Information Retrieval

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The slides are **adapted from those provided by Prof. Hinrich Schütze** at University of Munich (http://www.cis.lmu.de/~hs/teach/14s/ir/).

Chapter 8 Evaluation in information retrieval

- 8.1 Information retrieval system evaluation
- 8.2 Standard test collections
- 8.3 Evaluation of unranked retrieval sets
- 8.4 Evaluation of ranked retrieval results
- 8.5 Assessing relevance
- 8.6 A broader perspective: System quality and user utility
- 8.7 Results snippets
- 8.8 References and further reading

Outline

- 8.1 Information retrieval system evaluation
- 8.2 Standard test collections
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8.1 Information retrieval system evaluation

Measures for a search engine

- How fast does it index
  - e.g., number of bytes per hour
- How fast does it search
  - e.g., latency (延迟) as a function of queries per second
- What is the cost per query?
  - in dollars

8.1 Information retrieval system evaluation

- All of the preceding criteria are measurable (可以衡量的): we can quantify the speed/size/money

- However, the key measure for a search engine is user happiness
  - Speed of response
  - Size of index
  - Uncluttered (整洁的) UI
  - Most important: relevance (相关性)

  - Actually, maybe even more important: it's free

8.1 Information retrieval system evaluation

Who is the user? (1/2)

- Who is the user we are trying to make happy?
- Web search engine: searcher (搜索引擎用户). Success: Searcher finds what she was looking for. Measure: rate of return to this search engine
- Web search engine: advertiser (广告商). Success: Searcher clicks on advertisement. Measure: click-through rate (CTR).

8.1 Information retrieval system evaluation

Who is the user? (2/2)

- Ecommerce: buyer (购买者). Success: Buyer buys something. Measures: time to purchase, fraction of “conversions” (转化率) of searchers to buyers.
- Ecommerce: seller (销售者). Success: Seller sells something. Measure: profit per item sold.
- Enterprise: CEO. Success: Employees are more productive because of effective search. Measure: profit of the company.

8.1 Information retrieval system evaluation

Most common definition of user happiness: Relevance

- User happiness is equated with (等同于) the relevance of search results to the query.

- But how do you measure the relevance?
- Standard methodology in information retrieval consists of three elements.
  - A benchmark document collection
  - A benchmark suite of queries
  - An assessment of the relevance of each query-document pair

8.1 Information retrieval system evaluation

Relevance: query vs. information need (1/2)

- Information need i: “I am looking for information on whether drinking red wine is more effective at reducing your risk of heart attacks than white wine.”
- Query q: [red wine white wine heart attack]

- Consider document d': At the heart of his speech was an attack on the wine industry lobby (游说团) for downplaying the role of red and white wine in drunk driving.
- d' is an excellent match for query q ...
- d' is not relevant to the information need i

8.1 Information retrieval system evaluation

Relevance: query vs. information need (2/2)

- User happiness can only be measured by relevance to an **information need**, not by relevance to queries.
  - → query intent classification

- Our terminology is sloppy (草率的) in the textbook: we talk about query-document relevance judgments even though we mean information-need-document relevance judgments.

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8.2 Standard test collections

What we need for a benchmark

- A collection of documents: Documents should be representative of the documents we expect to see in reality.
- A collection of information needs (often incorrectly called queries): Information needs should be representative of the information needs we expect to see in reality.

- Human relevance assessments: We need to hire/pay “judges” or assessors to do this
  - Expensive, time consuming
  - Judges should be representative of the users we expect to see in reality

8.2 Standard test collections

First standard relevance benchmark: Cranfield

- Pioneering: first testbed allowing precise quantitative measures of information retrieval effectiveness
  - Late 1950s, UK
  - 1398 abstracts of aerodynamics journal articles, a set of 225 queries, exhaustive relevance judgments of all (query, document) pairs
  - Too small, too untypical for serious IR evaluation today

8.2 Standard test collections

Second-generation relevance benchmark: TREC

- TREC = Text Retrieval Conference (TREC)
- Organized by the U.S. National Institute of Standards and Technology (NIST, 美国国家标准与技术研究院)
- TREC is actually a set of several different relevance benchmarks.

8.2 Standard test collections

Information Retrieval Benchmark

- http://www.bigdatalab.ac.cn/benchmark/bm/Domain?domain=Information%20Retrieval

- https://www.microsoft.com/en-us/research/publication/letor-benchmark-collection-research-learning-rank-information-retrieval/

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8.3 Evaluation of unranked retrieval sets

Precision and recall (1/2)

- Precision(精确率) is the fraction of retrieved documents that are relevant

$$\text{Precision} = \frac{\#(\text{relevant items retrieved})}{\#(\text{retrieved items})} = P(\text{relevant}|\text{retrieved})$$

- Recall(召回率) is the fraction of relevant documents that are retrieved

$$\text{Recall} = \frac{\#(\text{relevant items retrieved})}{\#(\text{relevant items})} = P(\text{retrieved}|\text{relevant})$$

8.3 Evaluation of unranked retrieval sets

Precision and recall (2/2)

	Relevant	Nonrelevant
Retrieved	true positives (TP)	false positives (FP)
Not retrieved	false negatives (FN)	true negatives (TN)

$$P = TP/(TP + FP)$$
$$R = TP/(TP + FN)$$

8.3 Evaluation of unranked retrieval sets

Precision/recall tradeoff

- You can increase recall by returning more documents.
- Recall is a non-decreasing function of the number of docs retrieved.
- A system that returns all documents has 100% recall.

- Similarly, it is usually easy to get high precision for very low recall.

8.3 Evaluation of unranked retrieval sets

A combined measure: F

- F allows us to tradeoff precision against recall.

$$F = \frac{1}{\alpha\frac{1}{P} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2+1)PR}{\beta^2 P + R} \quad \text{where} \quad \beta^2 = \frac{1-\alpha}{\alpha}$$

$\alpha \in [0,1]$ and thus $\beta^2 \in [0,\infty]$

- Most frequently used: balanced F with $\beta = 1$ or $\alpha = 0.5$
  - This is the harmonic mean of P and R:

$$\frac{1}{F} = \frac{1}{2}\left(\frac{1}{P} + \frac{1}{R}\right)$$

8.3 Evaluation of unranked retrieval sets

Example for precision, recall, F1

	relevant	not relevant	
retrieved	20	40	60
not retrieved	60	1,000,000	1,000,060
	80	1,000,040	1,000,120

- $P = 20/(20+40) = 1/3$
- $R = 20/(20+60) = 1/4$
- $F_1 = 2\frac{1}{\frac{1}{\frac{1}{3}}+\frac{1}{\frac{1}{4}}} = 2/7$

8.3 Evaluation of unranked retrieval sets

Accuracy (准确率)

- Why do we use complex measures like precision, recall, and F?
- Why not something simple like accuracy?
- Accuracy is the fraction of decisions (relevant/nonrelevant) that are correct.

- In terms of the contingency table (列联表) in the previous page, accuracy = (TP + TN)/(TP + FP + FN + TN).

8.3 Evaluation of unranked retrieval sets

Exercise

- Compute precision, recall, F1 and accuracy for this result set:

	relevant	not relevant
retrieved	18	2
not retrieved	82	1,000,000,000

8.3 Evaluation of unranked retrieval sets

Why accuracy is a useless measure in IR

- Simple trick to maximize accuracy in IR: always say no and return nothing
  - You then get 99.99% accuracy on most queries.

- Searchers on the web (and in IR in general) want to find something and have a certain tolerance for junk.

- It's better to return some bad hits as long as you return something.
  → We use precision, recall, and F for evaluation, not accuracy.

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8.4 Evaluation of ranked retrieval results

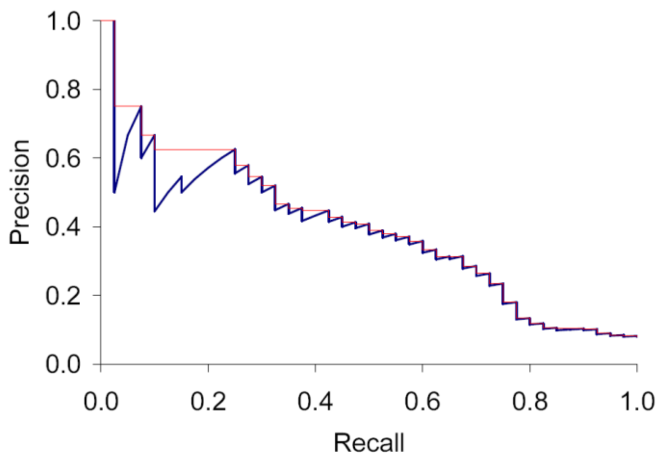
Precision-recall curve

- Precision/recall/F1 are measures for unranked sets.

- We can easily turn set measures into measures of ranked lists.
  - Just compute the set measure for each "**prefix**": the top 1, top 2, top 3, top 4 … results, e.g., Precision@k and Recall@k, k=1,2,3,…
  - Doing this for precision and recall gives you a precision-recall curve.

8.4 Evaluation of ranked retrieval results

A precision-recall curve



- Each point (in blue) corresponds to a result for the top k ranked hits (k = 1, 2, 3, 4, …). Precision@k usually decreases with larger k; Recall@k usually increases with larger k.
- Interpolation (插值, in red): Take maximum of all future points.
- Why use interpolation: the area under the red curve better represents the overall ranking performance than the area under the blue curve, <u>because a user is usually willing to look at more stuff if both precision and recall get better.</u>

8.4 Evaluation of ranked retrieval results

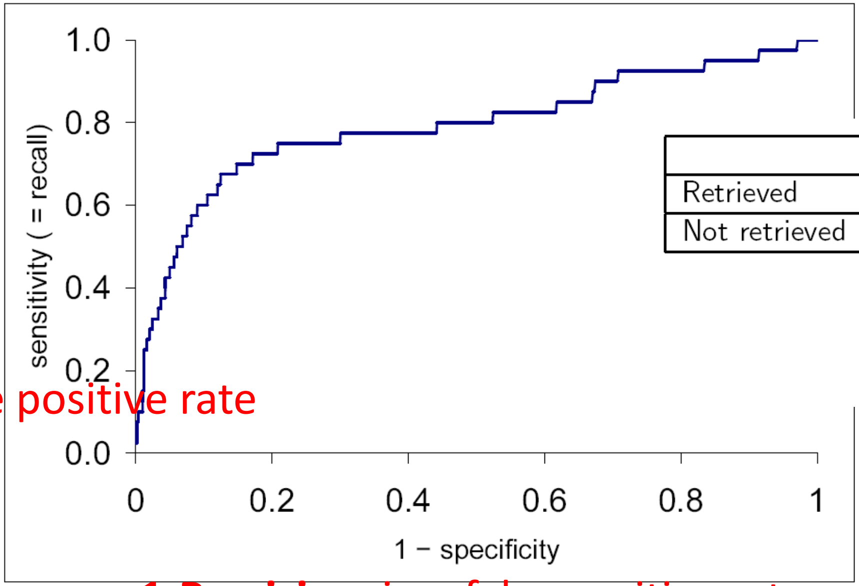
11-point interpolated average precision

- 11-point average: 0.425
- This measure measures performance at all recall levels.

Recall	Interpolated Precision
0.0	1.00
0.1	0.67
0.2	0.63
0.3	0.55
0.4	0.45
0.5	0.41
0.6	0.36
0.7	0.29
0.8	0.13
0.9	0.10
1.0	0.08

8.4 Evaluation of ranked retrieval results

ROC curve



Recall, i.e., true positive rate

1-Precision, i.e., false positive rate

	Relevant	Nonrelevant
Retrieved	true positives (TP)	false positives (FP)
Not retrieved	false negatives (FN)	true negatives (TN)

$$P = TP/(TP + FP)$$
$$R = TP/(TP + FN)$$

- For the ROC curve (receiver operating characteristic curve), we are only interested **in the small area in the lower left corner** (because when 1-Precision=1, i.e., Precision=0, we can always have Recall=1)

8.4 Evaluation of ranked retrieval results

Variance of measures like precision/recall

- For a test collection, it is usual that a system does badly on some information needs (e.g., P = 0.2 at R = 0.1) and really well on others (e.g., P = 0.95 at R = 0.1).

- Indeed, it is usually the case that the variance of the same system across queries is much larger than the variance of different systems on the same query.

- That is, there are easy information needs and hard information needs.

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8.5 Assessing relevance

Kappa measure (1/2)

- Relevance assessments by two judges are usable if they are consistent.
- How can we measure this consistency between two judges?
  → Kappa measure, how much two judges agree or disagree

$$\kappa = \frac{P(A) - P(E)}{1 - P(E)}$$

- P(A) = proportion of time that two judges agree, i.e., observed agreement
- P(E) = what agreement would we get by chance, i.e., expected agreement

8.5 Assessing relevance

Kappa measure (2/2)

		Judge 2 Relevance		
		Yes	No	Total
Judge 1	Yes	300	20	320
Relevance	No	10	70	80
	Total	310	90	400

Observed agreement

$P(A) = (300 + 70)/400 = 370/400 = 0.925$

Expected agreement

$P(E) = (80/400) \times (90/400) + (320/400) \times (310/400) = 0.665$

Kappa statistic

$\kappa = (P(A) - P(E))/(1 - P(E)) = (0.925 - 0.665)/(1 - 0.665) = 0.776$

Values in the interval [2/3, 1.0] are seen as acceptable.

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8.6 A broader perspective: System quality and user utility

Evaluation at large search engines

- Recall is difficult to measure on the web
- Search engines often use precision at top k, e.g., k = 10 ...

- Search engines also use non-relevance-based measures.
  - E.g., click-through rate (CTR) on first result

8.6 A broader perspective: System quality and user utility

A/B testing

- Purpose: Test a single innovation
- Prerequisite: You have a large search engine up and running.
  - Have most users use the old system
  - Divert (转移) a small proportion of traffic (e.g., 1%) to the new system that includes the innovation
  - Evaluate with an “automatic” measure like CTR on first result

- Probably the evaluation methodology that large search engines trust most

8.6 A broader perspective: System quality and user utility

Marginal relevance

- We’ve defined relevance for an isolated (query, document) pair.
- Alternative definition: marginal relevance
- The marginal relevance of the document d_k at position k in the result list is the **additional** information it contributes over and above the information that was contained in documents $d_1, \ldots, d_{k-1}$.

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8.7 Results snippets

How do we present results to the user?

- Most often: as a list – aka "10 blue links"
- How should each document in the list be described?
  - This description is crucial.
  - The user can often identify good hits (= relevant hits) based on the description.
  - No need to actually view any document.

8.7 Results snippets

Document description in result list

- Most commonly: doc title, URL, some metadata … and a summary
- How do we “compute” the summary?

8.7 Results snippets

Summaries

- Two basic kinds: (i) static (ii) dynamic
- A static summary of a document is always the same, regardless of the query that was issued by the user.
- Dynamic summaries are query dependent. They attempt to explain why the document was retrieved for the query at hand.

8.7 Results snippets

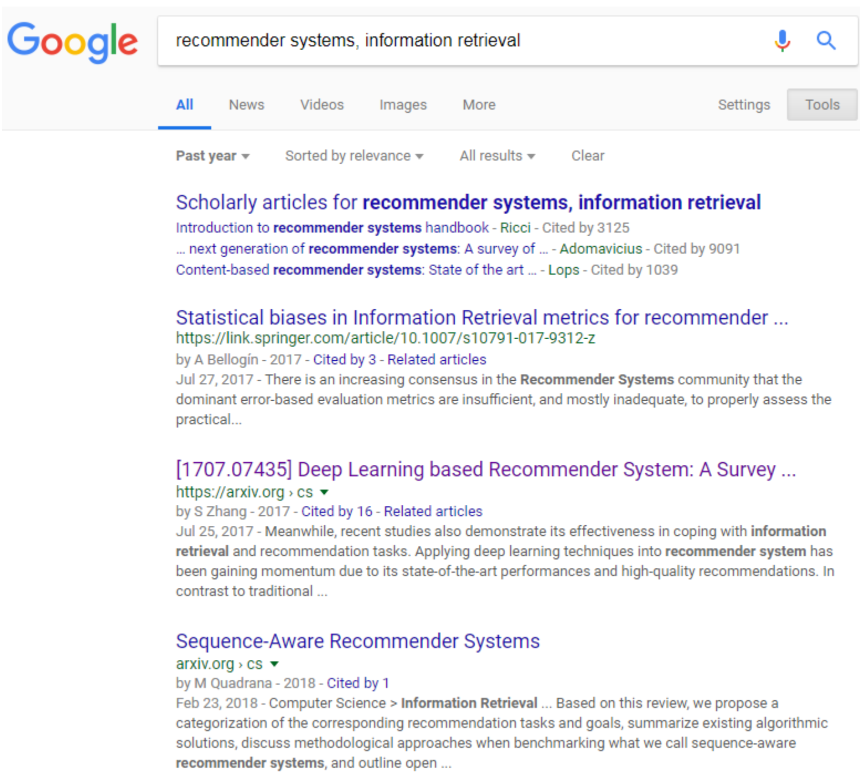
Static summaries

- In typical systems, the static summary is a subset of the document.
  - Simplest heuristic: the first 50 or so words of the document
  - More sophisticated: extract from each document a set of “key” sentences
    - Simple NLP heuristics to score each sentence
    - Summary is made up of top-scoring sentences.
  - …
- Most sophisticated: complex NLP to synthesize/generate a summary
  - For most IR applications: not quite ready for prime time yet

8.7 Results snippets

Dynamic summaries

- Present one or more “windows” or snippets within the document that contain several of the query terms.



8.7 Results snippets

Generating dynamic summaries

- Where do we get these other terms in the snippet from?
  - We cannot construct a dynamic summary from the positional inverted index – at least not efficiently.
  - We need to cache documents.
  - Note that the cached copy can be outdated
  - Don’t cache very long documents – just cache a short prefix

Summary

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