Information Access and Retrieval (GBX9MO23)

Evaluation of Information Retrieval Systems

M2R – MOSIG

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Outline

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8. Test Collection
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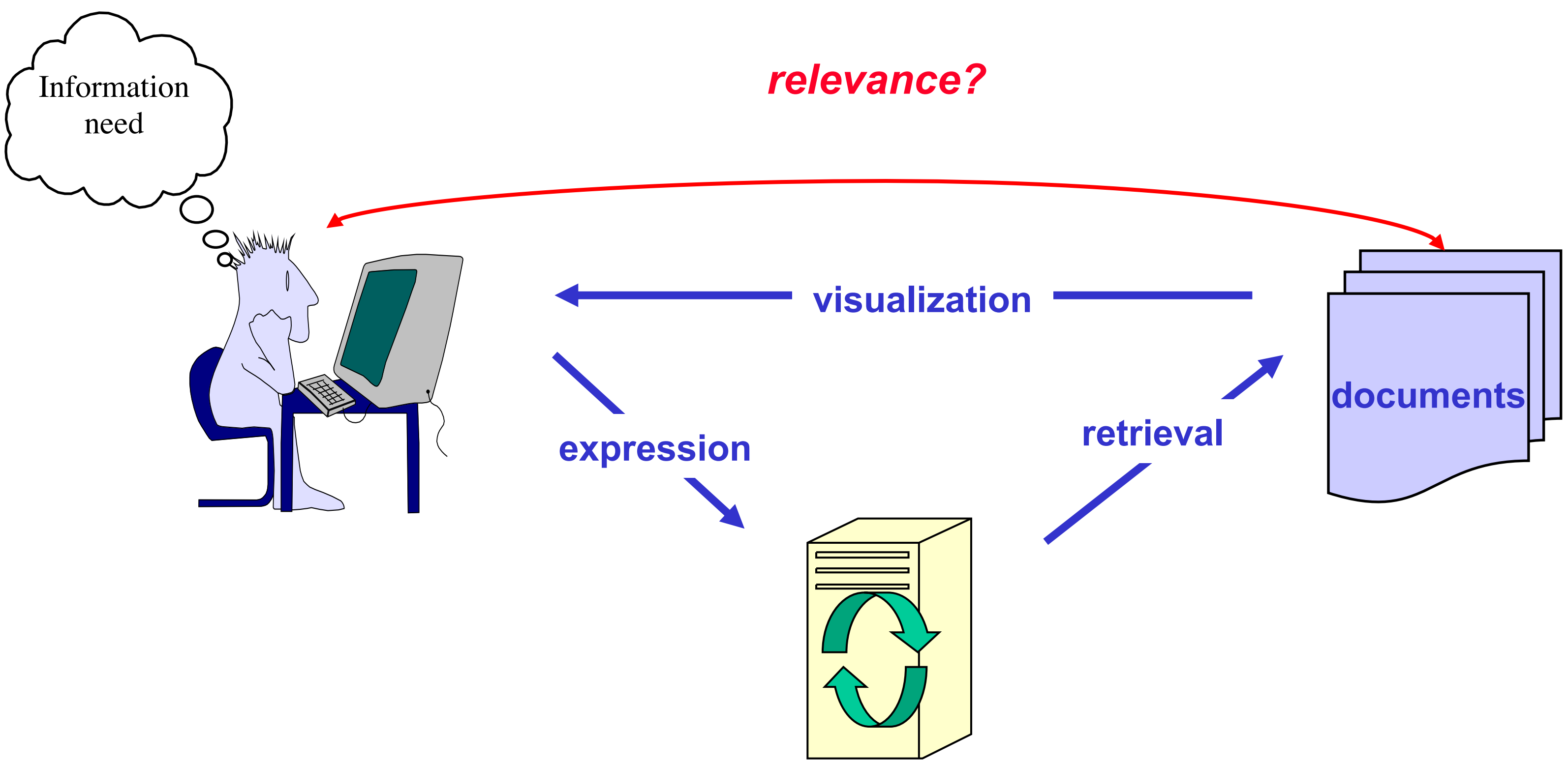
1. Introduction

- Challenge of Information Retrieval:
  - Content base access to documents that satisfy an user's information



1. Introduction

- Parameters
  - the effort, intellectual or physical, needed to users to express queries
  - response time
  - display of results (user's capability to use the retrieved documents)
  - corpus quality according to the user's needs
  - capability of the system to retrieve all the relevant documents and to avoid retrieving unrelevant ones.

1. Introduction

- For the last point (retrieval of relevant docs), comparing IRSs in a theoretical way (using their model) is a unsolved problem

⇒ so: use black box tests

We compare the results of a system with ideal answers to given queries.

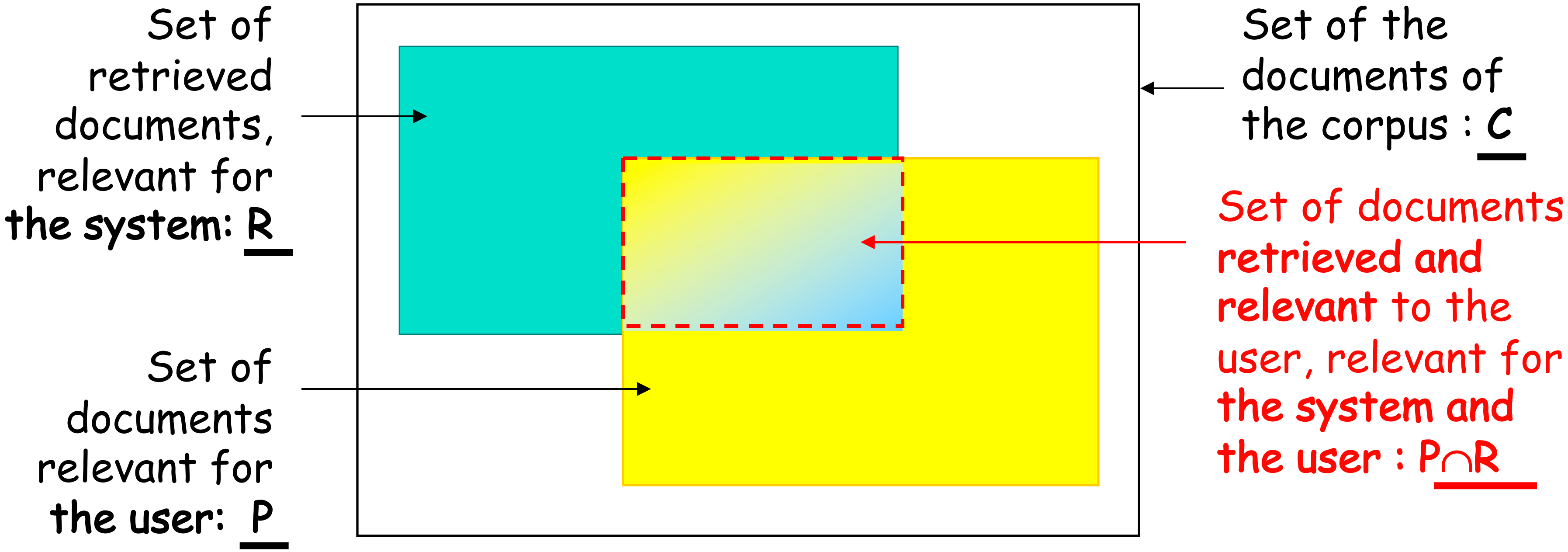
1. Introduction

- Test collection (Cranfield Paradigm)
  - a set of documents (corpus) C
  - a set of queries on C
  - a set of relevant documents for each query
    - Expert users that assess the relevance of each doc of the corpus according to each query

    → These are the ideal answers
  - one (or several) evaluation measure (s)
    - Well defined
    - That analyse one aspect of the quality of systems

2. Recall/precision measures

- To oompare user (ideal) and system relevances:



2. Recall/precision measures

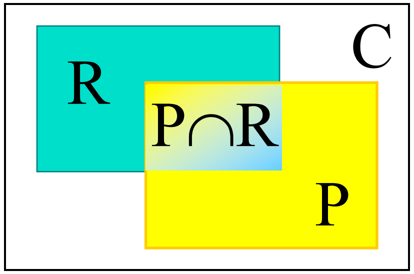
- The essential criteria are:
  - *recall*: ability of the system to give in the answer all the relevant documents according to the user
  - *precision*: ability of the system to give in the answer only relevant documents according to the user

These two criteria are antagonistic:

- Most of the time, when we improve one we degrade the other…

2. Recall/precision measures

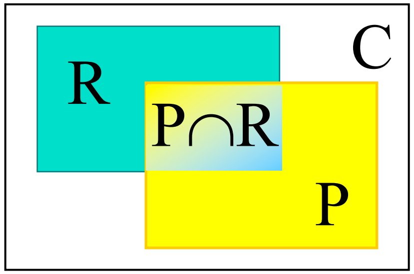
- The recall is the ratio of
  - The number of retrieved documents by the system and relevant to the user
  - Divided by the number of all the documents of the corpus that are relevant to the user



$$recall = \frac{|P \cap R|}{|P|} \in [0,1]$$

2. Recall/precision measures

- The precision is the ratio of
  - The number of retrieved documents by the system and relevant to the user
  - Divided by the number of the documents retrieved by the system



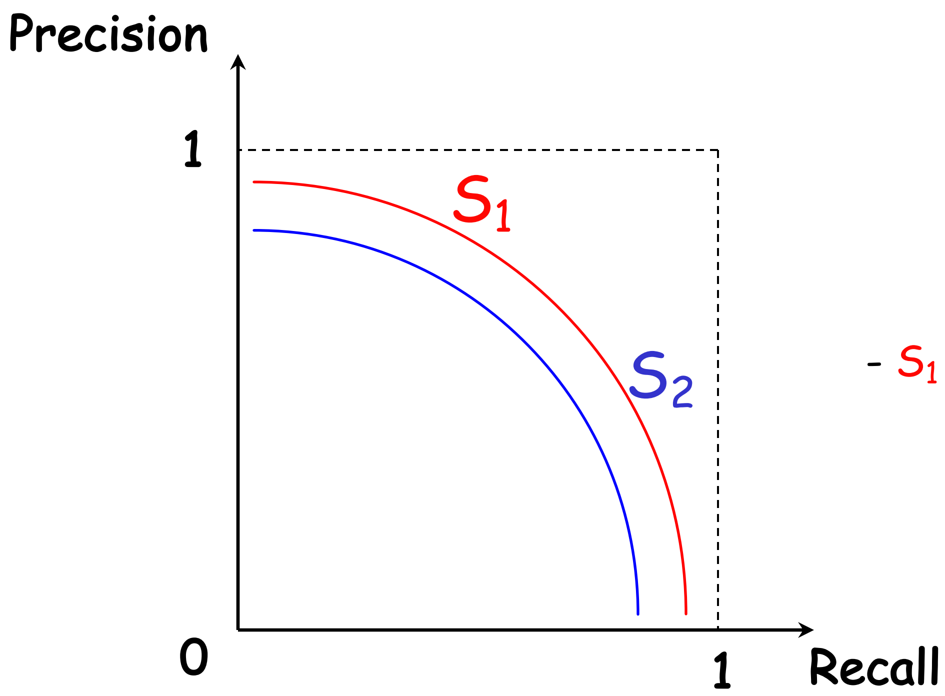
$$precision = \frac{|P \cap R|}{|R|} \qquad \in [0,1]$$

2. Recall/precision measures

- For one query and one system : 2 real values
  - Example: a system gives 5 documents, among them 3 are relevant, knowing that there are 10 relevant documents in the corpus:
    - Recall = 3 / 10
    - Precision = 3 / 5
- We need more detailed evaluations
  - Recall/precision diagrams

3. Recall/precision diagrams

- Comparison of 2 systems S1 et S2



- S_1 is better than S_2

3. Recall/precision diagrams

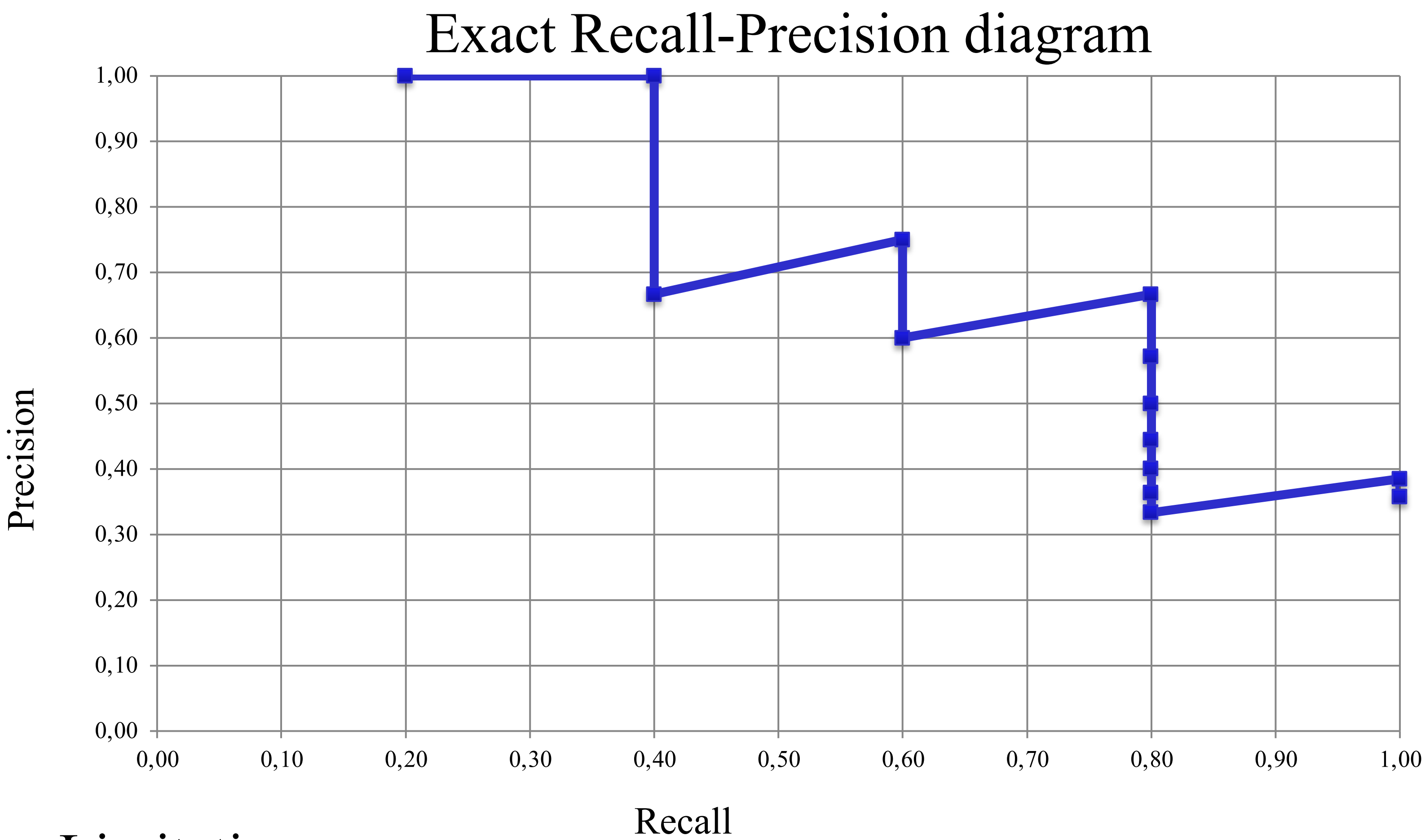
- Show the evolution of the precision and the recall with sorted results
- Method:
  - We compute the precision and the recall when considering only the first document as answer, then we do the same for the two first results of the system, and so on, until each retrieved document is processed.

3. Recall/precision diagrams

- Corpus of 200 documents, one query Q that have 5 relevant docs {572, 588, 589, 590, 592}

			recall	precision
		is relevant	p and r / p	p and r / r
1	588	X	0,20	1,00
2	589	X	0,40	1,00
3	576		0,40	0,67
4	590	X	0,60	0,75
5	986		0,60	0,60
6	592	X	0,80	0,67
7	884		0,80	0,57
8	988		0,80	0,50
9	578		0,80	0,44
10	985		0,80	0,40
11	103		0,80	0,36
12	591		0,80	0,33
13	572	X	1,00	0,38
14	990		1,00	0,36

3. Recall/precision diagrams



- Limitation

  Difficult to fuse exact R-P curves for several queries, as multiple recall values.

3. Recall/precision diagrams

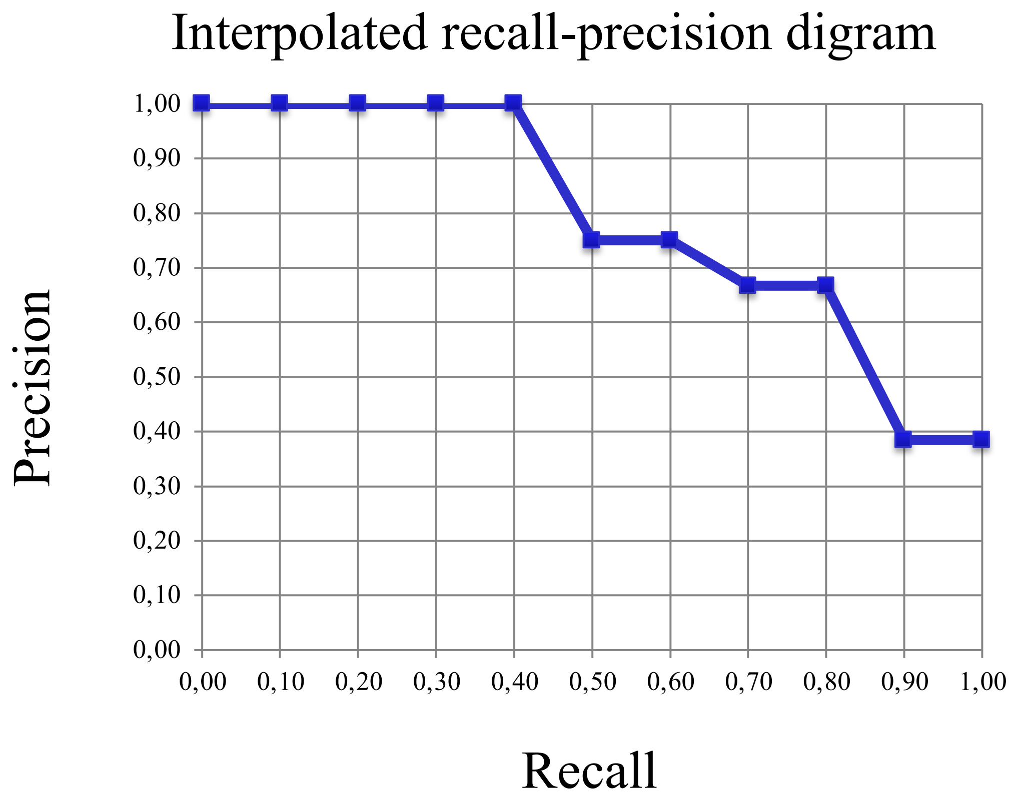
- Solution: Interpolated Recall/Precision diagrams
  - Fix 11 recall points R={0, 0.1, 0.2, …, 0.9, 1}
  - Rule of the maximum

    for each recall point v_r in R, keep the max of precision from recall greater or equal than v_r in exact table
  - For instance, in the table of slide 14:
    - When v_r= 0.1, the max precision = 1, obtained at recall 0.2
  - If a recall point has no precision value according to the rule of maximum, then we force the precision to 0 (i.e. the min precision value).

3. Recall/precision diagrams

Interpolated

Recall	Precision
0	1
0.1	1
0.2	1
0.3	1
0.4	1
0.5	0.75
0.6	0.75
0.7	0.6667
0.8	0.6667
0.9	0.3846
1	0.3846

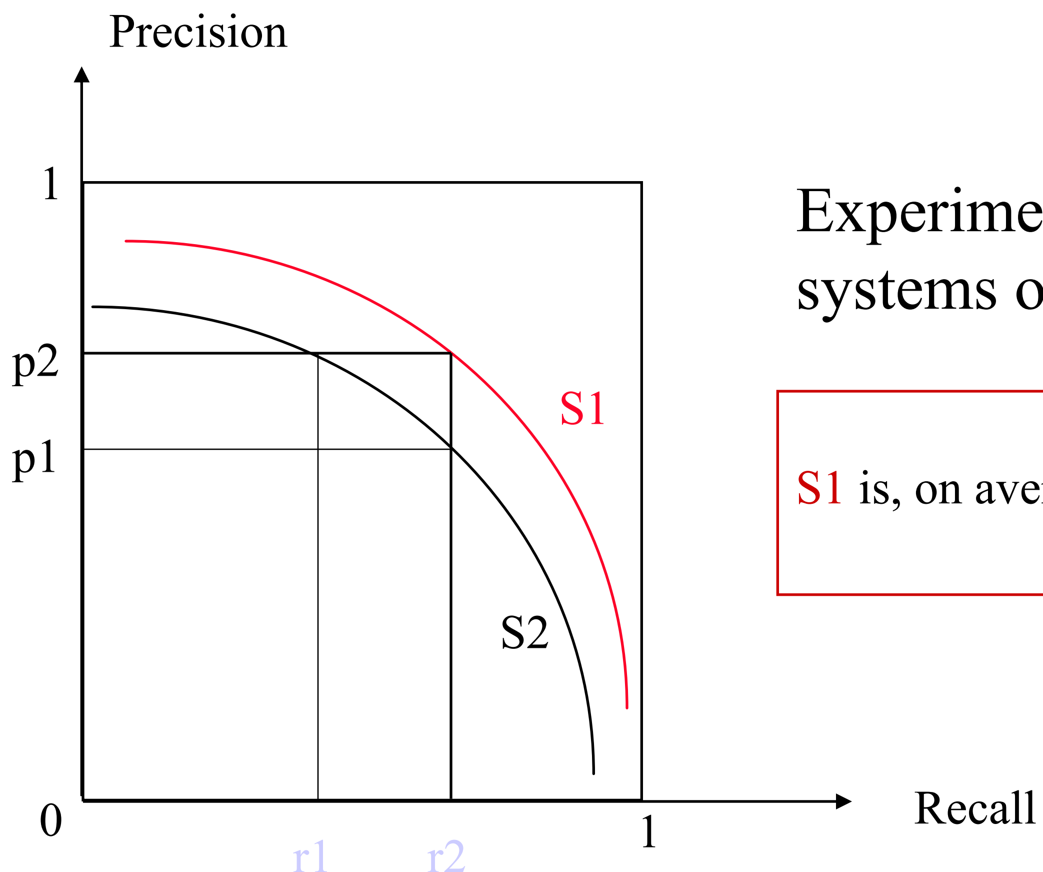


3. Recall/precision diagrams

- For nbQ queries > 1:
  1. Generate interpolated table for each query
  2. Average on each of the 11 recall points for all the nbQ queries
  3. Generate the overall recall/precision table + diagram of a system.

3. Recall/precision diagrams

- Comparing systems

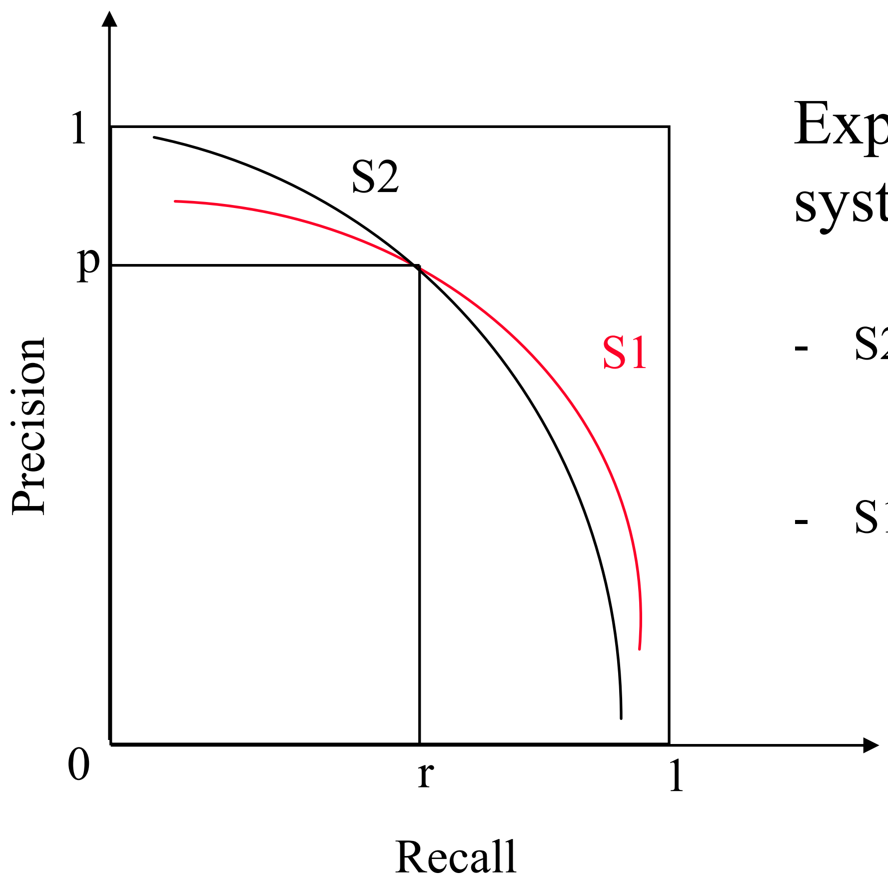


Experimental comparison of systems on a test collection :

S1 is, on average, always better than S2

3. Recall/precision diagrams

- Comparing systems

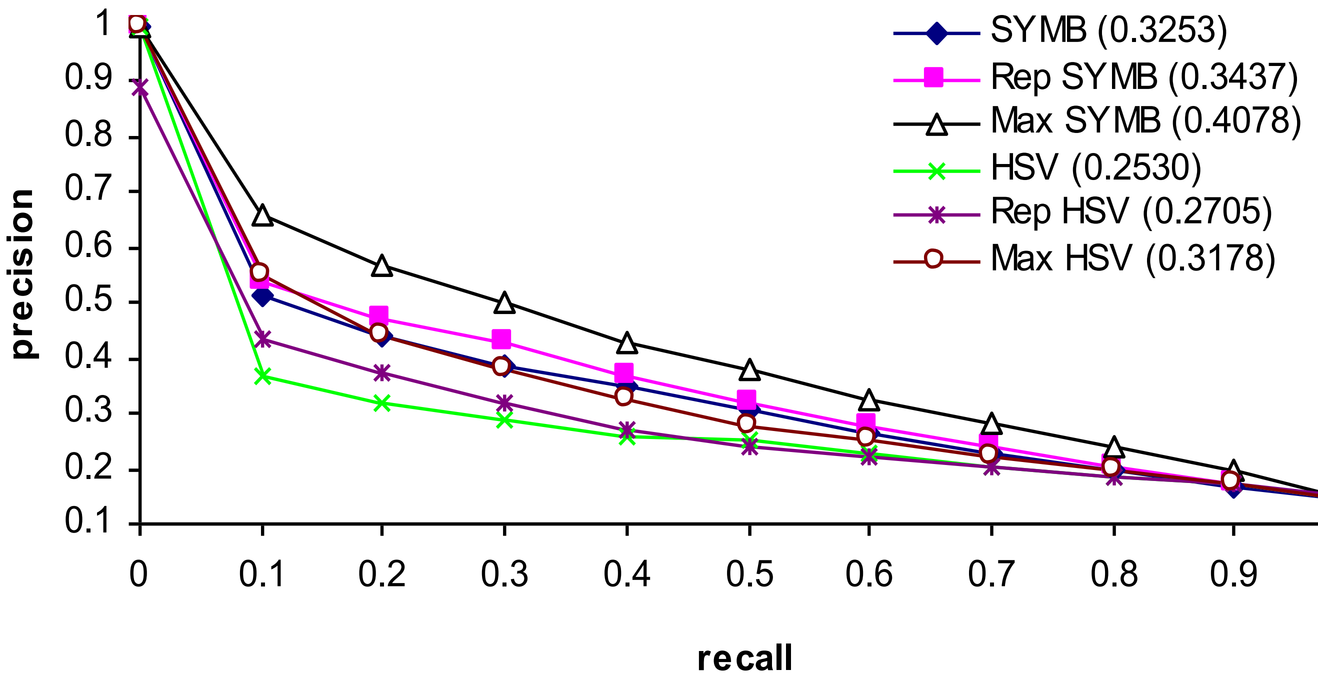


Experimental comparison of systems on a test collection :

- S2 is better than S1 for precision
  - Web search
- S1 is better than S2 for recall
  - Side effects of medicine drugs

3. Recall/precision diagrams

– A real diagram



4. Mean Average Precision

- AP and MAP
  - The idea here is to get a general view of the quality of a system, using only one value.
  - AP : average precision <u>for one query</u>
    - precision computed after each relevant document, averaged

$$AP = \frac{\sum_{k=1}^{n} \text{Prec(k)} \ . \ \text{rel(k)}}{|P|}$$

      - P : set of relevant documents, Prec(k) precision value at result k,

$$rel(k) = \begin{cases} \text{1 if document at position k is relevant} \\ \text{0 otherwise} \end{cases}$$

      - on the previous example: AP=0.76 (from table slide 14)
  - MAP mean of the average precision over all query

5. F-measure

- Integrates recall and precision in one value (harmonic mean)
- General form : $$F_\beta = \frac{(1+\beta^2).precision.recall}{\beta^2.precision + recall}$$
- In IR: $\beta = 1$

$$F_1 = \frac{2.precision.recall}{precision + recall}$$

6 Precision @x documents

- We evaluate the precision after x documents retrieved, and average over queries
- Useful when evaluating system for first results (10 or 20 for instance)
  - for instance in our example (table slide 14):
    - P@5 = 0.60
    - P@10=0.40
    - P@15=0.33

7. Discounted Cumulated Gain

- Cumulated Gain
  - Use of the result list from a system for a query: R
    - Ex: $R = <\overset{1}{d_{23}}, \overset{2}{d_{56}}, \overset{3}{d_{9}}, \overset{4}{d_{135}}, \overset{5}{d_{87}}, \overset{6}{d_{4}}>$
  - Obtain the gain value for each document:

$$G[j]=gain(R[j])$$

    - Ex : $G= <1, 2, 0, 0, 2, 1>$
  - Compute the discounted gain for each document:

$$DG[j]=gain(R[j])/\log_2(j+1))$$

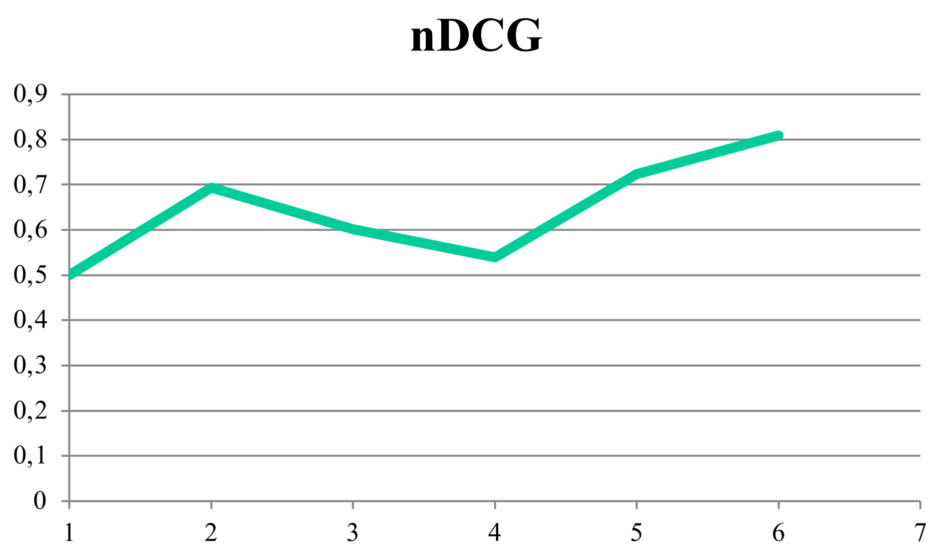
    - Ex : $DG = < 1, 1.26, 0, 0, 0.77, 0.36 >$
  - Compute cumulated gain at rank i: $DCG[i] = \sum_{j=1}^{i} DG[j]$
    - Ex : $DCG=<1, 2.26, 2.26, 2.26, 3.04, 3.39>$

7. Discounted Cumulated Gain

- Normalization by using an ideal list I, list of the gains of the relevant documents of R sorted by decreasing gain value (ex. 4 docs with relevance of 2, 2, 1, 1)
  - Ex : I=<2, 2, 1, 1, 0, 0>
- Discounted gain for the ideal list between the position 1 and i :
  - Ex : DCI=<2 3,26 3,76 4,19 4,19 4,19>
- Normalized Cumulated Gain : $nDCG[i] = \frac{DCG[i]}{DCI[i]}$
  - Ex : nDCG=<0,5 0,69 0,60 0,54 0,72 0,81>

7. Discounted Cumulated Gain

- curve obtained on the example



- Cumulated gain compares an ideal result list to the result obtained
- Uses importance in rank (top more important)
- Takes into account non binary values of relevance, which is good, but difficult to interpret results

8. Test collections

- To compute recall/precision/nDCG, we need test collections
- A test collection is composed of a set of resolved queries
  - queries representative of real user interests
  - diverse queries (subject, style, vocabulary)
  - large number (> 30)
- For a large corpus (100K or more), it is difficult to evaluate queries on the full corpus

→ use of *pooled* results [Voorhes 2001]

- we run the queries q_i on several state of the art systems S_j, each system gets a result list per query $R_{i,j}$
- we make a union of each results *sets* per query
- we evaluate user relevance on the sets generated (so, not all the collection)

8. Test collections

- Impact on "global" recall/precision values
  - potential decrease of precision
  - potential increase of recall
- BUT
  - For the MAP, it has been shown that the ranking of systems are kept.

- Note: it impacts if your system is not used in the pool, because results that may be relevant are marked non-relevant…

9. Trec-eval

- Software downloaded on internet. It generates the tables for the recall/precision diagrams and avg. prec. @ 5, 10, 20, 50 and 100 documents, and other measures
  - http://trec.nist.gov/trec_eval/trec_eval.8.1.tar.gz

10. Conclusion

- Limitations
  - Binary relevance assessments for precision/recall based measures (unrealistic but widely used). INEX tried to extend this on structured documents (interpolated recall/precision using characters).
  - Discounted Cumulated Gain used in eval
  - On large collections, difficult to make evaluations
    - One solution (TREC) pool the results for several systems.
  - Hypothesis: relevance is independent of the ranking
    - Not true in reality: If d_1 is presented before d_5, then may be d_5 is not relevant any more, because d_1 contains similar information that d_5 for the user need.

10. Conclusion

- To do
  - Understand classical IR evaluation (Cranfield Paradigm)
  - Understand recall/precision measures and disgrams (redo the example, and make others removing one relevant document found, etc.)
  - Understand the nDGC computation.

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