

Information Management

Information Retrieval

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Introduction

- ❑ Information retrieval is the process of locating the most relevant information to satisfy a specific information need.
- ❑ Traditionally, we used databases and keywords to locate information.
- ❑ The most common modern application is search engines.
- ❑ Historically, the technology has been developed from the mid-50's onwards, with a lot of fundamental research conducted pre-Internet!

Terminology

- Term
 - Individual word, or possibly phrase, from a document.
- Document
 - Set of terms, usually identified by a document identifier (e.g., filename).
- Query
 - Set of terms (and other semantics) that are a machine representation of the user's needs.
- Relevance
 - Whether or not a given document matches a given query.

More Terminology

- Searching/Querying
 - Retrieving all the possibly relevant results for a given query.
- Indexing
 - Creating indices of all the documents/data to enable faster searching/quiring.
- Ranked retrieval
 - Retrieval of a set of matching documents in decreasing order of estimated relevance to the query.

Models for IR

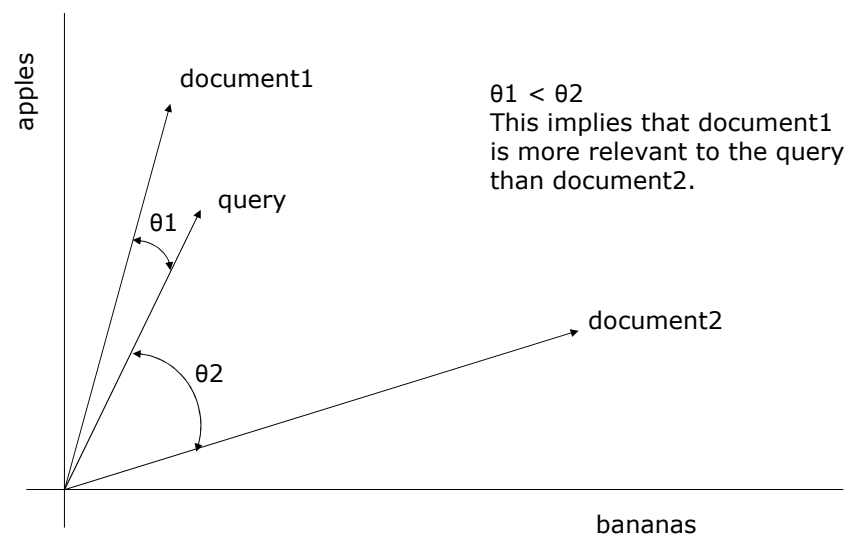
□ Boolean model

- Queries are specified as boolean expressions and only documents matching those criteria are returned.
 - e.g., apples AND bananas

□ Vector model

- Both queries and documents are specified as lists of terms and mapped into an n -dimensional space (where n is the number of possible terms). The relevance then depends on the angle between the vectors.

Vector Model in 2-D



Extended Boolean Models

- Any modern search engine that returns no results for a very long query probably uses some form of boolean model!
 - Altavista, Google, etc.
 - Vector models are not as efficient as boolean models.
- Some extended boolean models filter on the basis of boolean matching and rank on the basis of term weights (tf.idf).

Filtering and Ranking

- Filtering
 - Removal of non-relevant results.
 - Filtering restricts the number of results to those that are probably relevant.
- Ranking
 - Ordering of results according to calculated probability of relevance.
 - Ranking puts the most probably relevant results at the "top of the list".

Efficient Ranking

- ❑ Comparing every document to each query is very slow.
- ❑ Use inverted files to speed up ranking algorithms by possibly ignoring:
 - terms with zero occurrence in each document.
 - documents where terms have a very low occurrence value.
- ❑ We are only interested in those documents that contain the terms in the query.

Inverted (Postings) Files

- ❑ An inverted file for a term contains a list of document identifiers that correspond to that term.

Doc1	apples bananas apples apples
Doc2	bananas bananas apples bananas bananas

↑
original
documents

inverted files →

apples	Doc1: 3	4
	Doc2: 1	
bananas	Doc1: 1	5
	Doc2: 4	

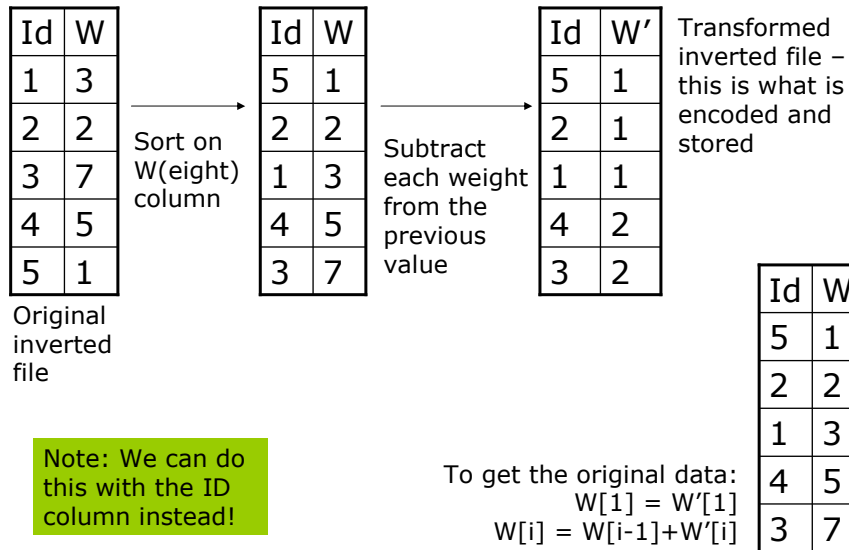
Implementation of Inverted Files

- Each term corresponds to a list of weighted document identifiers.
 - Each term can be a separate file, sorted by weight.
 - Terms, documents identifiers and weights can be stored in an indexed database.
- Search engine indices can easily take 2-6 times as much space as the original data.
 - The MG system (part of Greenstone) uses index compression and claims 1/3 as much space as the original data.

Inverted File Optimisations

- Use identifier hash/lookup table:
 - apples: 1 3 2 1
 - bananas: 1 1 2 4
- Sort weights and use differential values:
 - apples: 2 1 1 2
 - bananas: 1 1 2 3
- Aim: reduce values as much as possible so that optimal variable-length encoding schemes can be applied.
 - (For more information, read up on basic encoding schemes in data compression)

IF Optimisation Example



Boolean Ranking

- Assume a document D and a query Q are both n -term vectors.
- Then the inner product is a measure of how well D matches Q :

$$\text{Similarity} = D \cdot Q = \sum_{t=1}^n d_t \cdot q_t$$

- Normalise so that long vectors do not adversely affect the ranking.

$$\text{Similarity} = \frac{1}{|D||Q|} \sum_{t=1}^n d_t \cdot q_t$$

Boolean Ranking Example

- Suppose we have the document vectors $D1:(1, 1, 0)$ and $D2:(4, 0, 1)$ and the query $(1, 1, 0)$.

- Non-normalised ranking:

- $D1: (1, 1, 0) \cdot (1, 1, 0) = 1.1 + 1.1 + 0.0 = 2$
- $D2: (4, 0, 1) \cdot (1, 1, 0) = 4.1 + 0.1 + 1.0 = 4$
- Ranking: D2, D1

- Normalised ranking:

$$|D1| = \sqrt{\sum_{i=1}^m d_{1,i}^2} = \sqrt{1.1+1.1+0.0} = \sqrt{2} \quad |D2| = \sqrt{\sum_{i=1}^m d_{2,i}^2} = \sqrt{4.4+0.0+1.1} = \sqrt{17}$$

$$|Q| = \sqrt{\sum_{i=1}^m q_i^2} = \sqrt{1.1+1.1+0.0} = \sqrt{2}$$

- $D1: (1, 1, 0) \cdot (1, 1, 0) / \sqrt{2} \cdot \sqrt{2} = (1.1 + 1.1 + 0.0) / 2 = 1$
- $D2: (4, 0, 1) \cdot (1, 1, 0) / \sqrt{17} \cdot \sqrt{2} = (4.1 + 0.1 + 1.0) / \sqrt{34} = 4 / \sqrt{34}$
- Ranking: D1, D2

tf.idf

- Term frequency (tf)

- The number of occurrences of a term in a document – terms which occur more often in a document have higher tf.

- Document frequency (df)

- The number of documents a term occurs in – popular terms have a higher df.

- In general, terms with high “tf” and low “df” are good at describing a document and discriminating it from other documents – hence tf.idf (term frequency * inverse document frequency).

Inverse Document Frequency

- Common formulation:

$$w_t = \log_e \left(1 + \frac{N}{f_t} \right)$$

- Where f_t is the number of documents term t occurs in (document frequency) and N is the total number of documents.
- Many different formulae exist – all increase the importance of rare terms.
- Now, weight the query in the ranking formula to include an IDF with the TF.

$$Similarity = \frac{1}{|D||Q|} \sum_{t=1}^n d_t \cdot \log_e \left(1 + \frac{N}{f_t} \right)$$

Term Frequency

- Scale term frequency so that the subsequent occurrences have a lesser effect than earlier occurrences.
- Choose only terms in Q - as this is boolean - so prevent every term having a value of at least 1 (where before they were 0).

$$Similarity = \frac{1}{|D||Q|} \sum_{t \in Q \cap D} (1 + \log_e f_{d,t}) \cdot \log_e \left(1 + \frac{N}{f_t} \right)$$

- Lastly, eliminate $|Q|$ since it is constant.

$$Similarity = \frac{1}{|D|} \sum_{t \in Q \cap D} (1 + \log_e f_{d,t}) \cdot \log_e \left(1 + \frac{N}{f_t} \right)$$

Vector Ranking

- In n -dimensional Euclidean space, the angle between two vectors is given by:

$$\cos \theta = \frac{X \cdot Y}{|X||Y|}$$

- Note:
 - $\cos 90 = 0$ (orthogonal vectors shouldn't match)
 - $\cos 0 = 1$ (corresponding vectors have a perfect match)
- Cosine θ is therefore a good measure of similarity of vectors.
- Substituting good tf and idf formulae in $X \cdot Y$, we then get a similar formula to before (except we use all terms $t[1..N]$).

Term Document Space

- A popular view of inverted files is as a matrix of terms and documents.

documents

	Doc1	Doc2
Apples	3	1
Bananas	1	4

terms

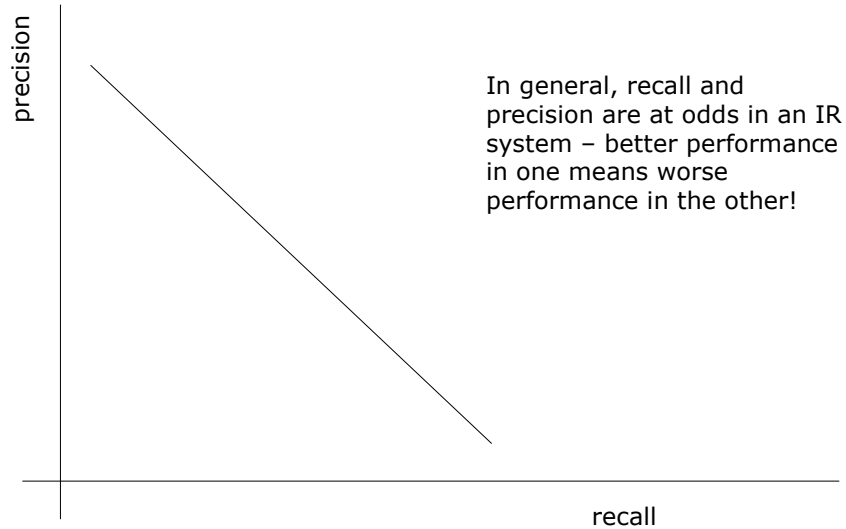
Clustering

- ❑ In term-document space, documents that are similar will have vectors that are “close together”.
- ❑ Even if a specific term of a query does not match a specific document, the clustering effect will compensate.
- ❑ Centroids of the clusters can be used as cluster summaries.
- ❑ Explicit clustering can be used to reduce the amount of information in T-D space.

Evaluation of Retrieval Algorithms

- ❑ Recall
 - The number of relevant results returned.
 - $\text{Recall} = \frac{\text{number retrieved and relevant}}{\text{total number relevant}}$
- ❑ Precision
 - The number of returned results that are relevant.
 - $\text{Precision} = \frac{\text{number retrieved and relevant}}{\text{total number retrieved}}$
- ❑ Relevance is determined by an “expert” in recall/precision experiments. High recall and high precision are desirable.

Typical Recall-Precision Graph



Other Techniques to Improve IR

- Stemming, Stopping
- Thesauri
- Metadata vs. Fulltext
- Relevance Feedback
- Inference Engines
- LSI
- PageRank
- HITS

Stemming and Case Folding

- Case Folding
 - Changing all terms to a standard case, e.g., lowercase
- Stemming
 - Changing all term forms to canonical versions.
 - e.g., studying, studies and study map to "study".
 - Stemming must avoid mapping words with different roots to the same term.
 - Porter's Stemming Algorithm for English applies a set of rules based on patterns of vowel-consonant transitions.

Stopping

- Stopwords are common words that do not help in discriminating in terms of relevance.
 - E.g., in for the a an of on
- Stopwords are not standard and depend on application and language.



Thesauri

- A thesaurus is a collection of words and their synonyms.
 - e.g., According to Merriam-Webster, the synonyms for "library" are "archive" and "athenaeum".
- An IR system can include all synonyms of a word to increase recall, but at a lower precision.
- Thesauri can also be used for cross-language retrieval.

Metadata vs. Full-text

- Text documents can be indexed by their contents or by their metadata.
- Metadata indexing is faster and uses less storage.
- Metadata can be obtained more easily (e.g., using open standards) while full text is often restricted.
- Full-text indexing does not rely on good quality metadata and can find very specific pieces of information.

Relevance Feedback

- ❑ After obtaining results, a user can specify that a given document is relevant or non-relevant.
- ❑ Terms that describe a (non-)relevant document can then be used to refine the query – an automatic summary of a document is usually better at describing the content than a user.

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Inference Engines

- ❑ Machine learning can be used to digest a document collection and perform query matching.
 - Connectionist models (e.g., neural networks)
 - Decision trees (e.g., C5)
- ❑ Combined with traditional statistical approaches, this can result in increased recall/precision.

Latent Semantic Indexing

- LSI is a technique to reduce the dimensionality of the term-document space, resulting in greater speed and arguably better results.
- Problems with traditional approach:
 - Synonymy – two different words that mean the same thing.
 - Polysemy – two different meanings for a single word.
- LSI addresses both of these problems by transforming data to its “latent semantics.”

Singular Value Decomposition

- SVD is used in LSI to factor the term-document matrix into constituents.
 - Calculations are based on eigenvalues and eigenvectors - many Mathematics packages can compute an SVD as a built-in function.

$$A = U \Sigma V^T = \begin{bmatrix} * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix} \begin{bmatrix} * \\ * \\ * \\ * \\ * \end{bmatrix} \begin{bmatrix} * & * & * \\ * & * & * \\ * & * & * \end{bmatrix}$$

SVD Sizes

- If A , the term-document matrix, is an $m \times n$ matrix,
 - U is an $m \times m$ orthogonal matrix
 - V is an $n \times n$ orthogonal matrix
 - Σ is the $m \times n$ diagonal matrix containing values on its diagonal in decreasing order of value.
i.e., $\sigma_1 \geq \sigma_2 \geq \sigma_3 \geq \dots \geq \sigma_{\min(m,n)}$
- Note:
 - m is the number of terms, represented by the rows of A
 - n is the number of documents, represented by the columns of A

Approximation

- Replace Σ with an approximation where the smallest values are zero.

$$\Sigma = \begin{bmatrix} 1.578 & & & & & \\ & 1.320 & & & & \\ & & 1.111 & & & \\ & & & 0.870 & & \\ & & & & 0.230 & \\ & & & & & & & & & & \end{bmatrix}$$

becomes,

$$\Sigma' = \begin{bmatrix} 1.578 & & & & & \\ & 1.320 & & & & \\ & & 1.111 & & & \\ & & & 0.0 & & \\ & & & & 0.0 & \\ & & & & & & & & & & \end{bmatrix}$$

Effect of Approximation

$$A' = U' \Sigma' V^{T'} = \begin{bmatrix} * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \\ * & * & 0 & 0 & 0 \end{bmatrix} \begin{matrix} * \\ * \\ 0 \end{matrix} \begin{bmatrix} * & * & * \\ * & * & * \\ 0 & 0 & 0 \end{bmatrix}$$

- If only p values are retained in Σ , then only p columns of U and p rows of V must be stored.

LSI Example 1/2

- Consider a document collection:
 - D1: apples bananas bananas bananas pears
 - D2: bananas bananas bananas
 - D3: pears
- With query: $q = \text{"apples"}$
- The term-document matrix will be:

	D1	D2	D3
apples	1	0	0
bananas	3	3	0
pears	1	0	1

LSI Example 2/3

```
svd.nb * -STUDENT VERSION-

Specify the term-document matrix.

In[1]:= A =  $\begin{pmatrix} 1 & 0 & 0 \\ 3 & 3 & 0 \\ 1 & 0 & 1 \end{pmatrix}$ 

Out[1]:= {{1, 0, 0}, {3, 3, 0}, {1, 0, 1}}

Create a query vector.

In[2]:= q = {1, 0, 0}

Out[2]:= {1, 0, 0}

Find the inner product of the query with every original document (column of A) by matrix/vector multiplication.

In[3]:= Transpose[A] . q

Out[3]:= {1, 0, 0}

Calculate the Singular Value Decomposition of A into three matrices.

In[4]:= {U, S, V} = SingularValues[N[A]]

Out[4]:= {{{-0.170644, -0.968737, -0.180079}, {0.34885, -0.23032, 0.908436},
{-0.921512, 0.0921986, 0.377247}}, {4.36877, 1.27413, 0.53895},
{{-0.745504, -0.665225, -0.0412197}, {0.44448, -0.5423, 0.712985},
{-0.496649, 0.513212, 0.699966}}}
```

LSI Example 3/3

```
svd.nb * -STUDENT VERSION-

Check that the SVD, when multiplied, gives back the original matrix.

In[5]:= Transpose[U] . DiagonalMatrix[S] . V

Out[5]:= {{1., -3.88578 × 10-16, 3.33067 × 10-16}, {3., 3., -2.498 × 10-16},
{1., 2.498 × 10-16, 1.}}

Create a truncated S diagonal matrix, with all elements being 0 except the first.

In[6]:= Sp = Table[If[i == 1, S[[i]], 0], {i, 1, 3}]

Out[6]:= {4.36877, 0, 0}

Multiply the new S with U and V, to create an approximation of the term-document space.

In[7]:= Ap = Transpose[U] . DiagonalMatrix[Sp] . V

Out[7]:= {{0.555777, 0.495928, 0.0307295}, {3.15511, 2.81536, 0.174449},
{0.586506, 0.523348, 0.0324285}}

Find the inner product of the query with every document of Ap, the approximated term-document space.

In[8]:= Transpose[Ap] . q

Out[8]:= {0.555777, 0.495928, 0.0307295}
```

Note: in practice, LSI does not generate the approximated matrix.

Advantages of LSI

- ❑ Smaller vectors and pre-calculations result in faster query matching.
- ❑ Smaller term-document space – less storage required.
- ❑ Automatic clustering of documents based on mathematical similarity (basis vector calculations).
- ❑ Elimination of “noise” in document collection.

Web Data Retrieval

- ❑ Web crawlers are often bundled with search engines to obtain data from the WWW.
- ❑ Crawlers follow each link (respecting robots.txt exclusions) in a hypertext document, obtaining an ever-expanding collection of data for indexing/querying.
- ❑ WWW search engines operate as follows:



PageRank

- ❑ PageRank (popularised by Google) determines the rank of a document based on the number of documents that point to it, implying that it is an “authority” on a topic.
- ❑ In a highly connected network of documents with lots of links, this works well. In a diverse collection of separate documents, this will not work.
- ❑ Google uses other techniques as well!

Simple PageRank

- ❑ PageRank works with a complete collection of linked documents.
- ❑ Pages are deemed important if
 - They are pointed to by many other pages,
 - Each also of high importance.
- ❑ Define
 - $r(i)$ = rank of a page
 - $B(i)$ = set of pages that point to i
 - $N(i)$ = number of pages that i points to

$$r(i) = \sum_{j \in B(i)} r(j) / N(j)$$

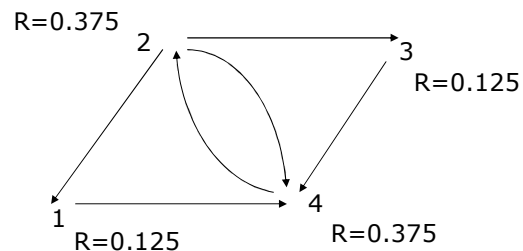
- ❑ Interpretation: $r(j)$ distributes its weight evenly to all its $N(j)$ children

Computing PageRank

- Choose a random set of ranks and iterate until the relative order doesn't change.
- Basic Algorithm:
 - s = random vector
 - Compute new $r(i)$ for each node
 - If $|r-s| < \epsilon$, r is the PageRank vector
 - $s = r$, and iterate.

PageRank Example

Node	B(i)	N(i)
1	2	1
2	4	3
3	2	1
4	123	1



Node	$r_0(i)$	$r_1(i)$	$r_2(i)$	$r_3(i)$...	$r_{200}(i)$
1	0.25	0.083	0.083	0.194	...	0.125
2	0.25	0.25	0.583	0.25	...	0.375
3	0.25	0.083	0.083	0.194	...	0.125
4	0.25	0.583	0.25	0.361	...	0.375

Sinks and Leaks

- In practice, some pages have no outgoing or incoming links.
- A “rank sink” is a set of connected pages with no outgoing links.
- A “rank leak” is a single page with no outgoing link.
- PageRank does the following:
 - Remove all leak nodes.
 - Introduce random perturbations into the iterative algorithm.

HITS

- Hypertext Induced Topic Search ranks the results of an IR query based on authorities and hubs.
- An authority is a page that many pages (hubs) point to.
 - E.g., www.uct.ac.za
- A hub is a page that points to many pages (authorities).
 - E.g., yahoo.com

HITS Algorithm 1/2

- Submit the query to an IR system and get a list of results.

- Create a focused subgraph as follows:
 - Let R = set of all result pages
 - Let $S = R$
 - Let $Q = \{\}$
 - For each page p in R
 - Add to Q all pages in S that p points to
 - Add to Q all pages (up to a limit) in S that point to p

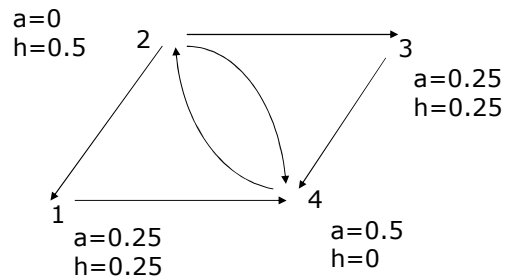
HITS Algorithm 2/2

- Initialise a_i and h_i for each node i to arbitrary values.

- Repeat until convergence:
 - a_i = sum of h_j values of all pages pointing to it
 - h_i = sum of a_j values of all pages it points to
 - Normalise the sum of a_i values to 1
 - Normalise the sum of h_i values to 1

HITS Example

Node	B(i)	F(i)
1	2	4
2	4	134
3	2	4
4	123	2



Node	$a_0(i)$	$h_0(i)$	$a_1(i)$	$h_1(i)$...	$a_{200}(i)$	$h_{200}(i)$
1	0.25	0.25	0.167	0.25	...	0.25	0.25
2	0.25	0.25	0.167	0.417	...	0.00	0.5
3	0.25	0.25	0.167	0.25	...	0.25	0.25
4	0.25	0.25	0.5	0.083	...	0.5	0.00

HITS vs PageRank vs LSI vs ...

- ▣ Under what circumstances can we use each?
- ▣ What are the advantages/disadvantages of each?
- ▣ How do they compare to traditional boolean/vector searching?

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