THE UNIVERSITY of EDINBURGH

Text Technologies for Data Science

INFR11145

IR Evaluation

Instructor:
Walid Magdy

17-Oct-2017

Lecture Objectives

- Learn about how to evaluate IR
  - Evaluation measures
  - P, R, F
  - MAP
  - nDCG
- Implement:
  - MAP
  - Some others

IR as an Experimental Science!

- Formulate a research question: the hypothesis
- Design an experiment to answer the question
- Perform the experiment
  - Compare with a baseline “control”
- Does the experiment answer the question?
  - Are the results significant? Or is it just luck?
- Report the results!
- Repeat…

Configure your system

- **About the system**:
  - Stopping? Tokenise? Stemming? n-gram char?
  - Use synonyms improve retrieval performance?
- Corresponding experiment?
  - Run your search for a set of queries with each setup and find which one will achieve the best performance
- **About the user**:
  - Is letting users weight search terms a good idea?
- Corresponding experiment?
  - Build two different interfaces, one with term weighting functionality, and one without; run a user study

Types of Evaluation Strategies

- **System-centered studies**:
  - Given documents, queries, and relevance judgments
  - Try several variations of the system
  - Measure which system returns the "best" hit list
  - Laboratory experiment
- **User-centered studies**
  - Given several users, and at least two retrieval systems
  - Have each user try the same task on both systems
  - Measure which system works the "best"

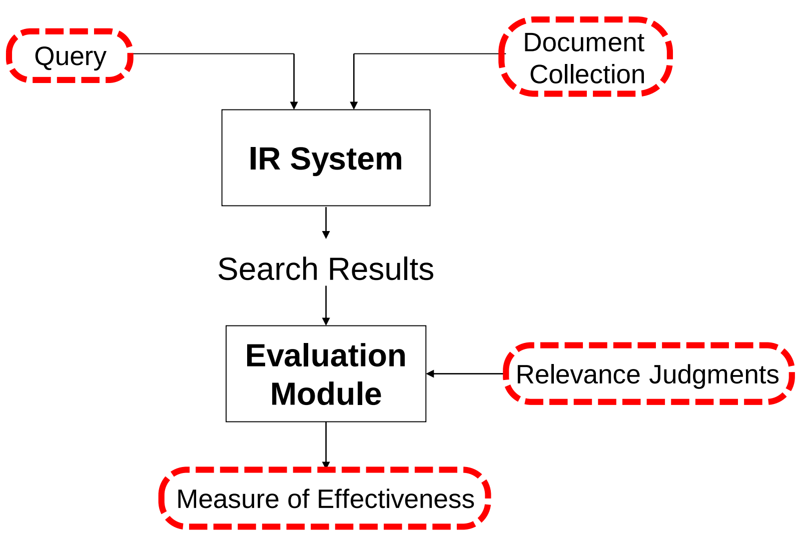
Importance of Evaluation

- The ability to measure differences underlies experimental science
  - How well do our systems work?
  - Is A better than B?
  - Is it really?
  - Under what conditions?
- Evaluation drives what to research
  - Identify techniques that work and don't work

The 3-dimensions of Evaluation

- **Effectiveness**
  - How “good” are the documents that are returned?
  - System only, human + system
- **Efficiency**
  - Retrieval time, indexing time, index size
- **Usability**
  - Learnability, flexibility
  - Novice vs. expert users

Cranfield Paradigm (Lab setting)



Reusable IR Test Collection

- **Collection of Documents**
  - Should be "representative" to a given IR task
  - Things to consider: size, sources, genre, topics, …
- **Sample of information need**
  - Should be "randomized" and "representative"
  - Usually formalized **topic** statements (query + description)
- **Known relevance judgments**
  - Assessed by humans, for each topic-document pair
  - Binary/Graded
- **Evaluation measure**

Good Effectiveness Measures

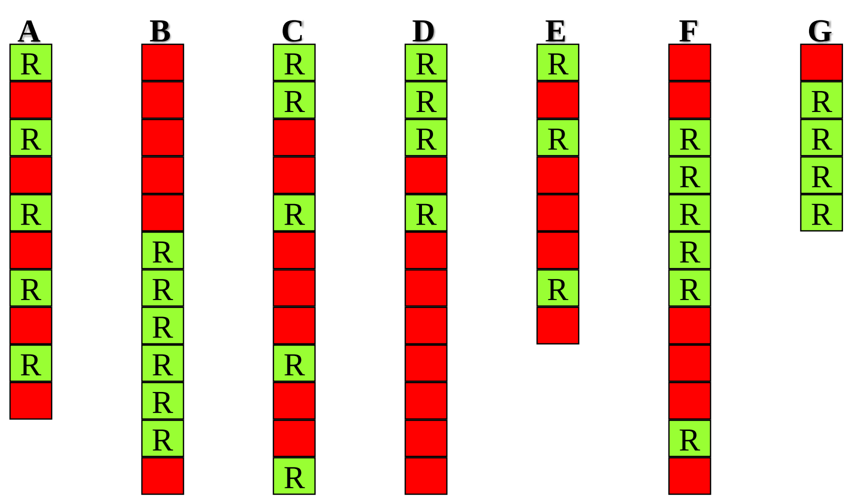
- Should capture some aspect of what the user wants
  - IR → Do the results satisfy user's information need?
- Should be easily replicated by other researchers
- Should be easily comparable
  - Optimally, expressed as a single number
    - Curves and multiple numbers are still accepted, but single numbers are much easier for comparison
- Should have predictive value for other situations
  - What happens with different queries on a different document collection?

Set Based Measures

- Assuming IR system returns sets of retrieved results without ranking
- Suitable with Boolean Search
- No certain number of results per query

Which looks the best IR system?

- For query **Q**, collection has **8 relevant documents**:



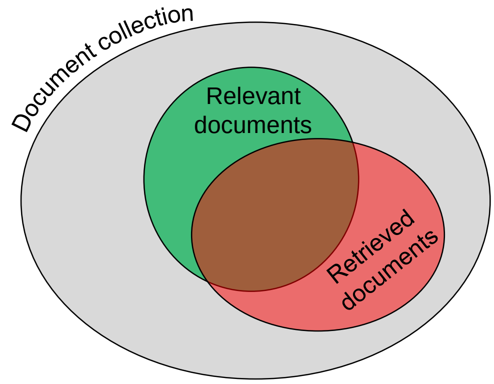
Precision and Recall

- **Precision**:
  What fraction of these retrieved docs are relevant?

$$P = \frac{rel \cap ret}{retrieved} = \frac{TP}{TP + FP}$$

- **Recall**:
  What fraction of the relevant docs were retrieved?

$$R = \frac{rel \cap ret}{relevant} = \frac{TP}{TP + FN}$$

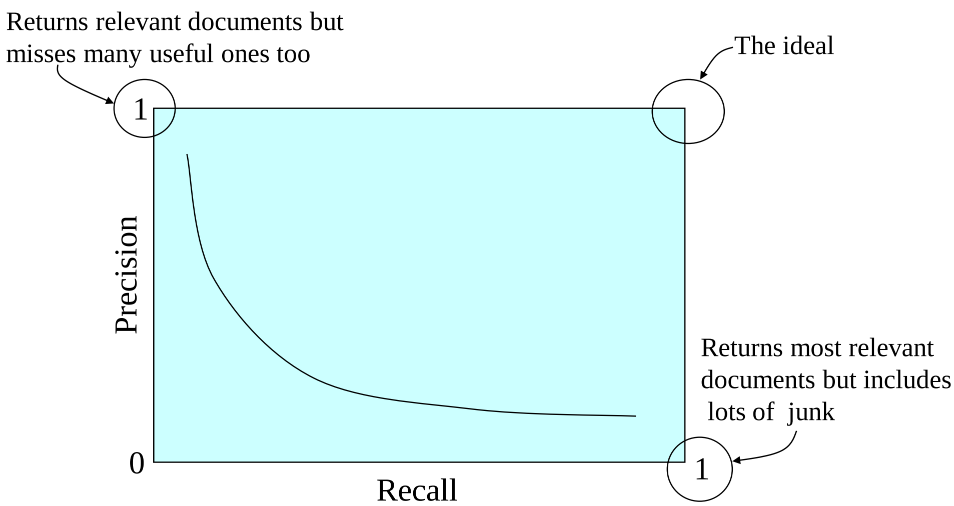


	retrieved	not retrieved
irrelevant	FP	TN
relevant	TP	FN

Trade-off between P & R

- Precision: The ability to retrieve top-ranked docs that are mostly relevant.
- Recall: The ability of the search to find all of the relevant items in the corpus.
- Retrieve more docs:
  - Higher chance to find all relevant docs → R ↑↑
  - Higher chance to find more irrelevant docs → P ↓↓

Trade-off between P & R



What about Accuracy?

- **Accuracy**:
  What fraction of docs was classified correctly?

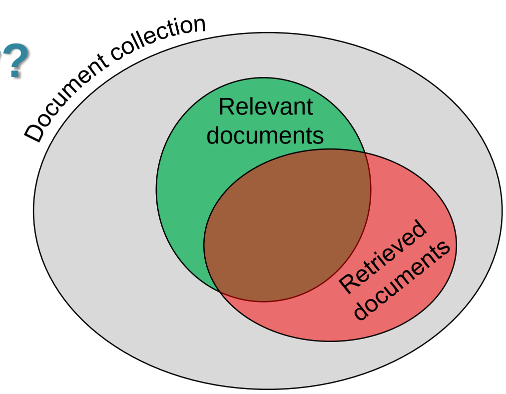
$$A = \frac{TP + TN}{TP + FP + TN + FN}$$

irrelevant >>>>> relevant

(needle in a haystack)

e.g.: N_{docs} = 1M docs, *ret*=10, *rel*=10

$TP\ =\ 5, \qquad FP\ =\ 5,$
$FN\ \ 5, \qquad TN = 1M - 15$
$\rightarrow A = 99.999\%$



	retrieved	not retrieved
irrelevant	FP	TN
relevant	TP	FN

One Measure? F-measure

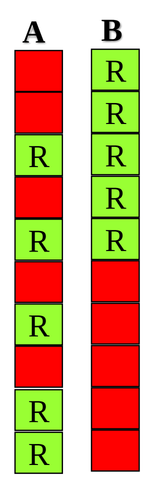
$$F1 = \frac{2 \cdot P \cdot R}{P + R}$$

$$F_{\beta} = \frac{(\beta^2 + 1)P \cdot R}{\beta^2 P + R}$$

- Harmonic mean of recall and precision
  - Emphasizes the importance of small values, whereas the arithmetic mean is affected more by outliers that are unusually large
- Beta (β) controls relative importance of P and R
  - β = 1, precision and recall equally important → $F1$
  - β = 5, recall five times more important than precision

Rank-based IR measures

- Consider systems A & B
  - Both retrieved 10 docs, only 5 are relevant
  - P, R & F are the same for both systems
    - Should their performances considered equal?
- Ranked IR requires taking "ranks" into consideration!
- How to do that?



Precision @ K

- *k* (a fixed number of documents)
- Have a cut-off on the ranked list at rank *k*, then calculate precision!
- Perhaps appropriate for most of web search: most people only check the top *k* results
- But: averages badly, Why?

R-Precision

- For a query with known *r* relevant documents
  → R-precision is the precision at rank *r* (P@*r*)
- *r* is different from one query to another
- Concept:
  It examines the ideal case: getting all relevant documents in the top ranks
- Is it realistic?

THE UNIVERSITY of EDINBURGH

When to cut-off?

- It is assumed that users needs to find relevant docs at the highest possible ranks
  → Precision is a good measure
- But, user would cut-off (stop inspecting results) at some point, say rank x
  →P@x
- What is the optimal x?
  When you think a user can stop?

When a user can stop?

- IR objective: "satisfy user information need"
- Assumption: a user will stop once his/her information need is satisfied
- How? user will keep looking for relevant docs in the ranked list, read them, then stop once he/she feels satisfied → <u>user will stop at a relevant document</u>
- P@x →x can be any rank where a relevant document appeared (*assume uniform distribution*)
- What about calculating the averages over all x's?
  - every time you find relevant doc, calculate P@x, then take the average at the end

Mean Average Precision (MAP)

Q_1 (has 4 rel. docs)

1	R	1/1=1.00
2	R	2/2=1.00
3		
4		
5	R	3/5=0.60
6		
7		
8		
9	R	4/9=0.44
10		

AP = 0.76

Q_2 (has 3 rel. docs)

1		
2		
3	R	1/3=0.33
4		
5		
6		
7	R	2/7=0.29
8		
⋮		$\frac{3}{\infty}$=0

AP = 0.207

Q_3 (has 7 rel. docs)

1		
2	R	1/2=0.50
3		
4		
5	R	2/5=0.40
6		
7		
8	R	3/8=0.375
9		
⋮		

AP = 0.182

MAP = (0.76+0.207+0.182)/3 = **0.383**

AP & MAP

$$AP = \frac{1}{r}\sum_{k=1}^{n} P(k) \times rel(k)$$

where, r: number of relevant docs for a given query
n: number of documents retrieved
$P(k)$ precision @ k
$rel(k)$: 1 if retrieved doc @ k is relevant, 0 otherwise.

$$MAP = \frac{1}{Q}\sum_{q=1}^{Q} AP(q)$$

where, Q: number of queries in the test collection

AP/MAP

$$AP = \frac{1}{r}\sum_{k=1}^{n} P(k) \times rel(k)$$

- A mix between precision and recall
- Highly focus on finding relevant document as early as possible
- When r=1 → MAP = MRR (mean reciprocal rank $\frac{1}{k}$)
- MAP is the most commonly used evaluation metric for most IR search tasks
- Uses binary relevance: rel = 0/1

Walid Magdy, TTDS 2017/2018

THE UNIVERSITY of EDINBURGH

Binary vs. Graded Relevance

- Some docs are more relevant to a query than other relevant ones!
  - We need non-binary relevance
- Two assumptions:
  - Highly relevant documents are more useful than marginally relevant
  - The lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined
- Discounted Cumulative Gain (DCG)
  - Uses graded relevance as a measure of the usefulness
  - The most popular for evaluating web search

Walid Magdy, TTDS 2017/2018

THE UNIVERSITY of EDINBURGH

Discounted Cumulative Gain (DCG)

- Gain is accumulated starting at the top of the ranking and may be reduced (*discounted*) at lower ranks
- Users care more about high-ranked documents, so we discount results by *1/log$_2$(rank)*
  - the discount at rank 4 is 1/2, and at rank 8 is 1/3
- DCG$_k$ is the total gain accumulated at a particular rank *k* (sum of DG up to rank *k*):

0, 1, 2, 3, … (graded)

$$DCG_k = rel_1 + \sum_{i=2}^{k} \frac{rel_i}{log_2 i}$$

Normalized DCG (nDCG)

- DCG numbers are averaged across a set of queries at specific rank values (DCG@*k*)
  - e.g., DCG at rank 5 is 6.89 and at rank 10 is 9.61
  - Can be any positive real number!
- DCG values are often normalized by comparing the DCG at each rank with the DCG value for the perfect ranking
  - makes averaging easier for queries with different numbers of relevant documents
- nDCG@*k* = DCG@*k* / iDCG@*k* (divide actual by ideal)
- nDCG ≤ 1 at any rank position
- To compare DCGs, normalize values so that a ideal ranking would have a normalized DCG of 1.0

Walid Magdy, TTDS 2017/2018
THE UNIVERSITY of EDINBURGH

nDCG

÷

k	G	DG	DCG@k	iG	iDG	iDCG@k	nDCG@k
1	3	3	3	3	3.00	3	1.00
2	2	2	5	3	3.00	6	0.83
3	3	1.89	6.89	3	1.89	7.89	0.87
4	0	0	6.89	2	1.00	8.89	0.78
5	0	0	6.89	2	0.86	9.75	0.71
6	1	0.39	7.28	2	0.77	10.52	0.69
7	2	0.71	7.99	1	0.36	10.88	0.73
8	2	0.67	8.66	0	0.00	10.88	0.80
9	3	0.95	9.61	0	0.00	10.88	0.88
10	0	0	9.61	0	0.00	10.88	0.88

Walid Magdy, TTDS 2017/2018

THE UNIVERSITY *of* EDINBURGH

Summary:

- IR test collection:
  - Document collection
  - Query set
  - Relevant judgements
  - IR measures
- IR measures:
  - R, P, F → not commonly used
  - P@k, R-precision → used sometimes
  - MAP → the most used IR measure
  - nDGC → the most used measure for web search

Walid Magdy, TTDS 2017/2018

THE UNIVERSITY *of* EDINBURGH

Resources

- Text book 1: Intro to IR, Chapter 8
- Text book 2: IR in Practice, Chapter 8