Introduction to

Information Retrieval

- Scoring and Term Weighting
- The Vector Space Model

Contents

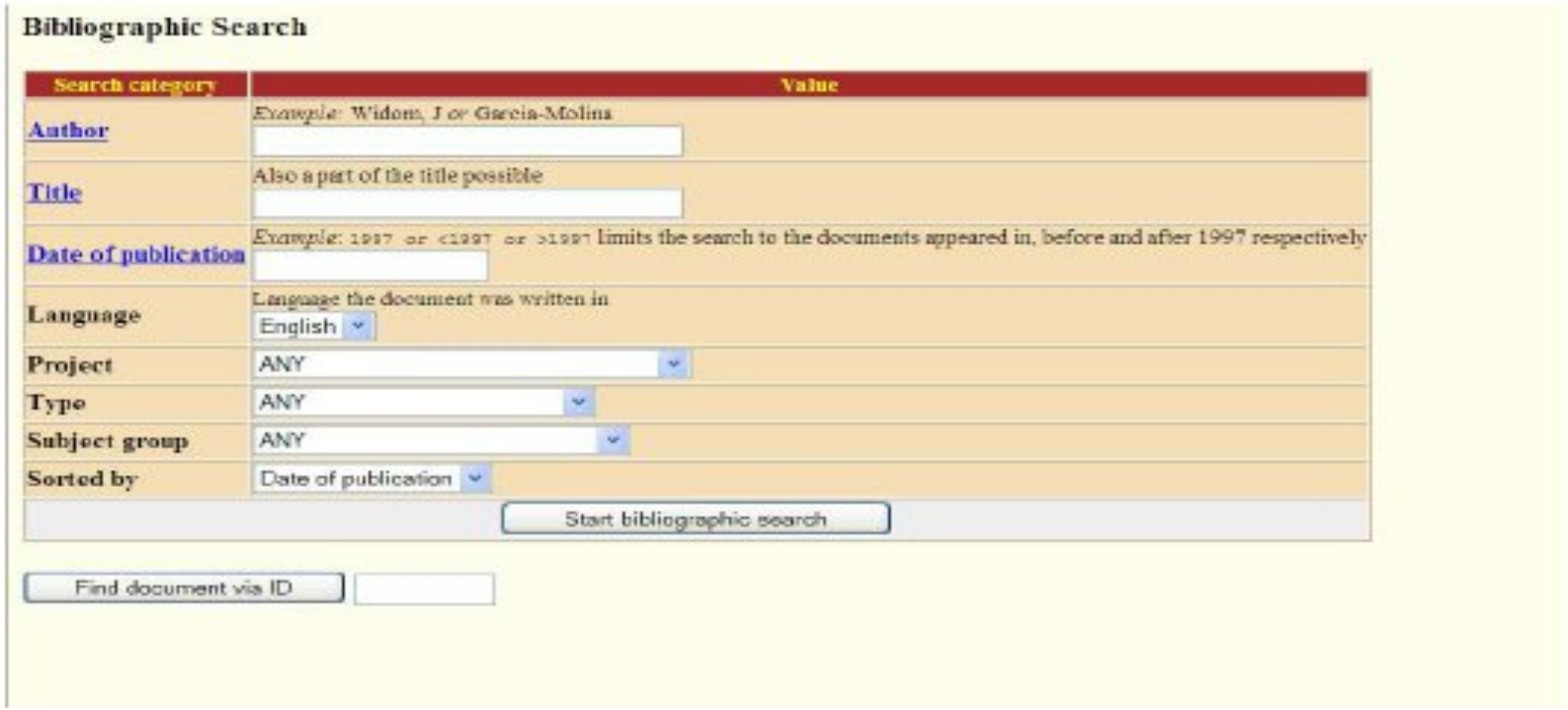
- Parametric and zone indexes
- Ranked retrieval
- Term Weighting schemes
- Vector space scoring

Parametric and zone indexes

- Each document has, in addition to text, some "meta-data" in fields e.g.,
  - Language = French
  - Format = pdf
  - Subject = Physics etc.
  - Date = Feb 2000

- A parametric search interface allows the user to combine a full-text query with selections on these field values e.g.,
  - language, date range, etc.

User view



Bibliographic Search

Search category	Value
Author	*Example:* Widom, J or Garcia-Molina
Title	Also a part of the title possible
Date of publication	*Example:* 1997 or <1997 or >1997 limits the search to the documents appeared in, before and after 1997 respectively
Language	Language the document was written in: English
Project	ANY
Type	ANY
Subject group	ANY
Sorted by	Date of publication
	Start bibliographic search

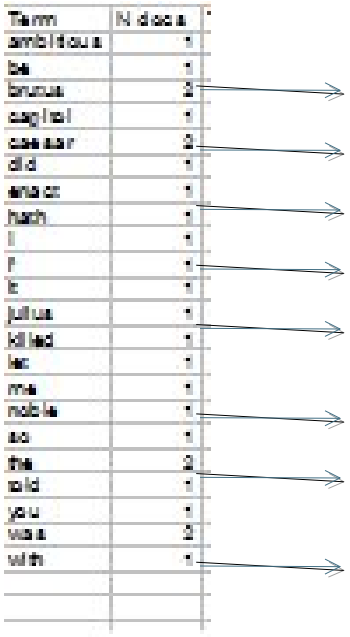
Find document via ID

► **Figure 6.1** Parametric search. In this example we have a collection with fields allowing us to select publications by zones such as Author and fields such as Language.

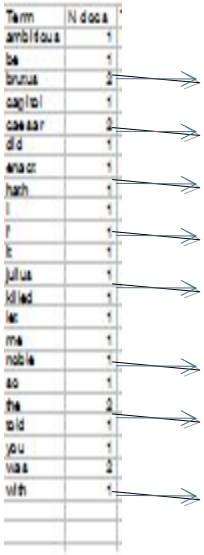
Zones

- A zone is an identified region within a doc
  - E.g., Title, Abstract, Bibliography
- Contents of a zone are free text
  - Not a “finite” vocabulary
- Indexes for each zone - allow queries like
  - find documents with merchant in the title and william in the author list and the phrase gentle rain in the body

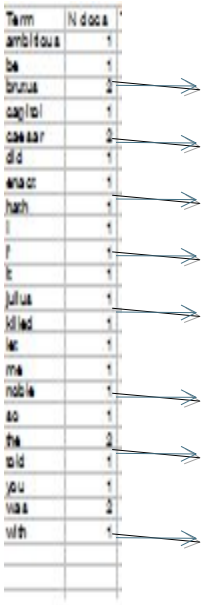
Zone indexes – simple view



Title



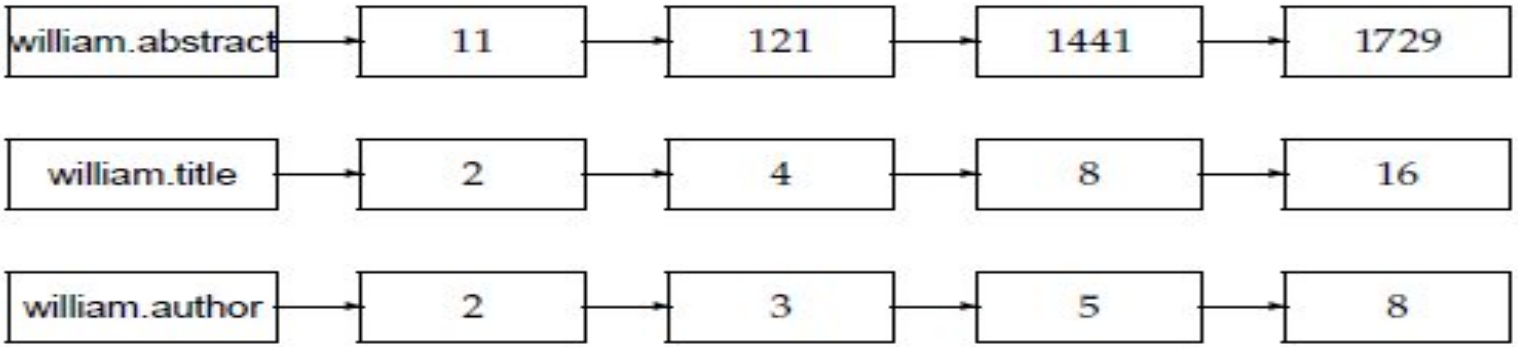
Author



Body

etc.

Zone indexes – common view



► **Figure 6.2** Basic zone index ; zones are encoded as extensions of dictionary entries.

► **Figure 6.3** Zone index in which the zone is encoded in the postings rather than the dictionary.

Weighted zone scoring

- Given a Boolean query *q and a document d*, *weighted zone scoring assigns* to the pair (*q*, *d*) *a score in the interval [0, 1]*,
  - *by computing a linear combination* of *zone scores*
  - *where each zone of the document contributes a Boolean* value.
- Specifically,
  - let there are L zones. Let $g1, \ldots, g_L \in [0, 1]$ *such that*
  - let s_i *be the* Boolean score denoting a match (or absence thereof) between *q and the ith* zone.
  - *Then*, the weighted zone score is defined to be

Example: Weighted zone scoring

- Query Q= shakespeare
- consider a collection in which each document has three zones: ***author, title and body***
- Suppose we set *g1 = 0.2, g2 = 0.3 and g3 = 0.5 where g1, g2 and g3 represents the* ***author, title and body*** *zone weights.*
- If the term shakespeare appear in the **title** and **body** zones but not the *author* zone of a document, the score of this document would be
- 0.8.

Ranked retrieval models

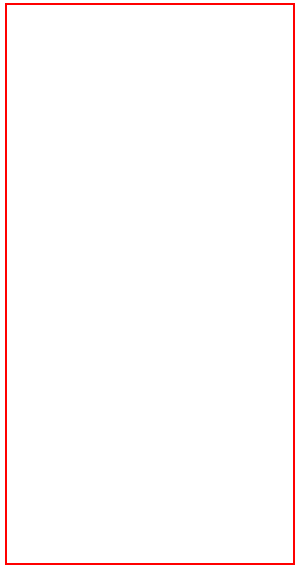
- Rather than a set of documents satisfying a query expression, in ranked retrieval, the system returns an ordering over the (top) documents in the collection for a query
- Free text queries: Rather than a query language of operators and expressions, the user's query is just one or more words in a human language

Recall (Lecture 1): Binary term-document incidence matrix

Each document is represented by a binary vector $\in \{0,1\}^{|V|}$

Term-document count matrices

- Consider the number of occurrences of a term in a document:
  - Each document is a count vector : a column below



Bag of words model

- Vector representation doesn't consider the ordering of words in a document
- *John is quicker than Mary* and *Mary is quicker than John* have the same vectors
- This is called the bag of words model.
- In a sense, this is a step back: The positional index was able to distinguish these two documents.
- We will look at "recovering" positional information later in this course.
- For now: bag of words model

Term frequency tf

- The term frequency $tf_{t,d}$ of term t in document d is defined as the number of times that t occurs in d.
- We want to use tf when computing query-document match scores. But how?
- Raw term frequency is not what we want:
  - A document with 10 occurrences of the term is more relevant than a document with 1 occurrence of the term.
  - But not 10 times more relevant.
- Relevance does not increase proportionally with term frequency.

NB: frequency = count in IR

Log-frequency weighting

- The log frequency weight of term t in d is

- $0 \rightarrow 0$, $1 \rightarrow 1$, $2 \rightarrow 1.3$, $10 \rightarrow 2$, $1000 \rightarrow 4$, etc.
- Score for a document-query pair: sum over terms *t* in both *q* and *d*:
- score

- The score is 0 if none of the query terms is present in the document.

Document frequency

- Rare terms are more informative than frequent terms
  - Recall stop words
- → We want a high weight for rare terms.

idf weight

- df_t is the document frequency of t: the number of documents that contain t
  - df_t is an inverse measure of the informativeness of t
  - $df_t \leq N$
- We define the idf (inverse document frequency) of t by

  - We use $\log (N/df_t)$ instead of N/df_t to "dampen" the effect of idf.

Will turn out the base of the log is immaterial.

idf example, suppose N = 806791

term	df_t	idf_t
car	18,165	1.65
auto	6723	2.08
insurance	19,241	1.62
best	25,235	1.5

There is one idf value for each term *t* in a collection.

tf-idf weighting

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

- Best known weighting scheme in information retrieval
  - Note: the "-" in tf-idf is a hyphen, not a minus sign!
  - Alternative names: tf.idf, tf x idf
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Binary → count → tf-idf weight matrix

Each document is now represented by a real-valued vector of tf-idf

Score for a document given a query

- There are many variants
  - How “tf” is computed (with/without logs)
  - Whether the terms in the query are also weighted
  - …

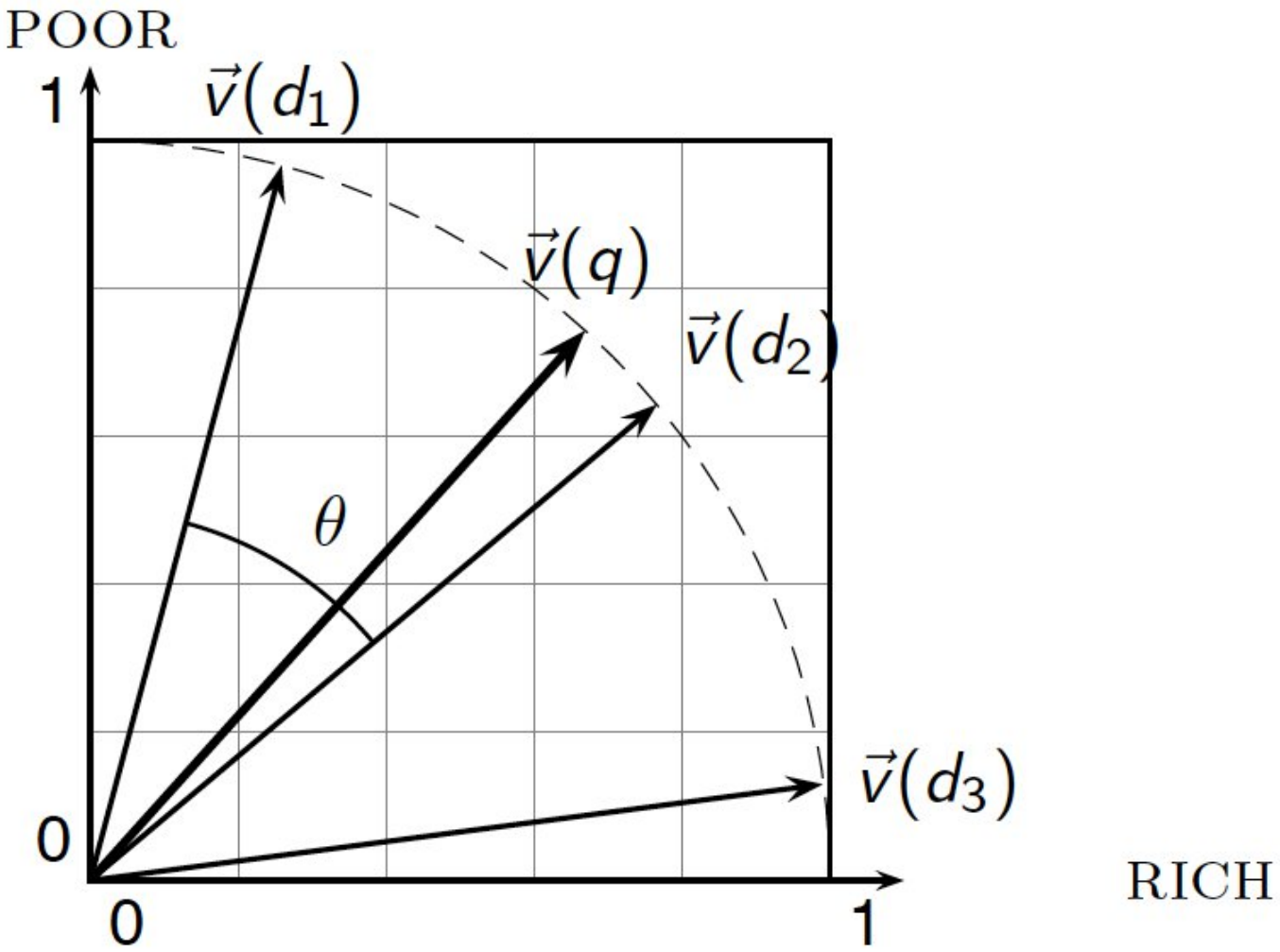
The Vector Space Model for Scoring

- The set of documents in a collection may be viewed as a set of vectors in a vector space.
  - Terms are axes of the space
  - Documents are points or vectors in this space
- Very high-dimensional: tens of millions of dimensions when you apply this to a web search engine
- These are very sparse vectors - most entries are zero.

Vector Similarity

- How do we quantify the similarity between two documents in this vector space?
- A first attempt : the magnitude of the vector difference between two document vectors.
  - Drawback: two documents with very similar content can have a significant vector difference simply because one is much longer than the other.
- **Solution** to compensate for the effect of document length is to compute the *cosine similarity*.

Cosine similarity illustrated



From angles to cosines

- The following two notions are equivalent.
  - Rank documents in decreasing order of the angle between query and document
  - Rank documents in increasing order of cosine(query,document)
- Cosine is a monotonically decreasing function for the interval [0°, 180°]

cosine(document,document)

DOT PRODUCT

$$\text{sim}(d_1, d_2) = \frac{\vec{V}(d_1) \cdot \vec{V}(d_2)}{|\vec{V}(d_1)||\vec{V}(d_2)|}, \qquad (2)$$

EUCLIDEAN LENGTH

The dot product $\vec{x} \cdot \vec{y}$ of two vectors is defined as $\sum_{i=1}^{M} x_i y_i$

The Euclidean length of d is defined to be $\sqrt{\sum_{i=1}^{M} \vec{V}_i^2(d)}$.

Cosine for length-normalized vectors

The effect of the denominator of Equation (2) is thus to *length-normalize* the vectors $\vec{V}(d_1)$ and $\vec{V}(d_2)$ to unit vectors $\vec{v}(d_1) = \vec{V}(d_1)/|\vec{V}(d_1)|$ and $\vec{v}(d_2) = \vec{V}(d_2)/|\vec{V}(d_2)|$.

Then we can rewrite the previous equation as:

$$\text{sim}(d_1, d_2) = \vec{v}(d_1) \cdot \vec{v}(d_2). \quad (3)$$

Example: N= 1,000,000

Document: *car insurance auto insurance*
Query: *best car insurance*

DF	Term
5000	auto
50000	best
10000	car
1000	insurance

Example: N= 1,000,000

Document: *car insurance auto insurance*

Query: *best car insurance*

Term	Query						Document				Prod
auto											
best											
car											
insurance											

Example: N= 1,000,000

Document: *car insurance auto insurance*

Query: *best car insurance*

Term	Query						Document				Prod
	tf-raw	tf-wt	df	idf	wt	n'lize	tf-raw	tf-wt	wt	n'lize	
auto	0	0	5000	2.3	0	0	1	1	2.3	0.47	0
best	1	1	50000	1.3	1.3	0.34	0	0	0	0	0
car	1	1	10000	2.0	2.0	0.53	1	1	2.0	0.41	0.22
insurance	1	1	1000	3.0	3.0	0.79	2	1.3	3.9	0.80	0.63

Query length = $\sqrt{0^2 + 1.3^2 + 2^2 + 3^2} \approx 3.8$

Doc length = $\sqrt{2.3^2 + 0^2 + 2^2 + 3.9^2} \approx 4.9$

Score = 0+0+0.22+0.63 = 0.85