CAIM: Cerca i Anàlisi d'Informació Massiva

FIB, Grau en Enginyeria Informàtica

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4. Evaluation and Relevance Feedback

Evaluation of Information Retrieval Usage, I

What are we exactly to do?

In the Boolean model, the specification is unambiguous:

We know what we are to do:

Retrieve and provide to the user
all those documents
that satisfy the query.

But, is this what the user really wants?

Sorry, but usually… no.

Evaluation of Information Retrieval Usage, II

Then, what exactly are we to optimize?

Notation:

$\mathcal{D}$: set of all our documents on which the user asks one query;

$\mathcal{A}$: 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!)

Unreachable goal: $\mathcal{A} = \mathcal{R}$, that is:

- $Pr(d \in \mathcal{A} | d \in \mathcal{R}) = 1$ and
- $Pr(d \in \mathcal{R} | d \in \mathcal{A}) = 1$.

The Recall and Precision measures

Let's settle for:

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

  $Pr(d \in \mathcal{A} | d \in \mathcal{R})$ not too much below 1,

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

  $Pr(d \in \mathcal{R} | d \in \mathcal{A})$ not too much below 1.

Difficult balance. More later.

Recall and Precision, II

Example: test for tuberculosis (TB)

- 1000 people, out of which 50 have TB
- test is positive on 40 people, of which 35 *really* have TB

Recall

% of true TB that test positive = 35 / 50 = 70 %

Precision

% of positives that really have TB = 35 / 40 = 87.5 %

- Large recall: few sick people go away undetected
- Large precision: few people are scared unnecessarily (few *false alarms*)

Recall and Precision, III. 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 = $\frac{|\mathcal{R}\cap\mathcal{A}|}{|\mathcal{A}|} = \frac{tp}{tp+fp}$

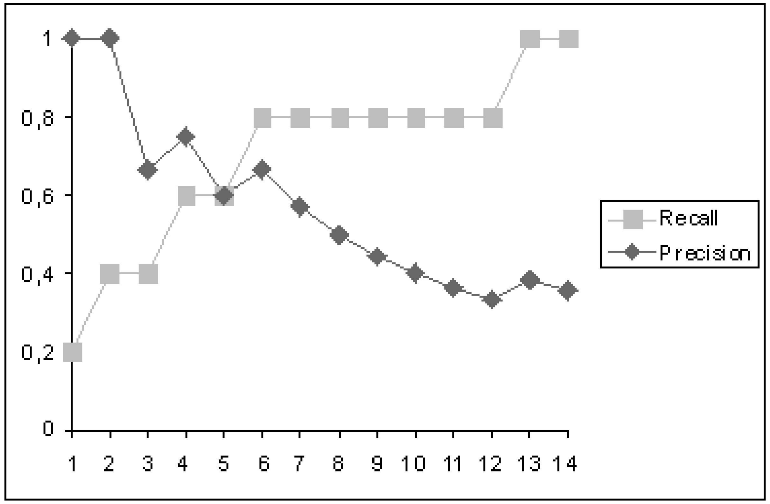
How many documents to show?

We rank all documents according to some measure.
How many should we show?

- 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.

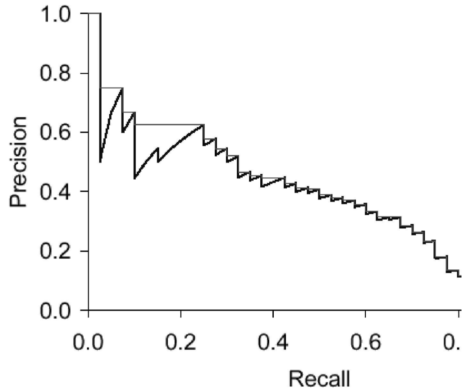
Rank-recall and rank-precision plots



(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: $\dfrac{2}{\frac{1}{\text{recall}} + \frac{1}{\text{precision}}}$
  - Harmonic mean. Closer to min of both than arithmetic mean
- α-F-measure: $\dfrac{2}{\frac{\alpha}{\text{recall}} + \frac{1-\alpha}{\text{precision}}}$

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, I

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

Relevance Feedback, II

How to create the new query?

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

Rocchio's Rule:

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

- 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.
- 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.