Introduction to

Information Retrieval

CS4611 Michel Schellekens

Slides adapted from Hinrich Schütze and Christina Lioma online slides

Lecture 8: Evaluation & Result Summaries

Overview

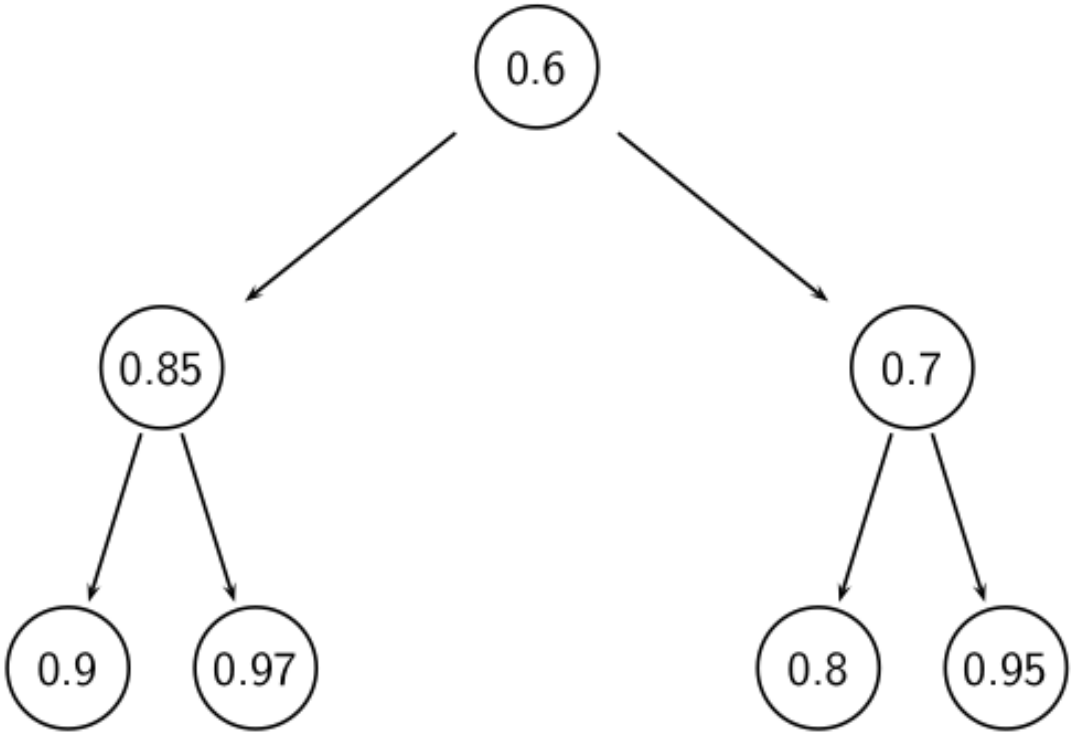
1. Recap
2. Unranked evaluation
3. Ranked evaluation
4. Evaluation benchmarks
5. Result summaries

Outline

Use min heap for selecting top *k* ouf of *N*

- Use a binary min heap
- A binary min heap is a binary tree in which each node's value is less than the values of its children.
- It takes $O(N \log k)$ operations to construct the k-heap containing the k largest values (where N is the number of documents).
- Essentially linear in N for small k and large N.

Binary min heap



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 $O(\log k)$)

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 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.

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/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. [if retrieved items low & relevant items large]

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*:

F: Example

	relevant		not relevant		
retrieved	20	TP	40	FP	60
not retrieved	60	FN	1,000,000	TN	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 = $(TP + TN)/(TP + FP + FN + TN)$.
- Why is accuracy not a useful measure for web information retrieval?

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.
- →We use precision, recall, and *F* for evaluation, not accuracy.

F: Why harmonic mean?

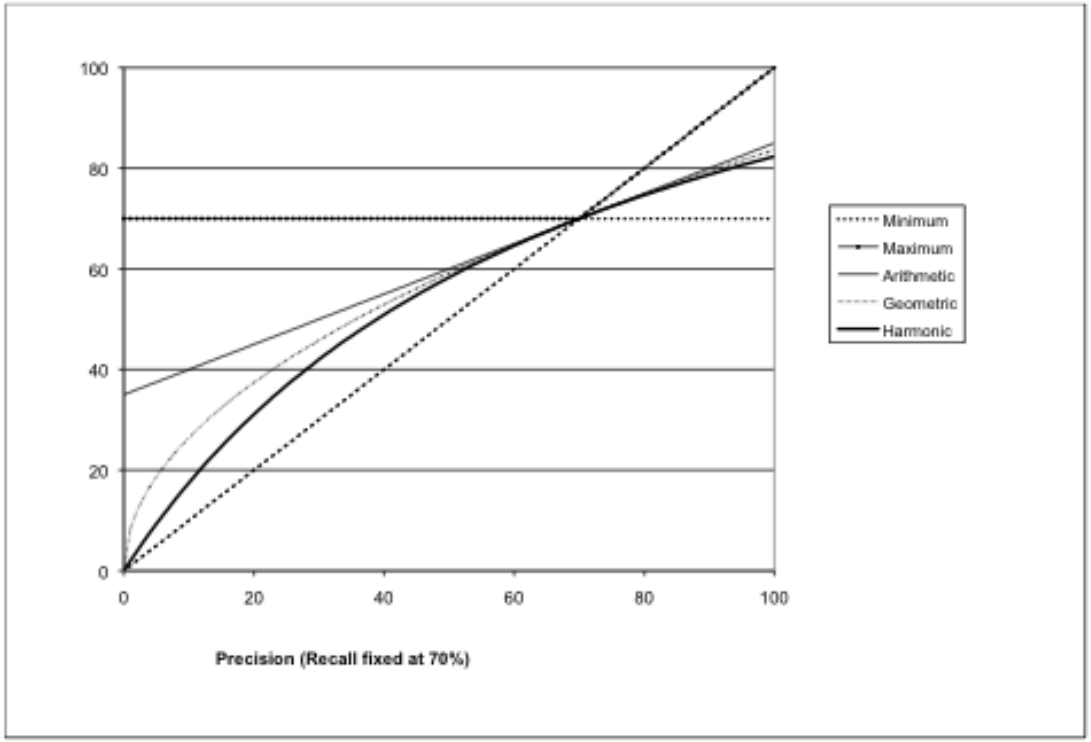
- Why don't we use a different mean of *P* and *R* as a measure?
  - e.g., the arithmetic mean
- The simple (arithmetic) mean is 50% for "return-everything" search engine, which is too high. See example next slide.
- Desideratum: Punish really bad performance on either precision or recall.
- Taking the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

Return everything example

	relevant		**not relevant**	
retrieved	20	TP	1,000,100 FP	1,000,120
not retrieved	0	FN	0 TN	1,000,060
	20		1,000,100	1,000,120

Arithmetic average ½ P + ½ Q = ½ 20/1,000,120 + ½ 20/20
≈ ½

F_1 and other averages



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

Outline

Outline

What we need for a benchmark

- A collection of documents
  - Documents must be representative of the documents we expect to see in reality.
- A collection of information needs
  - . . .which we will often incorrectly refer to as queries
  - Information needs must 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 must be representative of the users we expect to see in reality.

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

Standard 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.

Standard relevance benchmarks: Others

- GOV2
  - Another TREC/NIST collection
  - 25 million web pages
  - Used to be largest collection that is easily available
  - But still 3 orders of magnitude smaller than what Google/Yahoo/MSN index
- NTCIR
  - East Asian language and cross-language information retrieval
- Cross Language Evaluation Forum (CLEF)
  - This evaluation series has concentrated on European languages and cross-language information retrieval.
- Many others

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?
- → 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

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

- k =? for (i) chance agreement (ii) total agreement

Kappa measure (2)

- Values of *k* 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 Relevance	Yes	300	20	320
	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 $P(E)$ =

$P(nonrelevant)^2 + P(\text{relevant})^2 = 0.2125^2 + 0.7878^2 = 0.665$

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
- Suppose 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 . . .
- . . . 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
  - 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 a document at position k in the result list is the additional information it contributes over and above the information that was contained in documents $d_1 \ldots d_{k-1}$.

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 “click” on all documents sequentially

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
  - heuristics to score each sentence
  - Summary is made up of top-scoring sentences.
  - Machine learning approach
- Most sophisticated: complex NLP to synthesize/generate a summary
- For most IR applications: not quite ready 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.

A dynamic summary

Query: "new guinea economic development" Snippets (in bold) that were extracted from a document: . . . **In recent years, Papua New Guinea has faced severe economic difficulties and** economic growth has slowed, partly as a result of weak governance and civil war, and partly as a result of external factors such as the Bougainville civil war which led to the closure in 1989 of the Panguna mine (at that time the most important foreign exchange earner and contributor to Government finances), the Asian financial crisis, a decline in the prices of gold and copper, and a fall in the production of oil. **PNG's economic development record over the past few years is evidence that** governance issues underly many of the country's problems. Good governance, which may be defined as the transparent and accountable management of human, natural, economic and financial resources for the purposes of equitable and sustainable development, flows from proper public sector management, efficient fiscal and accounting mechanisms, and a willingness to make service delivery a priority in practice. . . .

Google example for dynamic summaries

Dynamic summaries

- Real estate on the search result page is limited ! 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.