

Information Retrieval

Behind the Scene of Web Search

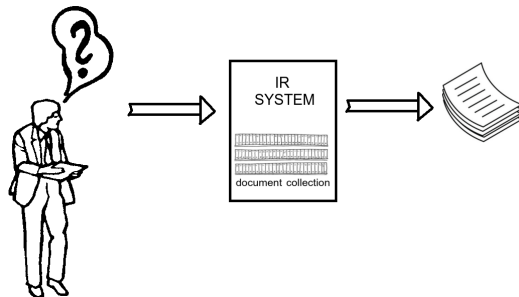
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UISEO

What is Information Retrieval?



A Definition

Information retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).

An Example

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Search

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Maps

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i am a query

Q

Web

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Search tools

About 451,000,000 results (0.21 seconds)

[AM Query Broadcast Station Search | FCC.gov](#)

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Nov 3, 2011 – The data files used for this **query** are updated each morning. Please refer any comments or suggestions on the **AM Query** to Dale Bickel, ...

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Dec 18, 2012 – Hello there, **I am** trying to figure a way to implement bi-directional fetch using hierarchical **query**. Table – CREATE TABLE DISA_OWNER.

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Negative feedback for Discogs Marketplace management - Generic Sleeve (again)
Latest 2 minutes ago; **I am** fairly new with a **query** Latest 27 minutes ago ...

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Dec 4, 2012 – None of that is important (in your **query** anyway—it's important to you the person of course.) **I am** looking for representation and appreciate you ...

[I am repeating my query - had availed housing loan - nationalised ...](#)

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[Query for a few features that I am seeking in pixlr](#)


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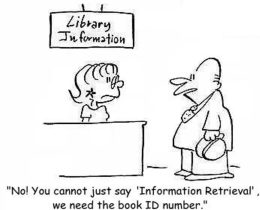
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Databases vs IR: getting a book from library

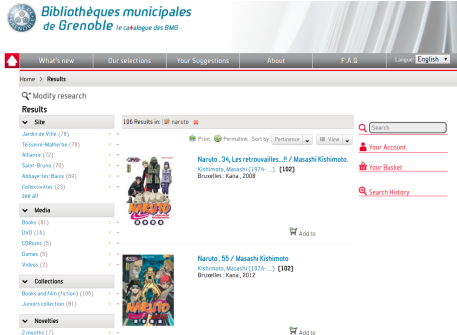
Structured Queries



Databases are fully structured, and require structured queries for retrieval.

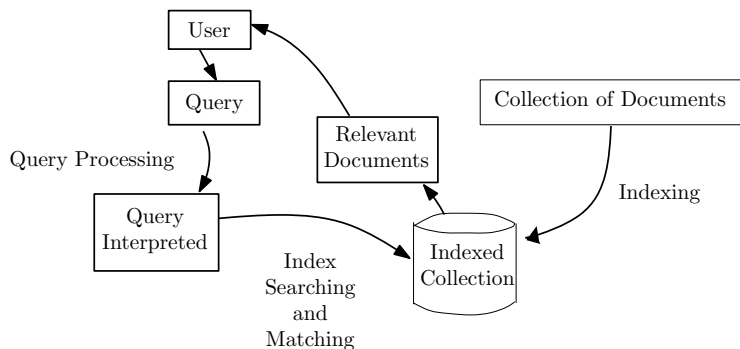
```
SELECT Title, Authors
FROM books
WHERE BookID="978-2-505"
```

Searching by Words

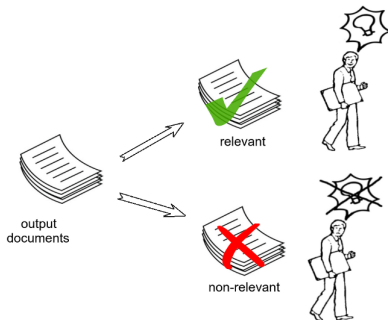


IR systems require words to find results containing those words.

IR Procedure



How Good is a System: Relevant and Non-relevant



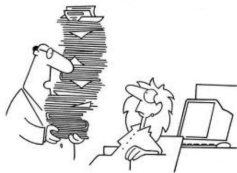
All that an IR system returns may not be relevant and required.

Precision

$$\textit{Precision} = \frac{\text{number of relevant documents retrieved}}{\text{number of all documents retrieved}}$$

Ranked Retrieval

Non-ranked Retrieval



The IR system returns a bunch of documents, without any ordering.

Ranked Retrieval



- The IR system returns a ranked document set.
- Documents are ranked based on score.
- Scores are given by different *scoring models*.

Evaluation of Ranked Retrieval Sets

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About 451,000,000 results (0.21 seconds)

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9:50

Evaluation of Ranked Retrieval Sets

Average Precision

$$AP_{q_j} = \frac{1}{m_j} \sum_{k=1}^{m_j} Precision(R_{jk})$$

- $q_j \rightarrow$ given query
- $D = \{d_1, \dots, d_{m_j}\} \rightarrow$ set of retrieved documents
- $R_{jk} \rightarrow$ is the set of ranked retrieval results from the top result until you get to document d_k

Mean Average Precision (MAP)

Let the query set is Q .

$$MAP = \frac{1}{|Q|} \sum_{j=1}^{|Q|} AP_{q_j}$$

Representing Text: Bag of Words

- A simplifying representation used in natural text processing
- A text (such as a sentence or a document) is represented as the bag of its words:
 - disregards: grammar, word ordering
 - maintains: multiplicity

I love this movie! It's sweet,
but with satirical humor. The
dialogue is great and the
adventure scenes are fun...
It manages to be whimsical
and romantic while laughing
at the conventions of the
fairy tale genre. I would
recommend it to just about
anyone. I've seen it several
times, and I'm always happy
to see it again whenever I
have a friend who hasn't
seen it yet!



it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
would	1
whimsical	1
times	1
sweet	1
satirical	1
adventure	1
genre	1
fairy	1
humor	1
have	1
great	1
...	...

Text to Matrix: Count Matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
anthony	157	73	0	0	0	1
brutus	4	157	0	2	0	0
caesar	232	227	0	2	1	0
calpurnia	0	10	0	0	0	0
cleopatra	57	0	0	0	0	0
mercy	2	0	3	8	5	8
worser	2	0	1	1	1	5

...

Each document is now represented as a count vector $\in \mathbb{N}^{|V|}$.

Vocabulary

Vocabulary is the set of unique words/terms present in the collection.

For example: {anthony, brutus, caesar...}

Text to Matrix: Count Matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
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...						

Each document is now represented as a **count vector** $\in \mathbb{N}^{|V|}$.

Vocabulary

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For example: {anthony, brutus, caesar...}

Term Frequency

- The term frequency $tf_{t,d}$ of term t in document d is defined as the **number of times that t occurs in d** .
- A document with $tf = 10$ occurrences of a term is more relevant than a document with $tf = 1$ occurrence of the term.
 - Relevance does not increase proportionally with term frequency.
- The frequency of the term in the collection...
 - Some terms are rare (e.g. EPISTEMOPHOBIA).
 - Some terms are frequent (e.g. INFORMATION)
 - Rare terms are more informative than frequent terms.
 - Rare terms should have **higher weights** than frequent terms.

- We want:
 - higher weights for rare terms like EPISTEMOPHOBIA.
 - lower (but positive) weights for frequent terms like INFORMATION.
- The document frequency df_t of a term t is the number of documents in the collection that t occurs in.
- Rare terms will have lower df than frequent terms.
- df_t is an **inverse measure of the informativeness** of term t .

- Inverse document frequency idf_t of term t is:

$$idf_t = \log \frac{N}{df_t}$$

(N is the number of documents in the collection.)

- idf_t is a **measure of the informativeness** of the term.
- In the query “epistemophobia information”, idf weighting increases the relative weight of EPISTEMOPHOBIA and decreases the relative weight of INFORMATION.

- The tf-idf weight of a document d w.r.t a query term t is the product of its $tf_{t,d}$ and idf_d .

$$score_{tf-idf}(t, d) = (tf_{t,d}) \cdot \left(\log \frac{N}{df_t} \right)$$

- The tf-idf score:
 - increases with the number of occurrences of t within d . (term frequency)
 - increases with the rarity of the term in the collection. (inverse document frequency)
- One of the classical weighting scheme in information retrieval.

Weight Matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
anthony	157	73	0	0	0	1
brutus	4	157	0	2	0	0
caesar	232	227	0	2	1	0
calpurnia	0	10	0	0	0	0
cleopatra	57	0	0	0	0	0
mercy	2	0	3	8	5	8
worser	2	0	1	1	1	5
...						

Weight Matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
anthony	5.25	3.18	0.0	0.0	0.0	0.35
brutus	1.21	6.10	0.0	1.0	0.0	0.0
caesar	8.59	2.54	0.0	1.51	0.25	0.0
calpurnia	0.0	1.54	0.0	0.0	0.0	0.0
cleopatra	2.85	0.0	0.0	0.0	0.0	0.0
mercy	1.51	0.0	1.90	0.12	5.25	0.88
worser	1.37	0.0	0.11	4.15	0.25	1.95

...

Each document is now represented as a **real-valued vector** of tf-idf weights $\in \mathbb{R}^{|V|}$.

$V \Rightarrow$ the vocabulary of the collection under consideration

Vector Space Model

- The Vector Space Model is an algebraic model for representing text documents as vectors
- In this model:
 - Each document d of a collection C is represented with a vector $\vec{d} \in \mathbb{R}^{|V|}$
 - Dimension of the vector \vec{d} is the size of the vocabulary $|V|$
 - Vector space constructed is a space of terms in which each dimension is associated with a term of the collection
- To score documents w.r.t queries:
 - 1 Each query q is similarly represented by a vector $\vec{q} \in \mathbb{R}^{|V|}$ of same dimension
 - 2 Rank documents according to their **similarity** to the query.
- Cosine similarity is used to measure similarity between query and document.

$$score_{vspace}(q, d) = \cos(\vec{q}, \vec{d}) = \frac{\vec{q} \cdot \vec{d}}{|\vec{q}| \cdot |\vec{d}|}$$

Key Idea

A term appearing in a small distinct number of documents with high frequency is far more important than the terms appearing in a large number of documents with very low frequency.

Elite Terms for a Document

Terms having a high term frequency in the document in question but low document frequency.

To score a document d for a word t in query q :

- the importance of term t in document d is **proportional to the term frequency** of t in d
- the importance of term t is **inversely proportional to the document frequency** of t
- the score is weighted by the number of occurrences of the term t inside the query q itself

Key Idea

A term appearing in a small distinct number of documents with high frequency is far more important than the terms appearing in a large number of documents with very low frequency.

Elite Terms for a Document

Terms having a high term frequency in the document in question but low document frequency.

BM25 equation

$$score_{BM25}(q, d) = \sum_{t \in q \cap d} \underbrace{\frac{(k_1 + 1) \times tf_t^d}{k_1 \left((1 - b) + b \frac{l_d}{l_{avg}} \right) + tf_t^d}}_{\text{term frequency}} \underbrace{\ln \left(\frac{N - df_t + 0.5}{df_t + 0.5} \right)}_{\text{document frequency}} \underbrace{\frac{(k_3 + 1) \times tf_t^q}{k_3 + tf_t^q}}_{\text{key frequency}}$$

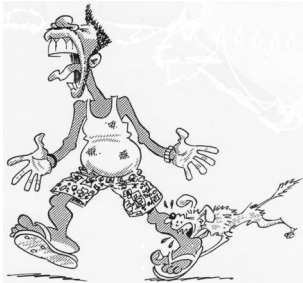
- Given a query and a collection of documents, a system must determine how well the documents satisfy the query.
 - An IR system makes an **uncertain guess** of whether a document satisfies the query.
- Probability theory provides a principled foundation for such **reasoning under uncertainty**.
 - Probabilistic models exploit this foundation to estimate how likely it is that a document is relevant to a query.

Probabilistic Approach

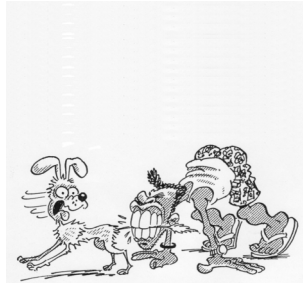
- Assume binary notion of relevance: $R_{d,q}$ is a random variable, such that
 - $R_{d,q} = 1$ if document d is relevant w.r.t query q
 - $R_{d,q} = 0$ otherwise
- Probabilistic ranking orders documents decreasingly by their estimated probability of relevance w.r.t. query: $P(R = 1|q, d)$
- Assume that the relevance of each document is independent of the relevance of other documents.
- The score is:

$$score_{prob}(q, d) = \log \prod_{t \in q} P(R = 1|q, d) = \sum_{t \in q} \log P(R = 1|q, d)$$

Information-Based Models



A snake has bitten a man.



A man has bitten a snake.

Surprisal of a message

Measure of information content called the self-information or *surprisal* of a message m :

$$I(m) = -\log[P(m)]$$

Information-Based Model

The more a word deviates in a document from its average behavior in the collection, the more likely it is *significant* for this particular document.

word behaves in a document as expected in collection \implies word has high probability (p) of occurrence in the document \implies information it brings to the document ($-\log p$) is small

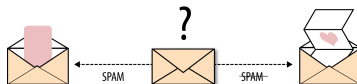
Similarly, if a word has a low probability of occurrence in the document \implies high information content.

Information Model Equation

$$score_{info}(q, d) = \sum_{t \in q \cap d} tf_t^q \{-\log P(X_t \geq tf_t^d | \lambda_t)\}$$

Using Machine Learning

- Document classification: a mail $\vec{d} \rightarrow \{spam, good\}$



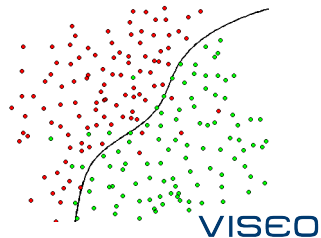
- \vec{d} : count vector or tf.idf vector
- Can we do same for retrieval? $\vec{d} \rightarrow \{relevant, not\}$
 - assume we have labels for learning, i.e. if \vec{d} is relevant or not



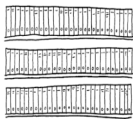
- Wrong feature set:
 - word or feature “obama”
 - highly relevant for query “44th US president”
 - useless for query “area of a parallelogram”
 - can classify for one particular query
 - solution? separate classifier for every query?

Learning to Rank

- Utilize the query, along with documents, as feature: a consistent feature set across all the queries
- Transform feature set: $f(q \times d) = \vec{X} \rightarrow \{\text{relevant}, \text{not}\}$
 - example features that have the same effect for any query:
 - BM25 score of query q against document d
 - tf.idf score of query q against document d
 - various count statistics of query words within documents:
e.g. number of query words in the title
 - and more...
 - Refer to LETOR features
- Training data: $\{R, X\}$
 - $R = \{-1, +1\}$: is d is relevant to q
 - X : is (d, q) pairs
- Learn any standard classifier
- Three types of learning to rank:
pointwise, pairwise, listwise



Test Collection



set of documents



set of queries



relevancy judgement
or 'qrels'

Testing Platform

- Different modules (e.g. indexing, query processing matching) are implemented.
- Some popular scoring models are implemented.
- Anyone can customize the platform at code level to implement any new developments.
- Mostly open source and free.

Popular IR Platforms

- **Terrier IR Platform.** Written in Java, and is developed at the School of Computing Science, University of Glasgow.
Ref: <http://terrier.org/>.
- **Indri (Lemur).** Written C++, and is developed at the Center for Intelligent Information Retrieval, University of Massachusetts and the Language Technologies Institute, Carnegie Mellon University.
Ref: <https://www.lemurproject.org/indri/>.

Popular Test Collections

- **Text REtrieval Conference (TREC).**
Ref: <http://trec.nist.gov/>.
- **Cross-Language Evaluation Forum (CLEF).**
Ref: <http://www.clef-initiative.eu/>

It's the beginning

Further Readings:

- Introduction to Information Retrieval. *Manning, Raghavan, Schütz*
 - Freely available: <https://nlp.stanford.edu/IR-book/>
- Recherche d'information: Applications, modes et algorithmes - Data mining, décisionnel et big data. *Massih-R Amini, Eric Gaussier*



Thank you!

Questions, Comments...

