CS47300: Web Information Search and Management

Text Clustering
Prof. Chris Clifton
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Borrows slides from Chris Manning, Ray Mooney and Soumen Chakrabarti

Clustering

- Document clustering
  - Motivations
  - Document representations
  - Success criteria
- Clustering algorithms
  - K-means
  - Model-based clustering (EM clustering)
What is clustering?

- **Clustering** is the process of grouping a set of physical or abstract objects into classes of similar objects
  - It is the commonest form of unsupervised learning
    - Unsupervised learning = learning from raw data, as opposed to supervised data where the correct classification of examples is given
  - It is a common and important task that finds many applications in IR and other places

Why cluster documents?

- Whole corpus analysis/navigation
  - Better user interface
- For improving recall in search applications
  - Better search results
- For better navigation of search results
- For speeding up vector space retrieval
  - Faster search
Navigating document collections

- Standard IR is like a book index
- Document clusters are like a table of contents
- People find having a table of contents useful

**Table of Contents**
1. Science of Cognition
   1.a. Motivations
      1.a.i. Intellectual Curiosity
      1.a.ii. Practical Applications
   1.b. History of Cognitive Psychology
2. The Neural Basis of Cognition
   2.a. The Nervous System
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3. Perception and Attention
   3.a. Sensory Memory
   3.b. Attention and Sensory Information Processing

Corpus analysis/navigation

- Given a corpus, partition it into groups of related docs
  - Recursively, can induce a tree of topics
  - Allows user to browse through corpus to find information
  - Crucial need: meaningful labels for topic nodes.
- Yahoo!: manual hierarchy
  - Often not available for new document collection
For improving search recall

- *Cluster hypothesis* - Documents with similar text are related
- Therefore, to improve search recall:
  - Cluster docs in corpus a priori
  - When a query matches a doc $D$, also return other docs in the cluster containing $D$
- Hope if we do this: The query “car” will also return docs containing *automobile*
  - Because clustering grouped together docs containing *car* with those containing *automobile*.
For better navigation of search results

- For grouping search results thematically – clusty.com / Vivisimo

For better navigation of search results

- And more visually: Kartoo.com
Navigating search results (2)

- One can also view grouping documents with the same sense of a word as clustering.
- Given the results of a search (e.g., jaguar, NLP), partition into groups of related docs.
- Can be viewed as a form of word sense disambiguation.
- E.g., *jaguar* may have senses:
  - The car company
  - The animal
  - The football team
  - The video game
- Recall query reformulation/expansion discussion.
For speeding up vector space retrieval

- In vector space retrieval, we must find nearest doc vectors to query vector
- This entails finding the similarity of the query to every doc – slow (for some applications)
- By clustering docs in corpus a priori
  - find nearest docs in cluster(s) close to query
  - inexact but avoids exhaustive similarity computation

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
- External criterion: The quality of a clustering is also measured by its ability to discover some or all of the hidden patterns or latent classes
  - Assessable with gold standard data
External Evaluation of Cluster Quality

- Assesses clustering with respect to ground truth
- Assume that there are $C$ gold standard classes, while our clustering algorithms produce $k$ clusters, $\pi_1, \pi_2, \ldots, \pi_k$ with $n_i$ members.
- Simple measure: purity, the ratio between the dominant class in the cluster $\pi_i$ and the size of cluster $\pi_i$

$$Purity(\pi_i) = \frac{1}{n_i} \max_j (n_{ij}) \quad j \in C$$

- Others are entropy of classes in clusters (or mutual information between classes and clusters)

Purity

Cluster I: Purity = 1/6 ($\max(5, 1, 0)$) = 5/6
Cluster II: Purity = 1/6 ($\max(1, 4, 1)$) = 4/6
Cluster III: Purity = 1/5 ($\max(2, 0, 3)$) = 3/5
Issues for clustering

- Representation for clustering
  - Document representation
    - Vector space? Normalization?
  - Need a notion of similarity/distance
- How many clusters?
  - Fixed a priori?
  - Completely data driven?
    - Avoid "trivial" clusters - too large or small
      - In an application, if a cluster's too large, then for navigation purposes you've wasted an extra user click without whittling down the set of documents much.

What makes docs "related"?

- Ideal: semantic similarity.
- Practical: statistical similarity
  - We will use cosine similarity.
  - Docs as vectors.
  - For many algorithms, easier to think in terms of a distance (rather than similarity) between docs.
  - We will describe algorithms in terms of cosine similarity.

Cosine similarity of normalized $D_j, D_k$:

$$
sim(D_j, D_k) = \sum_{i=1}^{m} w_{ij} \times w_{ik}
$$

Aka normalized inner product.
Recall doc as vector

- Each doc $j$ is a vector of $tf \times idf$ values, one component for each term.
- Can normalize to unit length.
- So we have a vector space
  - terms are axis - aka features
  - $n$ docs live in this space
  - even with stemming, may have 20,000+ dimensions
  - do we really want to use all terms?
    - Different from using vector space for search. Why?

Intuition

Postulate: Documents that are “close together” in vector space talk about the same things.
Clustering Algorithms

• Partitioning “flat” algorithms
  – Usually start with a random (partial) partitioning
  – Refine it iteratively
    • $k$ means/medoids clustering
    • Model based clustering

• Hierarchical algorithms
  – Bottom-up, agglomerative
  – Top-down, divisive

Partitioning Algorithms

• Partitioning 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: exhaustively enumerate all partitions
  – Effective heuristic methods: $k$-means and $k$-medoids algorithms
How hard is clustering?

• One idea is to consider all possible clusterings, and pick the one that has best inter and intra cluster distance properties
• Suppose we are given \( n \) points, and would like to cluster them into \( k \)-clusters
  – How many possible clusterings? \( k^n \)
• Too hard to do it brute force or optimally \( k! \)
• Solution: Iterative optimization algorithms
  – Start with a clustering, iteratively improve it (e.g., K-means)

K-Means

• Assumes documents are real-valued vectors.
• Clusters based on centroids (aka the center of gravity or mean) of points in a cluster, \( c \):

\[
\bar{\mu}(c) = \frac{1}{|c|} \sum_{\bar{x} \in c} \bar{x}
\]

• Reassignment of instances to clusters is based on distance to the current cluster centroids.
  – (Or one can equivalently phrase it in terms of similarities)
K-Means Algorithm

Let $d$ be the distance measure between instances.
Select $k$ random instances $\{s_1, s_2, \ldots , s_k\}$ as seeds.
Until clustering converges or other stopping criterion:

- For each instance $x_i$:
  - Assign $x_i$ to the cluster $c_j$ such that $d(x_i, s_j)$ is minimal.
  - (Update the seeds to the centroid of each cluster)

For each cluster $c_j$

$$s_j = \mu(c_j)$$

K Means Example
(K=2)

Pick seeds
Reassign clusters
Compute centroids
Reassign clusters
Compute centroids
Reassign clusters
Converged!
Termination conditions

- Several possibilities, e.g.,
  - A fixed number of iterations.
  - Doc partition unchanged.
  - Centroid positions don’t change.

Does this mean that the docs in a cluster are unchanged?

Time Complexity

- Assume computing distance between two instances is $O(m)$ where $m$ is the dimensionality of the vectors.
- Reassigning clusters: $O(kn)$ distance computations, or $O(knm)$.
- Computing centroids: Each instance vector gets added once to some centroid: $O(nm)$.
- Assume these two steps are each done once for $i$ iterations: $O(iknm)$.
- Linear in all relevant factors, assuming a fixed number of iterations, more efficient than hierarchical agglomerative methods.
Seed Choice

- Results can vary based on random seed selection.
- Some seeds can result in poor convergence rate, or convergence to sub-optimal clusterings.
  - Select good seeds using a heuristic (e.g., doc least similar to any existing mean)
  - Try out multiple starting points
  - Initialize with the results of another method.

In the above, if you start with B and E as centroids you converge to \{A,B,C\} and \{D,E,F\}.
If you start with D and F you converge to \{A,B,D,E\} \{C,F\}.

Example showing sensitivity to seeds

Recap

- Why cluster documents?
  - For improving recall in search applications
  - For speeding up vector space retrieval
  - Navigation
  - Presentation of search results

- \(k\)-means basic iteration
  - At the start of the iteration, we have \(k\) centroids.
  - Each doc assigned to the nearest centroid.
  - All docs assigned to the same centroid are averaged to compute a new centroid;
    - thus have \(k\) new centroids.
How Many Clusters?

- Number of clusters \( k \) is given
  - Partition \( n \) docs into predetermined number of clusters

- Finding the “right” number of clusters is part of the problem
  - Given docs, partition into an “appropriate” number of subsets.
  - E.g., for query results - ideal value of \( k \) not known up front - though UI may impose limits.

- Can usually take an algorithm for one flavor and convert to the other.

\( k \) not specified in advance

- Say, the results of a query.
- Solve an optimization problem: penalize having lots of clusters
  - application dependent, e.g., compressed summary of search results list.
- Tradeoff between having more clusters (better focus within each cluster) and having too many clusters
Given a clustering, define the **Benefit** for a doc to be the cosine similarity to its centroid

- Define the **Total Benefit** to be the sum of the individual doc Benefits.

**Why is there always a clustering of Total Benefit \( n \)?**

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**Penalize lots of clusters**

- For each cluster, we have a Cost \( C \).
- Thus for a clustering with \( k \) clusters, the **Total Cost** is \( kC \).
- Define the **Value** of a clustering to be \( \text{Total Benefit} - \text{Total Cost} \).
- Find the clustering of highest value, over all choices of \( k \).
  - Total benefit increases with increasing \( K \). But can stop when it doesn’t increase by “much”. The Cost term enforces this.
Convergence

Why should the K-means algorithm ever reach a fixed point?

– A state in which clusters don’t change.

K-means is a special case of a general procedure known as the *Expectation Maximization (EM) algorithm*.

– EM is known to converge.
– Number of iterations could be large.

Convergence of K-Means

Define goodness measure of cluster k as sum of squared distances from cluster centroid:

\[ G_k = \sum_i (v_i - c_k)^2 \] (sum all \( v_i \) in cluster k)

\[ G = \sum_k G_k \]

Reassignment monotonically reduces \( G \) since each vector is assigned to the closest centroid.

Recomputation monotonically decreases each \( G_k \) since: (\( m_k \) is number of members in cluster)

\[ \Sigma (v_{in} - a)^2 \text{ reaches minimum for:} \]

\[ \Sigma -2(v_{in} - a) = 0 \]
K-means issues, variations, etc.

- Recomputing the centroid after every assignment (rather than after all points are re-assigned) can improve speed of convergence of K-means.
- Assumes clusters are spherical in vector space.
  - Sensitive to coordinate changes, weighting etc.
- Disjoint and exhaustive.
  - Doesn’t have a notion of “outliers”

Soft Clustering

- Clustering typically assumes that each instance is given a “hard” assignment to exactly one cluster.
- Does not allow uncertainty in class membership or for an instance to belong to more than one cluster.
  - *Soft clustering* gives probabilities that an instance belongs to each of a set of clusters.
- Each instance is assigned a probability distribution across a set of discovered categories (probabilities of all categories must sum to 1).
Hierarchical Clustering

• Build a tree-based hierarchical taxonomy (dendrogram) from a set of unlabeled examples.

```
  animal
   |   |
  vertebrate  invertebrate
   |       |
  fish reptile amphib. mammal  worm insect crustacean
```

• One option to produce a hierarchical clustering is recursive application of a partitional clustering algorithm to produce a hierarchical clustering.

“The Curse of Dimensionality”

• Why document clustering is difficult
  – While clustering looks intuitive in 2 dimensions, many of our applications involve 10,000 or more dimensions…
  – High-dimensional spaces look different: the probability of random points being close drops quickly as the dimensionality grows.
  – One way to look at it: in large-dimension spaces, random vectors are almost all almost perpendicular. Why?

• Solution: Dimensionality reduction … important for text
Related Tasks

- **TDT**
  - Topic Detection: “Dynamic” Clustering
  - Topic Tracking: on-line categorization
  - Story Segmentation
  - First Story Detection
  - New Information Detection
  - Story Link Detection
- **TIDES**
  - All of the above in multilingual and multimedia
- **Word cloud**
- **And others…**