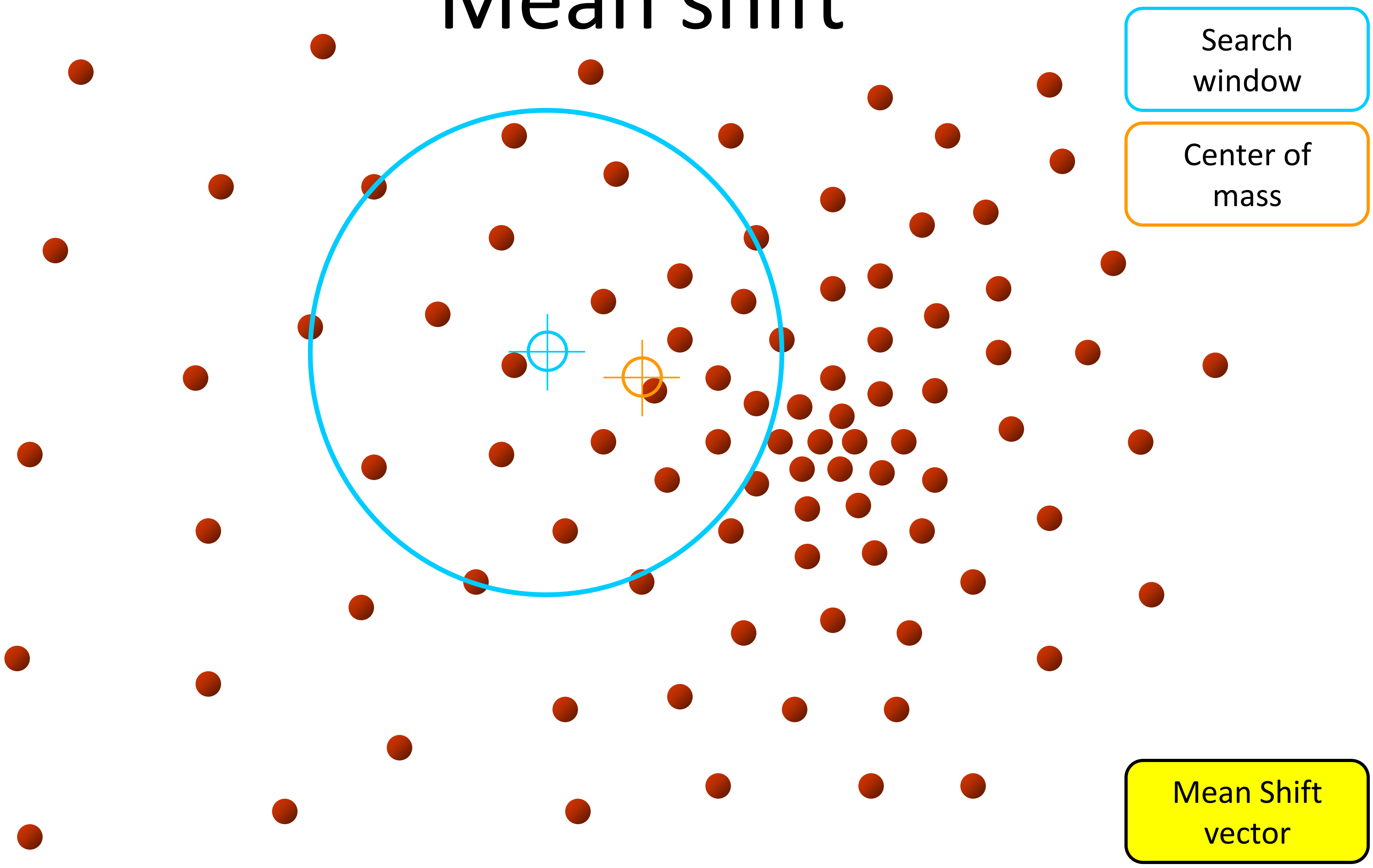


# Mean shift



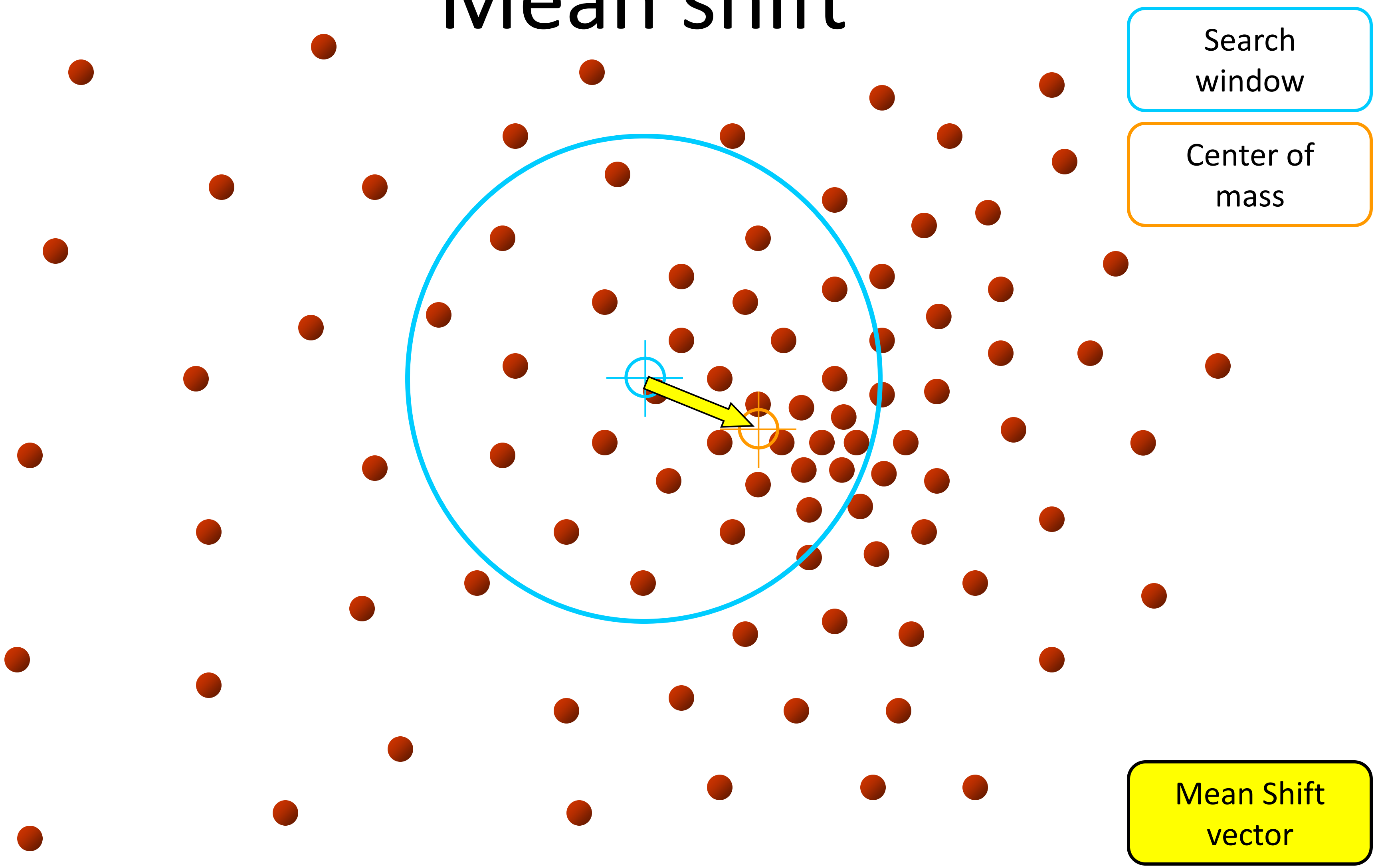

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



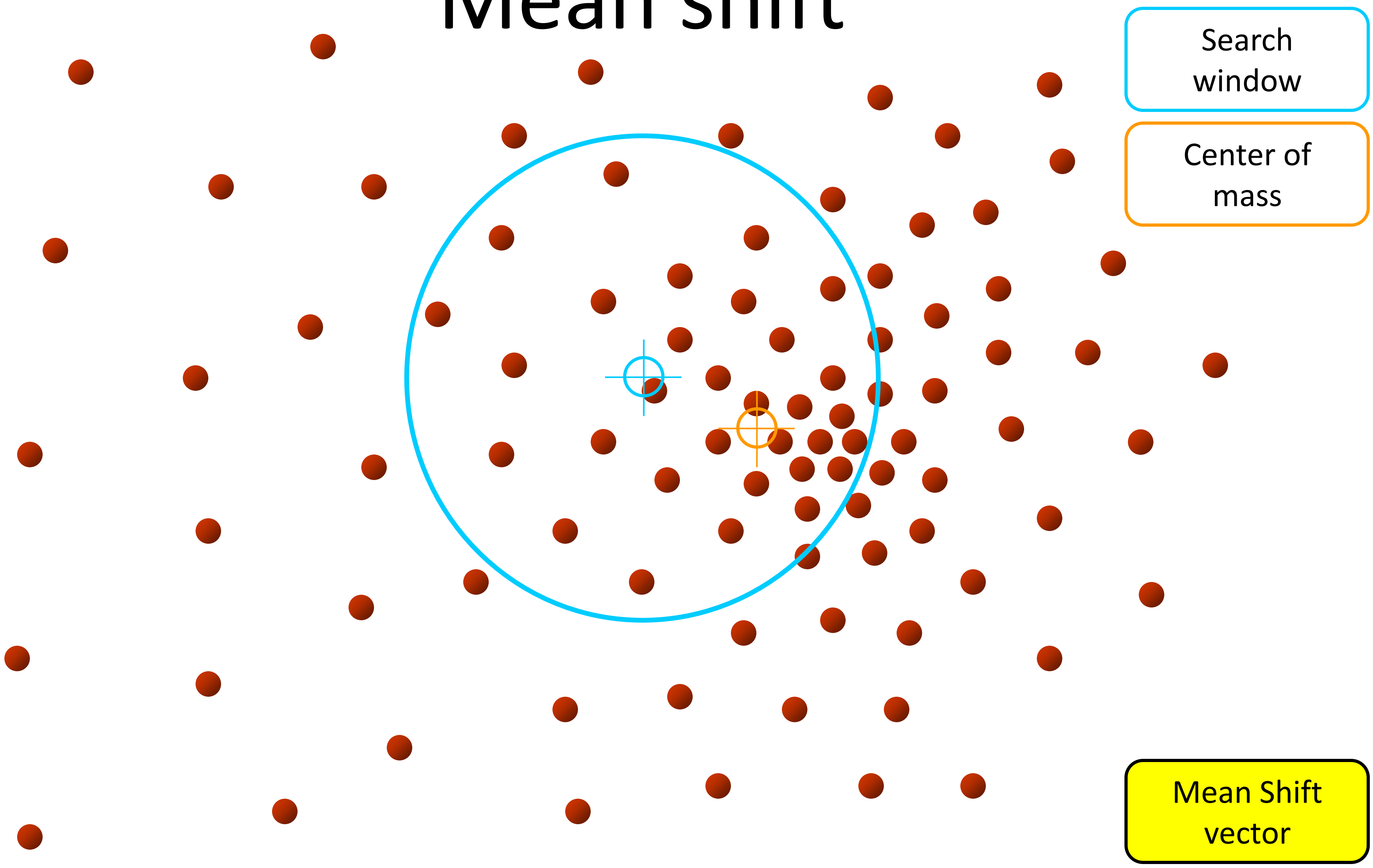

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



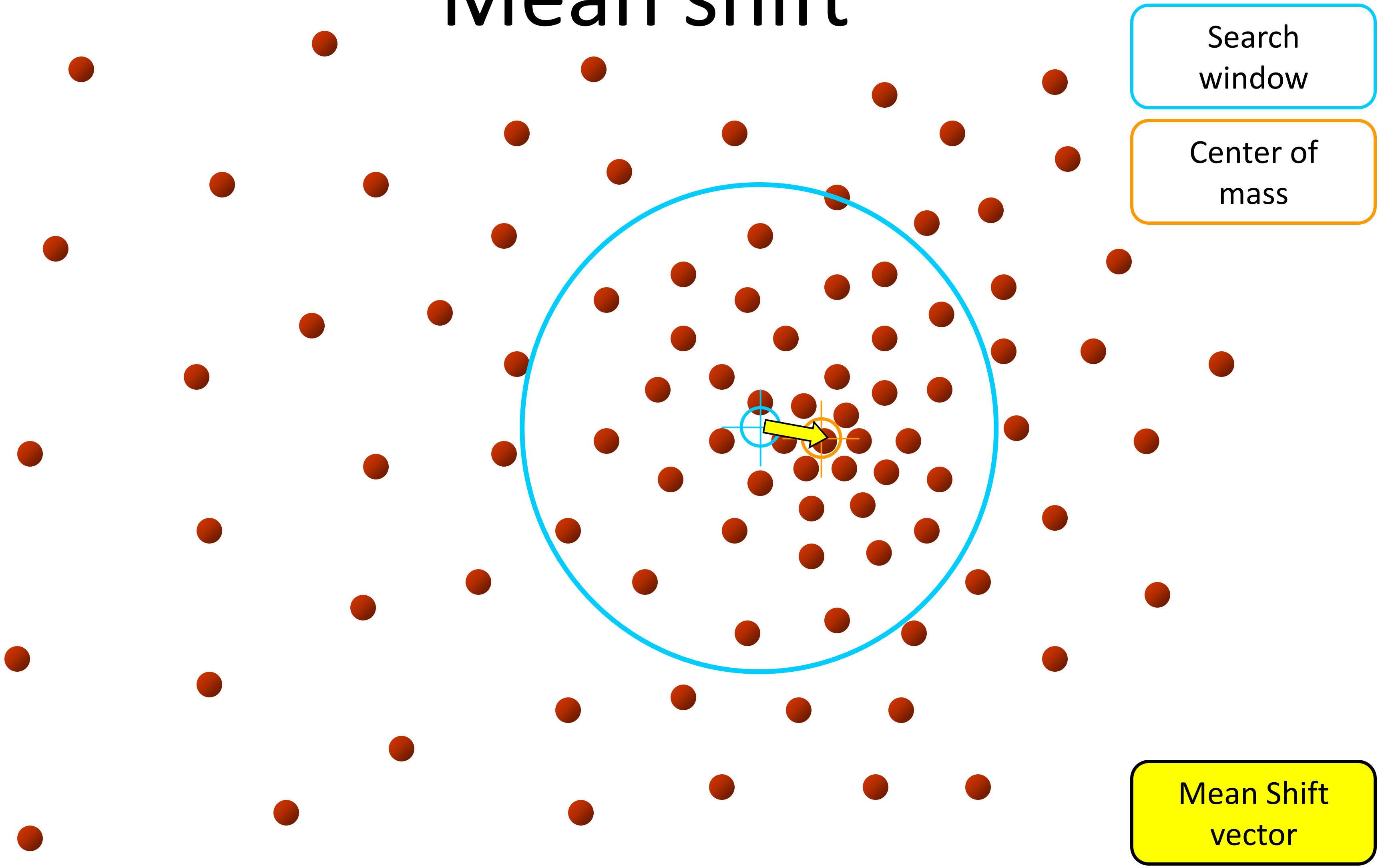

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



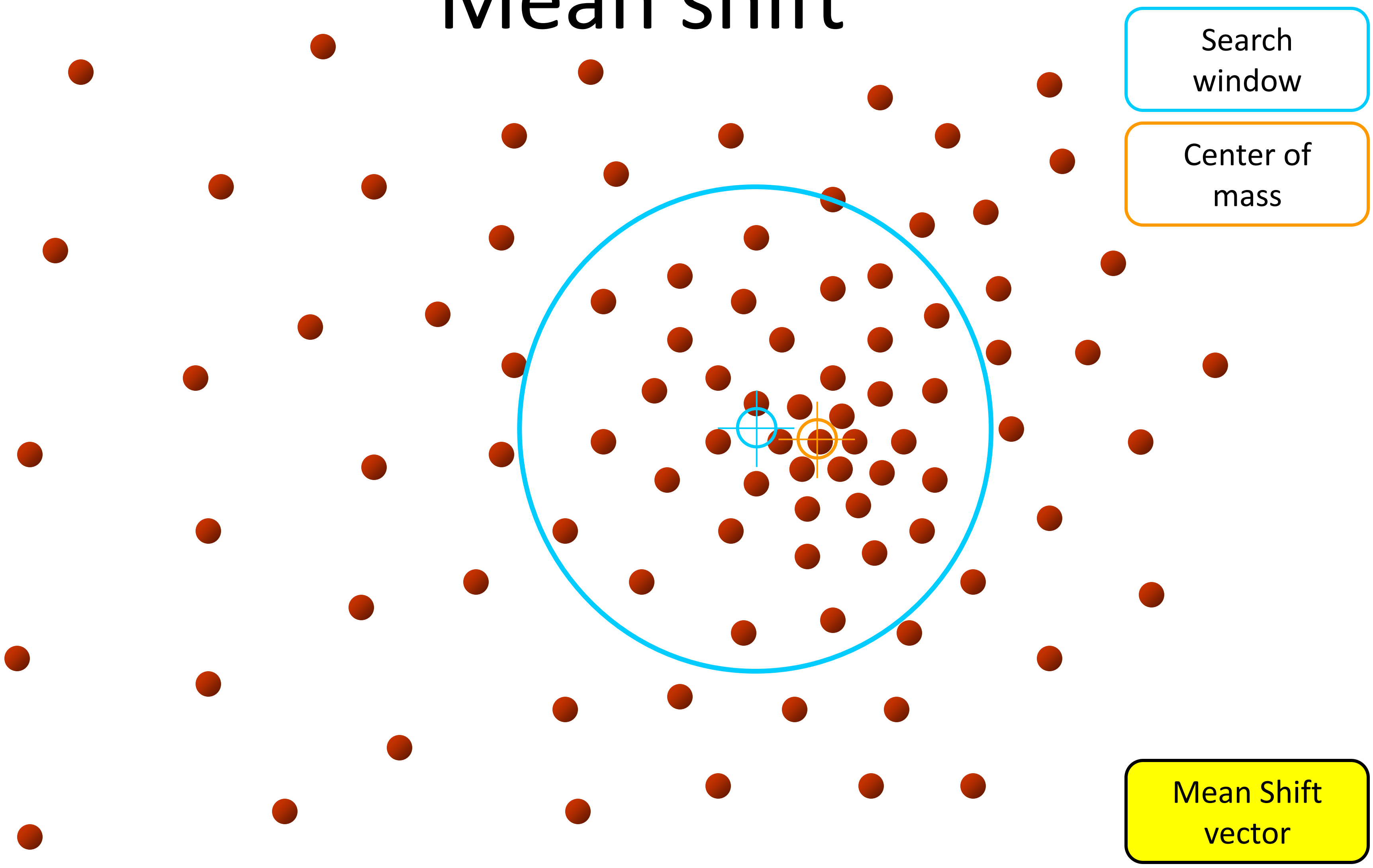

Slide by Y. Ukrainitz & B. Sarel

# Mean shift



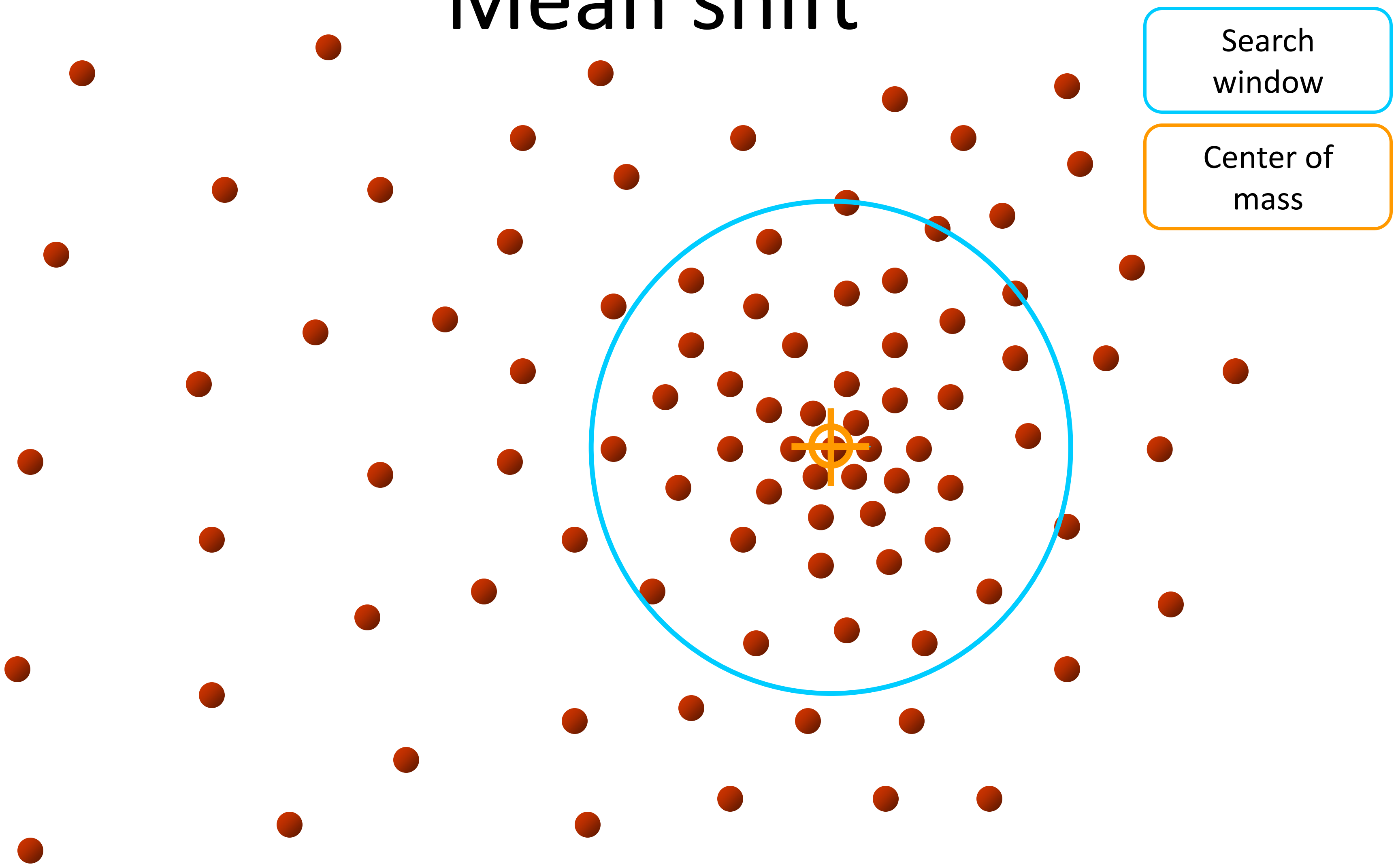

Slide by Y. Ukrainitz & B. Sarel

# Mean shift




Slide by Y. Ukrainitz & B. Sarel

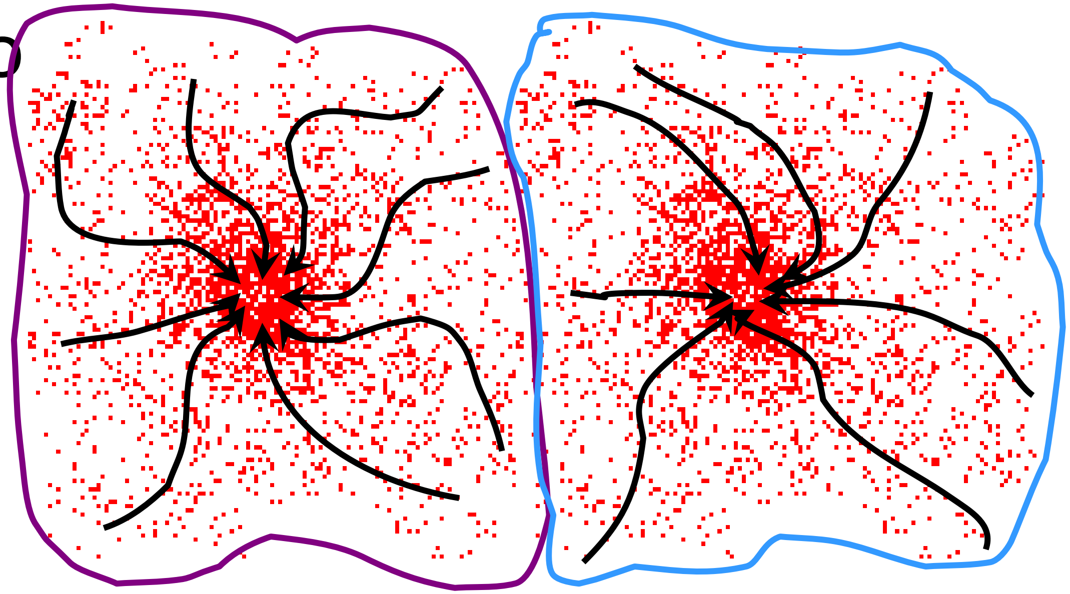
# Mean shift




Slide by Y. Ukrainitz & B. Sarel

# Mean shift clustering

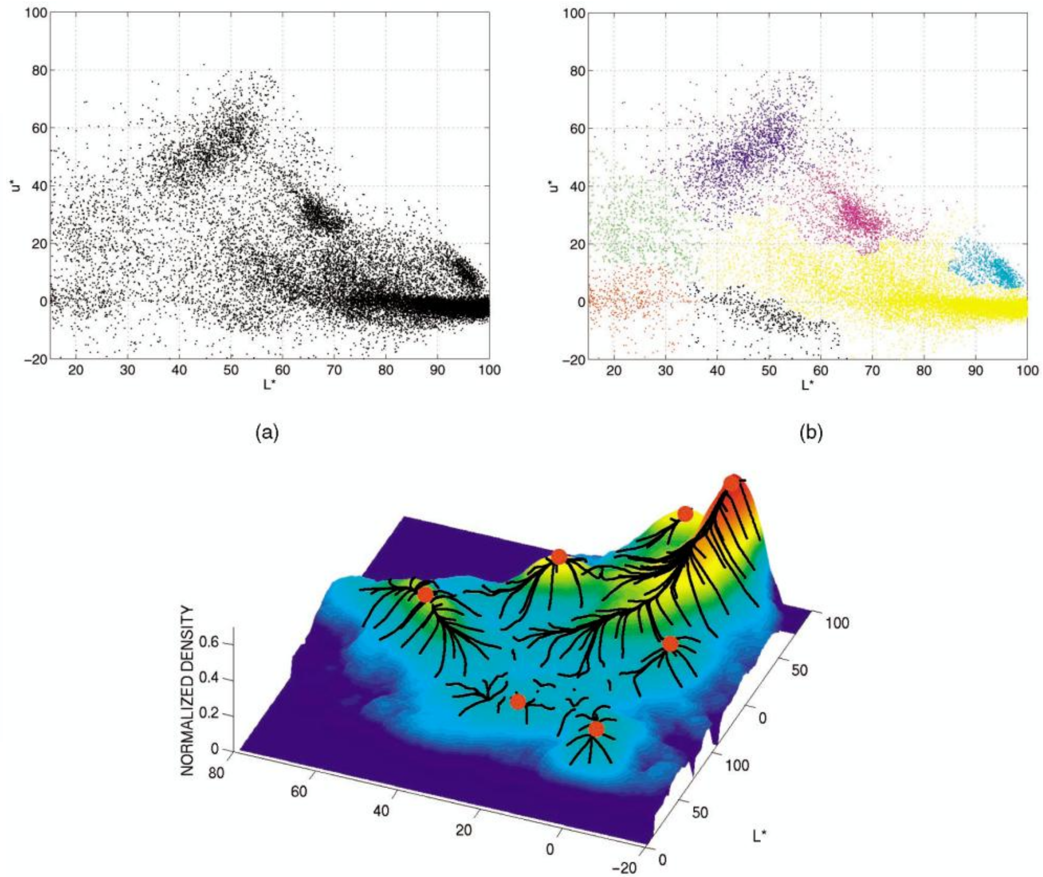
- Cluster: all data points in the attraction basin of a mode
- Attraction basin: the region for which all trajecto



Slide by Y. Ukrainitz & B. Sarel

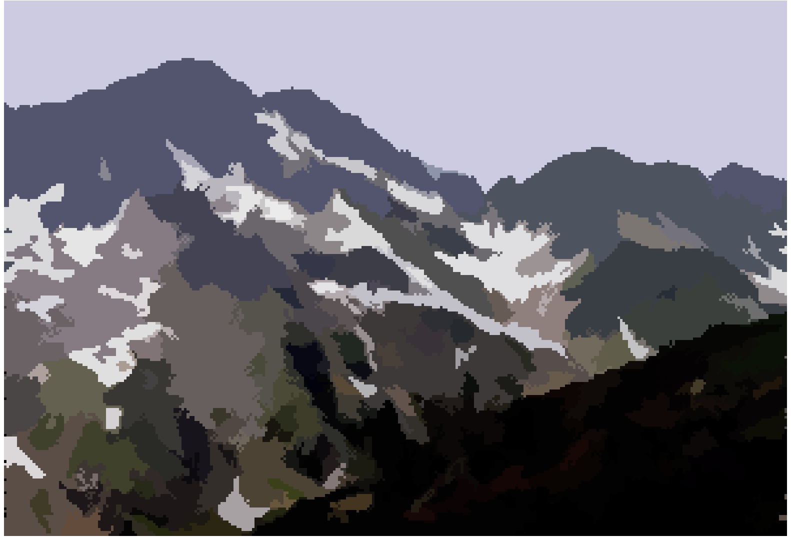
# Mean shift clustering/segmentation

- 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



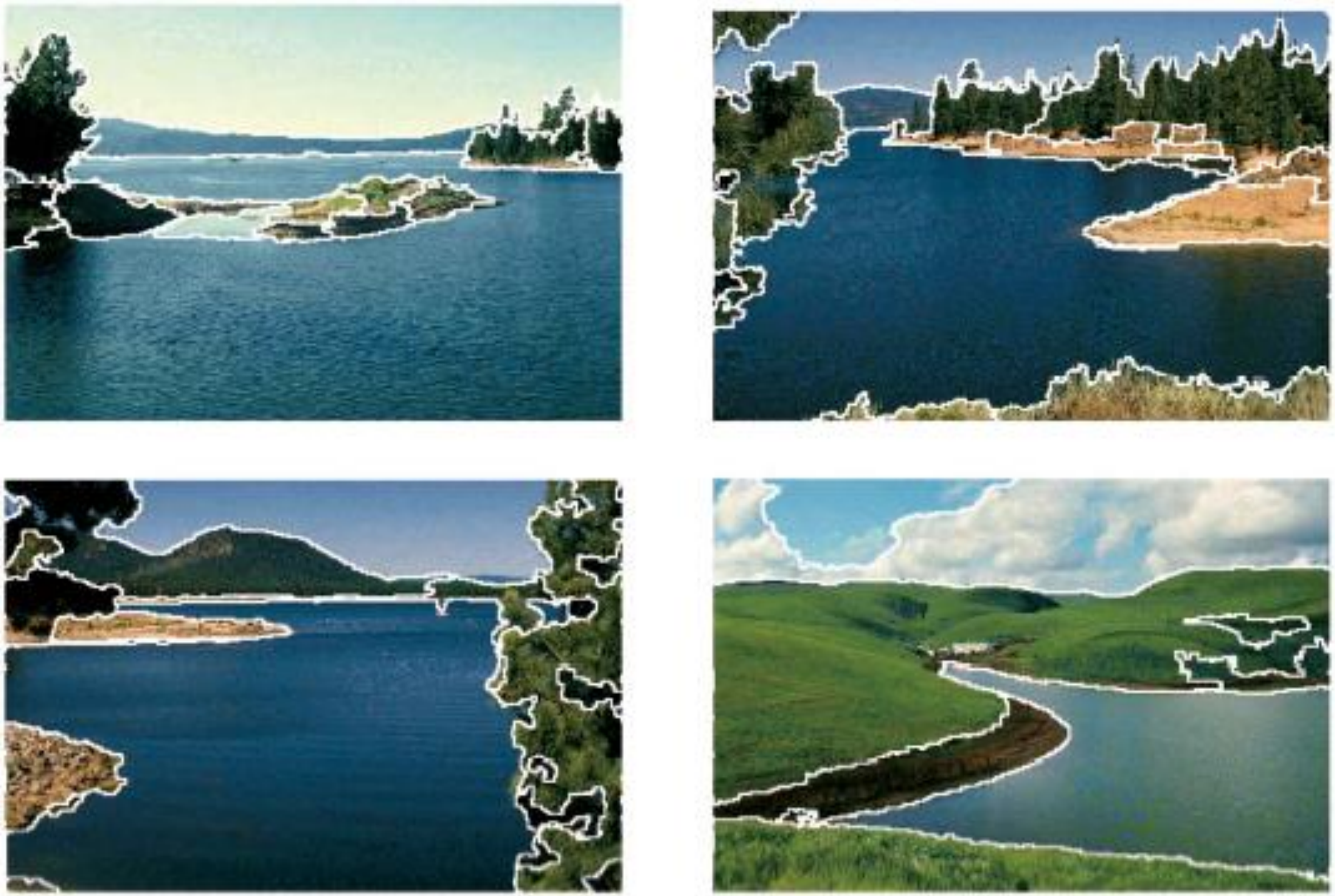
# Mean shift segmentation results



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

# Mean shift segmentation results



# Mean shift

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

Kristen Grauman

# Outline

- What are grouping problems in vision?

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  - Gestalt properties

- Bottom-up segmentation via clustering
  - Algorithms:
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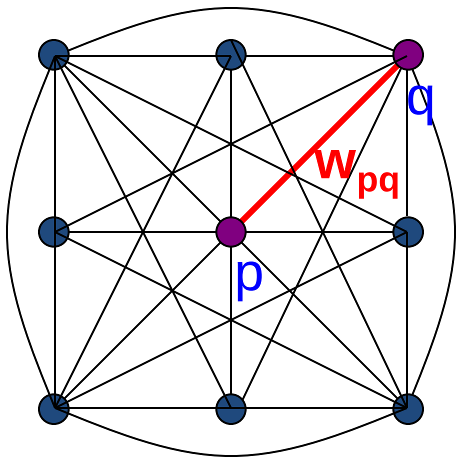
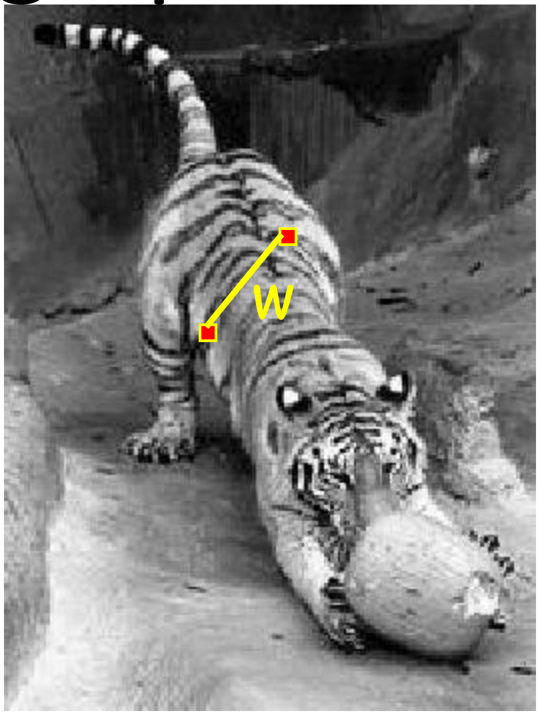
    - Graph-based: normalized cuts
  - Features: color, texture, …
    - Quantization for texture summaries

# Images as graphs




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

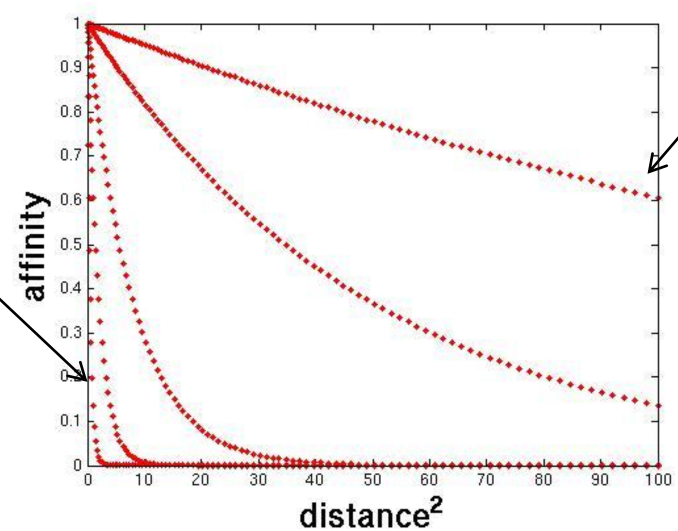
Source: Steve Seitz

# Measuring affinity

- One possibility:

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

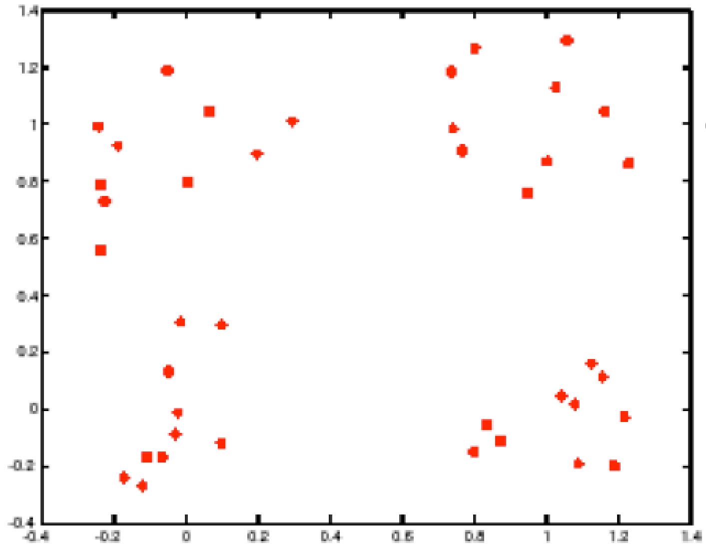
Small sigma: group only nearby points




Large sigma: group distant points

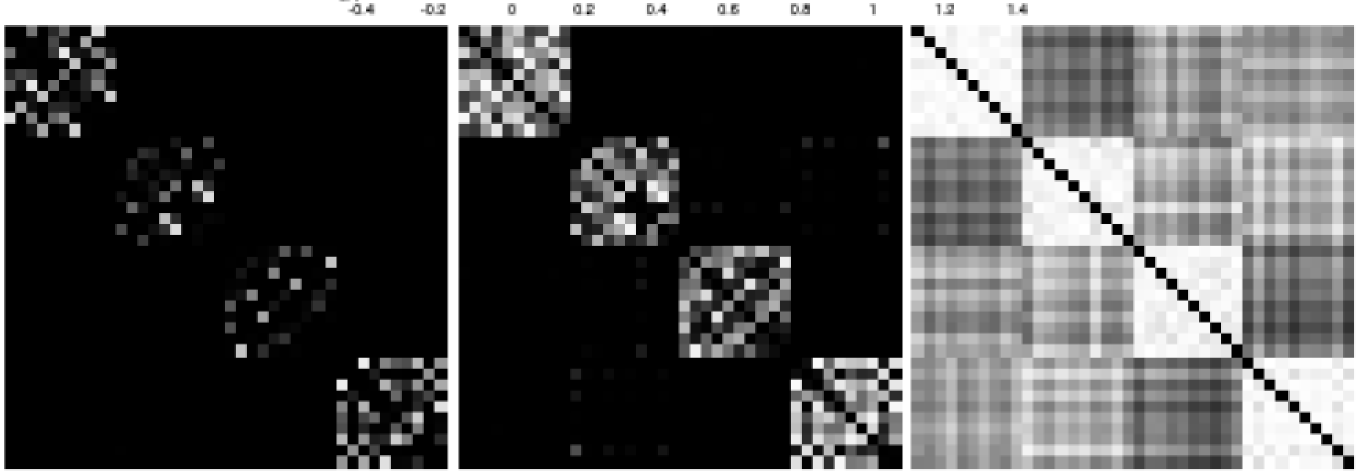
# Measuring affinity

**Data points**



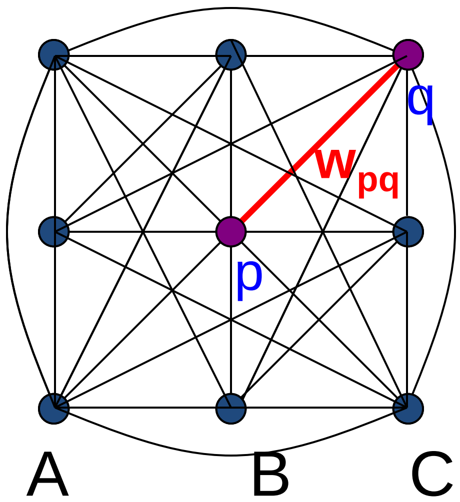
σ=.2

**Affinity matrices**



σ=.1 σ=.2 σ=1

# Segmentation by Graph Cuts

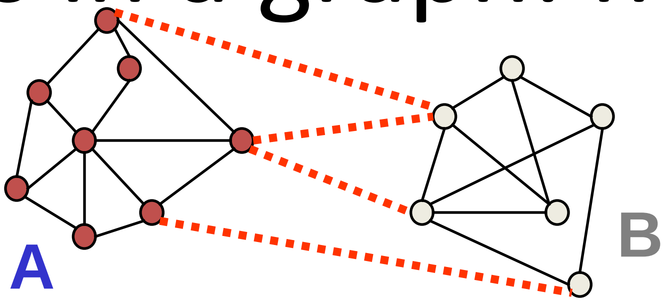




- Break Graph into Segments
  - Want to delete links that cross **between** segments
  - Easiest to break links that have low similarity (low weight)
    - similar pixels should be in the same segments
    - dissimilar pixels should be in different segments

Source: Steve Seitz

# 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.

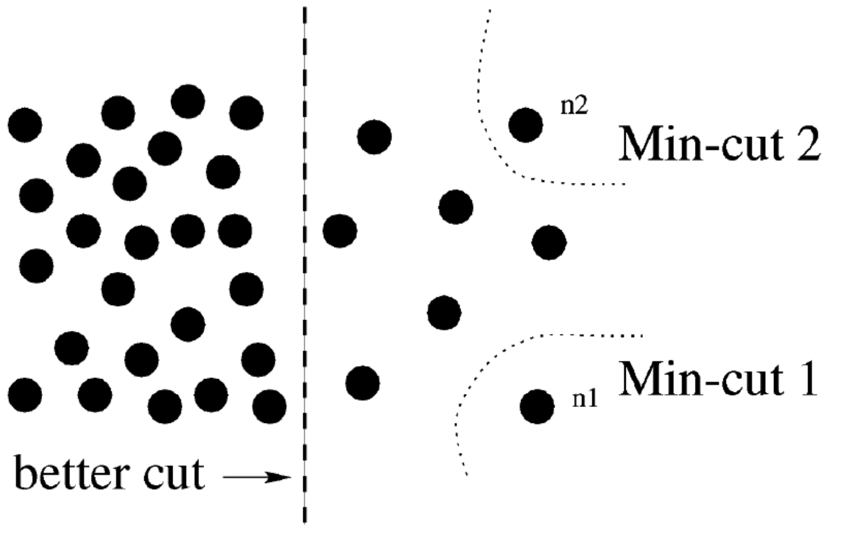
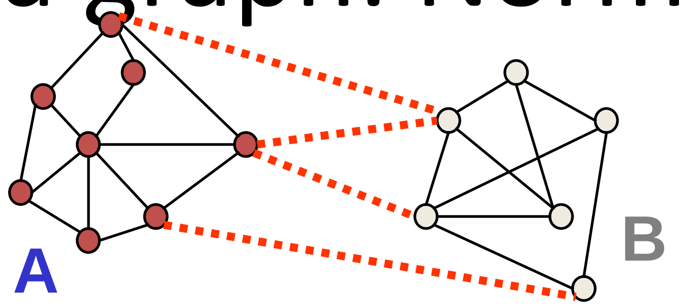



Fig. 1. A case where minimum cut gives a bad partition.

[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

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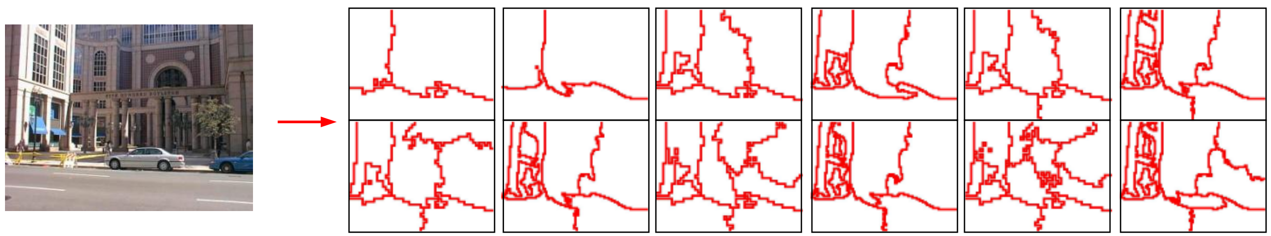
# Segments as primitives for recognition

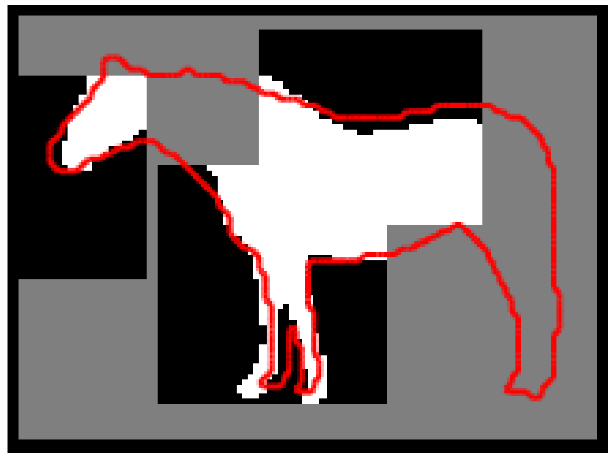
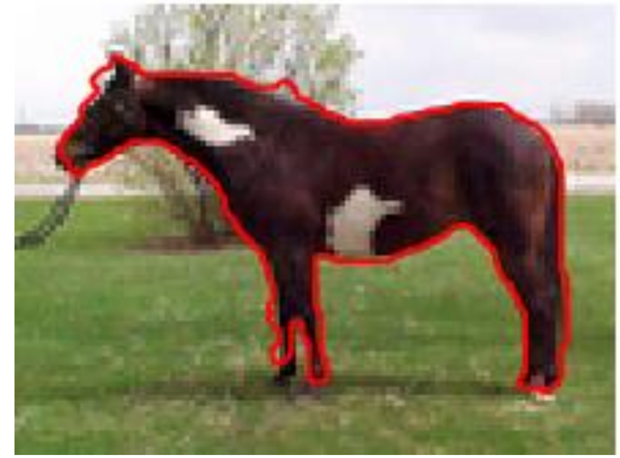




- B. Russell et al., [“Using Multiple Segmentations to Discover Objects and their Extent in Image Collections,”]() CVPR 2006

Slide credit: Lana Lazebnik

# Top-down segmentation

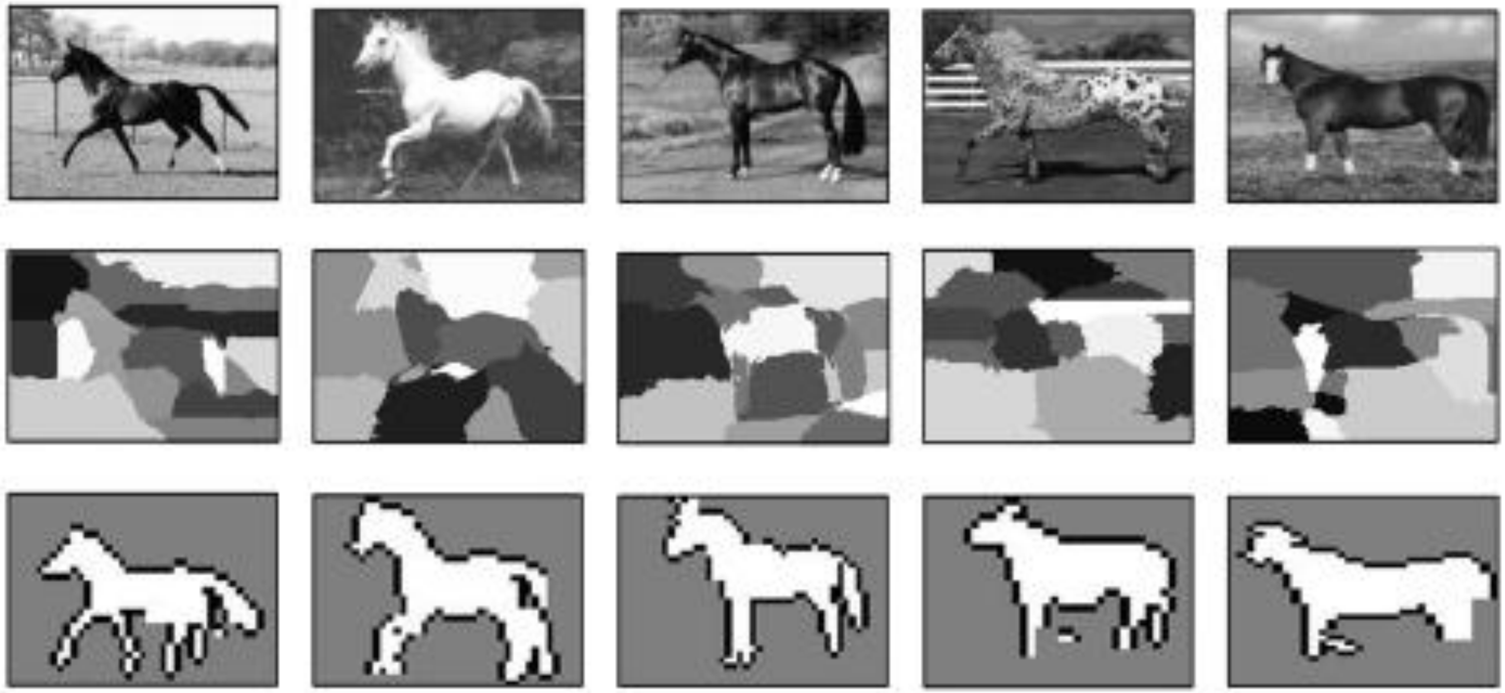




E. Borenstein and S. Ullman, “Class-specific, top-down segmentation,” ECCV 2002

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

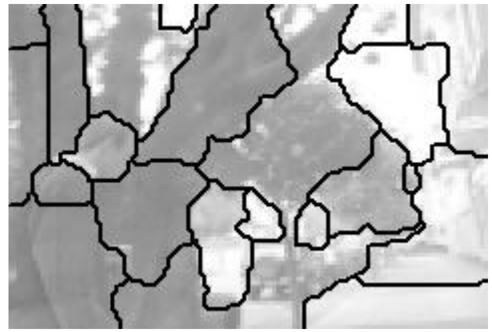


Image Segmentation

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.

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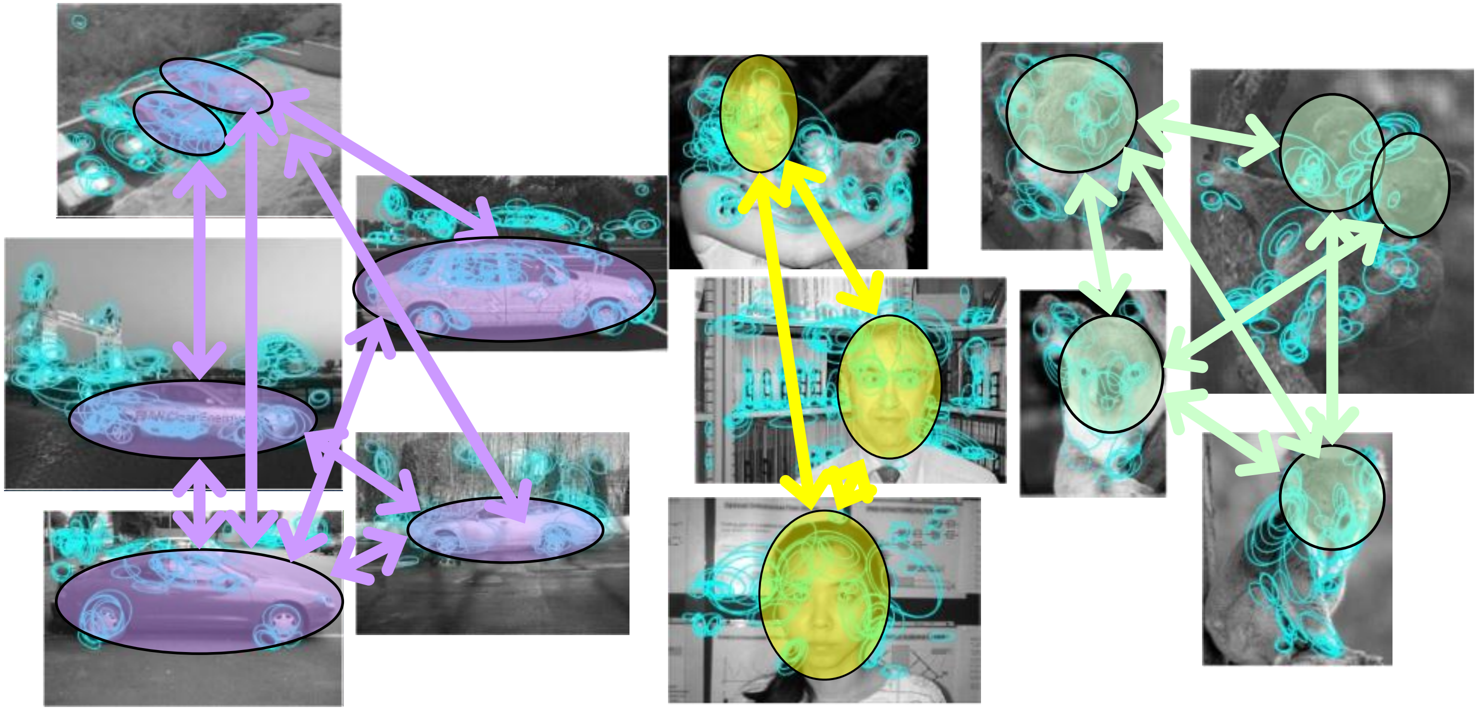
# Image grouping



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

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