Introduction to Information Retrieval

http://informationretrieval.org

IIR 8: Evaluation & Result Summaries

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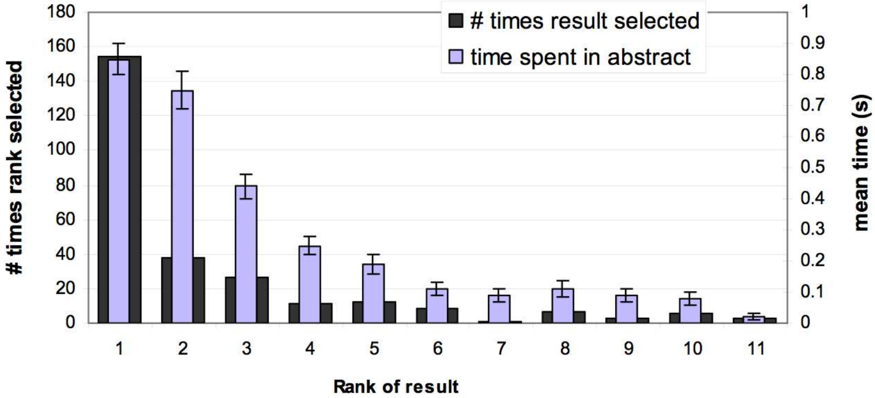
Overview

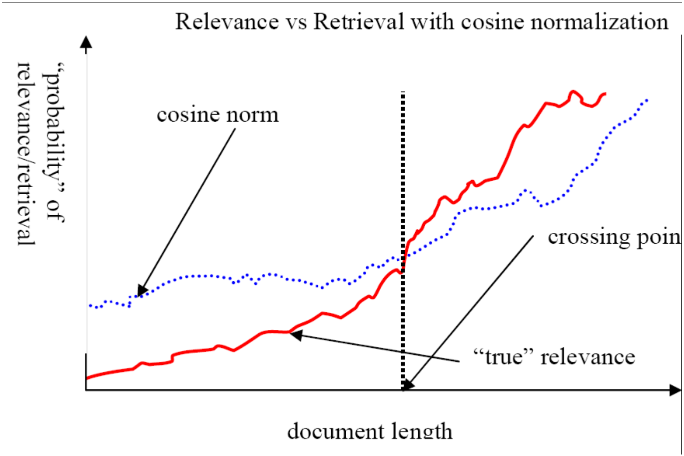
Outline

Looking vs. Clicking



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

Pivot normalization



source: Lillian Lee

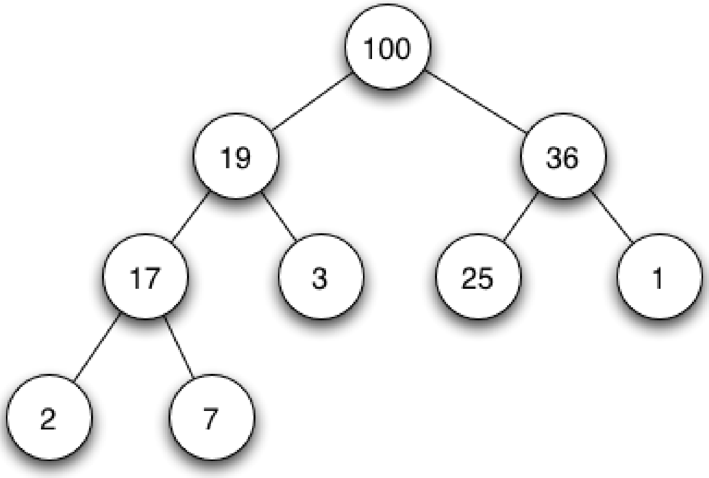
Now we also need term frequencies in the index

BRUTUS	⟶	1,2	7,3	83,1	87,2	...
CAESAR	⟶	1,1	5,1	13,1	17,1	...
CALPURNIA	⟶	7,1	8,2	40,1	97,3	

Use heap for selecting the top k in ranking

- A heap efficiently implements a priority queue.
- Takes $O(N)$ operations to construct (where N is the number of documents) ...
- ... then each of k winners can be read off in $O(k \log k)$ steps.
- Allows to rank in time linear in N (for small k and large N) – as opposed to $O(N \log N)$.

Binary max heap



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- What is the cost per query?
  - Given certain requirements, e.g., a 20-billion-page index

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- How can we quantify user happiness?

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- But has been very successful in IR.

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- 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

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Precision and recall

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

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

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- 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?

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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.
- Accuracy is not a good measure of user happiness, we'll use precision and recall instead.

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- For alternatives to using precision/recall and having to produce relevance judgments – see end of this lecture.

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- Suppose the document with the largest score is relevant. How can we maximize precision?

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- What value range of β do I choose for weighting recall higher than precision?

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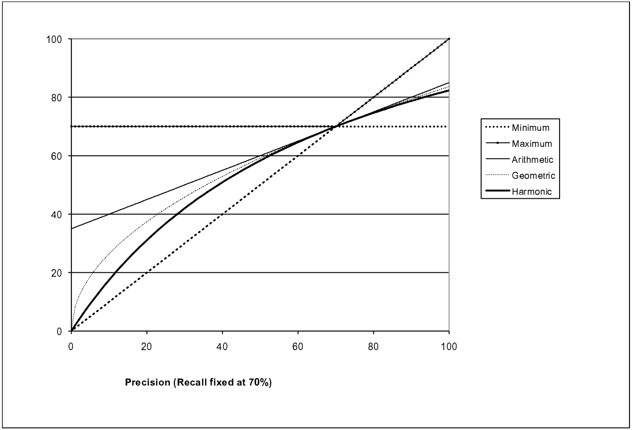
- F_1?

F_1 and other averages



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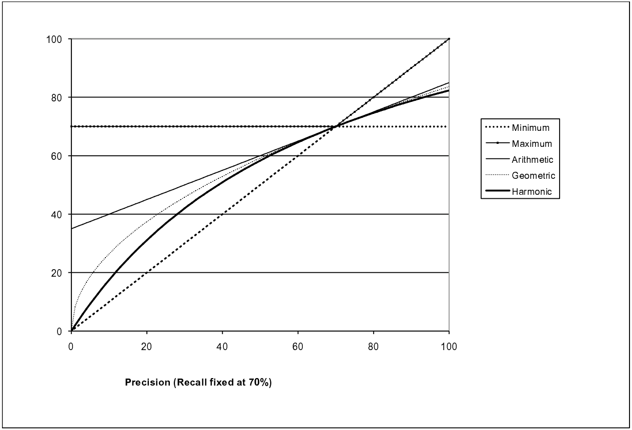

- We can view the harmonic mean as a kind of soft minimum

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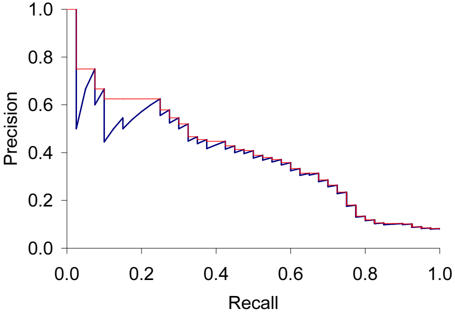
- We can easily turn set measures into measures of ranked lists.
- Just compute the set measure for each "prefix": the top 1, top 2, top 3, top 4 etc results
- Doing this for precision and recall gives you a precision-recall curve.

A precision-recall curve



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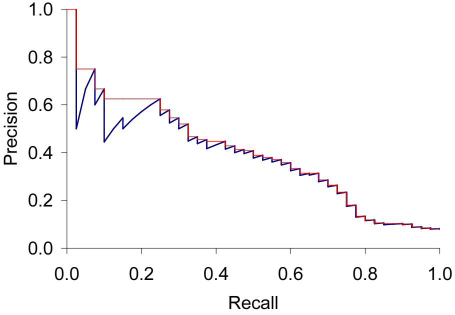

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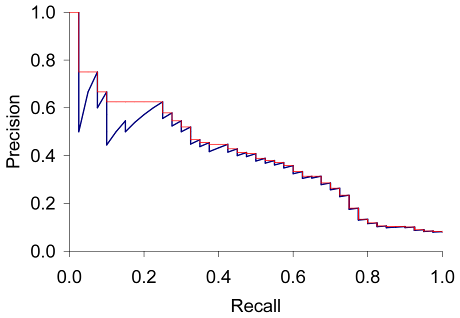

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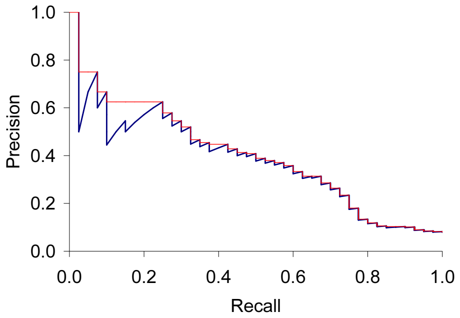
- Interpolation (in red): Take maximum of all future points

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.

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

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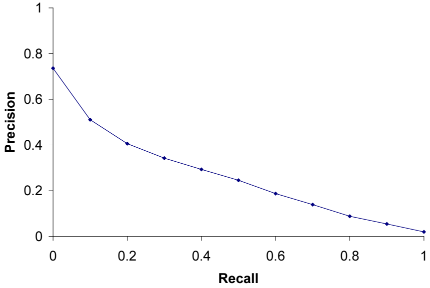
How can precision at 0.0 be > 0?

Averaged 11-point precision/recall graph



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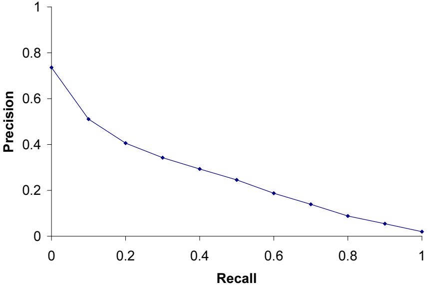

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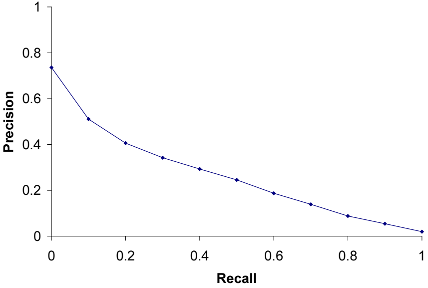

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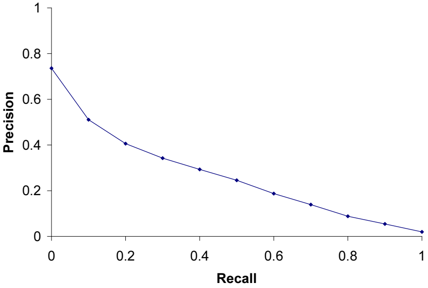

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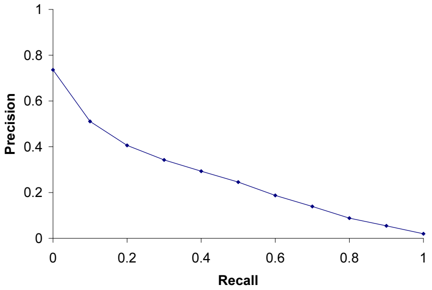

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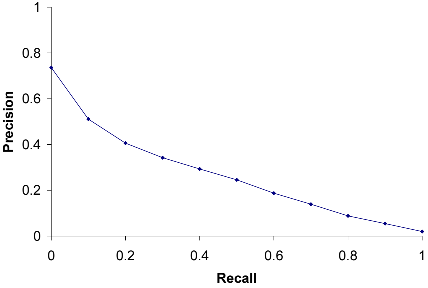

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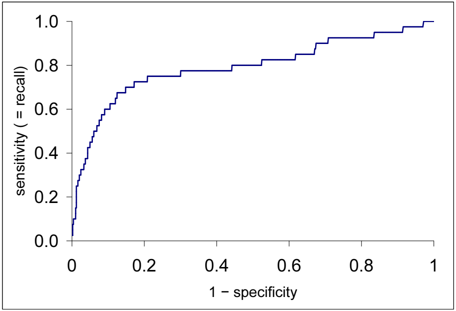
- This measure measures performance at all recall levels.
- The curve is typical of performance levels at TREC.

ROC curve


1.0
0.8
0.6
0.4
0.2
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sensitivity (= recall)
0
0.2
0.4
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0.8
1
1 − specificity

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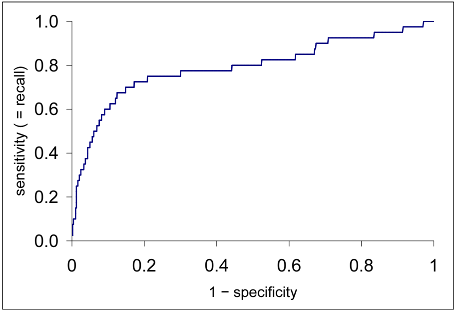

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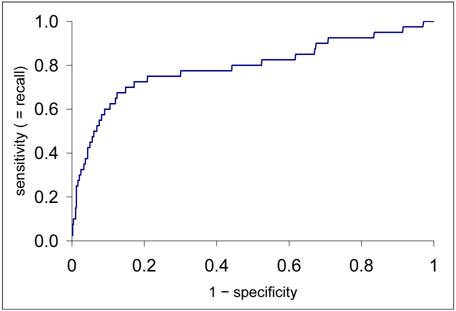

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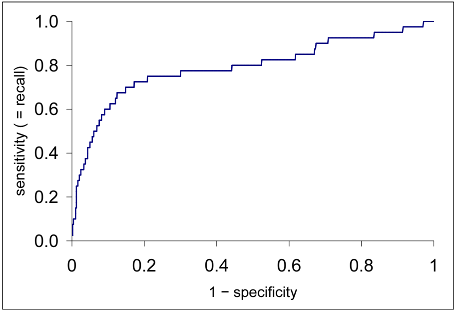

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- But we are only interested in the small area in the lower left corner.
- Precision-recall graph "blows up" this area.

Variance of measures like precision/recall

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

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- 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

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

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- Too small, too untypical for serious IR evaluation today

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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.

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

$P(E) = P(nonrelevant)^2 + P(relevant)^2 = 0.2125^2 + 0.7878^2 = 0.665$

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(still in acceptable range)

Interjudge agreement at TREC

information need	number of docs judged	disagreements	NR	R
51	211	6	4	2
62	400	157	149	8
67	400	68	37	31
95	400	110	108	2
127	400	106	12	94

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- An information retrieval experiment will give us a reliable answer to this question.

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- Variant: Give users the option to switch to new algorithm/interface

Outline

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- No need to "click" on all documents sequentially

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- A static summary of a document is always the same, regardless of the query that hit the document.
- Dynamic summaries are query-dependent. They attempt to explain why the document was retrieved for the query at hand.

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  - For most IR applications: not quite ready for prime time yet

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- 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 examples for dynamic summaries

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

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  - 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.

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- Google VP of Engineering on search quality evaluation at Google