PURDUE
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CS54701: Information Retrieval

Text Clustering

24 March 2016

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Borrows slides from Chris Manning, Ray Mooney and Soumen Chakrabarti

Indiana Center for Database Systems ™

Clustering

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

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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

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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

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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

Index
Aardvark, 15
Blueberry, 200
Capricorn, 1, 45-55
Dog, 79-99
Egypt, 65
Falafel, 78-90
Giraffes, 45-59
…

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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

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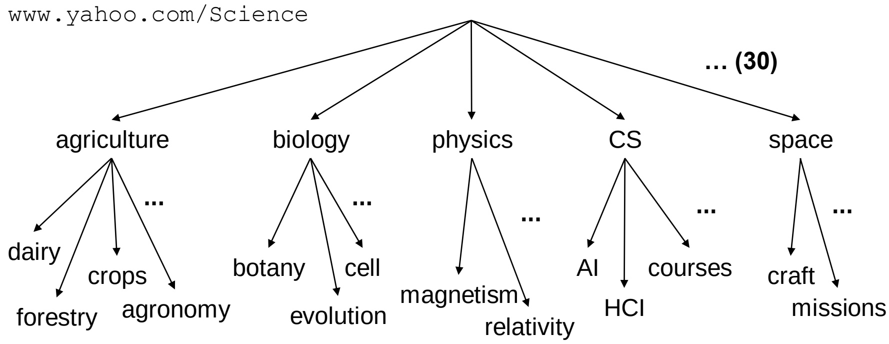
Yahoo! Hierarchy

www.yahoo.com/Science



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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.*

Why might this happen?

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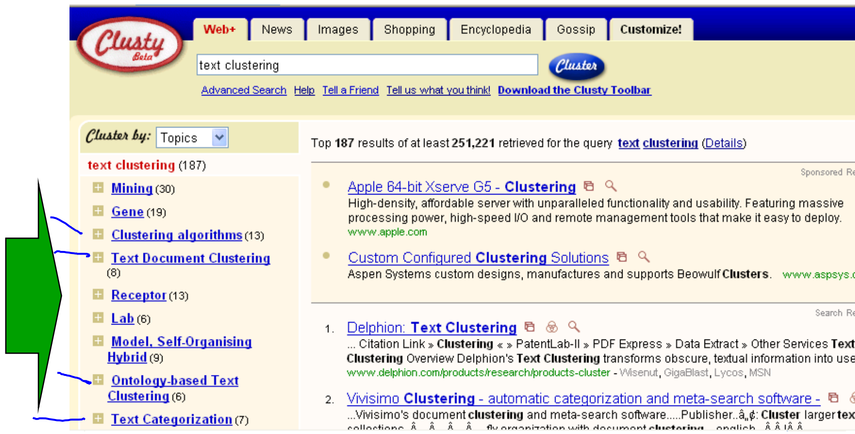
For better navigation of search results

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



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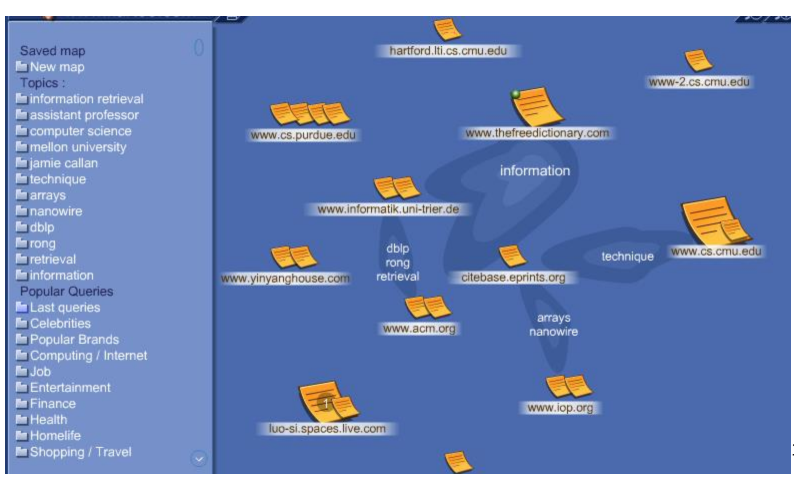
For better navigation of search results

- And more visually: Kartoo.com



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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

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Navigating search results (2)

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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

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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

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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, π_1, π_2, …, π_k with n_i members.
- Simple measure: purity, the ratio between the dominant class in the cluster π_i and the size of cluster π_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)

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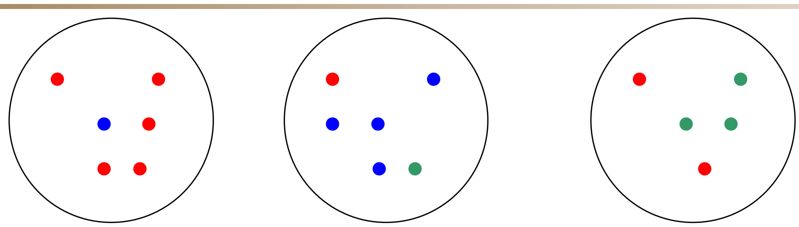
Purity



Cluster I Cluster II Cluster III

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

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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.

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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 <u>similarity</u>) 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.

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Recall doc as vector

- Each doc *j* is a vector of *tf*×*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?

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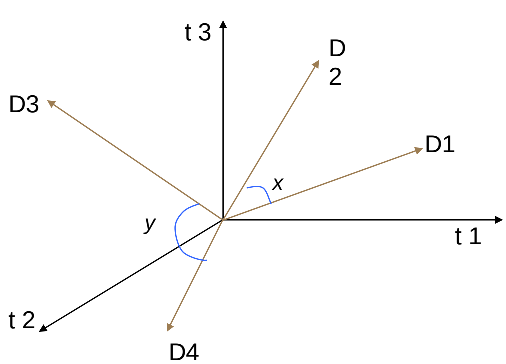
Intuition



Postulate: Documents that are "close together" in vector space talk about the same things.

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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

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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

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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?

$$\frac{k^n}{k!}$$

- Too hard to do it brute force or optimally
- Solution: Iterative optimization algorithms
  - Start with a clustering, iteratively improve it (eg. K-means)

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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*:

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

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

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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
        $s_j = \mu(c_j)$

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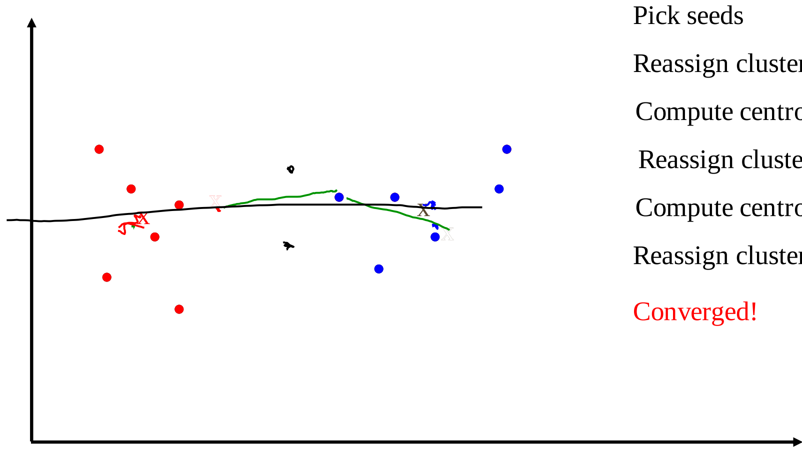
K Means Example
(K=2)



Pick seeds

Reassign clusters

Compute centroids

Reassign clusters

Compute centroids

Reassign clusters

Converged!

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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?

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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

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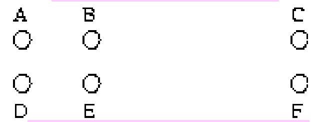
Seed Choice

- 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.

Example showing sensitivity to seeds



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}

Exercise: find good approach for finding good starting points

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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

k not specified in advance

- 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*?

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 =

  Total Benefit - 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:
  - $G_k = \Sigma_i (v_i - c_k)^2$ (sum all v_i in cluster k)
- $G = \Sigma_k G_k$
- 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)
  - $\Sigma (v_{in} - a)^2$ 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).

Model based clustering

- Algorithm optimizes a probabilistic model criterion
- Clustering is usually done by the Expectation Maximization (EM) algorithm
  - Gives a soft variant of the K-means algorithm
  - Assume k clusters: $\{c_1, c_2, \ldots c_k\}$
  - Assume a probabilistic model of categories that allows computing $P(c_i \mid E)$ for each category, c_i, for a given example, E.
  - For text, typically assume a naïve Bayes category model.
  - Parameters $\theta = \{P(c_i), P(w_j \mid c_i): i \in \{1, \ldots k\}, j \in \{1, \ldots, |V|\}\}$

Expectation Maximization (EM) Algorithm

- Iterative method for learning probabilistic categorization model from unsupervised data.
- Initially assume random assignment of examples to categories.
- Learn an initial probabilistic model by estimating model parameters θ from this randomly labeled data.
- Iterate following two steps until convergence:
  - Expectation (E-step): Compute $P(c_i \mid E)$ for each example given the current model, and probabilistically re-label the examples based on these posterior probability estimates.
  - Maximization (M-step): Re-estimate the model parameters, θ, from the probabilistically re-labeled data.

EM Experiment
[Soumen Chakrabarti]

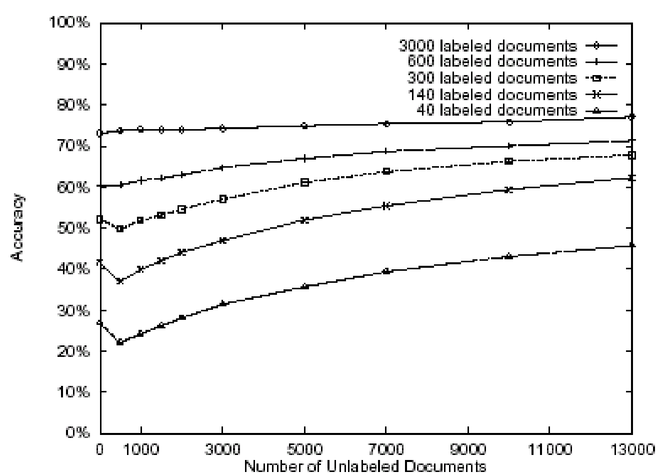
- Semi-supervised: some labeled and unlabeled data
- Take a completely labeled corpus D, and randomly select a subset as D_K.
- Also use the set $D^U \subseteq D$ of unlabeled documents in the EM procedure.
- Correct classification of a document
  => concealed class label = class with largest probability
- Accuracy with unlabeled documents > accuracy without unlabeled documents
  - Keeping labeled set of same size
- EM beats naïve Bayes with same size of labeled document set
  - Largest boost for small size of labeled set
  - Comparable or poorer performance of EM for large labeled sets

Belief in labeled documents

- Depending on one's faith in the initial labeling
  - Set before 1st iteration:
    - $\Pr(c_d \mid d) = 1 - \varepsilon$ and $\Pr(c' \mid d) = \varepsilon/(n-1)$ for all $c' \neq c_d$
  - With each iteration
    - Let the class probabilities of the labeled documents `smear' in reestimation process
- To limit 'drift' from initial labeled documents, one can add a damping factor in the E step to the contribution from unlabeled documents

Increasing D^U while holding D^K fixed also shows the advantage of using large unlabeled sets in the EM-like algorithm.

Purity

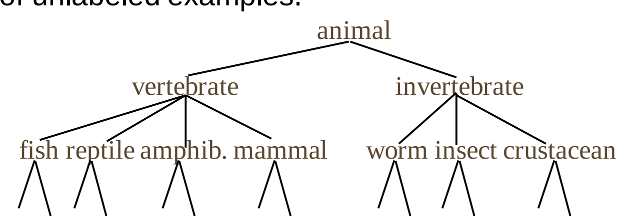


“The Curse of Dimensionality”

- 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

Hierarchical Clustering

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



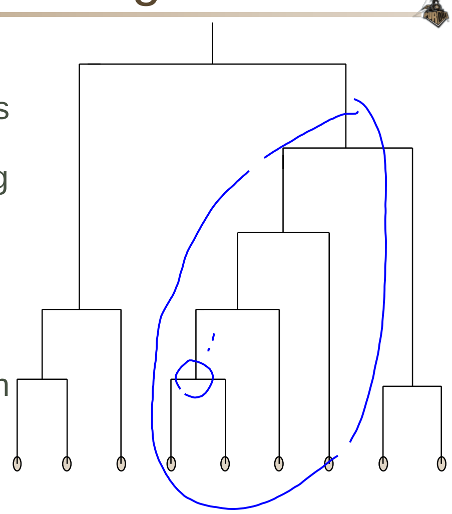
- One option to produce a hierarchical clustering is recursive application of a partitional clustering algorithm to produce a hierarchical clustering.

Hierarchical Agglomerative Clustering (HAC)

- Assumes a similarity function for determining the similarity of two instances.
- Starts with all instances in a separate cluster and then repeatedly joins the two clusters that are most similar until there is only one cluster.
- The history of merging forms a binary tree or hierarchy.

A Dendogram: Hierarchical Clustering

- Dendrogram: Decomposes data objects into a several levels of nested partitioning (tree of clusters).
- Clustering of the data objects is obtained by cutting the dendrogram at the desired level, then each connected component forms a cluster.



HAC Algorithm

Start with all instances in their own cluster.
Until there is only one cluster:

Among the current clusters, determine the two clusters, c_i and c_j, that are most similar.

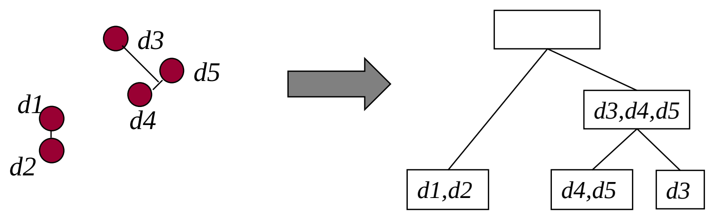
Replace c_i and c_j with a single cluster $c_i \cup c_j$

Hierarchical Clustering algorithms

- **Agglomerative (bottom-up):**
  - Start with each document being a single cluster.
  - Eventually all documents belong to the same cluster.
- **Divisive (top-down):**
  - Start with all documents belong to the same cluster.
  - Eventually each node forms a cluster on its own.
- Does not require the number of clusters ***k*** in advance
- Needs a termination/readout condition
  - The final mode in both Agglomerative and Divisive is of no use.

Dendrogram: Document Example

- As clusters *agglomerate*, docs likely to fall into a hierarchy of “topics” or concepts.



“Closest pair” of clusters

- Many variants to defining closest pair of clusters
- “Center of gravity”
  - Clusters whose centroids (centers of gravity) are the most cosine-similar
- Average-link
  - Average cosine between pairs of elements
- Single-link
  - Similarity of the most cosine-similar (single-link)
- Complete-link
  - Similarity of the “furthest” points, the least cosine-similar

Hierarchical Clustering

- Key problem: as you build clusters, how do you represent the location of each cluster, to tell which pair of clusters is closest?
- Euclidean case: each cluster has a *centroid* = average of its points.
  - Measure intercluster distances by distances of centroids.

Single Link Agglomerative Clustering

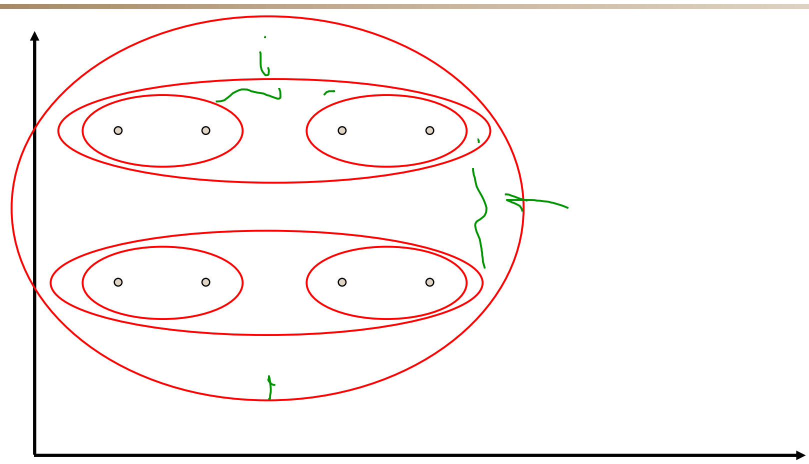
- Use maximum similarity of pairs:

$$sim(c_i, c_j) = \max_{x \in c_i, y \in c_j} sim(x, y)$$

- Can result in "straggly" (long and thin) clusters due to chaining effect.
  - Appropriate in some domains, such as clustering islands: "Hawaii clusters"
- After merging c_i and c_j, the similarity of the resulting cluster to another cluster, c_k, is:

$$sim((c_i \cup c_j), c_k) = \max(sim(c_i, c_k), sim(c_j, c_k))$$

Single Link Example



Complete Link Agglomerative Clustering

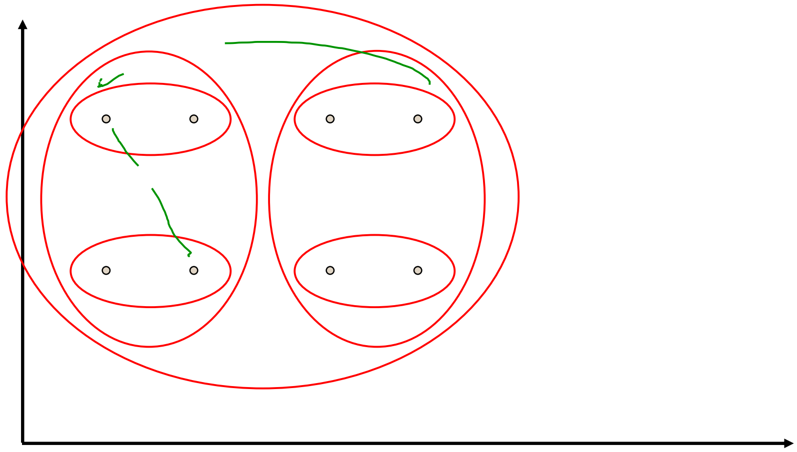
- Use minimum similarity of pairs:

$$sim(c_i, c_j) = \min_{x \in c_i, y \in c_j} sim(x, y)$$

- Makes "tighter," spherical clusters that are typically preferable.
- After merging c_i and c_j, the similarity of the resulting cluster to another cluster, c_k, is:

$$sim((c_i \cup c_j), c_k) = \min(sim(c_i, c_k), sim(c_j, c_k))$$

Complete Link Example



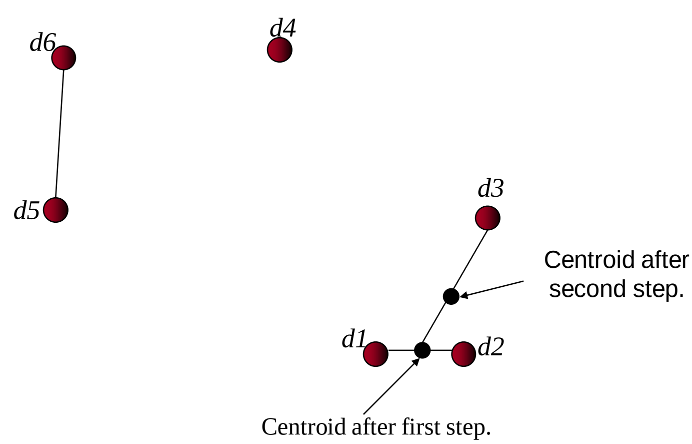
Computational Complexity

- In the first iteration, all HAC methods need to compute similarity of all pairs of n individual instances which is $O(n^2)$.
- In each of the subsequent n–2 merging iterations, it must compute the distance between the most recently created cluster and all other existing clusters.
  - Since we can just store unchanged similarities
- In order to maintain an overall $O(n^2)$ performance, computing similarity to each other cluster must be done in constant time.
  - Else $O(n^2 \log n)$ or $O(n^3)$ if done naively

Key notion: *cluster representative*

- We want a notion of a representative point in a cluster
- Representative should be some sort of "typical" or central point in the cluster, e.g.,
  - point inducing smallest radii to docs in cluster
  - smallest squared distances, etc.
  - point that is the "average" of all docs in the cluster
    - Centroid or center of gravity

Example: *n=6, k=3,* closest pair of centroids



Outliers in centroid computation

- Can ignore outliers when computing centroid.
- What is an outlier?
  - Lots of statistical definitions, e.g.

    Say 10.
  - *moment* of point to centroid > M × some cluster *moment*.

Group Average Agglomerative Clustering

- Use average similarity across all pairs within the merged cluster to measure the similarity of two clusters.

$$sim(c_i, c_j) = \frac{1}{|c_i \cup c_j|(|c_i \cup c_j| - 1)} \sum_{\vec{x} \in (c_i \cup c_j)} \sum_{\vec{y} \in (c_i \cup c_j): \vec{y} \neq \vec{x}} sim(\vec{x}, \vec{y})$$

- Compromise between single and complete link.
- Two options:
  - Averaged across all ordered pairs in the merged cluster
  - Averaged over all pairs between the two original clusters
- Some previous work has used one of these options; some the other. No clear difference in efficacy

Computing Group Average Similarity

- Assume cosine similarity and normalized vectors with unit length.
- Always maintain sum of vectors in each cluster.

$$\vec{s}(c_j) = \sum_{\vec{x} \in c_j} \vec{x}$$

- Compute similarity of clusters in constant time:

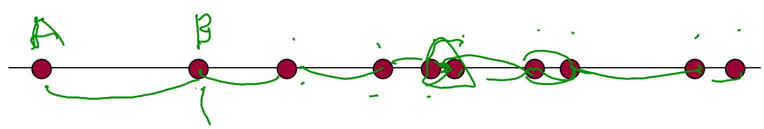
$$sim(c_i, c_j) = \frac{(\vec{s}(c_i) + \vec{s}(c_j)) \bullet (\vec{s}(c_i) + \vec{s}(c_j)) - (|c_i| + |c_j|)}{(|c_i| + |c_j|)(|c_i| + |c_j| - 1)}$$

Efficiency: Medoid As Cluster Representative

- The centroid does not have to be a document.
- Medoid: A cluster representative that is one of the documents
- For example: the document closest to the centroid
- One reason this is useful
  - Consider the representative of a large cluster (>1000 documents)
  - The centroid of this cluster will be a dense vector
  - The medoid of this cluster will be a sparse vector
- Compare: mean/centroid vs. median/medoid

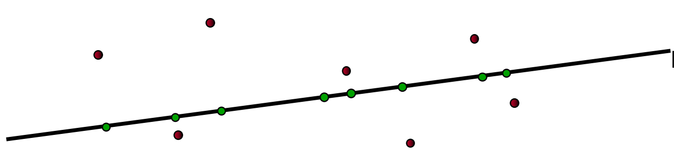
Exercise

- Consider agglomerative clustering on *n* points on a line. Explain how you could avoid n^3 distance computations - how many will your scheme use?



Efficiency: "Using approximations"

- In standard algorithm, must find closest pair of centroids at each step
- Approximation: instead, find nearly closest pair
  – use some data structure that makes this approximation easier to maintain
  – simplistic example: maintain closest pair based on distances in projection on a random line



Term vs. document space

- So far, we clustered docs based on their similarities in term space
- For some applications, e.g., topic analysis for inducing navigation structures, can “dualize”:
  - use docs as axes
  - represent (some) terms as vectors
  - proximity based on co-occurrence of terms in docs
  - now clustering terms, not docs

Term vs. document space

- Cosine computation
  - Constant for docs in term space
  - Grows linearly with corpus size for terms in doc space
- Cluster labeling
  - clusters have clean descriptions in terms of noun phrase co-occurrence
  - Easier labeling?
- Application of term clusters
  - Sometimes we want term clusters (example?)
  - If we need doc clusters, left with problem of binding docs to these clusters

Multi-lingual docs

- E.g., Canadian government docs.
- Every doc in English and equivalent French.
  - Must cluster by concepts rather than language
- Simplest: pad docs in one language with dictionary equivalents in the other
  - thus each doc has a representation in both languages
- Axes are terms in both languages

Feature selection

- Which terms to use as axes for vector space?
- Large body of (ongoing) research
- IDF is a form of feature selection
  - Can exaggerate noise e.g., mis-spellings
- Better is to use highest weight mid-frequency words – the most discriminating terms
- Pseudo-linguistic heuristics, e.g.,
  - drop stop-words
  - stemming/lemmatization
  - use only nouns/noun phrases
- Good clustering should “figure out” some of these

Major issue - labeling

- After clustering algorithm finds clusters - how can they be useful to the end user?
- Need pithy label for each cluster
  - In search results, say “Animal” or “Car” in the ***jaguar*** example.
  - In topic trees (Yahoo), need navigational cues.
    - Often done by hand, a posteriori.

How to Label Clusters

- Show titles of typical documents
  - Titles are easy to scan
  - Authors create them for quick scanning!
  - But you can only show a few titles which may not fully represent cluster
- Show words/phrases prominent in cluster
  - More likely to fully represent cluster
  - Use distinguishing words/phrases
    - Differential labeling
  - But harder to scan

Labeling

- Common heuristics - list 5-10 most frequent terms in the centroid vector.
  - Drop stop-words; stem.
- Differential labeling by frequent terms
  - Within a collection "Computers", clusters all have the word computer as frequent term.
  - Discriminant analysis of centroids.
- Perhaps better: distinctive noun phrase

PURDUE UNIVERSITY

CS54701: Information Retrieval

Text Clustering

31 March 2016

Prof. Chris Clifton

Borrows slides from Chris Manning, Ray Mooney and Soumen Chakrabarti

Indiana Center for Database Systems ™

Evaluation of clustering

- Perhaps the most substantive issue in data mining in general:
  - how do you measure goodness?
- Most measures focus on computational efficiency
  - Time and space
- For application of clustering to search:
  - Measure retrieval effectiveness

Approaches to evaluating

- Anecdotal
- User inspection
- Ground "truth" comparison
  - Cluster retrieval
- Purely quantitative measures
  - Probability of generating clusters found
  - Average distance between cluster members
- Microeconomic / utility

Anecdotal evaluation

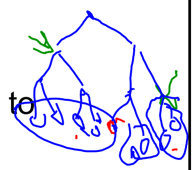
- Probably the commonest (and surely the easiest)
  - “I wrote this clustering algorithm and look what it found!”
- No benchmarks, no comparison possible
- Any clustering algorithm will pick up the easy stuff like partition by languages
- Generally, unclear scientific value.

User inspection

- Induce a set of clusters or a navigation tree
- Have subject matter experts evaluate the results and score them
  - some degree of subjectivity
- Often combined with search results clustering
- Not clear how reproducible across tests.
- Expensive / time-consuming

Ground “truth” comparison

- Take a union of docs from a taxonomy & cluster
  - Yahoo!, ODP, newspaper sections …
- Compare clustering results to baseline
  - e.g., 80% of the clusters found map “cleanly” to taxonomy nodes
  - How would we measure this?
- But is it the “right” answer?
  - There can be several equally right answers
- For the docs given, the static prior taxonomy may be incomplete/wrong in places
  - the clustering algorithm may have gotten right things not in the static taxonomy



“Subjective”

Ground truth comparison

- Divergent goals
- Static taxonomy designed to be the “right” navigation structure
  - somewhat independent of corpus at hand
- Clusters found have to do with vagaries of corpus
- Also, docs put in a taxonomy node may not be the most representative ones for that topic
  - cf Yahoo!

Microeconomic viewpoint

- Anything - including clustering - is only as good as the economic utility it provides
- For clustering: net economic gain produced by an approach (vs. another approach)
- Strive for a concrete optimization problem
- Examples
  - recommendation systems
  - clock time for interactive search
    - expensive

Evaluation example: Cluster retrieval

- Ad-hoc retrieval
- Cluster docs in returned set
- Identify best cluster & only retrieve docs from it
- How do various clustering methods affect the quality of what's retrieved?
- Concrete measure of quality:
  - Precision as measured by user judgements for these queries
- Done with TREC queries

Evaluation

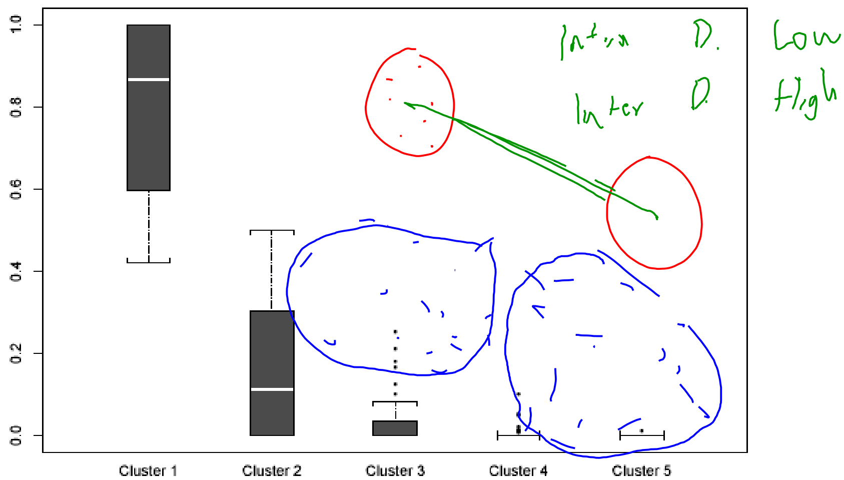
- Compare two IR algorithms
  - 1. send query, present ranked results
  - 2. send query, cluster results, present clusters
- Experiment was simulated (no users)
  - Results were clustered into 5 clusters
  - Clusters were ranked according to percentage relevant documents
  - Documents within clusters were ranked according to similarity to query

Sim-Ranked vs. Cluster-Ranked

	Precision at Cutoffs		
CutOff	Sim-Ranked	Cluster-Ranked	% Increase
5	.342	.428	.252
10	.314	.401	.277
20	.276	.363	.312

Table 4: Precision at small document cutoff levels for the one-step algorithm.

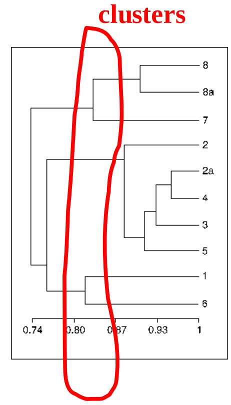
Relevance Density of Clusters



Buckshot Algorithm

- Another way to an efficient implementation:
  - Cluster a sample, then assign the entire set
- Buckshot combines HAC and K-Means clustering.
- First randomly take a sample of instances of size $\sqrt{n}$
- Run group-average HAC on this sample, which takes only O(*n*) time.
- Use the results of HAC as initial seeds for K-means.
- Overall algorithm is O(*n*) and avoids problems of bad seed selection.

Cut where You have k clusters



Uses HAC to bootstrap K-means

Bisecting K-means

- Divisive hierarchical clustering method using K-means
- For I=1 to k-1 do {
  - Pick a leaf cluster C to split
  - For J=1 to ITER do {
    - Use K-means to split C into two sub-clusters, C_1 and C_2
    - Choose the best of the above splits and make it permanent}

    }

  }

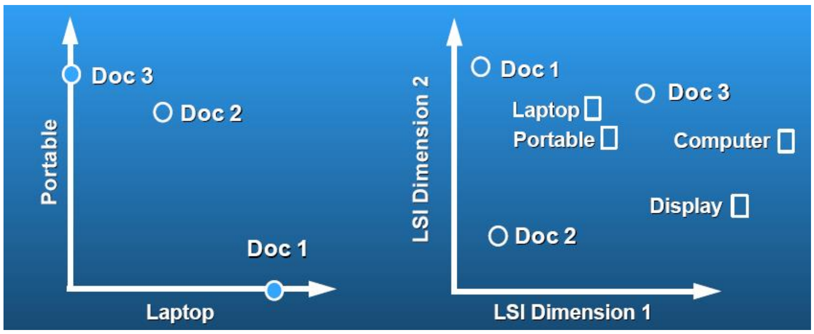
- Steinbach et al. suggest HAC is better than k-means but Bisecting K-means is better than HAC for their text experiments

Resources

- Scatter/Gather: A Cluster-based Approach to Browsing Large Document Collections (1992)
  - Cutting/Karger/Pedersen/Tukey
  - http://citeseer.ist.psu.edu/cutting92scattergather.html
- Data Clustering: A Review (1999)
  - Jain/Murty/Flynn
  - http://citeseer.ist.psu.edu/jain99data.html
- A Comparison of Document Clustering Techniques
  - Michael Steinbach, George Karypis and Vipin Kumar. TextMining Workshop. KDD. 2000.

Latent Semantic Analysis

- **Latent semantic space**: illustrative example



courtesy of Susan Dumais

Performing the maps

- Each row and column of *A* gets mapped into the *k*-dimensional LSI space, by the SVD.
- Claim – this is not only the mapping with the best (Frobenius error) approximation to *A*, but in fact *improves* retrieval.
- A query q is also mapped into this space, by

$$q_k = q^T U_k \Sigma_k^{-1}$$

  – Query NOT a sparse vector.

Empirical evidence

- Experiments on TREC 1/2/3 – Dumais
- Lanczos SVD code (available on netlib) due to Berry used in these expts
  - Running times of ~ one day on tens of thousands of docs
- Dimensions – various values 250-350 reported
  - (Under 200 reported unsatisfactory)
- Generally expect recall to improve – what about precision?

Empirical evidence

- Precision at or above median TREC precision
  - Top scorer on almost 20% of TREC topics
- Slightly better on average than straight vector spaces
- Effect of dimensionality:

Dimensions	Precision
250	0.367
300	0.371
346	0.374

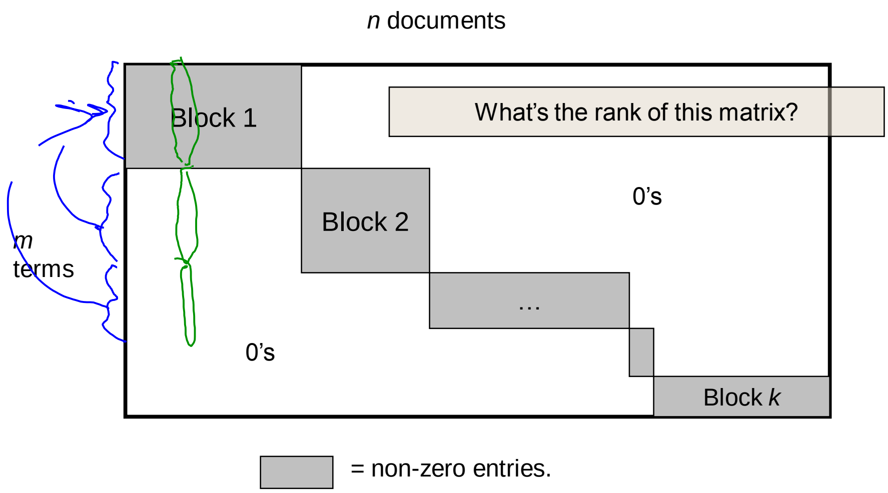
Failure modes

- Negated phrases
  - TREC topics sometimes negate certain query/terms phrases – automatic conversion of topics to
- Boolean queries
  - As usual, freetext/vector space syntax of LSI queries precludes (say) “Find any doc having to do with the following 5 companies”
- See Dumais for more.

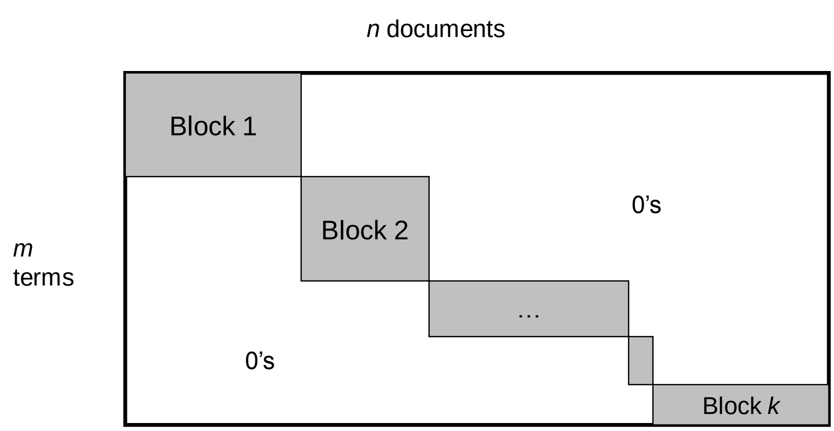
But why is this clustering?

- We’ve talked about docs, queries, retrieval and precision here.
- What does this have to do with clustering?
- Intuition: Dimension reduction through LSI brings together “related” axes in the vector space.

Intuition from block matrices

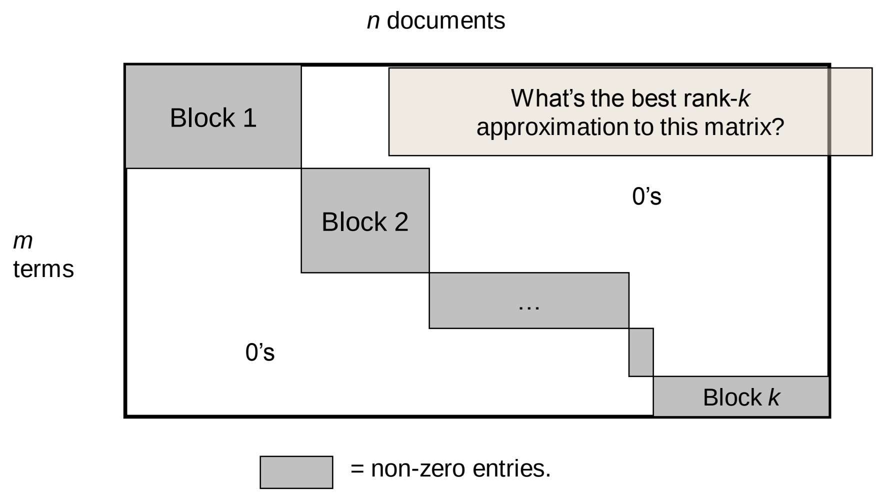


Intuition from block matrices

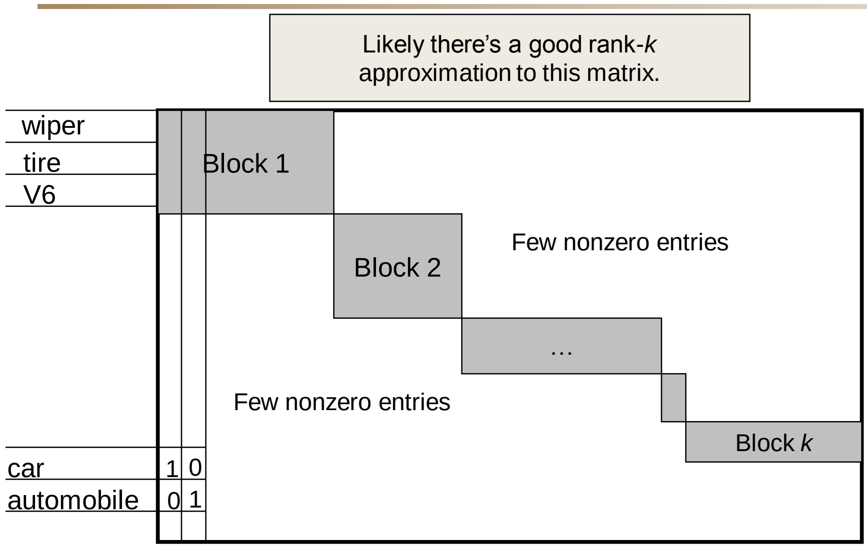


Vocabulary partitioned into *k* topics (clusters); each doc discusses only one topic.

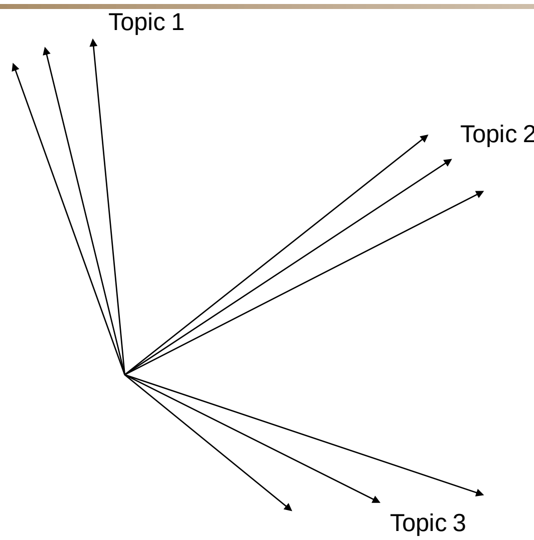
Intuition from block matrices



Intuition from block matrices



Simplistic picture



Some wild extrapolation

- The “dimensionality” of a corpus is the number of distinct topics represented in it.
- More mathematical wild extrapolation:
  – if A has a rank k approximation of low Frobenius error, then there are no more than k distinct topics in the corpus.

LSI has many other applications

- In many settings in pattern recognition and retrieval, we have a feature-object matrix.
  - For text, the terms are features and the docs are objects.
  - Could be opinions and users … more in 276B.
- This matrix may be redundant in dimensionality.
  - Can work with low-rank approximation.
  - If entries are missing (e.g., users' opinions), can recover if dimensionality is low.
- Powerful general analytical technique
  - Close, principled analog to clustering methods.

Resources

- http://www.cs.utk.edu/~berry/lsi++/
- http://lsi.argreenhouse.com/lsi/LSIpapers.html
- Dumais (1993) LSI meets TREC: A status report.
- Dumais (1994) Latent Semantic Indexing (LSI) and TREC-2.
- Dumais (1995) Using LSI for information filtering: TREC-3 experiments.
- M. Berry, S. Dumais and G. O'Brien. *Using linear algebra for intelligent information retrieval*. SIAM Review, 37(4):573--595, 1995.