Introduction to

Information Retrieval

Lecture 8: Evaluation

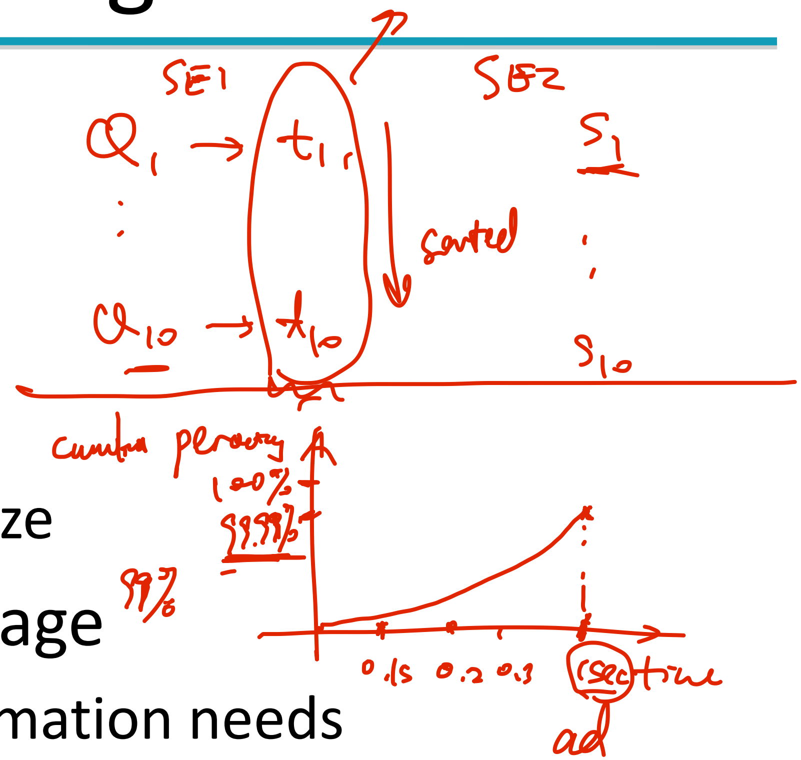
This lecture

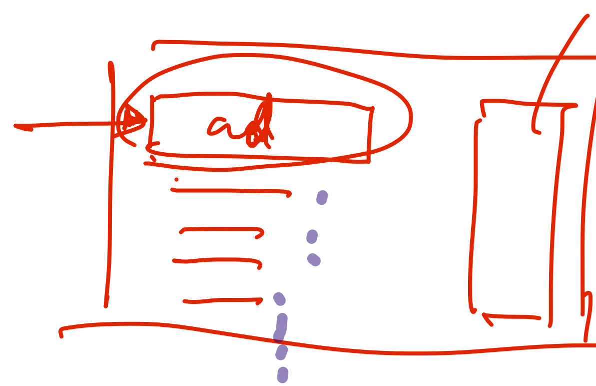
- How do we know if our results are any good?
  - Evaluating a search engine
    - Benchmarks
    - Precision and recall

EVALUATING SEARCH ENGINES

Measures for a search engine

- How fast does it index
  - Number of documents/hour
  - (Average document size)
- How fast does it search
  - Latency as a function of index size
- Expressiveness of query language
  - Ability to express complex information needs
  - Speed on complex queries
- Uncluttered UI
- Is it free?





Measures for a search engine

- All of the preceding criteria are *measurable*: we can quantify speed/size
  - we can make expressiveness precise
- The key measure: user happiness
  - What is this?
  - Speed of response/size of index are factors
  - But blindingly fast, useless answers won't make a user happy
- Need a way of quantifying user happiness

Measuring user happiness

- Issue: who is the user we are trying to make happy?
  - Depends on the setting
- Web engine:
  - User finds what they want and return to the engine
    - Can measure rate of return users
  - User completes their task – search as a means, not end
  - See Russell http://dmrussell.googlepages.com/JCDL-talk-June-2007-short.pdf
- eCommerce site: user finds what they want and buy
  - Is it the end-user, or the eCommerce site, whose happiness we measure?
  - Measure time to purchase, or fraction of searchers who become buyers?

Measuring user happiness

- Enterprise (company/govt/academic): Care about “user productivity”
  - How much time do my users save when looking for information?
  - Many other criteria having to do with breadth of access, secure access, etc.

Happiness: elusive to measure

- Most common proxy: *relevance* of search results
- But how do you measure relevance?
- We will detail a methodology here, then examine its issues
- Relevance measurement requires 3 elements:
  1. A benchmark document collection
  2. A benchmark suite of queries
  3. A usually binary assessment of either Relevant or Nonrelevant for each query and each document
     - Some work on more-than-binary, but not the standard

$(Q_i, D_j) \rightarrow R / NR$

4
3

5

1

assessors

Evaluating an IR system

- Note: the **information need** is translated into a **query**
- Relevance is assessed relative to the **information need** *not* the **query**
- E.g., Information need: *I'm looking for information on whether drinking red wine is more effective at reducing your risk of heart attacks than white wine.*
- Query: ***wine red white heart attack effective***
- You evaluate whether the doc addresses the information need, not whether it has these words

Standard relevance benchmarks

- TREC - National Institute of Standards and Technology (NIST) has run a large IR test bed for many years
- Reuters and other benchmark doc collections used
- "Retrieval tasks" specified
  - sometimes as queries
- Human experts mark, for each query and for each doc, Relevant or Nonrelevant
  - or at least for subset of docs that some system returned for that query

Unranked retrieval evaluation: Precision and Recall

- **Precision**: fraction of retrieved docs that are relevant = P(relevant|retrieved)
- **Recall**: fraction of relevant docs that are retrieved = P(retrieved|relevant)

	Relevant	Nonrelevant
Retrieved	tp	fp
Not Retrieved	fn	tn

- Precision P = tp/(tp + fp)
- Recall R = tp/(tp + fn)

Should we instead use the accuracy measure for evaluation?

- Given a query, an engine classifies each doc as “Relevant” or “Nonrelevant”
- The **accuracy** of an engine: the fraction of these classifications that are correct
  - (tp + tn) / (tp + fp + fn + tn)
- **Accuracy** is a commonly used evaluation measure in machine learning classification work
- Why is this not a very useful evaluation measure in IR?

Why not just use accuracy?

- How to build a 99.9999% accurate search engine on a low budget….

- People doing information retrieval *want to find something* and have a certain tolerance for junk.

Precision/Recall

- You can get high recall (but low precision) by retrieving all docs for all queries!
- Recall is a non-decreasing function of the number of docs retrieved

- In a good system, precision decreases as either the number of docs retrieved or recall increases
  - This is not a theorem, but a result with strong empirical confirmation

Difficulties in using precision/recall

- Should average over large document collection/query ensembles
- Need human relevance assessments
  - People aren't reliable assessors
- Assessments have to be binary
  - Nuanced assessments?
- Heavily skewed by collection/authorship
  - Results may not translate from one domain to another

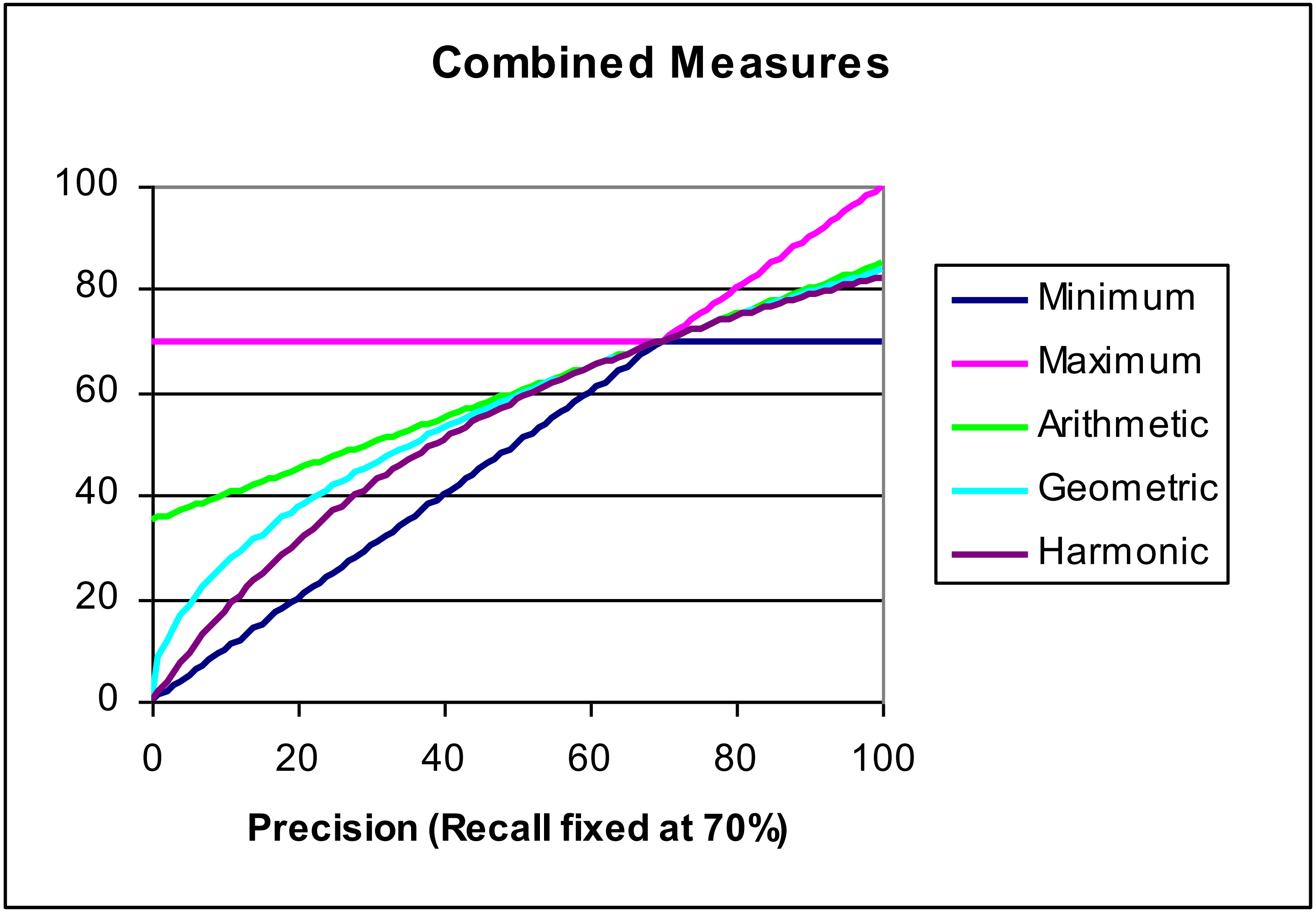
A combined measure: *F*

- Combined measure that assesses precision/recall tradeoff is **F measure** (weighted harmonic mean):

$$F = \frac{1}{\alpha \frac{1}{P} + (1-\alpha)\frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

- People usually use balanced F_1 measure
  - i.e., with $\beta = 1$ or $\alpha = ½$
- Harmonic mean is a conservative average
  - See CJ van Rijsbergen, *Information Retrieval*

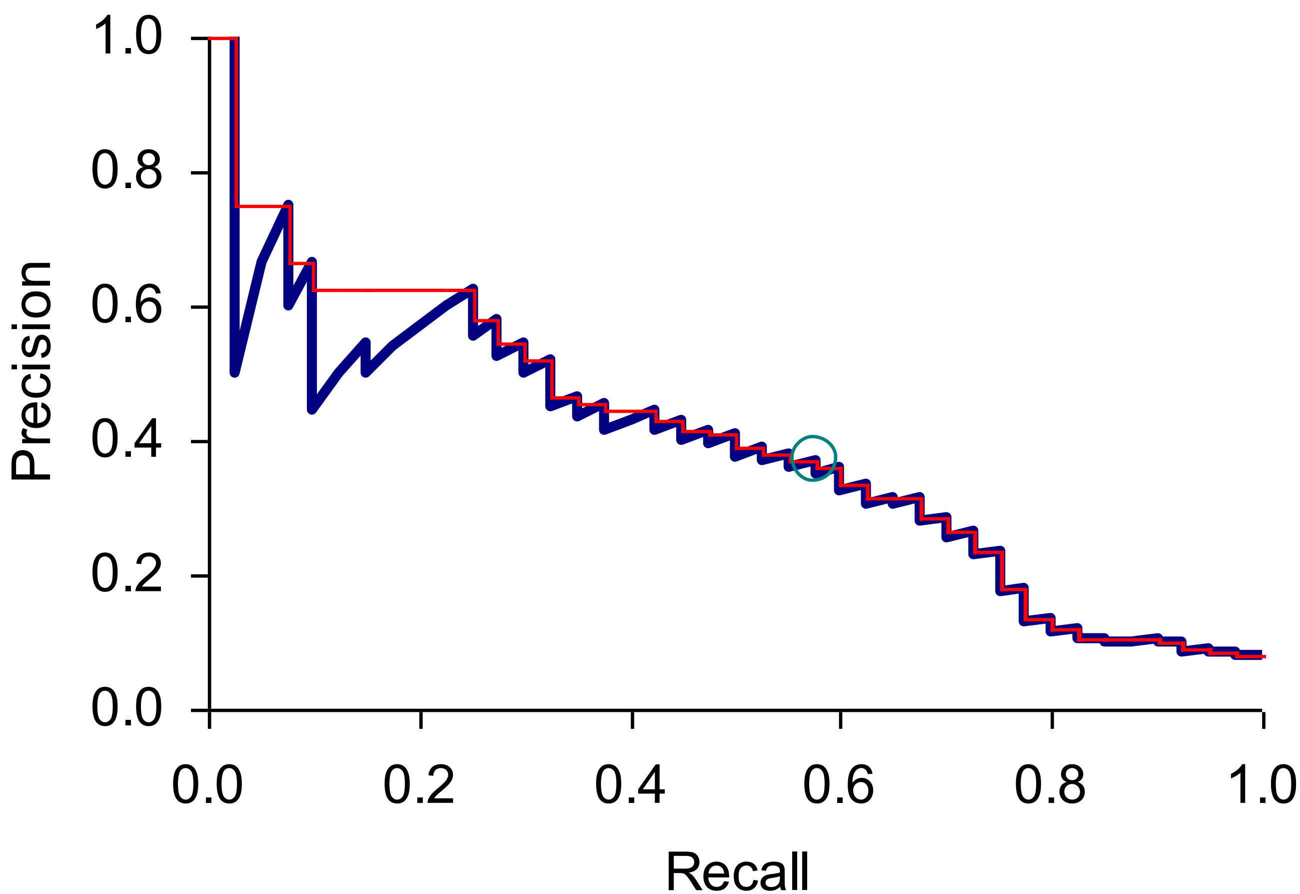
F_1 and other averages



Evaluating ranked results

- Evaluation of ranked results:
  - The system can return any number of results
  - By taking various numbers of the top returned documents (levels of recall), the evaluator can produce a *precision-recall curve*

A precision-recall curve

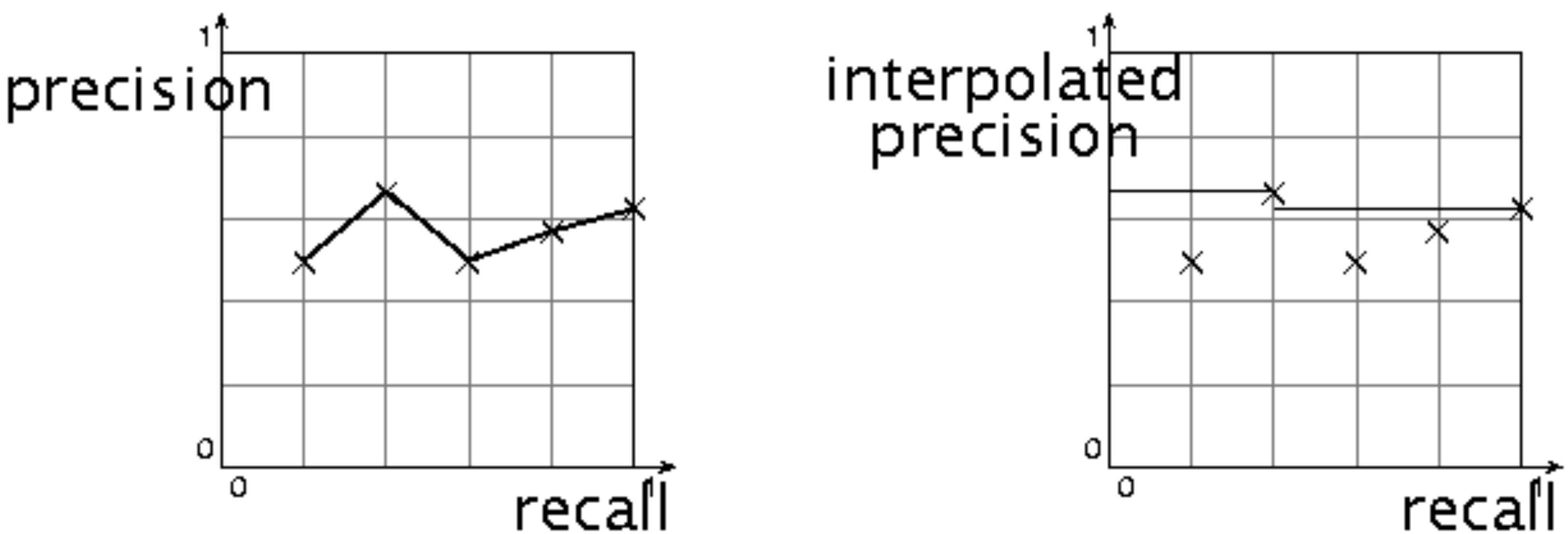


Averaging over queries

- A precision-recall graph for one query isn't a very sensible thing to look at
- You need to average performance over a whole bunch of queries.
- But there's a technical issue:
  - Precision-recall calculations place some points on the graph
  - How do you determine a value (interpolate) between the points?

Interpolated precision

- Idea: If locally precision increases with increasing recall, then you should get to count that…
- So you max of precisions to right of value

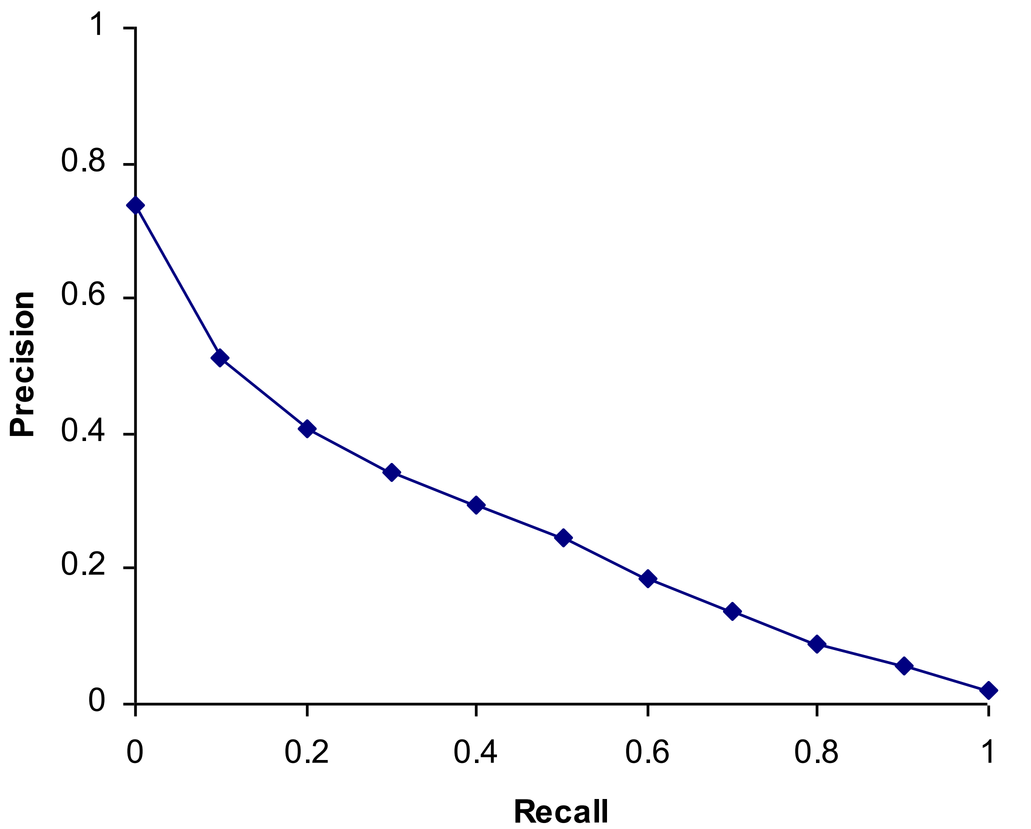


Evaluation

- Graphs are good, but people want summary measures!
  - Precision at fixed retrieval level
    - Precision-at-*k*: Precision of top *k* results
    - Perhaps appropriate for most of web search: all people want are good matches on the first one or two results pages
    - But: averages badly and has an arbitrary parameter of *k*
  - 11-point interpolated average precision
    - The standard measure in the early TREC competitions: you take the precision at 11 levels of recall varying from 0 to 1 by tenths of the documents, using interpolation (the value for 0 is always interpolated!), and average them
    - Evaluates performance at all recall levels

Typical (good) 11 point precisions

- SabIR/Cornell 8A1 11pt precision from TREC 8 (1999)



Yet more evaluation measures…

- Mean average precision (MAP)
  - Average of the precision value obtained for the top *k* documents, each time a relevant doc is retrieved
  - Avoids interpolation, use of fixed recall levels
  - MAP for query collection is arithmetic ave.
    - Macro-averaging: each query counts equally
- R-precision
  - If have known (though perhaps incomplete) set of relevant documents of size *Rel,* then calculate precision of top *Rel* docs returned
  - Perfect system could score 1.0.

Variance

- For a test collection, it is usual that a system does crummily on some information needs (e.g., MAP = 0.1) and excellently on others (e.g., MAP = 0.7)
- Indeed, it is usually the case that the variance in performance 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!

CREATING TEST COLLECTIONS FOR IR EVALUATION

Test Collections

TABLE 4.3 Common Test Corpora

Collection	*NDocs*	*NQrys*	*Size (MB)*	*Term/Doc*	*Q-D RelAss*
ADI	82	35			
AIT	2109	14	2	400	>10,000
CACM	3204	64	2	24.5	
CISI	1460	112	2	46.5	
Cranfield	1400	225	2	53.1	
LISA	5872	35	3		
Medline	1033	30	1		
NPL	11,429	93	3		
OSHMED	34,8566	106	400	250	16,140
Reuters	21,578	672	28	131	
TREC	740,000	200	2000	89-3543	» 100,000

From document collections to test collections

- Still need
  - Test queries
  - Relevance assessments
- Test queries
  - Must be germane to docs available
  - Best designed by domain experts
  - Random query terms generally not a good idea
- Relevance assessments
  - Human judges, time-consuming
  - Are human panels perfect?

Unit of Evaluation

- We can compute precision, recall, F, and ROC curve for different units.
- Possible units
  - Documents (most common)
  - Facts (used in some TREC evaluations)
  - Entities (e.g., car companies)
- May produce different results. Why?

Kappa measure for inter-judge (dis)agreement

- Kappa measure
  - Agreement measure among judges
  - Designed for categorical judgments
  - Corrects for chance agreement
- Kappa = [P(A) – P(E)] / [1 – P(E)]
- P(A) – proportion of time judges agree
- P(E) – what agreement would be by chance
- Kappa = 0 for chance agreement, 1 for total agreement.

Kappa Measure: Example

P(A)? P(E)?

	Judge 2: Relevant	Judge 2: Nonrelevant
Judge 1: Relevant	**300**	**20**
Judge 1: Nonrelevant	**10**	**70**

Total assessment:400

- P(A) = 370/400 = 0.9250
- P(nonrelevant) = (10+20+70+70)/800 = 0.2125
- P(relevant) = (10+20+300+300)/800 = 0.7875
- P(E) = 0.2125^2 + 0.7875^2 = 0.6653
- Kappa = (0.9250 – 0.6653)/(1-0.6653) = 0.7759

Using pooled marginals

Kappa Example

- P(A) = 370/400 = 0.9250
- P(nonrelevant) = (10+20+70+70)/800 = 0.2125
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- Kappa > 0.8 = good agreement
- 0.67 < Kappa < 0.8 -> “tentative conclusions” (Carletta ’96)
- Depends on purpose of study
- For >2 judges: average pairwise kappas

TREC

- TREC Ad Hoc task from first 8 TRECs is standard IR task
  - 50 detailed information needs a year
  - Human evaluation of pooled results returned
  - More recently other related things: Web track, HARD
- A TREC query (TREC 5)

  <top>

  <num> Number: 225

  <desc> Description:

  What is the main function of the Federal Emergency Management Agency (FEMA) and the funding level provided to meet emergencies? Also, what resources are available to FEMA such as people, equipment, facilities?

  </top>

Standard relevance benchmarks: Others

- GOV2
  - Another TREC/NIST collection
  - 25 million web pages
  - 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

Interjudge Agreement: TREC 3

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

Impact of Inter-judge Agreement

- Impact on absolute performance measure can be significant (0.32 vs 0.39)
- Little impact on ranking of different systems or relative performance
- Suppose we want to know if algorithm A is better than algorithm B
- A standard information retrieval experiment will give us a reliable answer to this question.

Critique of pure relevance

- Relevance vs Marginal Relevance
  - A document can be redundant even if it is highly relevant
  - Duplicates
  - The same information from different sources
  - Marginal relevance is a better measure of utility for the user.
- Using facts/entities as evaluation units more directly measures true relevance.
- But harder to create evaluation set

$$MMR \stackrel{\text{def}}{=} \operatorname{Arg} \max_{D_i \in R \setminus S} \left[\lambda (Sim_1(D_i, Q) - (1-\lambda) \max_{D_j \in S} Sim_2(D_i, D_j)) \right]$$

Can we avoid human judgment?

- No
- Makes experimental work hard
  - Especially on a large scale
- In some very specific settings, can use proxies
  - E.g.: for approximate vector space retrieval, we can compare the cosine distance closeness of the closest docs to those found by an approximate retrieval algorithm
- But once we have test collections, we can reuse them (so long as we don't overtrain too badly)

Evaluation at large search engines

- Search engines have test collections of queries and hand-ranked results
- Recall is difficult to measure on the web
- Search engines often use precision at top k, e.g., k = 10
- . . . or measures that reward you more for getting rank 1 right than for getting rank 10 right.
  - **NDCG** (Normalized Cumulative Discounted Gain)
- Search engines also use non-relevance-based measures.
  - Clickthrough on first result
    - Not very reliable if you look at a single clickthrough … but pretty reliable in the aggregate.
  - Studies of user behavior in the lab
  - 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
- In principle less powerful than doing a multivariate regression analysis, but easier to understand

RESULTS PRESENTATION

Result Summaries

- Having ranked the documents matching a query, we wish to present a results list
- Most commonly, a list of the document titles plus a short summary, aka “10 blue links”

John McCain
John McCain 2008 - The Official Website of **John McCain**'s 2008 Campaign for President ... African American Coalition; Americans of Faith; American Indians for **McCain**; Americans with ...
www.**johnmccain**.com · Cached page

JohnMcCain.com - **McCain**-Palin 2008
John McCain 2008 - The Official Website of **John McCain**'s 2008 Campaign for President ... African American Coalition; Americans of Faith; American Indians for **McCain**; Americans with ...
www.**johnmccain**.com/Informing/Issues · Cached page

John McCain News- msnbc.com
Complete political coverage of **John McCain**. ... Republican leaders said Saturday that they were worried that Sen. **John McCain** was heading for defeat unless he brought stability to ...
www.msnbc.msn.com/id/16438320 · Cached page

John McCain | Facebook
Welcome to the official Facebook Page of **John McCain**. Get exclusive content and interact with **John McCain** right from Facebook. Join Facebook to create your own Page or to start ...
www.facebook.com/**johnmccain** · Cached page

Resources for this lecture

- IIR 8
- MIR Chapter 3
- MG 4.5
- Carbonell and Goldstein 1998. The use of MMR, diversity-based reranking for reordering documents and producing summaries. SIGIR 21.