Lecture 12: Clustering and Segmentation

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What we will learn today

- Introduction to segmentation and clustering
- Gestalt theory for perceptual grouping
- Agglomerative clustering

Reading: [FP] Chapters: 14.2, 14.4

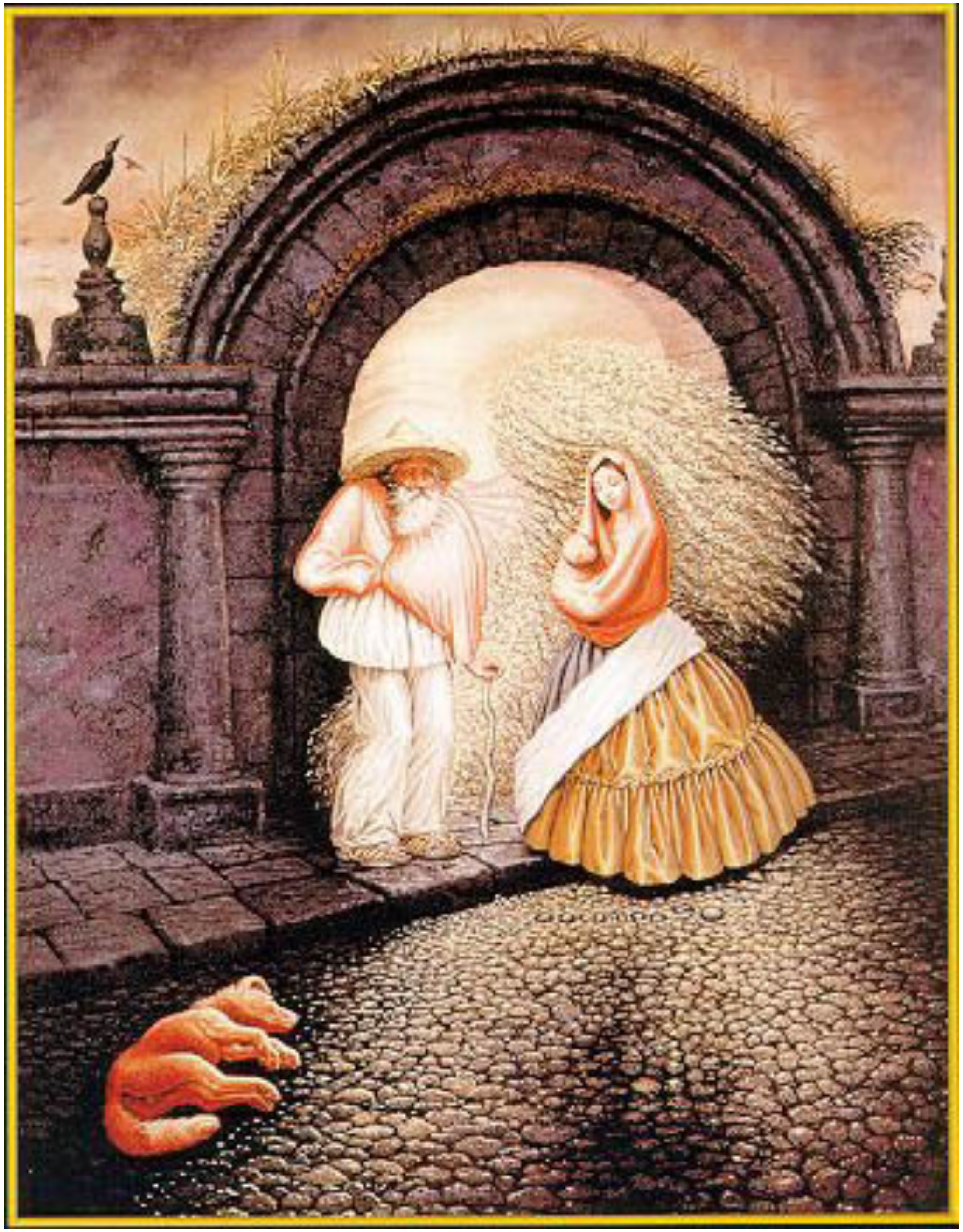
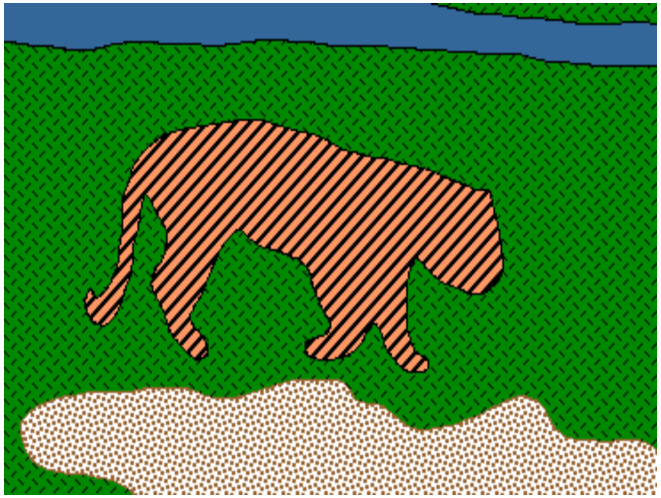


Image Segmentation

- Goal: identify groups of pixels that go together



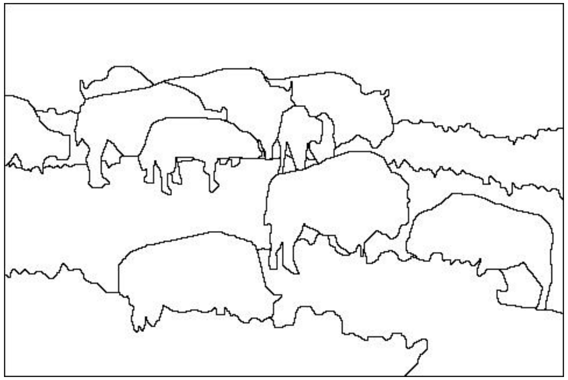
Slide credit: Steve Seitz, Kristen Grauman

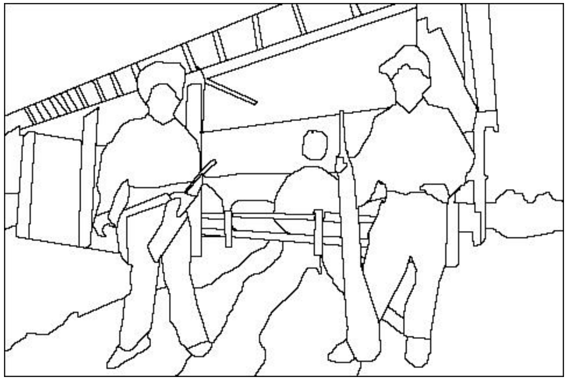
The Goals of Segmentation

- Separate image into coherent "objects"

Image

Human segmentation



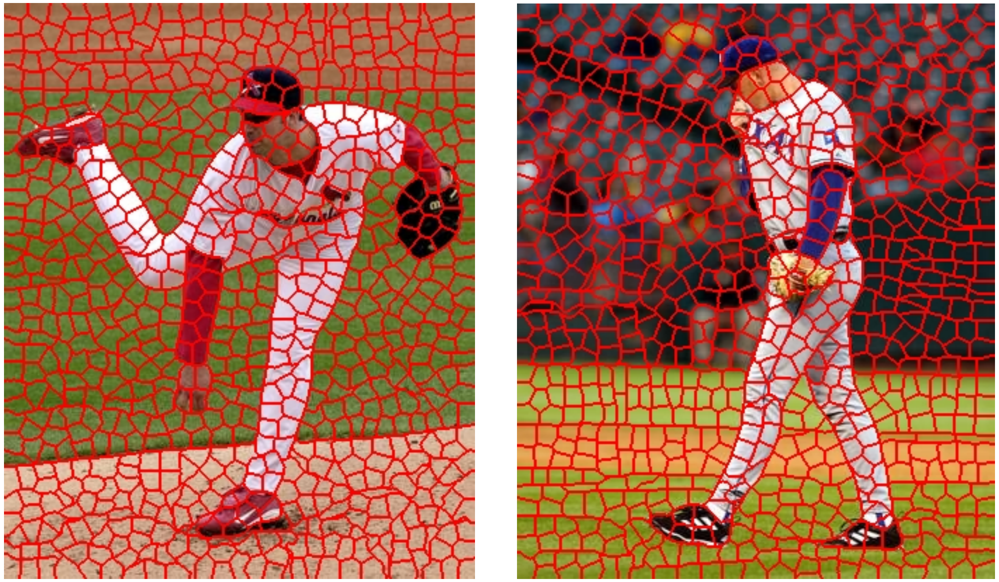


Slide credit: Svetlana Lazebnik

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.

Slide credit: Svetlana Lazebnik

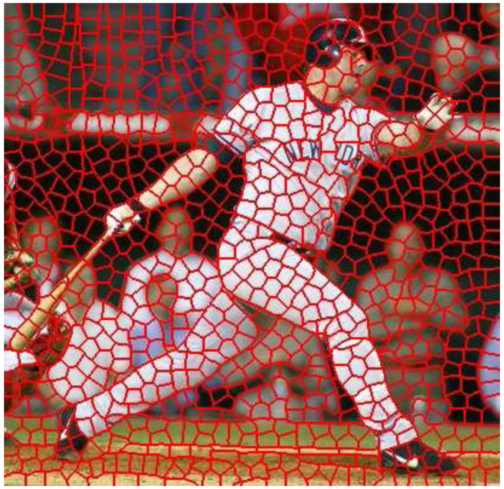
Segmentation for feature support

Slide: Derek Hoiem

Segmentation for efficiency

[Felzenszwalb and Huttenlocher 2004]

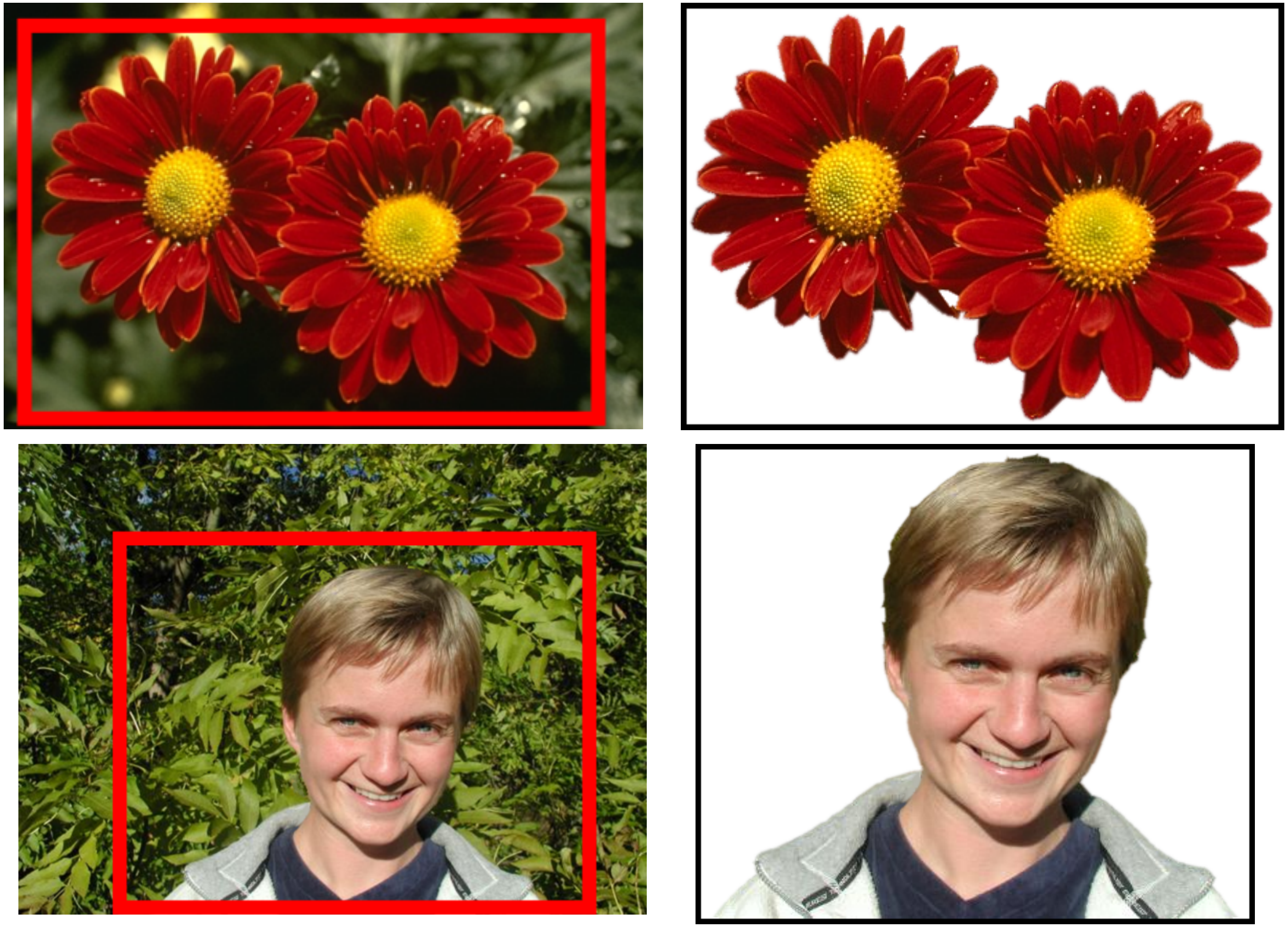
[Hoiem et al. 2005, Mori 2005]



[Shi and Malik 2001]

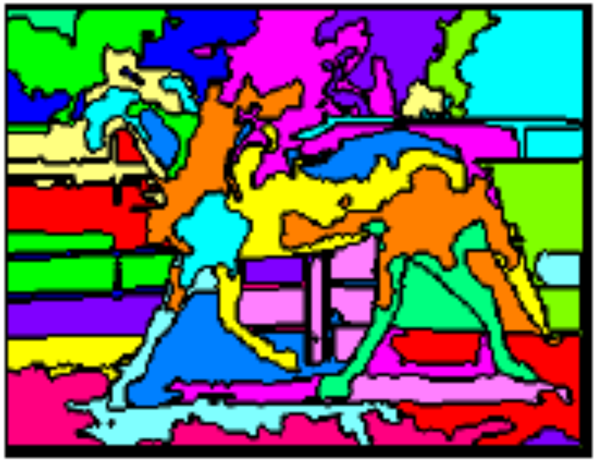
Slide: Derek Hoiem

Segmentation as a result

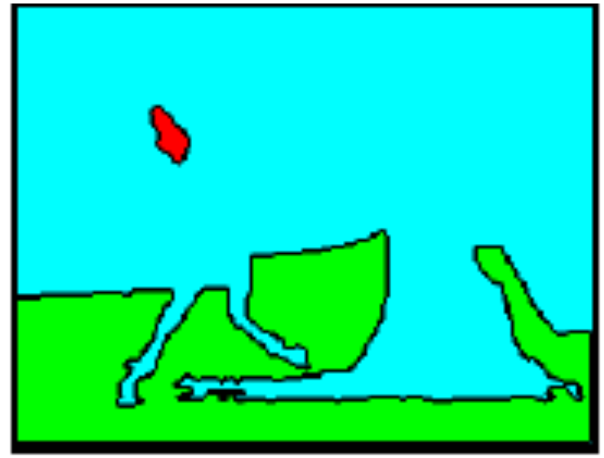


Rother et al. 2004

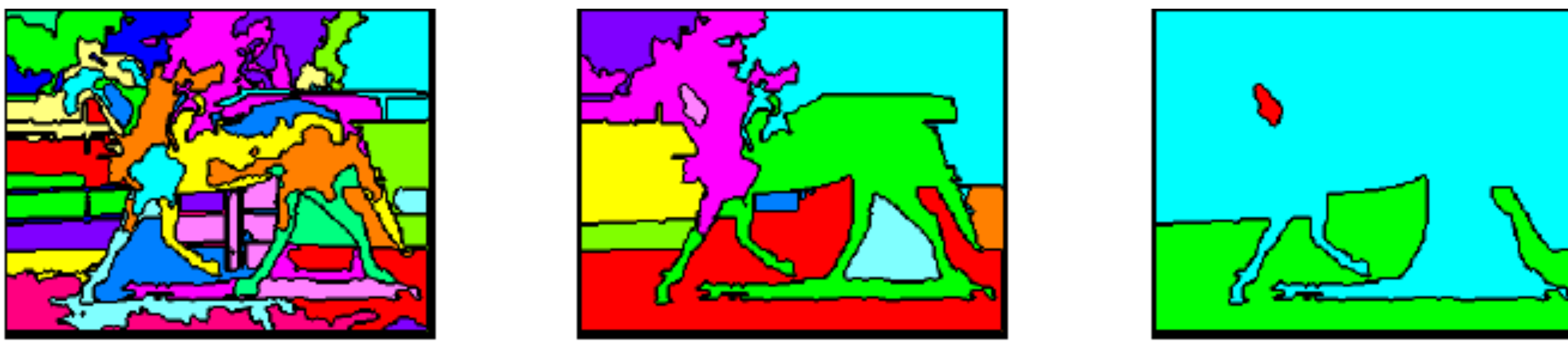
Types of segmentations



Oversegmentation



Undersegmentation



Multiple Segmentations

One way to think about “segmentation” is Clustering

Clustering: group together similar points and represent them with a single token

Key Challenges:

1) What makes two points/images/patches similar?

2) How do we compute an overall grouping from pairwise similarities?

Slide: Derek Hoiem

Why do we cluster?

- **Summarizing data**
  – Look at large amounts of data
  – Patch-based compression or denoising
  – Represent a large continuous vector with the cluster number

- **Counting**
  – Histograms of texture, color, SIFT vectors

- **Segmentation**
  – Separate the image into different regions

- **Prediction**
  – Images in the same cluster may have the same labels

Slide: Derek Hoiem

How do we cluster?

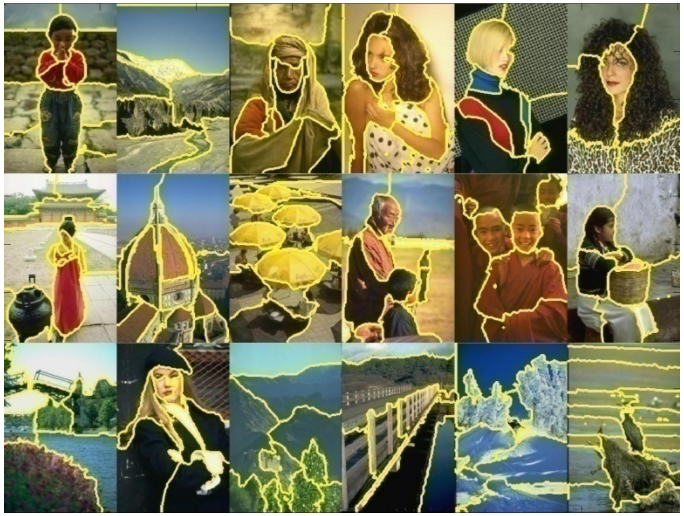
- Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- K-means (next lecture)
  - Iteratively re-assign points to the nearest cluster center
- Mean-shift clustering (next lecture)
  - Estimate modes of pdf
- Spectral clustering (CS231a)
  - Split the nodes in a graph based on assigned links with similarity weights

General ideas

- Tokens
  - whatever we need to group (pixels, points, surface elements, etc., etc.)
- Bottom up clustering
  - tokens belong together because they are locally coherent
- Top down clustering
  - tokens belong together because they lie on the same visual entity (object, scene…)

> These two are not mutually exclusive

Examples of Grouping in Vision



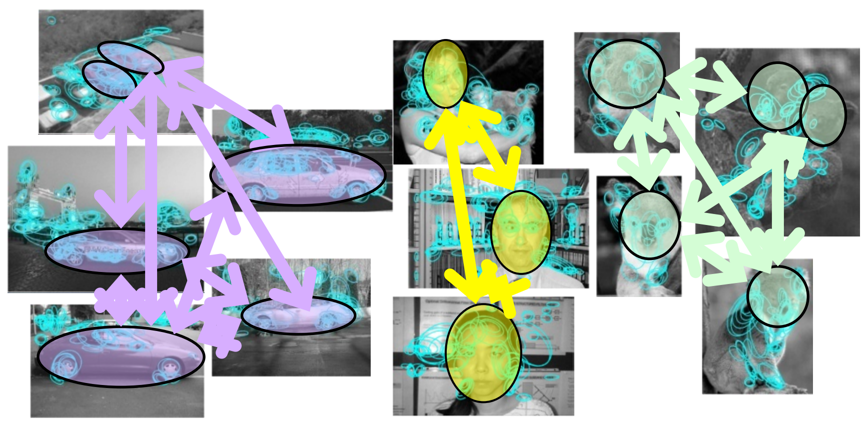
Determining image regions

Grouping video frames into shots

Figure-ground

What things should be grouped?

What cues indicate groups?



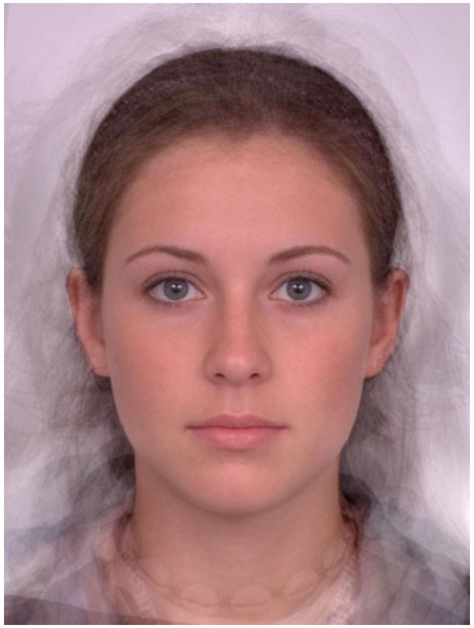
Object-level grouping

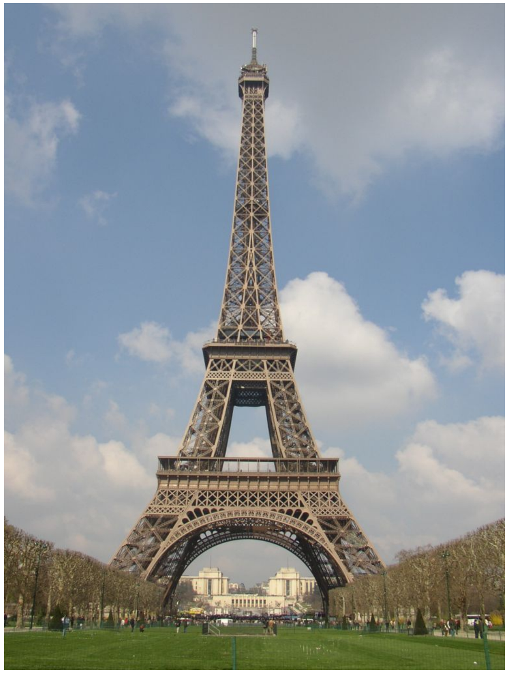
Slide credit: Kristen Grauman

Similarity

Slide credit: Kristen Grauman

Symmetry





Slide credit: Kristen Grauman

Common Fate

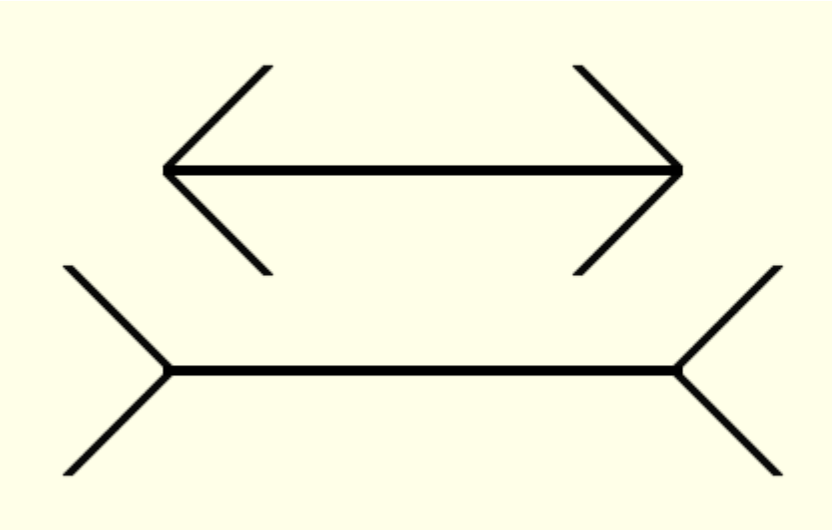
Image credit: Arthus-Bertrand (via F. Durand)

Slide credit: Kristen Grauman

Proximity

Slide credit: Kristen Grauman

Muller-Lyer Illusion



- What makes the bottom line look longer than the top line?

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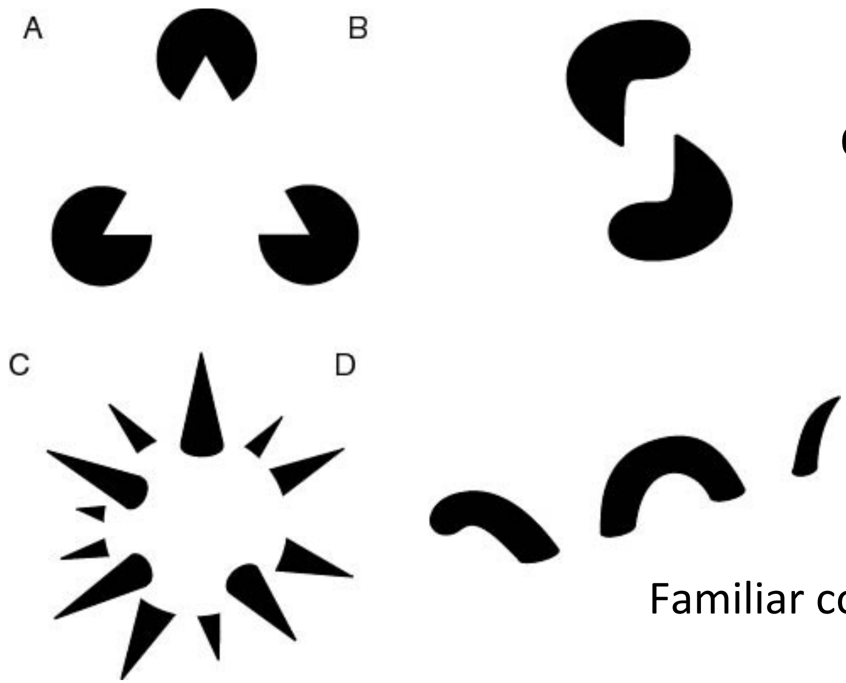
The Gestalt School

- Grouping is key to visual perception
- Elements in a collection can have properties that result from relationships
  - "The whole is greater than the sum of its parts"

Illusory/subjective contours

Occlusion



Familiar configuration

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

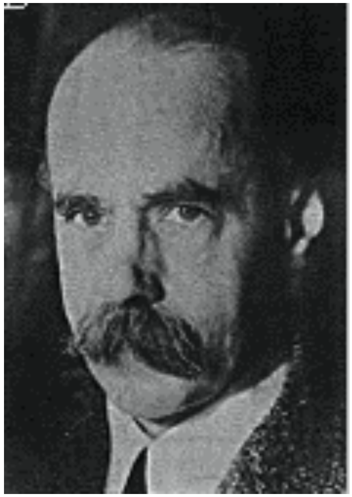
Slide credit: Svetlana Lazebnik

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)

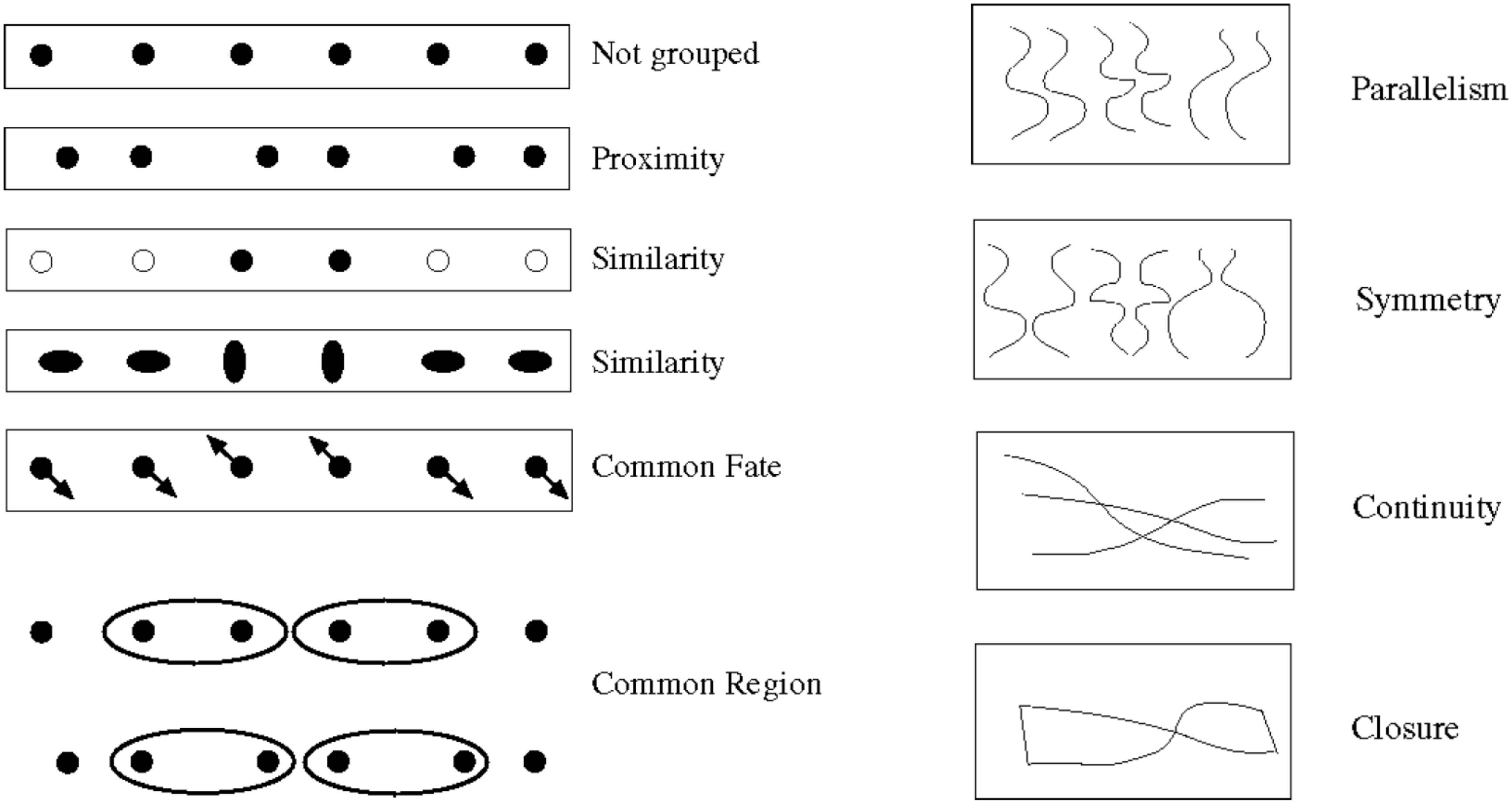
“I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees.”

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

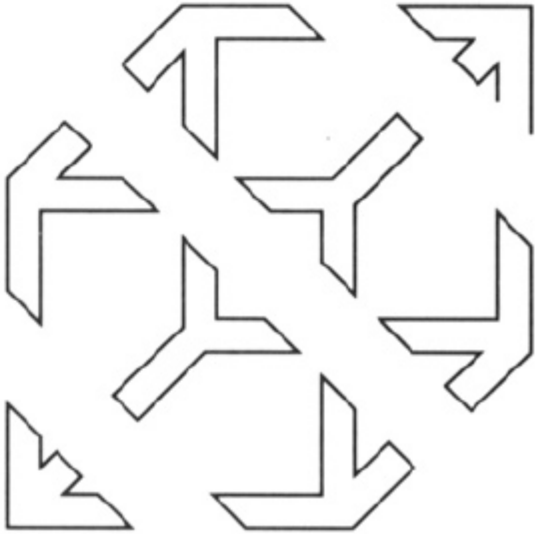
Gestalt Factors



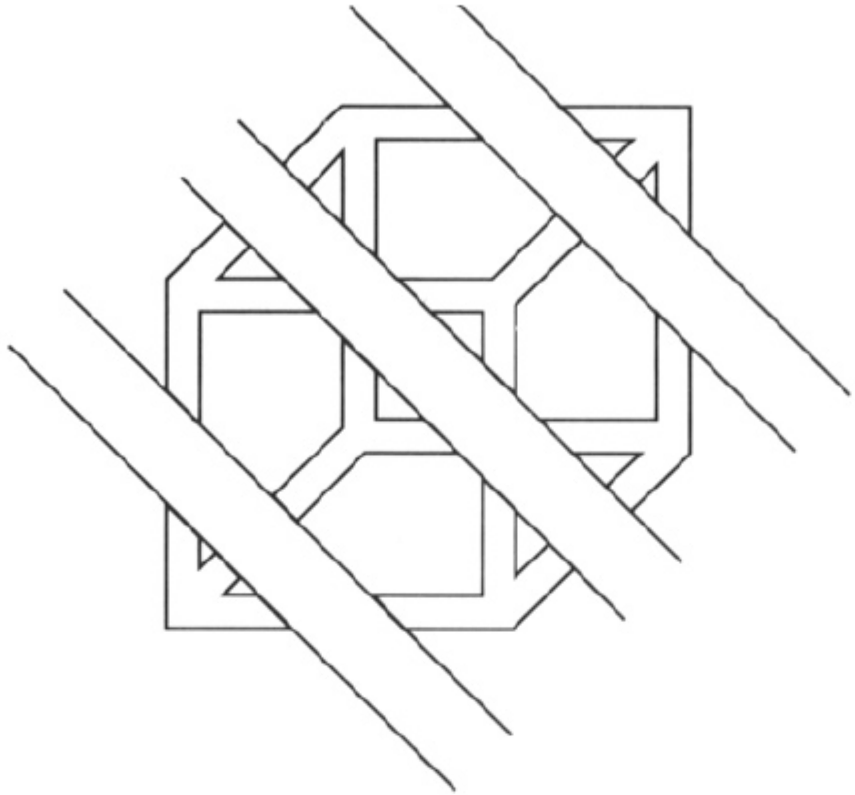
- These factors make intuitive sense, but are very difficult to translate into algorithms.

Image source: Forsyth & Ponce

Continuity through Occlusion Cues



Continuity through Occlusion Cues



Continuity, explanation by occlusion

Continuity through Occlusion Cues

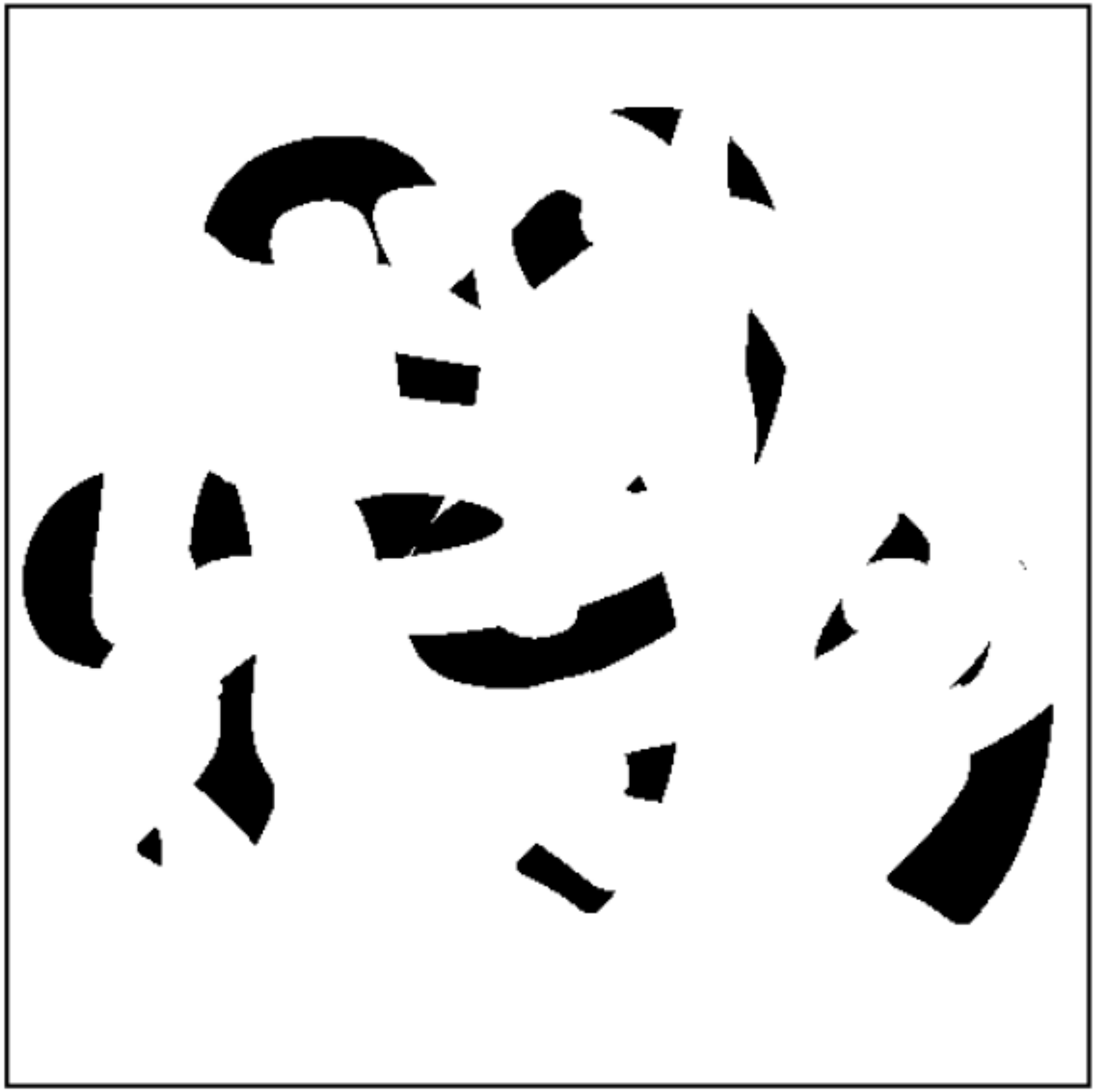
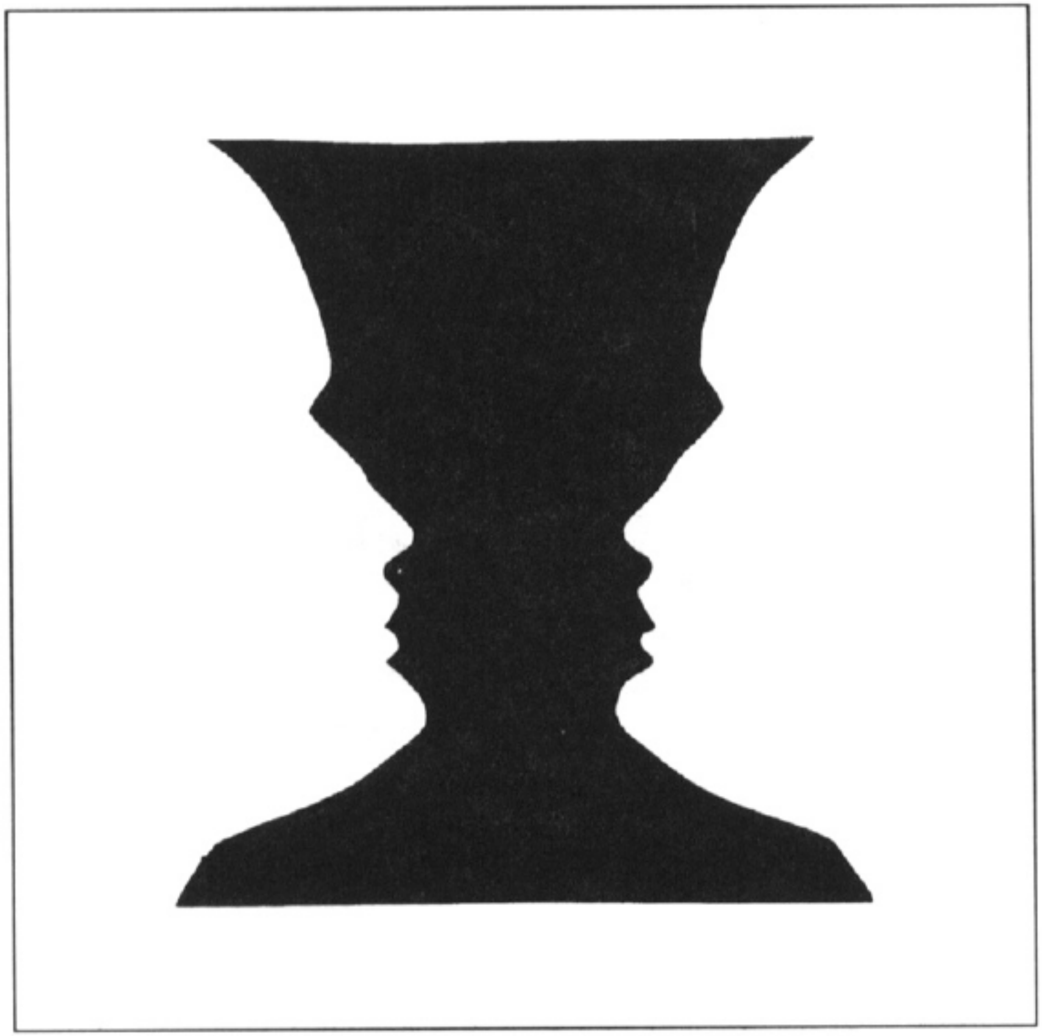


Image source: Forsyth & Ponce

Continuity through Occlusion Cues

Image source: Forsyth & Ponce

Figure-Ground Discrimination



The Ultimate Gestalt?

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Clustering: distance measure

Clustering is an unsupervised learning method. Given items $x_1, \ldots, x_n \in \mathbb{R}^D$, the goal is to group them into clusters. We need a pairwise distance/similarity function between items, and sometimes the desired number of clusters.

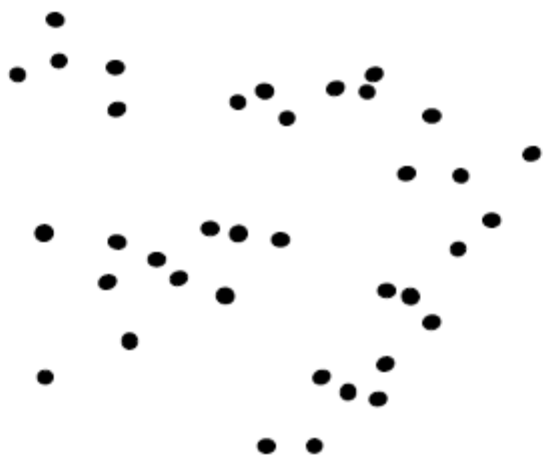
When data (e.g. images, objects, documents) are represented by feature vectors, a commonly used similarity measure is the *cosine similarity.* Let x, x' be two data vectors. There is angle θ between the two vectors x, x' . The cosine similarity is defined as

$$
\begin{aligned}
sim(x, x') &= \cos(\theta) \\
&= \frac{x^\top x'}{\|x\| \cdot \|x'\|} \\
&= \frac{x^\top x'}{\sqrt{x^\top x}\sqrt{x'^\top x'}}.
\end{aligned}
$$

In contrast, Euclidean distance measure would be

$$
sim(x, x') = x^\top x'
$$

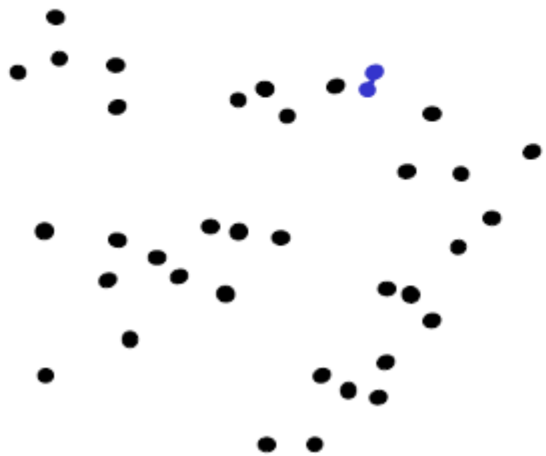
Agglomerative clustering



1. Say "Every point is its own cluster"

Slide credit: Andrew Moore

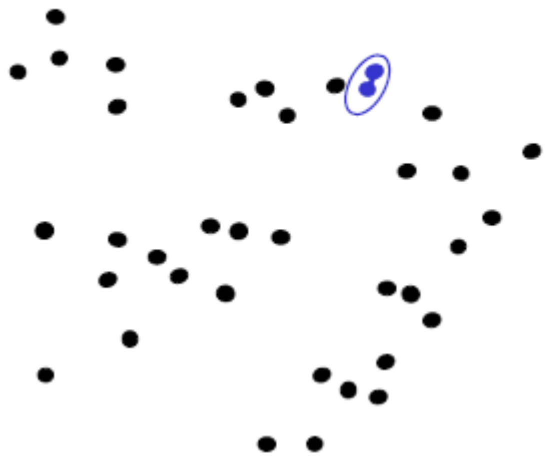
Agglomerative clustering



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

Slide credit: Andrew Moore

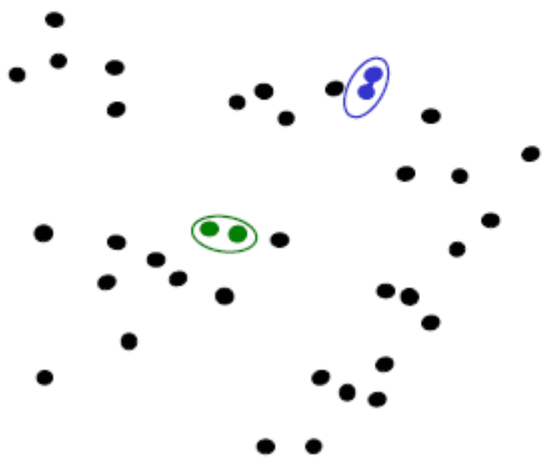
Agglomerative clustering



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

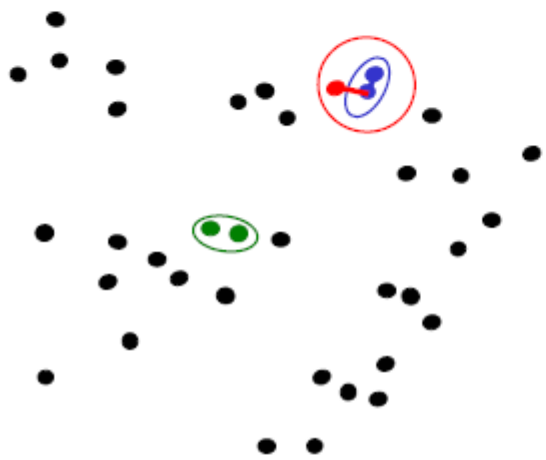
Agglomerative clustering



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"
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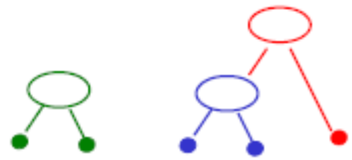
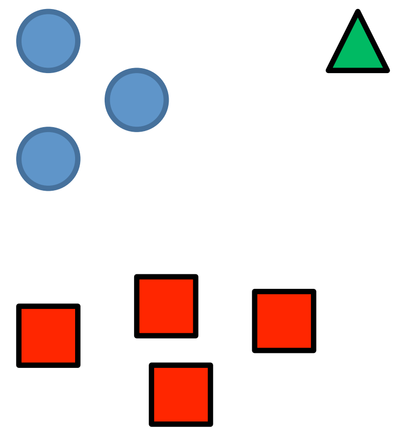


Slide credit: Andrew Moore

Agglomerative clustering

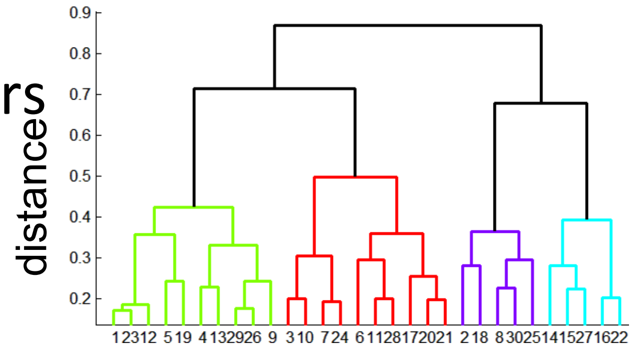
How to define cluster similarity?

- Average distance between points,
- maximum distance
- minimum distance
- Distance between means or medoids



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

1. Initially each item $x_1, \ldots, x_n$ is in its own cluster $C_1, \ldots, C_n$.
2. Repeat until there is only one cluster left:
3. Merge the nearest clusters, say C_i and C_j.

Different ways to define the "nearest clusters":

- $d(C_i, C_j) = \min_{x \in C_i, x' \in C_j} d(x, x')$. This is known as *single-linkage*. It is equivalent to the minimum spanning tree algorithm. One can set a threshold and stop clustering once the distance between clusters is above the threshold. Single-linkage tends to produce long and skinny clusters.
- $d(C_i, C_j) = \max_{x \in C_i, x' \in C_j} d(x, x')$. This is known as *complete-linkage*. Clusters tend to be compact and roughly equal in diameter.
- $d(C_i, C_j) = \frac{\sum x \in C_i, x' \in C_j \, d(x, x')}{|C_i| \cdot |C_j|}$. This is the average distance between items. Somewhere between single-linkage and complete-linkage.
- and a million other ways you can think of ...

Conclusions: Agglomerative Clustering

Good

- Simple to implement, widespread application
- Clusters have adaptive shapes
- Provides a hierarchy of clusters

Bad

- May have imbalanced clusters
- Still have to choose number of clusters or threshold
- Need to use an “ultrametric” to get a meaningful hierarchy

What we have learned today?

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