Text Clustering

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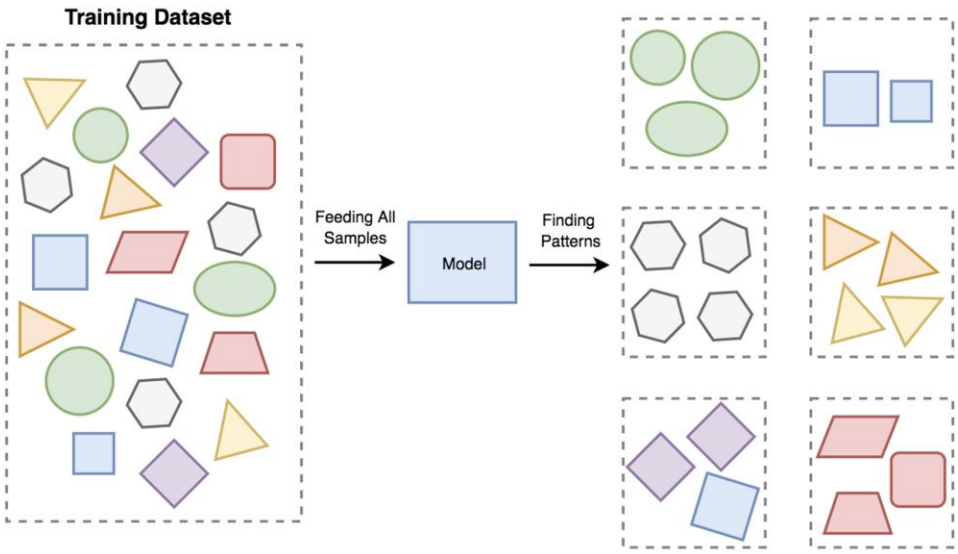
Introduction to Text Mining with R

Lecture's plan

1. What is text clustering?
2. What are the applications?
3. How to cluster text data?

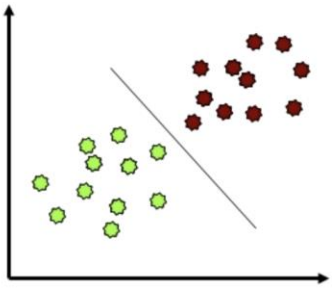
Unsupervised learning



Clustering versus classification

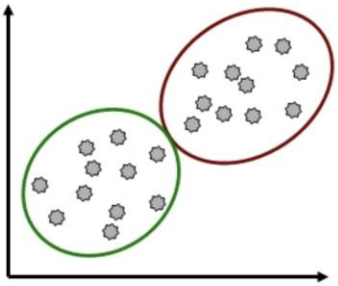
CLASSIFICATION

- Labeled data points
- Want a "rule" that assigns labels to new points
- Supervised learning



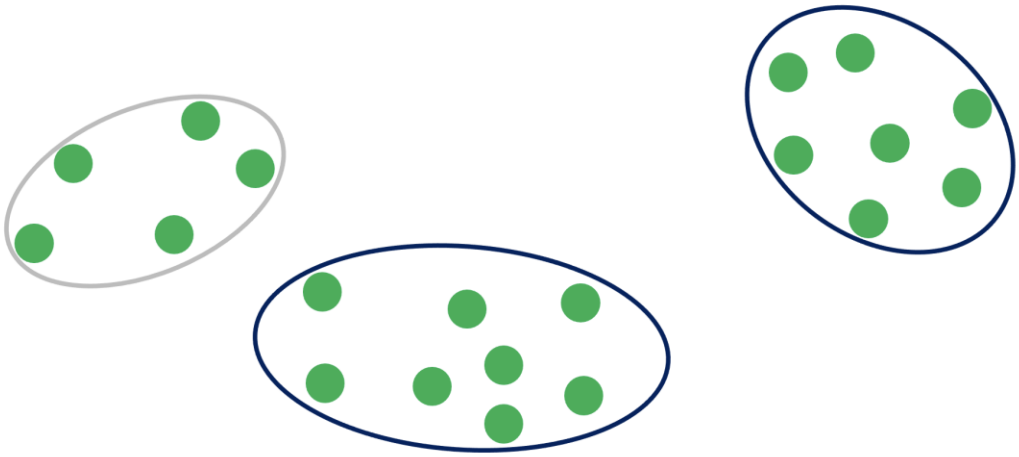
CLUSTERING

- Data is not labeled
- Group points that are "close" to each other
- Identify structure or patterns in data
- Unsupervised learning



Clustering

- Clustering: the process of grouping a set of objects into clusters of similar objects
- Discover "natural structure" of data
  - What is the criterion?
  - How to identify them?
  - How to evaluate the results?

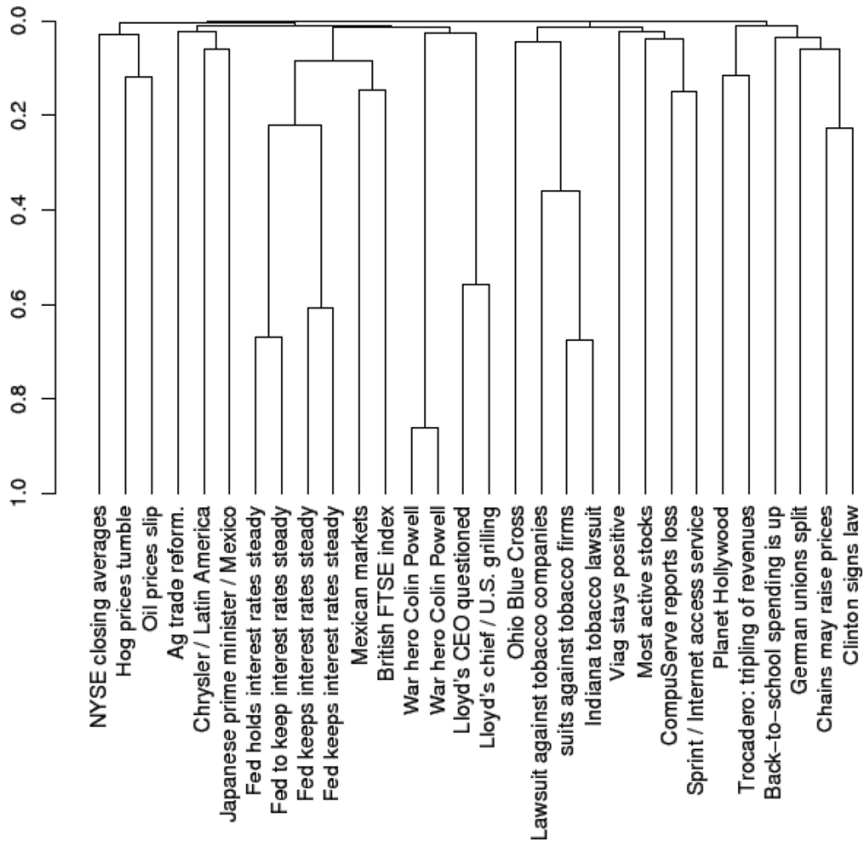


Clustering

- Basic criteria
  - high intra-cluster similarity
  - low inter-cluster similarity
- No (little) supervision signal about the underlying clustering structure
- Need similarity/distance as guidance to form clusters

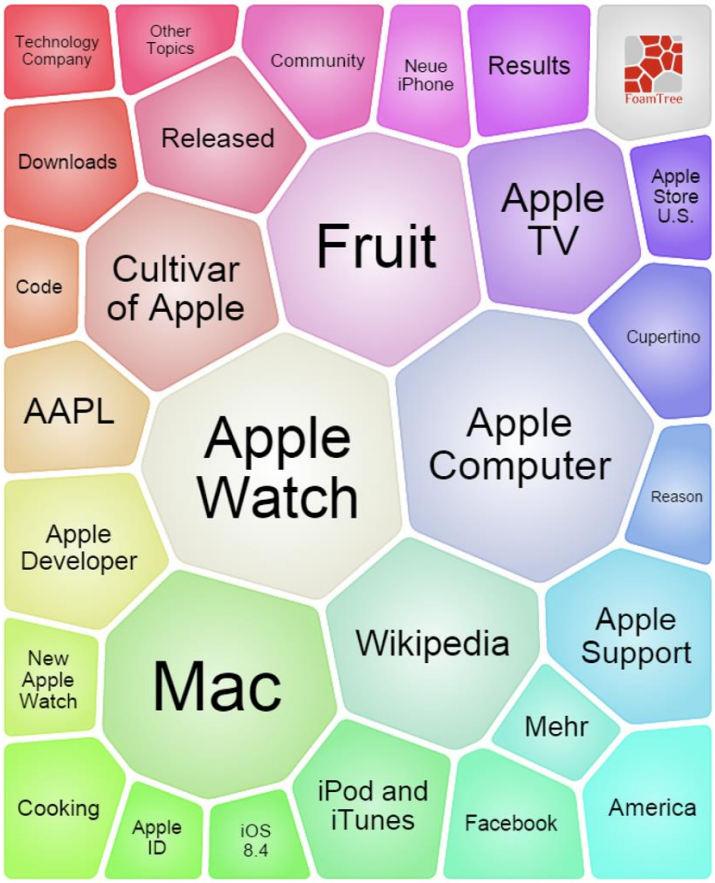
Applications of text clustering

- Organize document collections
  - Automatically identify hierarchical/topical relation among documents



Applications of text clustering

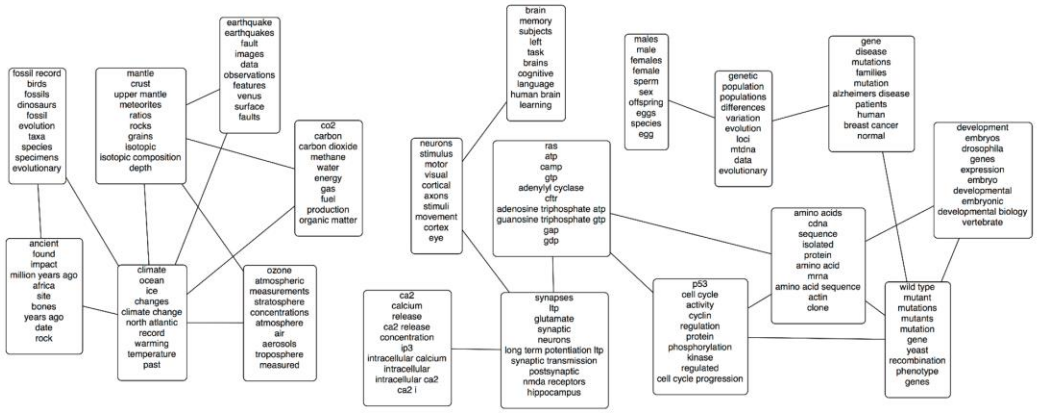
- Grouping search results
  - Organize documents by topics
  - Facilitate user browsing



http://search.carrot2.org/stable/search

Applications of text clustering

- Topic modeling
  - Grouping words into topics



Clustering algorithms

Clustering algorithms

- Partitional clustering
- Hierarchical clustering
- Topic modeling

Hard versus soft clustering

- Hard clustering: Each document belongs to exactly one cluster
  - More common and easier to do
- Soft clustering: A document can belong to more than one cluster.

Partitional clustering

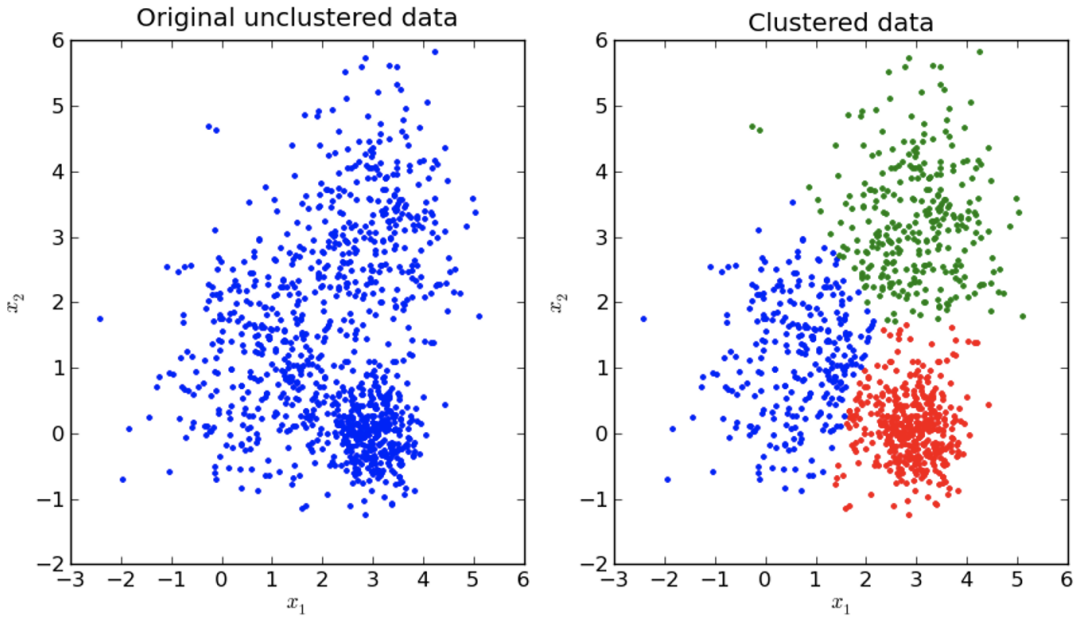
Partitional clustering algorithms

- Partitional clustering method: Construct a partition of n documents into a set of K clusters
- Given: a set of documents and the number K
- Find: a partition of K clusters that optimizes the chosen partitioning criterion
  - Globally optimal

        - Intractable for many objective functions
        - Ergo, exhaustively enumerate all partitions
    - Effective heuristic methods: K-means and K-medoids algorithms

Partitional clustering algorithms

- Typical partitional clustering algorithms
    - k-means clustering
        - Partition data by its closest mean



K-Means algorithm

- Assumes documents are real-valued vectors.
- Clusters based on centroids of points in a cluster, c:

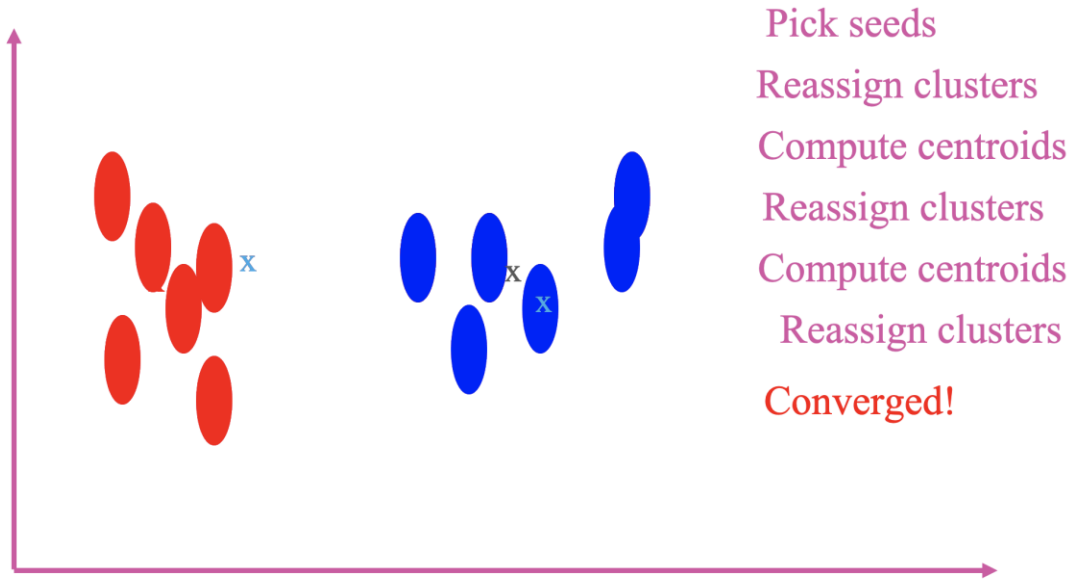
$$\vec{\mu}(c) = \frac{1}{|c|}\sum_{\vec{a}\in c}\vec{x}$$

- Reassignment of instances to clusters is based on distance to the current cluster centroids.

K-Means algorithm

- Select K random docs $\{s_1, s_2, \ldots s_K\}$ as seeds.
- Until clustering converges (or other stopping criterion):
  - For each doc d_i:
    - Assign d_i to the cluster c_j such that $dist(x_i, s_j)$ is minimal.
  - (Next, update the seeds to the centroid of each cluster)
  - For each cluster cj
    - $s_j = \mu(c_j)$

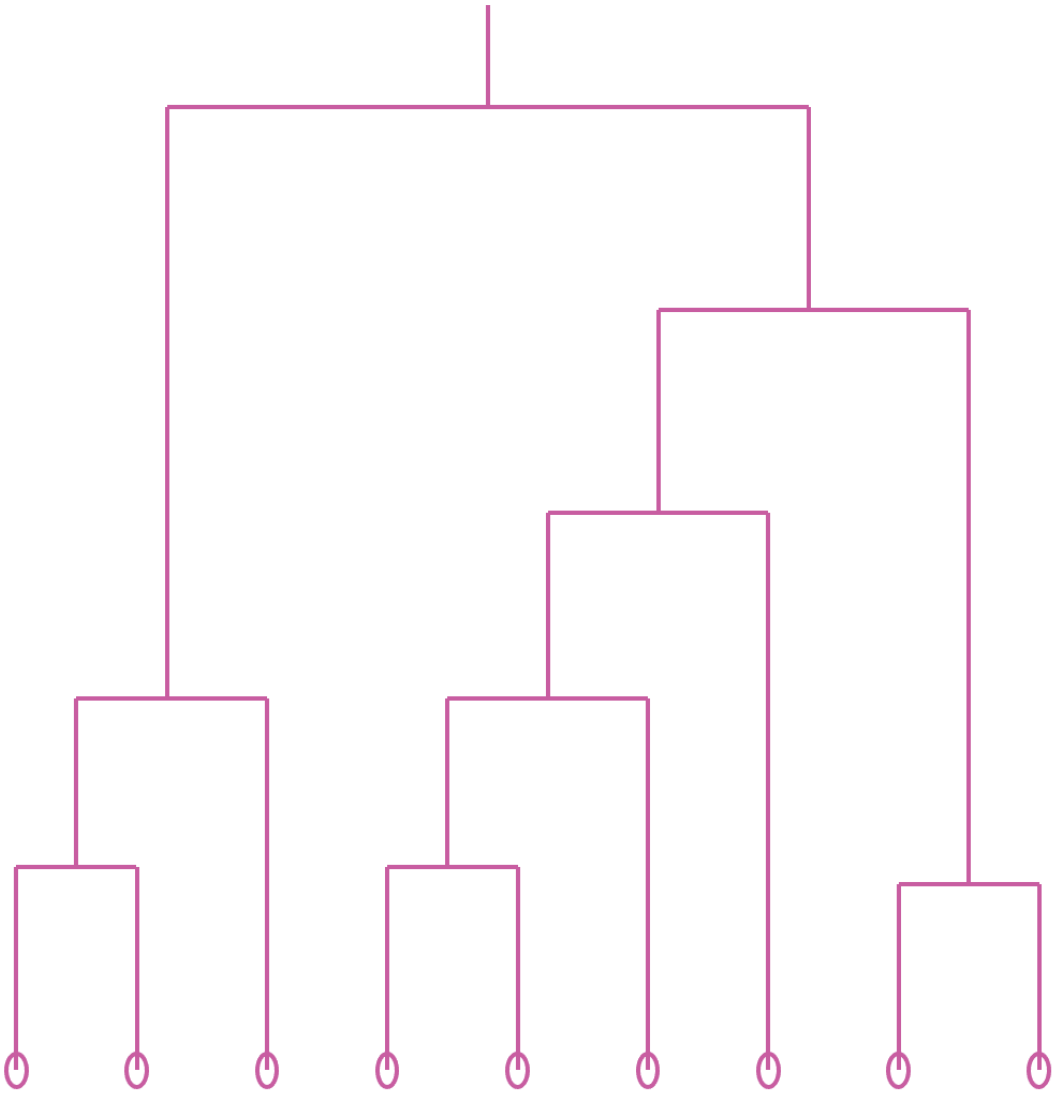
K-Means example (K=2)



Hierarchical Clustering

Dendrogram: Hierarchical clustering

- Build a tree-based hierarchical taxonomy (dendrogram) from a set of documents.
- Clustering obtained by cutting the dendrogram at a desired level: each connected component forms a cluster.

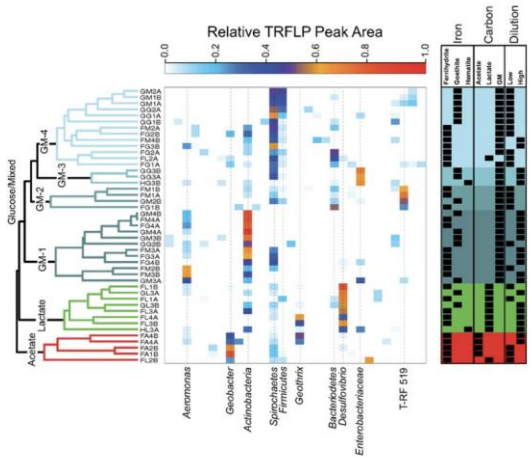


Clustering algorithms

- Typical hierarchical clustering algorithms
  - Bottom-up agglomerative clustering
    - Start with individual objects as separated clusters

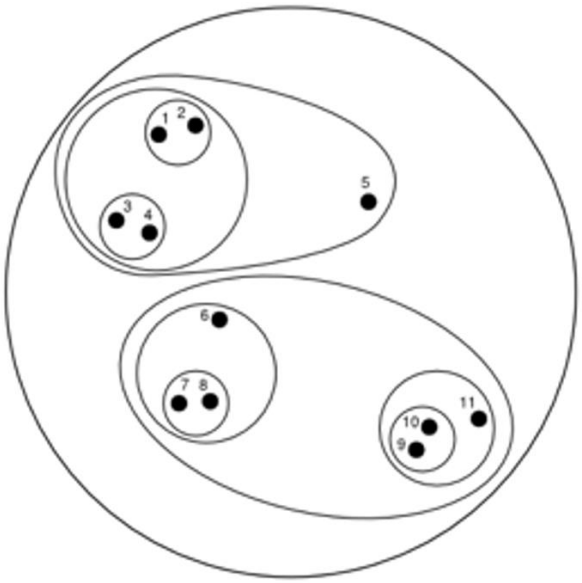
- Repeatedly merge closest pair of clusters

Most typical usage: gene sequence analysis



Clustering algorithms

- Typical hierarchical clustering algorithms
  - Top-down divisive clustering
    - Start with all data as one cluster
    - Repeatedly splitting the remaining clusters into two



Hierarchical Agglomerative Clustering (HAC)

- Starts with each doc in a separate cluster
  - then repeatedly joins the closest pair of clusters, until there is only one cluster.
- The history of merging forms a binary tree or hierarchy.

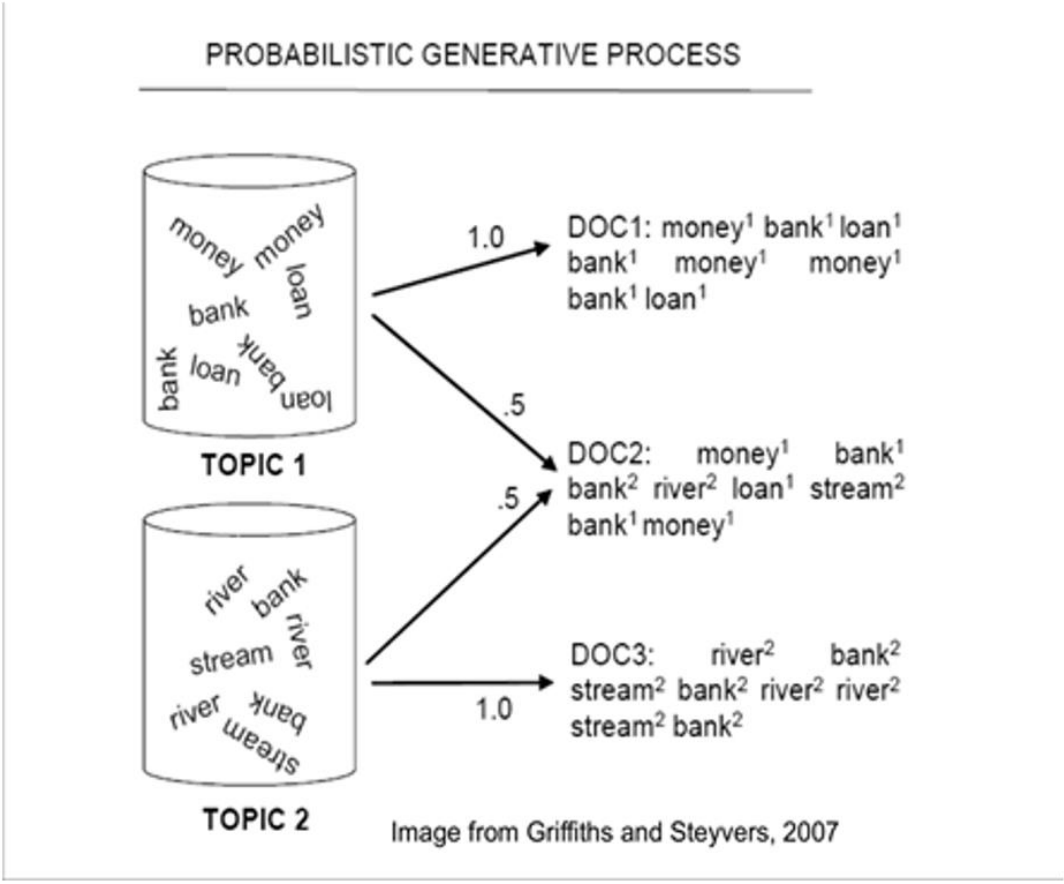
Closest pair of clusters

- Many variants to defining closest pair of clusters (linkage methods):
  - Single-link
    - Similarity of the most cosine-similar
  - Complete-link
    - Similarity of the "furthest" points, the least cosine-similar
  - Centroid
    - Clusters whose centroids (centers of gravity) are the most cosine-similar
  - Average-link
    - Average cosine between pairs of elements
  - Ward's linkage
    - Ward's minimum variance method, much in common with analysis of variance (ANOVA)
    - The distance between two clusters is computed as the increase in the "error sum of squares" (ESS) after fusing two clusters into a single cluster.

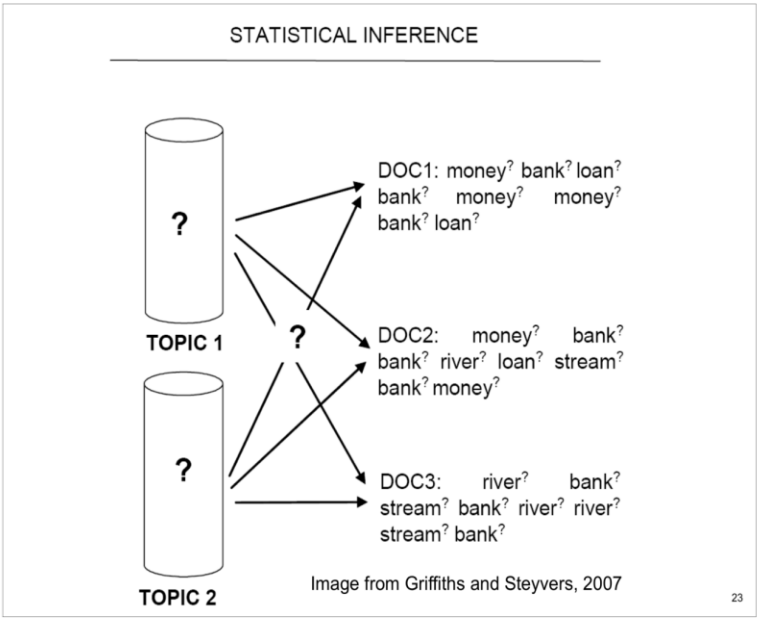
Topic Modeling

Topic models

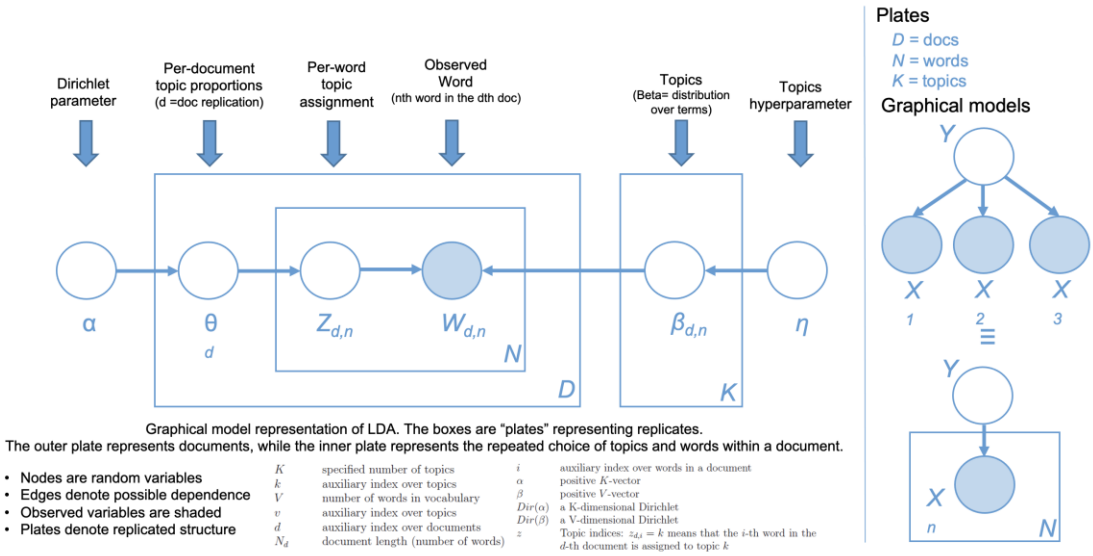
- Three concepts: words, topics, and documents
- Documents are a collection of words and have a probability distribution over topics
- Topics have a probability distribution over words
- Model:
  - Topics made up of words used to generate documents



Topic models | Reality: Documents observed, infer topics



LDA graphical model



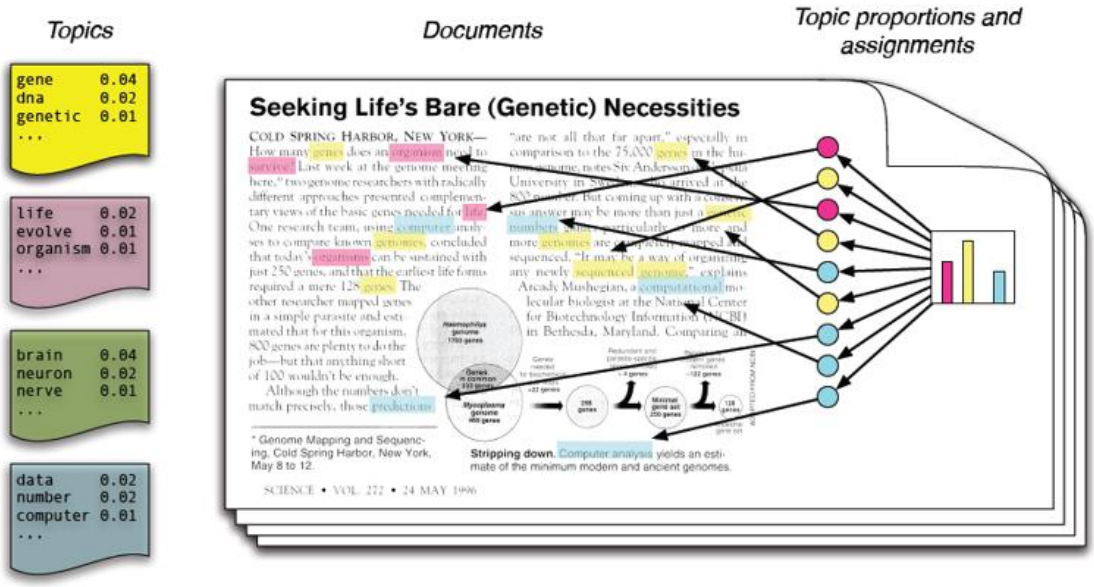
Probabilistic modeling

1. Treat data as observations that arise from a generative probabilistic process that includes hidden variables: For documents, the hidden variables reflect the thematic structure of the collection.

2. Infer the hidden structure using posterior inference: What are the topics that describe this collection?

3. Situate new data into the estimated model: How does this query or new document fit into the estimated topic structure?

LDA: Identifying structure in text



Cluster Validation

Desirable properties of clustering algorithms

- Scalability
  - Both in time and space
- Ability to deal with various types of data
  - No/less assumption about input data
  - Minimal requirement about domain knowledge
- Interpretability and usability

What is a good clustering?

- Internal criterion: A good clustering will produce high quality clusters in which:
  - the intra-class (that is, intra-cluster) similarity is high
  - the inter-class similarity is low
  - The measured quality of a clustering depends on both the document representation and the similarity measure used

Cluster validation

- Criteria to determine whether the clusters are meaningful
  - Internal validation
    - Stability and coherence
  - External validation
    - Match with known categories

Internal validation

- Coherence
  - Inter-cluster similarity v.s. intra-cluster similarity
  - Davies–Bouldin index
    - $DB = \frac{1}{k}\sum_{i=1}^{k} \max_{j \neq i}(\frac{\sigma_i + \sigma_j}{d(c_i, c_j)})$ ← Evaluate every pair of clusters
      - where k is total number of clusters, σ_i is average distance of all elements in cluster i from the cluster center, $d(c_i, c_j)$ is the distance between cluster centroid c_i and c_j.

We prefer smaller DB-index!

External criteria for clustering quality

- Quality measured by its ability to discover some or all of the hidden patterns or latent classes in gold standard data
- Assesses a clustering with respect to ground truth … requires labeled data
- Assume documents with C gold standard classes, while our clustering algorithms produce K clusters, ω_1, ω_2, …, ω_K with n_i members.

Summary

Summary

- Text clustering
- In clustering, clusters are inferred from the data without human input (unsupervised learning)
- Many ways of influencing the outcome of clustering: number of clusters, similarity measure, representation of documents
- Evaluation

Practical 5