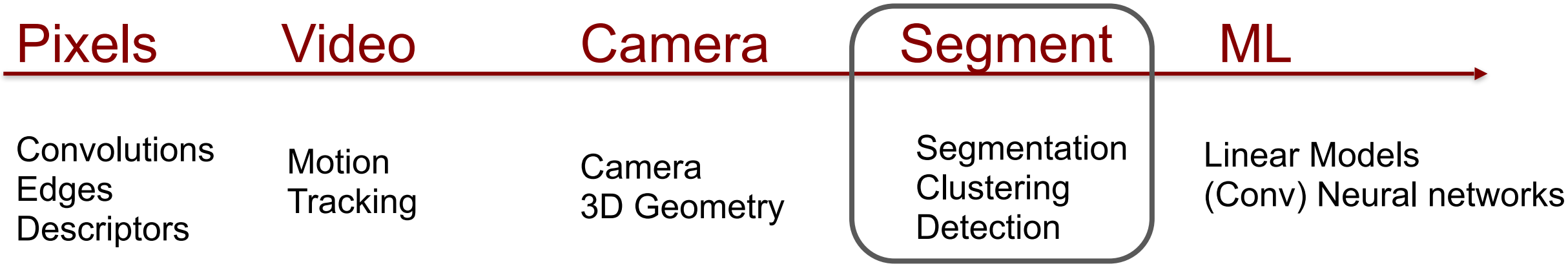
Lecture 14

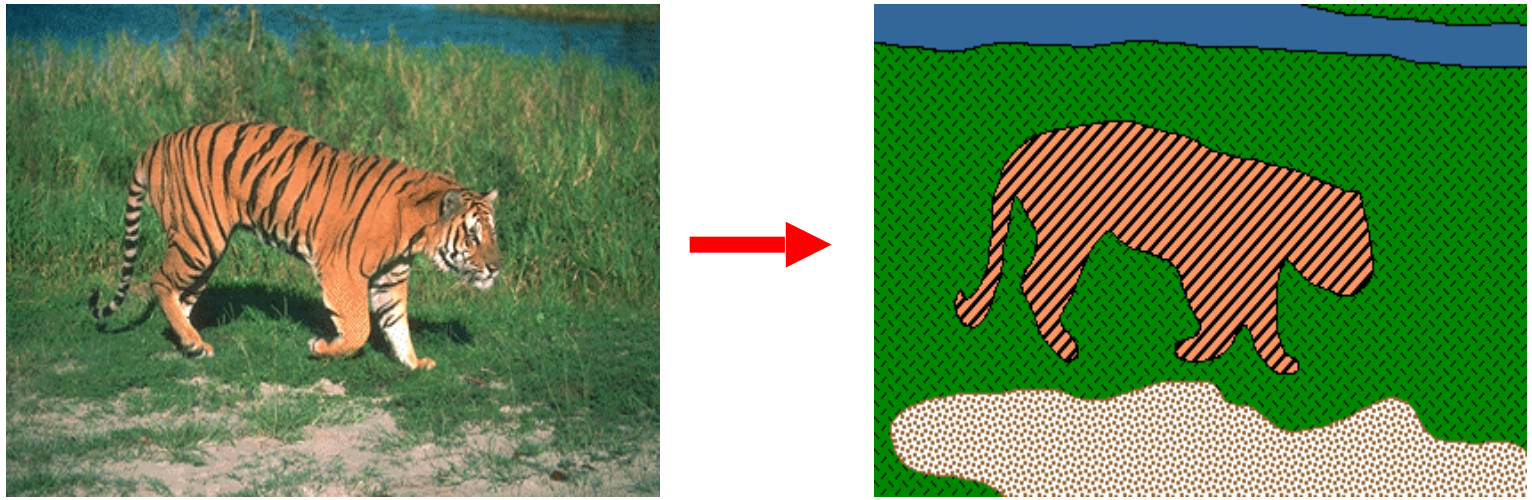
Segmentation and clustering

CS455 Roadmap



What is image segmentation?

- Identify groups of pixels that go together and are meaningful in some sense.



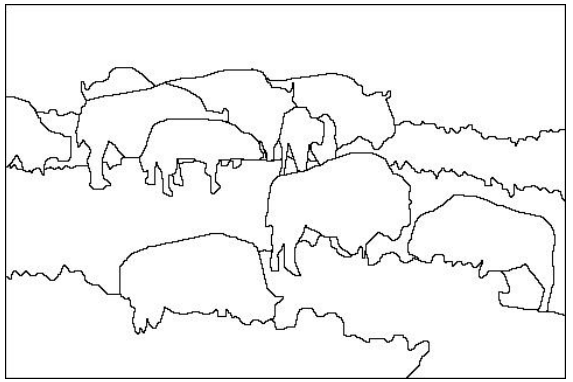
Slide credit: Steve Seitz, Kristen Grauman

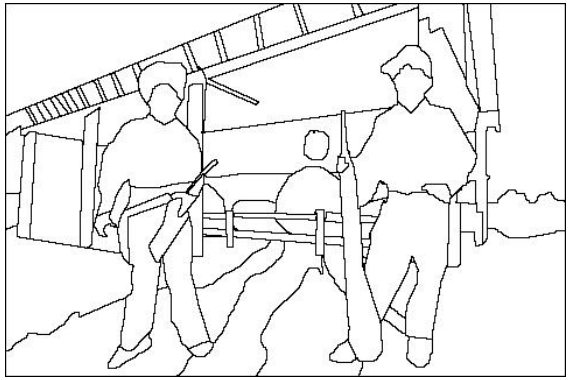
Why do we segment?

- Separate image into coherent “objects”

Image

Human segmentation



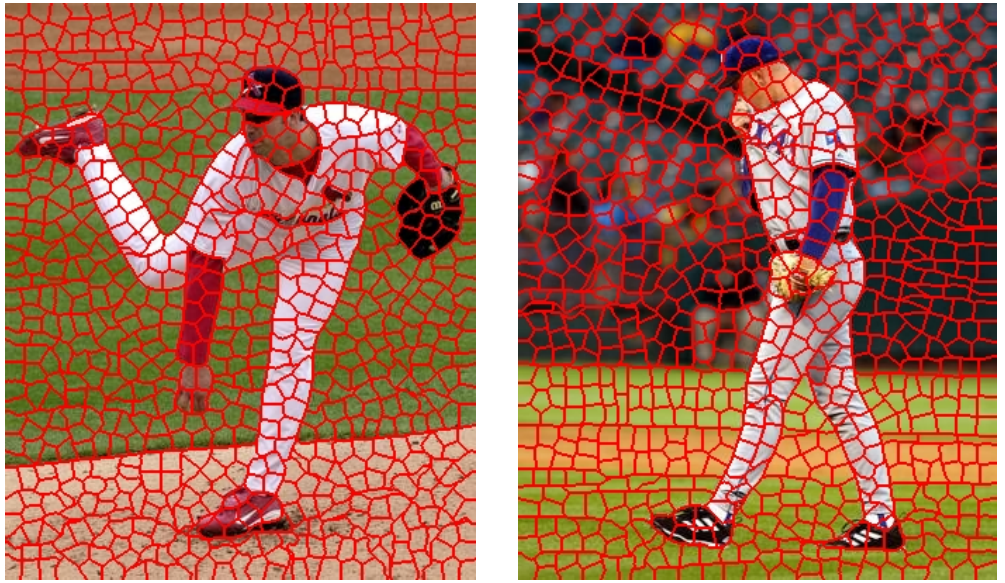


Slide credit: Svetlana Lazebnik

Why do we segment?

- 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.

Why do we segment?

- **Summarizing data**
  - Look at large amounts of data
    - Find group of pixels
    - Represent each group of pixels with feature vectors e.g., HoG
- **Counting**
  - Histograms of texture, color, SIFT vectors
- **Foreground-background separation**
  - Separate the image into different regions
- **Prediction**
  - Images in the same group may have the same labels

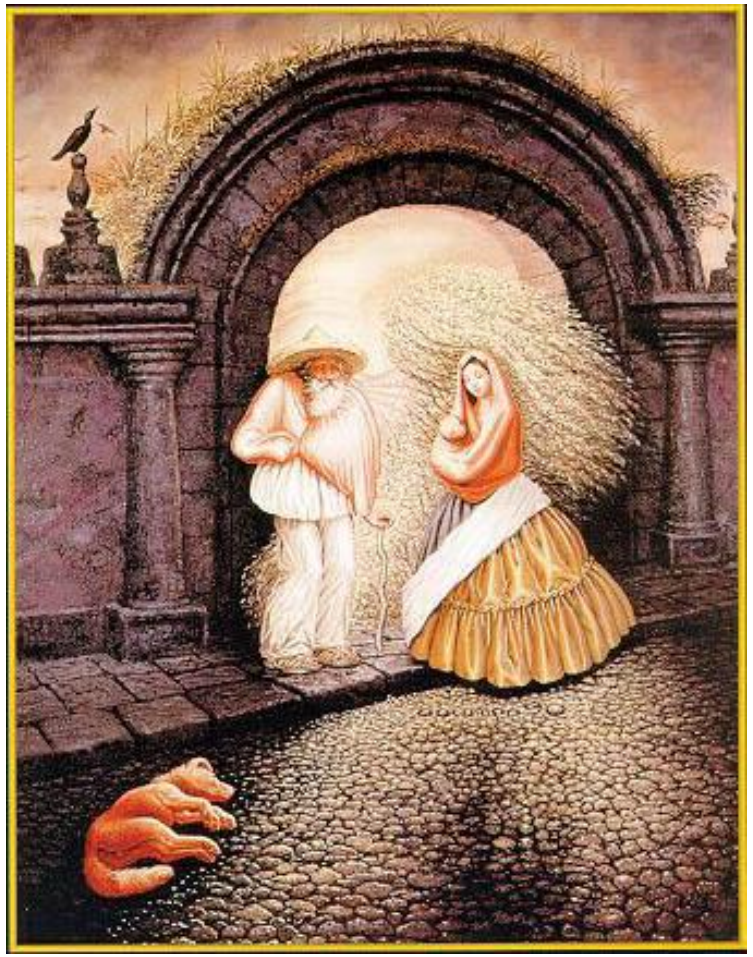
Slide: Derek Hoiem

Segmentation is used in Adobe photoshop to remove background

Rother et al. 2004

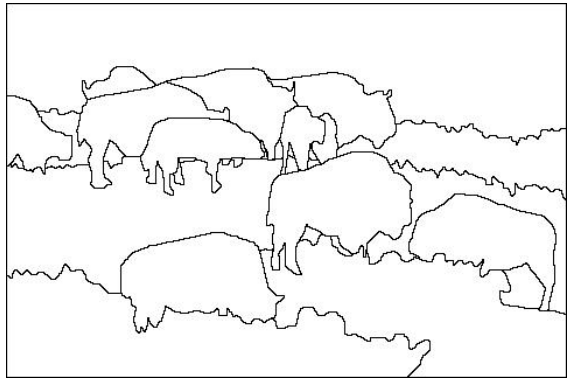
Segment Anything [2023]

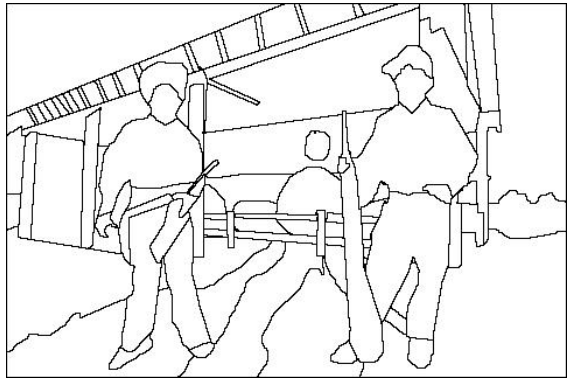
Segmentation is ill-defined problem, “correct” segments depends on the context



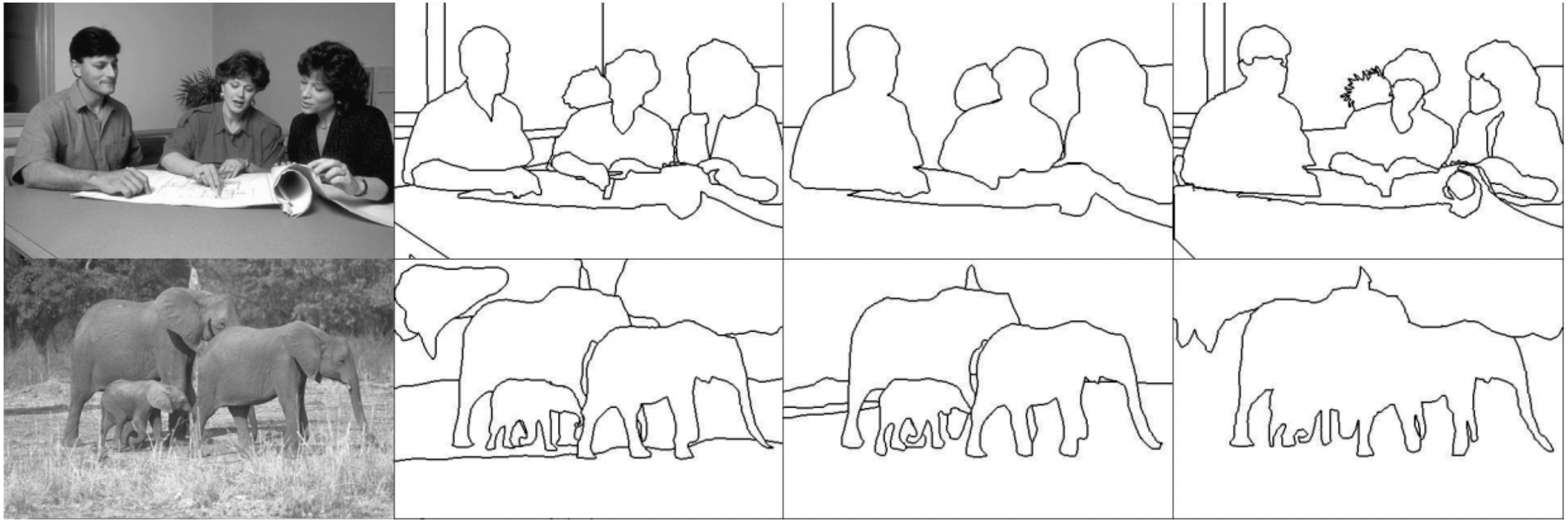
Image

Human segmentation





Segmentation in humans: subjective, intuitive



User 1 User 2 User 3

[Martin 2001]

Today's agenda

- Gestalt theory for perceptual grouping
- Segmentation as clustering
- Agglomerative clustering

Reading:

Szeliski, 2nd edition, Chapter 7.5

Today’s agenda

- Gestalt theory for perceptual grouping
- Segmentation as clustering
- Agglomerative clustering

Reading:

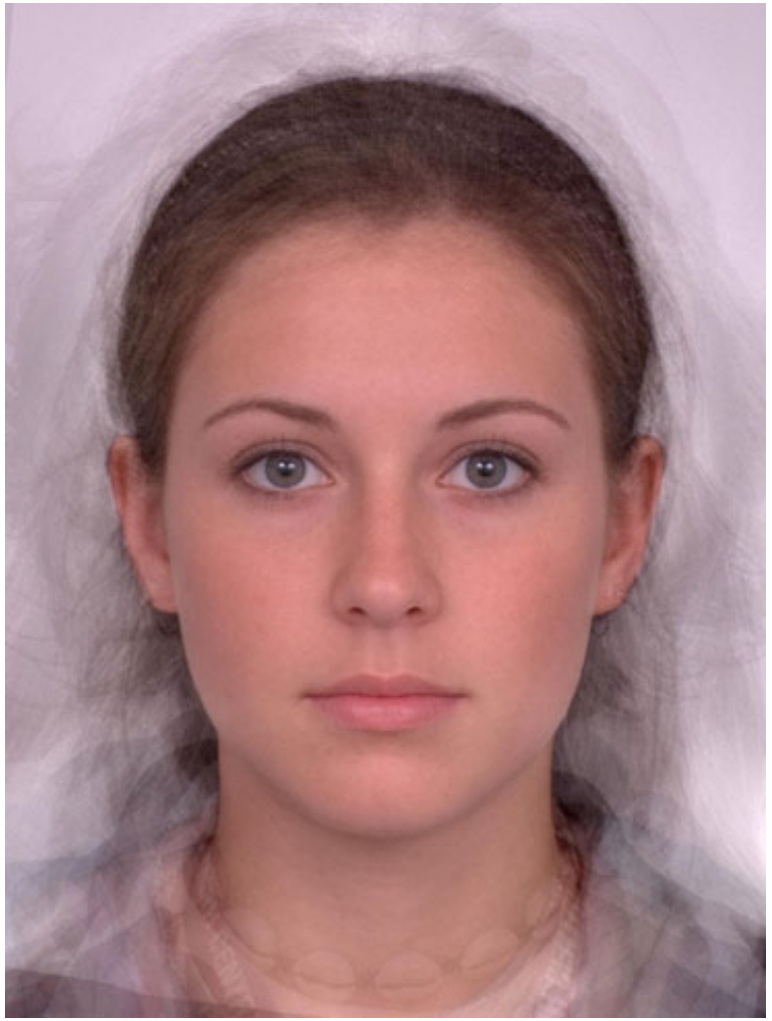
Szeliski, 2nd edition, Chapter 7.5

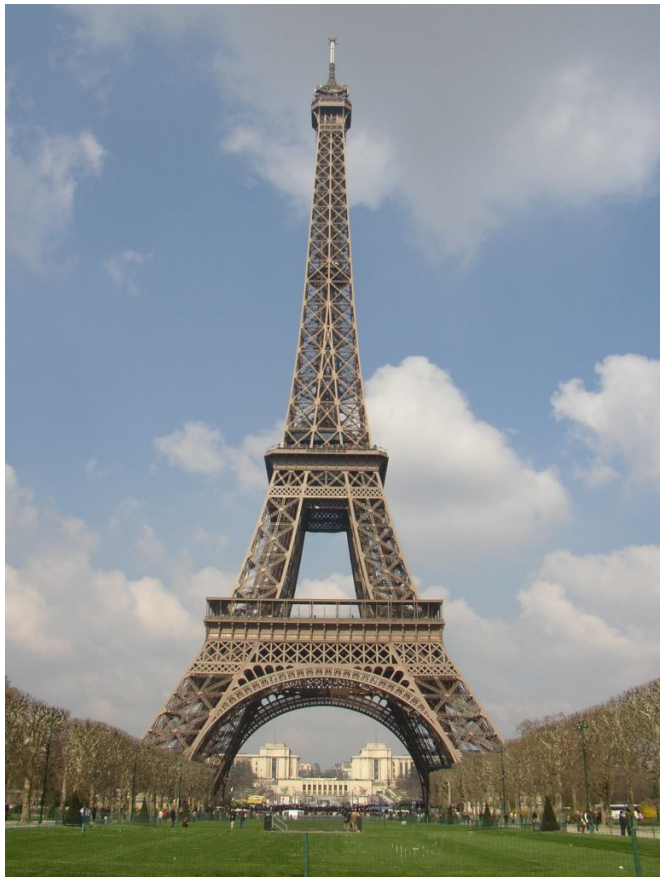
Similarity

What things should be grouped?

What cues indicate groups?

Symmetry





Slide credit: Kristen Grauman

Common Fate

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

Slide credit: Kristen Grauman

Proximity

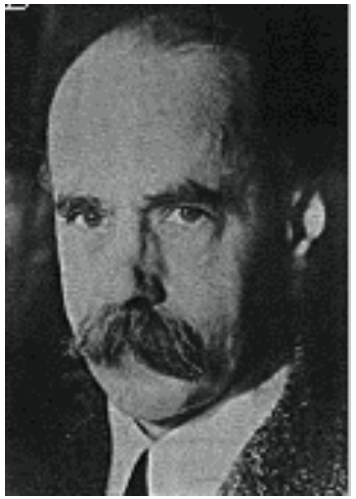
Gestalt Theory

Gestalt Theory

- 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)

"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees."

Max Wertheimer (1880-1943)

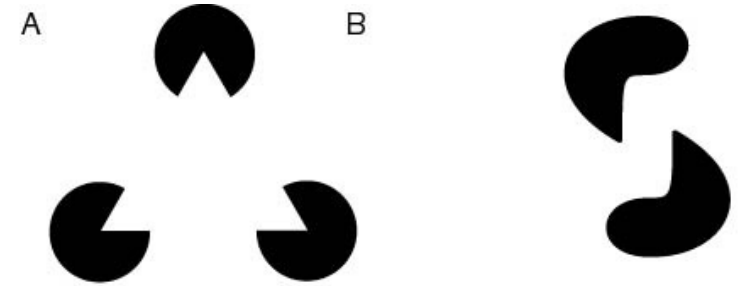


Untersuchungen zur Lehre von der Gestalt,
***Psychologische Forschung*, Vol. 4, pp. 301-350, 1923**
http://psy.ed.asu.edu/~classics/Wertheimer/Forms/forms.htm

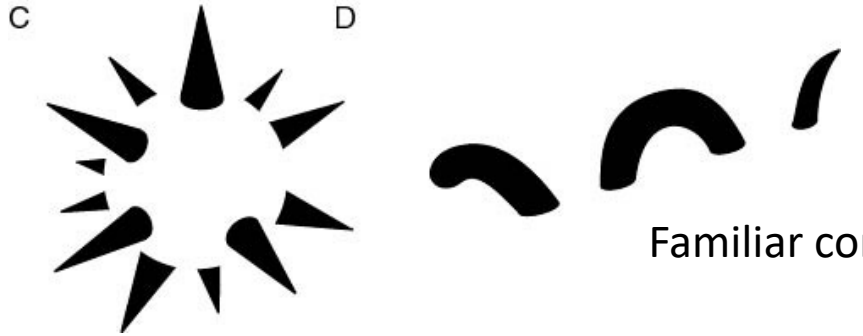
Gestalt Theory

- Grouping is key to visual perception
- Elements in a collection can have properties that result from different **relationships (space, affordance, etc.)**
  - "The whole is greater than the sum of its parts"

Illusory/subjective contours



Occlusion

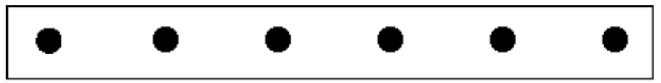


Familiar configuration

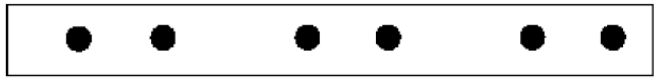
http://en.wikipedia.org/wiki/Gestalt_psychology

Gestalt Factors

These factors make intuitive sense, but are very difficult to translate into algorithms.



Not grouped

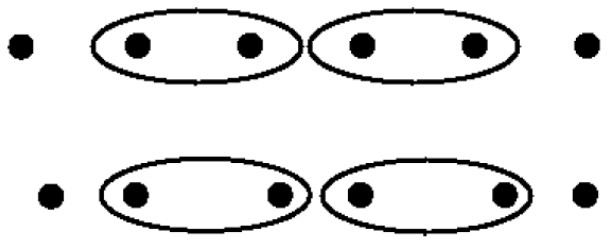


Proximity

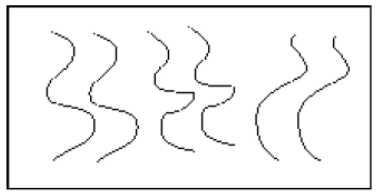
Similarity

Similarity

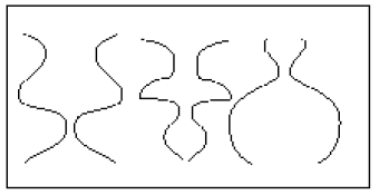
Common Fate



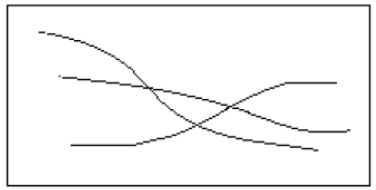
Common Region



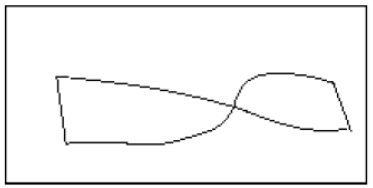
Parallelism



Symmetry

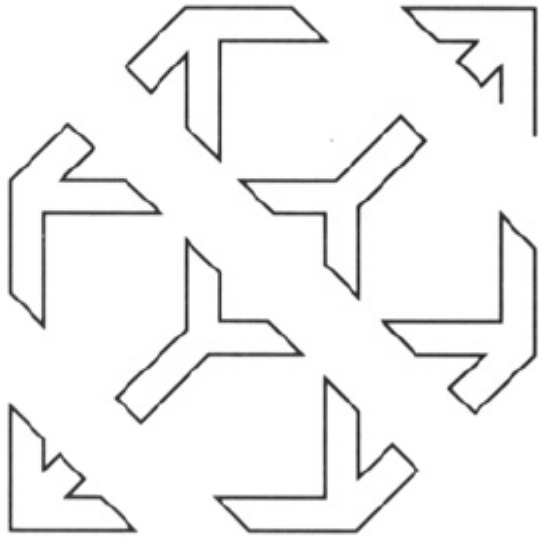


Continuity

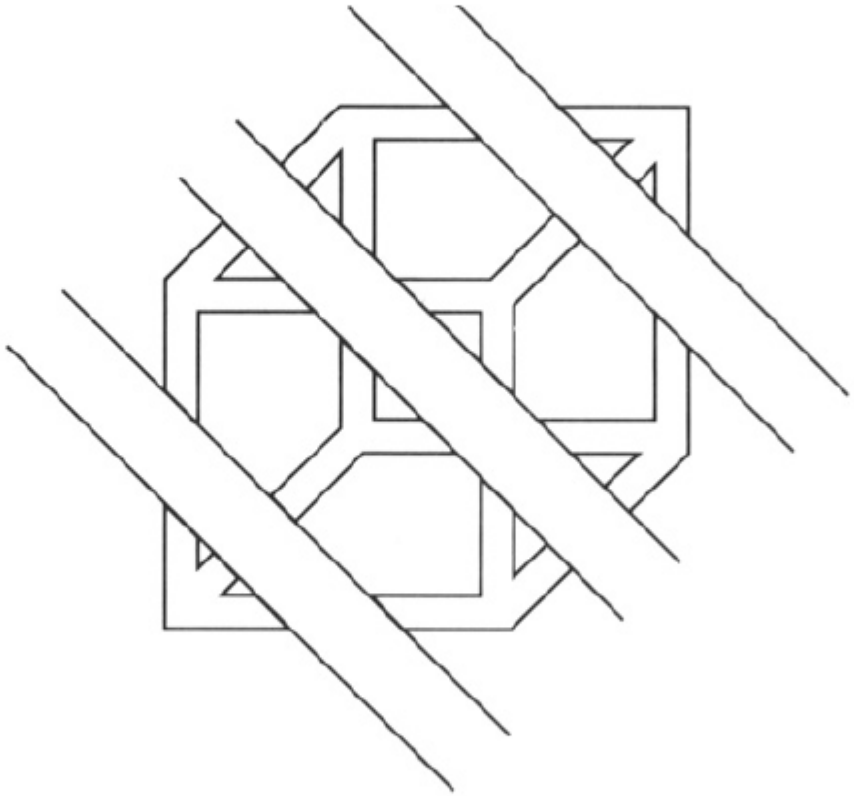


Closure

Continuity through Occlusion Cues



Continuity through Occlusion Cues



Continuity, explanation by occlusion

Today’s agenda

- Gestalt theory for perceptual grouping
- Segmentation as clustering
- Agglomerative clustering

Segmentation strategies

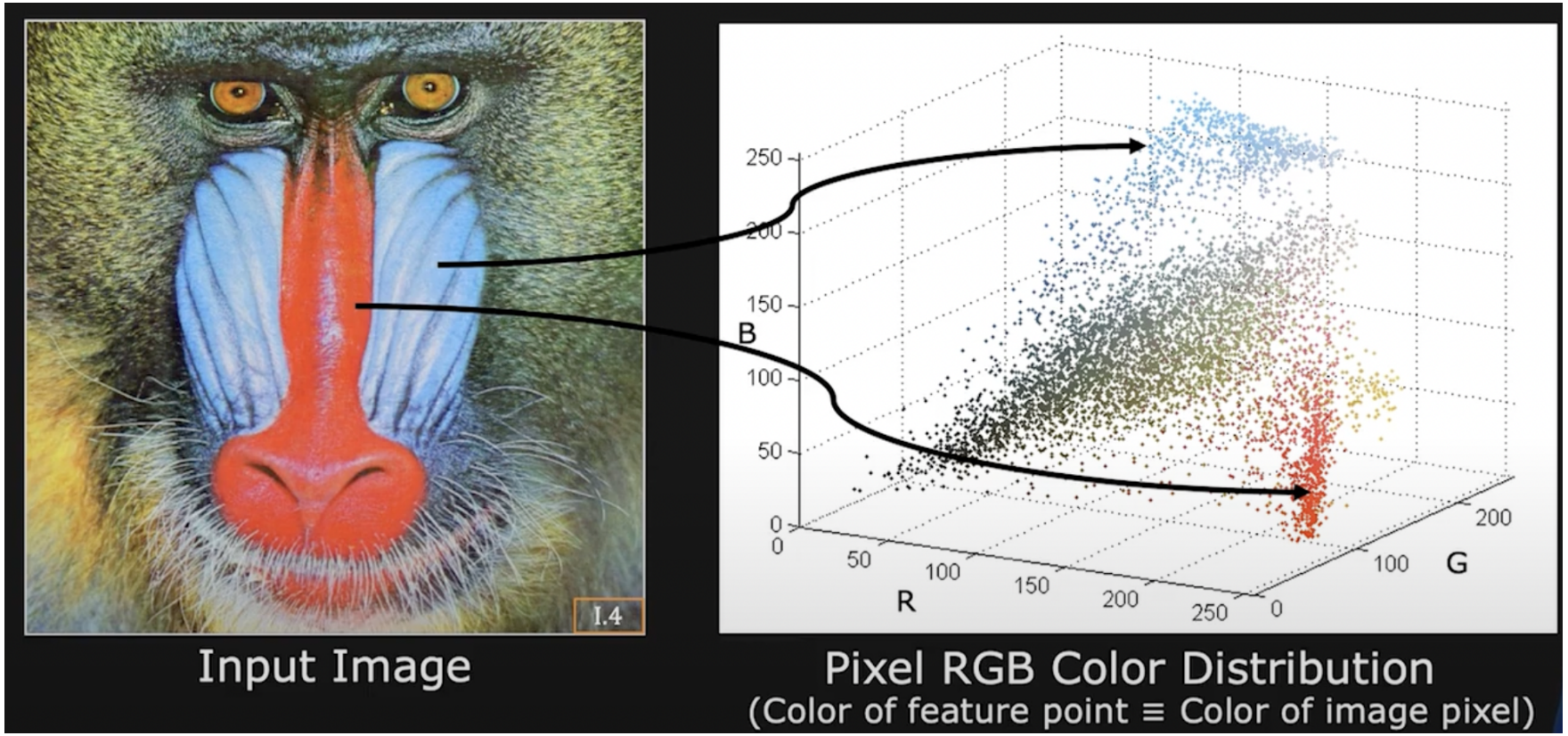
- Top down clustering
  - pixels belong together because they lie on the same visual entity (object, scene…)

- Bottom up clustering
  - pixels belong together because they look similar

These two are not mutually exclusive!

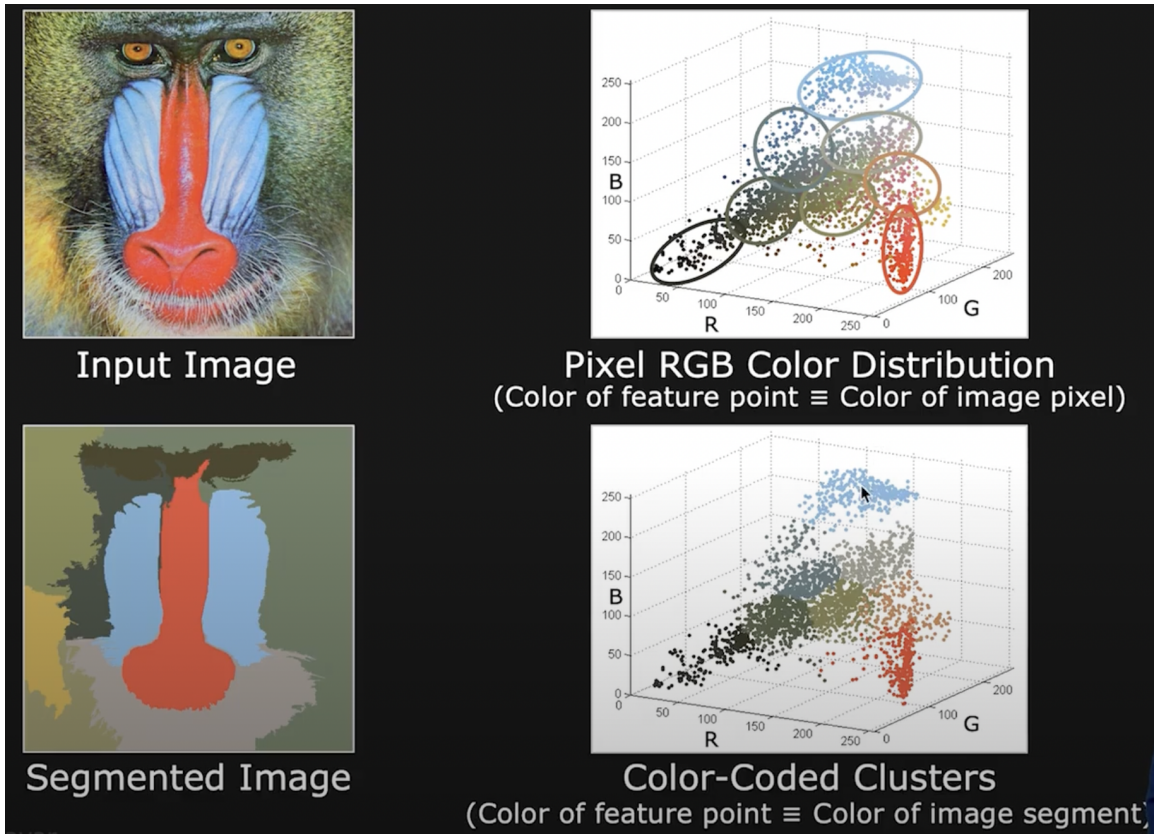
Segmentation as clustering

Clustering: group together similar data points, usually in feature space



Segmentation as clustering

Clustering: group together similar data points, usually in feature space



What are good pixel features?

- Use RGB values?
  - v = [r, g, b]
  - It is 3-dimensional
- Use location?
  - v = [x, y]
  - 2-dim
- Use RGB + location?
  - v = [x, y, r, g, b]
  - 5-dim
- Use gradient magnitude?
  - v = [df/dx, df/dy]
  - 2-d

Segmentation as clustering

Clustering: group together similar data points, usually in feature space

Key Challenges:

- What makes two points/images/patches similar?
  - Distance measures
- How do we compute an overall grouping from pairwise similarities?

Slide: Derek Hoiem

Distance Measures

Clustering is an unsupervised learning method. Given items $v_1, v_2, \ldots, v_n \in \mathcal{R}^D$, the goal is to group them into clusters.

We need a pairwise distance/similarity function between items, and sometimes the desired number of clusters.

When data (e.g. images, objects, documents) are represented by feature vectors, commonly used measures are:

- *Euclidean distance.*
- *Cosine similarity.*

Distance Measures

Let x and x’ be two objects from the universe of possible objects.
The distance (or similarity) between x and x’ is a real number:

- The Euclidean distance is defined as $$dist(v_1, v_2) = \sqrt{\sum_i (v_{1i} - v_{2i})^2}$$

- In contrast, the cosine similarity measure would be

$$dist(v_1, v_2) = 1 - cos(v_1, v_2)$$

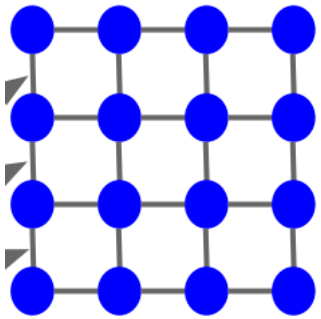
$$= 1 - \frac{v_1^T v_2}{||v_1|| \cdot ||v_2||}$$

How do we cluster?

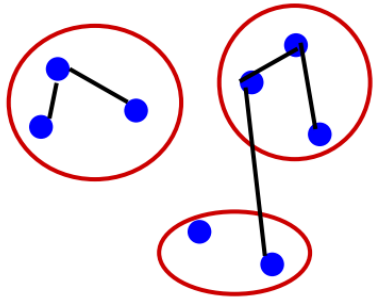
- **Agglomerative clustering**
  - Start with each point as its own cluster and iteratively merge the closest clusters
- **K-means**
  - Iteratively re-assign points to the nearest cluster center
- **Mean-shift clustering**
  - Estimate modes of pdf

Image as a Graph - Features and weights

- Every pixel is connected to its 8 neighboring pixels
- The edges between neighbors have weights that are determined by the distance between them.
- Edge weights between pixels are determined using dist(x, x') distance in feature space.
  - where x and x' are two neighboring pixels



Segmentation using graph-cut



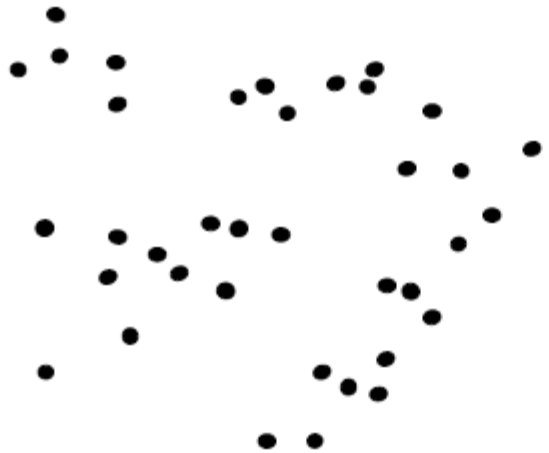
- Graph G = (V, E)
- V is set of nodes (i.e. pixels)
- E is a set of undirected edges between pairs of pixe
- dist(v_i , v_j) is the weight/distance of the edge between nodes v_i and v_j.

- S is a segmentation of a graph G such that G' = (V, E') where E' $\subset$ E.
  - That is, **we keep all vertices**, but **select a subset E'** from all initial edges E.
- S divides G into G' such that it contains distinct clusters C.

Today’s agenda

- Gestalt theory for perceptual grouping
- Segmentation as clustering
- Agglomerative clustering

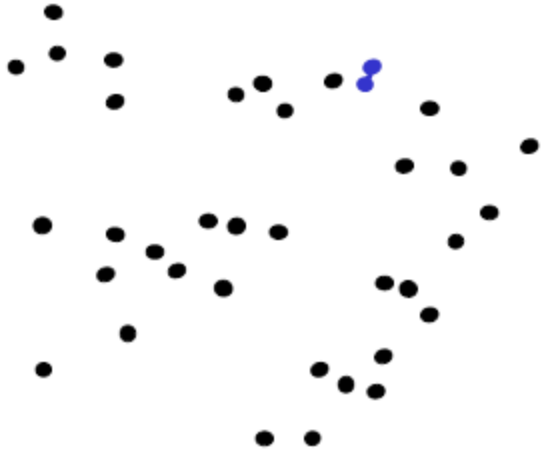
Agglomerative clustering



1. Say "Every point is its own cluster"

Slide credit: Andrew Moore

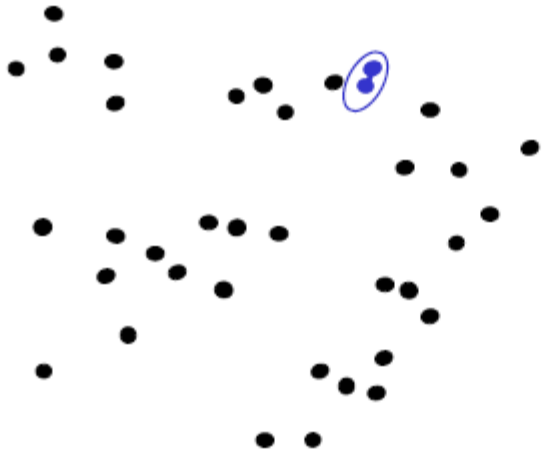
Agglomerative clustering



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters

Slide credit: Andrew Moore

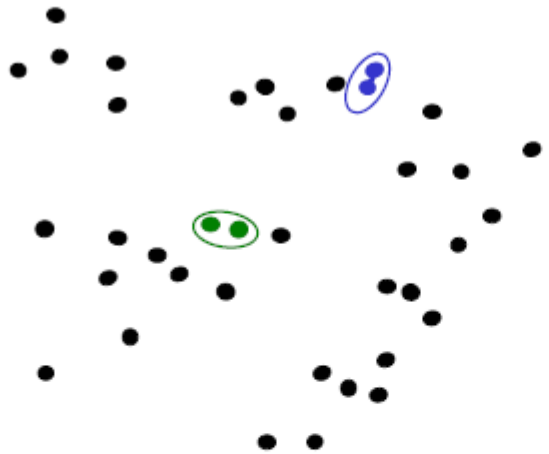
Agglomerative clustering



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster

Slide credit: Andrew Moore

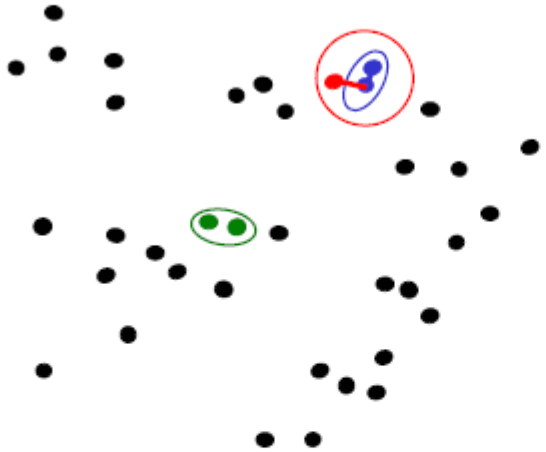
Agglomerative clustering



1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat

Slide credit: Andrew Moore

Agglomerative clustering



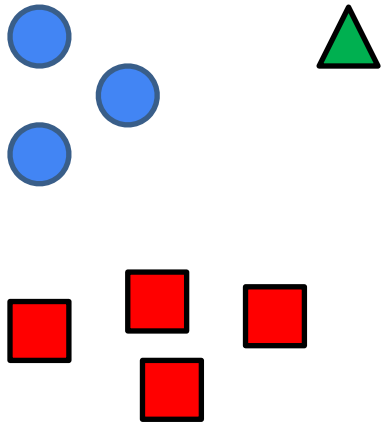
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat

Slide credit: Andrew Moore

Agglomerative clustering

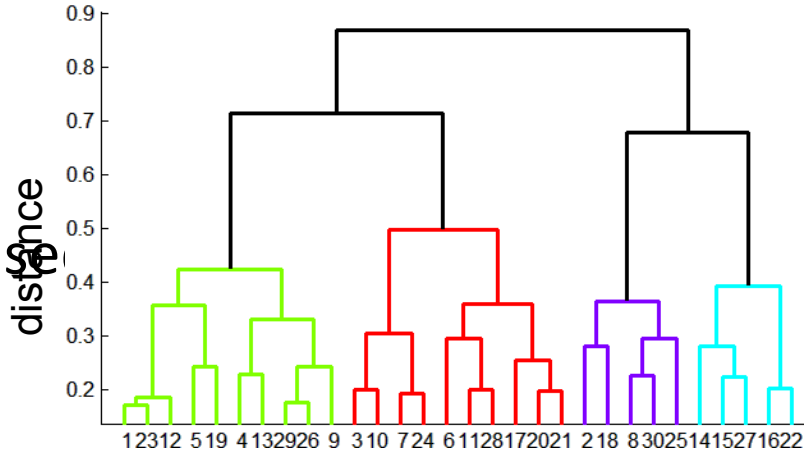
How to define cluster similarity?

- Average distance between all pixels between the two cluster?
- Maximum distance?
- Minimum distance?
- Distance between means?



How many clusters?

- Clustering creates a dendrogram (a tree)
- Threshold based on max number of clusters or based on distance between merges



Agglomerative Hierarchical Clustering - Algorithm

Inputs:

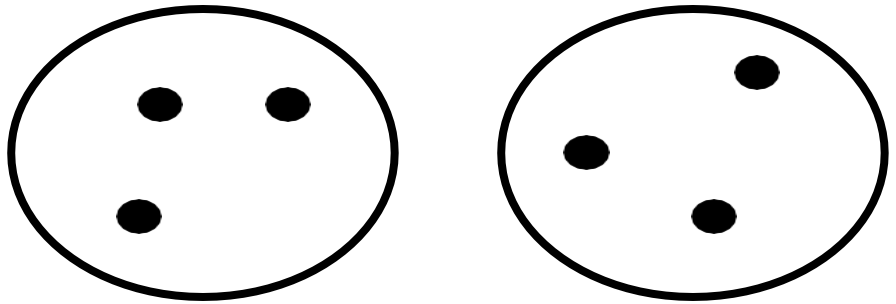
- An input image
- Feature representation for each pixel
- Distance metric dist(-,-)

➢ Initially, each pixel v_1, …, v_n is its own cluster C_1, …, C_n

➢ While True:

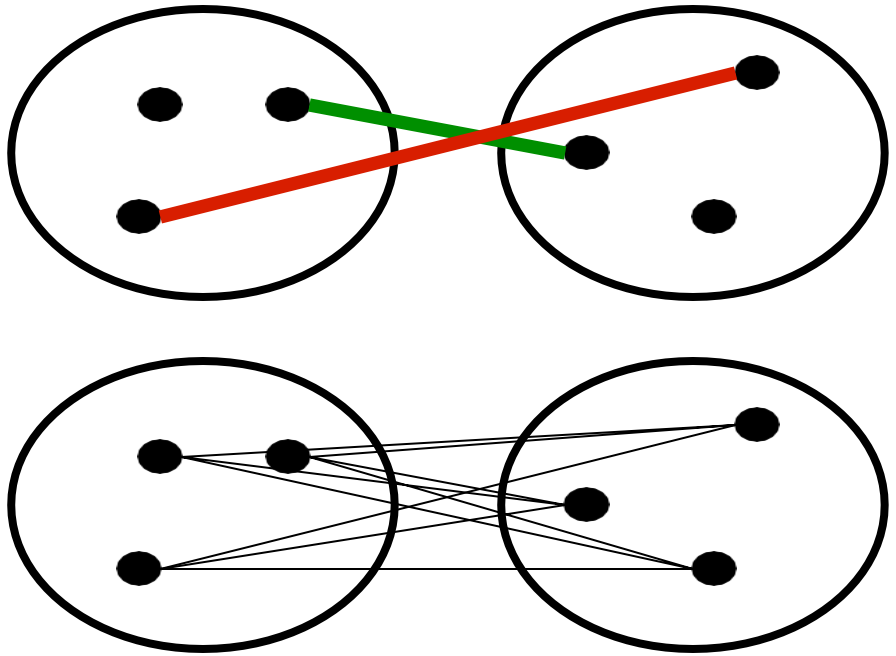
- Find two nearest clusters according to dist(C_i, C_j)
- Merge C = (C_i, C_j)
- If only 1 cluster is left:
  - break

How should we define “closest” for clusters with multiple pixels already in it?



How should we define “closest” for clusters with multiple pixels already in it?

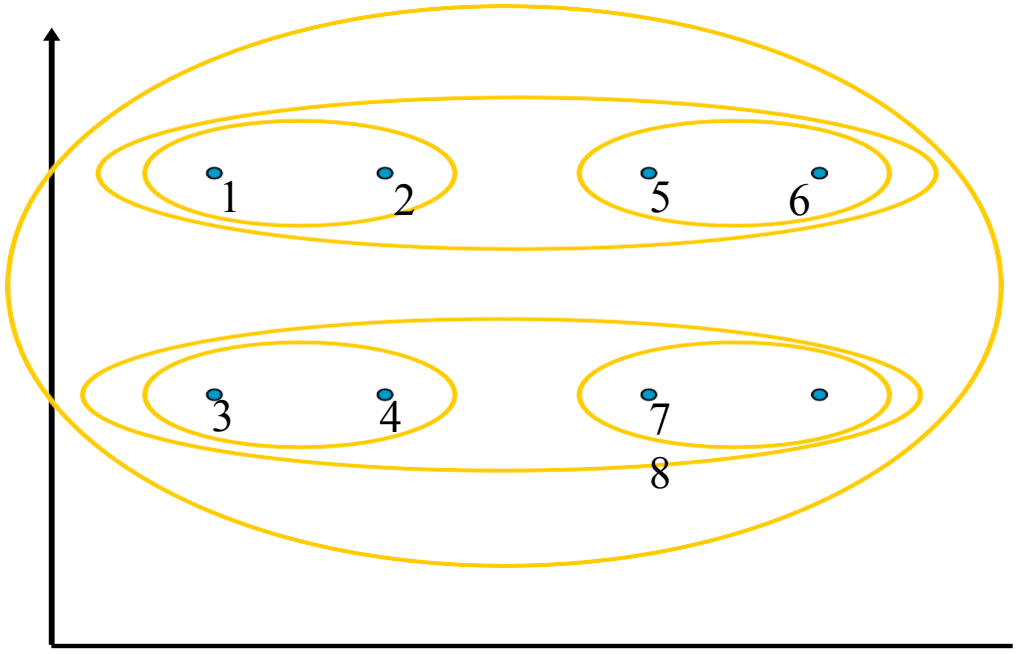
- Closest pair
  (single-link clustering)
- Farthest pair
  (complete-link clustering)
- Average of all pairs



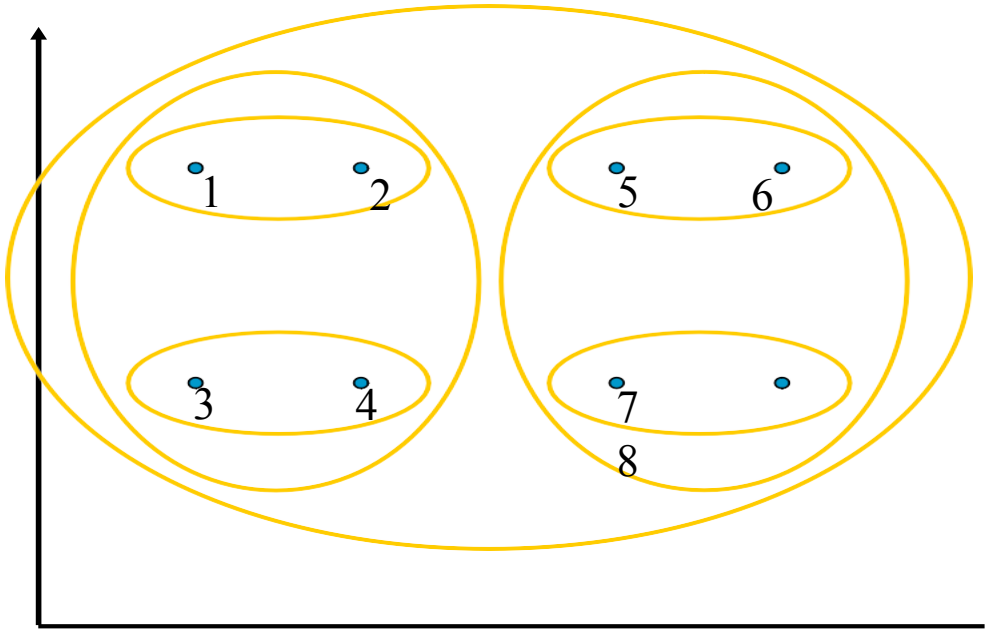
Different choices create different clustering behaviors

How should we define “closest” for clusters with multiple pixels already in it?

Closest pair
(single-link clustering)



Farthest pair
(complete-link clustering)

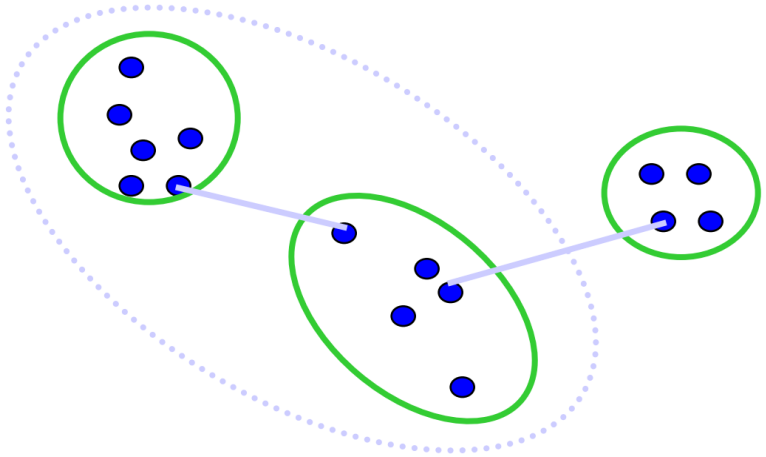


[Pictures from Thorsten Joachims]

Single Linkage distance measure

$$dist(C_i, C_j) = \min_{v_i \in C_i, v_j \in C_j, (C_i, C_j) \in E} dist(v_i, v_j)$$

Connects the clusters based on the distance of their closest pixels
It produces “long” clusters.

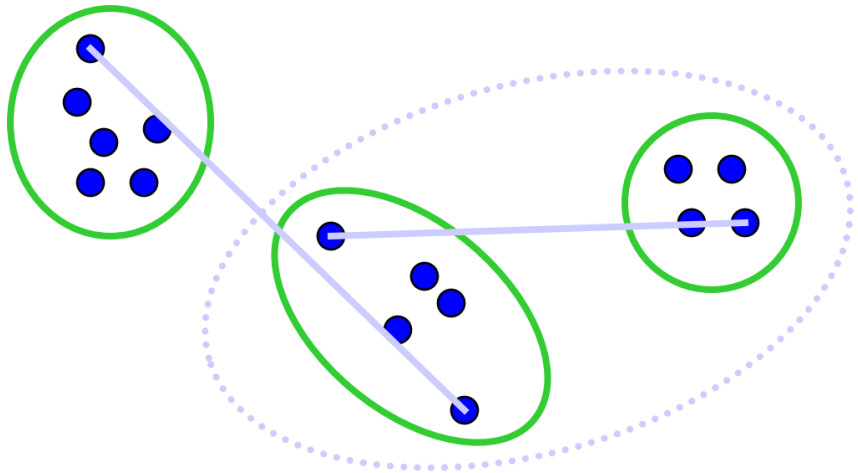


Long, skinny clusters

Complete Link distance measure

$$dist(C_i, C_j) = \max_{v_i \in C_i, v_j \in C_j, (C_i, C_j) \in E} dist(v_i, v_j)$$

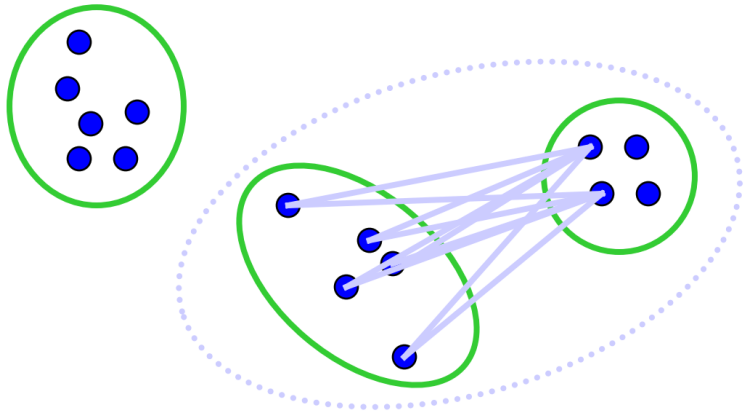
Produces compact clusters that are similar in diameter



Tight clusters

Average Link distance measures

$$dist(C_i, C_j) = \frac{\sum_{v_i \in C_i, v_j \in C_j, (C_i, C_j) \in E} dist(v_i, v_j)}{|C_i||C_j|}$$



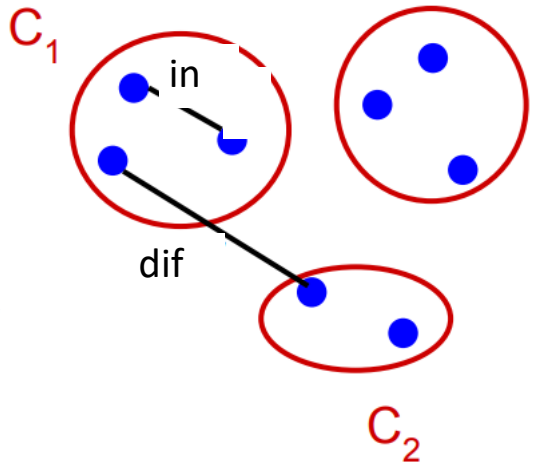
Robust against noise.

Inlier-outlier linkage distance measure

$$Merge(C_1, C_2) = \begin{cases} True & if\ dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

Where

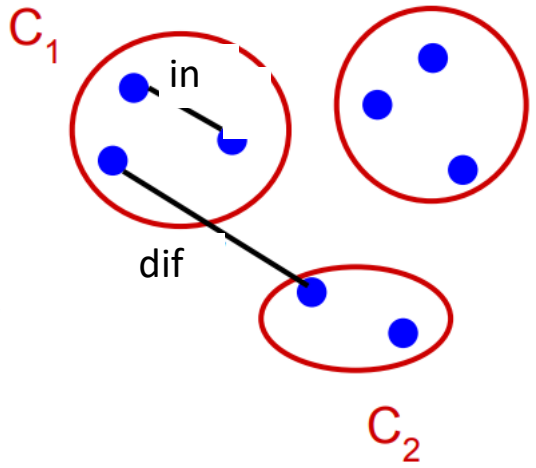
- dif(C1 , C2) is the difference between two clusters.
- in(C1 , C2) is the internal difference in the clusters C1 and C2



Inlier-outlier linkage distance measure

$$Merge(C_1, C_2) = \begin{cases} True & if\ dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

$$dif(C_i, C_j) = \min_{v_i \in C_i, v_j \in C_j, (C_i, C_j) \in E} dist(v_i, v_j)$$



Where

- dif(C1 , C2) is the difference between two clusters.
- in(C1 , C2) is the internal difference in the clusters C1 and C2

Inlier-outlier linkage distance measure

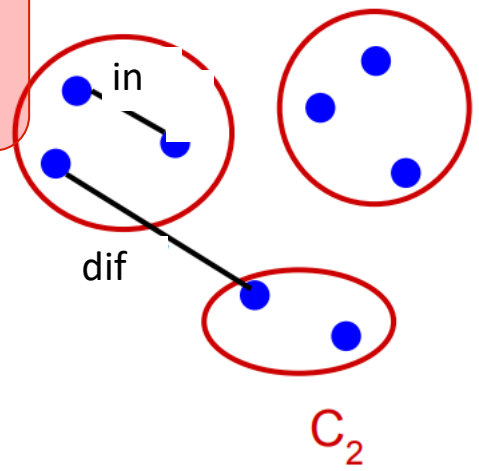
$$Merge(C_1, C_2) = \begin{cases} True & if\ dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

$$dif(C_i, C_j) = \min_{v_i \in C_i, v_j \in C_j, (C_i, C_j) \in E} dist(v_i, v_j)$$

$$in(C_i, C_j) = \min_{C \in \{C_i, C_j\}} [\max_{v_i, v_j \in C} [dist(v_i, v_j) + \frac{k}{|C|}]]$$

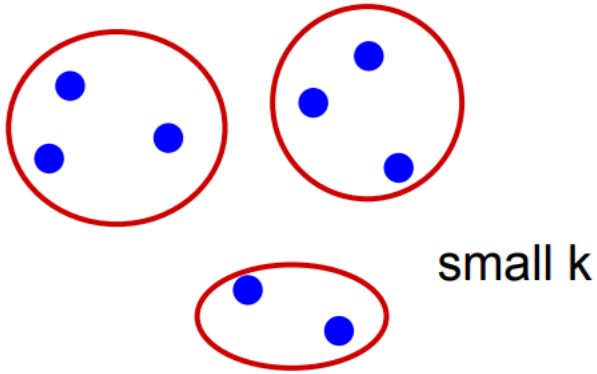
Where

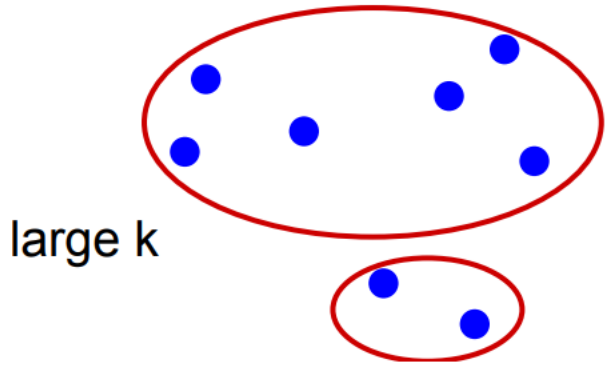
- dif(C1 , C2) is the difference between two clusters.
- in(C1 , C2) is the internal difference in the clusters C1 and C2



inlier-outlier linkage for Segmentation

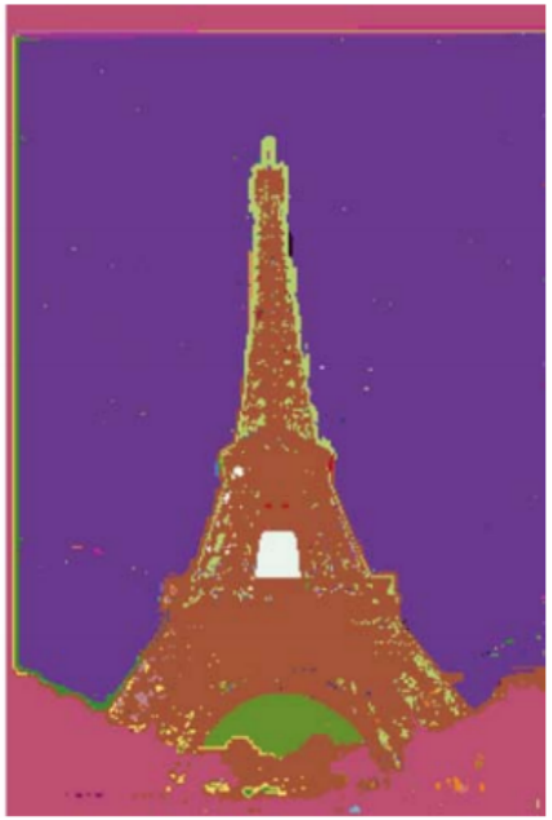
- k/|C| sets the threshold by which the clusters need to be different from the internal pixels in a cluster.
- Effect of k:
  - **If k is large, it causes a preference for larger objects.**





Results



Conclusions: Agglomerative Clustering

Pros:

- Simple to implement, widespread application.
- Clusters have adaptive shapes.
- Provides a hierarchy of clusters.
- No need to specify number of clusters **in advance**.

Cons:

- May have imbalanced clusters.
- Still have to choose number of clusters eventually for an application
- Does not scale well. Runtime of atleast $O(n^2)$.
- Can get stuck at a local optima.

Next time

K-means and mean shift