Introduction to Information Retrieval

http://informationretrieval.org

IIR 8: Evaluation & Result Summaries

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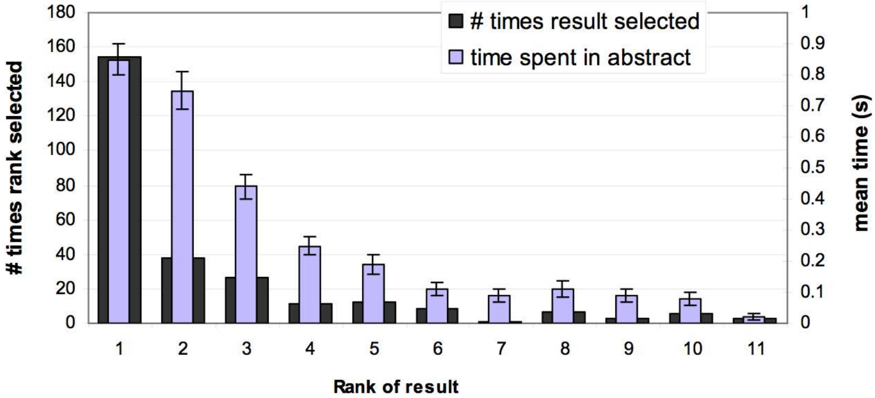
Overview

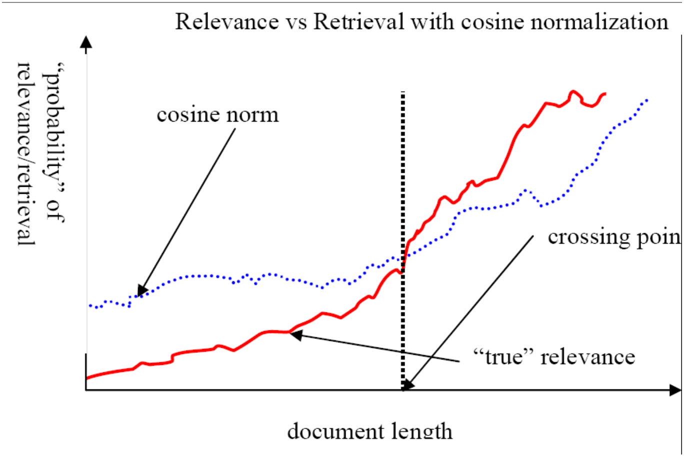
Outline

Looking vs. Clicking



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

Pivot normalization



source:
Lillian Lee

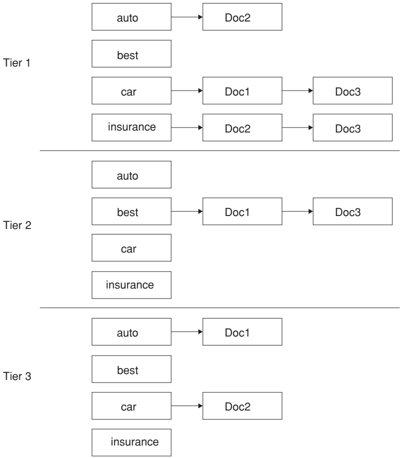
Selecting k top scoring documents in $O(N \log k)$

- 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



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- Evaluation of unranked and ranked retrieval

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  - e.g., number of bytes per hour

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- What is the cost per query?
  - in dollars

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- How can we quantify user happiness?

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- 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.

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- 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

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Precision and recall

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

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

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- 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?

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- What value range of β weights recall higher than precision?

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retrieved	20	40	60
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- $F_1 = 2\frac{1}{\frac{1}{\frac{1}{3}} + \frac{1}{\frac{1}{4}}} = 2/7$

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- 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

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- 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?

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- 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.

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- But minimum is not smooth and hard to weight.
- F (harmonic mean) is a kind of smooth minimum.

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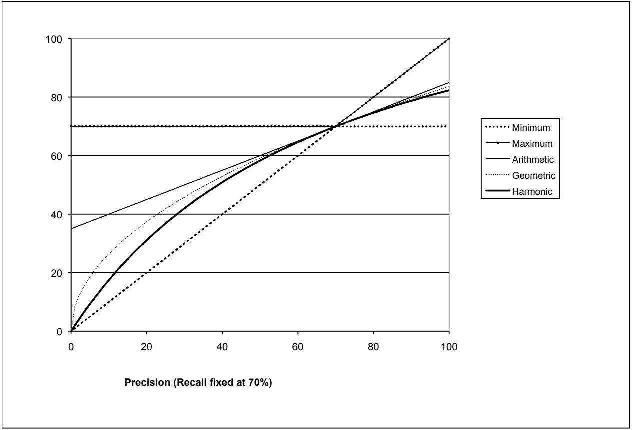

- We can view the harmonic mean as a kind of soft minimum

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.

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- 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.

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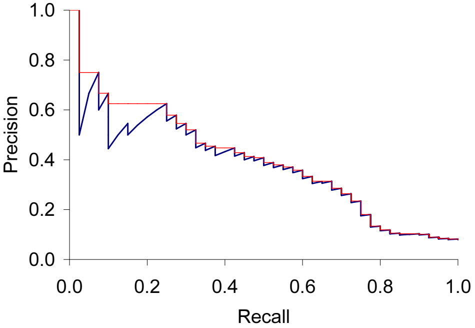

- Each point corresponds to a result for the top k ranked hits ($k = 1, 2, 3, 4, \ldots$).

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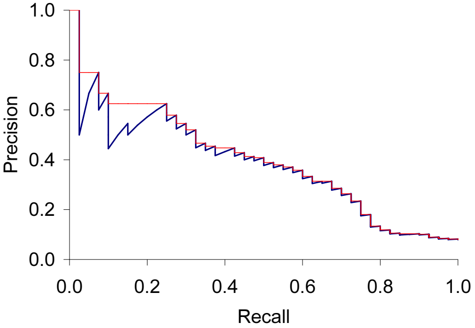

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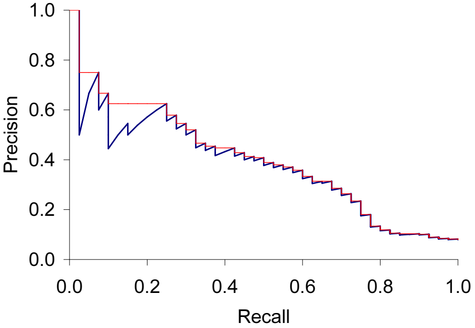

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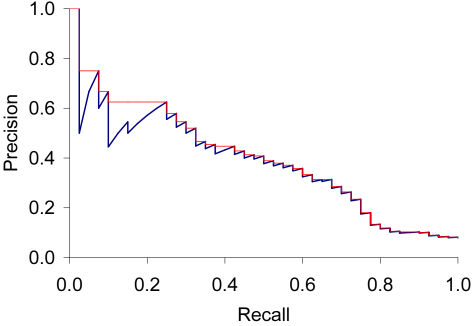

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- Questions?

11-point interpolated average precision

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0.2	0.63
0.3	0.55
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0.5	0.41
0.6	0.36
0.7	0.29
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11-point average: $\approx$ 0.425

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How can precision at 0.0 be > 0?

Averaged 11-point precision/recall graph

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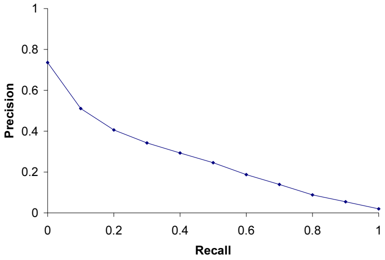

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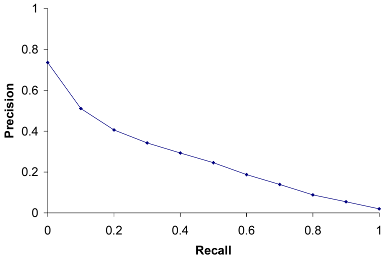

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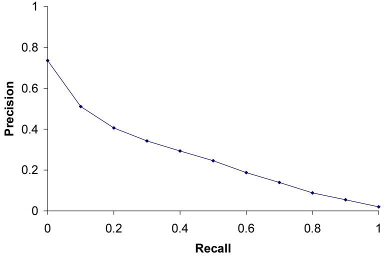

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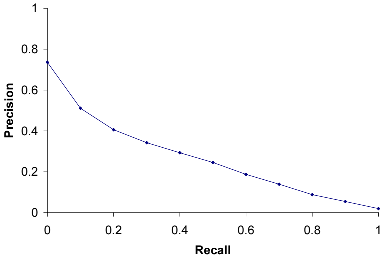

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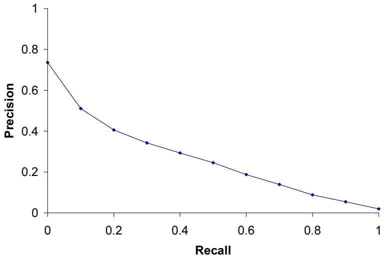

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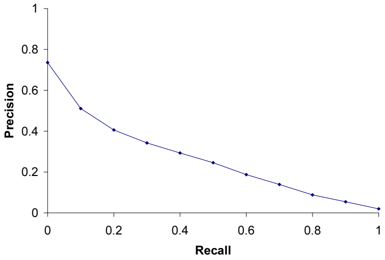

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- Note that performance is not very good!

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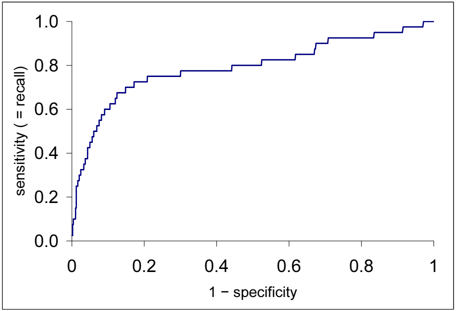

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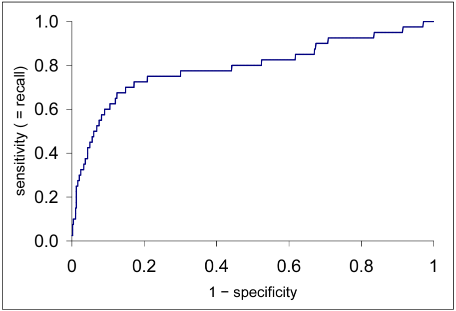

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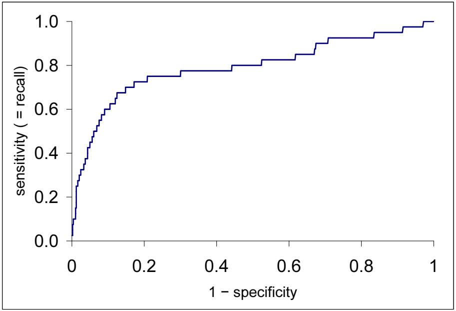

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- Precision-recall graph "blows up" this area.

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

Outline

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- 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.

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- With smaller values: need to redesign relevance assessment methodology used etc.

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		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)

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

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- Probably the evaluation methodology that large search engines trust most

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  - 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?

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- No need to actually view any document

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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.

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- Most sophisticated: complex NLP to synthesize/generate a summary
  - For most IR applications: not quite ready for prime time yet

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- 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
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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 ...
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Running on a **vegetarian diet** – Top tips | Freedom2Train Blog
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- Good example that snippet selection is non-trivial.

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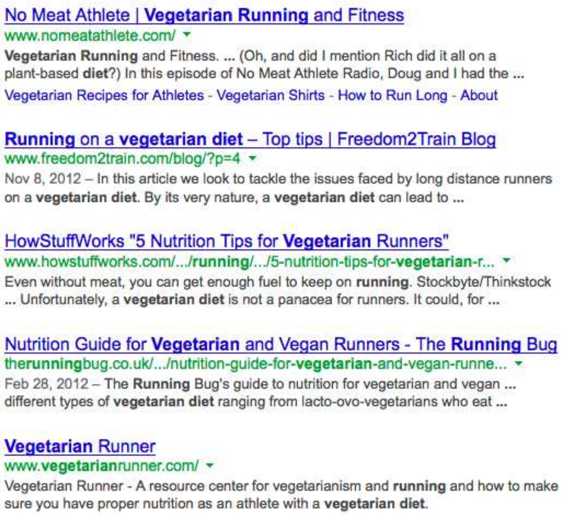
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- Good example that snippet selection is non-trivial.
- Criteria: occurrence of keywords, density of keywords, coherence of snippet, number of different snippets in summary, good cutting points etc

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- Don't cache very long documents – just cache a short prefix

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  - . . . 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