Evaluation & Benchmark Collections

Kuan-Yu Chen (陳冠宇)

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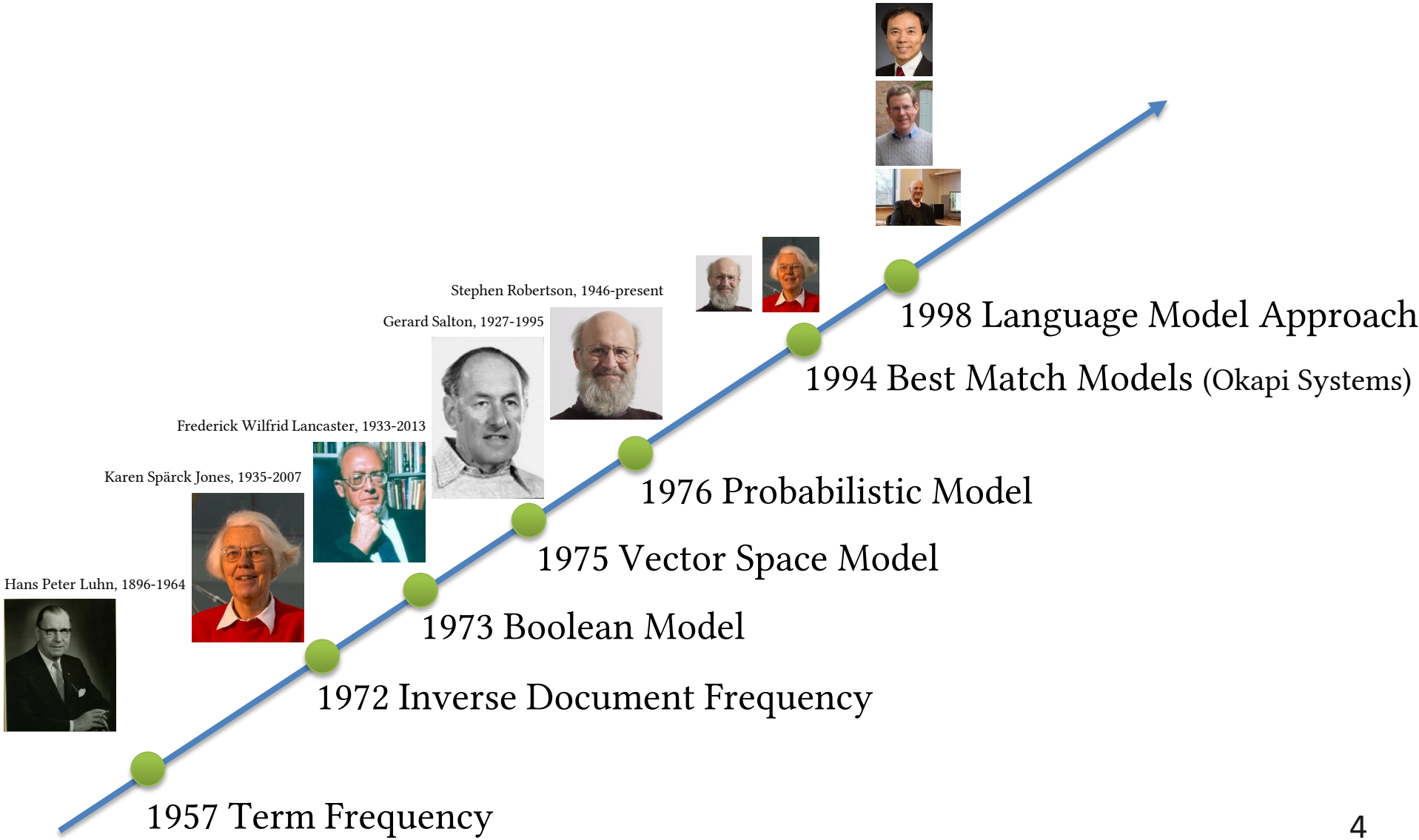
Tentative Syllabus

Date	Syllabus	Homework
9/14	Course Overview & Introduction	
9/21	Classic Models	Homework-1
9/28	Extended Probabilistic Models	
10/5	Evaluation & Benchmark Collections	Homework-2
10/12	Latent Semantic Analysis and Topic Models	Homework-3
10/19	Midterm Exam	
10/26	Pseudo-Relevance Feedback & Query Models	Homework-4
11/2	Search Results Diversification	
11/9	Supervised Approaches	
11/16	Neural Retrieval Models	Homework-5
11/23	Clustering and Special Issues in (Web) IR	
11/30	Final Exam	Final Project
12/7	Retrieval Models for Extractive Summarization (Prof. Shih-Hung Liu, Delta Electronics, Inc.)	
12/14	TBD (Prof. Meng-Sung Wu, Industrial Technology Research Institute)	
12/21	TBD	
12/28	Presentations - 1	
1/4	Presentations - 2	
1/11		Final Project Deadline

Final Project

- The project contains two parts
  - Implementation (10%)
  - Presentation (10%)
    - 15 min. + 3 min. QA
- Each group contains 2~3 students
- Please submit your member list before 10/19 (Midterm Exam)
- The paper can be found from
  - Conference: AAAI, SIGIR, CIKM, KDD, ICML, ICME, WSDM, IJCAI, arXiv, etc.
  - Journal: TKDE, TASLP, JASIST, IP&M, TOIS, KAIS, etc.

Review


Hans Peter Luhn, 1896-1964
Karen Spärck Jones, 1935-2007
Frederick Wilfrid Lancaster, 1933-2013
Gerard Salton, 1927-1995
Stephen Robertson, 1946-present
1957 Term Frequency
1972 Inverse Document Frequency
1973 Boolean Model
1975 Vector Space Model
1976 Probabilistic Model
1994 Best Match Models (Okapi Systems)
1998 Language Model Approach

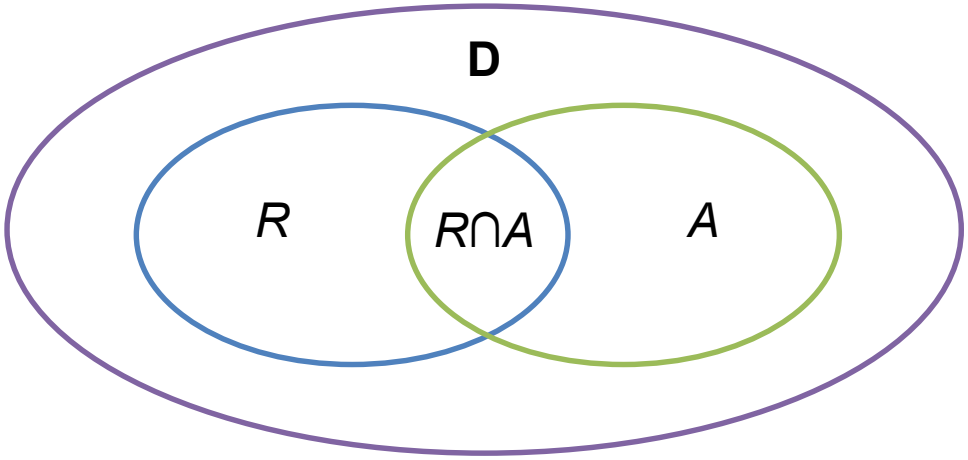
Introduction

- 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

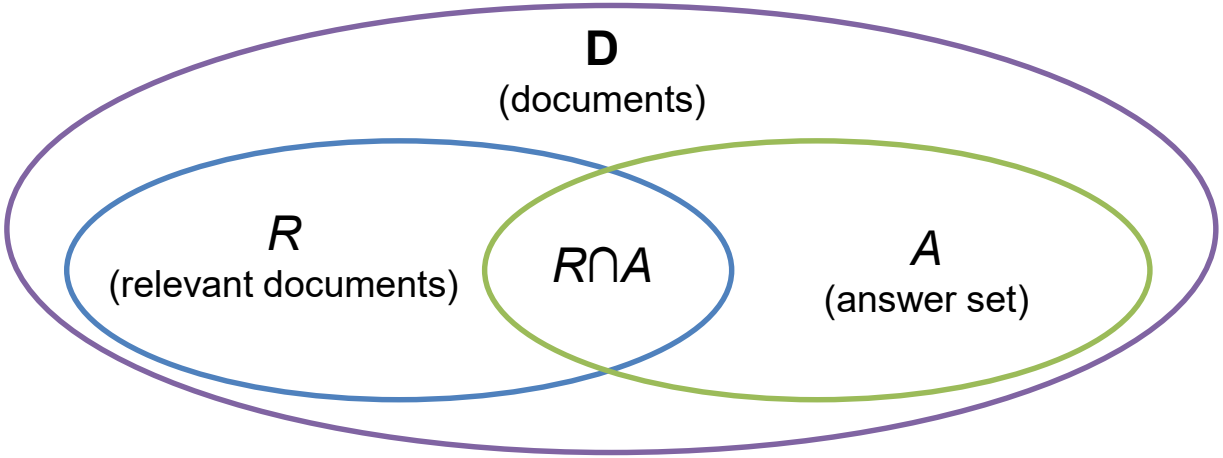
- Without proper retrieval evaluation, one cannot
  - determine how well the IR system is performing
  - objectively compare the performance of the IR system with that of other systems

Notations

- For a given query (information need)
  - **D**: the set of documents
  - R: the set of relevant documents
  - A: the answer set generated by an IR system
  - $R \cap A$: relevant documents in the answer set



Precision & Recall – Definition



- **Recall** (召回率) is the fraction of the relevant documents which has been retrieved

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

- **Precision** (準確率) is the fraction of the retrieved documents which is relevant

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

Precision & Recall

- The definition of precision and recall assumes that all documents in the answer set have been examined

- In reality, User sees a ranked set of documents and examines them starting from the top
  - Precision and recall vary as the user proceeds with their examination of the answer set

- Most appropriate then is to plot a **curve of precision versus recall**

Example – 1

- For a given query q and a set of relevant documents R_q for the query

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

- If an IR model that provides a ranking list for the query q

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 ●

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

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

Example – 2

- 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

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{123}	d_{84}	d_{56}	d_6	d_8	d_9	d_{511}	d_{129}	d_{187}	d_{25}	d_{38}	d_{48}	d_{250}	d_{113}	d_3
	●		●			●				●					●
R(%)	10		20			30				40					50
P(%)	100		66.6			50				40					33.3

Interpolated Recall-Precision Curve – 1

- For a given query q and a set of relevant documents R_q for the query

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

- If an IR model that provides a ranking list for the query q

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 ●

Interpolated Recall-Precision Curve – 2

- If we examine this ranking, we observe that
  - 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%)

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

Interpolated Recall-Precision Curve – 3

- An interpolated precision at a standard 11 recall level can be calculated

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

R	0	10	20	30	40	50	60	70	80	90	100
P	33.3	33.3	33.3	33.3	25	25	25	20	20	20	20

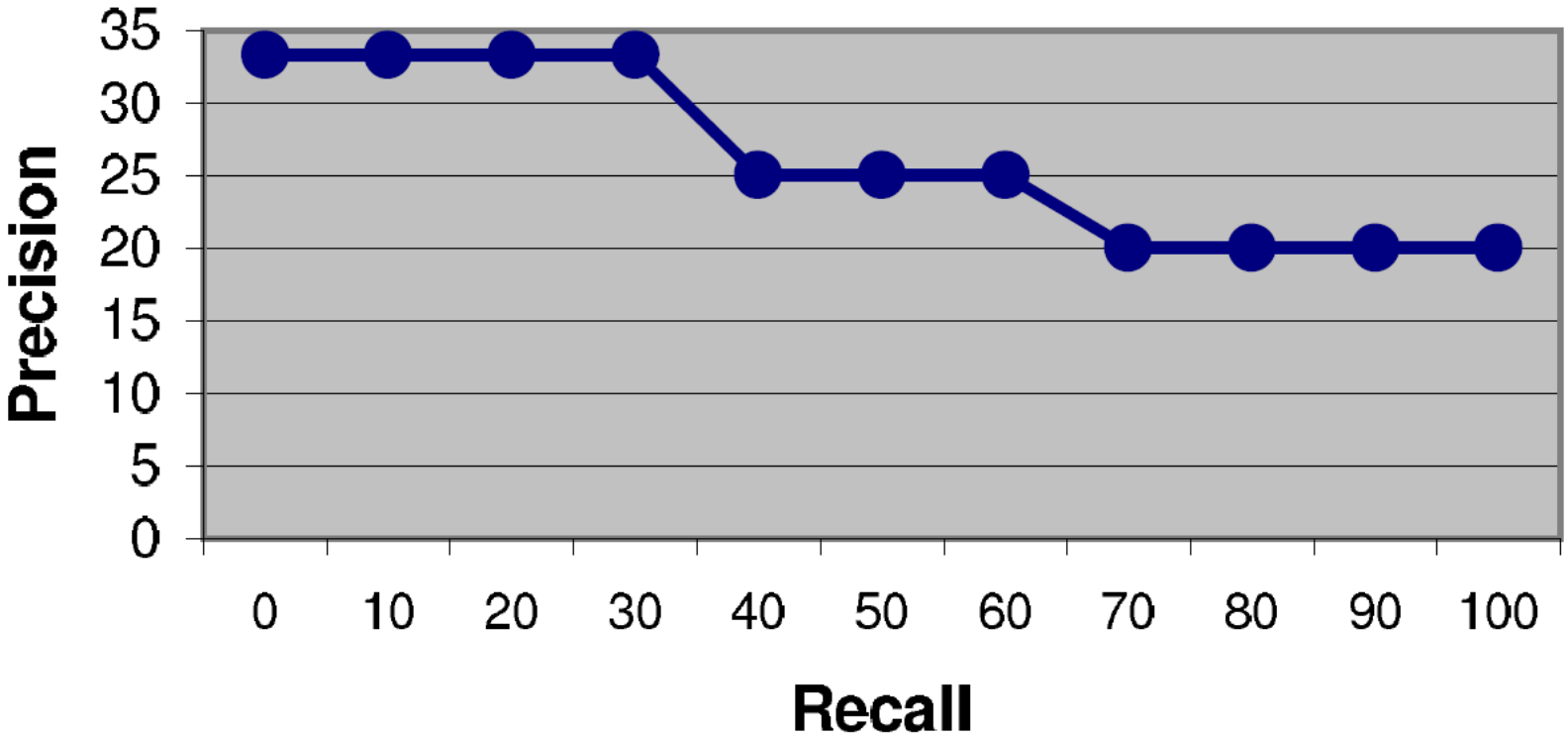
$(R, P) = (33.3\%, 33.3\%)$ $(R, P) = (66.6\%, 25\%)$ $(R, P) = (100\%, 20\%)$

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

Interpolated Recall-Precision Curve – 4

- Consequently, an interpolated recall-precision curve can be illustrated

R	0	10	20	30	40	50	60	70	80	90	100
P	33.3	33.3	33.3	33.3	25	25	25	20	20	20	20



Average Recall-Precision Curve – 1

- Usually, retrieval algorithms are evaluated by running them for several distinct test queries

- To evaluate the retrieval performance for $|\mathbf{Q}|$ queries, we average the precision at each recall level as follows

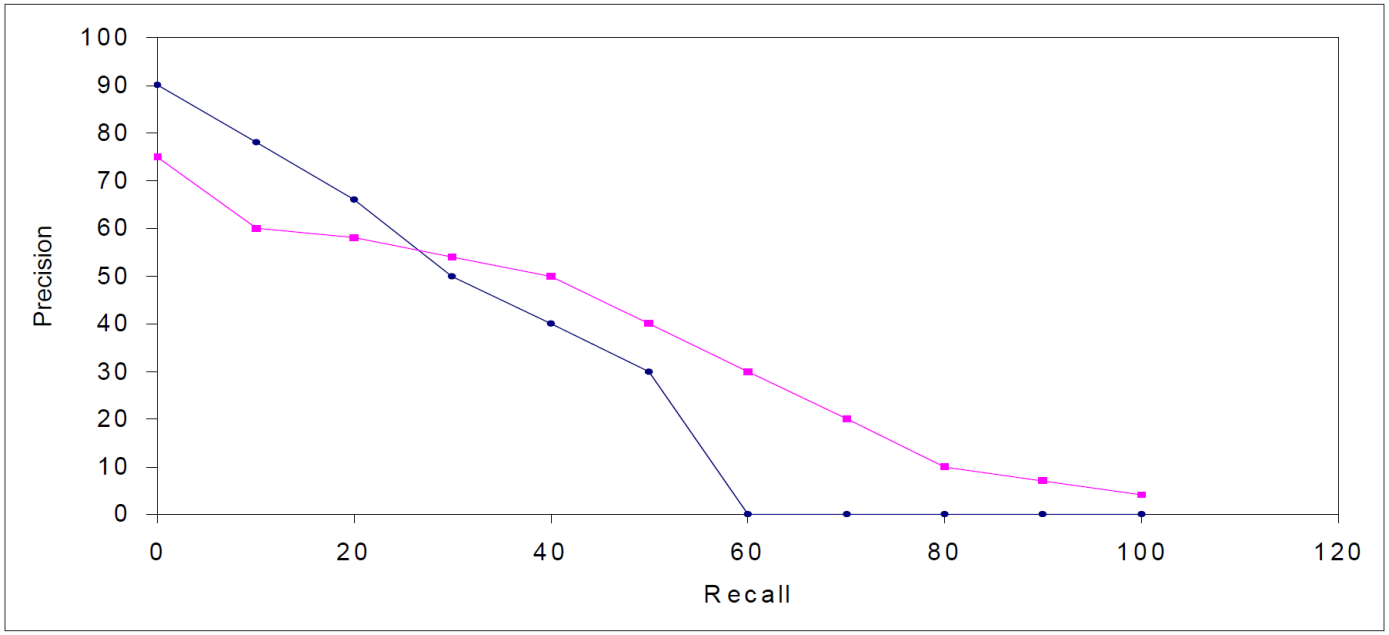
$$\bar{P}'(r) = \sum_{i=1}^{|\mathbf{Q}|} \frac{\bar{P}_i(r)}{|\mathbf{Q}|}$$

  - $\bar{P}'(r)$ is the average precision at the recall level r
  - $\bar{P}_i(r)$ is the precision at recall level r for the i-th query

Average Recall-Precision Curve – 2

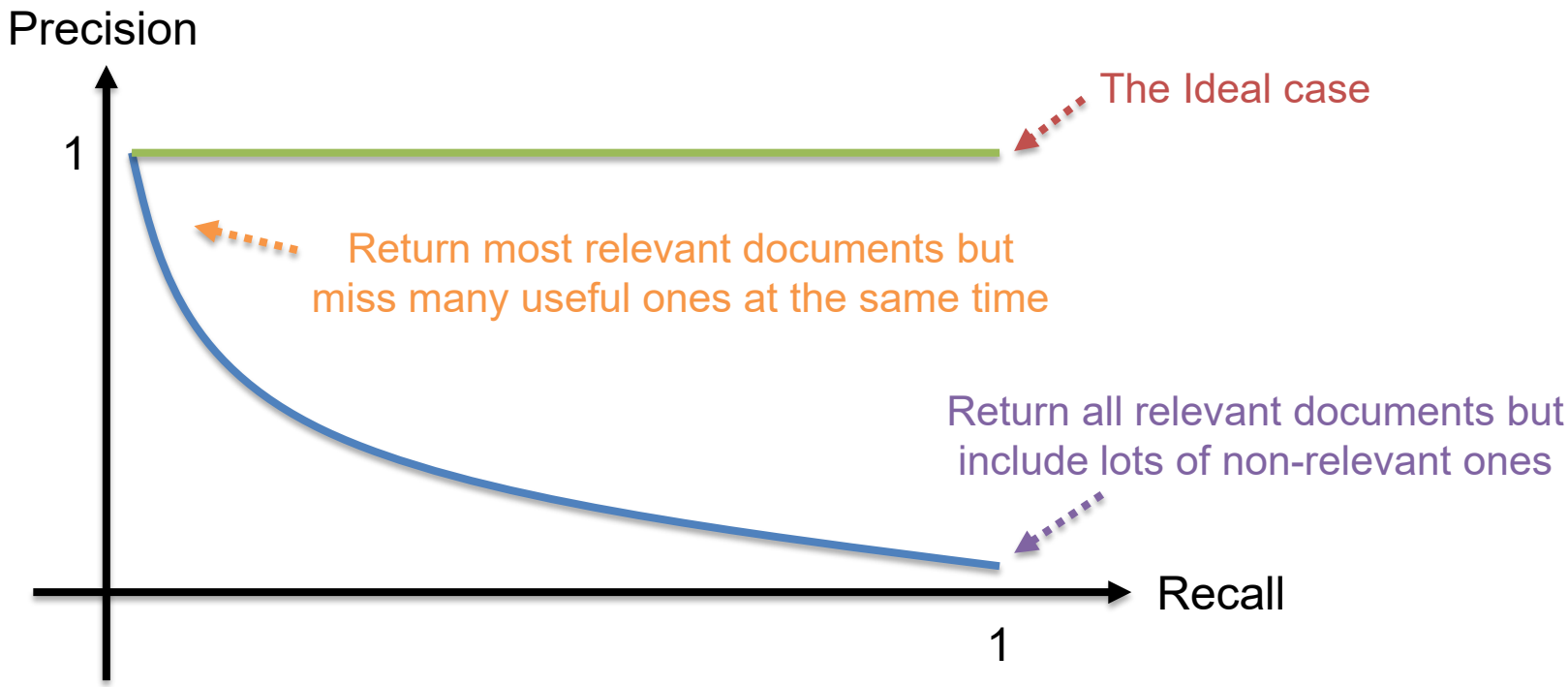
- Average precision-recall curves are normally used to compare the performance of distinct IR algorithms

- The figure below illustrates average precision-recall curves for two distinct retrieval algorithms
  - Difficult to figure out that which system is better!



Recall-Precision Curve

- Trade-off between recall and precision



Pros and Cons

- 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
  - The estimation of recall score for a query requires detailed knowledge of all the documents in the collection
  - For systems which require a weak ordering though, recall and precision might be inadequate

Single Value Summaries – Precision@*K*

- Precision@K
  - A single value summary measure the precision when first K retrieved documents have been seen
  - It favors systems which retrieve relevant docs quickly
    - 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

$$P@5 = \frac{2}{5} = 0.4 \qquad P@15 = \frac{5}{15} = 0.33$$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{123}	d_{84}	d_{56}	d_6	d_8	d_9	d_{511}	d_{129}	d_{187}	d_{25}	d_{38}	d_{48}	d_{250}	d_{113}	d_3
	●		●			●				●					●
P(%)	100		66.6			50				40					33.3

Single Value Summaries – MAP

- Mean Average Precision (MAP)
  - The idea here is to average the precision figures obtained after each new relevant document is observed
    - Averaged at relevant documents and across queries
    - Widely used in IR performance evaluation

$$MAP = \frac{1}{|\mathbf{Q}|} \sum_{q \in \mathbf{Q}} MAP_q$$

  - For example (AP):
    - the collection contains fifteen documents
    - five of them are relevant documents for a given query

$$AP = \frac{1.0 + 0.66 + 0.5 + 0.4 + 0.33}{5} = 0.578$$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{123}	d_{84}	d_{56}	d_6	d_8	d_9	d_{511}	d_{129}	d_{187}	d_{25}	d_{38}	d_{48}	d_{250}	d_{113}	d_3
	●		●			●				●					●
P(%)	100		66.6			50				40					33.3

Single Value Summaries – MAP

- For example (MAP):
  - the collection contains fifteen documents
  - five of them are relevant documents for the first query

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{123}	d_{84}	d_{56}	d_6	d_8	d_9	d_{511}	d_{129}	d_{187}	d_{25}	d_{38}	d_{48}	d_{250}	d_{113}	d_3
	●		●			●				●					●
P(%)	100		66.6			50				40					33.3

  - three of them are relevant documents for the second query

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{84}	d_{56}	d_{123}	d_{129}	d_8	d_6	d_{511}	d_9	d_{187}	d_3	d_{48}	d_{38}	d_{25}	d_{113}	d_{250}
			●			●				●					
P(%)			33.3			33.3				30					

$$MAP = \frac{1}{2} \times \left(\frac{1.0 + 0.66 + 0.5 + 0.4 + 0.33}{5} + \frac{0.33 + 0.33 + 0.30}{3} \right) = 0.449$$

Single Value Summaries – *R*-Precision

- R is the total number of relevant documents for a given query

- R-Precision is to compute the precision at the R-th position in the ranking list
  - For the first query: $R - Precision = \frac{2}{5} = 40\%$

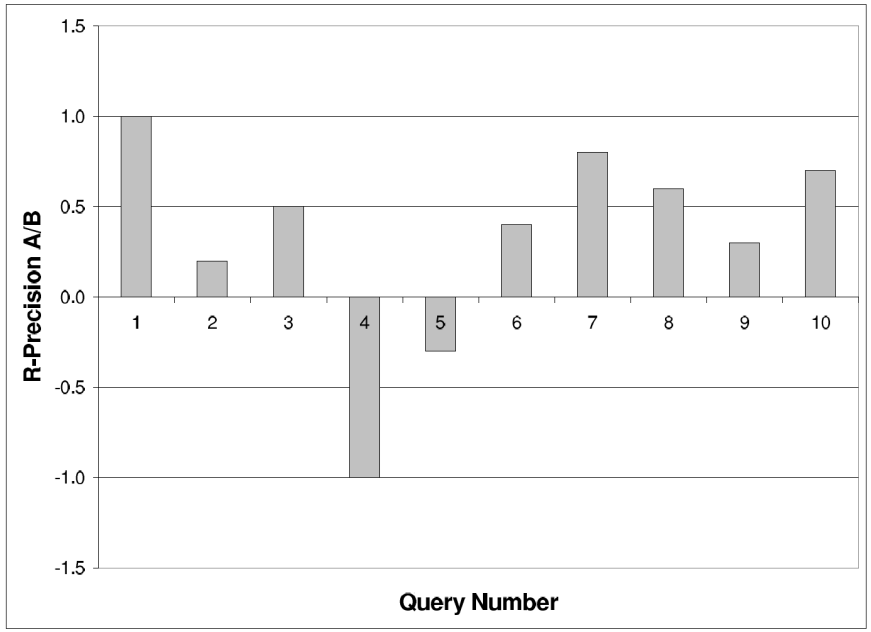
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{123}	d_{84}	d_{56}	d_6	d_8	d_9	d_{511}	d_{129}	d_{187}	d_{25}	d_{38}	d_{48}	d_{250}	d_{113}	d_3
	●		●			●				●					●
P(%)	100		66.6			50				40					33.3

  - For the second query: $R - Precision = \frac{1}{3} = 33.3\%$

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	d_{84}	d_{56}	d_{123}	d_{129}	d_8	d_6	d_{511}	d_9	d_{187}	d_3	d_{48}	d_{38}	d_{25}	d_{113}	d_{250}
			●			●				●					
P(%)			33.3			33.3				30					

Single Value Summaries – Precision Histograms

- R-Precision can be used to compare two algorithms
  - A visual inspection
  - For each query, the difference of R-Precision for two algorithms (A and B) can be computed
    - $RP_A(i)$: R-precision for algorithm A for the i-th query
    - $RP_B(i)$: R-precision for algorithm B for the i-th query



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

Single Value Summaries – MRR

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

$$MRR_i(q) = \begin{cases} \frac{1}{rank} & , if\ the\ position\ of\ the\ first\ relevant\ document < i \\ 0 & , otherwise \end{cases}$$

$$MRR_i(\mathbf{Q}) = \frac{1}{|\mathbf{Q}|} \sum_{q \in \mathbf{Q}} MRR_i(q)$$

Single Value Summaries – MRR

$$MRR_5(\mathbf{Q}) = \frac{1}{3} \times (\frac{1}{1} + 0 + \frac{1}{3}) = \frac{4}{9}$$

- For the first query

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

- For the second query

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

- For the third query

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

Single Value Summaries – F-Measure

- F-Measure combines recall and precision
  - Harmonic Mean (調和平均)

$$F(i) = \frac{2}{\frac{1}{R(i)} + \frac{1}{P(i)}} = \frac{2 \times P(i) \times R(i)}{P(i) + R(i)}$$

  - $E(i)$ is the harmonic mean at the i-th position in the ranking
  - $R(i)$ is the recall at the i-th position in the ranking
  - $P(i)$ is the precision at the i-th position in the ranking

- Properties
  - $0 \leq F(i) \leq 1$
  - $F(i) = 0$: no relevant documents were retrieved
  - $F(i) = 1$: all ranked documents are relevant
  - A high $F(i)$ achieved when both recall and precision are high

Single Value Summaries – E-Measure

- E-Measure combines recall and precision
  - It allows the user to specify whether he is more interested in recall or precision

$$E(i) = 1 - \frac{1 + b^2}{\frac{b^2}{R(i)} + \frac{1}{P(i)}} = 1 - \frac{(1 + b^2) \times P(i) \times R(i)}{b^2 \times P(i) + R(i)}$$

  - $E(i)$ is the E-Measure at the i-th position in the ranking
  - $R(i)$ is the recall at the i-th position in the ranking
  - $P(i)$ is the precision at the i-th position in the ranking
  - $b \geq 0$ is a user specified parameter
    - $b = 0 \;\Rightarrow\; E(i) = 1 - P(i)$
    - $b \to \infty \;\Rightarrow lim_{b \to \infty} E(i) = 1 - R(i)$
    - $b = 1 \;\Rightarrow E(i) = 1 - \underbrace{\frac{2 \times P(i) \times R(i)}{P(i) + R(i)}}_{\text{F-Measure}}$

User-Oriented Measures

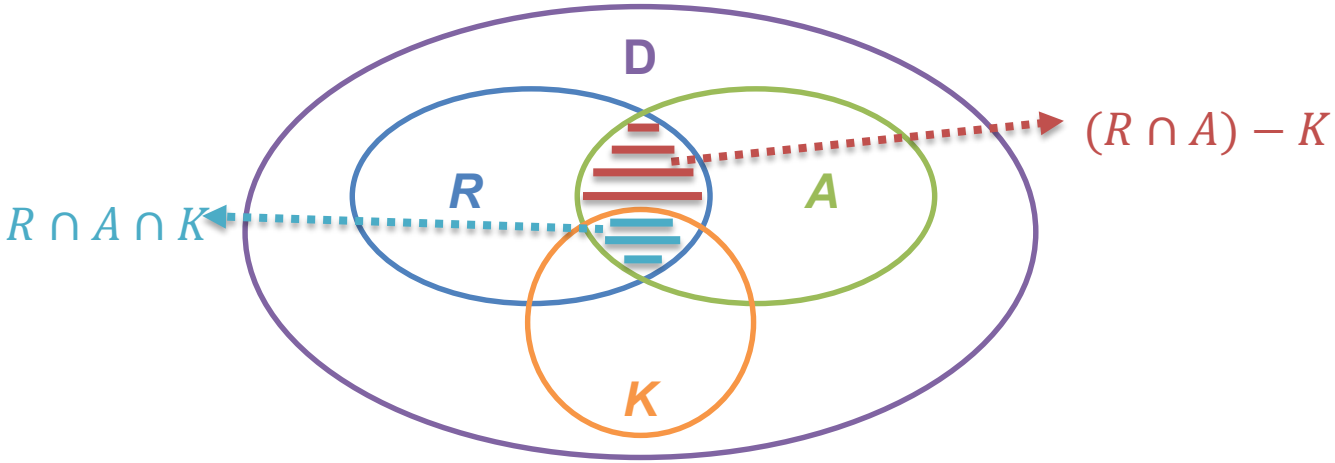
- Recall and precision assume that the set of relevant documents for a query is independent of the users

- However, different users might have different relevance interpretations

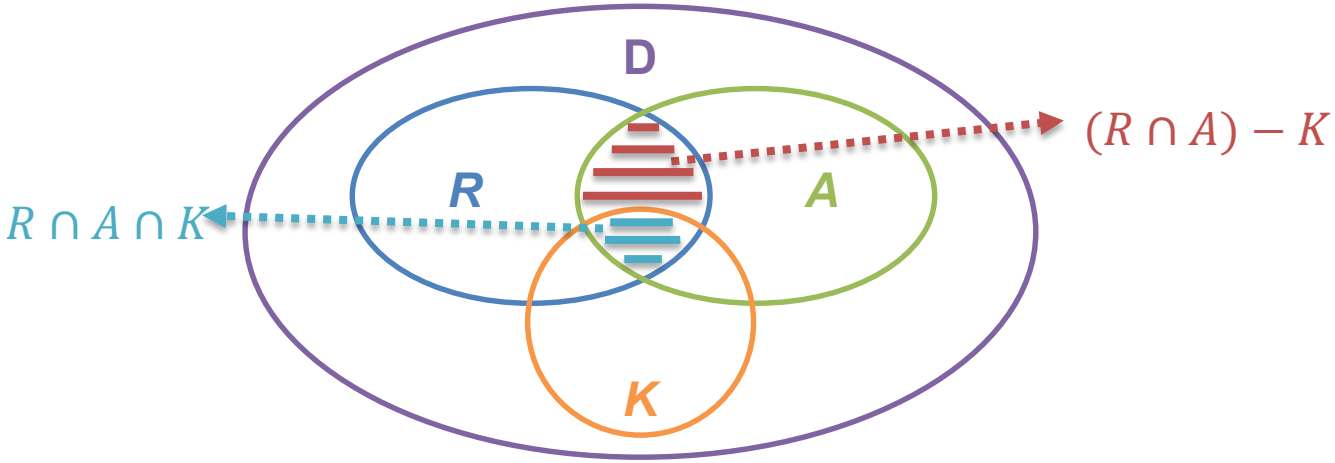
- User-oriented measures have been proposed
  - Coverage ratio
  - Novelty ratio
  - Relative recall
  - Recall effect

User-Oriented Measures – Notations

- For a given query (information need)
  - **D**: the set of documents
  - R: the set of relevant documents
  - A: the answer set generated by an IR system
  - K: the set of documents known to the user
    - $R \cap A \cap K$: the set of relevant documents that have been retrieved and are known to the user
    - $(R \cap A) - K$: the set of relevant documents that have been retrieved but are not known to the user



User-Oriented Measures – 1



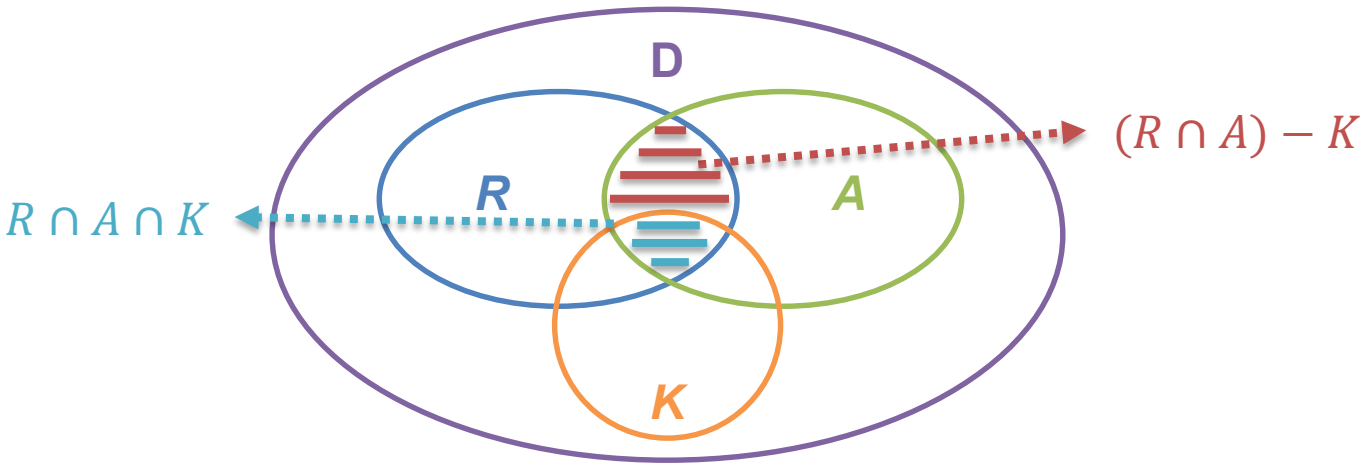
- The **coverage ratio** is the fraction of the documents known to eh user and relevant that are in the answer set

$$Coverage = \frac{|R \cap A \cap K|}{|R \cap K|}$$

- The **novelty ratio** is the fraction of the relevant docs in the answer set that are not known to the user

$$Novelty = \frac{|(R \cap A) - K|}{|R \cap A|}$$

User-Oriented Measures – 2



- The **relative recall** is the ratio between the number of relevant docs found by the system and the number of relevant documents known to the user

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

- The **recall effort** is the ratio between the number of relevant documents known to the user and the number of documents found by the system

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

Discounted Cumulated Gain (DCG)

- Precision and recall allow only binary relevance assessments
  - No distinction between highly relevant documents and mildly relevant documents

- 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
  - 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

DCG – 1

- 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:

$$R_{q_1} = \{[d_3, 3], [d_5, 3], [d_9, 3], [d_{25}, 2], [d_{39}, 2], [d_{44}, 2], [d_{56}, 1], [d_{71}, 1], [d_{89}, 1], [d_{123}, 1]\}$$

$$R_{q_2} = \{[d_3, 3], [d_{56}, 2], [d_{129}, 1]\}$$

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

DCG – 2

- For a ranking algorithm, top 15 documents are generated for both queries

$$A_{q_1} = \{d_{71}, d_2, d_{56}, d_3, d_4, d_9, d_{11}, d_{12}, d_{13}, d_{25}, d_{21}, d_{22}, d_{23}, d_{24}, d_5\}$$

$$A_{q_2} = \{d_{71}, d_2, d_{56}, d_5, d_4, d_9, d_{11}, d_{129}, d_{13}, d_{25}, d_{21}, d_{22}, d_{23}, d_{24}, d_3\}$$

- The **gain vectors** for the two queries are

$$G_{q_1} = \{1,0,1,0,0,3,0,0,0,2,0,0,0,0,3\}$$
$$G_{q_2} = \{0,0,2,0,0,0,0,1,0,0,0,0,0,0,3\}$$

DCG – 3

- The **cumulated gain vectors** can then be obtained

$$CG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ G[i] + CG[i-1] & ,otherwise \end{cases}$$

  - For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$CG_{q_1} = \{1, 1, 2, 2, 2, 5, 5, 5, 5, 7, 7, 7, 7, 7, 10\}$$

  - For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$CG_{q_2} = \{0, 0, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 6\}$$

DCG – 4

- Let's 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
    - For position 2, the discounting factor is $log_2 2$
    - For position 3, the discounting factor is $log_2 3$

- The **discounted cumulated gain vectors** can be obtained

$$DCG\ [i] = \begin{cases} G[1] & , if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & , otherwise \end{cases}$$

DCG – 5.

$$DCG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & ,otherwise \end{cases}$$

- For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

- For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

DCG – 5..

$$DCG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & ,otherwise \end{cases}$$

– For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$\frac{0}{log_2 2} + 1$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

– For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

DCG – 5…

$$DCG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & ,otherwise \end{cases}$$

- For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$\frac{1}{log_2 3} + 1$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

- For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

DCG – 5….

$$DCG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & ,otherwise \end{cases}$$

– For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$\frac{0}{log_2 4} + 1.6$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

– For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

DCG – 5.....

$$DCG\,[i] = \begin{cases} G[1] & ,if\ i = 1 \\ \dfrac{G[i]}{log_2(i)} + DCG[i-1] & ,otherwise \end{cases}$$

– For the first query

$$G_{q_1} = \{1, 0, 1, 0, 0, 3, 0, 0, 0, 2, 0, 0, 0, 0, 3\}$$

$$\frac{3}{log_2 6} + 1.6$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

– For the second query

$$G_{q_2} = \{0, 0, 2, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 3\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

CG vs. DCG

- Discounted cumulated gains are much less affected by relevant documents at the end of the ranking

$$CG_{q_1} = \{1, 1, 2, 2, 2, 5, 5, 5, 5, 7, 7, 7, 7, 7, 10\}$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

$$CG_{q_2} = \{0, 0, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 6\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

CG & DCG Curves – 1

- To produce CG and DCG curves over a set of test queries, we need to average them over all queries

- Given a set of queries $\mathbf{Q}$, average $\overline{CG}[i]$ and $\overline{DCG}[i]$ over all queries are computed as follows

$$\overline{CG}[i] = \sum_{q \in \mathbf{Q}} \frac{CG_q[i]}{|\mathbf{Q}|}$$

$$CG_{q_1} = \{1, 1, 2, 2, 2, 5, 5, 5, 5, 7, 7, 7, 7, 7, 10\}$$

$$CG_{q_2} = \{0, 0, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 6\}$$

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

$$\overline{DCG}[i] = \sum_{q \in \mathbf{Q}} \frac{DCG_q[i]}{|\mathbf{Q}|}$$

$$DCG_{q_1} = \{1, 1, 1.6, 1.6, 1.6, 2.8, 2.8, 2.8, 2.8, 3.4, 3.4, 3.4, 3.4, 3.4, 4.2\}$$

$$DCG_{q_2} = \{0, 0, 1.3, 1.3, 1.3, 1.3, 1.3, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 1.6, 2.4\}$$

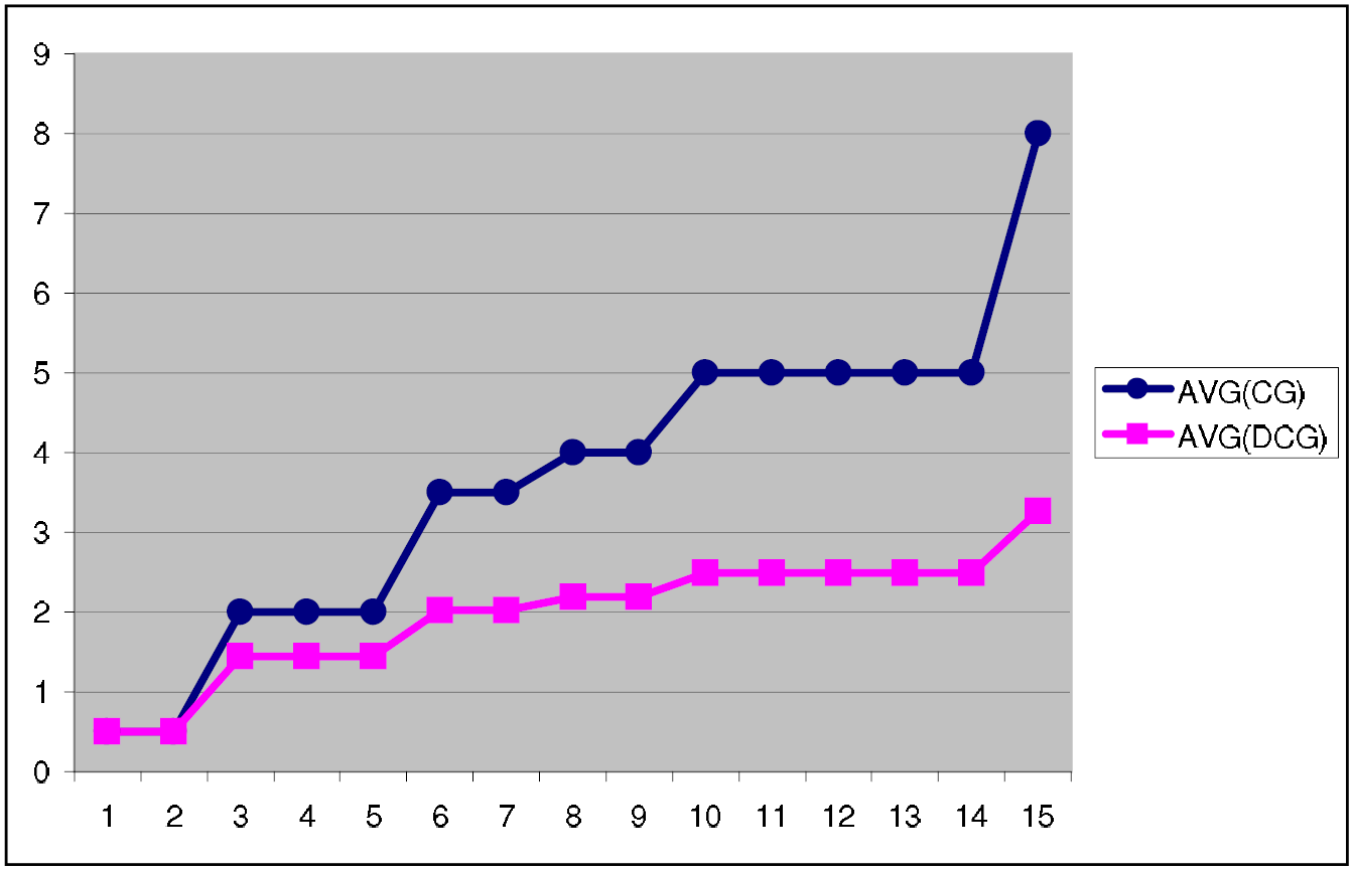
$$\overline{DCG} = \{0.5, 0.5, 1.5, 1.5, 1.5, 2.1, 2.1, 2.2, 2.2, 2.5, 2.5, 2.5, 2.5, 2.5, 3.3\}$$

CG & DCG Curves – 2

- Average curves can then be drawn by varying the rank positions from 1 to a pre-established threshold

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

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



Ideal G & CG & DCG – 1

- Since the relevant documents with their graded score for queries q_1 and q_2 are:

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

- The ideal gain vectors are:

$$IG_{q_1} = \{3,3,3,2,2,2,1,1,1,1,0,0,0,0,0\}$$
$$IG_{q_2} = \{3,2,1,0,0,0,0,0,0,0,0,0,0,0,0\}$$

- The ideal cumulated gain vectors

$$ICG_{q_1} = \{3,6,9,11,13,15,16,17,18,19,19,19,19,19,19\}$$
$$ICG_{q_2} = \{3,5,6,6,6,6,6,6,6,6,6,6,6,6,6\}$$

Ideal G & CG & DCG – 2

- Consequently, the ideal discounted cumulated gain vectors

$$IDCG_{q_1} = \{3.0, 6.0\ , 7.9, 8.9, 9.8, 10.5, 10.9, 11.2, 11.5, 11.8, 11.8, 11.8, 11.8, 11.8, 11.8\}$$

$$IDCG_{q_2} = \{3.0, 5.0, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6, 5.6\}$$

- Further, the average $\overline{ICG}[i]$ and $\overline{IDCG}[i]$ can also be obtained

$$\overline{ICG} = \{3.0, 5.5, 7.5, 8.5, 9.5, 10.5, 11.0, 11.5, 12.0, 12.5, 12.5, 12.5, 12.5, 12.5, 12.5\}$$

$$\overline{IDCG} = \{3.0, 5.5, 6.8, 7.3, 7.7, 8.1, 8.3, 8.4, 8.6, 8.7, 8.7, 8.7, 8.7, 8.7, 8.7\}$$

- 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 CG & DCG – 1

- Given a set of queries, the normalized CG and DCG can be computed by:

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

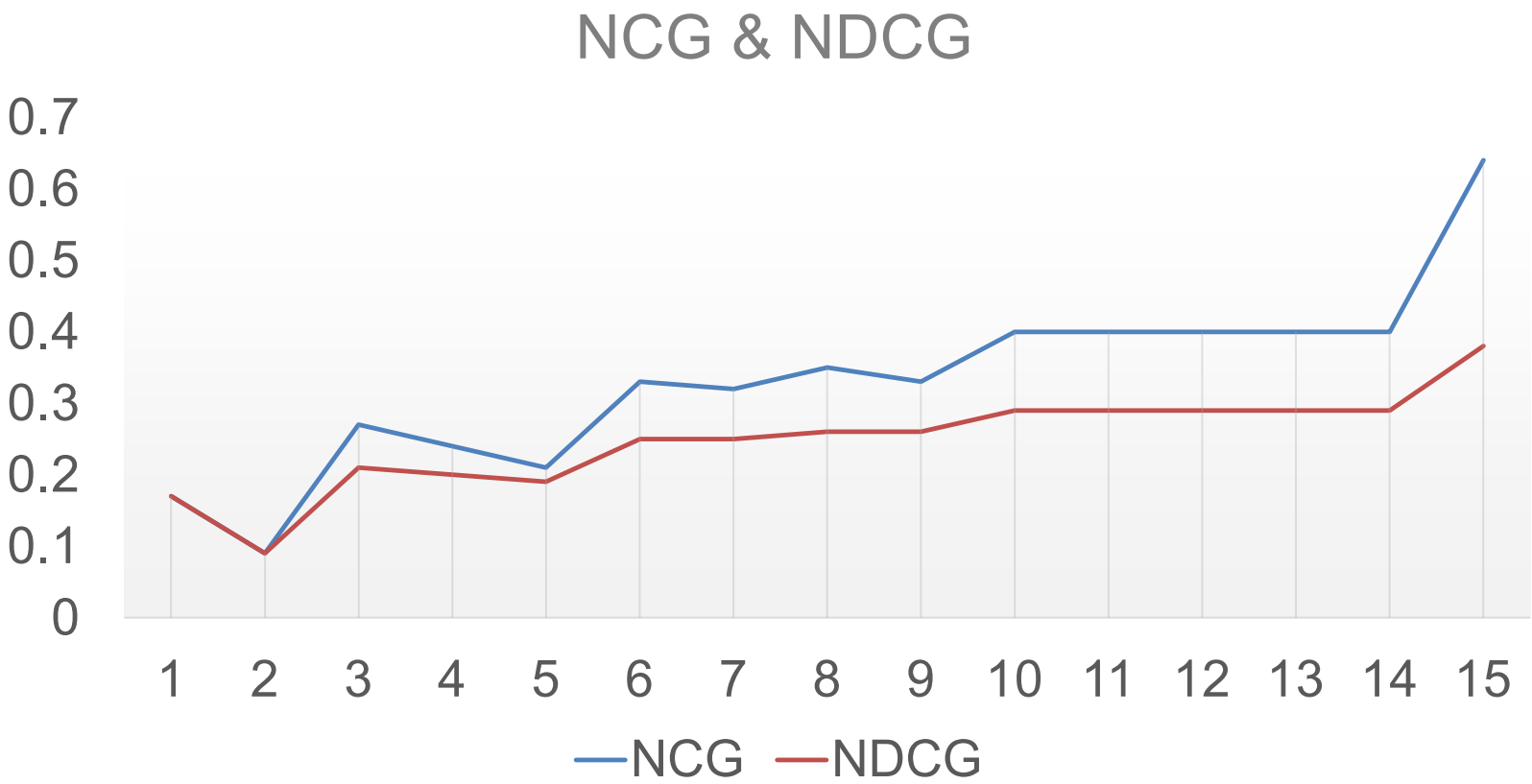
- In our example, the NCG and NDCG vectors are:

$$\overline{CG} = \{0.5, 0.5, 2.0, 2.0, 2.0, 3.5, 3.5, 4.0, 4.0, 5.0, 5.0, 5.0, 5.0, 5.0, 8.0\}$$
$$\overline{ICG} = \{3.0, 5.5, 7.5, 8.5, 9.5, 10.5, 11.0, 11.5, 12.0, 12.5, 12.5, 12.5, 12.5, 12.5, 12.5\}$$
$$NCG = \{0.17, 0.09, 0.27, 0.24, 0.21, 0.33, 0.32, 0.35, 0.33, 0.40, 0.40, 0.40, 0.40, 0.40, 0.64\}$$

$$\overline{DCG} = \{0.5, 0.5, 1.5, 1.5, 1.5, 2.1, 2.1, 2.2, 2.2, 2.5, 2.5, 2.5, 2.5, 2.5, 3.3\}$$
$$\overline{IDCG} = \{3.0, 5.5, 6.8, 7.3, 7.7, 8.1, 8.3, 8.4, 8.6, 8.7, 8.7, 8.7, 8.7, 8.7, 8.7\}$$
$$NDCG = \{0.17, 0.09, 0.21, 0.20, 0.19, 0.25, 0.25, 0.26, 0.26, 0.29, 0.29, 0.29, 0.29, 0.29, 0.38\}$$

Normalized CG & DCG – 2

- The area under the NCG and NDCG curves represent the quality of the ranking algorithm
  - Larger the area, better the results



Pros & Cons for NDCG

- Advantages
  - CG and DCG metrics aim at taking into account multiple level relevance assessments
    - It can distinguish highly relevant documents from mildly relevant ones
  - Discounted cumulated gain allows down weighting the impact of relevant documents found late in the ranking

- Disadvantages
  - The relevance assessments are harder and more time consuming to generate

The TREC Collection

- **T**ext **RE**trieval **C**onference (TREC)
  - Established in 1991, co-sponsored by the National Institute of Standards and Technology (NIST, 美國國家標準技術研究所) and the Defense Advanced Research Projects Agency (DARPA, 國防高等研究計劃署)
  - Evaluation of large scale IR problems
  - The premier annual conference was held at NIST in Nov. 1992

http://trec.nist.gov/

The Goal of TREC

- To encourage **research in information retrieval** based on large test collections
- To increase **communication among industry, academia, and government** by creating an open forum for the exchange of research ideas
- To speed the **transfer of technology from research labs into commercial products**
- To increase the availability of **appropriate evaluation techniques** for use by industry and academia

TREC Collection

- A TREC collection is composed of three parts:
  - the documents
  - the example information requests (called **topics**)
  - a set of relevant documents for each example information request

- The main TREC collection has been growing steadily over the years
  - The TREC-3 collection has roughly 2 gigabytes
  - The TREC-6 collection has roughly 5.8 gigabytes
  - The TREC-15 collection has roughly 426 gigabytes
    - 25 million (25,000,000) Web documents

TREC Document

- An example of a TREC document

```
<doc>

<docno> WSJ880406-0090 </docno>
<hl> AT&T Unveils Services to Upgrade Phone Networks
Under Global Plan </hl>
<author> Janet Guyon (WSJ Staff) </author>
<dateline> New York </dateline>

<text>
American Telephone & Telegraph Co introduced the first
of a new generation of phone services with broad ...
</text>

</doc>
```

TREC Topic

- An example of an information request is the topic numbered 168 used in TREC-3

```
<top>

<num> Number:  168
<title> Topic:  Financing AMTRAK

<desc> Description:
A document will address the role of the Federal Government in
financing the operation of the National Railroad Transportation
Corporation (AMTRAK)
<narr> Narrative:  A relevant document must provide information on
the government's responsibility to make AMTRAK an economically viable
entity.  It could also discuss the privatization of AMTRAK as an
alternative to continuing government subsidies.  Documents comparing
government subsidies given to air and bus transportation with those
provided to AMTRAK would also be relevant

</top>
```

taken as a short query

taken as a long query

describe the criteria for relevance, used by the people doing relevance judgments, and not taken as a query

TREC Judgments – Pooling Method

- The set of relevant documents for each topic is obtained from a pool of possible relevant documents
  - This pool is created by taking the top $\mathbb{K}$ documents (usually, $\mathbb{K}$=100) in the rankings generated by various retrieval systems

- The documents in the pool are then shown to human assessors who ultimately decide on the relevance of each document

- This technique of assessing relevance is called the pooling method and is based on two assumptions:
  - Vast majority of relevant documents is collected in the assembled pool
  - Documents not in the pool were considered to be irrelevant

Popular Collections

- TREC: http://trec.nist.gov/
- CLEF: http://www.clef-initiative.eu
- NTCIR: http://research.nii.ac.jp/ntcir/index-en.html
- FIRE: http://fire.irsi.res.in/fire/static/resources
- Note that these web sites host the publications, current meeting information, and also where to get the test collections for use outside of the evaluations

Homework 2

- In this project, you will have a set of ranking lists for 16 queries and the assessments

- Our goal is to implement an evaluation function, which can return the MAP score a set of queries

$$MAP = \frac{1}{|\mathbf{Q}|} \sum_{q \in \mathbf{Q}} MAP_q$$

- You will have a sample ranking list and a sample assessment for 16 queries
  - The MAP score is 0.117248

Homework 2 – solution.txt

solution.txt

```
Query,RetrievedDocuments
20001.query,VOM19980510.0730.0264 VOM19980605.0730.0117 VOM19980227.0900.1692 VOM19980507.07
20002.query,VOM19980326.0700.0207 VOM19980403.0700.0528 VOM19980624.0700.0122 VOM19980503.07
20005.query,VOM19980602.0700.0245 VOM19980224.0700.0382
20013.query,VOM19980618.0900.0204 VOM19980623.0700.0114 VOM19980504.0700.0456 VOM19980526.07
20015.query,VOM19980316.0900.0320 VOM19980621.0730.0064 VOM19980316.0700.0180 VOM19980602.07
20020.query,VOM19980303.0900.2332 VOM19980503.0700.0546
20023.query,VOM19980228.0700.1239 VOM19980522.0700.0456 VOM19980319.0700.0722 VOM19980523.07
20039.query,VOM19980618.0700.0144 VOM19980410.0900.0146 VOM19980319.0700.0399 VOM19980521.09
20048.query,VOM19980303.0700.2287 VOM19980319.0900.0647 VOM19980314.0700.3062
20070.query,VOM19980228.0700.2873
20071.query,VOM19980225.0700.0999 VOM19980223.0900.0265
20076.query,VOM19980325.0900.2077 VOM19980226.0900.0170 VOM19980630.0730.0002 VOM19980315.07
20088.query,VOM19980503.0730.0204 VOM19980609.0900.0255 VOM19980327.0900.1937 VOM19980507.07
20089.query,VOM19980317.0900.0224 VOM19980326.0900.2611 VOM19980311.0700.2138 VOM19980624.07
20091.query,VOM19980509.0700.0089 VOM19980312.0900.1827 VOM19980306.0700.0555 VOM19980507.07
20096.query,VOM19980302.0700.2191 VOM19980626.0730.0227 VOM19980508.0700.0549 VOM19980224.09
```

Homework 2 – submission.txt

submission.txt

```
Query,RetrievedDocuments
20001.query,VOM19980619.0700.0347 VOM19980225.0700.0510 VOM19980317.0900.0192 VOM19980317.0900.0330 VOM199802
00.0173 VOM19980302.0700.0241 VOM19980303.0700.2287 VOM19980530.0730.0166 VOM19980404.0700.2088 VOM19980616.0
216 VOM19980614.0700.0357 VOM19980626.0700.0409 VOM19980403.0700.0489 VOM19980523.0730.0220 VOM19980524.0730.
VOM19980624.0900.0077 VOM19980625.0700.0363 VOM19980605.0730.0152 VOM19980602.0730.0102 VOM19980603.0730.0280
9980522.0730.0037 VOM19980228.0700.0327 VOM19980414.0900.0260 VOM19980223.0700.0765 VOM19980505.0700.0529 VOM
503.0730.0136 VOM19980319.0900.3416 VOM19980620.0730.0034 VOM19980302.0700.0209 VOM19980302.0900.2091 VOM1998
0900.0207 VOM19980305.0900.1926 VOM19980521.0730.0029 VOM19980504.0700.0376 VOM19980314.0700.0239 VOM19980619.
.0137 VOM19980611.0700.0150 VOM19980326.0700.2112 VOM19980522.0900.0269 VOM19980503.0700.0412 VOM19980428.090
4 VOM19980422.0900.0021 VOM19980605.0700.0194 VOM19980611.0700.0046 VOM19980223.0700.2728 VOM19980614.0730.02
M19980303.0700.0696 VOM19980326.0900.0149 VOM19980505.0700.0481 VOM19980614.0730.0034 VOM19980226.0900.1964 VO
80523.0730.0083 VOM19980316.0700.0356 VOM19980609.0900.0009 VOM19980314.0700.2300 VOM19980302.0700.2137 VOM199
4.0700.0458 VOM19980319.0900.2169 VOM19980305.0700.2126 VOM19980515.0700.0472 VOM19980403.0700.0129 VOM199806
30.0142 VOM19980618.0700.0234 VOM19980319.0900.0647 VOM19980527.0700.0528 VOM19980607.0730.0033 VOM19980305.0
20002.query,VOM19980530.0730.0101 VOM19980611.0900.0216 VOM19980506.0900.0089 VOM19980624.0700.0434 VOM199803
00.2021 VOM19980604.0900.0246 VOM19980606.0700.0562 VOM19980303.0900.2085 VOM19980225.0700.0999 VOM19980312.0
171 VOM19980220.0900.1979 VOM19980305.0700.0763 VOM19980627.0700.0360 VOM19980225.0700.0302 VOM19980529.0700.
VOM19980612.0730.0192 VOM19980319.0700.2737 VOM19980630.0700.0071 VOM19980526.0730.0131 VOM19980403.0700.0489
9980430.0900.0192 VOM19980502.0700.0307 VOM19980616.0700.0420 VOM19980319.0900.3468 VOM19980303.0900.1926 VOM
223.0900.1787 VOM19980625.0700.0514 VOM19980305.0900.2053 VOM19980504.0700.0170 VOM19980222.0700.2100 VOM1998
0700.1040 VOM19980314.0700.3494 VOM19980221.0700.2025 VOM19980609.0700.0085 VOM19980220.0700.0448 VOM19980314.
.2995 VOM19980626.0900.0044 VOM19980302.0900.2091 VOM19980511.0730.0003 VOM19980325.0900.0905 VOM19980504.073
9 VOM19980501.0700.0556 VOM19980223.0700.0373 VOM19980609.0900.0148 VOM19980614.0730.0196 VOM19980610.0700.05
M19980515.0700.0434 VOM19980314.0700.0239 VOM19980623.0700.0472 VOM19980311.0700.1701 VOM19980223.0900.0719 VO
80326.0900.2958 VOM19980302.0900.0368 VOM19980222.0700.0340 VOM19980619.0730.0105 VOM19980317.0900.0757 VOM199
3.0700.0428 VOM19980612.0730.0286 VOM19980228.0700.0327 VOM19980619.0900.0252 VOM19980413.0900.0207 VOM199806
00.2071 VOM19980611.0700.0187 VOM19980303.0900.3480 VOM19980305.0900.2797 VOM19980605.0900.0273 VOM19980621.07
20005.query,VOM19980306.0700.0593 VOM19980226.0900.3539 VOM19980410.0900.0207 VOM19980224.0700.0382 VOM199802
00.0113 VOM19980304.0700.0737 VOM19980302.0900.3462 VOM19980503.0700.0412 VOM19980316.0900.1194 VOM19980626.07
943 VOM19980224.0700.0330 VOM19980524.0730.0085 VOM19980302.0900.0207 VOM19980521.0900.0007 VOM19980302.0900.
VOM19980220.0900.1197 VOM19980223.0700.0882 VOM19980317.0700.3414 VOM19980624.0730.0216 VOM19980605.0730.0276
9980303.0900.2085 VOM19980509.0730.0002 VOM19980530.0730.0266 VOM19980226.0900.0434 VOM19980522.0900.0269 VOM
```

Questions?

kychen@mail.ntust.edu.tw