Text Analytics & Business Application

Text Clustering

Qinglai He
Department of Operations and Information Management
Wisconsin School of Business

WISCONSIN SCHOOL OF BUSINESS

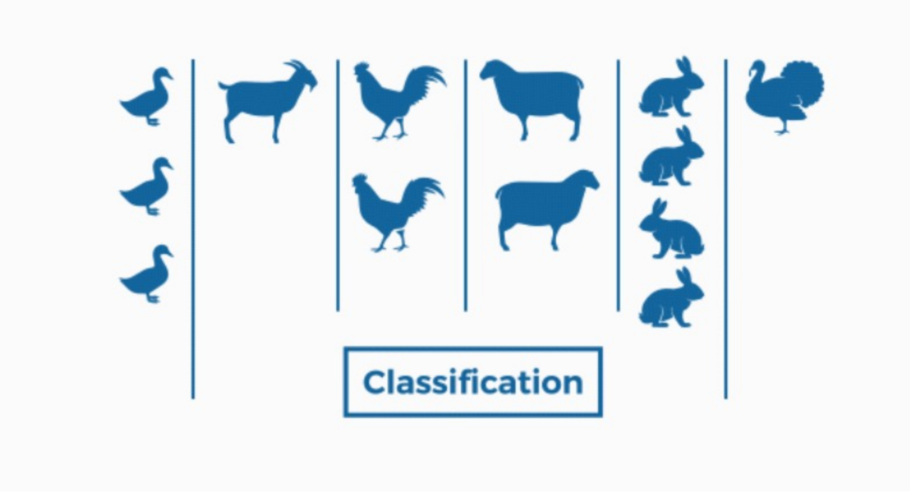
Outline of Text Clustering

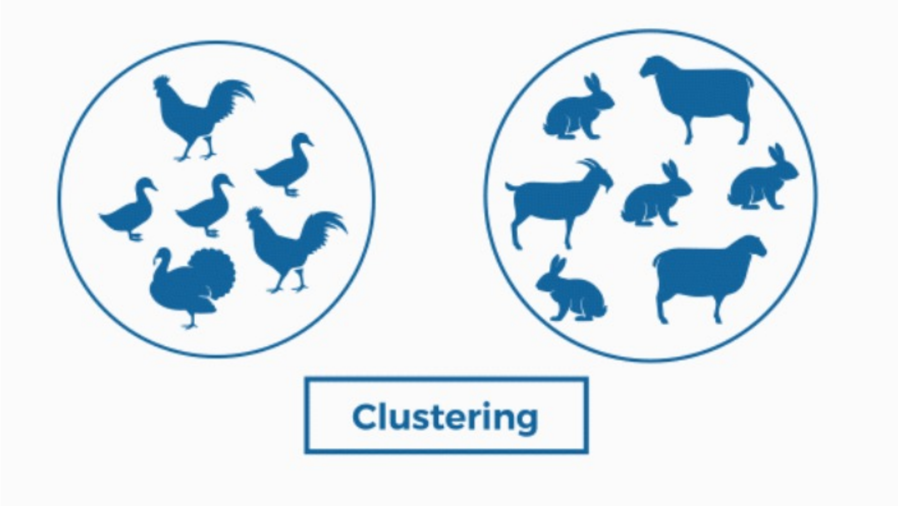
- Intro to text clustering
- Clustering method
  - K-means
  - Agglomerative clustering

Intro to Text Clustering

Classification vs. Clustering

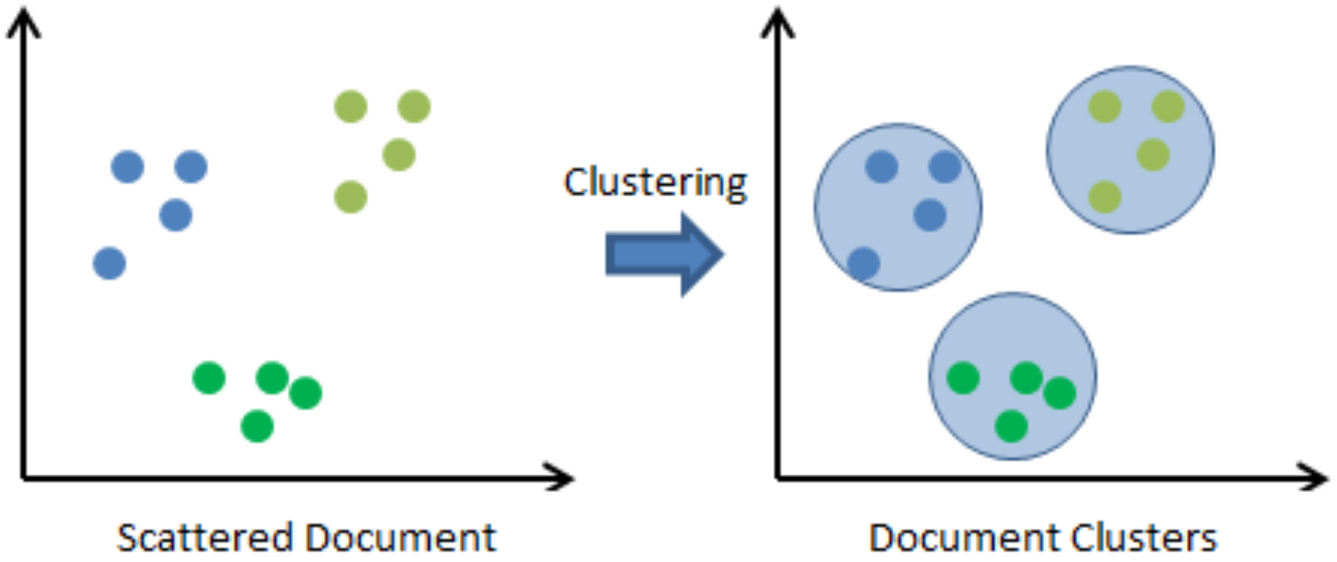
- **Classification** is supervised learning
  - It has labeled target variable
  - Example algorithms:
    - Logistic regression
    - Naive Bayes classifier
    - Support vector machines
- **Clustering** is unsupervised Learning
  - It does not have labeled target variable
  - Grouping the instances based on their similarity
  - Example algorithms:
    - K-means
    - Fuzzy algorithm
    - Gaussian (EM) clustering algorithm





Text Clustering

- Clustering can be incredibly useful for exploratory text analysis.
- With text data, each instance is a single document or utterance, and the features are its tokens, vocabulary, structure, metadata, etc.



Clustering by Document Similarity

- Many features of a document can inform similarity, from words and phrases to grammar and structure.
- For example:
  - We might group medical records by reported symptoms, saying two patients are similar if both have “nausea and exhaustion.”

Clustering by Document Similarity

- There are a number of different measures that can be used to determine document similarity:

String Matching	Distance Metrics	Relational Matching	Other Matching
Edit Distance - Levenstein - Smith-Waterman - Affine **Alignment** - Jaro-Winkler - Soft-TFIDF - Monge-Elkan **Phonetic** - Soundex - Translation	- Euclidean - Manhattan - Minkowski **Text Analytics** - Jaccard - TFIDF - Cosine similarity	**Set Based** - Dice - Tanimoto (Jaccard) - Common Neighbors - Adar Weighted **Aggregates** - Average values - Max/Min values - Medians - Frequency (Mode)	- Numeric distance - Boolean equality - Fuzzy matching - Domain specific **Gazettes** - Lexical matching - Named Entities (NER)

Applications of Text Clustering

Marketing Segmentation

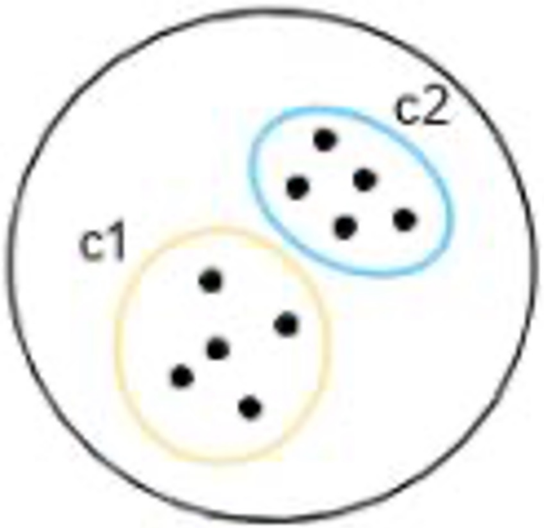
Search Engines

Clustering Method (1)

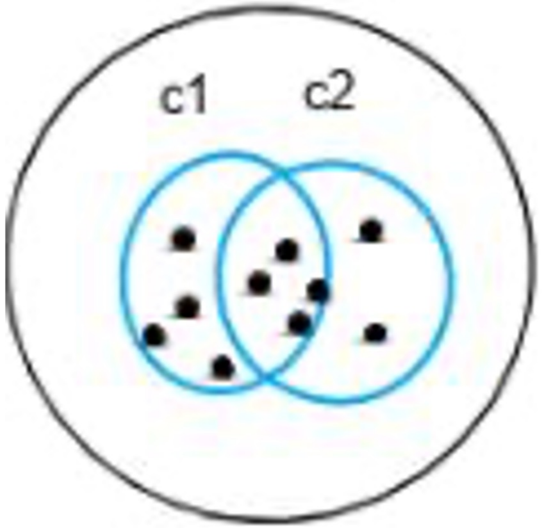
K-means

Clustering Methods

- The various types of clustering are:
  - Partitioning clustering
  - Hierarchical clustering
- Partitioning clustering
  - K-Means clustering
  - Fuzzy C-Means clustering
- Hierarchical clustering
  - Agglomerative clustering
  - Divisive clustering



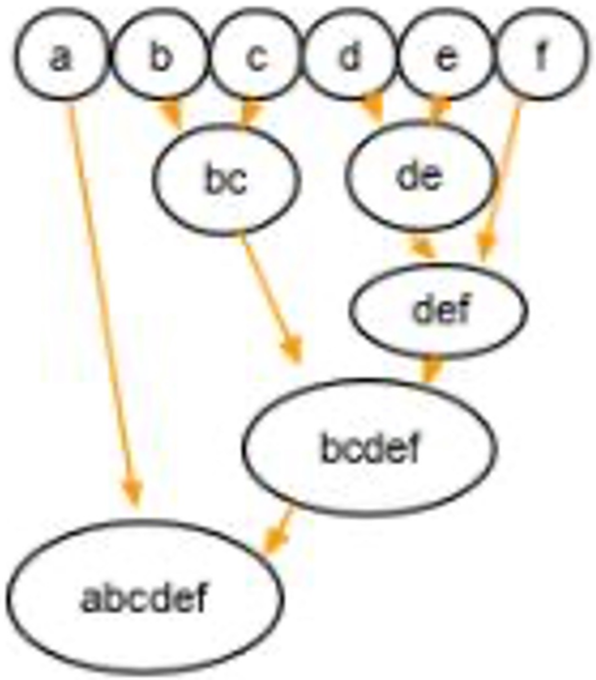
K-Means



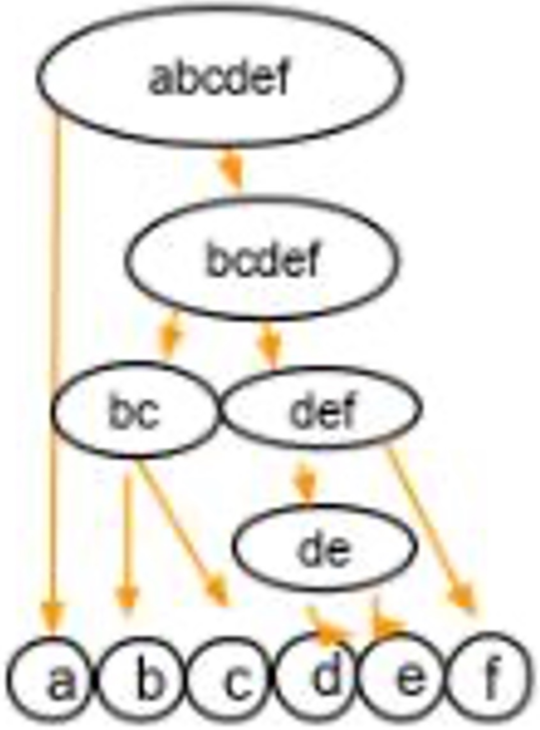
Fuzzy C-Means

Clustering Methods

- The various types of clustering are:
  - Partitioning clustering
  - Hierarchical clustering
- Partitioning clustering
  - K-Means clustering
  - Fuzzy C-Means clustering
- Hierarchical clustering
  - Agglomerative clustering
  - Divisive clustering



Agglomerative clustering



Divisive clustering

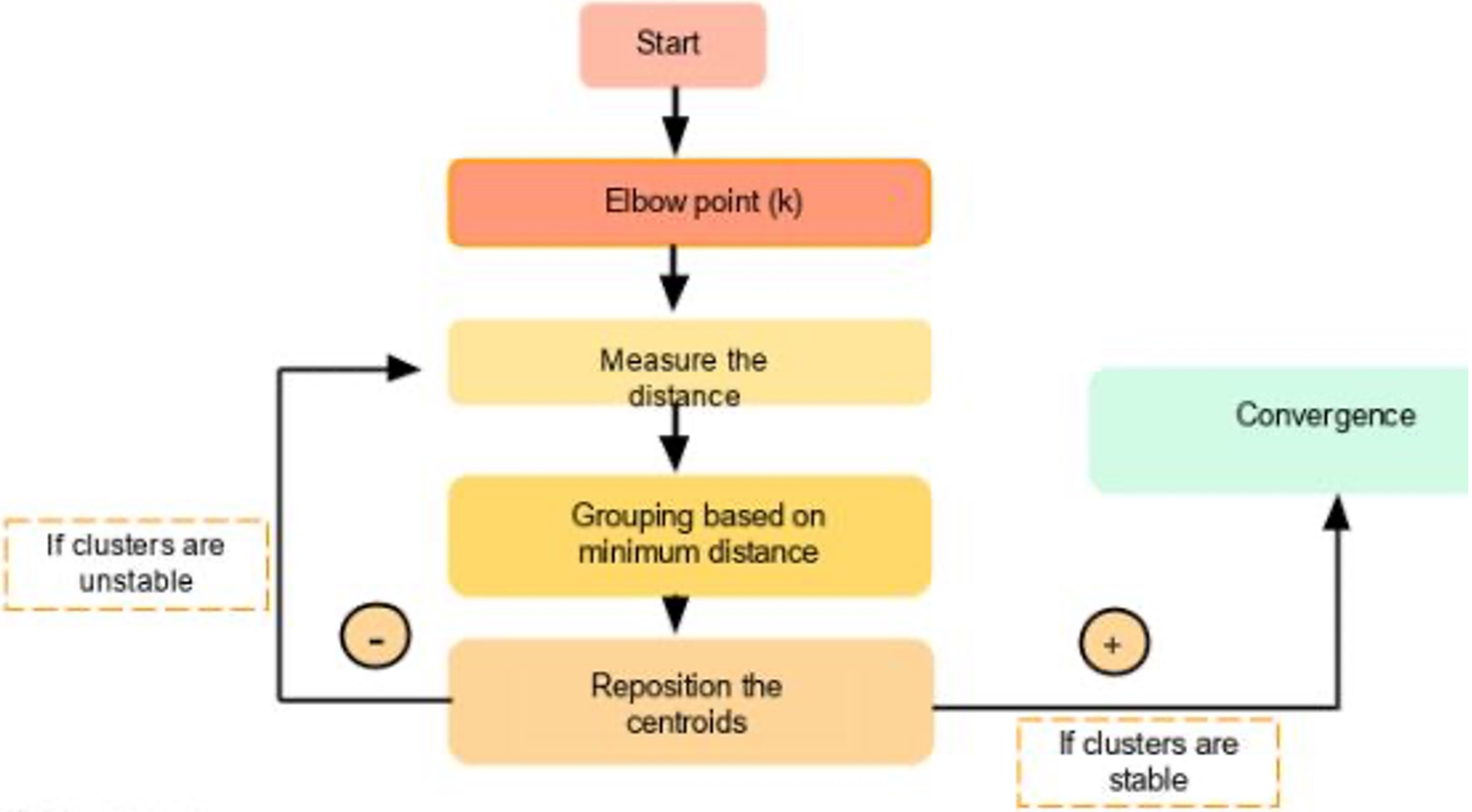
Partitioning Clustering

- **Partitioning clustering** separates documents into groups whose members share maximum similarity as defined by some distance metric.
- It partitions instances into groups that are represented by a central vector (the centroid) or described by a density of documents per cluster.
  - Centroids represent an aggregated value (e.g., mean or median) of all member documents and are a convenient way to describe documents in that cluster.

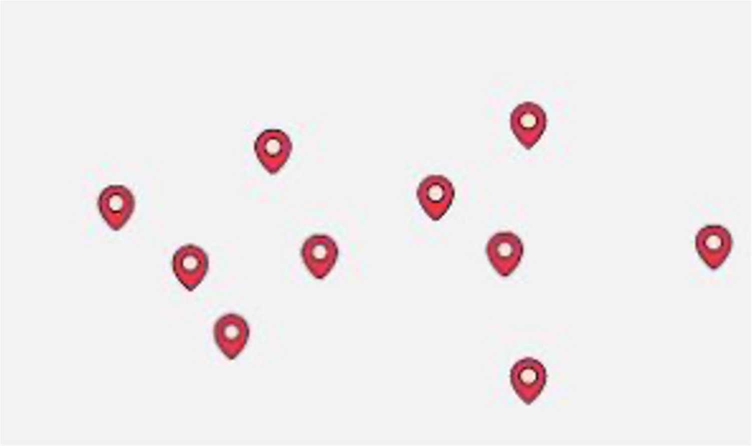
K-means Clustering

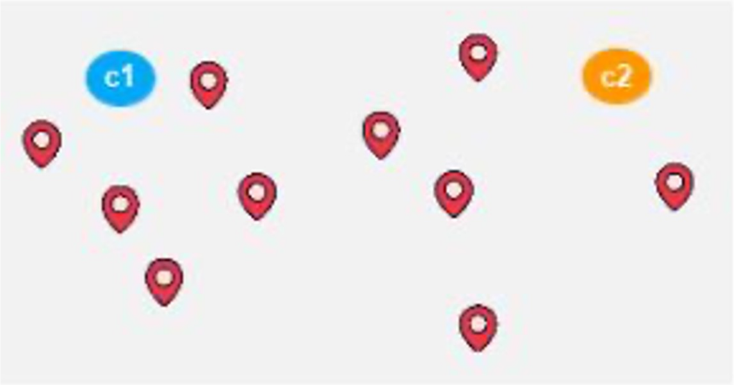
- The *k*-means algorithm is based on the choice of the initial cluster centers. The general process is below.
    1. Specify the *k* value
    2. Randomly assign *k* observations as cluster centers
    3. Assign each observation to its nearest cluster center
    4. Calculate cluster centroids
    5. Reassign each observation to a cluster with the nearest centroid
    6. Recalculate the cluster centroids, and repeat step 5
    7. Stop when reassigning observations can no longer improve within-cluster dispersion.
- Dispersion is defined as the sum of Euclidean distances of observations for their respective cluster centers.
- Results from *k*-means clustering are highly sensitive to the random process for finding the initial cluster centers as well as implementing specific algorithms.

K-means Clustering

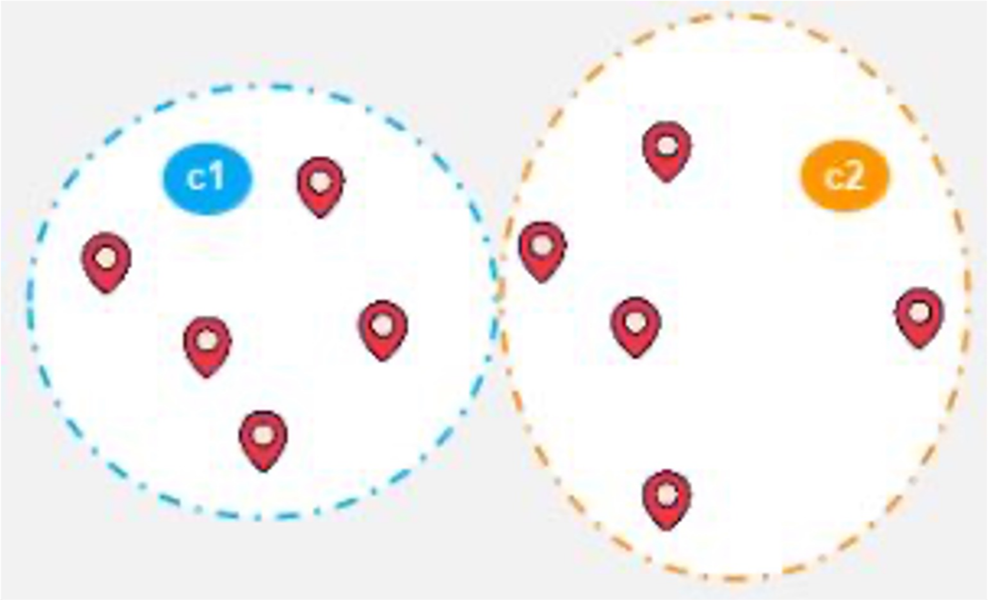


K-means Clustering Steps



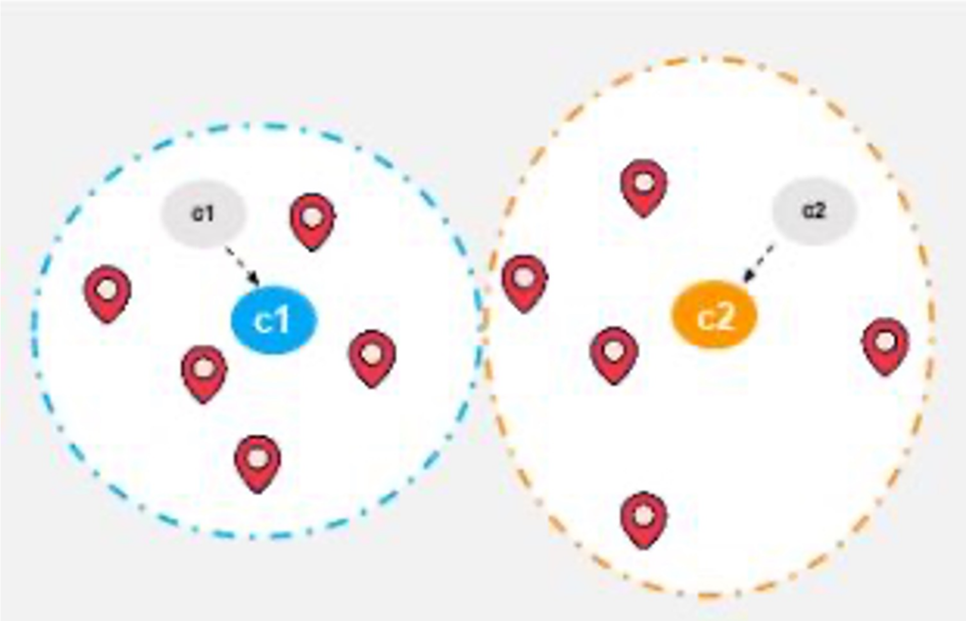


Randomly initiate two cluster centroids

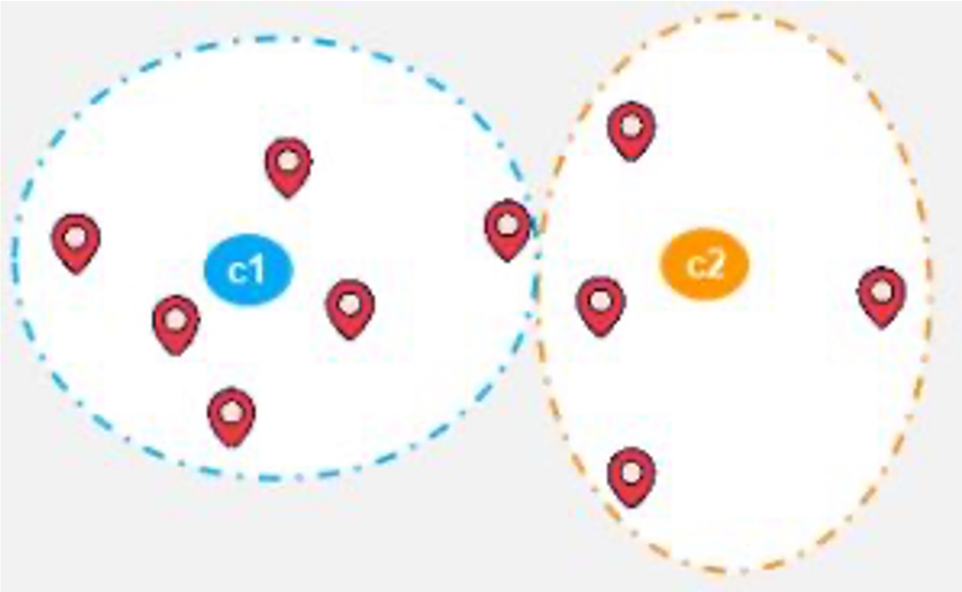


Based on the distance between each data point and centroids, assign each point to a nearest centroid. Then, we form two groups.

K-means Clustering Steps



Compute the actual centroids for each group. Reposition the initial random centroids to the actual centroids.



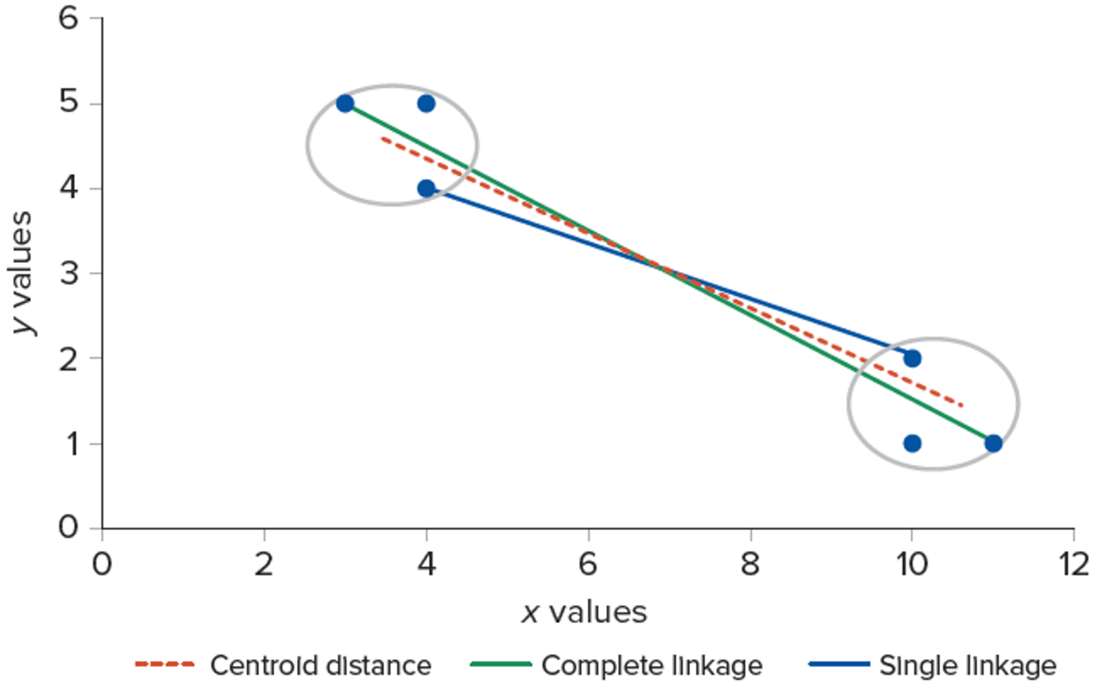
Iterate the centroid update many times until the cluster becomes static.

K-means Clustering

- The objective is to divide the sample into a prespecified number *k* of **non-overlapping** clusters so that each of these *k* clusters is as homogenous as possible.
- The number of clusters *k* needs to be specified prior to performing the analysis.
- We may experiment with different values of *k* until we obtain a desired result.
- In addition, we may have prior knowledge or theories about the subjects under study and can determine the appropriate number of clusters based on domain knowledge.
- The *k*-means clustering method can only be applied to data with numerical variables. For categorical variables, we need to convert them into numerical.

Multiple Linkage Methods to Evaluation (dis)Similarity Between Clusters

- **Single**: nearest distance between a pair of observations not in the same cluster
- **Complete**: farthest distance between a pair of observations not in the same cluster
- **Centroid**: distance between the center/centroid or mean values of the clusters
- **Average**: average distance between all pairs of observations not in the same cluster
- **Ward's**: uses error sum of squares (ESS/WCSS), which is the squared difference between individual observations and the cluster mean; measures the loss of information that occurs when observations are clustered.



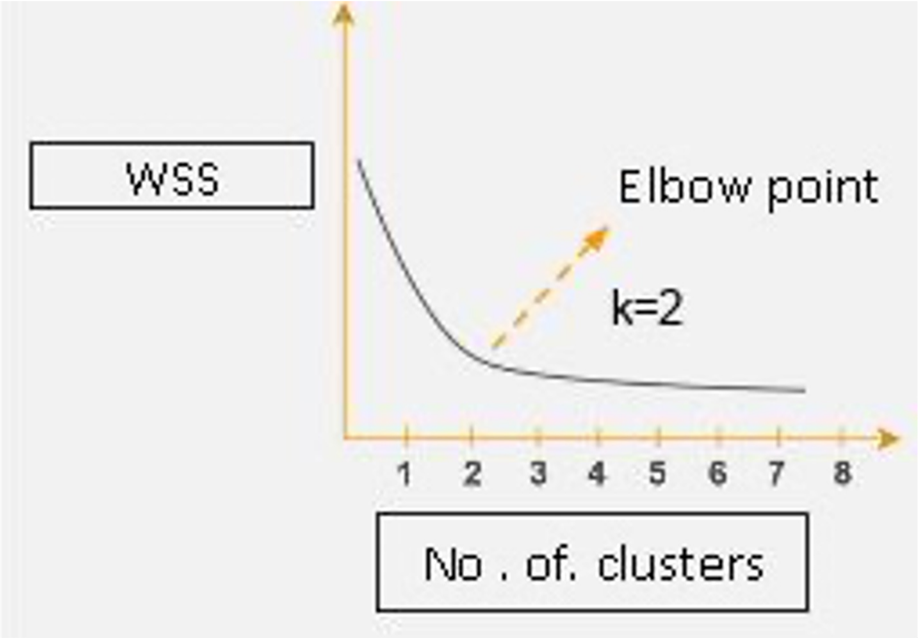
How Should We Choose the Optimal K?

Elbow technique

We need to calculate within-sum-of-squares (WSS or WCSS). WSS is defined as the sum of the squared distance between each member of the cluster and its centroid.

$$WSS = \sum_{i=1}^{m} (x_i - c_i)^2$$

Where x_i = data point and c_i = closest point to centroid



K=2 is the optimal value. There is a gradual change in the value of WSS as the K value increase from 2. Beyond that, increasing the K will not dramatically change the value of WSS.

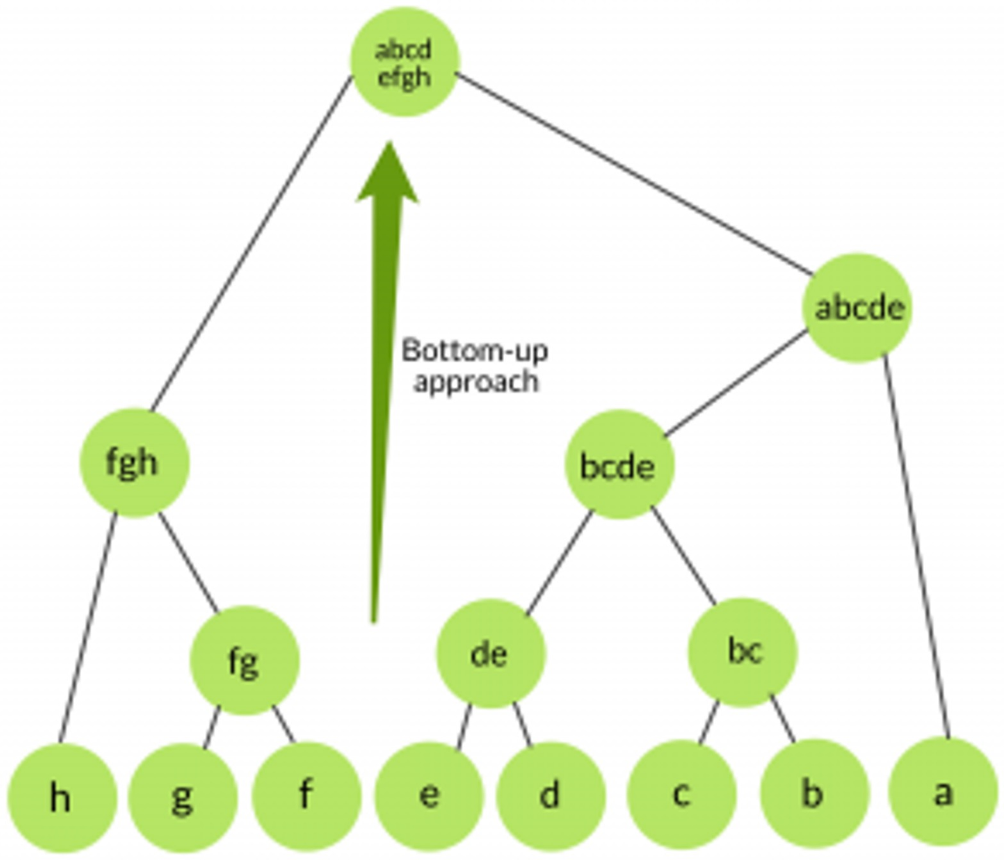

QUIZ

Clustering Method (2)

Agglomerative Clustering

Agglomerative clustering

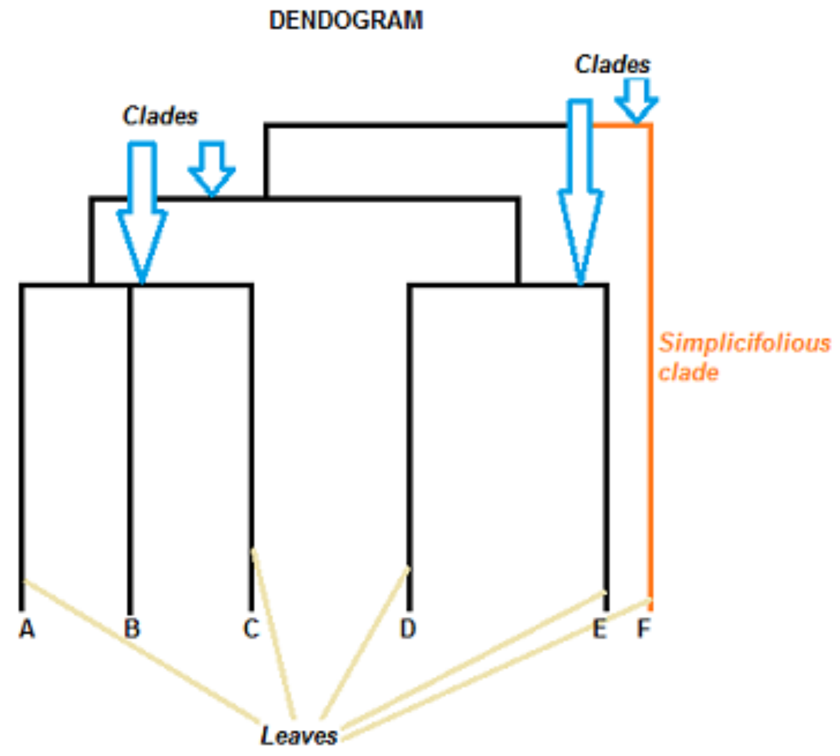
- With AGNES, each observation in the data initially forms its own cluster.
- The algorithm then successively merges these clusters into larger clusters based on their similarity until all observations are merged into one final cluster, referred to as a root.
- Uses (dis)similarity measures.
  - Numeric variable: Euclidean distance or Manhattan distance
  - Categorical variable: matching, Jaccard's coefficient



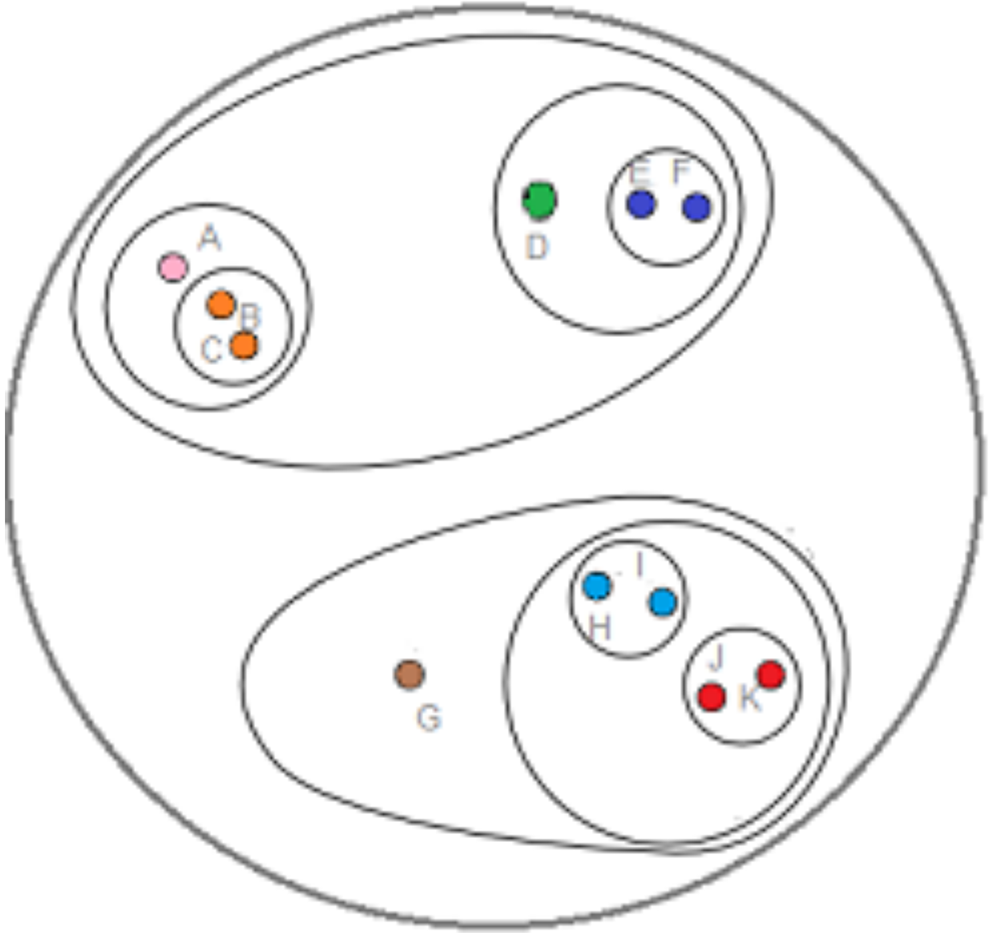
Hierarchical agglomerative clustering

Agglomerative clustering

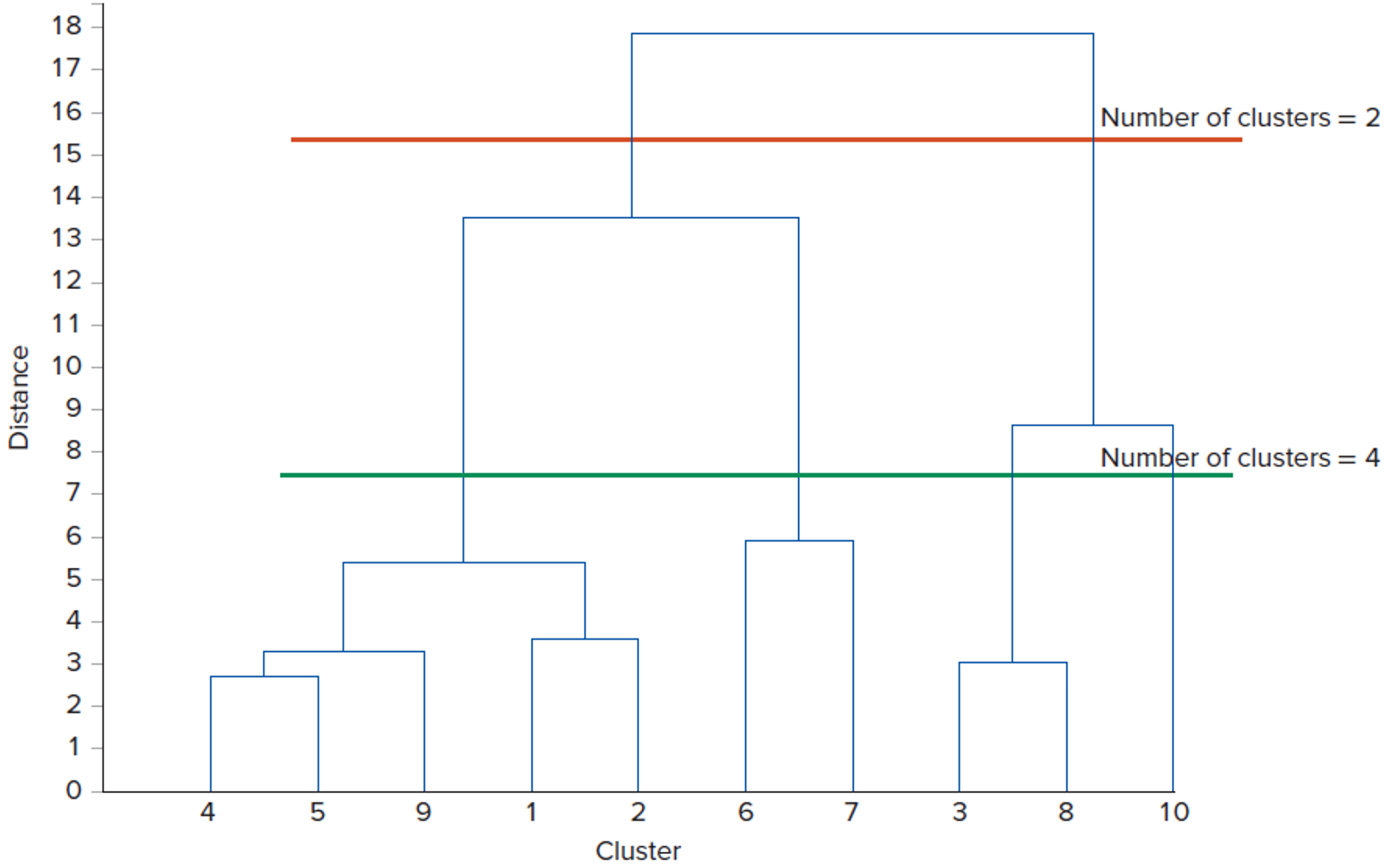
- Once AGNES completes the clustering process, data are usually represented in a tree-like structure.
  - Called a dendrogram
  - Branches are clusters
  - An observation is a "leaf"
  - Visually inspect the clustering result and determine the appropriate number of clusters
- The height of each branch (cluster) or sub-branch (sub-cluster) indicates how dissimilar it is from the other branches or sub-branches with which it is merged.
- The greater the height, the more distinctive the cluster is from the other clusters.



AGNES Dendrogram

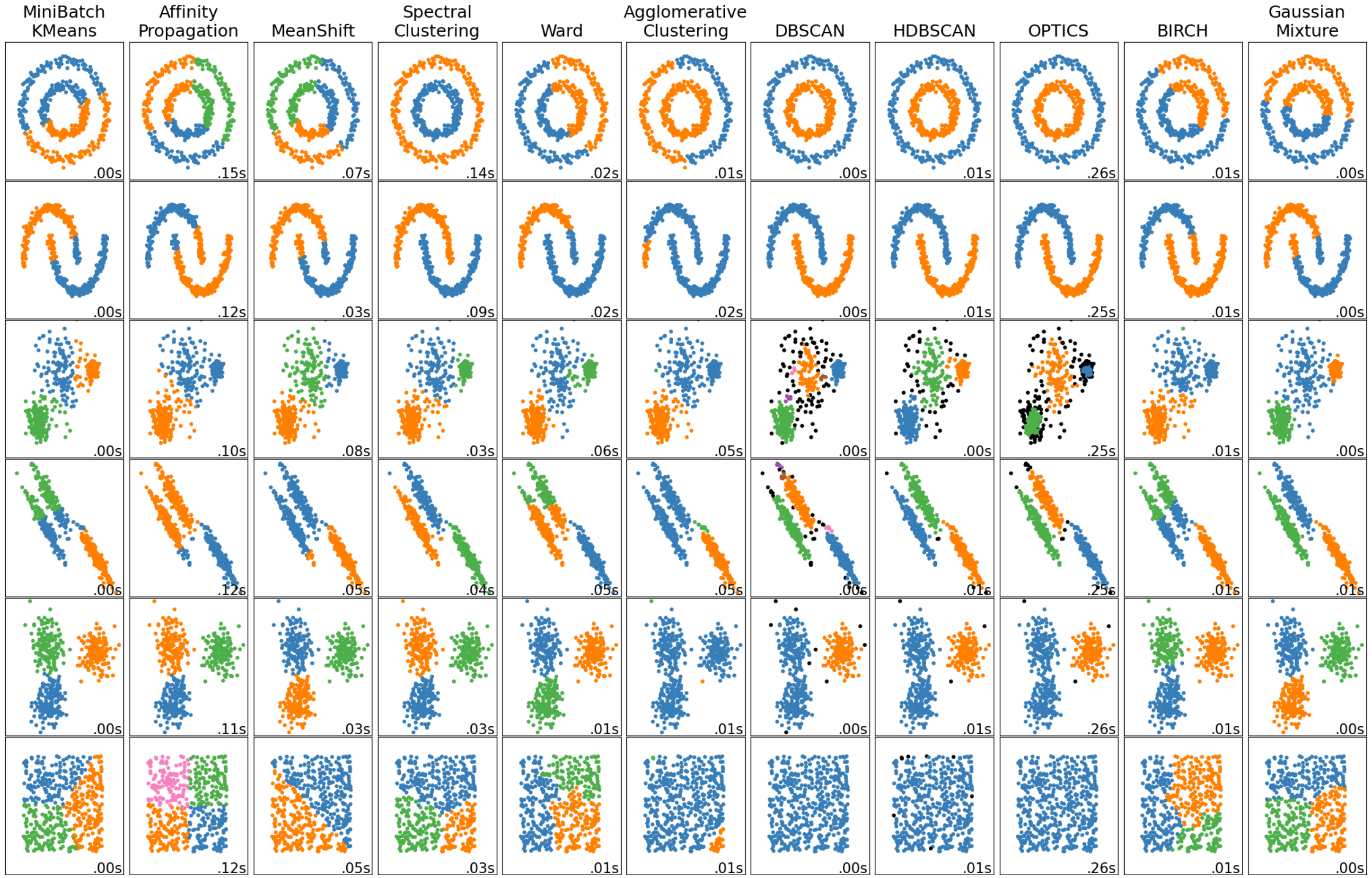


Agglomerative Clustering (Dendrogram)



Other popular clustering methods

- DBSCAN
- BIRCH
- GMM
- Fuzzy clustering
- …



https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_comparison.html

Exercises using Google Colab