# Information Retrieval

## Lecture 7 - Evaluation in Information Retrieval

Seminar für Sprachwissenschaft

International Studies in Computational Linguistics

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## Introduction

Framework for the evaluation of an IR system:

- *test collection* consisting of (i) a document collection, (ii) a test suite of information needs and (iii) a set of relevance judgements for each *doc-query* pair
- *gold-standard* judgement of relevance
  → classification of a document either as relevant or as irrelevant wrt an information need
- NB: the test collection must cover at least *50 information needs*



## Overview







## Standard test collection

- **Cranfield collection**: 1398 abstracts of journal articles about aerodynamics, gathered in UK in the 1950s, plus 255 queries and exhaustive relevance judgements
- **TREC** (Text REtrieval Conference): collection maintained by the US National Institute of Standards and Technology since 1992

  **TREC Ad Hoc Track**: test collection used for 8 evaluation campaigns led from 1992 to 1999, contains 1.89 million documents and relevance judgements for 450 topics

  **TREC 6-8**: test collection providing 150 information needs over 528000 newswires
  → current state-of-the-art test collection
  → note that the relevance judgements are not exhaustive

## Standard test collection (continued)

- **GOV2**: collection also maintained by the NIST, containing 25 millions of webpages (larger than other test collections, but smaller than current collection supported by WWW search engines)
- **NTCIR** (Nii Test Collection for IR systems): various test collections focussing on East Asian languages, mainly used for cross-language IR
- **CLEF** (Cross Language Evaluation Forum): collection focussing on European languages
  `http://www.clef-campaign.org`
- **REUTERS**: Reuters 21578 and REUTERS RCV1 containing respectively 21 578 newswire articles and 806 791 documents, mainly used for text classification





## Overview







## Evaluation for unranked retrieval: basics

- 2 basic effectiveness measures: *precision* and *recall*

$$Precision = \frac{\#relevant\ retrieved}{\#retrieved}$$

$$Recall = \frac{\#relevant\ retrieved}{\#relevant}$$

- In other terms:

| | Relevant | Not relevant |
|---|---|---|
| Retrieved | true positive | false positive |
| Not retrieved | false negative | true negative |

$$Precision = \frac{tp}{tp + fp}$$

$$Recall = \frac{tp}{tp + fn}$$





## Evaluation for unranked retrieval: basics (continued)

- *Accuracy*: proportion of the classification relevant/not relevant that is correct

$$accuracy = \frac{tp + tn}{tp + fp + tn + fn}$$

  Problem: 99.9 % of the collection is usually not relevant to a given query (potential high rate of false positives)

- Recall and precision are inter-dependent measures:
  - precision usually decreases while the number of retrieved documents increases
  - recall increases while the number of retrieved documents increases

## Evaluation for unranked retrieval: F-measure

- Measure relating precision and recall:

$$F = \frac{1}{\alpha \times \frac{1}{Pr} + (1-\alpha) \times \frac{1}{Re}}$$

- When the coefficient $\alpha = 0.5$:

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

- Uses a harmonic mean rather than an arithmetic one for dealing with extreme values





## Overview







## Evaluation for ranked retrieval

- NB1: precision, recall and F-measure are set-based measures (order of documents not taken into account)
- NB2: if we consider the first $k$ retrieved documents, we can compute the precision and recall values

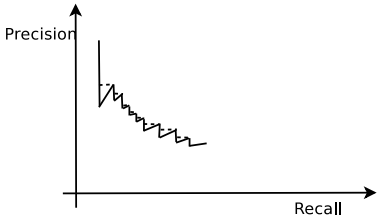
  $\rightarrow$ we can plot the relation between precision and recall for each value of $k$
- if the (k+1)$^{st}$ is not relevant $\Rightarrow$ recall is the same, but precision decreases
- if the (k+1)$^{st}$ is relevant $\Rightarrow$ recall and precision increase





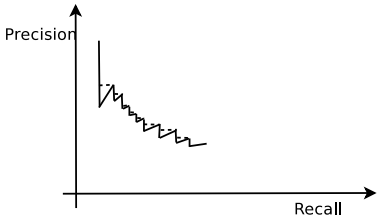
## Evaluation for ranked retrieval (continued)

- Precision-recall curve:




## Evaluation for ranked retrieval (continued)

- Precision-recall curve:




- Interpolation of the precision (smoothing):

$$P_{inter}(r) = max_{r' \geq r} P(r')$$

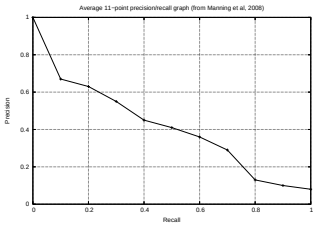




## Ranked retrieval: efficiency measures

- **11-point interpolated average precision**:
  For each information need, the value $P_{inter}$ is measured for the 11 recall values 0.0, 0.1, 0.2, ... 1.0

  The arithmetic mean of $P_{inter}$ for a given recall value over the information needs is then computed








## Ranked retrieval: efficiency measures (continued)

- **Mean Average Precision** (MAP):
  For an information need, the average precision is the arithmetic mean of the precisions for the set of top $k$ documents retrieved after each relevant document is retrieved

$q_j \in Q$ : information need

$\{d_1 \dots d_j\}$ : relevant documents for $q_j$

$R_{jk}$ : set of ranked retrieved document from top to $d_k$

$$MAP(Q) = \frac{1}{|Q|} \sum_{j=1}^{|Q|} \frac{1}{m_j} \sum_{k=1}^{m_j} Precision(R_{jk})$$

NB: when $d_l$ $(1 \leq l \leq j)$ is not retrieved, $Precision(R_{jl}) = 0$





## Ranked retrieval: efficiency measures (continued)

- **Precision at k**:
  For www search engines, we are interested in the proportion of good results among the k first answers (say the first 3 pages)

  → precision at a fixed level

  Pros : does not need an estimate of the set of relevant documents

  Cons : unstable measure, does not average well

## Ranked retrieval: efficiency measures (continued)

- **R-precision**:
  Alternative for *precision at k*. R-precision refers to the best precision on the precision/recall curve when considering a set of *rel* relevant documents and looking at the *rel* first answers

$$Pr = \frac{r}{rel} \qquad Re = \frac{r}{rel}$$

  where $r$ is the number of relevant retrieved documents

  NB: also called *break-even point*





## Ranked retrieval: efficiency measures (continued)

- **Normalized Discounted Cumulative Gain** (NDCG):
  Evaluation made for the top $k$ results

$$NDCG(Q,k) = \frac{1}{|Q|}\sum_{j=1}^{|Q|} Z_k \sum_{m=1}^{k} \frac{2^{R(j,m)}-1}{log(1+m)}$$

  where:

  $R(j,d)$ is the score given by assessors to document $d$ for query $j$ (NB: non-binary notion of relevance)

  $Z_k$ is a normalization factor (perfect ranking at k = 1)





## Overview







## Assessing relevance

- How good is an IR system at satisfaying an information need ?
- Needs an agreement between judges

  → computable via the **kappa** statistic:

$$kappa = \frac{P(A)-P(E)}{1-P(E)}$$

  where:
  $P(A)$ is the proportion of agreements within the judgements
  $P(E)$ is the proportion of expected agreements
- In case of binary decisions (*e.g.* relevant vs not relevant), $P(E) = 0.5$
- Otherwise, a *marginal* statistic is used (see below)

## Assessing relevance: an example

Consider the following judgements (from Manning et al., 2008):

| | | Judge 2 | | |
|---|---|---|---|---|
| | | Yes | No | Total |
| Judge 1 | Yes | 300 | 20 | 320 |
| | No | 10 | 70 | 80 |
| | Total | 310 | 90 | 400 |





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- $P(A) = \frac{370}{400}$ $P(rel) = \frac{320+310}{800}$ $P(notrel) = \frac{80+90}{800}$





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- $P(A) = \frac{370}{400}$ $P(rel) = \frac{320+310}{800}$ $P(notrel) = \frac{80+90}{800}$
- $P(E) = P(rel)^2 + P(notrel)^2$ $k = 0.776$





## Assessing relevance (continued)

- Interpretation of the kappa statistic $k$:
  - $k \geq 0.8$ good agreement
  - $0.67 \leq k < 0.8$ fair agreement
  - $k < 0.67$ bad agreement
- Note that the kappa statistic can be negative if the agreements between judgements are worse than random
- In case of large variations between judgements, one can choose an assessor as a gold-standard

  → considerable impact on the *absolute* assessment
  → little impact on the *relative* assessment

## Assessing relevance: limits

- Limit of the assessment: does the relevance of a document change in context (*i.e.* when the document appears after some other document) ?
- Case of www search engines: duplicates
- How to evaluate the marginal relevance ?
  → evaluating diversity or novelty.





## Overview







## System quality and user utility

- Ultimate interest: how satisfied is the user with the results the system gives for each of its information needs ?
- Evaluation criteria for an IR system:
  - fast indexing
  - fast searching
  - expressivity of the query language
  - size of hte collection supported
  - user interface (clearness of the input form and of the output list, *e.g.* snippets, etc)





## System quality and user utility (continued)

- Quantifying user happiness ?
  - for www search engines: "do the users find the information they are looking for ?" can be quantified by evaluating the proportion of users getting back to the engine
  - for intranet search engines: this efficiency can be evaluated by the time spent searching for a given piece of information
  - general case: user studies evaluating the adequacy of the search engine with the expected usage (eCommerce, etc)

## Refining a deployed system

- **A/B test**:
  Standard test for evaluating changes, particularly used for www search engines

  → concerns the modification of *1 functionality* between 2 variants A and B of a system

  → 10 % of the users are *blindly* redirected to the new variant B

  → the results of the two systems A and B are then studied
- Example: ranking algorithm

  → comparison of the result clicking between users of system A and those of system B





## Overview







## Conclusion

- Standard test collections: Cranfield, TREC, CLEF, etc.
- Evaluation for unranked retrieval: *precision*, *recall* and *f-measure*
- Evaluation for ranked retrieval: *11-point interpolation*, *Mean Average Precision*, *R-precision* and *Normalized Discounted Cumulative Gain*
- Assessing relevance: *kappa statistic*
- Discussion about system quality, user utility and system refining





## References


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