IRRS: Information Retrieval and Recommender Systems FIB, Master in Data Science

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2. Information Retrieval Models

Information Retrieval Models, I

Setting the stage to think about IR

What is an Information Retrieval Model?

We need to clarify:

- A proposal for a logical view of documents (what info is stored/indexed about each document?),
- a query language

(what kinds of queries will be allowed?),

and a notion of relevance

(how to handle each document, given a query?).

Information Retrieval Models, II

A couple of IR models

Focus for this course:

- Boolean model,
 - Boolean queries, exact answers;
 - extension: phrase queries.
- Vector model,
 - weights on terms and documents;
 - similarity queries, approximate answers, ranking.

Boolean Model of Information Retrieval

Relevance assumed binary

Documents:

A document is completely identified by the set of terms that it contains.

- Order of occurrence considered irrelevant,
- number of occurrences considered irrelevant

(but a closely related model, called **bag-of-words** or **BoW**, does consider relevant the number of occurrences).

Thus, for a set of terms $\mathcal{T} = \{t_1, \ldots, t_T\}$, a document is just a subset of \mathcal{T} .

Each document can be seen as a bit vector of length T, $d = (d_1, \ldots, d_T)$, where

- ▶ $d_i = 1$ if and only if t_i appears in d, or, equivalently,
- $d_i = 0$ if and only if t_i does not appear in d.

Queries in the Boolean Model, I

Boolean queries, exact answers

Atomic query:

a single term.

The answer is the set of documents that contain it.

Combining queries:

- OR, AND: operate as union or intersection of answers;
- Set difference, t_1 BUTNOT $t_2 \equiv t_1$ AND NOT t_2 ;
- motivation: avoid unmanageably large answer sets.

In Lucene: +/- signs on query terms, Boolean operators.

Queries in the Boolean Model, II

A close relative to propositional logic

Analogy:

- Terms act as propositional variables;
- documents act as propositional models;
- a document is relevant for a term if it contains the term, that is, if, as a propositional model, satisfies the variable;
- queries are propositional formulas (with a syntactic condition of avoiding global negation);
- a document is relevant for a query if, as a propositional model, it satisfies the propositional formula.



Consider 7 documents with a vocabulary of 6 terms:

- d1 = one three
- d2 = two two three
- d3 = one three four five five five
- d4 = one two two two two three six six
- d5 = three four four six
- d6 = three three six six
- d7 = four five

Example, II

Our documents in the Boolean model

		five	four	one	six	three	two	
14	r	0	0	-	0	-	0	-
d1 =	l	0	0	1	0	1	0	
d2 =	[0	0	0	0	1	1]
d3 =	[1	1	1	0	1	0]
d4 =	[0	0	1	1	1	1]
d5 =	[0	1	0	1	1	0]
d6 =	[0	0	0	1	1	0]
d7 =	[1	1	0	0	0	0	1

(Invent some queries and compute their answers!)

Queries in the Boolean Model, III

No ranking of answers

Answers are not quantified:

A document either

- matches the query (is fully relevant),
- or does not match the query (is fully irrelevant).

Depending on user needs and application, this feature may be good or may be bad.

Phrase Queries, I

Slightly beyond the Boolean model

Phrase queries: conjunction plus adjacency

Ability to answer with the set of documents that have the terms of the query consecutively.

- A user querying "Keith Richards" may not wish a document that mentions both Keith Emerson and Emil Richards.
- Requires extending the notion of "basic query" to include adjacency.

Phrase Queries, II

Options to "hack them in"

Options:

Run as conjunctive query, then doublecheck the whole answer set to filter out nonadjacency cases.

> This option may be very slow in cases of large amounts of "false positives".

- Keep in the index dedicated information about adjacency of any two terms in a document (e.g. positions).
- Keep in the index dedicated information about a choice of "interesting pairs" of words.

Vector Space Model of Information Retrieval, I

Basis of all successful approaches

- Order of words still irrelevant.
- Frequence is relevant.
- Not all words are equally important.
- For a set of terms $\mathcal{T} = \{t_1, \dots, t_T\}$, a document is a vector $d = (w_1, \dots, w_T)$ of floats instead of bits.
- \blacktriangleright w_i is the weight of t_i in d.

Vector Space Model of Information Retrieval, II

Moving to vector space

- A document is now a vector in \mathbb{R}^T .
- The document collection conceptually becomes a matrix terms × documents.

but we never compute the matrix explicitly.

• Queries may also be seen as vectors in \mathbb{R}^T .

The tf-idf scheme

A way to assign weight vector to documents

Two principles:

- The more frequent t is in d, the higher weight it should have.
- The more frequent t is in the whole collection, the less it discriminates among documents, so the lower its weight should be in all documents.

The tf-idf scheme, II

The formula

A document is a vector of weights

$$d = [w_{d,1}, \ldots, w_{d,i}, \ldots, w_{d,T}].$$

Each weight is a product of two terms

$$w_{d,i} = tf_{d,i} \cdot idf_i.$$

The term frequency term tf is

$$tf_{d,i} = \frac{f_{d,i}}{\max_j f_{d,j}},$$
 where $f_{d,j}$ is the frequency of t_j in d .

And the inverse document frequency *idf* is

 $idf_i = \log_2 \frac{D}{df_i}$, where D = number of documents and df_i = number of documents that contain term t_i .

Example, I

		five	four	one	six	three	two	$\max f$
d1 =	[0	0	1	0	1	0] 1
d2 =	[0	0	0	0	1	2] 2
d3 =	[3	1	1	0	1	0] 3
d4 =	[0	0	1	2	1	4] 4
d5 =	[0	3	0	1	1	0] 3
d6 =	[0	0	0	2	3	0] 3
d7 =	[1	1	0	0	0	0] 1
10		2	2		-	0	2	
$\mathbf{df} =$		2	3	3	3	6	2	

Example, II

$\mathbf{df} =$			2	3	3	3	6	2	
d3 =		[3	1	1	0	1	0]
$\overrightarrow{d3} =$		[$\frac{3}{3}\log_2\frac{7}{2}$	$\frac{1}{3}\log_2 \frac{7}{3}$	$\frac{1}{3}\log_2\frac{7}{3}$	$\frac{0}{3}\log_2\frac{7}{3}$	$\frac{1}{3}\log_2\frac{7}{6}$	$\frac{0}{3}\log_2\frac{7}{2}$]
	=	[1.81	0.41	0.41	0	0.07	0]
d4 =		[0	0	1	2	1	4]
d4 =		[$\frac{0}{4}\log_2\frac{7}{2}$	$\frac{0}{4}\log_2\frac{7}{3}$	$\frac{1}{4}\log_2 \frac{7}{3}$	$\frac{2}{4}\log_2\frac{7}{3}$	$\frac{1}{4}\log_2 \frac{7}{6}$	$\tfrac{4}{4}\log_2 \tfrac{7}{2}$]
	=	[0	0	0.61	1.22	0.11	3.61]

Similarity of Documents in the Vector Space Model

The cosine similarity measure

- Similar vectors" may happen to have very different sizes.
- We better compare only their directions.
- Equivalently, we normalize them before comparing them to have the same Euclidean length.

$$sim(d1, d2) = \frac{d1 \cdot d2}{|d1| |d2|} = \frac{d1}{|d1|} \cdot \frac{d2}{|d2|}$$

where

$$v \cdot w = \sum_{i} v_i \cdot w_i$$
, and $|v| = \sqrt{v \cdot v} = \sqrt{\sum_{i} v_i^2}$.



Therefore, all cosines / similarities are between 0 and 1.

Cosine similarity, Example

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$$d3 = \begin{bmatrix} 1.81 & 0.41 & 0.41 & 0 & 0.07 & 0 \end{bmatrix}$$
$$d4 = \begin{bmatrix} 0 & 0 & 0.61 & 1.22 & 0.11 & 3.61 \end{bmatrix}$$
Then
$$|d3| = 1.898, \quad |d4| = 3.866, \quad d3 \cdot d4 = 0.26$$

and sim(d3, d4) = 0.035 (i.e., small similarity).

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Query Answering

- Queries can be transformed to vectors too.
- Sometimes, tf-idf weights; often, binary weights.
- ▶ $sim(doc, query) \in [0, 1].$
- Answer: List of documents sorted by decreasing similarity.
- We will find uses for comparing sim(d1, d2) too.