Lecture: Segmentation

Juan Carlos Niebles and Ranjay Krishna
Stanford Vision and Learning Lab

CS 131 Roadmap

Pixels	Segments	Images	Videos	Web
Convolutions Edges Descriptors	Resizing Segmentation Clustering	Recognition Detection Machine learning	Motion Tracking	Neural networks Convolutional neural networks

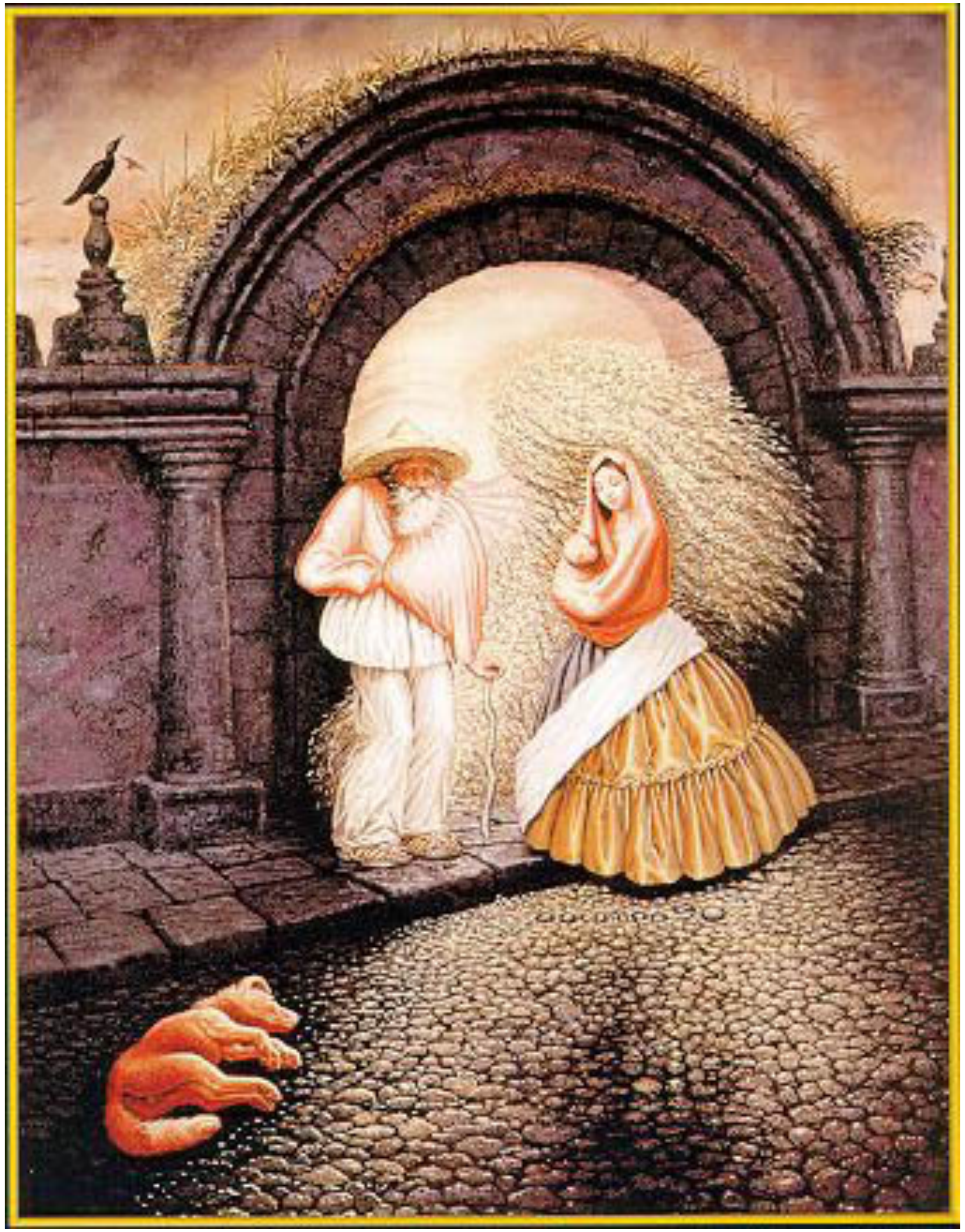
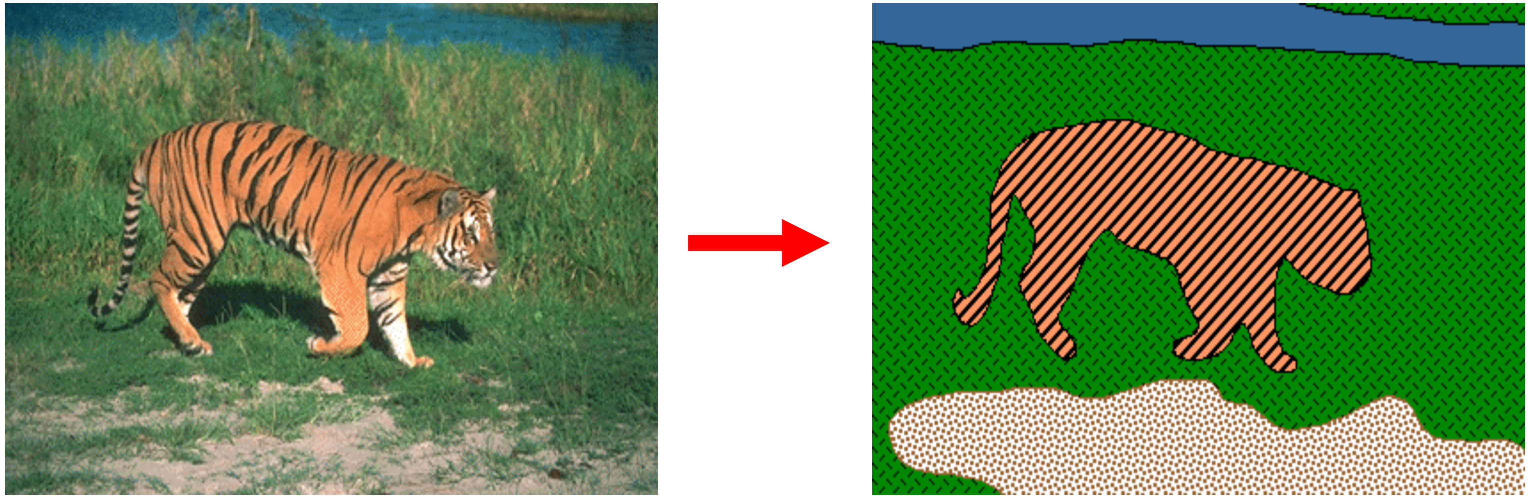


Image Segmentation

- Goal: identify groups of pixels that go together

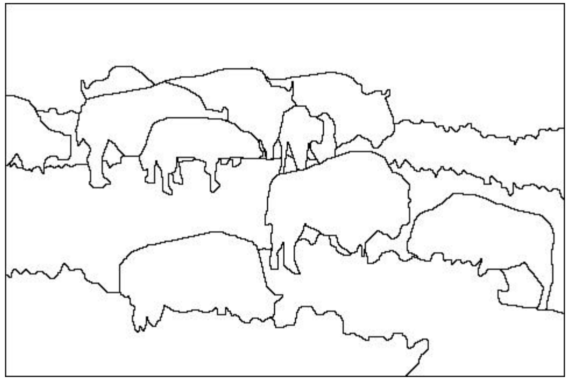


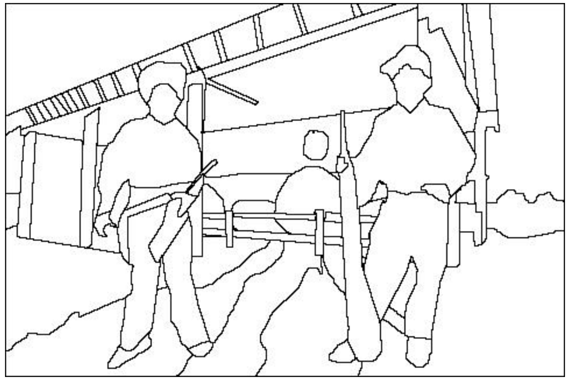
Slide credit: Steve Seitz, Kristen Grauman

The Goals of Segmentation

- Separate image into coherent "objects"

Image | Human segmentation



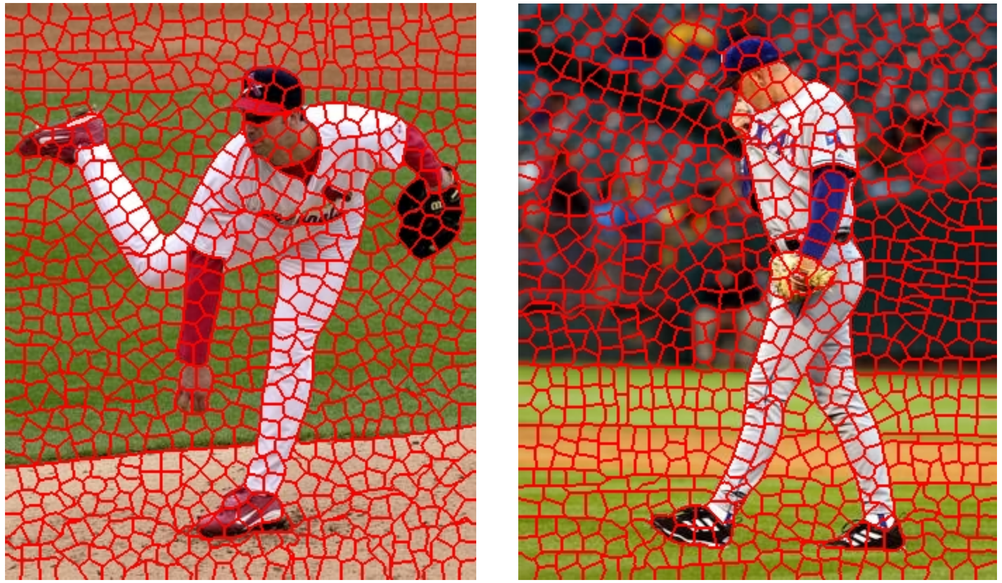


Slide credit: Svetlana Lazebnik

The Goals of Segmentation

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

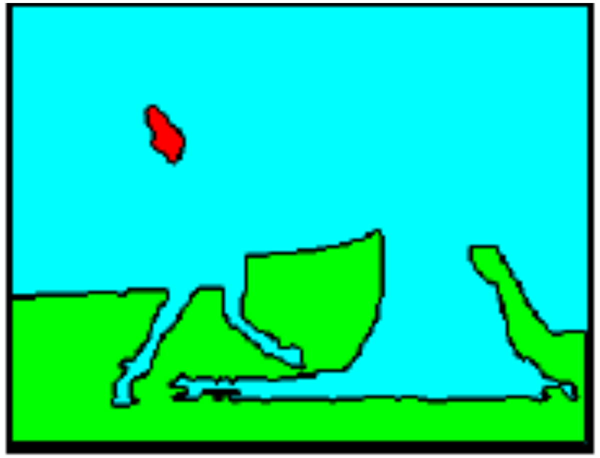
“superpixels”



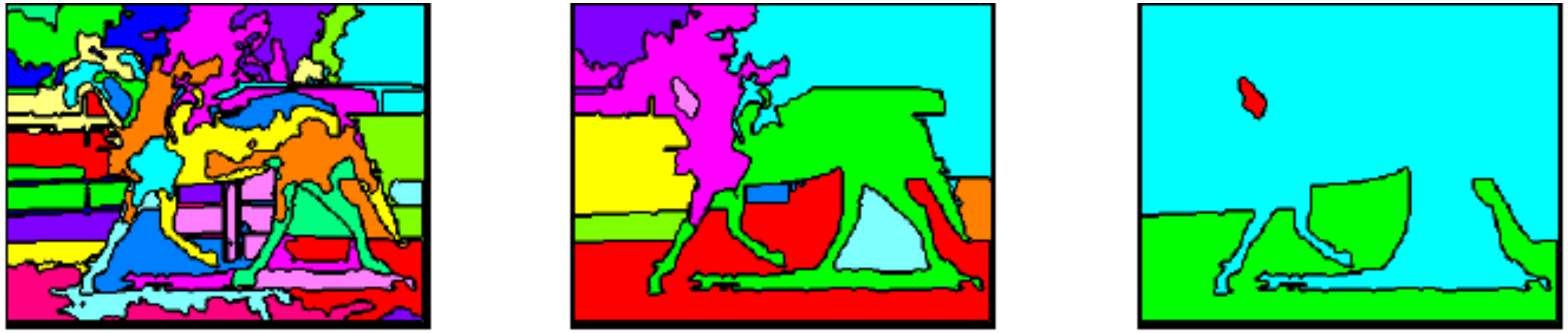
X. Ren and J. Malik. [Learning a classification model for segmentation.] ICCV 2003.

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?

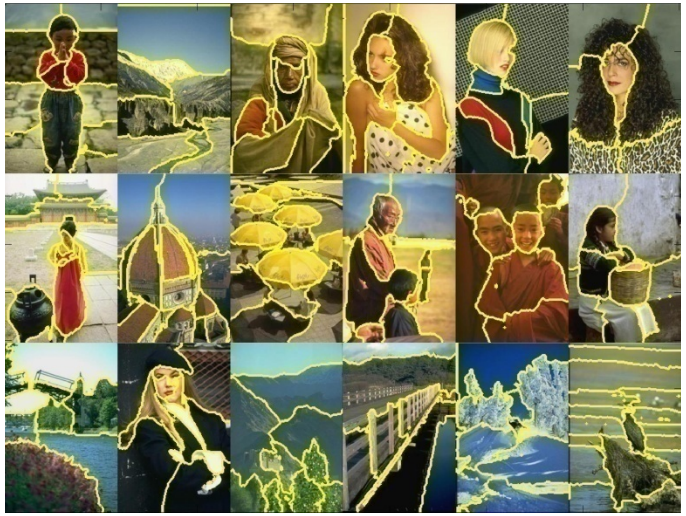
Slide: Derek Hoiem

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

Examples of Grouping in Vision



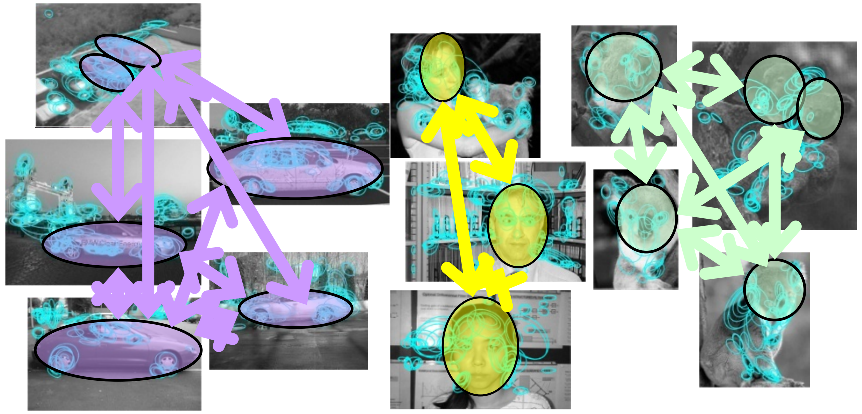
Determining image regions

Grouping video frames into shots

Figure-ground

What things should be grouped?

What cues indicate groups?



Object-level grouping

Slide credit: Kristen Grauman

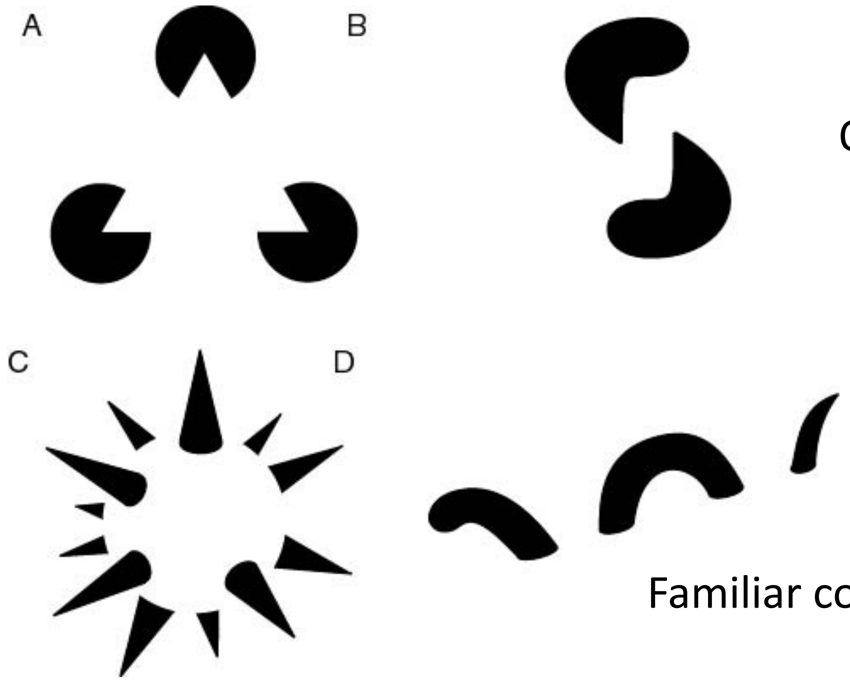
What we will learn today

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

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

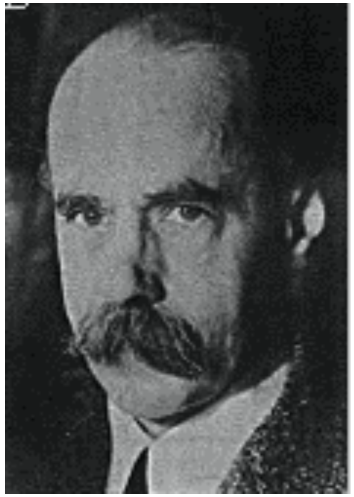
Slide credit: Svetlana Lazebnik

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)

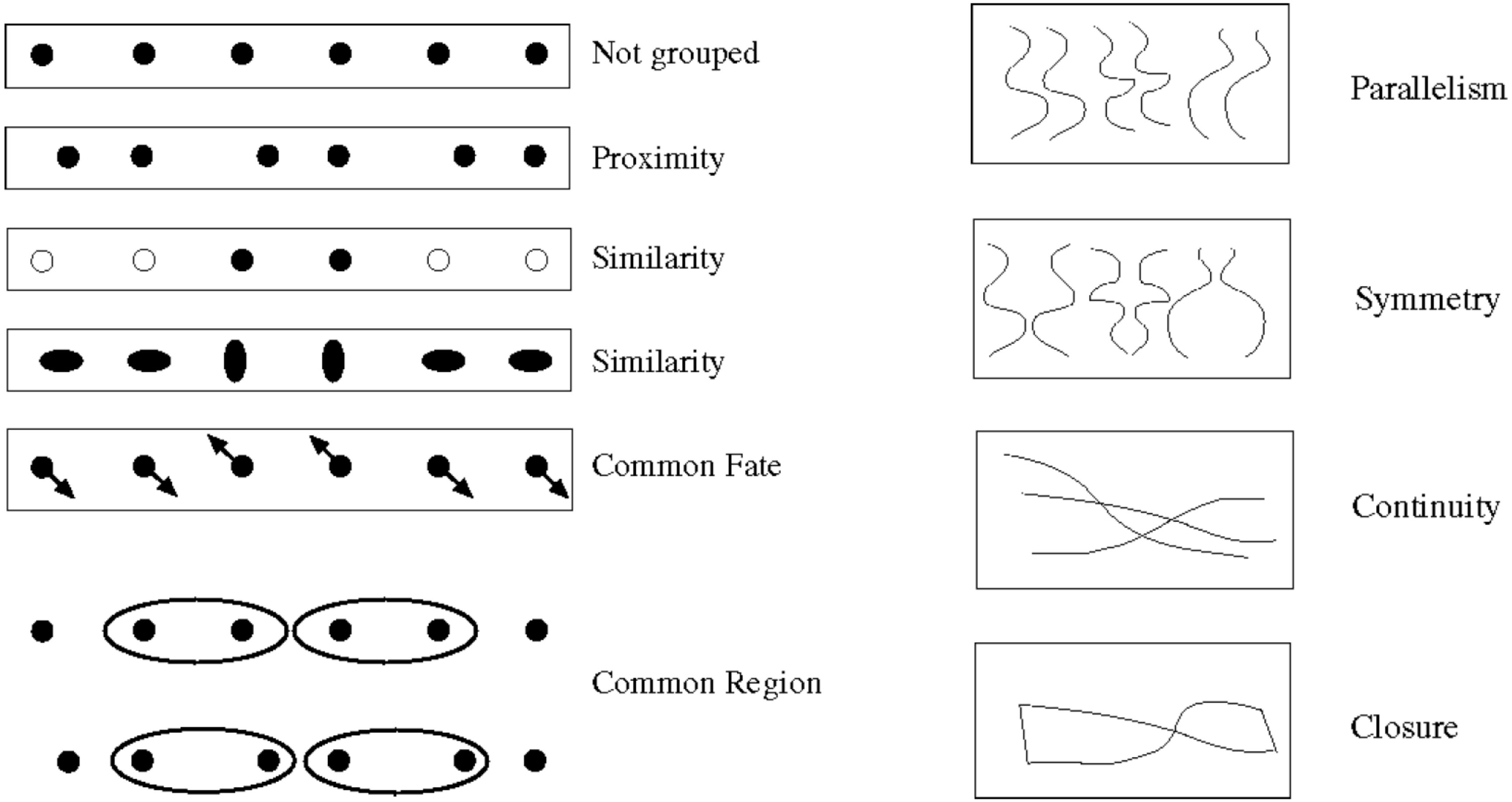
"I stand at the window and see a house, trees, sky. Theoretically I might say there were 327 brightnesses and nuances of colour. Do I have "327"? No. I have sky, house, and trees."

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

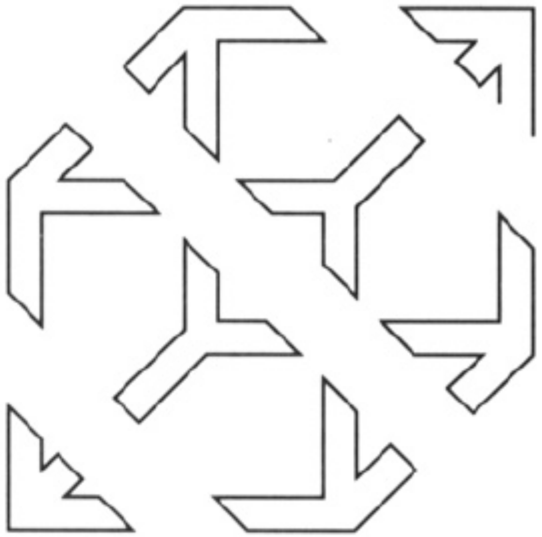
Gestalt Factors



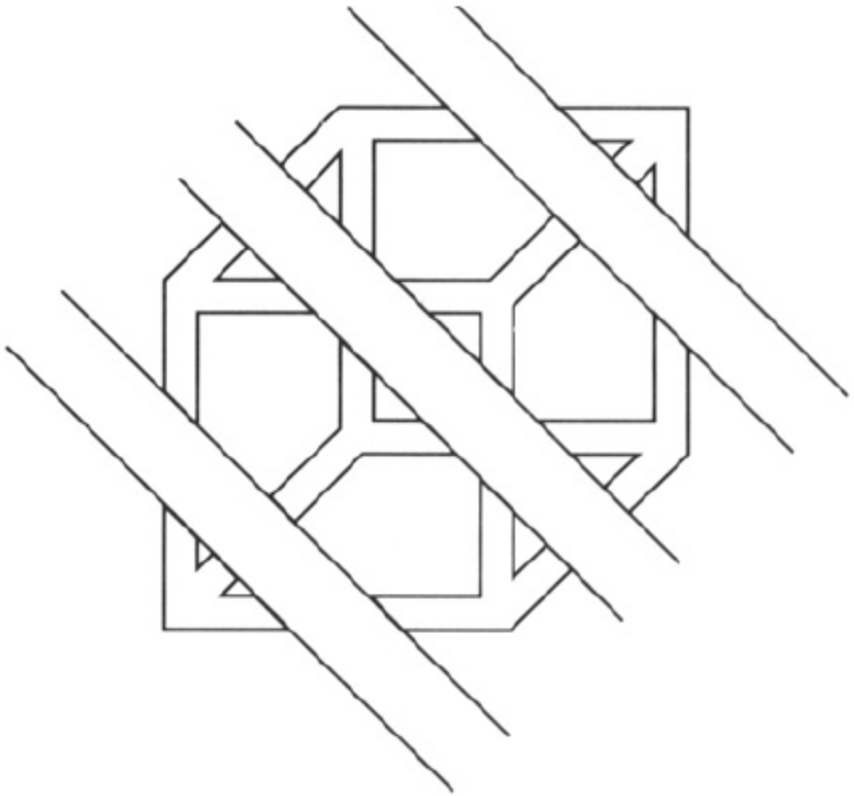
- These factors make intuitive sense, but are very difficult to translate into algorithms.

Image source: Forsyth & Ponce

Continuity through Occlusion Cues



Continuity through Occlusion Cues



Continuity, explanation by occlusion

Continuity through Occlusion Cues

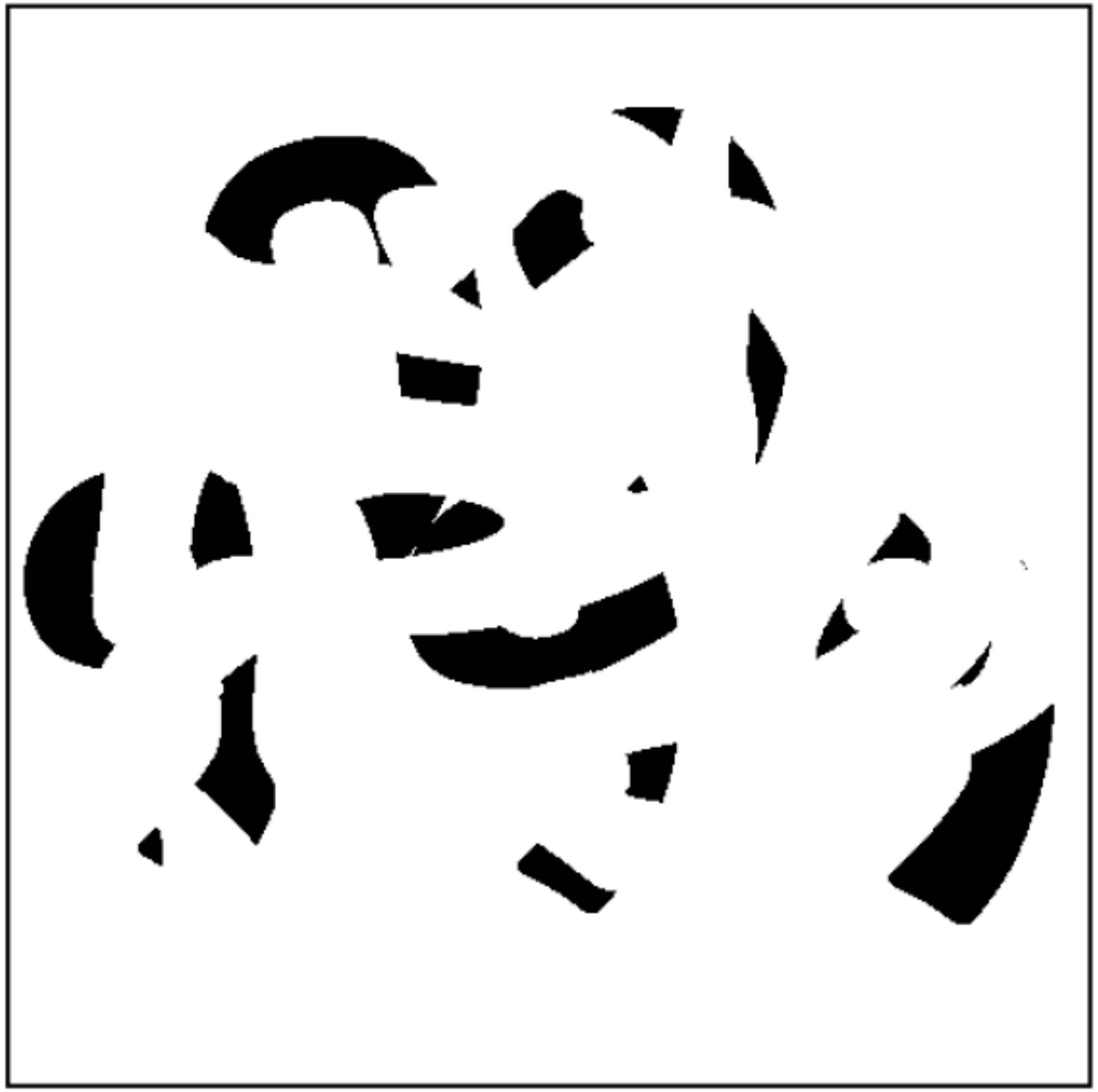
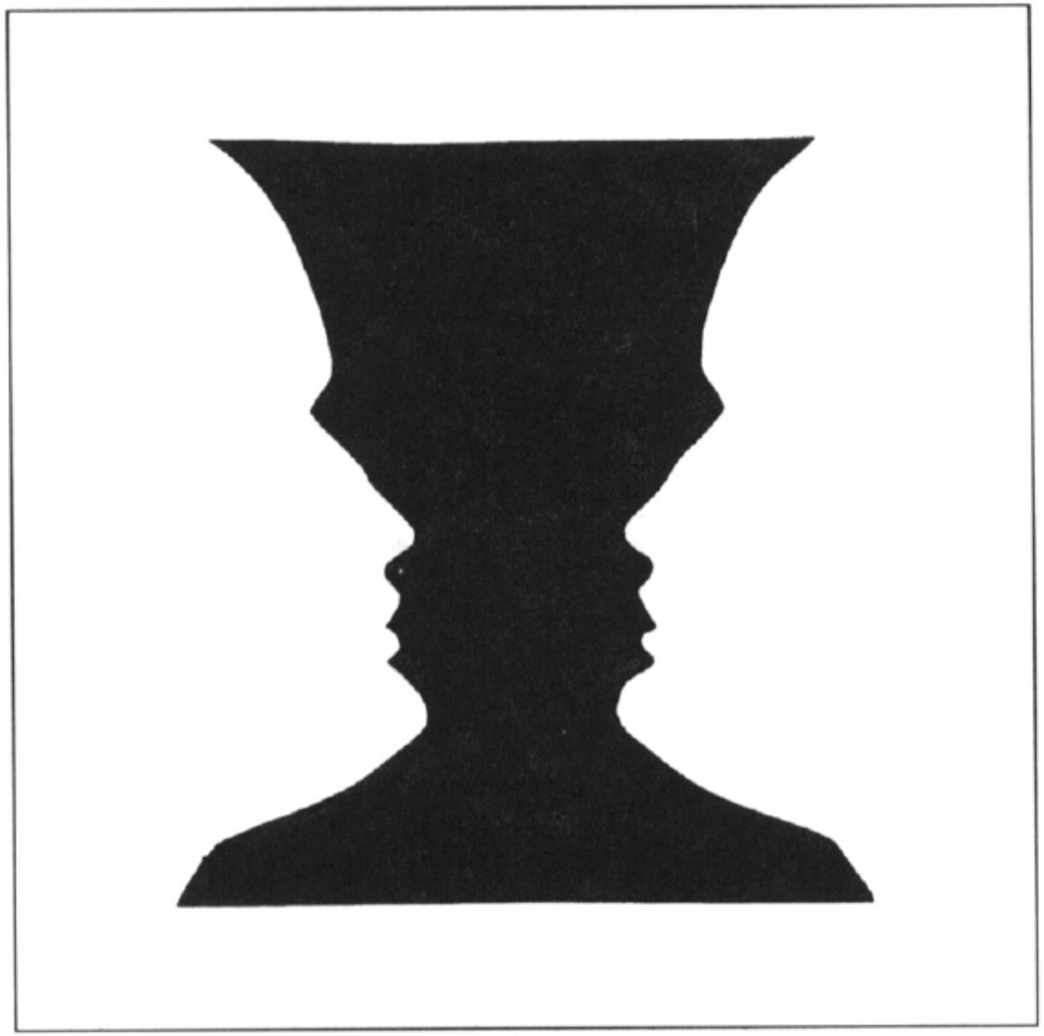


Image source: Forsyth & Ponce

Continuity through Occlusion Cues

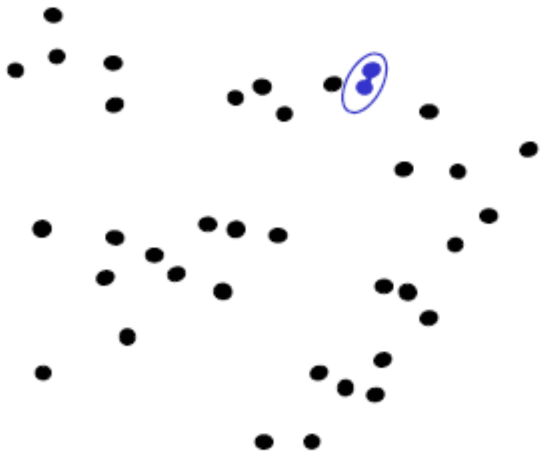
Image source: Forsyth & Ponce

Figure-Ground Discrimination



The Ultimate Gestalt?

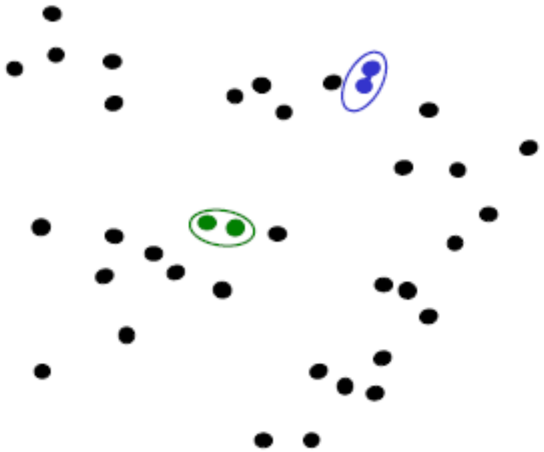
Agglomerative clustering



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



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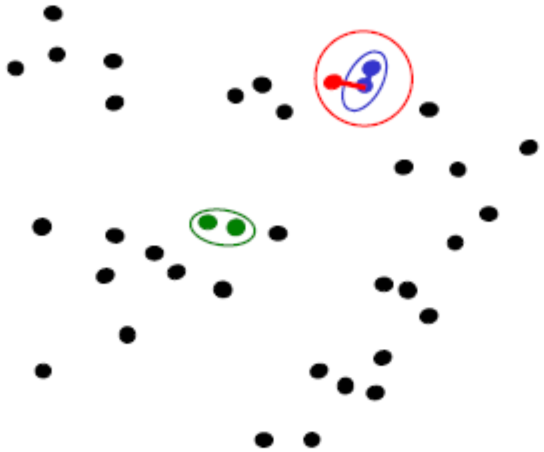
Agglomerative clustering



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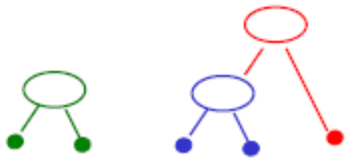
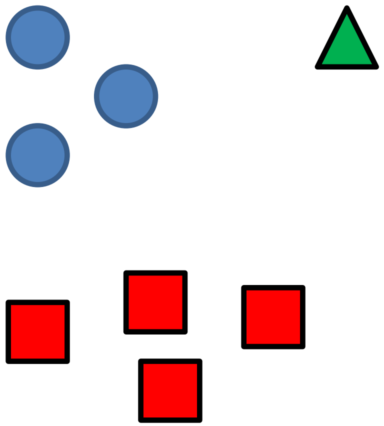


Slide credit: Andrew Moore

Agglomerative clustering

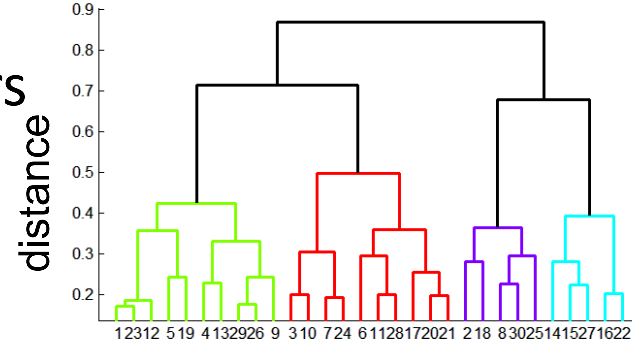
How to define cluster similarity?

- 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



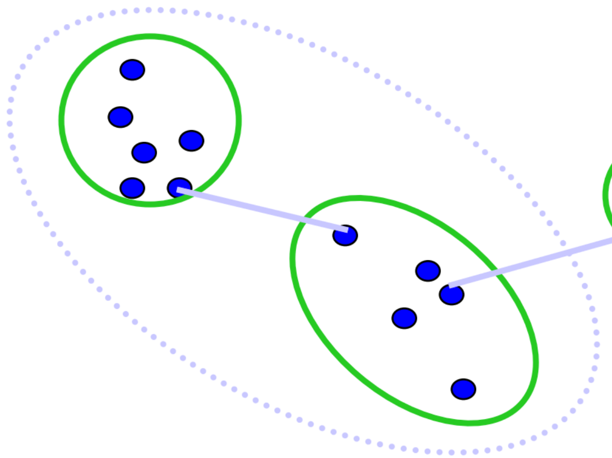
Agglomerative Hierarchical Clustering - Algorithm

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.

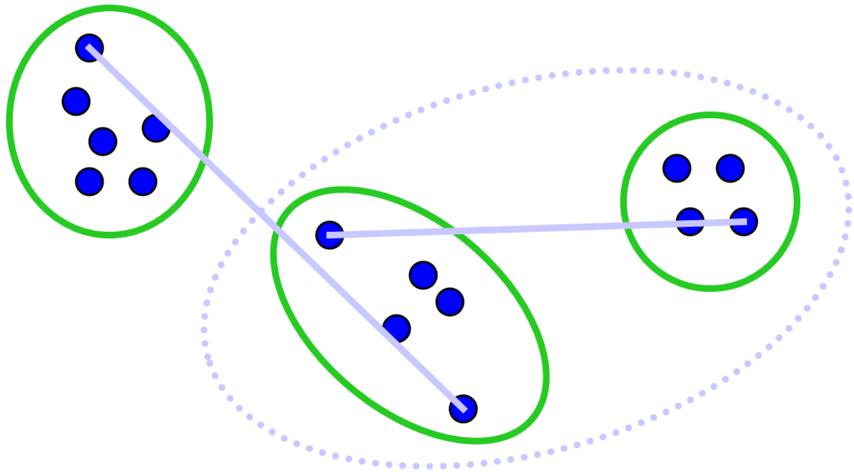


Long, skinny clusters

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.

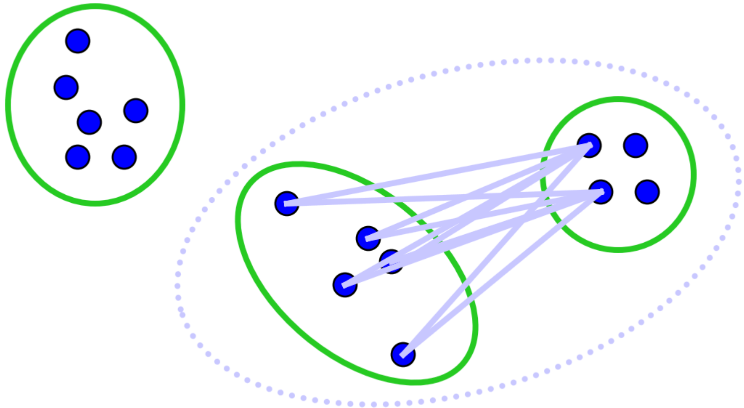


Tight clusters

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.