COMPUTER VISION
LECTURE 10 – CLUSTERING AND SEGMENTATION

Prof. Dr. Francesco Maurelli

2018-10-05

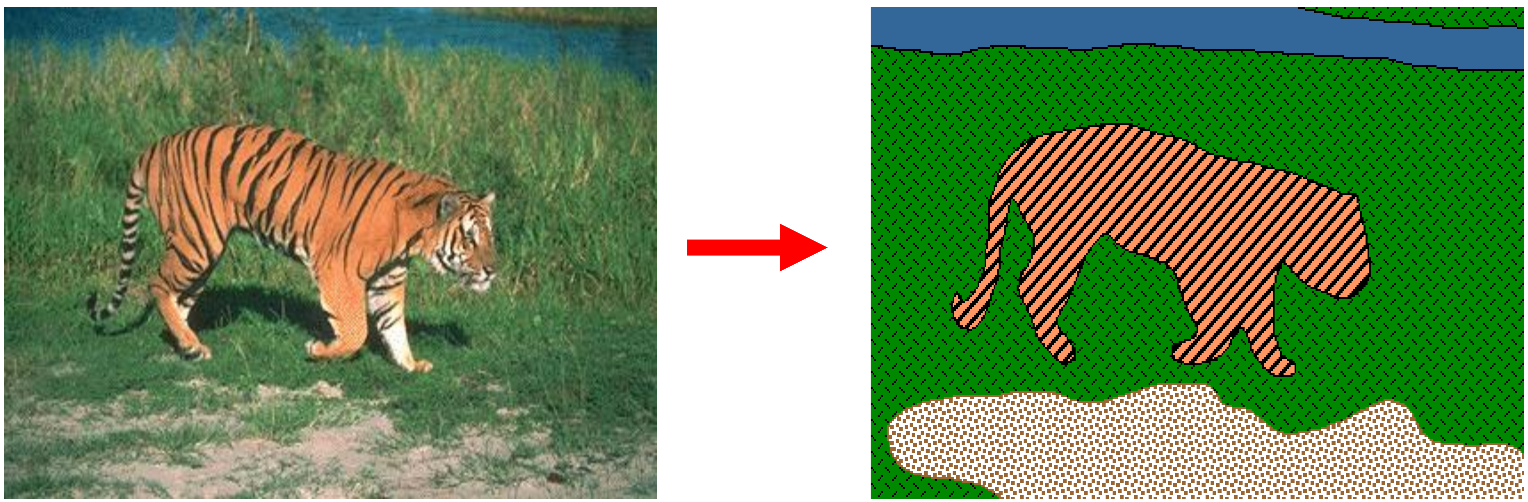
What we will learn today

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

Reading: [Forsyth & Ponce] 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”

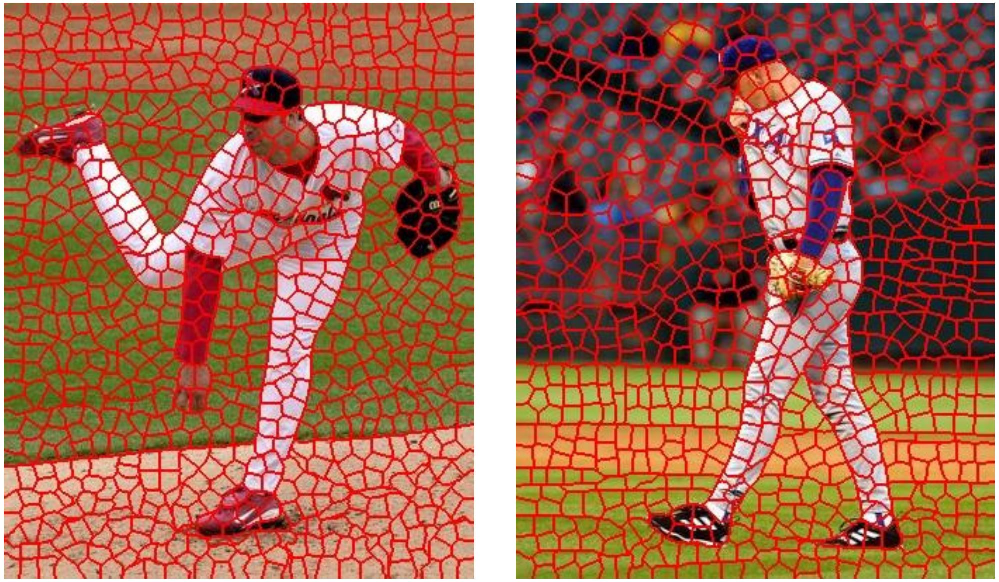
Image | Human segmentation

Slide credit: Svetlana Lazebnik

The Goals of Segmentation

- Separate image into coherent “objects”
- Group together similar-looking pixels for efficiency of further processing

“superpixels”



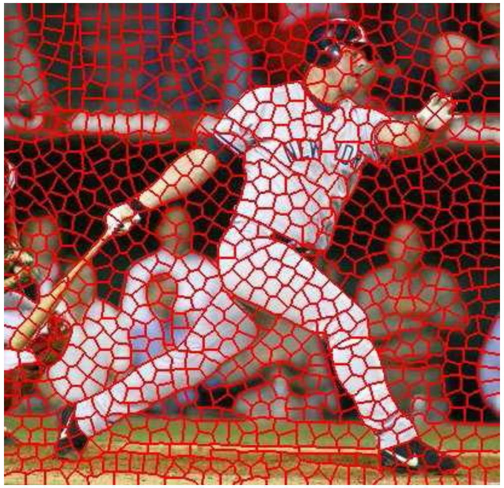
X. Ren and J. Malik. Learning a classification model for segmentation. ICCV 2003.

Slide credit: Svetlana Lazebnik

Segmentation for efficiency

[Felzenszwalb and Huttenlocher 2004]

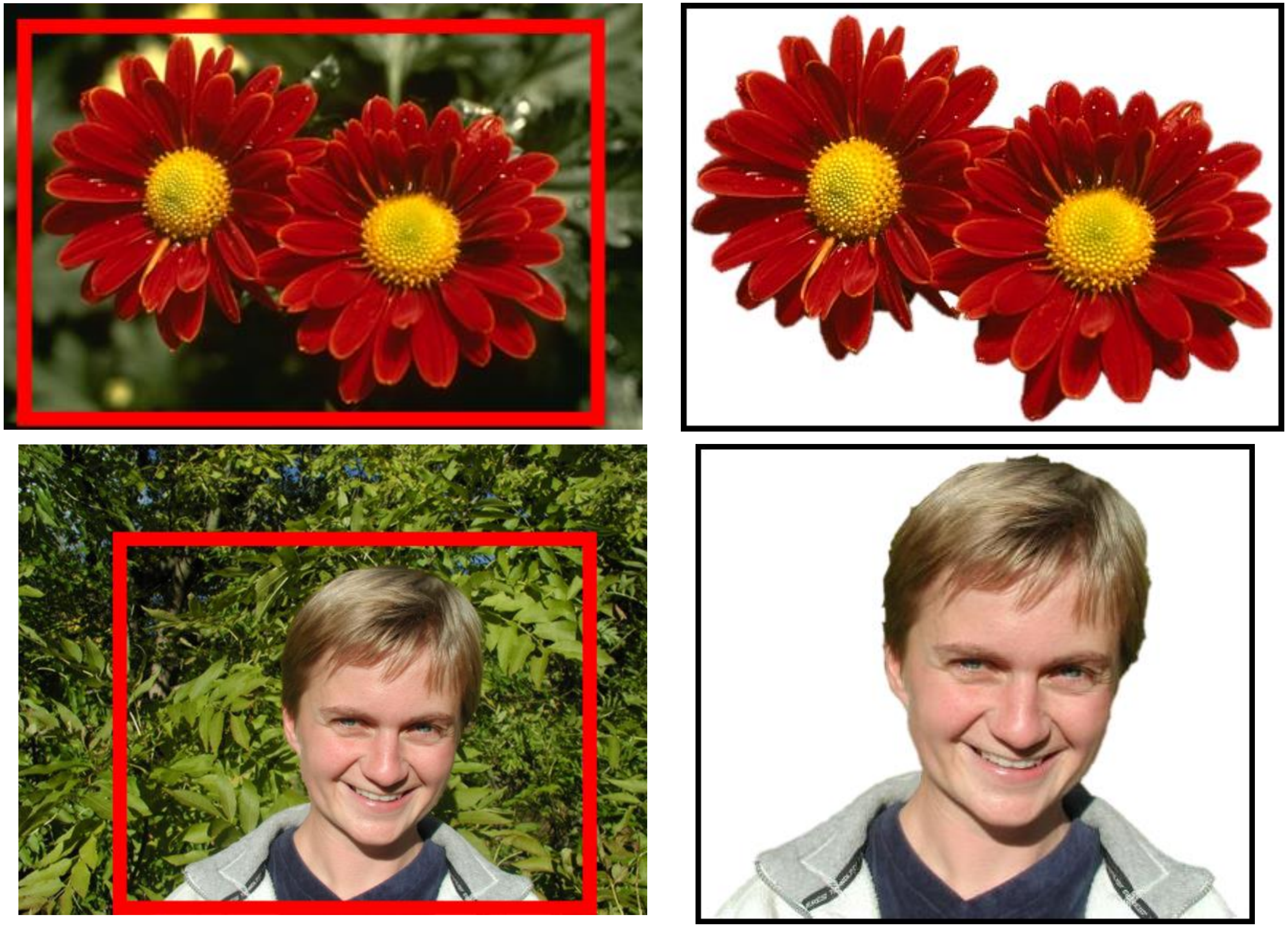
[Hoiem et al. 2005, Mori 2005]



[Shi and Malik 2001]

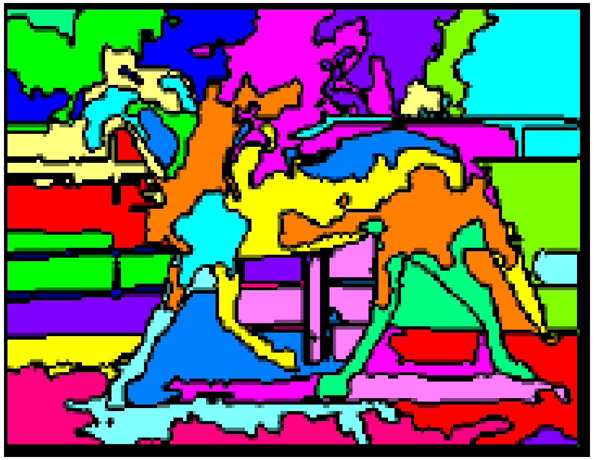
Slide: Derek Hoiem

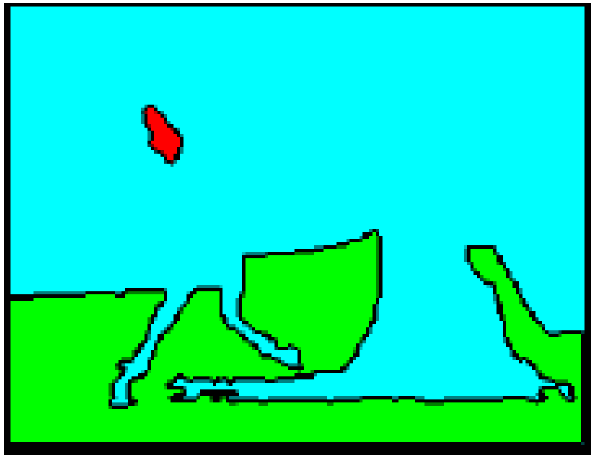
Segmentation as a result

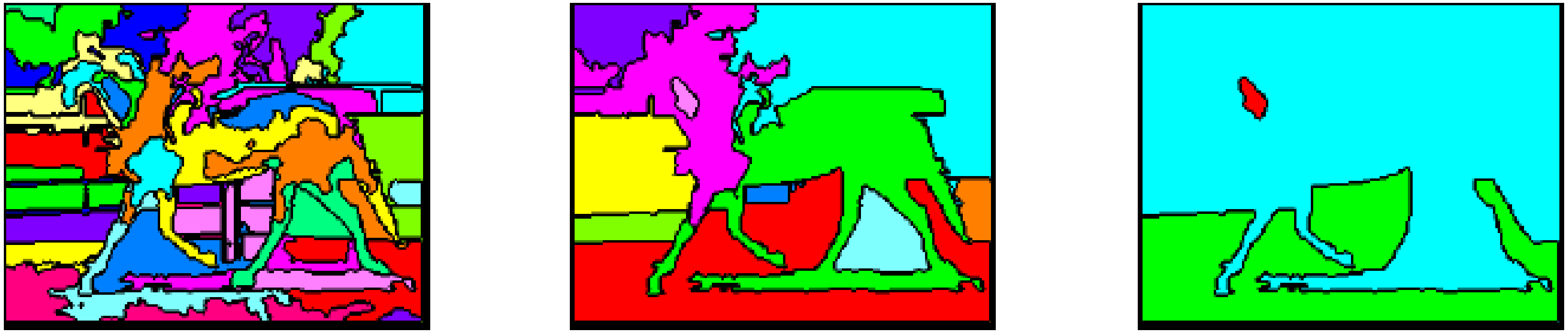


Rother et al. 2004

Types of segmentations


Oversegmentation


Undersegmentation



Multiple Segmentations

One way to think about "segmentation" is Clustering

Clustering: group together similar data 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?

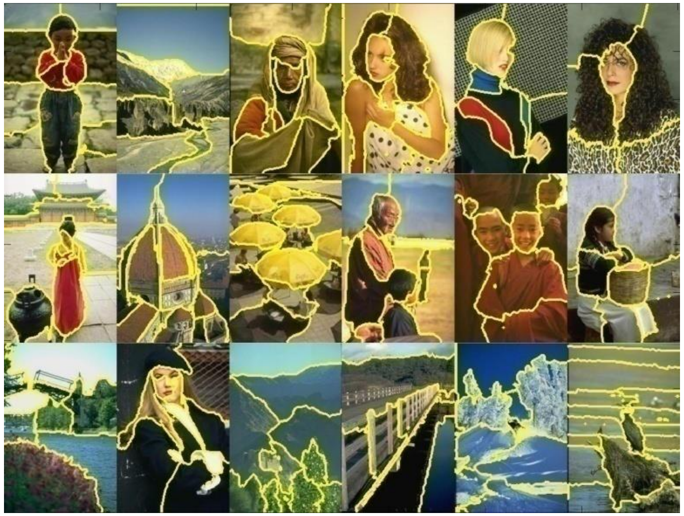
- Agglomerative clustering
  - Start with each point as its own cluster and iteratively merge the closest clusters
- K-means (next lecture)
  - Iteratively re-assign points to the nearest cluster center
- Mean-shift clustering (next lecture)
  - Estimate modes of pdf

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

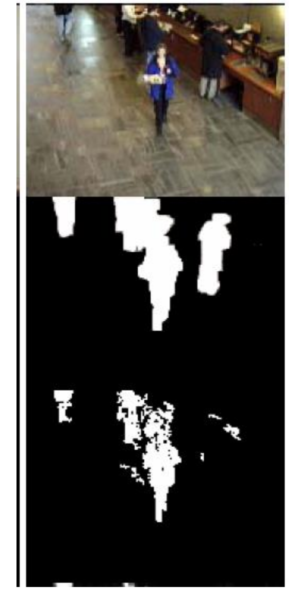
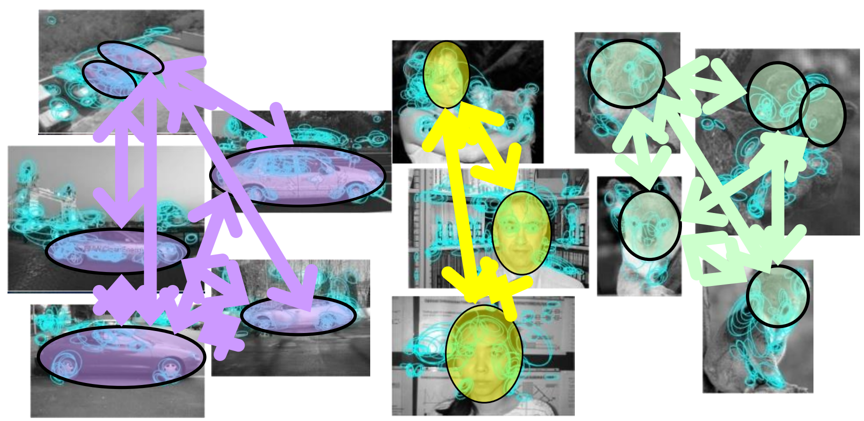


Figure-ground

What things should be grouped?

What cues indicate groups?



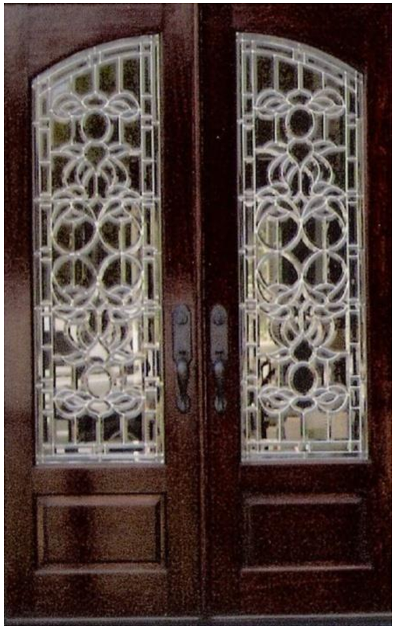
Object-level grouping

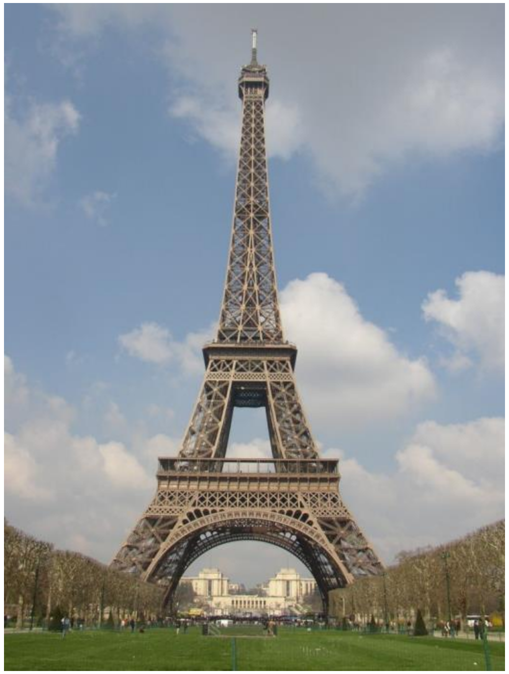
Slide credit: Kristen Grauman

Similarity

Slide credit: Kristen Grauman

Symmetry





Slide credit: Kristen Grauman

Common Fate

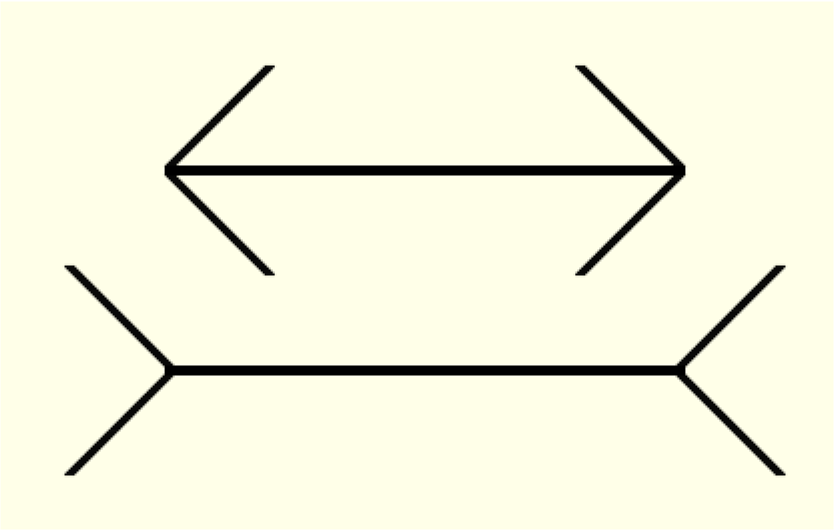
Image credit: Arthus-Bertrand (via F. Durand)

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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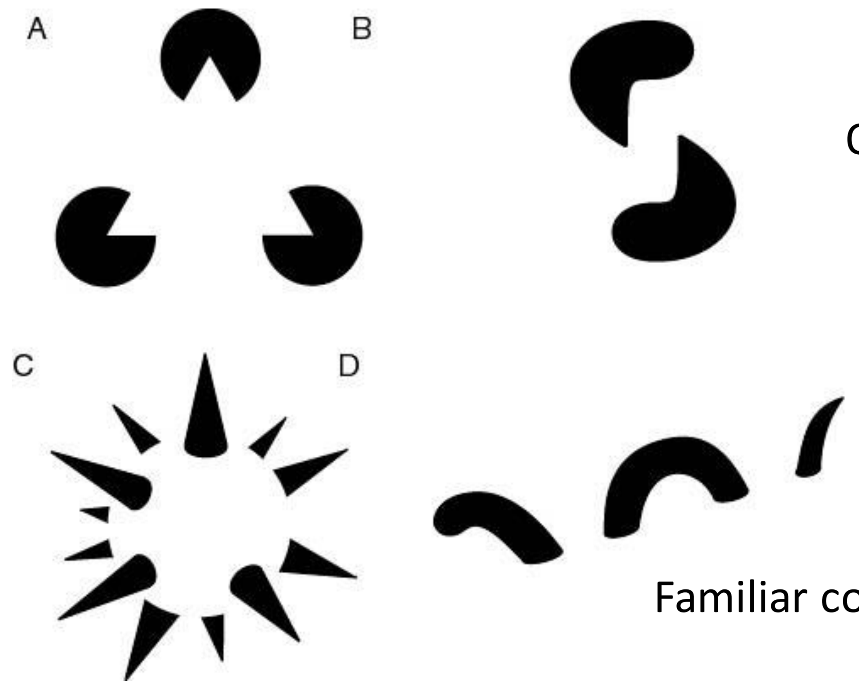
The Gestalt School

- 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

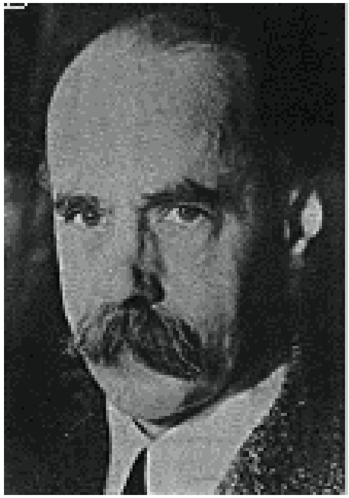
Slide credit: Svetlana Lazebnik

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)

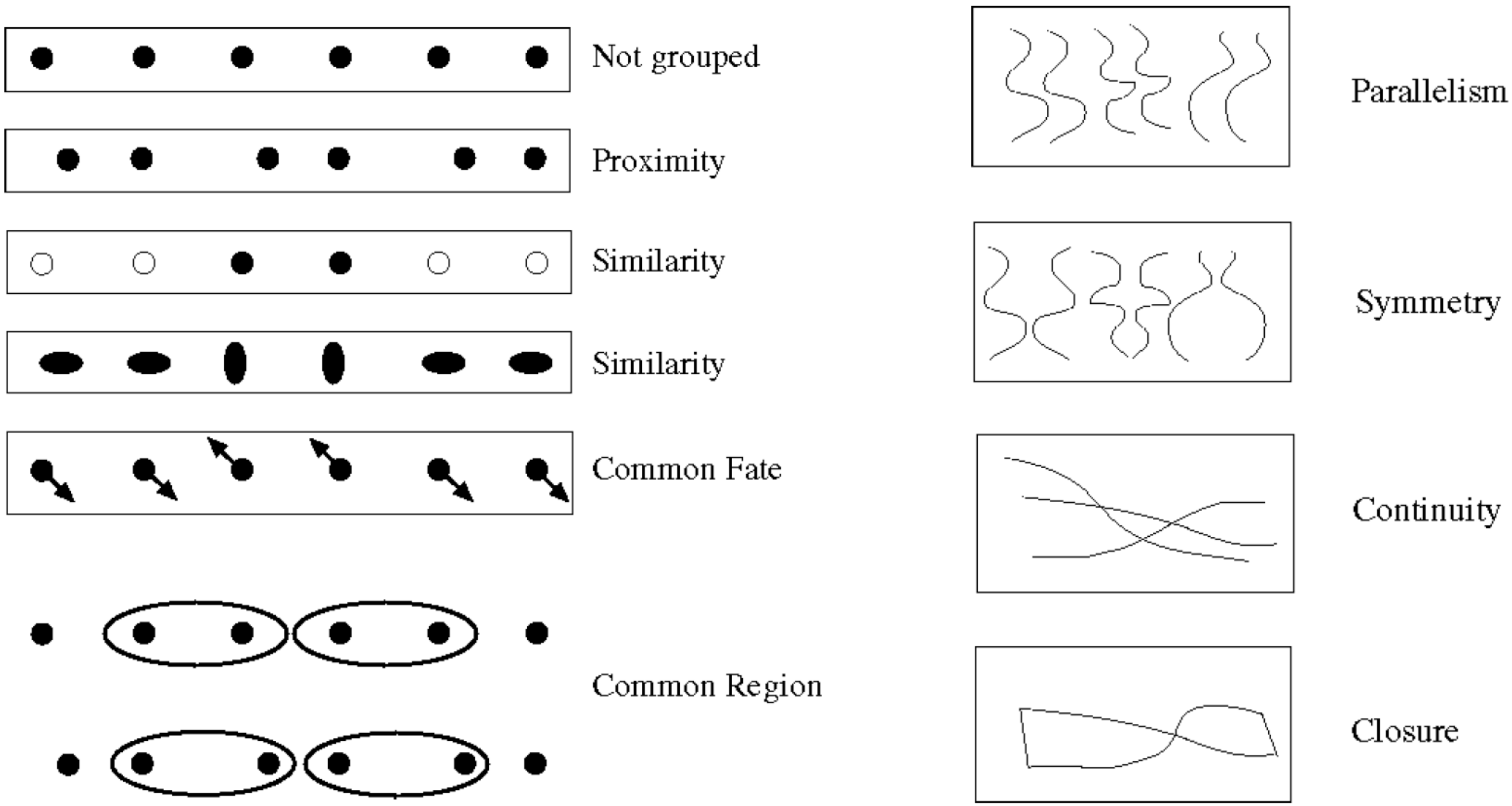
"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees."

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

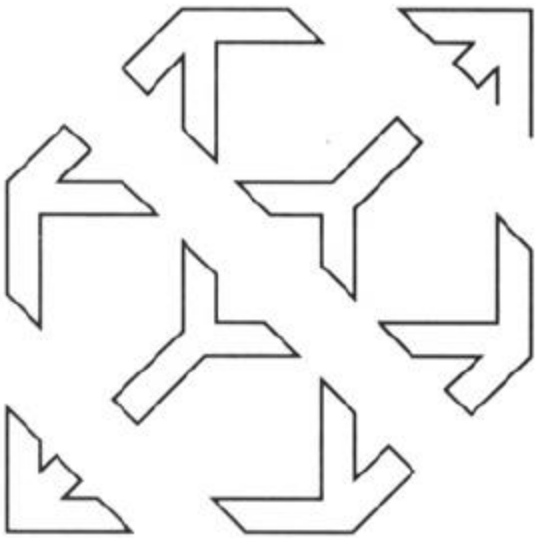
Gestalt Factors



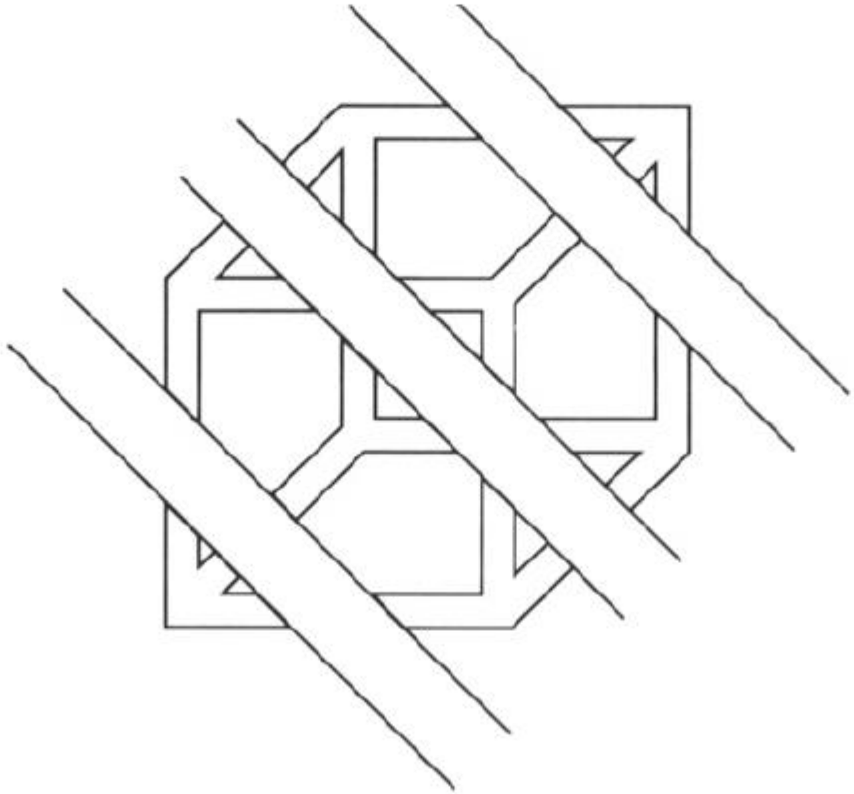
- These factors make intuitive sense, but are very difficult to translate into algorithms.

Image source: Forsyth & Ponce

Continuity through Occlusion Cues

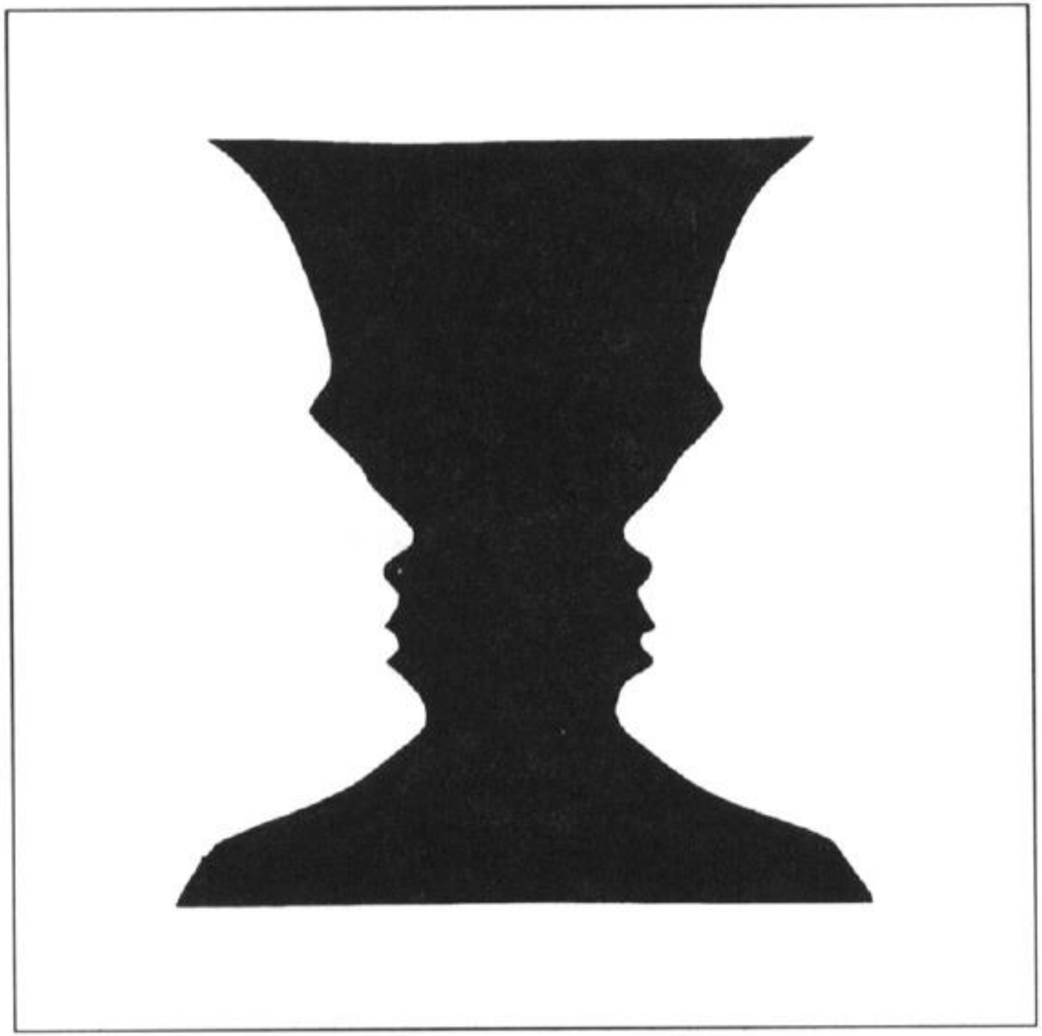


Continuity through Occlusion Cues



Continuity, explanation by occlusion

Figure-Ground Discrimination



The Ultimate Gestalt?

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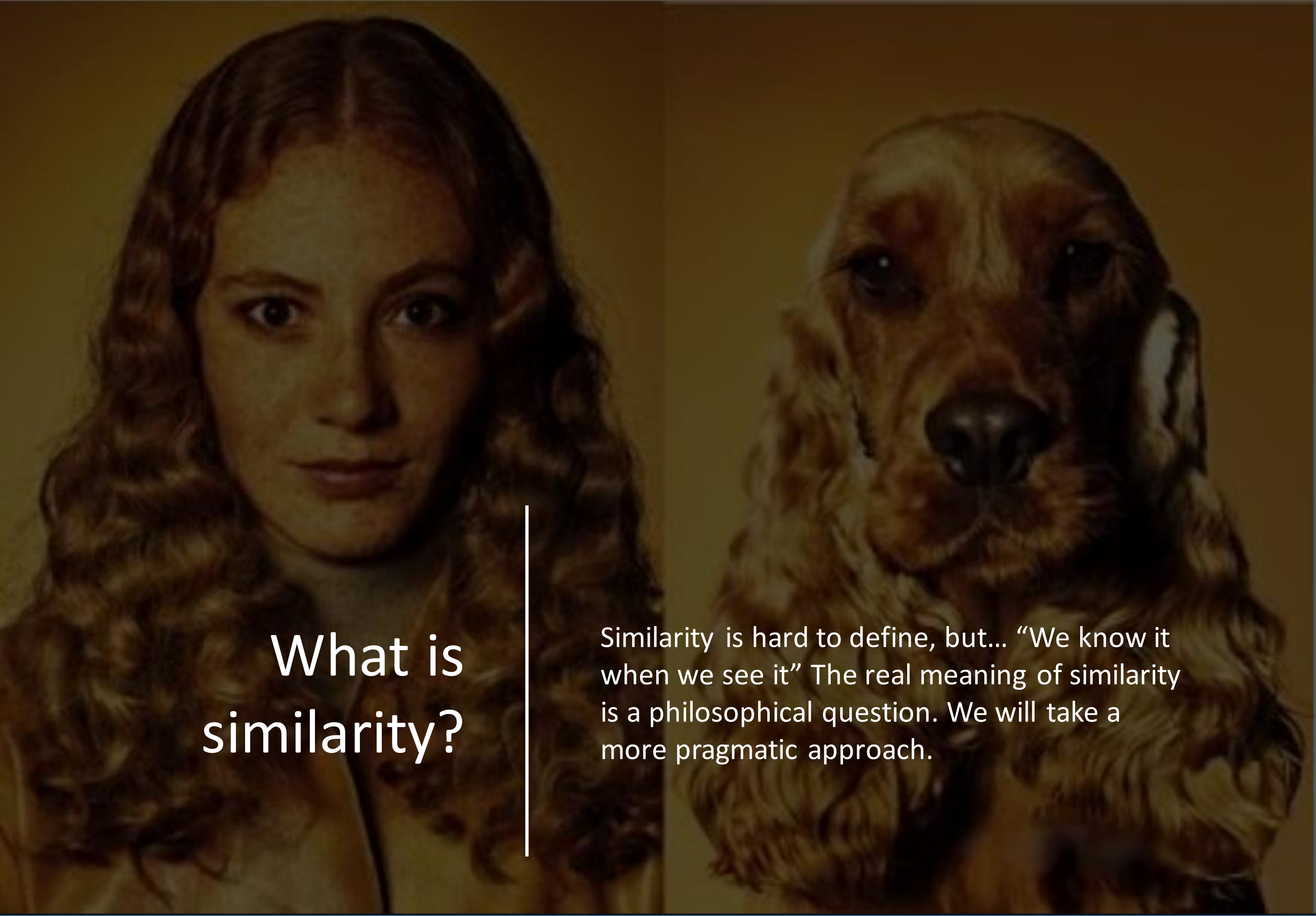


What is similarity?

Similarity is hard to define, but… “We know it when we see it” The real meaning of similarity is a philosophical question. We will take a more pragmatic approach.

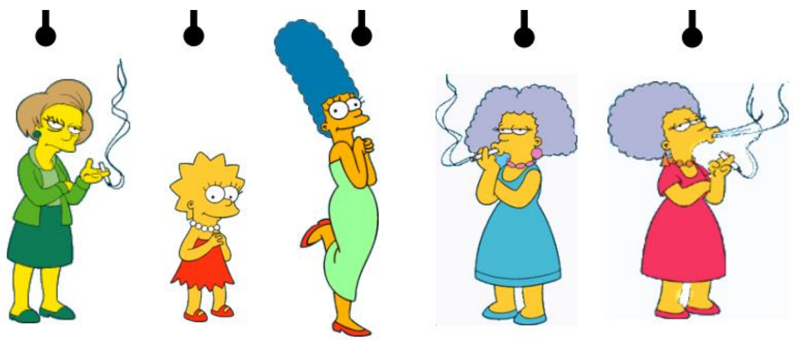
Clustering: distance measure

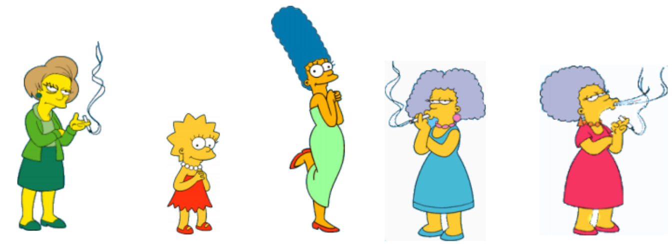
Clustering is an unsupervised learning method. Given items $x_1, \ldots, x_n \in \mathbb{R}^D$, the goal is to group them into clusters. We need a pairwise distance/similarity function between items, and sometimes the desired number of clusters.

Desirable Properties of a Clustering Algorithms

- Scalability (in terms of both time and space)
- Ability to deal with different data types
- Minimal requirements for domain knowledge to determine input parameters
- Interpretability and usability Optional
  - Incorporation of user-specified constraints

Animated example

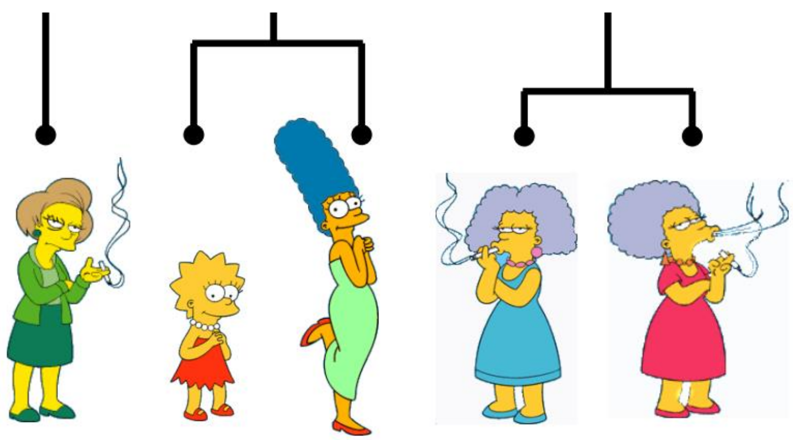


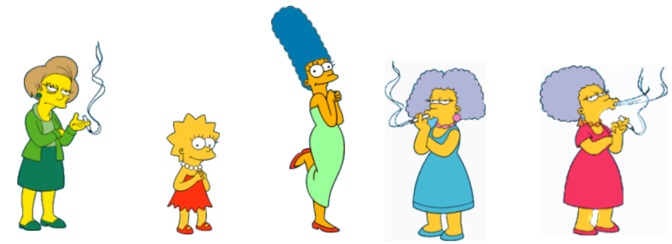


0	8	8	7	7
	0	2	4	4
		0	3	3
			0	1
				0

[source]

Animated example





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[source]

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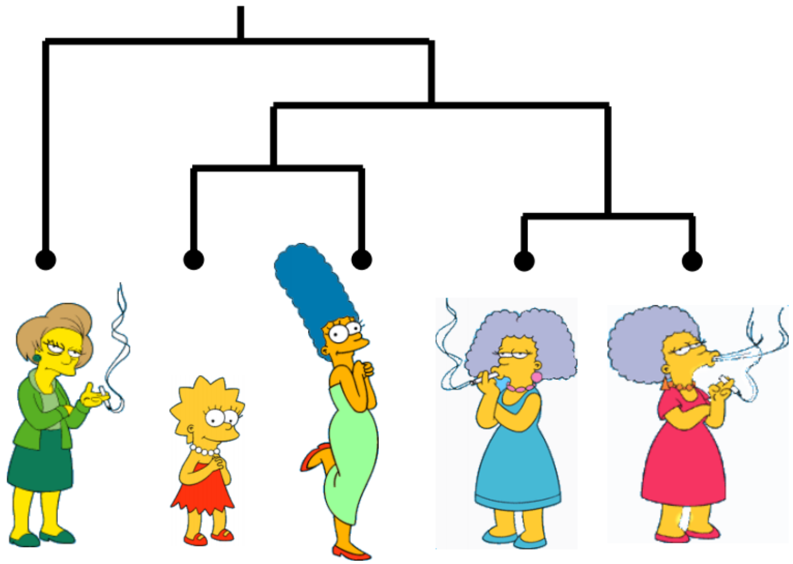

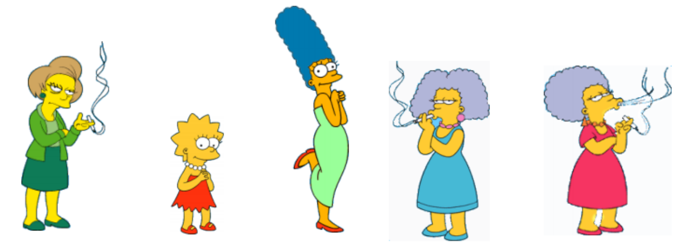

0	8	8	7	7
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			0	1
				0

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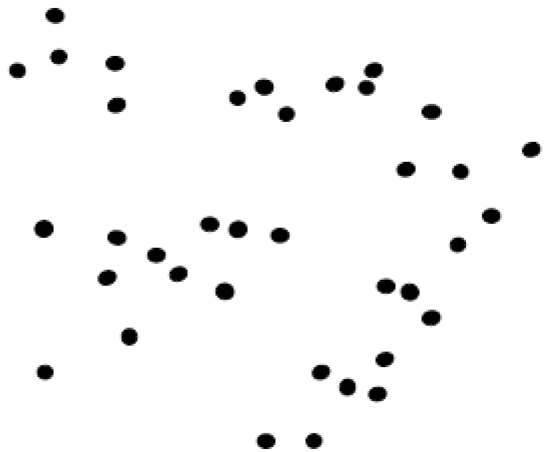
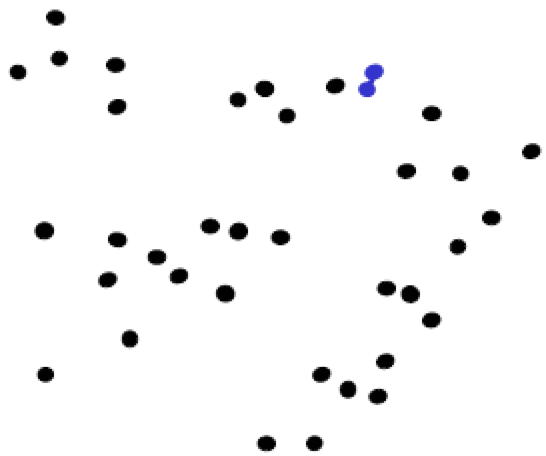
Agglomerative clustering



1. Say "Every point is its own cluster"

Slide credit: Andrew Moore

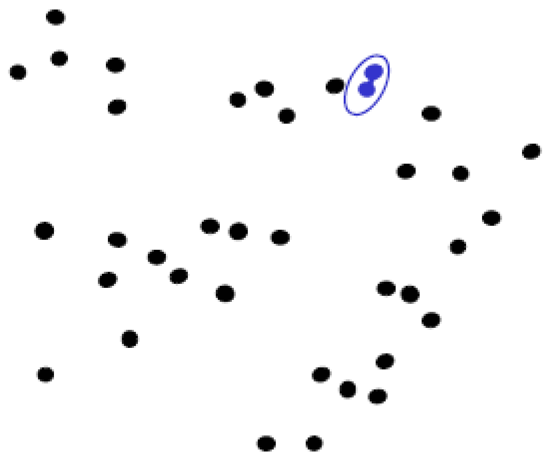
Agglomerative clustering



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

Slide credit: Andrew Moore

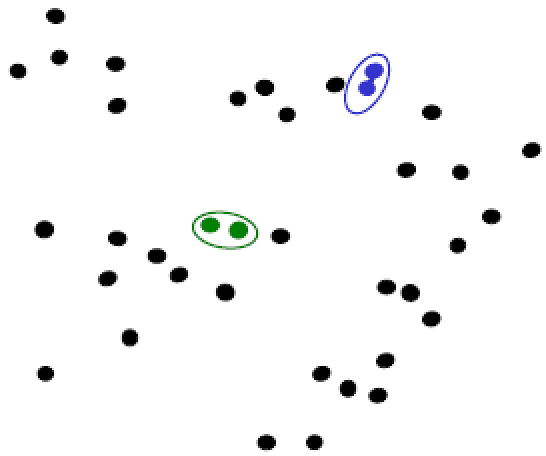
Agglomerative clustering



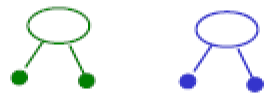
1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster

Slide credit: Andrew Moore

Agglomerative clustering

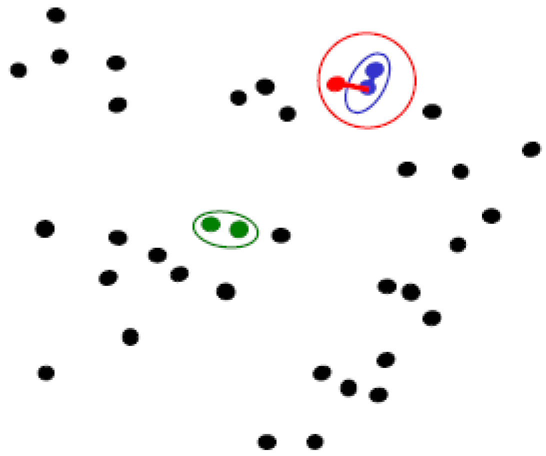


1. Say "Every point is its own cluster"
2. Find "most similar" pair of clusters
3. Merge it into a parent cluster
4. Repeat



Slide credit: Andrew Moore

Agglomerative clustering



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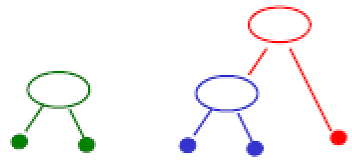
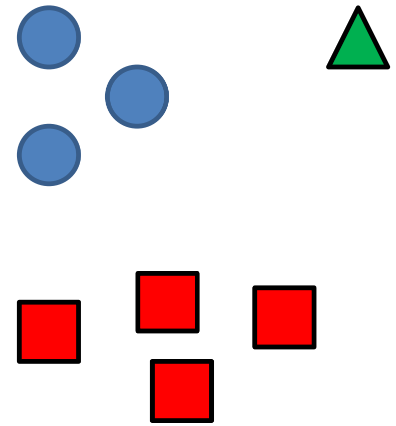


Slide credit: Andrew Moore

Agglomerative clustering

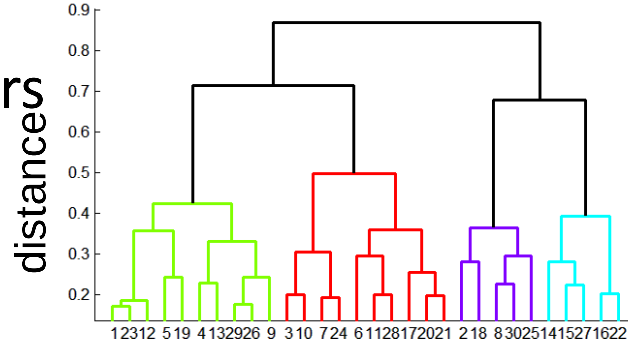
How to define cluster similarity?



- 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



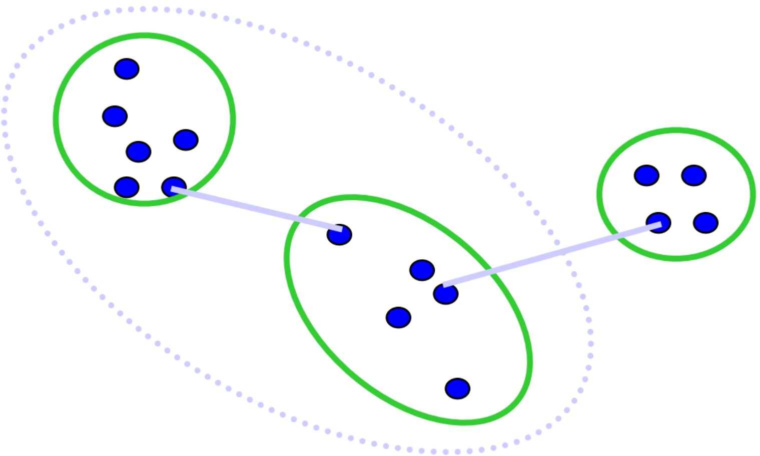
Agglomerative Hierarchical Clustering - Algorithm

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 measures of nearest clusters

Single Link

- $d(C_i, C_j) = \min_{x \in C_i, x' \in C_j} d(x, x')$. 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.

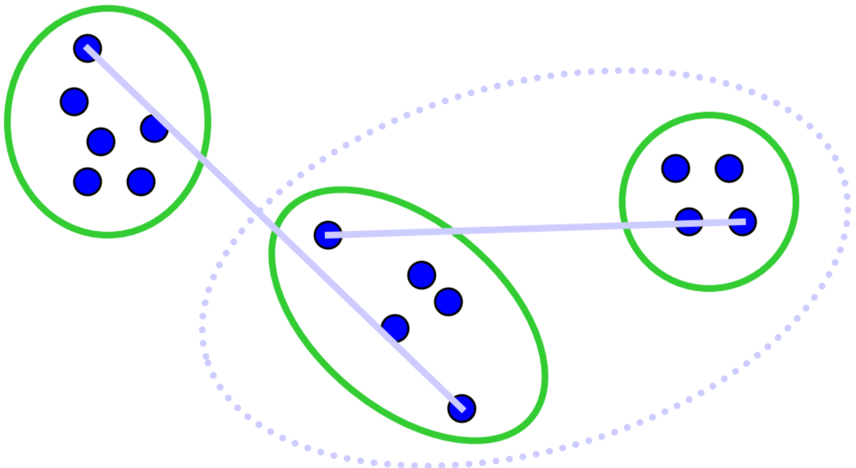


Long, skinny clusters

Different measures of nearest clusters

Complete Link

- $d(C_i, C_j) = \max_{x \in C_i, x' \in C_j} d(x, x')$. This is known as *complete-linkage*. Clusters tend to be compact and roughly equal in diameter.

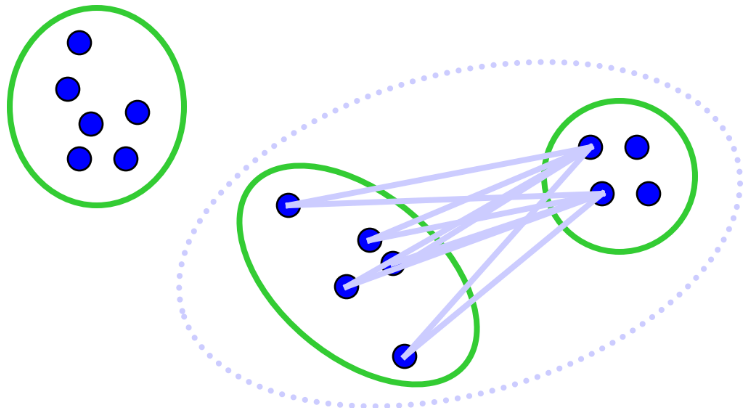


Tight clusters

Different measures of nearest clusters

Average Link

- $d(C_i, C_j) = \frac{\sum x \in C_i, x' \in C_j \, d(x, x')}{|C_i| \cdot |C_j|}$. This is the average distance between items. Somewhere between single-linkage and complete-linkage.



Robust against noise.

Conclusions: Agglomerative Clustering

Good

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

Bad

- May have imbalanced clusters.
- Still have to choose number of clusters or threshold.
- Does not scale well. Runtime of $O(n^3)$.
- Can get stuck at a local optima.

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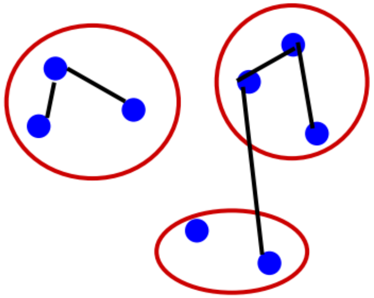
How do we segment using Clustering?

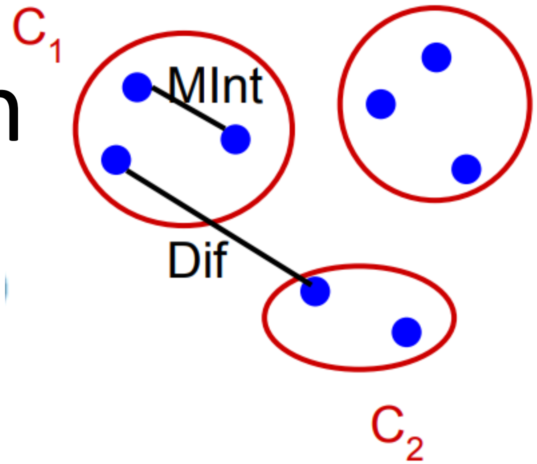
- Solution: Oversegmentation algorithm
  - Introduced by *Felzenszwalb and Huttenlocher* in the paper titled *Efficient Graph-Based Image Segmentation.*

Problem Formulation



- Graph G = (V, E)
- V is set of nodes (i.e. pixels)
- E is a set of undirected edges between pairs of pixels
- w(vi , vj) is the weight of the edge between nodes vi and vj .
- S is a segmentation of a graph G such that G’ = (V, E’) where E’ ⊂ E.
- S divides G into G’ such that it contains distinct clusters C.

Predicate for Segmentation



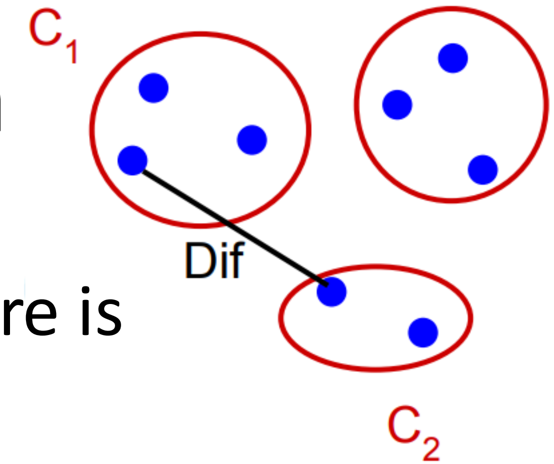
- Predicate D determines whether there is a boundary for segmentation.

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

Where

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

Predicate for Segmentation



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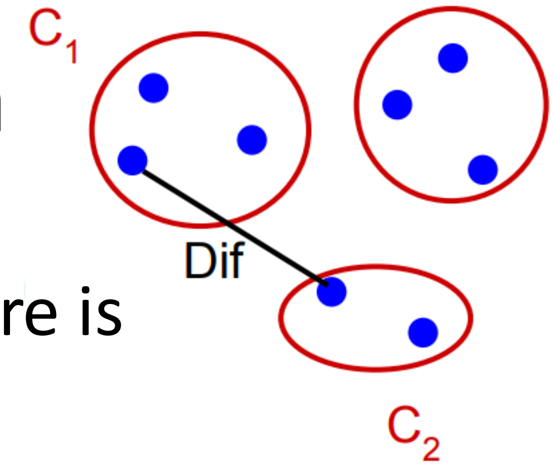
$$Merge(C_1, C_2) = \begin{cases} True & \text{if } dif(C_1, C_2) < in(C_1, C_2) \\ False & otherwise \end{cases}$$

$$dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (C_1, C_2) \in E} w(v_i, v_j)$$

The different between two components is the minimum weight edge that connects a node v_i in clusters C1 to node v_j in C2

Predicate for Segmentation



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$$dif(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (C_1, C_2) \in E} w(v_i, v_j)$$

$$in(C_1, C_2) = \min_{C \in \{C_1, C_2\}} \left[\max_{v_i, v_j \in C} \left[w(v_i, v_j) + \frac{k}{|C|} \right] \right]$$

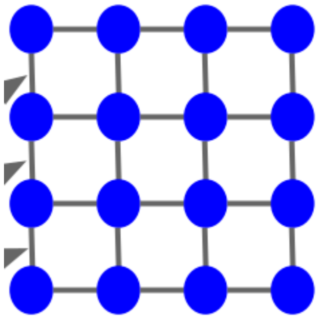
In(C1, C2) is to the maximum weight edge that connects two nodes in the same component.

Predicate for Segmentation

- $k/|C|$ sets the threshold by which the components need to be different from the internal nodes in a component.
- Properties of constant k:
  - If k is large, it causes a preference of larger objects.
  - k does not set a minimum size for components.

Features and weights

- Project every pixel into feature space defined by (x, y, r, g, b).
- Every pixel is connected to its 8 neighboring pixels and the weights are determined by the difference in intensities.
- Weights between pixels are determined using L2 (Euclidian) distance in feature space.



- Edges are chosen for only top ten nearest neighbors in feature space to ensure run time of O(n log n) where n is number of pixels.

Results

What we have learned today?

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