Retrieval Performance Evaluation

- Measures

Berlin Chen
Department of Computer Science & Information Engineering
National Taiwan Normal University

Reference:

1. *Modern Information Retrieval*, chapter 3

Introduction

- Functional analysis
  - Functionality test or error analysis instead

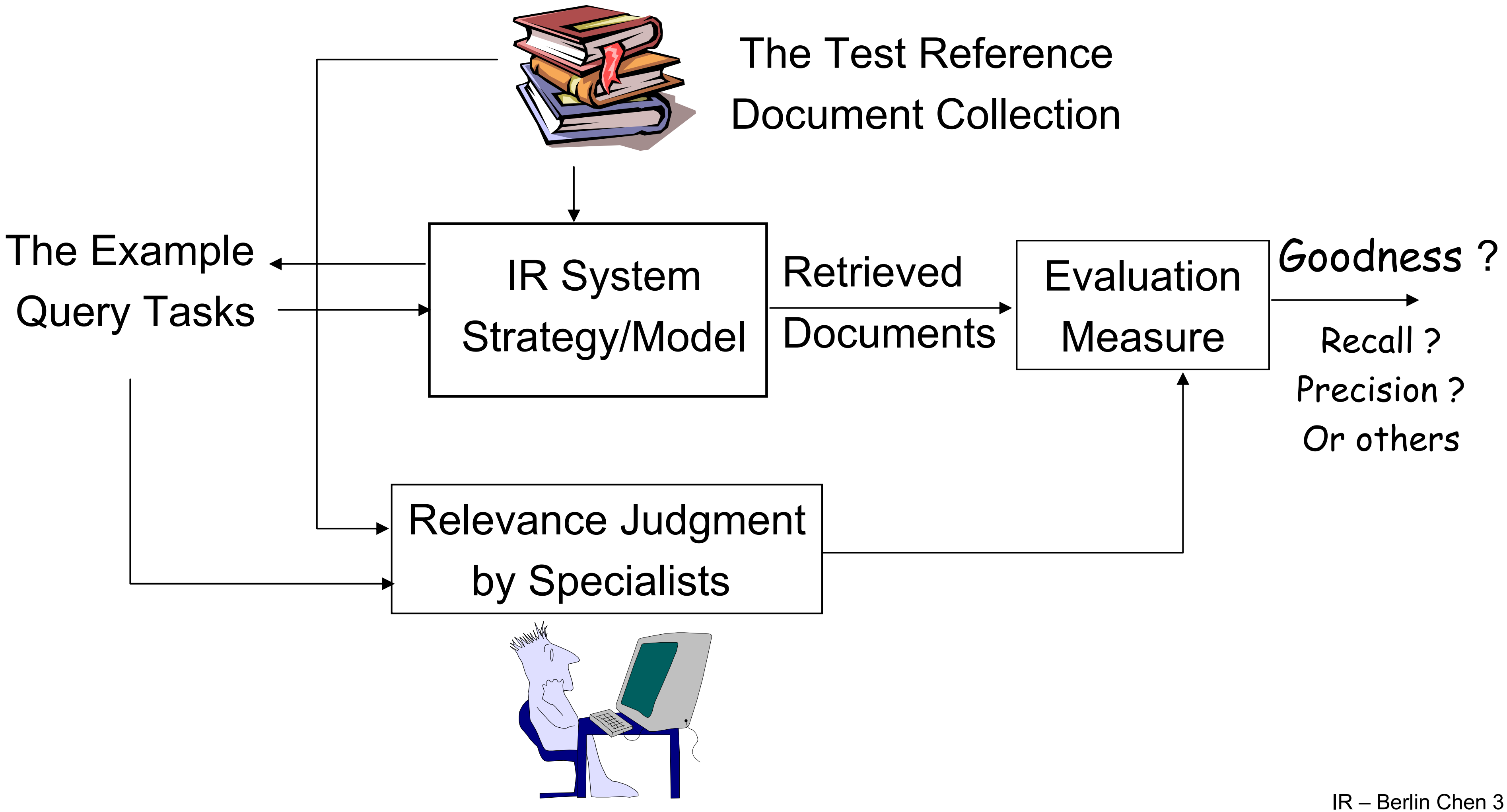
- Performance evaluation
  - E.g.: **Data retrieval system**
    - The shorter the response time, the smaller the space used, the better the system is
    - Tradeoff between time and space

- Retrieval performance evaluation
  - E.g.: **information retrieval system**
    - Relevance of retrieved documents is important, besides time and space (quality of the answer set)
  - Discussed here !

Different objectives

Introduction (cont.)

- Retrieval performance evaluation (cont.)



Introduction (cont.)

- The Test Reference Collection
  - A collection of documents
  - A set of example information requests (queries)
  - A set of relevant documents for each information request

- Evaluation measure
  - Qualify the similarity between the set of documents retrieved and the set of relevant documents provided (by the specialists)
  - Provide an estimation of the **goodness** of the retrieval strategy

Batch and Interactive Mode

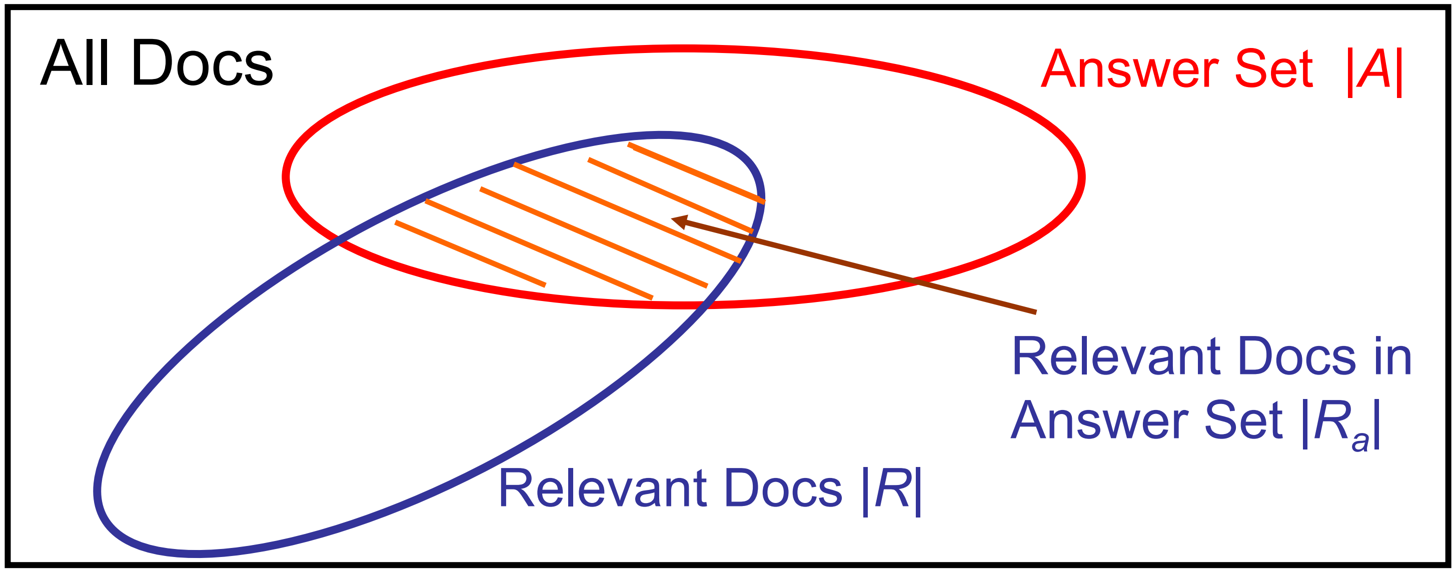
Consider retrieval performance evaluation

- Batch mode (laboratory experiments)
  - The user submits a query and receives an answer back
  - **Measure**: the quality of the generated answer set
  - Still the dominant evaluation (Discussed here !)
    - Main reasons: repeatability and scalability

- Interactive mode (real life situations)
  - The user specifies his information need through a series of interactive steps with the system
  - **Measure**: user effort, interface design, system's guidance, session duration
  - Get a lot more attention in 1990s

Recall and Precision

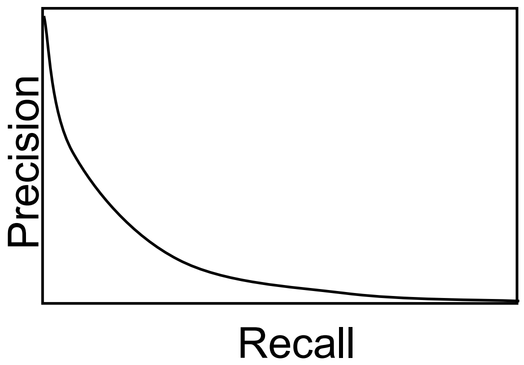
- Recall $\left(\frac{|R_a|}{|R|} \right)$
  - The fraction of the relevant documents which has been retrieved
- Precision $\left(\frac{|R_a|}{|A|} \right)$
  - The fraction of the retrieved documents which is relevant



Recall and Precision (cont.)

- Recall and precision assume that all the documents in the answer set have been examined (or seen)

- However, the user is not usually presented with all the documents in the answer set A at once
  - Sort the document in A according to a degree of relevance
  - Examine the ranked list starting from the top document (*increasing in recall*, but *decreasing in precision*)
    - Varying of recall and precision measures
    - A precision versus recall curve can be plotted



Recall and Precision (cont.)

- Example 3.2
  - $R_q=\{d_3, d_5, d_9, d_{25}, d_{39}, d_{44}, d_{56}, d_{71}, d_{89}, d_{123}\}$
    - Ten relevant documents, five included in Top 15
  - A ranking of the documents for the given query *q*

1. d_{123} •
2. d_{84}
3. d_{56} •
4. d_6
5. d_8
6. d_9 •
7. d_{511}
8. d_{129}
9. d_{187}
10. d_{25} •
11. d_{38}
12. d_{48}
13. d_{250}
14. d_{113}
15. d_3 •

$(P,R)_1$=(100%,10%)

$(P,R)_3$=(66%,20%)

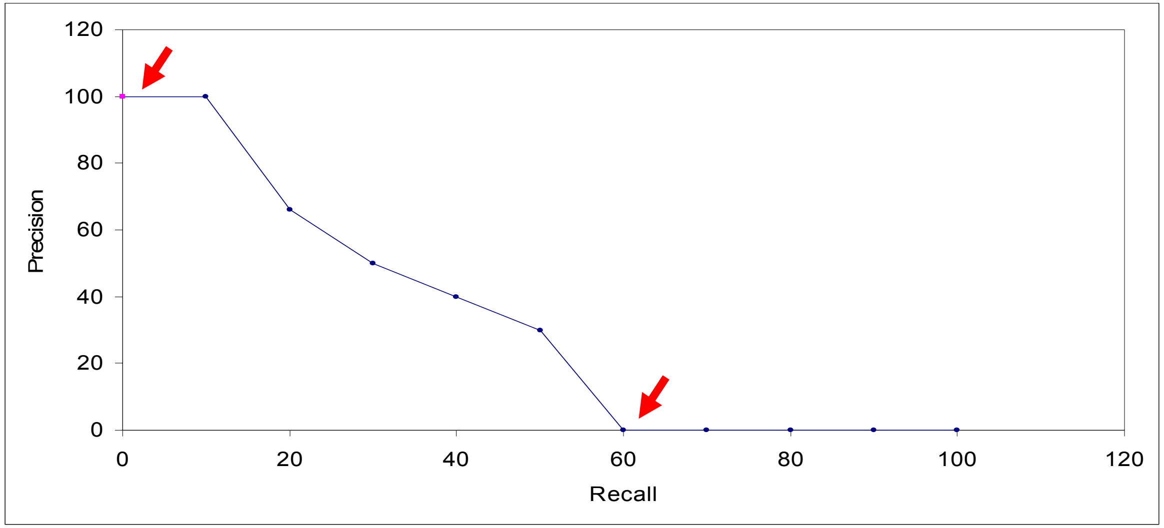
$(P,R)_6$=(50%,30%)

$(P,R)_{10}$=(40%,40%)

$(P,R)_{15}$=(33%,50%)

Recall and Precision (cont.)

- Example 3.2 (count.)



  - The precision versus recall curve is usually plotted based on 11 standard recall levels: 0%,10%,….,100%
  - In this example
    - The precisions for recall levels higher than 50% drop to 0 because no relevant documents were retrieved
    - There was *an interpolation* for the recall level 0%

Interpolated Recall-Precision Curve

- Since the recall levels for each query might be distinct from the 11 standard recall levels

Salton, 1983

  - Utilization of an interpolation procedure is necessary !
- Example 3.3
  - $R_q=\{d_3, d_{56}, d_{129}\}$
    - Three relevant documents

1. d_{123}	6. d_9	11. d_{38}
2. d_{84}	7. d_{511}	12. d_{48}
3. d_{56} •	8. d_{129} •	13. d_{250}
4. d_6	9. d_{187}	14. d_{113}
5. d_8	10. d_{25}	15. d_3 •
$(P,R)_3$=(33.3%,33.3%)	$(P,R)_8$=(25%,66.6%)	$(P,R)_{15}$=(20%,100%)

  - How about the precisions at recall levels 0%, 10%,... ,90%

Interpolated Recall-Precision Curve (cont.)

- Interpolated Precisions at standard recall levels

$$\overline{P}(r_j) = \max_{r_j \le r \le r_{j+1}} P(r)$$

  – the j-th standard recall level (e.g., r_5 is recall level 50%)

- Example 3.3 (cont.)

$(P,R)_3$=(33.3%,33.3%)

$(P,R)_8$=(25%,66.6%)

$(P,R)_{15}$=(20%,100%)

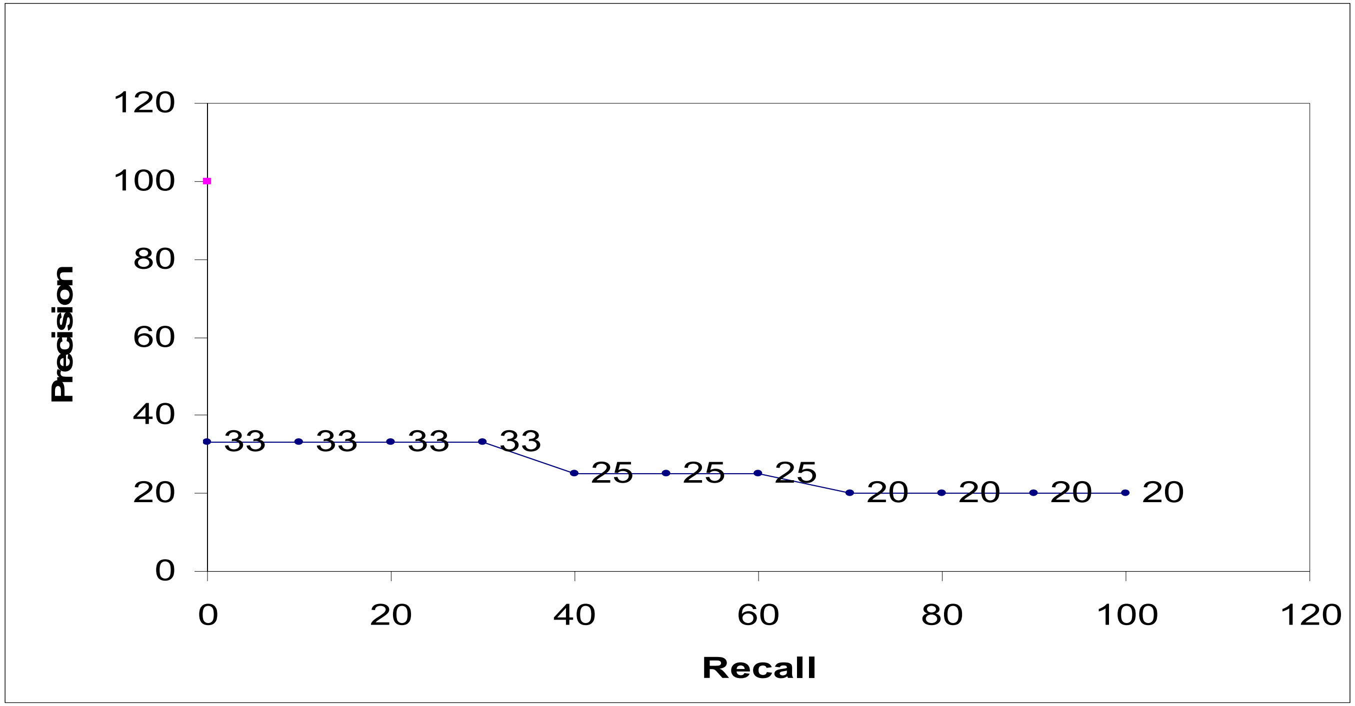
Precision	Recall
33.3%	0%
33.3%	10%
33.3%	20%
33.3%	30%
25%	40%
25%	50%
25%	60%
20%	70%
20%	80%
20%	90%
20%	100%

$$\overline{P}_i(r_j) = \max_{r_j \le r \le r_{j+1}} P_i(r)$$

query i

Interpolated Recall-Precision Curve (cont.)

- Example 3.3 (cont.)
  - Interpolated precisions at 11 standard recall levels



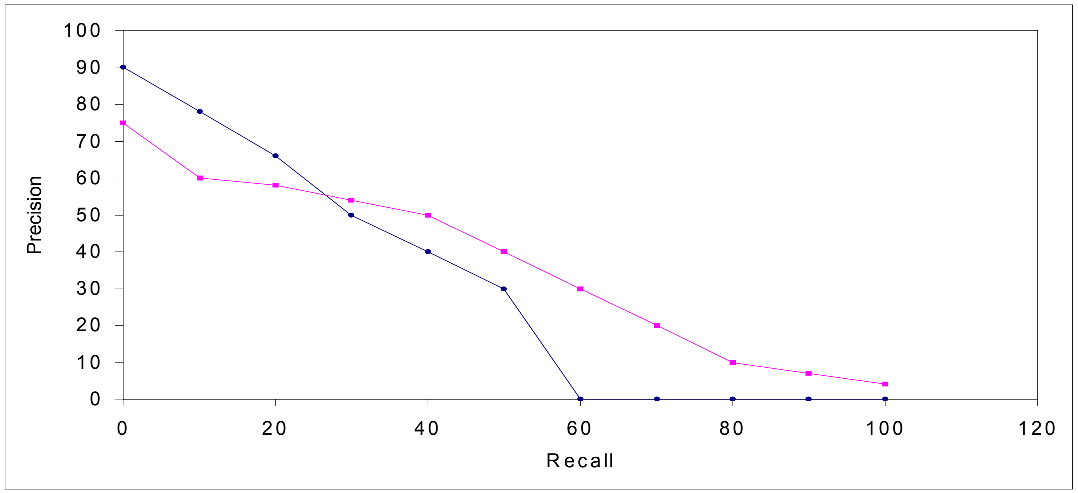
Interpolated Recall-Precision Curve (cont.)

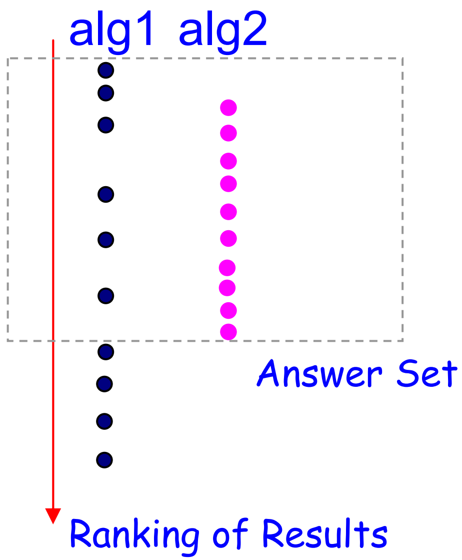
- Evaluate (average) the retrieval performance over *all queries*

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

On different recall levels

- Example 3.4: *average interpolated recall-precision curves for two distinct retrieval algorithms*

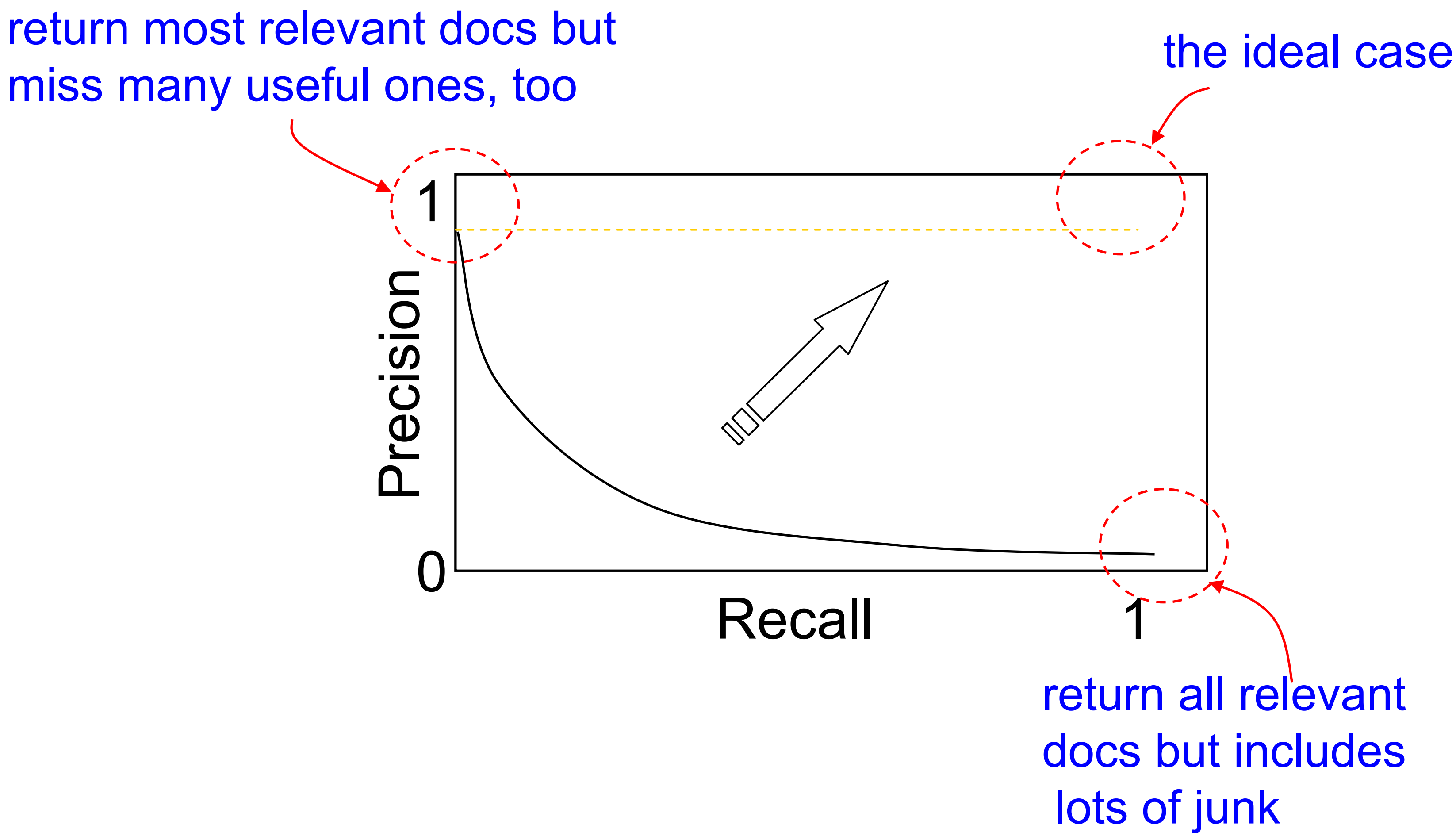




  – Difficult to determine which of these two results is better

Interpolated Recall-Precision Curve (cont.)

- Trade-off between Recall and Precision



Interpolated Recall-Precision Curve (cont.)

- Alternative: average precision at a given document cutoff values (levels)
  - E.g.: compute the average precision when Top 5, 10, 15, 20, 30, 50 or 100 relevant documents have been seen
  - Focus on how well the system ranks the Top *k* documents
    - Provide additional information on the retrieval performance of the ranking algorithm
  - We can take (weighted) average over results

Interpolated Recall-Precision Curve (cont.)

- Advantages
  - Simple, intuitive, and combined in single curve
  - Provide quantitative evaluation of the answer set and comparison among retrieval algorithms
  - *A standard evaluation strategy* for IR systems

- Disadvantages
  - Can't know true recall value except in small document collections (document cutoff levels are needed!)
  - Assume a strict document rank ordering

Single Value Summaries

- Interpolated recall-precision curve
  - Compare the performance of retrieval algorithms over a set of example queries
    - Might disguise the important anomalies
  - How is the performance for each individual query ?
- A single precision value (for each query) is used instead
  - Interpreted as a summary of the corresponding precision versus recall curve
    - Just evaluate the precision based on the top 1 relevant document ?
    - Or averaged over all relevant documents

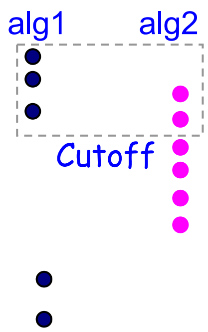
Single Value Summaries (cont.)

- Method 1: **Average Precision** at Seen Relevant Documents
  - A single value summary of the ranking by averaging the precision figures obtained after *each new relevant doc* is observed

Example 3.2

1. d_{123} • (*P*=1.0)	6. d_{9} • (*P*=0.5)	11. d_{38}
2. d_{84}	7. d_{511}	12. d_{48}
3. d_{56} • (*P*=0.66)	8. d_{129}	13. d_{250}
4. d_{6}	9. d_{187}	14. d_{113}
5. d_{8}	10. d_{25} • (*P*=0.4)	15. d_{3} • (*P*=0.3)

(1.0+0.66+0.5+0.4+0.3)/5=0.57



  - It favors systems which retrieve relevant docs quickly (*early in the ranking*)
  - But when *doc cutoff levels* were used
    - An algorithm might present a good average precision at seen relevant docs but have a poor performance in terms of overall recall

Mean Average Precision (*m*AP)

- Averaged at relevant docs and across queries
  - E.g. relevant docs ranked at 1, 5, 10, precisions are 1/1, 2/5, 3/10,
    - non-interpolated average precision (or called *Average Precision at Seen Relevant Documents* in textbook) =(1/1+2/5+3/10)/3
  - Mean average Precision (*m*AP)

$$\frac{1}{|Q|}\sum_{q=1}^{|Q|}(\text{non}-\text{interpolated average precision})_q$$

- Widely used in IR performance evaluation

Single Value Summaries (cont.)

- Method 2: R-Precision
  - Generate a single value summary of ranking by computing the precision at the *R*-th position in the ranking
    - Where *R* is the total number of relevant docs for the current query

1. d_{123} ●	6. d_9 ●	11. d_{38}
2. d_{84}	7. d_{511}	12. d_{48}
3. d_{56} ● ■	8. d_{129} ■	13. d_{250}
4. d_6	9. d_{187}	14. d_{113}
5. d_8	10. d_{25} ●	15. d_3 ● ■

R_q={$d_3, d_5, d_9, d_{25}, d_{39}, d_{44}, d_{56}, d_{71}, d_{89}, d_{123}$}

•10 relevant documents (●)

=> *R*-precision = 4/10=0.4

R_q={d_3, d_{56}, d_{129}}

•3 relevant document (■)

=>*R*-precision=1/3=0.33

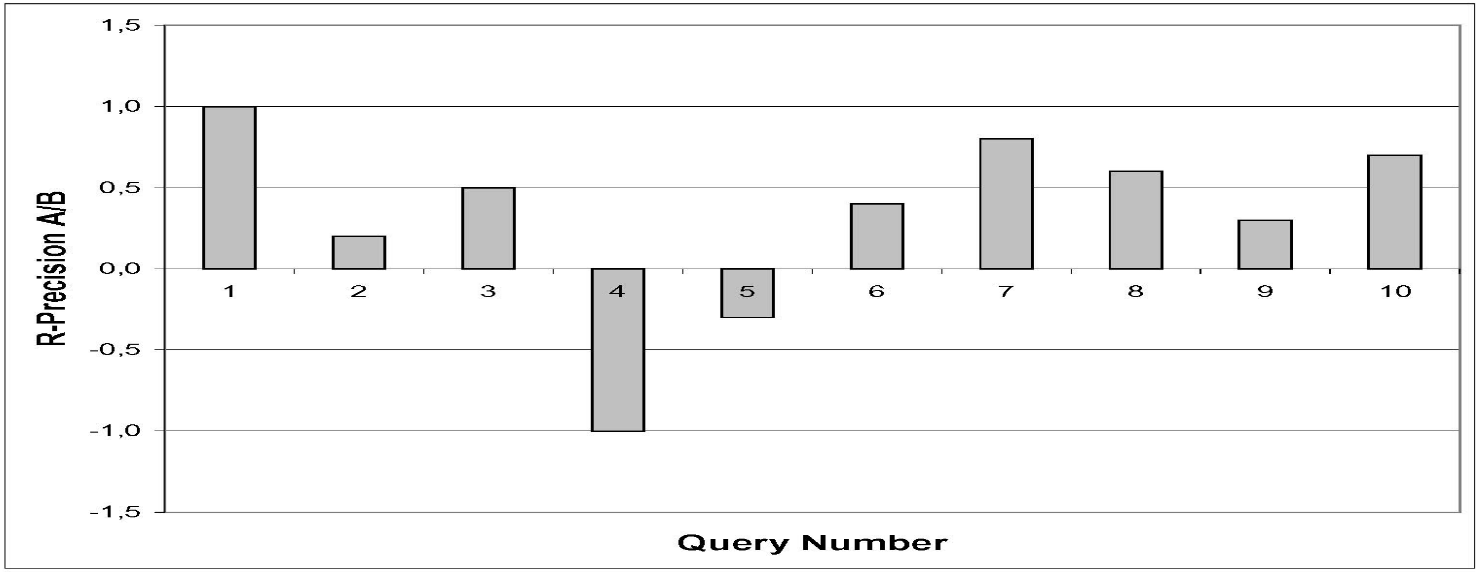
Single Value Summaries (cont.)

- Method 3: Precision Histograms
  - Compare the retrieval history of two algorithms using the R-precision graph for several queries
    - A visual inspection
  - Example 3.5
    - Algorithms *A, B*
    - The difference of R-precision for the *i*-th query:

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

Single Value Summaries (cont.)

- Method 3: *Precision Histograms* (cont.)
  - Example 3.5 (cont.)



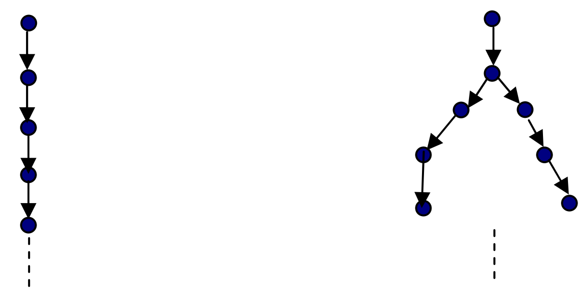
- A positive $RP_{A/B}(i)$ indicates that the algorithm *A* is better than *B* for the *i*-th query and vice versa

Single Value Summaries (cont.)

- Method 4: Summary Table Statistics
  - A statistical summary regarding the set of all the queries in a retrieval task
    - The number of queries used in the task
    - The total number of documents retrieved by all queries
    - The total number of relevant documents which were effectively retrieved when all queries are considered
    - The total number of relevant documents which could have been retrieved by all queries
    - …

Precision and Recall Appropriateness

- The proper estimation of maximal recall requires knowledge of all the documents in the collection
- Recall and precision are related measures which capture different aspects of the set of retrieved documents
- Recall and precision measure the effectiveness over queries in batch mode
- Recall and precision are defined under the enforcement of linear ordering of the retrieved documents
  - Partial Ordering ?



Alternative Measures

- Method 1: The Harmonic Mean (F Measure)
  - The harmonic mean *F* of recall and precision

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

    - *r*(*j*): the recall for the *j*-th document in the ranking
    - *P*(*j*): the precision for the *j*-th document in the ranking
  - Characteristics
    - F = 0: no relevant documents were retrieved
    - F = 1: all ranked documents are relevant
    - A high F achieved only when both recall and precision are high
    - Determination of the maximal F can be interpreted as an attempt to find the best possible compromise between recall and precision

Alternative Measures (cont.)

- Method 2: The E Measure

van Rijsbergen 1979

  - Another measure which combines recall and precision
  - Allow the user to specify whether he is more interested in recall or precision

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

  - Characteristics
    - $b = 1$: act as the complement of F Measure
    - $b > 1$: more interested in recall
    - $b < 1$: more interested in precision

Wrong statements in the Textbook!

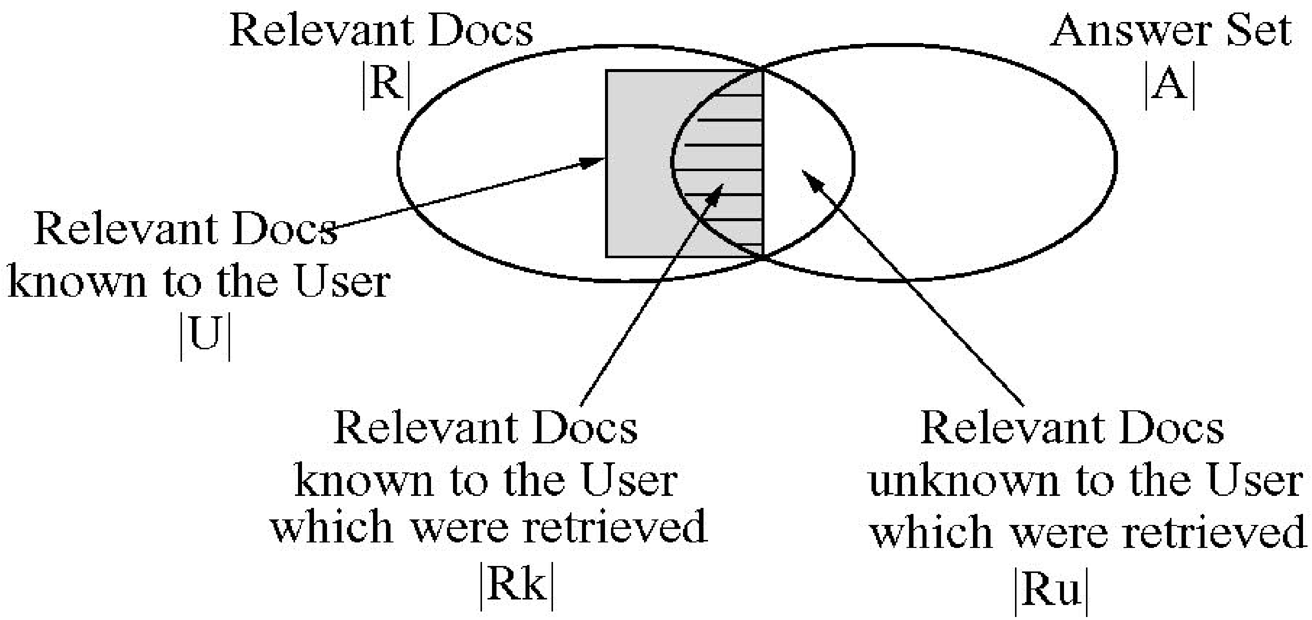
Alternative Measures (cont.)

- Method 3: *User-Oriented Measures*
  - Problematic assumption of recall and precision
    - The set of relevant documents for a query is the same, independent of the user
  - However, different users have a different interpretation of document relevance

  - *User-oriented measures* are therefore proposed
    - Coverage ratio
    - Novelty ratio
    - Relative recall
    - Recall effect

Alternative Measures (cont.)

- Method 3: *User-Oriented Measures* (cont.)



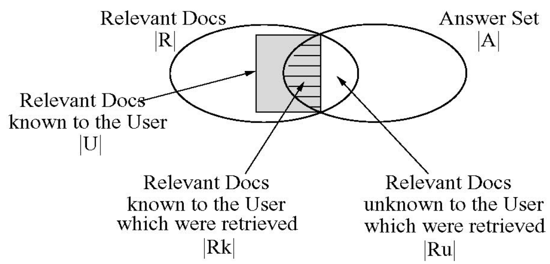
- **Coverage ratio** = $\frac{|Rk|}{|U|}$
- **Novelty ratio** = $\frac{|Ru|}{|Ru|+|Rk|}$
- Relative recall = $\frac{|R_k|+|Ru|}{|U|}$
- Recall effect = $\frac{|U|}{|A|}$

Measure the ability to reveal new relevant docs

Alternative Measures (cont.)

- Coverage ratio
  - The fraction of relevant docs **known** to the user which has been retrieved
  - High →find most of the relevant docs user expected to see

$$\frac{|Rk|}{|U|}$$



- Novelty ratio
  - The fraction of relevant docs retrieved which is **unknown** to the user
  - High →find (reveal) many new relevant docs (information) the user previously unknown

$$\frac{|Ru|}{|Ru|+|Rk|}$$

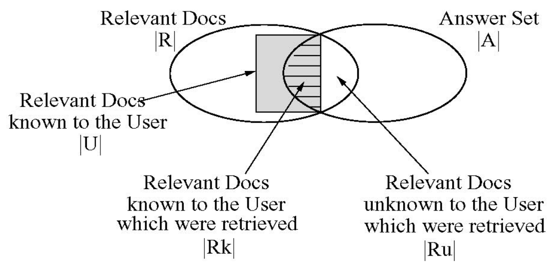
Alternative Measures (cont.)

- Relative recall
  - The ratio between the number of relevant docs found by the system and the number of relevant docs the user expects to find

$$\frac{|R_k| + |Ru|}{|U|}$$

- Recall effect
  - The ratio between the number of relevant docs the user expects to find and the number of docs found by the system

$$\frac{|U|}{|A|}$$



Homework - 1

Homework #1 :Evaluation Measures

The the query-document relevance information (AssessmentTrainSet.txt) for a set of queries (16 queries) and a collection of 2,265 documents is provided. An IR model is then tested on this query set and save the corresponding ranking results in a file (ResultsTrainSet.txt) . Please evaluate the overall model performance using the following two measures.

1. Interpolated Recall-Precision Curve:

$$\overline{P}_i(r_j) = \max_{r_j \le r \le r_{j-1}} P_i(r)$$ (for each query)

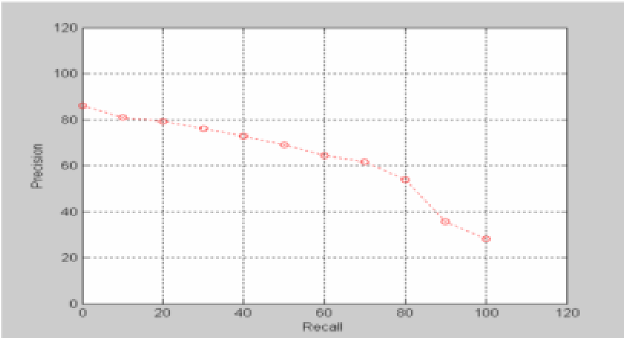
$$\overline{P}_{all}(r_j) = \frac{1}{N_q} \sum_{i=1}^{N_q} \overline{P}_i(r_j)$$ (overall performance)

2. (Non-interpolated) Mean Average Precision:

$$\frac{1}{|Q|} \sum_{q=1}^{|Q|} (\text{non} - \text{interpolated average precision})_q$$

, where "non-interpolated average precision" is "average precision at seen relevant documents" introduced in the textbook.

Example 1: Interpolated Recall-Precision Curve



Example 2: (Non-interpolated) Mean Average Precision

mAP=0.63787418