Retrieval Evaluation

Advanced Search Techniques for Large Scale Data Analytics

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Outline

- The Cranfield Paradigm
- Retrieval Performance Evaluation
- Evaluation Using Reference Collections
- Interactive Systems Evaluation
- Search Log Analysis using Clickthrough Data

Introduction

- To evaluate an IR system is to measure how well the system meets the information needs of the users
  - This is troublesome, given that a same result set might be interpreted differently by distinct users
  - To deal with this problem, some metrics have been defined that, on average, have a correlation with the preferences of a group of users
- Without proper *retrieval evaluation*, one cannot
  - determine how well the IR system is performing
  - compare the performance of the IR system with that of other systems, objectively
- **Retrieval evaluation** is a critical and integral component of any modern IR system

The Cranfield Paradigm

The Cranfield Paradigm

- Cleverdon obtained a grant from the National Science Foundation to compare distinct indexing systems
- These experiments provided interesting insights, that culminated in the modern metrics of precision and recall
  - **Recall ratio:** the fraction of relevant documents retrieved
  - **Precision ratio:** the fraction of documents retrieved that are relevant
- For instance, it became clear that, in practical situations, the majority of searches does not require high recall
- Instead, the vast majority of the users require just a few relevant answers

The Cranfield Paradigm

- The next step was to devise a set of experiments that would allow evaluating each indexing system in isolation more thoroughly
- The result was a **test reference collection** composed of documents, queries, and relevance judgements
  - It became known as the *Cranfield-2* collection
- The reference collection allows using the same set of documents and queries to evaluate different ranking systems
- The uniformity of this setup allows quick evaluation of new ranking functions

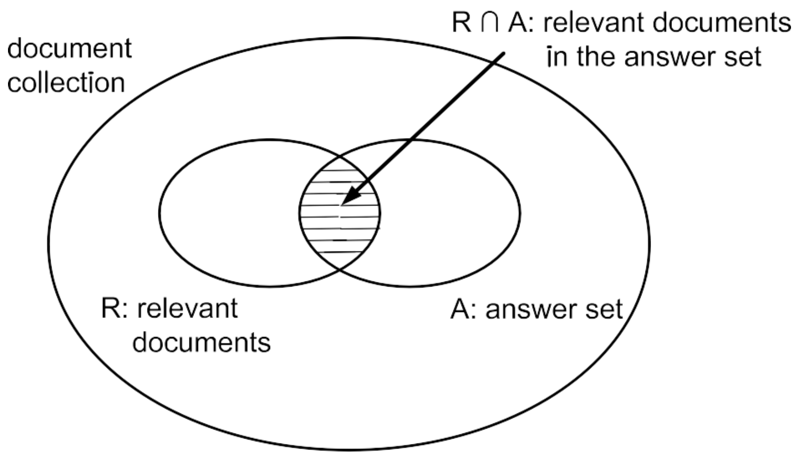
Reference Collections

- Reference collections, which are based on the foundations established by the Cranfield experiments, constitute the most used evaluation method in IR
- A reference collection is composed of:
  - A set D of pre-selected documents
  - A set I of information need descriptions used for testing
  - A set of relevance judgements associated with each pair $[i_m, d_j]$, $i_m \in I$ and $d_j \in D$
- The relevance judgement has a value of 0 if document d_j is non-relevant to i_m, and 1 otherwise
- These judgements are produced by human specialists

Precision and Recall

Precision and Recall

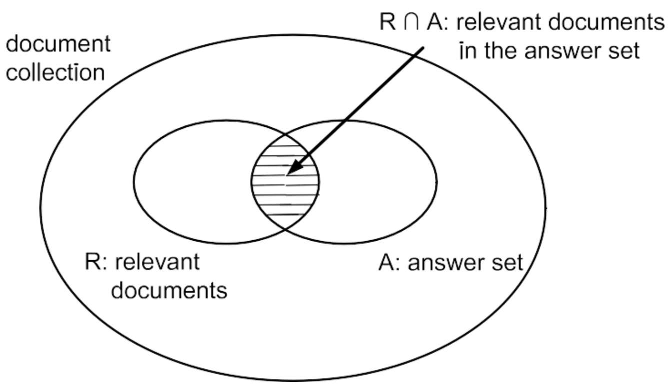
- Consider,
  - I: an information request
  - R: the set of relevant documents for I
  - A: the answer set for I, generated by an IR system
  - $R \cap A$: the intersection of the sets R and A



Precision and Recall

- The recall and precision measures are defined as follows
  - **Recall** is the fraction of the relevant documents (the set *R*) which has been retrieved i.e.,

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



  - **Precision** is the fraction of the retrieved documents (the set *A*) which is relevant i.e.,

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

Precision and Recall

- The definition of precision and recall assumes that all docs in the set A have been examined
- However, the user is not usually presented with all docs in the answer set A at once
  - User sees a ranked set of documents and examines them starting from the top
- Thus, precision and recall vary as the user proceeds with their examination of the set A
- Most appropriate then is to plot a **curve of precision versus recall**

Precision and Recall

- Consider a reference collection and a set of test queries
- Let R_{q_1} be the set of relevant docs for a query q_1:
  - $R_{q_1} = \{d_3, d_5, d_9, d_{25}, d_{39}, d_{44}, d_{56}, d_{71}, d_{89}, d_{123}\}$
- Consider a new IR algorithm that yields the following answer to q_1 (relevant docs are marked with a bullet):

01. d_{123} •	06. d_9 •	11. d_{38}
02. d_{84}	07. d_{511}	12. d_{48}
03. d_{56} •	08. d_{129}	13. d_{250}
04. d_6	09. d_{187}	14. d_{113}
05. d_8	10. d_{25} •	15. d_3 •

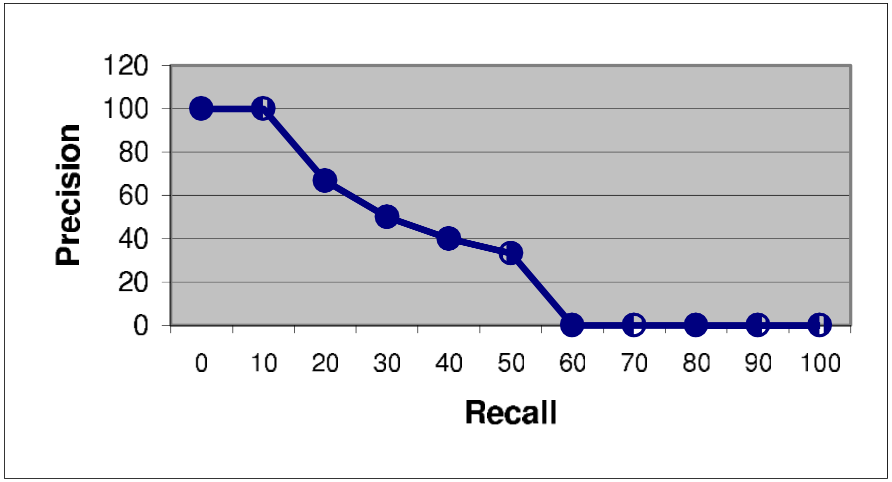
Precision and Recall

- If we examine this ranking, we observe that
  - The document d_{123}, ranked as number 1, is relevant
    - This document corresponds to 10% of all relevant documents
    - Thus, we say that we have a precision of 100% at 10% recall
  - The document d_{56}, ranked as number 3, is the next relevant
    - At this point, two documents out of three are relevant, and two of the ten relevant documents have been seen
    - Thus, we say that we have a precision of 66.6% at 20% recall

01. d_{123} •	06. d_{9} •	11. d_{38}
02. d_{84}	07. d_{511}	12. d_{48}
03. d_{56} •	08. d_{129}	13. d_{250}
04. d_{6}	09. d_{187}	14. d_{113}
05. d_{8}	10. d_{25} •	15. d_{3} •

Precision and Recall

- If we proceed with our examination of the ranking generated, we can plot a curve of precision versus recall as follows:



Recall	Precision
0	100
10	100
20	66.6
30	50
40	40
50	33.3
60	0
70	0
80	0
90	0
100	0

Precision and Recall

- Consider now a second query q_2 whose set of relevant answers is given by

$$R_{q_2} = \{d_3, d_{56}, d_{129}\}$$

- The previous IR algorithm processes the query q_2 and returns a ranking, as follows

01. d_{425}	06. d_{615}	11. d_{193}
02. d_{87}	07. d_{512}	12. d_{715}
03. d_{56} •	08. d_{129} •	13. d_{810}
04. d_{32}	09. d_4	14. d_5
05. d_{124}	10. d_{130}	15. d_3 •

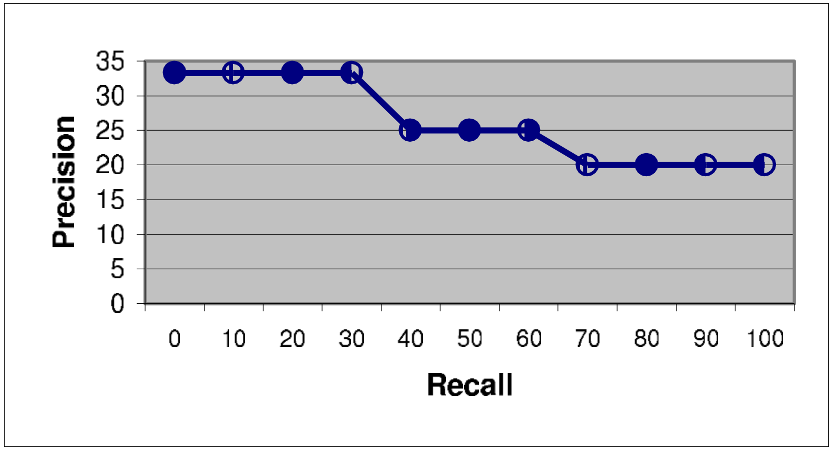
Precision and Recall

- If we examine this ranking, we observe
  - The first relevant document is d_{56}
    - It provides a recall and precision levels equal to 33.3%
  - The second relevant document is d_{129}
    - It provides a recall level of 66.6% (with precision equal to 25%)
  - The third relevant document is d_3
    - It provides a recall level of 100% (with precision equal to 20%)

01. d_{425}	06. d_{615}	11. d_{193}
02. d_{87}	07. d_{512}	12. d_{715}
03. d_{56} •	08. d_{129} •	13. d_{810}
04. d_{32}	09. d_{4}	14. d_{5}
05. d_{124}	10. d_{130}	15. d_{3} •

Precision and Recall

- The precision figures at the 11 standard recall levels are interpolated as follows
- Let $r_j, j \in \{0, 1, 2, \ldots, 10\}$, be a reference to the j-th standard recall level
- Then, $\boxed{P(r_j) = max_{\forall r \mid r_j \leq r} \; P(r)}$
- In our last example, this interpolation rule yields the precision and recall figures illustrated below



Recall	Precision
0	33.3
10	33.3
20	33.3
30	33.3
40	25
50	25
60	25
70	20
80	20
90	20
100	20

Precision and Recall

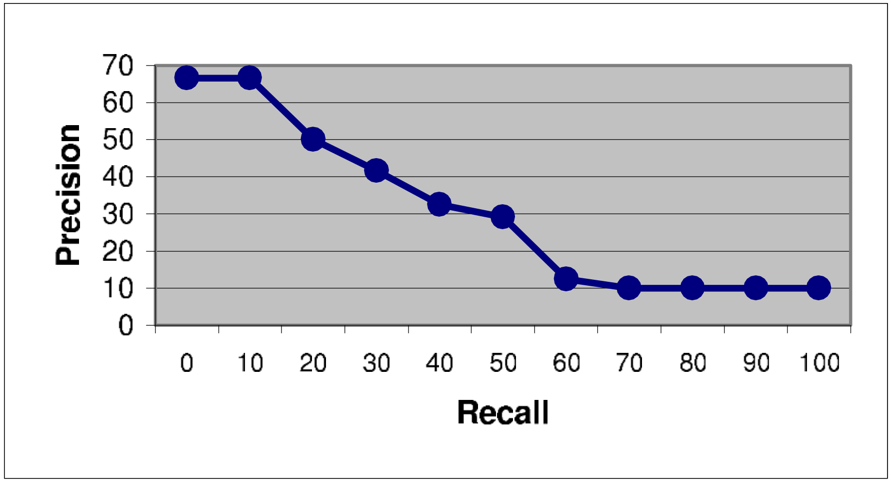
- In the examples above, the precision and recall figures have been computed for single queries
- Usually, however, retrieval algorithms are evaluated by running them for several distinct test queries
- To evaluate the retrieval performance for N_q queries, we average the precision at each recall level as follows

$$\overline{P}(r_j) = \sum_{i=1}^{N_q} \frac{P_i(r_j)}{N_q}$$

- where
  - $\overline{P}(r_j)$ is the average precision at the recall level r_j
  - $P_i(r_j)$ is the precision at recall level r_j for the i-th query

Precision and Recall

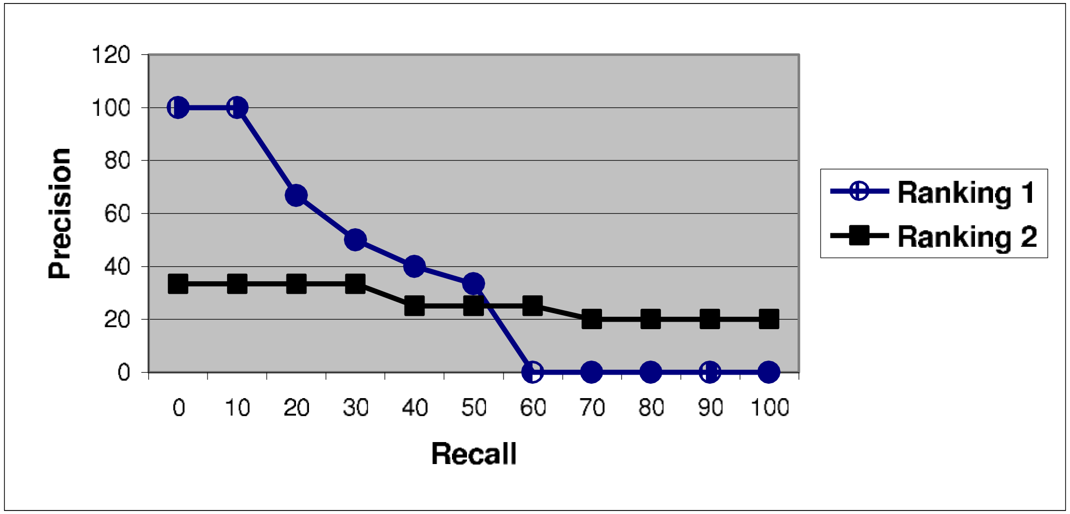
- To illustrate, the figure below illustrates precision-recall figures averaged over queries q_1 and q_2



Recall	Precision
0	66.6
10	66.6
20	49.9
30	41.6
40	32.5
50	29.1
60	12.5
70	10
80	10
90	10
100	10

Precision and Recall

- Average precision-recall curves are normally used to compare the performance of distinct IR algorithms
- The figure below illustrates average precision-recall curves for two distinct retrieval algorithms



P@5 and *P@10*

- In the case of Web search engines, the majority of searches does not require high recall
- Higher the number of relevant documents at the top of the ranking, more positive is the impression of the users
- Precision at 5 (*P@5*) and at 10 (*P@10*) measure the precision when 5 or 10 documents have been seen
- These metrics assess whether the users are getting relevant documents at the top of the ranking or not

$P@5$ and $P@10$

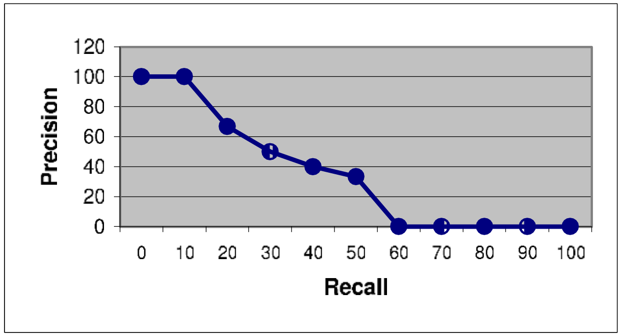
- To exemplify, consider again the ranking for the example query q_1 we have been using:

01. d_{123} •	06. d_9 •	11. d_{38}
02. d_{84}	07. d_{511}	12. d_{48}
03. d_{56} •	08. d_{129}	13. d_{250}
04. d_6	09. d_{187}	14. d_{113}
05. d_8	10. d_{25} •	15. d_3 •

- For this query, we have $P@5 = 40\%$ and $P@10 = 40\%$
- Further, we can compute $P@5$ and $P@10$ averaged over a sample of 100 queries, for instance
- These metrics provide an early assessment of which algorithm might be preferable in the eyes of the users

MAP: Mean Average Precision

- The idea here is to average the precision figures obtained after each new relevant document is observed
  - For relevant documents not retrieved, the precision is set to 0
- To illustrate, consider again the precision-recall curve for the example query q_1



Recall	Precision
0	100
10	100
20	66.6
30	50
40	40
50	33.3
60	0
70	0
80	0
90	0
100	0

- The mean average precision (MAP) for q_1 is given by

$$MAP_1 = \frac{1 + 0.66 + 0.5 + 0.4 + 0.33 + 0 + 0 + 0 + 0 + 0}{10} = 0.28$$

R-Precision

- Let R be the total number of relevant docs for a given query
- The idea here is to compute the precision at the R-th position in the ranking
- For the query q_1, the R value is 10 and there are 4 relevants among the top 10 documents in the ranking
- Thus, the R-Precision value for this query is 0.4
- The R-precision measure is a useful for observing the behavior of an algorithm for individual queries
- Additionally, one can also compute an average R-precision figure over a set of queries
  - However, using a single number to evaluate a algorithm over several queries might be quite imprecise

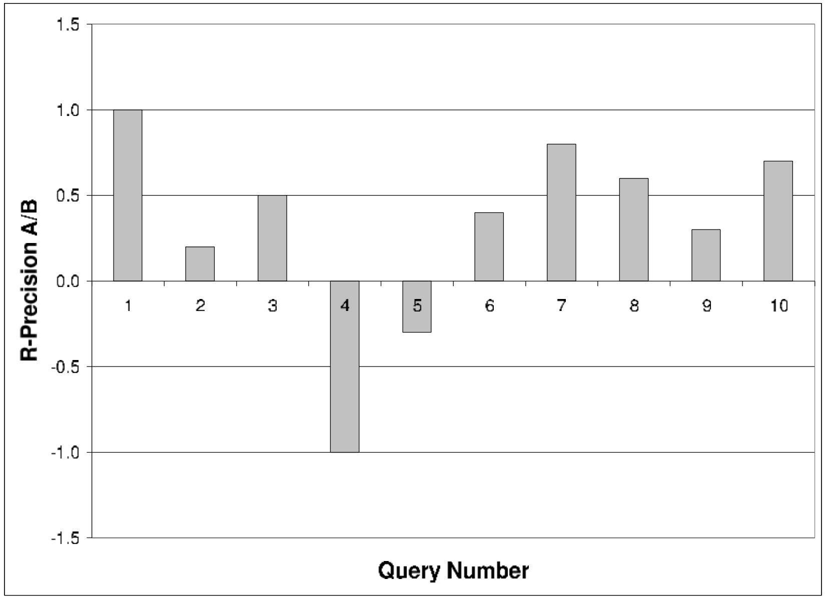
Precision Histograms

- The R-precision computed for several queries can be used to compare two algorithms as follows
- Let,
  - $RP_A(i)$: R-precision for algorithm A for the i-th query
  - $RP_B(i)$: R-precision for algorithm B for the i-th query
- Define, for instance, the difference

$$RP_{A/B}(i) = RP_A(i) - RP_B(i)$$

Precision Histograms

- Figure below illustrates the $RP_{A/B}(i)$ values for two retrieval algorithms over 10 example queries



- The algorithm A performs better for 8 of the queries, while the algorithm B performs better for the other 2 queries

MRR: Mean Reciprocal Rank

- MRR is a good metric for those cases in which we are interested in the first correct answer such as
  - Question-Answering (QA) systems
  - Search engine queries that look for specific sites
    - URL queries
    - Homepage queries

MRR: Mean Reciprocal Rank

- Let,
  - R_i: ranking relative to a query q_i
  - $S_{correct}(R_i)$: position of the first correct answer in R_i
  - S_h: threshold for ranking position
- Then, the reciprocal rank $RR(R_i)$ for query q_i is given by

$$RR(\mathcal{R}_i) = \begin{cases} \frac{1}{S_{correct}(\mathcal{R}_i)} & \text{if } S_{correct}(\mathcal{R}_i) \leq S_h \\ 0 & \text{otherwise} \end{cases}$$

- The mean reciprocal rank (MRR) for a set Q of N_q queries is given by

$$\boxed{MRR(Q) = \sum_i^{N_q} RR(\mathcal{R}_i)}$$

The E-Measure

- A measure that combines recall and precision
- The idea is to allow the user to specify whether he is more interested in recall or in precision
- The E measure is defined as follows

$$E(j) = 1 - \frac{1 + b^2}{\frac{b^2}{r(j)} + \frac{1}{P(j)}}$$

- where
  - $r(j)$ is the recall at the j-th position in the ranking
  - $P(j)$ is the precision at the j-th position in the ranking
  - $b \geq 0$ is a user specified parameter
  - $E(j)$ is the E metric at the j-th position in the ranking

The E-Measure

- The parameter b is specified by the user and reflects the relative importance of recall and precision
- If $b = 0$
  - $E(j) = 1 - P(j)$
  - low values of b make $E(j)$ a function of precision
- If $b \to \infty$
  - $lim_{b \to \infty} \; E(j) = 1 - r(j)$
  - high values of b make $E(j)$ a function of recal
- For $b = 1$, the E-measure becomes the F-measure

F-Measure: Harmonic Mean

- The F-measure is also a single measure that combines recall and precision

$$F(j) = \frac{2}{\frac{1}{r(j)} + \frac{1}{P(j)}}$$

where

- $r(j)$ is the recall at the j-th position in the ranking
- $P(j)$ is the precision at the j-th position in the ranking
- $F(j)$ is the harmonic mean at the j-th position in the ranking

F-Measure: Harmonic Mean

- The function F assumes values in the interval $[0, 1]$
- It is 0 when no relevant documents have been retrieved and is 1 when all ranked documents are relevant
- Further, the harmonic mean F assumes a high value only when both recall and precision are high
- To maximize F requires finding the best possible compromise between recall and precision
- Notice that setting $b = 1$ in the formula of the E-measure yields

$$F(j) = 1 - E(j)$$

DCG — Discounted Cumulated Gain

Discounted Cumulated Gain

- Precision and recall allow only binary relevance assessments
- As a result, there is no distinction between highly relevant docs and mildly relevant docs
- These limitations can be overcome by adopting graded relevance assessments and metrics that combine them
- The **discounted cumulated gain** (DCG) is a metric that combines graded relevance assessments effectively

Discounted Cumulated Gain

- When examining the results of a query, two key observations can be made:
  - highly relevant documents are preferable at the top of the ranking than mildly relevant ones
  - relevant documents that appear at the end of the ranking are less valuable

Discounted Cumulated Gain

- Consider that the results of the queries are graded on a scale 0–3 (0 for non-relevant, 3 for strong relevant docs)
- For instance, for queries q_1 and q_2, consider that the graded relevance scores are as follows:

$$
\begin{aligned}
R_{q_1} &= \{\ [d_3, 3], [d_5, 3], [d_9, 3], [d_{25}, 2], [d_{39}, 2], \\
&\qquad [d_{44}, 2], [d_{56}, 1], [d_{71}, 1], [d_{89}, 1], [d_{123}, 1]\ \} \\
R_{q_2} &= \{\ [d_3, 3], [d_{56}, 2], [d_{129}, 1]\ \}
\end{aligned}
$$

- That is, while document d_3 is highly relevant to query q_1, document d_{56} is just mildly relevant

Discounted Cumulated Gain

- Given these assessments, the results of a new ranking algorithm can be evaluated as follows
- Specialists associate a graded relevance score to the top 10–20 results produced for a given query q
  - This list of relevance scores is referred to as the *gain vector G*
- Considering the top 15 docs in the ranking produced for queries q_1 and q_2, the gain vectors for these queries are:

$$G_1 = (1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3)$$
$$G_2 = (0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3)$$

Discounted Cumulated Gain

- By summing up the graded scores up to any point in the ranking, we obtain the cumulated gain (CG)
- For query q_1, for instance, the cumulated gain at the first position is 1, at the second position is 1+0, and so on
- Thus, the *cumulated gain vectors* for queries q_1 and q_2 are given by

$$
\begin{aligned}
CG_1 &= (1, 1, 2, 2, 2, 5, 5, 5, 5, 7, 7, 7, 7, 7, 10) \\
CG_2 &= (0, 0, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 6)
\end{aligned}
$$

- For instance, the cumulated gain at position 8 of CG_1 is equal to 5

Discounted Cumulated Gain

- In formal terms, we define
  - Given the gain vector G_j for a test query q_j, the CG_j associated with it is defined as

$$CG_j[i] = \begin{cases} G_j[1] & \texttt{if } i = 1; \\ \\ G_j[i] + CG_j[i-1] & \texttt{otherwise} \end{cases}$$

where $CG_j[i]$ refers to the cumulated gain at the *i*-th position of the ranking for query q_j

Discounted Cumulated Gain

- We also introduce a discount factor that reduces the impact of the gain as we move upper in the ranking
- A simple discount factor is the logarithm of the ranking position
- If we consider logs in base 2, this discount factor will be $\log_2 2$ at position 2, $\log_2 3$ at position 3, and so on
- By dividing a gain by the corresponding discount factor, we obtain the discounted cumulated gain (DCG)

Discounted Cumulated Gain

- More formally,
  - Given the gain vector G_j for a test query q_j, the vector DCG_j associated with it is defined as

$$DCG_j[i] = \begin{cases} G_j[1] & \texttt{if } i = 1; \\ \frac{G_j[i]}{\log_2 i} + DCG_j[i-1] & \texttt{otherwise} \end{cases}$$

where $DCG_j[i]$ refers to the discounted cumulated gain at the i-th position of the ranking for query q_j

Discounted Cumulated Gain

- For the example queries q_1 and q_2, the DCG vectors are given by

$$DCG_1 = (1.0, 1.0, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2)$$
$$DCG_2 = (0.0, 0.0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4)$$

- Discounted cumulated gains are much less affected by relevant documents at the end of the ranking
- By adopting logs in higher bases the discount factor can be accentuated

DCG Curves

- To produce CG and DCG curves over a set of test queries, we need to average them over all queries
- Given a set of N_q queries, average $\overline{CG}[i]$ and $\overline{DCG}[i]$ over all queries are computed as follows

$$\boxed{\overline{CG}[i] = \sum_{j=1}^{N_q} \frac{CG_j[i]}{N_q}; \qquad \overline{DCG}[i] = \sum_{j=1}^{N_q} \frac{DCG_j[i]}{N_q}}$$

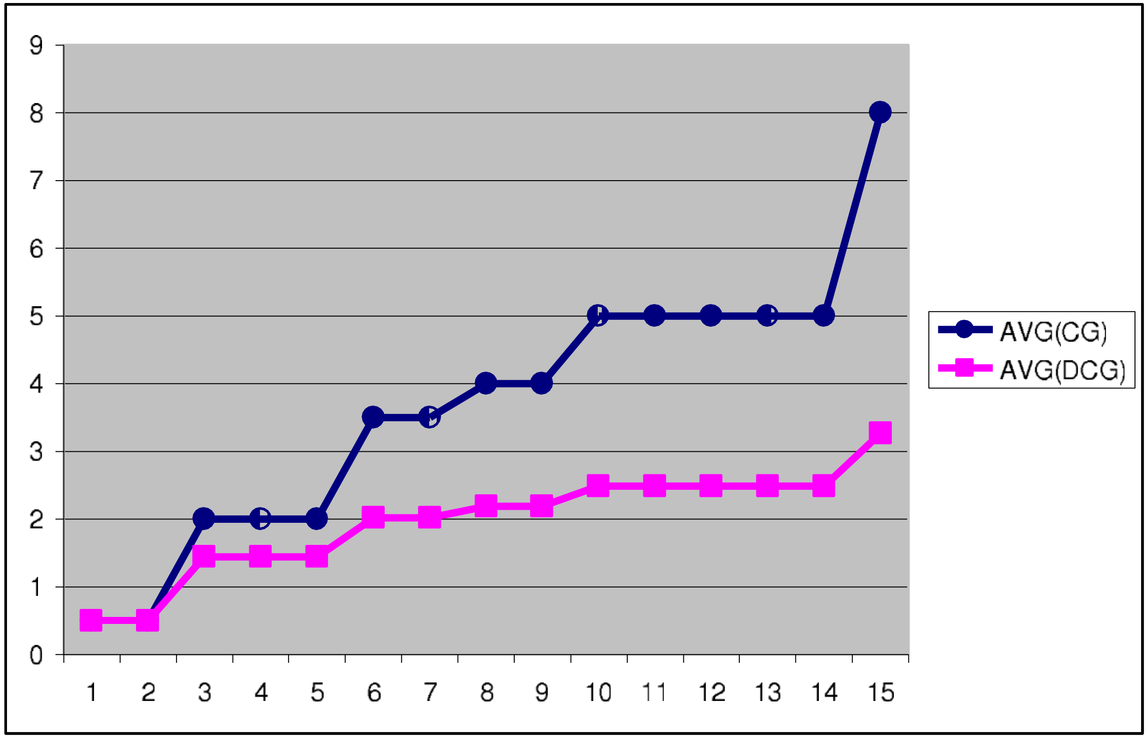
- For instance, for the example queries q_1 and q_2, these averages are given by

$$\overline{CG} = (0.5, 0.5, 2.0, 2.0, 2.0, 3.5, 3.5, 4.0, 4.0, 5.0, 5.0, 5.0, 5.0, 5.0, 8.0)$$

$$\overline{DCG} = (0.5, 0.5, 1.5, 1.5, 1.5, 2.1, 2.1, 2.2, 2.2, 2.5, 2.5, 2.5, 2.5, 2.5, 3.3)$$

DCG Curves

- Then, average curves can be drawn by varying the rank positions from 1 to a pre-established threshold



Ideal CG and DCG Metrics

- Recall and precision figures are computed relatively to the set of relevant documents
- CG and DCG scores, as defined above, are not computed relatively to any baseline
- This implies that it might be confusing to use them directly to compare two distinct retrieval algorithms
- One solution to this problem is to define a baseline to be used for normalization
- This baseline are the ideal CG and DCG metrics, as we now discuss

Ideal CG and DCG Metrics

- For a given test query q, assume that the relevance assessments made by the specialists produced:
  - n_3 documents evaluated with a relevance score of 3
  - n_2 documents evaluated with a relevance score of 2
  - n_1 documents evaluated with a score of 1
  - n_0 documents evaluated with a score of 0
- The ideal gain vector IG is created by sorting all relevance scores in decreasing order, as follows:

$$IG = (3, \ldots, 3, 2, \ldots, 2, 1, \ldots, 1, 0, \ldots, 0)$$

- For instance, for the example queries q_1 and q_2, we have

$$IG_1 = (3, 3, 3, 2, 2, 2, 1, 1, 1, 1, 0, 0, 0, 0, 0)$$
$$IG_2 = (3, 2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0)$$

Ideal CG and DCG Metrics

- Ideal CG and ideal DCG vectors can be computed analogously to the computations of CG and DCG
- For the example queries q_1 and q_2, we have

$$ICG_1 = (3, 6, 9, 11, 13, 15, 16, 17, 18, 19, 19, 19, 19, 19, 19)$$
$$ICG_2 = (3, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6)$$

- The ideal DCG vectors are given by

$$IDCG_1 = (3.0, 6.0, 7.9, 8.9, 9.8, 10.5, 10.9, 11.2, 11.5, 11.8, 11.8, 11.8, 11.8, 11.8, 11.8)$$
$$IDCG_2 = (3.0, 5.0, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6)$$

Ideal CG and DCG Metrics

- Further, average $\overline{ICG}$ and average $\overline{IDCG}$ scores can be computed as follows

$$\overline{ICG}[i] = \sum_{j=1}^{N_q} \frac{ICG_j[i]}{N_q}; \qquad \overline{IDCG}[i] = \sum_{j=1}^{N_q} \frac{IDCG_j[i]}{N_q}$$

- For instance, for the example queries q_1 and q_2, $\overline{ICG}$ and $\overline{IDCG}$ vectors are given by

$$\overline{ICG} = (3.0, 5.5, 7.5, 8.5, 9.5, 10.5, 11.0, 11.5, 12.0, 12.5, 12.5, 12.5, 12.5, 12.5, 12.5)$$
$$\overline{IDCG} = (3.0, 5.5, 6.8, 7.3, 7.7, 8.1, 8.3, 8.4, 8.6, 8.7, 8.7, 8.7, 8.7, 8.7, 8.7)$$

- By comparing the average CG and DCG curves for an algorithm with the average ideal curves, we gain insight on how much room for improvement there is

Normalized DCG

- Precision and recall figures can be directly compared to the ideal curve of 100% precision at all recall levels
- DCG figures, however, are not build relative to any ideal curve, which makes it difficult to compare directly DCG curves for two distinct ranking algorithms
- This can be corrected by normalizing the DCG metric
- Given a set of N_q test queries, normalized CG and DCG metrics are given by

$$\boxed{NCG[i] = \frac{\overline{CG}[i]}{\overline{ICG}[i]}; \qquad NDCG[i] = \frac{\overline{DCG}[i]}{\overline{IDCG}[i]}}$$

Normalized DCG

- For instance, for the example queries q_1 and q_2, NCG and NDCG vectors are given by

$$
\begin{aligned}
NCG &= (0.17, 0.09, 0.27, 0.24, 0.21, 0.33, 0.32, \\
&\quad 0.35, 0.33, 0.40, 0.40, 0.40, 0.40, 0.40, 0.64) \\
NDCG &= (0.17, 0.09, 0.21, 0.20, 0.19, 0.25, 0.25, \\
&\quad 0.26, 0.26, 0.29, 0.29, 0.29, 0.29, 0.29, 0.38)
\end{aligned}
$$

- The area under the NCG and NDCG curves represent the quality of the ranking algorithm
- Higher the area, better the results are considered to be
- Thus, normalized figures can be used to compare two distinct ranking algorithms

Discussion on DCG Metrics

- CG and DCG metrics aim at taking into account multiple level relevance assessments
- This has the advantage of distinguishing highly relevant documents from mildly relevant ones
- The inherent disadvantages are that multiple level relevance assessments are harder and more time consuming to generate

Discussion on DCG Metrics

- Despite these inherent difficulties, the CG and DCG metrics present benefits:
  - They allow systematically combining document ranks and relevance scores
  - Cumulated gain provides a single metric of retrieval performance at any position in the ranking
  - It also stresses the gain produced by relevant docs up to a position in the ranking, which makes the metrics more imune to outliers
  - Further, discounted cumulated gain allows down weighting the impact of relevant documents found late in the ranking

Rank Correlation Metrics

Rank Correlation Metrics

- Precision and recall allow comparing the relevance of the results produced by two ranking functions
- However, there are situations in which
  - we cannot directly measure relevance
  - we are more interested in determining how differently a ranking function varies from a second one that we know well
- In these cases, we are interested in comparing the relative ordering produced by the two rankings
- This can be accomplished by using statistical functions called **rank correlation metrics**

Rank Correlation Metrics

- Let rankings R_1 and R_2
- A rank correlation metric yields a correlation coefficient $C(R_1, R_2)$ with the following properties:
  - $-1 \leq C(R_1, R_2) \leq 1$
  - if $C(R_1, R_2) = 1$, the agreement between the two rankings is perfect i.e., they are the same.
  - if $C(R_1, R_2) = -1$, the disagreement between the two rankings is perfect i.e., they are the reverse of each other.
  - if $C(R_1, R_2) = 0$, the two rankings are completely independent.
  - increasing values of $C(R_1, R_2)$ imply increasing agreement between the two rankings.

The Spearman Coefficient

The Spearman Coefficient

- The Spearman coefficient is likely the mostly used rank correlation metric
- It is based on the differences between the positions of a same document in two rankings
- Let
  - $s_{1,j}$ be the position of a document d_j in ranking R_1 and
  - $s_{2,j}$ be the position of d_j in ranking R_2

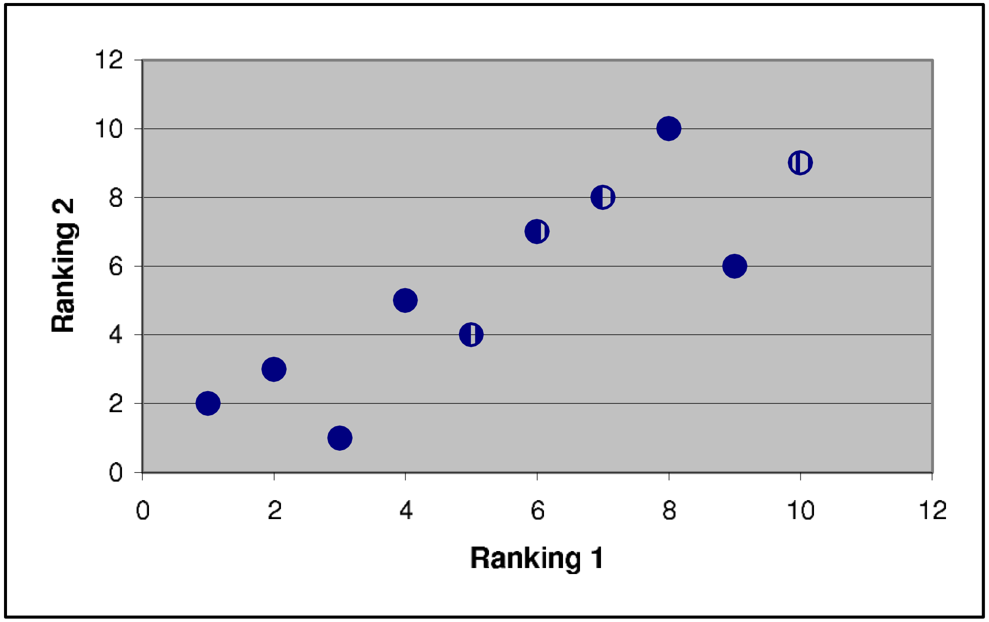
The Spearman Coefficient

- Consider 10 example documents retrieved by two distinct rankings R_1 and R_2. Let $s_{1,j}$ and $s_{2,j}$ be the document position in these two rankings, as follows:

documents	$s_{1,j}$	$s_{2,j}$	$s_{i,j} - s_{2,j}$	$(s_{1,j} - s_{2,j})^2$
d_{123}	1	2	-1	1
d_{84}	2	3	-1	1
d_{56}	3	1	+2	4
d_{6}	4	5	-1	1
d_{8}	5	4	+1	1
d_{9}	6	7	-1	1
d_{511}	7	8	-1	1
d_{129}	8	10	-2	4
d_{187}	9	6	+3	9
d_{25}	10	9	+1	1
Sum of Square Distances				24

The Spearman Coefficient

- By plotting the rank positions for R_1 and R_2 in a 2-dimensional coordinate system, we observe that there is a strong correlation between the two rankings



The Spearman Coefficient

- To produce a quantitative assessment of this correlation, we sum the squares of the differences for each pair of rankings
- If there are K documents ranked, the maximum value for the sum of squares of ranking differences is given by

$$\frac{K \times (K^2 - 1)}{3}$$

- Let $K = 10$
  - If the two rankings were in perfect disagreement, then this value is $(10 \times (10^2 - 1))/3$, or 330
  - On the other hand, if we have a complete agreement the sum is 0

The Spearman Coefficient

- Let us consider the fraction

$$\frac{\sum_{j=1}^{K}(s_{1,j} - s_{2,j})^2}{\frac{K \times (K^2 - 1)}{3}}$$

- Its value is
  - 0 when the two rankings are in perfect agreement
  - +1 when they are in perfect disagreement
- If we multiply the fraction by 2, its value shifts to the range $[0, +2]$
- If we now subtract the result from 1, the resultant value shifts to the range $[-1, +1]$

The Spearman Coefficient

- This reasoning suggests defining the correlation between the two rankings as follows
- Let $s_{1,j}$ and $s_{2,j}$ be the positions of a document d_j in two rankings R_1 and R_2, respectively
- Define

$$\boxed{S(\mathcal{R}_1, \mathcal{R}_2) = 1 - \frac{6 \times \sum_{j=1}^{K} (s_{1,j} - s_{2,j})^2}{K \times (K^2 - 1)}}$$

where

- $S(R_1, R_2)$ is the *Spearman rank correlation coefficient*
- K indicates the size of the ranked sets

The Spearman Coefficient

- For the rankings in Figure below, we have

$$S(\mathcal{R}_1, \mathcal{R}_2) = 1 - \frac{6 \times 24}{10 \times (10^2 - 1)} = 1 - \frac{144}{990} = 0.854$$

documents	$s_{1,j}$	$s_{2,j}$	$s_{i,j} - s_{2,j}$	$(s_{1,j} - s_{2,j})^2$
d_{123}	1	2	-1	1
d_{84}	2	3	-1	1
d_{56}	3	1	+2	4
d_{6}	4	5	-1	1
d_{8}	5	4	+1	1
d_{9}	6	7	-1	1
d_{511}	7	8	-1	1
d_{129}	8	10	-2	4
d_{187}	9	6	+3	9
d_{25}	10	9	+1	1
Sum of Square Distances				24

The Kendall Tau Coefficient

The Kendall Tau Coefficient

- It is difficult to assign an operational interpretation to Spearman coefficient
- One alternative is to use a coefficient that has a natural and intuitive interpretation, as the Kendall Tau coefficient

The Kendall Tau Coefficient

- When we think of rank correlations, we think of how two rankings tend to vary in similar ways
- To illustrate, consider two documents d_j and d_k and their positions in the rankings R_1 and R_2
- Further, consider the differences in rank positions for these two documents in each ranking, i.e.,

$$
\begin{array}{ccc}
s_{1,k} & - & s_{1,j} \\
s_{2,k} & - & s_{2,j}
\end{array}
$$

- If these differences have the same sign, we say that the document pair $[d_k, d_j]$ is **concordant** in both rankings
- If they have different signs, we say that the document pair is **discordant** in the two rankings

The Kendall Tau Coefficient

- Consider the top 5 documents in rankings R_1 and R_2

documents	$s_{1,j}$	$s_{2,j}$	$s_{i,j} - s_{2,j}$
d_{123}	1	2	-1
d_{84}	2	3	-1
d_{56}	3	1	+2
d_{6}	4	5	-1
d_{8}	5	4	+1

- The ordered document pairs in ranking R_1 are

$[d_{123}, d_{84}]$, $[d_{123}, d_{56}]$, $[d_{123}, d_{6}]$, $[d_{123}, d_{8}]$,

$[d_{84}, d_{56}]$, $[d_{84}, d_{6}]$, $[d_{84}, d_{8}]$,

$[d_{56}, d_{6}]$, $[d_{56}, d_{8}]$,

$[d_{6}, d_{8}]$

for a total of $\frac{1}{2} \times 5 \times 4$, or 10 ordered pairs

The Kendall Tau Coefficient

- Repeating the same exercise for the top 5 documents in ranking R_2, we obtain

$$[d_{56}, d_{123}],\ [d_{56}, d_{84}],\ [d_{56}, d_{8}],\ [d_{56}, d_{6}],$$
$$[d_{123}, d_{84}],\ [d_{123}, d_{8}],\ [d_{123}, d_{6}],$$
$$[d_{84}, d_{8}],\ [d_{84}, d_{6}],$$
$$[d_{8}, d_{6}]$$

- We compare these two sets of ordered pairs looking for concordant and discordant pairs

The Kendall Tau Coefficient

- Let us mark with a C the concordant pairs and with a D the discordant pairs
- For ranking R_1, we have

$$\begin{array}{l} C, D, C, C, \\ D, C, C, \\ C, C, \\ D \end{array}$$

- For ranking R_2, we have

$$\begin{array}{l} D, D, C, C, \\ C, C, C, \\ C, C, \\ D \end{array}$$

The Kendall Tau Coefficient

- That is, a total of 20, i.e., $K(K-1)$, ordered pairs are produced jointly by the two rankings
- Among these, 14 pairs are concordant and 6 pairs are discordant
- The Kendall Tau coefficient is defined as

$$\tau(R_1, R_2) = P(R_1 = R_2) - P(R_1 \neq R_2)$$

- In our example

$$\begin{aligned} \tau(R_1, R_2) &= \frac{14}{20} - \frac{6}{20} \\ &= 0.4 \end{aligned}$$

The Kendall Tau Coefficient

- Let,
  - $\Delta(R_1, R_2)$: number of discordant document pairs in R_1 and R_2
  - $K(K-1) - \Delta(R_1, R_2)$: number of concordant document pairs in R_1 and R_2
- Then,

$$P(R_1 = R_2) = \frac{K(K-1) - \Delta(R_1, R_2)}{K(K-1)}$$

$$P(R_1 \neq R_2) = \frac{\Delta(R_1, R_2)}{K(K-1)}$$

which yields $$\boxed{\tau(R_1, R_2) = 1 - \frac{2 \times \Delta(R_1, R_2)}{K(K-1)}}$$

The Kendall Tau Coefficient

- For the case of our previous example, we have
  - $\Delta(R_1, R_2) = 6$
  - $K = 5$
  - Thus,

$$\tau(R_1, R_2) = 1 - \frac{2 \times 6}{5(5-1)} = 0.4$$

  as before

- The Kendall Tau coefficient is defined only for rankings over a same set of elements
- Most important, it has a simpler algebraic structure than the Spearman coefficient

Side-by-Side Panels

Side-by-Side Panels

- A form of evaluating two different systems is to evaluate their results side by side
- Typically, the top 10 results produced by the systems for a given query are displayed in side-by-side panels
- Presenting the results side by side allows controlling:
  - differences of opinion among subjects
  - influences on the user opinion produced by the ordering of the top results

Side-by-Side Panels

- Side by side panels for Yahoo! and Google
  - Top 5 answers produced by each search engine, with regard to the query *“information retrieval evaluation”*

[PDF] Pharmaceutical **Information** Flyer
PDF/Adobe Acrobat
PHARMACEUTICAL **INFORMATION RETRIEVAL** AND **EVALUATION** SERVICE. Future Solutions Now ... **information** need, • **retrieval** of the appropriate documents, • **evaluation** ...
www.**uiowa.edu**/~idis/Pharm_Info_Flyer.pdf

ROMIP: Russian **Information Retrieval Evaluation** Seminar
Russian **information retrieval evaluation** initiative was launched in 2002 with ... a basis for independent **evaluation** of **information retrieval** methods, aimed to be ...
romip.ru/en

[PDF] Reflections on **Information Retrieval Evaluation** Mei-Mei Wu & Diane ...
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Reflections on **Information Retrieval Evaluation**. Mei-Mei Wu ... Research and **evaluation** in **information retrieval**. Journal of Documentation , 53 (1), 51-57. ...
pnclink.org/annual/annual1999/1999pdf/wu-mm.pdf

Information retrieval - Wikipedia, the free encyclopedia
Information retrieval (IR) is the science of searching for ... that was needed for **evaluation** of text **retrieval** methodologies on a very large text collection. ...
en.wikipedia.org/wiki/**Information**_**retrieval**

The Music **Information Retrieval Evaluation** eXchange (MIREX)
The 2005 Music **Information Retrieval Evaluation** eXchange (MIREX 2005): Preliminary Overview. ... Music **Information Retrieval** Systems **Evaluation** Laboratory: ...
www.**dlib.org**/dlib/december06/downie/12downie.html

[PDF] Reflections on **Information Retrieval Evaluation** Mei-Mei Wu & Diane ...
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digital library initiatives, **information retrieval** (IR) **evaluation** has ...... **Evaluation** of **evaluation** in **information retrieval**. Proceedings of the ...
pnclink.org/annual/annual1999/1999pdf/wu-mm.pdf -

[PDF] **Retrieval Evaluation** with Incomplete **Information**
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The philosophy of **information**. **retrieval evaluation**. In **Evaluation** of Cross-Language. **Information Retrieval** Systems. Proceedings of CLEF ...
www.nist.gov/itl/iad/IADpapers/2004/p102-buckley.pdf

Evaluation criteria for **information retrieval** systems. - [Traduzir esta página]
The contrast between the value placed on discriminatory power in discussions of indexing and classification and on the transformation of a query into a set ...
informationr.net/ir/4-4/paper62.html - 36k

Information retrieval - Wikipedia, the free encyclopedia - [Traduzir esta página]
The aim of this was to look into the **information retrieval** community by supplying the infrastructure that was needed for **evaluation** of text **retrieval** ...
en.wikipedia.org/wiki/**Information_retrieval** - 59k

[PDF] **Information Retrieval** System **Evaluation**: Effort, Sensitivity, and ...
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Information Retrieval System **Evaluation**:. Effort, Sensitivity, and Reliability. Mark Sanderson. Department of **Information** Studies, University of ...
dis.shef.ac.uk/mark/publications/my_papers/SIGIR2005.pdf

Side-by-Side Panels

- The side-by-side experiment is simply a judgement on which side provides better results for a given query
  - By recording the interactions of the users, we can infer which of the answer sets are preferred to the query
- Side by side panels can be used for quick comparison of distinct search engines

A/B Testing & Crowdsourcing

Crowdsourcing

- There are a number of limitations with current approaches for relevance evaluation
- For instance, the Cranfield paradigm is expensive and has obvious scalability issues
- Recently, crowdsourcing has emerged as a feasible alternative for relevance evaluation
- Crowdsourcing is a term used to describe tasks that are outsourced to a large group of people, called “workers”
- It is an open call to solve a problem or carry out a task, one which usually involves a monetary value in exchange for such service

Crowdsourcing

- To illustrate, crowdsourcing has been used to validate research on the quality of search snippets
- One of the most important aspects of crowdsourcing is to design the experiment carefully
- It is important to ask the right questions and to use well-known usability techniques
- Workers are not information retrieval experts, so the task designer should provide clear instructions