Introduction to Information Retrieval

http://informationretrieval.org

IIR 8: Evaluation & Result Summaries

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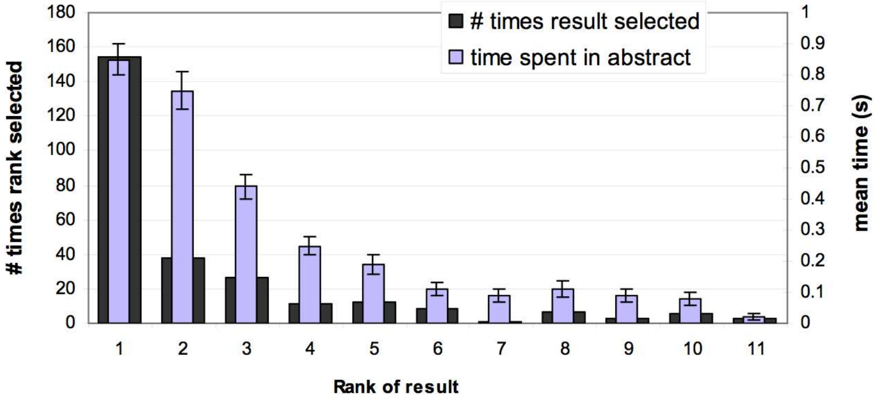
Overview

Outline

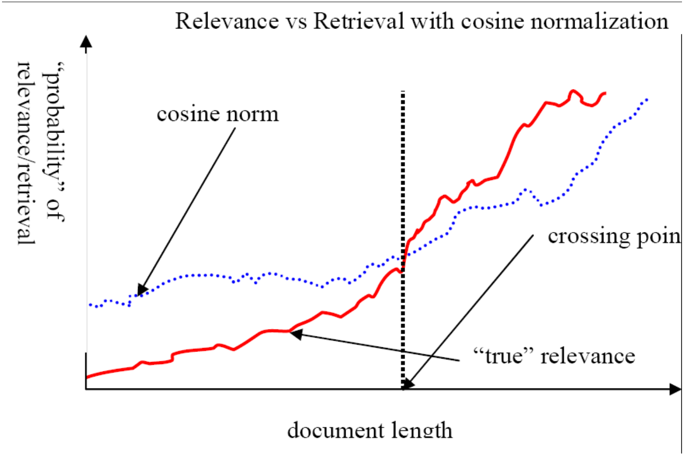
Looking vs. Clicking



- Users view results one and two more often / thoroughly
- Users click most frequently on result one

Google

Pivot normalization



source: Lillian Lee

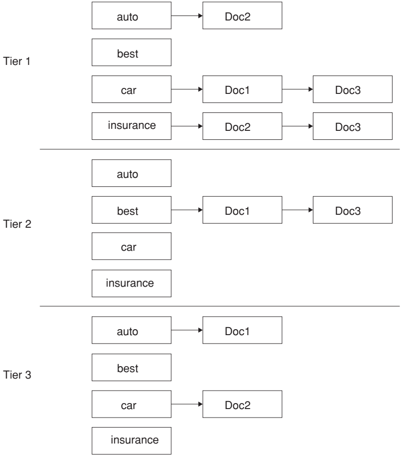
Selecting k top scoring documents in $O(N \log k)$

- Goal: Keep the k top documents seen so far
- Use a binary min heap
- To process a new document d' with score s':
  - Get current minimum h_m of heap (in $O(1)$)
  - If $s' \leq h_m$ skip to next document
  - If $s' > h_m$ heap-delete-root (in $O(\log k)$)
  - Heap-add d'/s' (in $O(1)$)
  - Reheapify (in $O(\log k)$)

Heuristics for finding the top k even faster

- Document-at-a-time processing
  - We complete computation of the query-document similarity score of document d_i before starting to compute the query-document similarity score of d_{i+1}.
  - Requires a consistent ordering of documents in the postings lists
- Term-at-a-time processing
  - We complete processing the postings list of query term t_i before starting to process the postings list of t_{i+1}.
  - Requires an accumulator for each document "still in the running"
- The most effective heuristics switch back and forth between term-at-a-time and document-at-a-time processing.

Tiered index



Take-away today

- Introduction to evaluation: Measures of an IR system
- Evaluation of unranked and ranked retrieval
- Evaluation benchmarks
- Result summaries

Outline

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 as a function of queries per second
- What is the cost per query?
  - in dollars

Measures for a search engine

- All of the preceding criteria are measurable: we can quantify speed / size / money
- However, the key measure for a search engine is user happiness.
- What is user happiness?
- Factors include:
  - Speed of response
  - Size of index
  - Uncluttered UI
  - Most important: relevance
  - (actually, maybe even more important: it's free)
- Note that none of these is sufficient: blindingly fast, but useless answers won't make a user happy.
- How can we quantify user happiness?

Who is the user?

- Who is the user we are trying to make happy?
- Web search engine: searcher. Success: Searcher finds what she was looking for. Measure: rate of return to this search engine
- Web search engine: advertiser. Success: Searcher clicks on ad. Measure: clickthrough rate
- Ecommerce: buyer. Success: Buyer buys something. Measures: time to purchase, fraction of "conversions" of searchers to buyers
- Ecommerce: seller. 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

Most common definition of user happiness: Relevance

- User happiness is equated with the relevance of search results to the query.
- But how do you measure 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

Relevance: query vs. information need

- Relevance to what?
- First take: relevance to the query
- "Relevance to the query" is very problematic.
- 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."
- This is an information need, not a query.
- 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 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.

Relevance: query vs. information need

- User happiness can only be measured by relevance to an information need, not by relevance to queries.
- Our terminology is sloppy in these slides and in IIR: we talk about query-document relevance judgments even though we mean information-need-document relevance judgments.

Outline

Precision and recall

- Precision (P) 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 (R) is the fraction of relevant documents that are retrieved

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

Precision and recall

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

$$\begin{aligned} P &= TP/(TP+FP) \\ R &= TP/(TP+FN) \end{aligned}$$

Precision/recall tradeoff

- You can increase recall by returning more docs.
- Recall is a non-decreasing function of the number of docs retrieved.
- A system that returns all docs has 100% recall!
- The converse is also true (usually): It's easy to get high precision for very low recall.
- Suppose the document with the largest score is relevant. How can we maximize precision?

A combined measure: F

- F allows us to trade off 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: $\frac{1}{F} = \frac{1}{2}(\frac{1}{P} + \frac{1}{R})$
- What value range of β weights recall higher than precision?

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

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

Accuracy

- 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 above,
  accuracy $= (TP + TN)/(TP + FP + FN + TN)$.

Exercise

- Compute precision, recall and F_1 for this result set:

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

- The snoogle search engine below always returns 0 results ("0 matching results found"), regardless of the query. Why does snoogle demonstrate that accuracy is not a useful measure in IR?

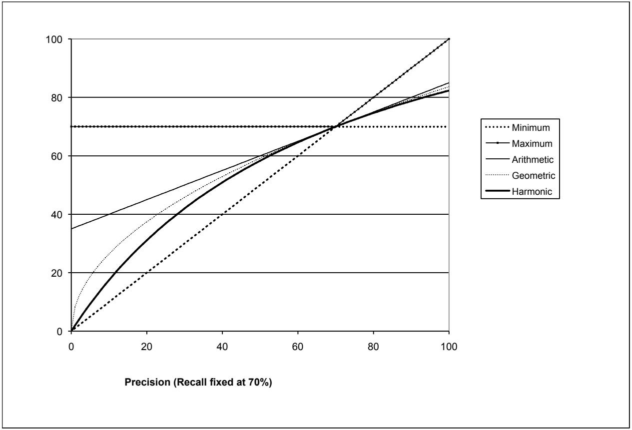
Why accuracy is a useless measure in IR

- 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.
- $\rightarrow$ We use precision, recall, and F for evaluation, not accuracy.

F: Why harmonic mean?

- Why don't we use a different mean of P and R as a measure?
  - e.g., the arithmetic mean
- The simple (arithmetic) mean is close to 50% for snoogle search engine – which is too high.
- Desideratum: Punish really bad performance on either precision or recall.
- Taking the minimum achieves this.
- But minimum is not smooth and hard to weight.
- F (harmonic mean) is a kind of smooth minimum.

F_1 and other averages



- We can view the harmonic mean as a kind of soft minimum

Difficulties in using precision, recall and F

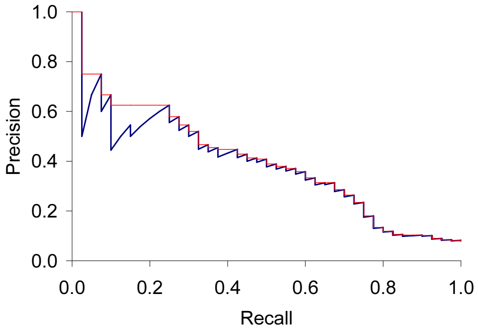
- We need relevance judgments for information-need-document pairs – but they are expensive to produce.
- For alternatives to using precision/recall and having to produce relevance judgments – see end of this lecture.

Outline

Precision-recall curve

- Precision/recall/F 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 etc results
- Doing this for precision and recall gives you a precision-recall curve.

A precision-recall curve



- Each point corresponds to a result for the top k ranked hits ($k = 1, 2, 3, 4, \ldots$).
- Interpolation (in red): Take maximum of all future points
- Rationale for interpolation: The user is willing to look at more stuff if both precision and recall get better.
- Questions?

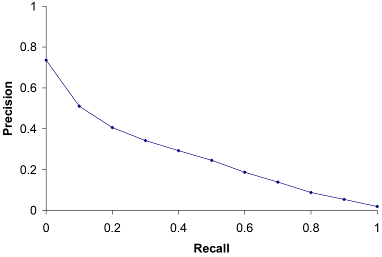
11-point interpolated average precision

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

11-point average: $\approx$ 0.425

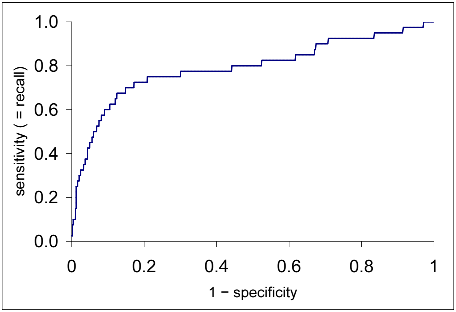
How can precision at 0.0 be > 0?

Averaged 11-point precision/recall graph



- Compute interpolated precision at recall levels 0.0, 0.1, 0.2, . . .
- Do this for each of the queries in the evaluation benchmark
- Average over queries
- This measure measures performance at all recall levels.
- The curve is typical of performance levels at TREC.
- Note that performance is not very good!

ROC curve



- Similar to precision-recall graph
- But we are only interested in the small area in the lower left corner.
- Precision-recall graph "blows up" this area.

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 greater than the variance of different systems on the same query.
- That is, there are easy information needs and hard ones.

Outline

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.

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

Second-generation relevance benchmark: TREC

- TREC = Text Retrieval Conference (TREC)
- Organized by the U.S. National Institute of Standards and Technology (NIST)
- TREC is actually a set of several different relevance benchmarks.
- Best known: TREC Ad Hoc, used for first 8 TREC evaluations between 1992 and 1999
- 1.89 million documents, mainly newswire articles, 450 information needs
- No exhaustive relevance judgments – too expensive
- Rather, NIST assessors' relevance judgments are available only for the documents that were among the top k returned for some system which was entered in the TREC evaluation for which the information need was developed.

Example of more recent benchmark: ClueWeb09

- 1 billion web pages
- 25 terabytes (compressed: 5 terabyte)
- Collected January/February 2009
- 10 languages
- Unique URLs: 4,780,950,903 (325 GB uncompressed, 105 GB compressed)
- Total Outlinks: 7,944,351,835 (71 GB uncompressed, 24 GB compressed)

Validity of relevance assessments

- Relevance assessments are only usable if they are consistent.
- If they are not consistent, then there is no "truth" and experiments are not repeatable.
- How can we measure this consistency or agreement among judges?
- $\rightarrow$ Kappa measure

Kappa measure

- Kappa is measure of how much judges agree or disagree.
- Designed for categorical judgments
- Corrects for chance agreement
- $P(A) =$ proportion of time judges agree
- $P(E) =$ what agreement would we get by chance
- $$\kappa = \frac{P(A) - P(E)}{1 - P(E)}$$
- $\kappa =$? for (i) chance agreement (ii) total agreement

Kappa measure (2)

- Values of κ in the interval $[2/3, 1.0]$ are seen as acceptable.
- With smaller values: need to redesign relevance assessment methodology used etc.

Calculating the kappa statistic

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

Observed proportion of the times the judges agreed
$P(A) = (300 + 70)/400 = 370/400 = 0.925$
Pooled marginals
$P(nonrelevant) = (80 + 90)/(400 + 400) = 170/800 = 0.2125$
$P(relevant) = (320 + 310)/(400 + 400) = 630/800 = 0.7878$
Probability that the two judges agreed by chance $P(E) = P(nonrelevant)^2 + P(relevant)^2 = 0.2125^2 + 0.7878^2 = 0.665$
Kappa statistic $\kappa = (P(A) - P(E))/(1 - P(E)) = (0.925 - 0.665)/(1 - 0.665) = 0.776$ (still in acceptable range)

Interjudge agreement at TREC

information need	number of docs judged	disagreements
51	211	6
62	400	157
67	400	68
95	400	110
127	400	106

Impact of interjudge disagreement

- Judges disagree a lot. Does that mean that the results of information retrieval experiments are meaningless?
- No.
- Large impact on absolute performance numbers
- Virtually no impact on ranking of systems
- Supposes we want to know if algorithm A is better than algorithm B
- An information retrieval experiment will give us a reliable answer to this question . . .
- . . . even if there is a lot of disagreement between judges.

Evaluation at large search engines

- Recall is difficult to measure on the web
- Search engines often use precision at top k, e.g., $k = 10 \dots$
- . . . or use measures that reward you more for getting rank 1 right than for getting rank 10 right.
- Search engines also use non-relevance-based measures.
  - Example 1: clickthrough on first result
  - Not very reliable if you look at a single clickthrough (you may realize after clicking that the summary was misleading and the document is nonrelevant) . . .
  - . . . but pretty reliable in the aggregate.
  - Example 2: Ongoing studies of user behavior in the lab – recall last lecture
  - Example 3: A/B testing

A/B testing

- Purpose: Test a single innovation
- Prerequisite: You have a large search engine up and running.
- Have most users use old system
- Divert a small proportion of traffic (e.g., 1%) to the new system that includes the innovation
- Evaluate with an "automatic" measure like clickthrough on first result
- Now we can directly see if the innovation does improve user happiness.
- Probably the evaluation methodology that large search engines trust most

Critique of pure 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 $d_1 \dots d_{k-1}$.
- Exercise
  - Why is marginal relevance a more realistic measure of user happiness?
  - Give an example where a non-marginal measure like precision or recall is a misleading measure of user happiness, but marginal relevance is a good measure.
  - In a practical application, what is the difficulty of using marginal measures instead of non-marginal measures?

Outline

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 often can identify good hits (= relevant hits) based on the description.
- No need to actually view any document

Doc description in result list

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

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.

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.
  - Machine learning approach: see IIR 13
- Most sophisticated: complex NLP to synthesize/generate a summary
  - For most IR applications: not quite ready for prime time yet

Dynamic summaries

- Present one or more "windows" or snippets within the document that contain several of the query terms.
- Prefer snippets in which query terms occurred as a phrase
- Prefer snippets in which query terms occurred jointly in a small window
- The summary that is computed this way gives the entire content of the window – all terms, not just the query terms.

Google dynamic summaries for [vegetarian diet running]

No Meat Athlete | **Vegetarian Running** and Fitness
www.nomeatathlete.com/
Vegetarian Running and Fitness. ... (Oh, and did I mention Rich did it all on a plant-based **diet**?) In this episode of No Meat Athlete Radio, Doug and I had the ...
Vegetarian Recipes for Athletes - Vegetarian Shirts - How to Run Long - About

Running on a **vegetarian diet** – Top tips | Freedom2Train Blog
www.freedom2train.com/blog/?p=4
Nov 8, 2012 – In this article we look to tackle the issues faced by long distance runners on a **vegetarian diet**. By its very nature, a **vegetarian diet** can lead to ...

HowStuffWorks "5 Nutrition Tips for **Vegetarian** Runners"
www.howstuffworks.com/.../**running**/.../5-nutrition-tips-for-**vegetarian**-r...
Even without meat, you can get enough fuel to keep on **running**. Stockbyte/Thinkstock ... Unfortunately, a **vegetarian diet** is not a panacea for runners. It could, for ...

Nutrition Guide for **Vegetarian** and Vegan Runners - The **Running** Bug
therunningbug.co.uk/.../nutrition-guide-for-**vegetarian**-and-vegan-runne...
Feb 28, 2012 – The **Running** Bug's guide to nutrition for vegetarian and vegan ... different types of **vegetarian diet** ranging from lacto-ovo-vegetarians who eat ...

Vegetarian Runner
www.**vegetarian**runner.com/
Vegetarian Runner - A resource center for vegetarianism and **running** and how to make sure you have proper nutrition as an athlete with a **vegetarian diet**.

- Good example that snippet selection is non-trivial.
- Criteria: occurrence of keywords, density of keywords, coherence of snippet, number of different snippets in summary, good cutting points etc

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.
- The positional index tells us: query term occurs at position 4378 in the document.
- Byte offset or word offset?
- Note that the cached copy can be outdated
- Don't cache very long documents – just cache a short prefix

Dynamic summaries

- Real estate on the search result page is limited $\rightarrow$ snippets must be short . . .
- . . . but snippets must be long enough to be meaningful.
- Snippets should communicate whether and how the document answers the query.
- Ideally: linguistically well-formed snippets
- Ideally: the snippet should answer the query, so we don't have to look at the document.
- Dynamic summaries are a big part of user happiness because . . .
  - . . . we can quickly scan them to find the relevant document we then click on.
  - . . . in many cases, we don't have to click at all and save time.

Take-away today

- Introduction to evaluation: Measures of an IR system
- Evaluation of unranked and ranked retrieval
- Evaluation benchmarks
- Result summaries

Resources

- Chapter 8 of IIR
- Resources at `http://cislmu.org`
  - The TREC home page – TREC had a huge impact on information retrieval evaluation.
  - Originator of F-measure: Keith van Rijsbergen
  - More on A/B testing
  - Too much A/B testing at Google?
  - Tombros & Sanderson 1998: one of the first papers on dynamic summaries
  - Google VP of Engineering on search quality evaluation at Google