Segmentation and Grouping

April 21st, 2020

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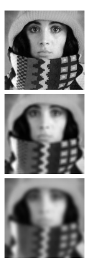
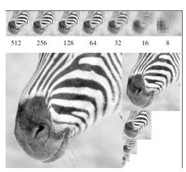
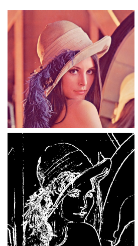
UC Davis

Features and filters







Transforming and describing images; textures, edges

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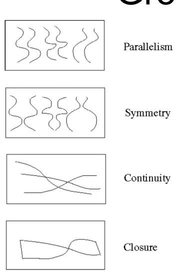
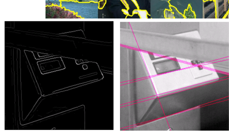
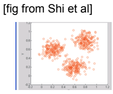
Grouping and fitting





[fig from Shi et al]



Clustering, segmentation, fitting; what parts belong together?

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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

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Slide credit: Kristen Grauman

Grouping in vision

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

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Slide credit: Kristen Grauman

Examples of grouping in vision

[Figure by J. Shi]

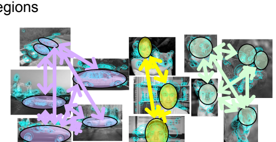
Determine image regions

[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

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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.

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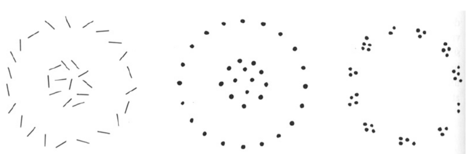
Slide credit: Kristen Grauman



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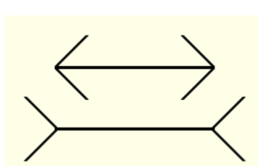
Slide credit: Kristen Grauman

Muller-Lyer illusion



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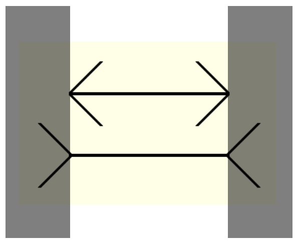
Slide credit: Kristen Grauman

Muller-Lyer illusion



Slide credit: Devi Parikh

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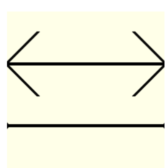
Muller-Lyer illusion



Slide credit: Devi Parikh

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Muller-Lyer illusion

Slide credit: Devi Parikh

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What things should be grouped?
What cues indicate groups?

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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 a set of elements to be grouped (by human visual system)

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Slide credit: Kristen Grauman

Gestalt

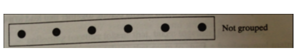

Figure 14.4 from Forsyth and Ponce

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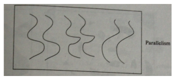
Gestalt



Slide credit: Devi Parikh

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Similarity

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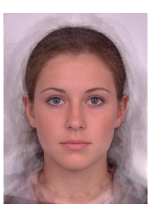
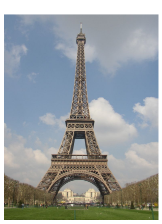
http://chicagoist.com/attachments/chicagoist_alicia/GEESE.jpg, http://wwwdelivery.superstock.com/WI/223/1532/PreviewComp/SuperStock_1532R-0831.jpg

Symmetry





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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)

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Slide credit: Kristen Grauman

Proximity

Slide credit: Kristen Grauman

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

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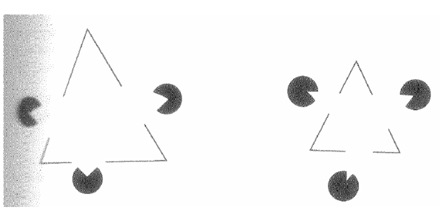
Illusory contours



Interesting tendency to explain by occlusion

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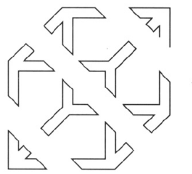
In *Vision*, D. Marr, 1982



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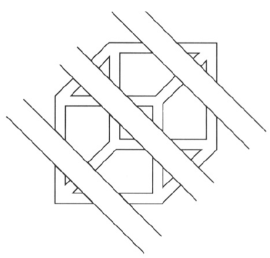
Slide credit: Kristen Grauman



Continuity, explanation by occlusion

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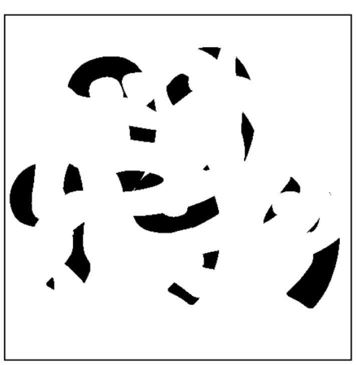
Slide credit: Kristen Grauman



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D. Forsyth

D. Forsyth

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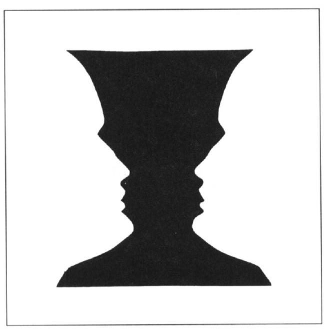
Figure-ground



D. Forsyth

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D. Forsyth

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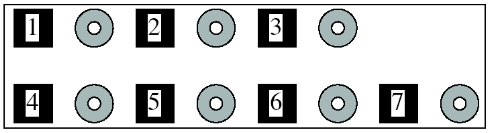
Grouping phenomena in real life



Forsyth & Ponce, Figure 14.7

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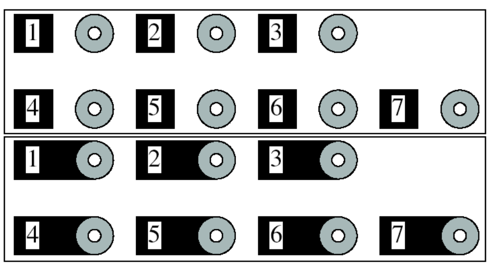
Slide credit: Kristen Grauman

Grouping phenomena in real life



Forsyth & Ponce, Figure 14.7

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Slide credit: Kristen Grauman

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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Slide credit: Kristen Grauman

Outline

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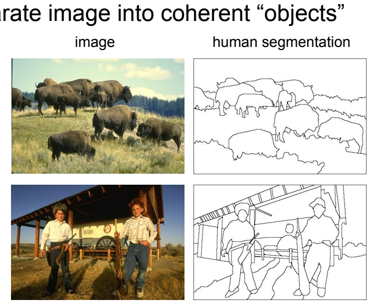
The goals of segmentation

Separate image into coherent "objects"



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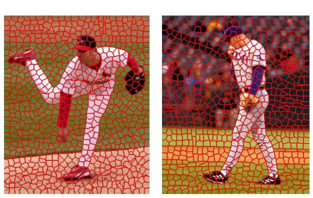
Source: Lana Lazebnik

The goals of segmentation

Separate image into coherent "objects"

Group together similar-looking pixels for efficiency of further processing

"superpixels"

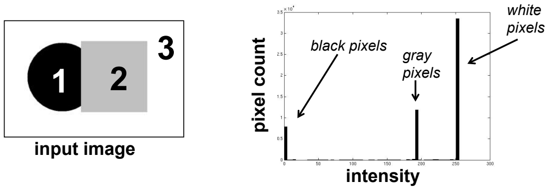


X. Ren and J. Malik. Learning a classification model for segmentation. ICCV 2003.

33

Source: Lana Lazebnik

Image segmentation: toy example



- 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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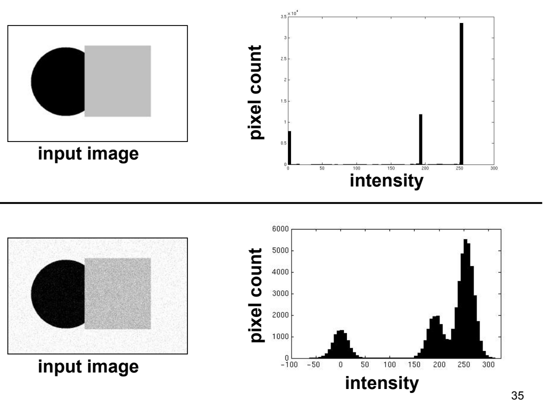

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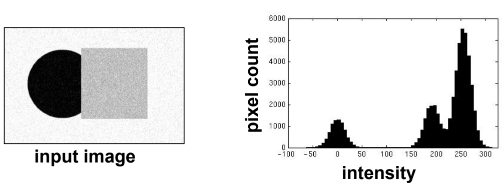

- Now how to determine the three main intensities that define our groups?
- We need to ***cluster.***

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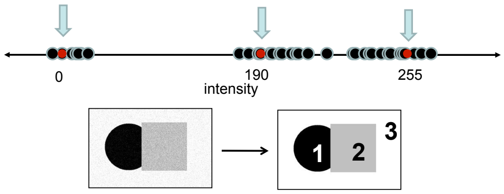

- Goal: choose three "centers" as the representative intensities, and label every pixel according to which of these centers it is nearest to.
- Best cluster centers are those that minimize SSD between all points and their nearest cluster center c_i:

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

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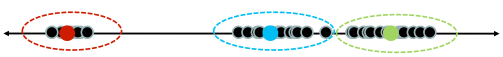
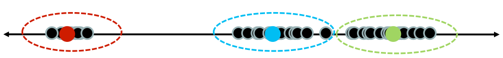
Clustering

- 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, $c_1, ..., c_K$
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:

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

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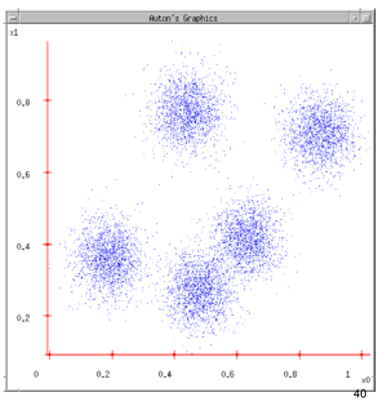
Source: Steve Seitz

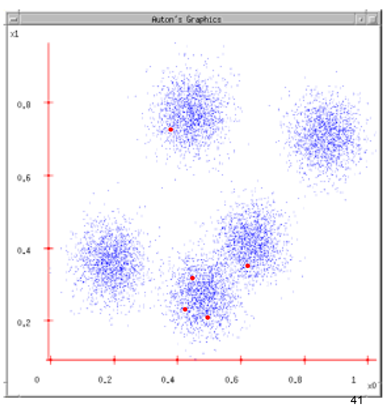
K-means

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



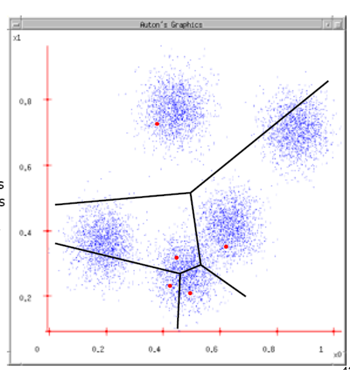
K-means

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



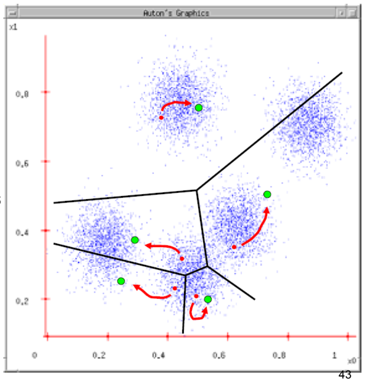
K-means

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



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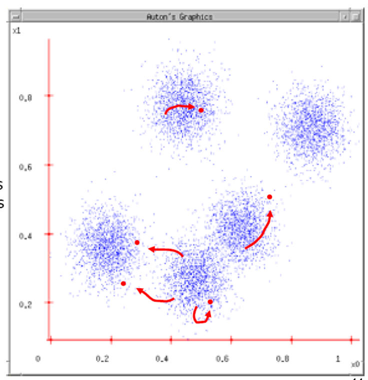
K-means

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!



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K-means clustering

- Demo

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

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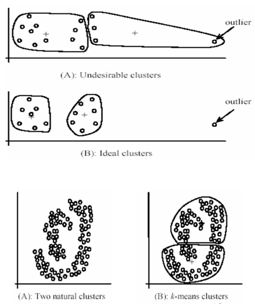
Slide credit: Kristen Grauman

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



Slide credit: Kristen Grauman

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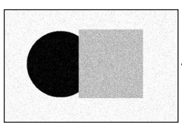
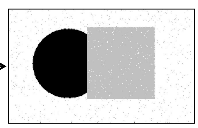
An aside: Smoothing out cluster assignments

- Assigning a cluster label per pixel may yield outliers:



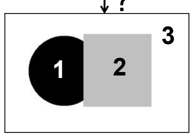
original



labeled by cluster center's intensity

?

- How to ensure they are spatially smooth?



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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

Feature space: intensity value (1-d)

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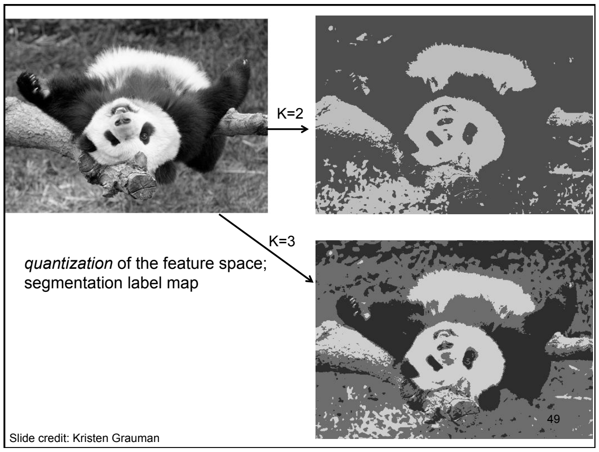
Slide credit: Kristen Grauman



quantization of the feature space;
segmentation label map

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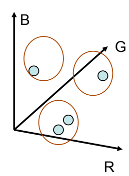
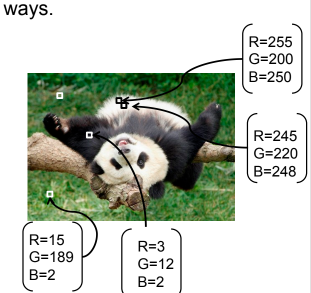
Slide credit: Kristen Grauman

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)

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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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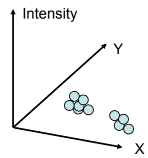
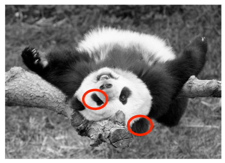
Segmentation as clustering

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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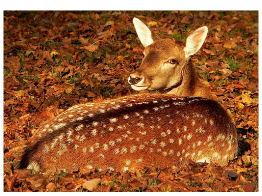
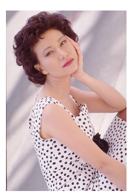
Segmentation as clustering

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





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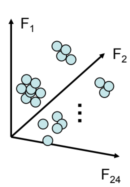
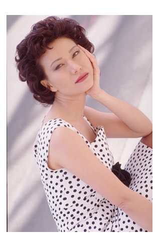
Slide credit: Kristen Grauman

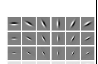
Segmentation as clustering

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

Grouping pixels based on **texture** similarity







Filter bank of 24 filters

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

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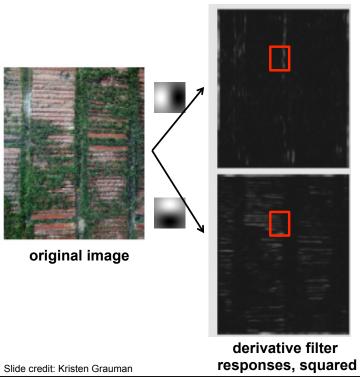
Recall: texture representation example



	mean d/dx value	mean d/dy value
Win. #1	4	10
Win.#2	18	7
⋮		
Win.#9	20	20

⋮

statistics to summarize patterns in small windows

Slide credit: Kristen Grauman

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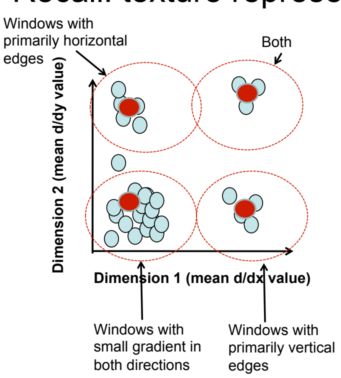
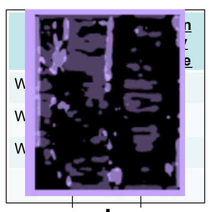
Recall: texture representation example





statistics to summarize patterns in small windows

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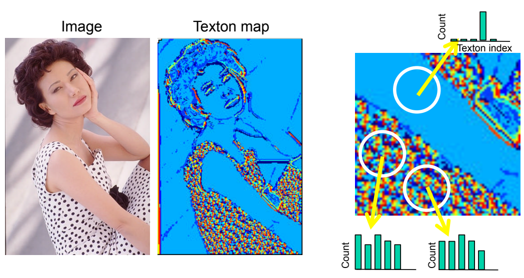
Segmentation with texture features

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



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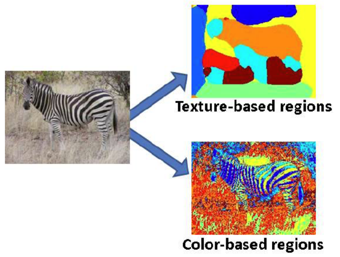
Malik, Belongie, Leung and Shi. IJCV 2001.

Image segmentation example



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Color vs. texture

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

How would their *texture* distributions compare?

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Material classification example

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

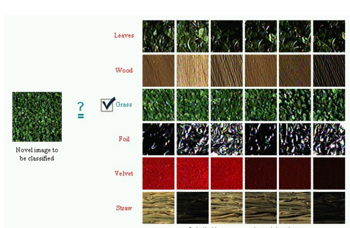

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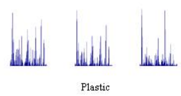
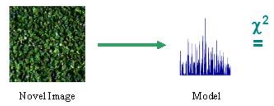
Figure from Varma & Zisserman, IJCV 2005

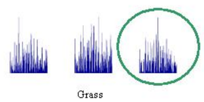
Material classification example

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

Slide credit: Kristen Grauman

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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

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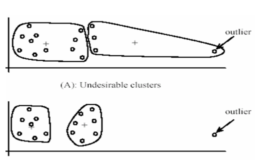
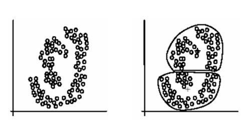
Slide credit: Kristen Grauman

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





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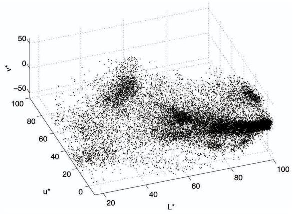
Mean shift algorithm

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

image

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



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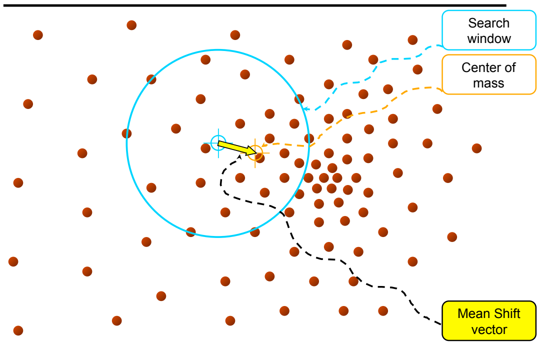
Slide credit: Kristen Grauman

Mean shift



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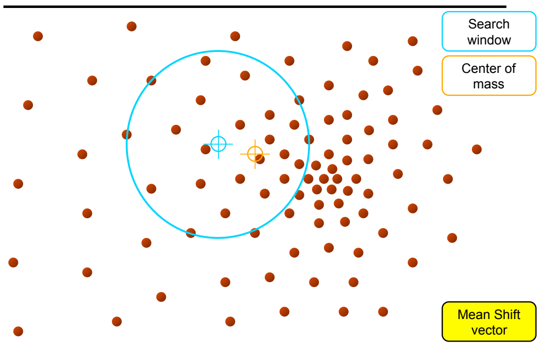
Slide by Y. Ukrainitz & B. Sarel

Mean shift



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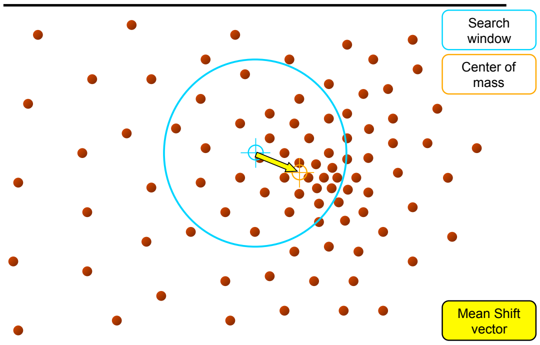
Mean shift



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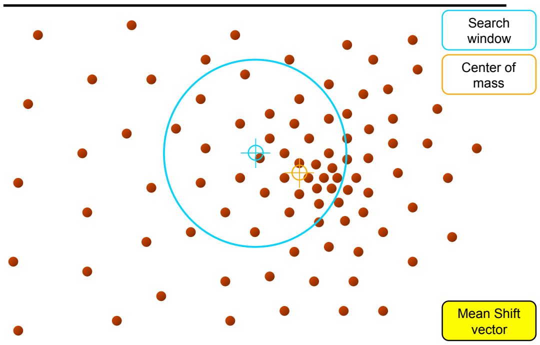
Mean shift



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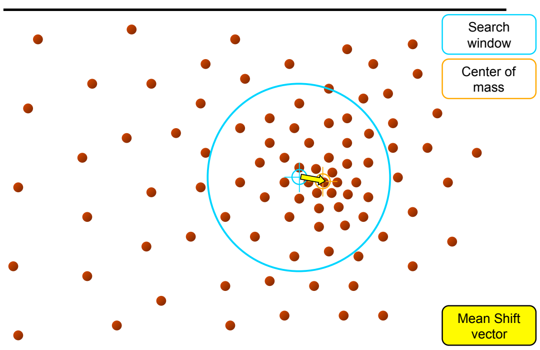
Mean shift



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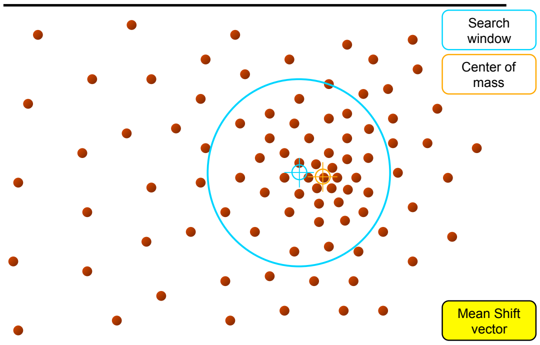
Mean shift



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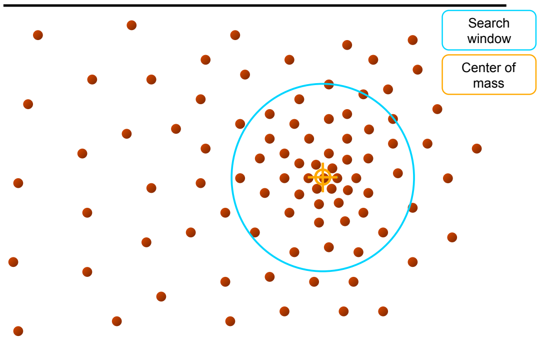
Mean shift



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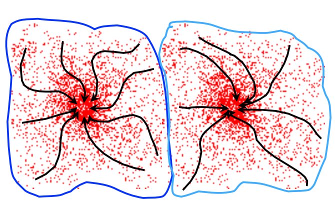
Mean shift clustering

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



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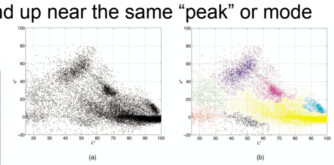
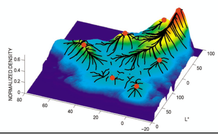
Mean shift clustering/segmentation

- 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





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Slide credit: Kristen Grauman

Mean shift segmentation results

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Slide credit: Kristen Grauman

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

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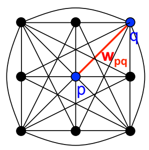
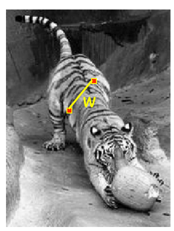
Images as graphs





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…)

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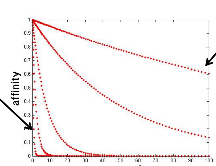
Source: Steve Seitz

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

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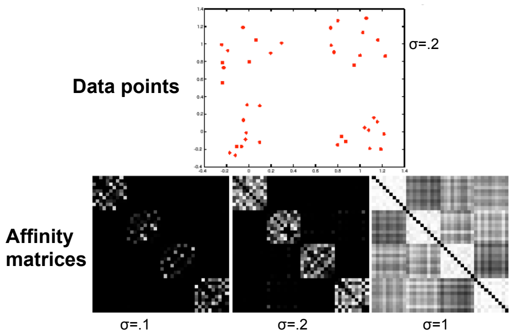
Measuring affinity



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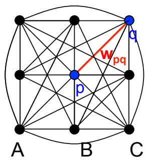
Slide credit: Kristen Grauman

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

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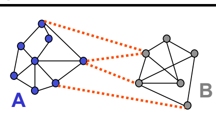
Source: Steve Seitz

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

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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.

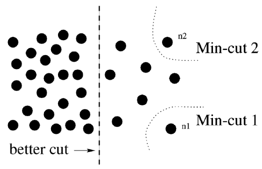

Fig. 1. A case where minimum cut gives a bad partition.

[Shi & Malik, 2000 PAMI]

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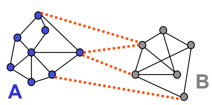
Slide credit: Kristen Grauman

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 in A to all nodes V

- 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.

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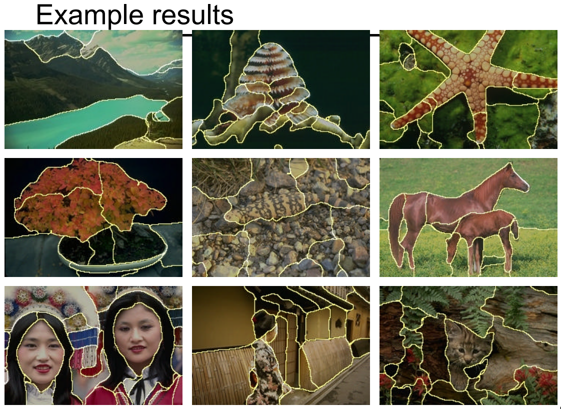
J. Shi and J. Malik, Normalized Cuts and Image Segmentation, CVPR, 1997

Source: Steve Seitz

Example results



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Slide credit: Kristen Grauman

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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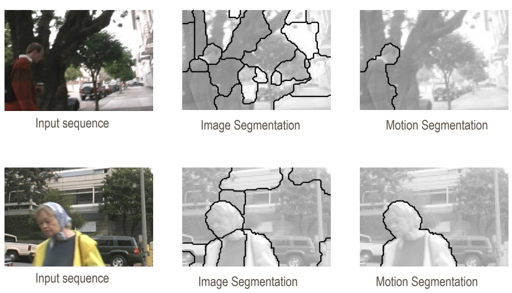
Motion segmentation



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

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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

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Slide credit: Kristen Grauman

Questions?

See you Thursday!

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