Processamento e Recuperação de Informação

Evaluation of IR and IE Systems

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Bibliography

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Outline

IR System Evaluation

Why evaluate?

- Measure the benefit of using an IR system
- Measure how well an IR system fulfills its goal
- Compare IR systems

What to evaluate?

- Collection coverage
- Processing time
- Output presentation
- User effort
- Recall and Precision

Elements of an information retrieval performance evaluation experiment

The Cranfield Paradigm

An IR experiment, as devised by Cyril Cleverdon (1950s), must include:

1. A reference collection
2. Relevance judgments
3. An evaluation metric

Relevant Documents

Recall and Precision

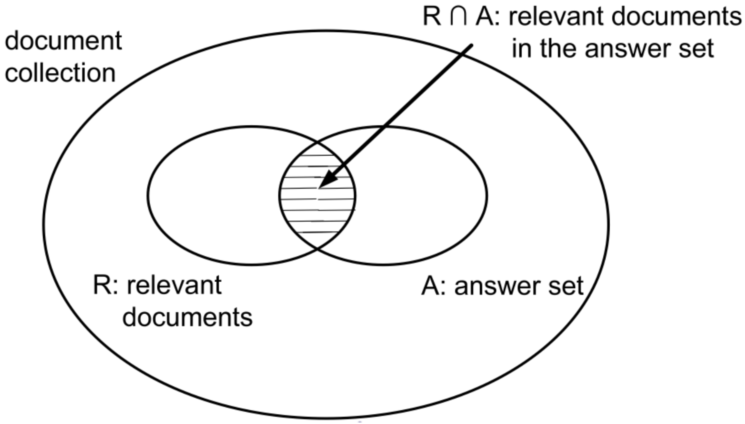
Measure the ability of a system to return relevant documents.

Relevance

- Subjective notion
- Usually evaluated by a set of experts

Outline

Evaluating Prediction



Measuring Precision and Recall

Definition

Let A be the set of documents retrieved for query Q.
Let R be the set of documents that are relevant to query Q.
Precision is the proportion of retrieved documents that are relevant, i.e.:

$$Pr = \frac{|R \cap A|}{|A|}$$

Recall is the proportion of relevant documents retrieved, i.e.:

$$Re = \frac{|R \cap A|}{|R|}$$

Precision-Recall Curves

- Retrieved documents are ordered $\Rightarrow$ we are interested in measuring how precision changes as recall increases

Example

Let $A = \{d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}\}$ be an ordered set of retrieved documents, for a query Q.
Let $R = \{d_2, d_5, d_8, d_{15}\}$ be the set of relevant documents for query Q.

Re	Pr
0.25	0.50
0.50	0.40
0.75	0.38

Interpolated Precision-Recall

- Precision is usually measured at 10 standard recall points: $0\%, 10\%, 20\%, ..., 90\%, 100\%$
- Precision at $r\%$ recall is defined as

$$P(r) = \max_{i \geq r} P(i)$$

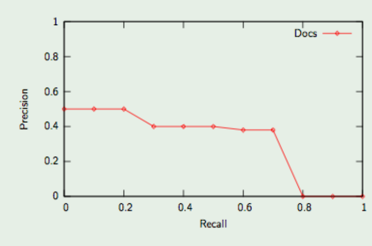
- Precision is zero after no more relevant documents are found

Interpolated Precision-Recall (cont.)

Let $A = \{d_1, d_2, d_3, d_4, d_5, d_6, d_7, d_8, d_9, d_{10}\}$ be an ordered set of retrieved documents, for a query Q. Let $R = \{d_2, d_5, d_8, d_{15}\}$ be the set of relevant documents for query Q.

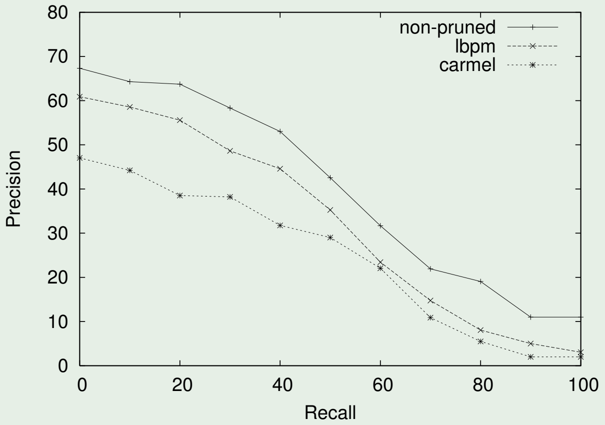
Re	Pr
0.25	0.50
0.50	0.40
0.75	0.38

Re	Pr
0.00	0.50
0.10	0.50
0.20	0.50
0.30	0.40
0.40	0.40
0.50	0.40
0.60	0.38
0.70	0.38
0.80	0.00
0.90	0.00
1.00	0.00



Interpolated Precision-Recall (cont.)

Example



Outline

P@N, R-precision

P@N – Precision at the N-th retrieved document

Most commonly used

- P@5,
- P@10
- P@20

Usefull for Web retrieval

R-precision - Precision at the R-th document, where R is the number of relevant documents

F-measure

Harmonic mean of precision and recall:

$$F_1 = \frac{2 \times Re \times Pr}{Re + Pr}$$

AP, MAP

- **AP** - Average of the values for the precision at each recall point

$$AP = \frac{\sum_{i=1}^{N} Pr@i \times R_i}{|R|}$$

  where $R_i = 1$ if document at rank i is relevant and $R_i = 0$ otherwise.

- **MAP** - Mean Average Precision

$$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AP}_q}{Q}$$

- AP can also be interpolated

Discounted Cumulative Gain

Cumulative gain: sum the relevance weights

- **DCG** - Discounted cumulative gain

$$\mathrm{DCG}_p = R_1 + \sum_{i=2}^{p} \frac{R_i}{\log_2 i}$$

where $R_i = 1$ if document at rank i is relevant and $R_i = 0$ otherwise.

- **nDCG** - Normalized discounted cumulative gain

$$\mathrm{nDCG}_p = \frac{\mathrm{DCG_p}}{\mathrm{Ideal\,DCG}_p}$$

MRR

MRR - Mean Reciprocal Rank

$$\text{MRR} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{\text{rank}_i}$$

where rank_1 is the rank of the first relevant document.

Ranking Comparison

Spearman Coefficient

Computes the difference between the positions of a same document in two rankings

$$\rho(X, Y) = 1 - \frac{6 \sum_{i=1}^{N} d_i^2}{N(N^2 - 1)}$$

where $d_i = \text{rank}(X)_i - \text{rank}(Y)_i$ is the difference in rankings of document i.

Ranking Comparison (cont.)

Kendall's Tau

Let $(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)$, where each x_i is the rank of document i in ranking X, and y_i is the rank of document i in ranking Y.

$$\tau = \frac{|\text{concordant pairs}| - |\text{discordant pairs}|}{N(N-1)/2}$$

where a pair (x_i, y_i) is concordant with (x_j, y_j) if either:

$$\begin{cases} x_i > x_j \wedge y_i > y_j \\ x_i < x_j \wedge y_i < y_j \end{cases}$$

and discordant if either:

$$\begin{cases} x_i > x_j \wedge y_i < y_j \\ x_i < x_j \wedge y_i > y_j \end{cases}$$

Outline

Reference Collections

TREC	Various collections of documents (Ad hoc, Web, Blog, Clinical Decision Support, ...)
CACM	Articles from Communications of the ACM
ISI	Information science papers
CFC	Cystic Fibrosis Collection
...	

- Standards for research in IR
- Provide sets queries + evaluated documents

Human Experimentation in the Lab

- User preferences are affected by the characteristics of the user interface (UI)
  - For instance, the users of search engines look first at the upper left corner of the results page.
  - Changing the layout is likely to affect the assessment made by the users and their behavior.
- Proper evaluation of the user interface requires going beyond the framework of the Cranfield experiments

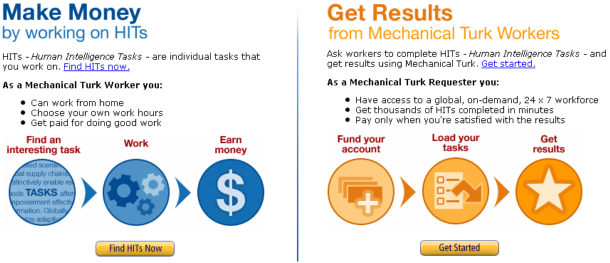
A/B Testing

- A/B testing consists of displaying to selected users a modification in the layout of a page
  - The group of selected users constitute a fraction of all users such as, for instance, 1%
  - The method works well for sites with large audiences
- By analysing how the users react to the change, it is possible to analyse if the modification proposed is positive or not

A/B testing provides a form of human experimentation, even if the setting is not that of a lab

Crowdsourcing

Amazon Mechanical Turk



https://www.mturk.com

- The participants execute human intelligence tasks, called HITs, in exchange for small sums of money
- The tasks are filed by requesters who have an evaluation need
- While the identity of participants is not known to requesters, the service produces evaluation results of high quality (except for free-loaders, etc)

Evaluation using Clickthrough Data

A promising alternative...

The data can be obtained by observing how frequently the users click on a given document, when it is shown in the answer set for a given query

Attractive, because...

The data can be collected at a low cost without overhead for the use

Outline

Classifier Evaluation

- Previous lectures have shown that tasks such as document classification or information extraction from text can be modeled as classification problems
  - I.e., techniques in this section also apply to IE systems
- Goal in supervised classification is the minimization of classification error on test data
- We can evaluate through measures like recall, precision, and accuracy (i.e., one minus error)
  - But classification tasks can involve more than two classes (i.e., more than distinguishing relevant from non-relevant)

Confusion Matrix

- $M[i, j]$ is the number of test documents belonging to class i which were assigned to class j
- Perfect classifier: diagonal elements $M[i, i]$ would be nonzero
- Example:

$$M = \left\{ \begin{array}{c|c|c} 5 & 0 & 0 \\ \hline 1 & 3 & 0 \\ \hline 1 & 2 & 4 \end{array} \right\}$$

- If M is large, we use

$$\text{accuracy} = \sum_i M[i, i] / \sum_{i,j} M[i, j]$$

- Notice that accuracy is not a good measure for *small* classes

Micro-Averaged Precision

In a problem with n classes, let C_i be the number of documents in class i and let C'_i be the number of documents estimated to be of class i by the classifier

- Micro-averaged precision is defined as

$$\frac{\sum_{i=1}^{n} C'_i \cap C_i}{\sum_{i=1}^{n} C'_i}$$

- Micro-averaged recall is defined as

$$\frac{\sum_{i=1}^{n} C'_i \cap C_i}{\sum_{i=1}^{n} C_i}$$

- Micro-averaged precision/recall measures correctly classified documents, thus favoring large classes

Macro-Averaged Precision

In a problem with n classes, let P_i and R_i be the precision and recall, respectively, achieved by a classifier for class i

- Macro-averaged precision is defined as

$$\frac{1}{n}\sum_{i=1}^{n} P_n$$

- Macro-averaged recall is defined as

$$\frac{1}{n}\sum_{i=1}^{n} R_n$$

- Macro-averaged precision/recall measures performance per class, giving all classes equal importance

F_1 measure

The F_1 measure is also commonly used

$$F_1 = \frac{2 \times P_i \times R_i}{P_i + R_i}$$

- Harmonic mean between precision and recall
- Discourages classifiers that trade one for the other

Questions?