Introduction to Information Retrieval
http://informationretrieval.org

IIR 8: Evaluation & Result Summaries

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(Based on slides by Hinrich Schütze at informationretrieval.org)

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Motivation

Facebook CEO Mark Zuckerberg speaks during the awarding ceremony of the newly established Axel Springer Award in Berlin Thursday, Feb. 25, 2016. (Kay Nietfeld/pool photo via AP)

Mark Zuckerberg takes on fake news, the importance of the news industry and the rise of filter bubbles in new manifesto

http://www.poynter.org/2017/mark-zuckerberg-stands-up-for-the-news-in-new-manifesto/449287/

Motivation

https://www.wired.com/2017/02/veles-macedonia-fake-news/

Overview

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

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:

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- 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?

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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: $\frac{1}{F} = \frac{1}{2}(\frac{1}{P} + \frac{1}{R})$
- $\beta < 1$ emphasizes...
- $\beta > 1$ emphasizes...

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

Example for precision, recall, F1

	relevant	not relevant	
retrieved	20	40	60
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	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 (both relevant and 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?

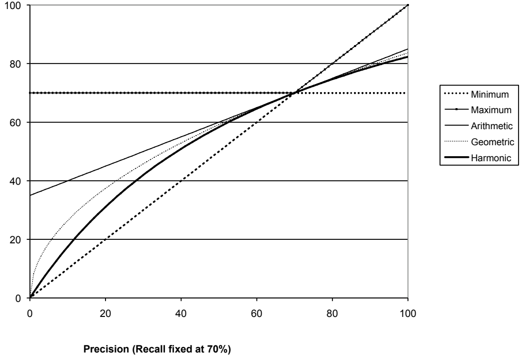
Why accuracy is a useless measure in IR

- 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 50% for "return-everything" search engine, which is too high.
- Desideratum: Punish really bad performance on either precision or recall.
- Taking the minimum achieves this.
- But the minimum ignores what happens to the other measure...
- Intuition: 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

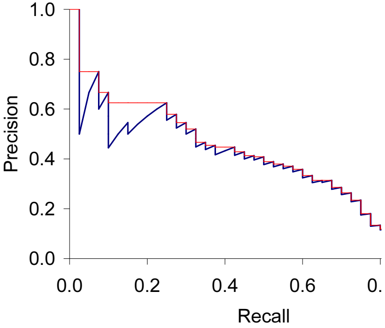
- We need relevance judgments for information-need-document pairs – but they are expensive to produce.
- P/R are not always the best measures. Why?

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 ($k = 1, 2, 3, 4, \dots$). When is P@1 the best evaluation measure?
- 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?

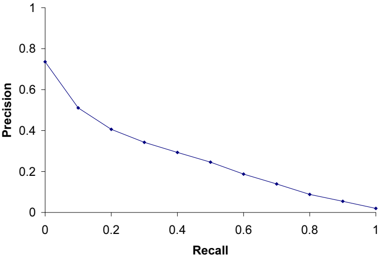
11-point interpolated average precision

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 interpolated precision at 0.0 recall 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 of information retrieval systems.
- Note that performance is not very good!

Mean Average Precision (MAP)

$$MAP(Q) = \frac{1}{|Q|} \sum_{j=1}^{|Q|} \frac{1}{m_j} \sum_{k=1}^{m_j} Precision(R_{jk})$$

where:

- m_j – number of relevant documents for query j
- R_{jk} – number of documents until we get to the relevant document d_k for query j

MAP is roughly the area under the curve for the previous graph!

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.

Other measures: Mean Reciprocal Rank (MRR)

- Very useful when you care about the position of the top answer(s). When is that? When is MRR a better measure than MAP?

$$MRR(Q) = \frac{1}{|Q|} \sum_{j=1}^{|Q|} \frac{1}{rank_j}$$

where:

- $rank_j$ – position of top correct answer for query j

Other measures: NDCG

- Normalized discounted cumulative gain (NDCG): designed for non-binary document relevance scores. (actual formula *not* required for the exams)
- Very useful to web retrieval.
- Do you need it for your Watson project?

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.
- How are these defined for your project?

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 a 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 measures 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:
$P(\mathit{nonrelevant}) = (80 + 90)/(400 + 400) = 170/800 = 0.2125$
$P(\mathit{relevant}) = (320 + 310)/(400 + 400) = 630/800 = 0.7878$
Probability that the two judges agreed by chance:
$P(E) = P(\mathit{nonrelevant})^2 + P(\mathit{relevant})^2 = 0.2125^2 + 0.7878^2 = 0.665$
Kappa statistic
$\kappa = (P(A) - P(E))/(1 - P(E)) = (0.925 - 0.665)/(1 - 0.665) = 0.776$
(lower but 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., $k = 10$, or NDCG.
- . . . or use measures that reward you more for getting rank 1 right than for getting rank 10 right. Which measure does this?
- 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

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. Which site would be a good fit for a static summary?
- Dynamic summaries are query-dependent. They attempt to explain why the document was retrieved for the query at hand. These are the most common.

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
  - Few outperform the "first *k* words" baseline ...

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.

Criteria for Keywords in Context (KWIC)

- Must be maximally informative for the query.
- Must be self-contained, easy to read.
- Short enough, so they don't take too much real estate on the page.

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
the**running**bug.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

A dynamic summary must be coherent!

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. . . .

Generating dynamic summaries requires document caching

- 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 → 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