CAI: Cerca i Anàlisi d'Informació
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Two Information Retrieval Models

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Contents

A couple of IR models

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

A couple of IR models

Both are Bag of Words models:

- Order of the words in the document is forgotten
- So document = set of pairs (order, frequency)

Boolean model additionally forgets about frequency

Example

A very simple toy case

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 four six

d6 = three three three six six

d7 = four five

Example

Our documents in the Boolean model

$$
\begin{array}{lcccccccc}
 & & five & four & one & six & three & two & \\
d1 = & [& 0 & 0 & 1 & 0 & 1 & 0 &] \\
d2 = & [& 0 & 0 & 0 & 0 & 1 & 2 &] \\
d3 = & [& 3 & 1 & 1 & 0 & 1 & 0 &] \\
d4 = & [& 0 & 0 & 1 & 2 & 1 & 4 &] \\
d5 = & [& 0 & 3 & 0 & 1 & 1 & 0 &] \\
d6 = & [& 0 & 0 & 0 & 2 & 3 & 0 &] \\
d7 = & [& 1 & 1 & 0 & 0 & 0 & 0 &]
\end{array}
$$

Note that we sort the terms alphabetically. See why later.

Example

. . . in sparse representation

(Omitting the quotes around strings in your programming language. . .)

d1 = [(one,1), (three,1)]

d2 = [(three,1), (two,2)]

d3 = [(five,3), (four,1), (one,1), (three,1)]

d4 = [(one,1), (six,2), (three,1), (two,4)]

d5 = [(four,3), (six,1), (three,1)]

d6 = [(six,2), (three,3)]

d7 = [(five,1), (four,1)]

Boolean Model of Information Retrieval

Documents:

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

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

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.

Relevance in the Boolean Model

The set of documents that satisfy a query is defined recursively:

- Single-term queries define the set of docs that contain it.
- View AND, OR, BUTNOT as set operations, proceed recursively.

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So: Relevance is binary: A document is either totally relevant or totally irrelevant.

No ranking.

This may be good or bad depending of user intent.

Example

Our documents in a Bag-of-Words model

$$
\begin{array}{lcccccc}
 & five & four & one & six & three & two \\
d1 = & [\ 0 & 0 & 1 & 0 & 1 & 0\ ] \\
d2 = & [\ 0 & 0 & 0 & 0 & 1 & 1\ ] \\
d3 = & [\ 1 & 1 & 1 & 0 & 1 & 0\ ] \\
d4 = & [\ 0 & 0 & 1 & 1 & 1 & 1\ ] \\
d5 = & [\ 0 & 1 & 0 & 1 & 1 & 0\ ] \\
d6 = & [\ 0 & 0 & 0 & 1 & 1 & 0\ ] \\
d7 = & [\ 1 & 1 & 0 & 0 & 0 & 0\ ]
\end{array}
$$

Exercise

Invent some queries and give their answers

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.

  Slow if many “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

Basis of all successful approaches

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

Vector Space Model of Information Retrieval

Moving to vector space

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

  terms $\times$ 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 vectors 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

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

And the inverse document frequency idf is

$$idf_i = \log_2 \frac{D}{df_i}, \qquad \text{where } D = \text{number of documents}$$

and df_i = number of documents that contain term t_i.

Example, I

	five	*four*	*one*	*six*	*three*	*two*	**maxf**
$d1 =$	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
df $=$	2	3	3	3	6	2	

Example, II

$$
\begin{array}{lcccccccc}
\mathbf{df} = & & 2 & & 3 & & 3 & & 3 & & 6 & & 2 & \\
d3 = & [& 3 & & 1 & & 1 & & 0 & & 1 & & 0 &] \\
\rightarrow & & & & & & & & & & & & & \\
d3 = & [& \frac{3}{3}\log_2\frac{7}{2} & & \frac{1}{3}\log_2\frac{7}{3} & & \frac{1}{3}\log_2\frac{7}{3} & & \frac{0}{3}\log_2\frac{7}{3} & & \frac{1}{3}\log_2\frac{7}{6} & & \frac{0}{3}\log_2\frac{7}{2} &] \\
 & = & [& 1.81 & & 0.41 & & 0.41 & & 0 & & 0.07 & & 0 &] \\
d4 = & [& 0 & & 0 & & 1 & & 2 & & 1 & & 4 &] \\
\rightarrow & & & & & & & & & & & & & \\
d4 = & [& \frac{0}{4}\log_2\frac{7}{2} & & \frac{0}{4}\log_2\frac{7}{3} & & \frac{1}{4}\log_2\frac{7}{3} & & \frac{2}{4}\log_2\frac{7}{3} & & \frac{1}{4}\log_2\frac{7}{6} & & \frac{4}{4}\log_2\frac{7}{2} &] \\
 & = & [& 0 & & 0 & & 0.61 & & 1.22 & & 0.11 & & 3.61 &]
\end{array}
$$

Tweaking tf-idf

Many variations possible. Just two:

- Boost the $tf_{d,i}$ term if i appears in the title, or in boldface, or in the metadata of d.
- Laplace correction: Define $idf_i = \log \frac{D+1}{df_i+1}$. Allows to define it for terms i not in the index.

  With a generating mindframe, accounts for terms so infrequent in the document source that did not appear in any of the D sampled documents.

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

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

- Our weights are all nonnegative.
- Therefore, all cosines / similarities are between 0 and 1.

Cosine similarity, Example

$$\begin{array}{rcl} d3 & = & [\ 1.81 \quad 0.41 \quad 0.41 \quad 0 \quad 0.07 \quad 0\ ] \\ d4 & = & [\ 0 \quad 0 \quad 0.61 \quad 1.22 \quad 0.11 \quad 3.61\ ] \end{array}$$

Then

$$|d3| = 1.898, \quad |d4| = 3.866, \quad d3 \cdot d4 = 0.26$$

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

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.

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- Sometimes, tf-idf weights; often, binary weights.
- $sim(doc, query) \in [0, 1]$.
- Answer: List of documents sorted by decreasing similarity.

- Note that $sim(d1, d2)$ make sense too.

Evaluation of Information Retrieval Usage

Start in the Boolean model. Notation:

- $\mathcal{D}$: set of all our documents;
- $\mathcal{A}$: answer set: documents that the system retrieves as answer;

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Start in the Boolean model. Notation:

- $\mathcal{D}$: set of all our documents;
- $\mathcal{A}$: answer set: documents that the system retrieves as answer;
- $\mathcal{R}$: relevant documents: those that the user actually wishes to see as answer.

  (But no one knows this set, not even the user!)

The Recall and Precision measures

Let's settle for:

- recall, $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{R}|}$:

  $Pr(d \in \mathcal{A} | d \in \mathcal{R})$

- precision, $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{A}|}$:

  $Pr(d \in \mathcal{R} | d \in \mathcal{A})$

Difficult to get both high recall and high precision.

Recall and Precision, confusion matrix

Equivalent definition

Confusion matrix

		Answered	
		relevant	not relevant
Reality	relevant	tp	fn
	not relevant	fp	tn

- $|\mathcal{R}| = tp + fn$
- $|\mathcal{A}| = tp + fp$
- $|\mathcal{R} \cap \mathcal{A}| = tp$

- Recall = $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{R}|} = \frac{tp}{tp+fn}$
- Precision = $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{A}|} = \frac{tp}{tp+fp}$

Recall and Precision, confusion matrix

Equivalent definition

Confusion matrix

		Answered	
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Reality	relevant	tp	fn
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- $|\mathcal{R}| = tp + fn$
- $|\mathcal{A}| = tp + fp$
- $|\mathcal{R} \cap \mathcal{A}| = tp$

- Recall = $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{R}|} = \frac{tp}{tp+fn}$
- Precision = $\frac{|\mathcal{R} \cap \mathcal{A}|}{|\mathcal{A}|} = \frac{tp}{tp+fp}$

In information retrieval, usually tn is huge.
Accuracy in the Machine Learning sense is not interesting (99.9%).

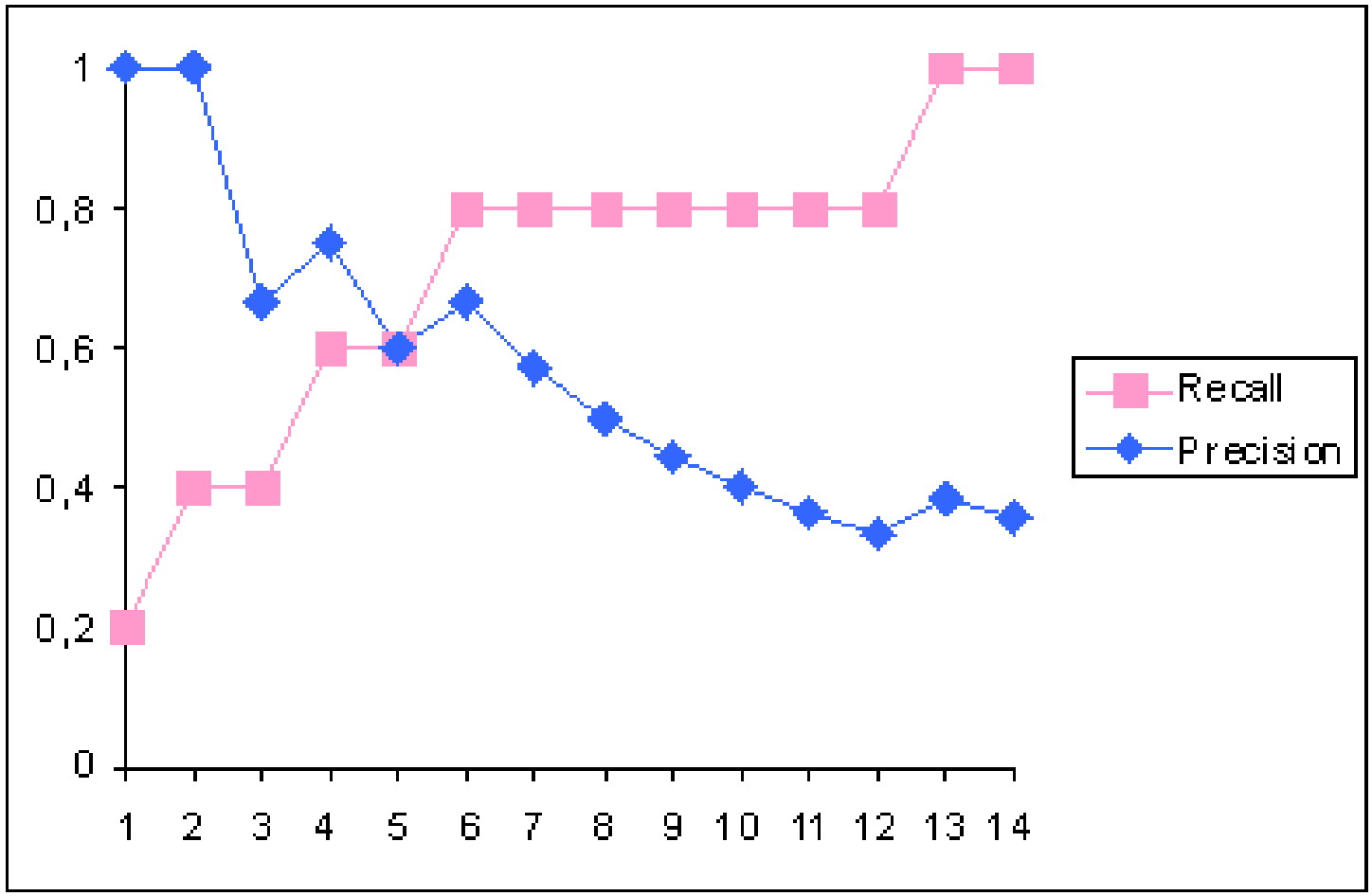
How many documents to show?

Now think of the Vector Model. Relevance is a real number.

- Users won't read too large answers.
- Long answers are likely to exhibit low precision.
- Short answers are likely to exhibit low recall.

We analyze precision and recall as functions of the number of documents k provided as answer.

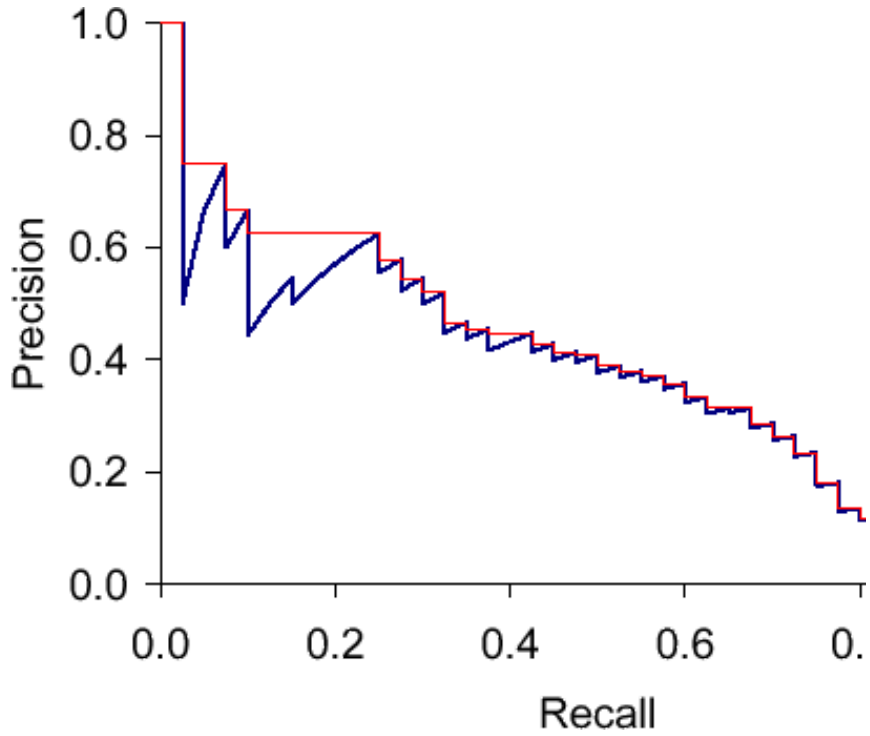
Rank-recall and rank-precision plots



(Source: Prof. J. J. Paijmans, Tilburg)

A single “precision and recall” curve

x-axis for recall, and y-axis for precision.
(Similar to, and related to, the ROC curve in predictive models.)



(Source: Stanford NLP group)
Often: Plot 11 points of interpolated precision, at 0%, 10%, 20%, . . . , 100% recall

Other measures of effectiveness

- AUC: Area under the curve of the plots above, relative to best possible
- F-measure: $\frac{2}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}}$
  - Harmonic mean. Closer to min(.,.) than arithmetic mean
- α-F-measure: $\frac{1}{\frac{\alpha}{\text{recall}} + \frac{1-\alpha}{\text{precision}}}$

  (F-measure is α-F-measure for $\alpha = 0.5$. Check!)
  (other α's give different importance to recall and precision)

Other measures of effectiveness, II

Take into account *the documents previously known to the user*.

- Coverage:

  |relevant & known & retrieved| / |relevant & known|

- Novelty:

  |relevant & retrieved & UNknown| / |relevant & retrieved|

Relevance Feedback

Going beyond what the user asked for

The user relevance cycle:

1. Get a query q
2. Retrieve relevant documents for q
3. Show top k to user
4. Ask user to mark them as relevant / irrelevant
5. Use answers to refine q
6. If desired, go to 2

Rocchio's rule

One way to create the new query

Given a query q, and a set of documents, split into relevant R and nonrelevant NR sets, build a new query q':

$$q' = \alpha \cdot q + \beta \cdot \frac{1}{|R|} \cdot \sum_{d \in R} d - \gamma \cdot \frac{1}{|NR|} \cdot \sum_{d \in NR} d$$

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- All vectors q and d's must be normalized (e.g., unit length).
- Weights α, β, γ, scalars, with $\alpha > \beta > \gamma \geq 0$; often $\gamma = 0$.
  - α: degree of trust on the original user's query,
  - β: weight of positive information (terms that do not appear on the query but do appear in relevant documents),
  - γ: weight of negative information.

Relevance Feedback, III

In practice, often:

- good improvement of the recall for first round,
- marginal for second round,
- almost none beyond.

In web search, precision matters much more than recall, so the extra computation time and user patience may not be productive.

Relevance Feedback, IV

. . . as Query Expansion

It is a form of Query Expansion:

The new query has non-zero weights on words
that were not in the original query

Pseudorelevance feedback

Do not ask anything from the user!

- User patience is precious resource. They'll just walk away.

Pseudorelevance feedback

Do not ask anything from the user!

- User patience is precious resource. They'll just walk away.
- Assume you did great in answering the query!
- That is, top-k documents in the answer are all relevant
- No interaction with user
- But don't forget that the search will feel slower.
- Stop, at the latest, when you get the same top k documents.

Pseudorelevance feedback, II

Alternative sources of feedback / query refinement:

- Links clicked / not clicked on.
- Think time / time spent looking at item.
- User's previous history.
- Other users' preferences!
- Co-occurring words: Add words that often occur with words in the query - for query expansion.