Introduction to

Information Retrieval

CS276

Information Retrieval and Web Search

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Lecture 8: Evaluation

This lecture

- How do we know if our results are any good?
  - Evaluating a search engine
    - Benchmarks
    - Precision and recall
- Results summaries:
  - Making our good results usable to a user

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

How do you tell if users are happy?

- Search returns products relevant to users
  - How do you assess this at scale?
- Search results get clicked a lot
  - Misleading titles/summaries can cause users to click
- Users buy after using the search engine
  - Or, users spend a lot of $ after using the search engine
- Repeat visitors/buyers
  - Do users leave soon after searching?
  - Do they come back within a week/month/… ?

Measuring user happiness

- Issue: who is the user we are trying to make happy?
  - Depends on the setting
- Web engine:
  - User finds what s/he wants and returns to the engine
    - Can measure rate of return users
  - User completes task – search as a means, not end
  - See Russell http://dmrussell.googlepages.com/JCDL-talk-June-2007-short.pdf
- eCommerce site: user finds what s/he wants and buys
  - 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

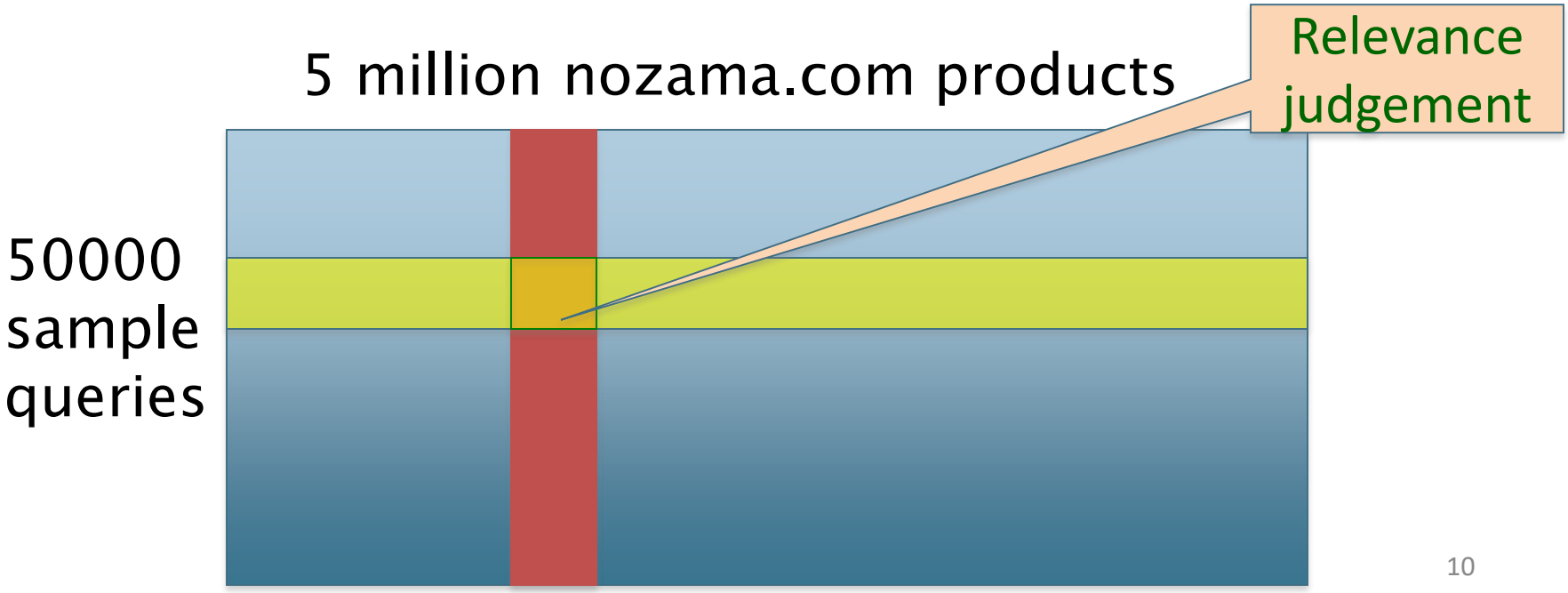
- Enterprise (company/govt/academic): Care about "user productivity"
  - How much time do my users save when looking for information?
  - Many other criteria having to do with breadth of access, secure access, etc.

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

So you want to measure the quality of a new search algorithm

- Benchmark documents – nozama's products
- Benchmark query suite – more on this
- Judgments of document relevance for each query



Relevance judgments

- Binary (relevant vs. non-relevant) in the simplest case, more nuanced (0, 1, 2, 3 …) in others
- What are some issues already?
- 5 million times 50K takes us into the range of a quarter trillion judgments
  - If each judgment took a human 2.5 seconds, we'd still need 10^{11} seconds, or nearly $300 million if you pay people $10 per hour to assess
  - 10K new products per day

Crowd source relevance judgments?

- Present query-document pairs to low-cost labor on online crowd-sourcing platforms
  - Hope that this is cheaper than hiring qualified assessors
- Lots of literature on using crowd-sourcing for such tasks
- Main takeaway – you get some signal, but the variance in the resulting judgments is very high

What else?

- Still need test queries
  - Must be germane to docs available
  - Must be representative of actual user needs
  - Random query terms from the documents generally not a good idea
  - Sample from query logs if available
- Classically (non-Web)
  - Low query rates – not enough query logs
  - Experts hand-craft “user needs”

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***
- 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

Some public 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

Typical TREC

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

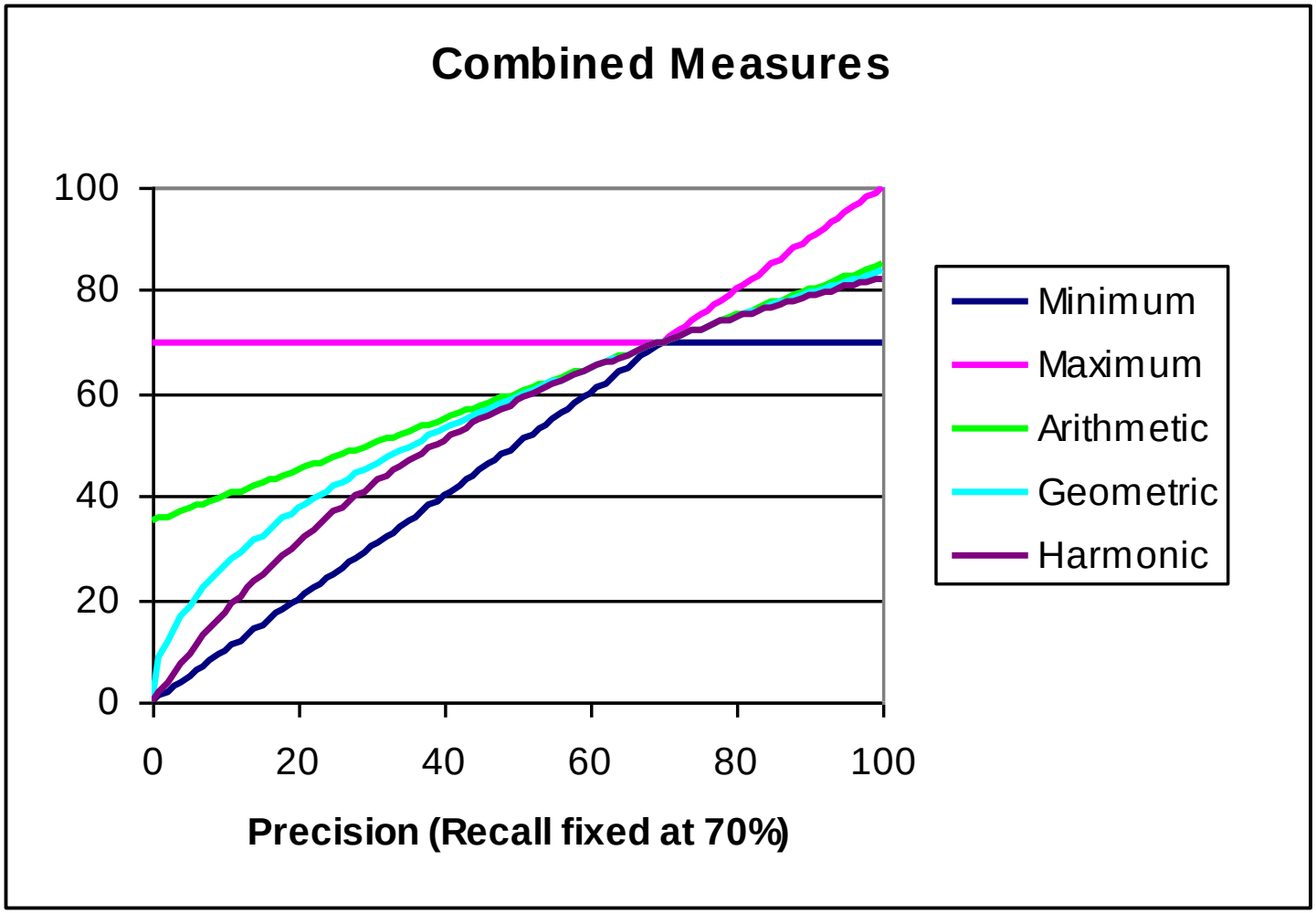
A combined measure: *F*

- 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*

Rank-Based Measures

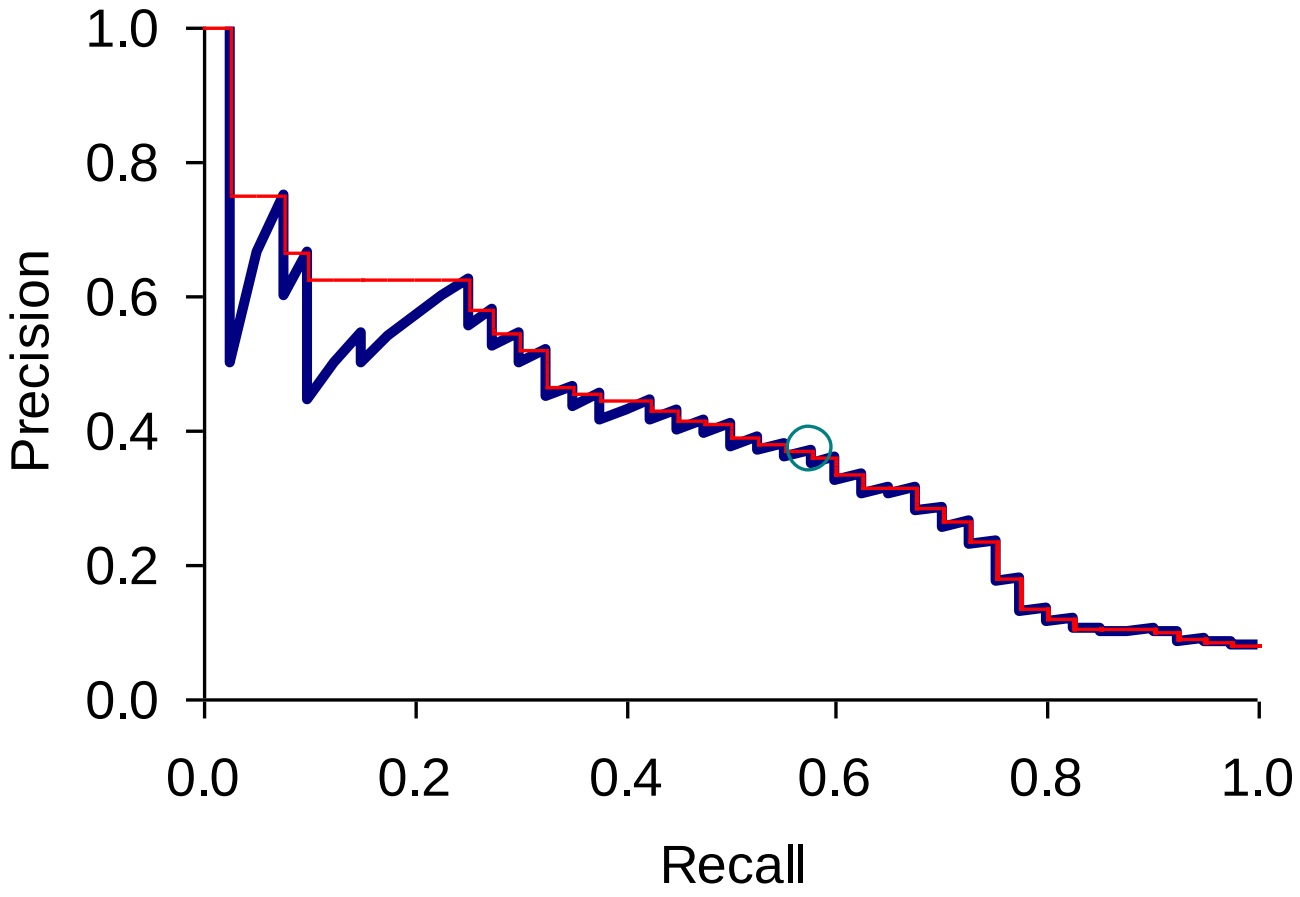
- Binary relevance
  - Precision@K (P@K)
  - Mean Average Precision (MAP)
  - Mean Reciprocal Rank (MRR)
- Multiple levels of relevance
  - Normalized Discounted Cumulative Gain (NDCG)

Precision@K

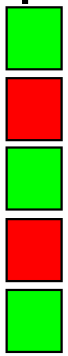
- Set a rank threshold K
- Compute % relevant in top K
- Ignores documents ranked lower than K
- Ex:
  - Prec@3 of 2/3
  - Prec@4 of 2/4
  - Prec@5 of 3/5

- In similar fashion we have Recall@K

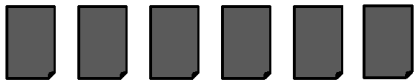
A precision-recall curve



Mean Average Precision

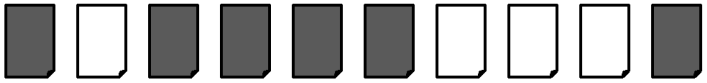
- Consider rank position of each ***relevant*** doc
  - K_1, K_2, … K_R
- Compute Precision@K for each K_1, K_2, … K_R
- Average precision = average of P@K
- Ex:  has AvgPrec of $\frac{1}{3}\cdot\left(\frac{1}{1}+\frac{2}{3}+\frac{3}{5}\right)\approx 0.76$
- MAP is Average Precision across multiple queries/rankings

Average Precision



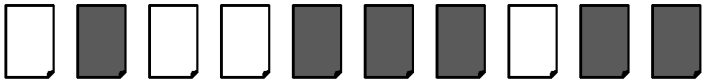
= the relevant documents

Ranking #1



Recall	0.17	0.17	0.33	0.5	0.67	0.83	0.83	0.83	0.83	1.0
Precision	1.0	0.5	0.67	0.75	0.8	0.83	0.71	0.63	0.56	0.6

Ranking #2



Recall	0.0	0.17	0.17	0.17	0.33	0.5	0.67	0.67	0.83	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.5	0.56	0.6

$$\text{Ranking \#1: } (1.0 + 0.67 + 0.75 + 0.8 + 0.83 + 0.6)/6 = 0.78$$

$$\text{Ranking \#2: } (0.5 + 0.4 + 0.5 + 0.57 + 0.56 + 0.6)/6 = 0.52$$

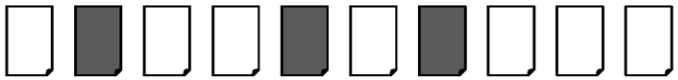
MAP

= relevant documents for query 1

Ranking #1

Recall	0.2	0.2	0.4	0.4	0.4	0.6	0.6	0.6	0.8	1.0
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

= relevant documents for query 2

Ranking #2 

Recall	0.0	0.33	0.33	0.33	0.67	0.67	1.0	1.0	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.33	0.43	0.38	0.33	0.3

$$average\ precision\ query\ 1 = (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$$
$$average\ precision\ query\ 2 = (0.5 + 0.4 + 0.43)/3 = 0.44$$

$$mean\ average\ precision = (0.62 + 0.44)/2 = 0.53$$

Mean average precision

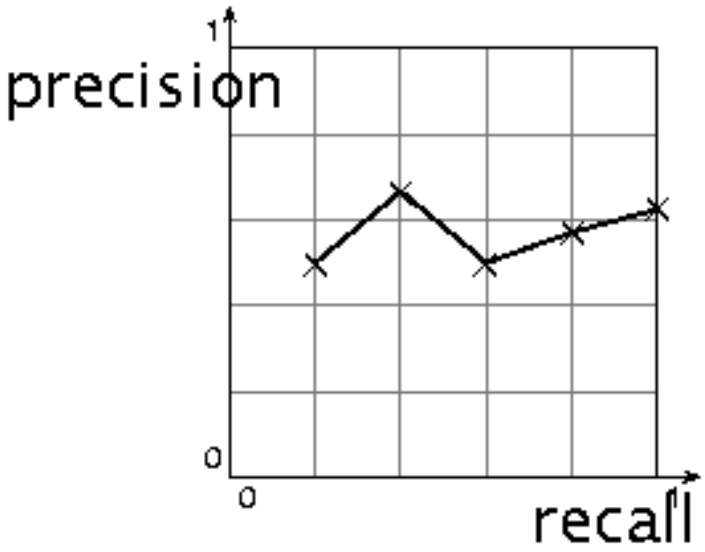
- If a relevant document never gets retrieved, we assume the precision corresponding to that relevant doc to be zero
- MAP is macro-averaging: each query counts equally
- Now perhaps most commonly used measure in research papers
- Good for web search?
- MAP assumes user is interested in finding many relevant documents for each query
- MAP requires many relevance judgments in text collection

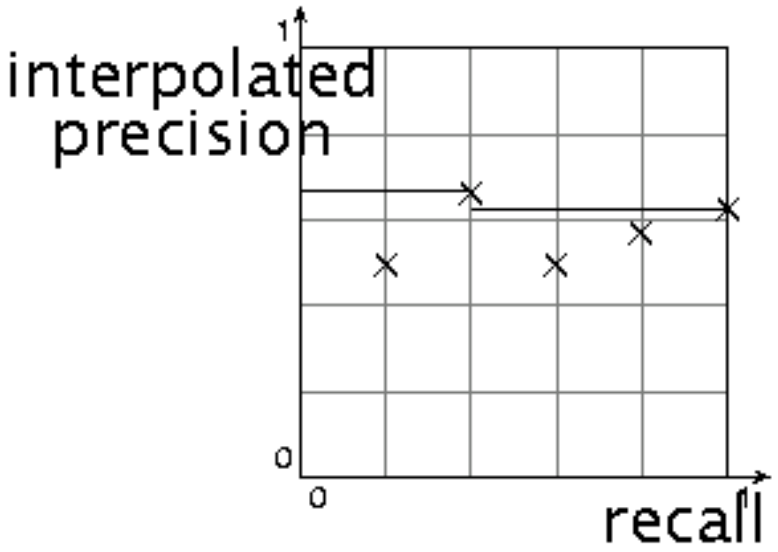
Averaging over queries

- 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 take the max of precisions to right of value



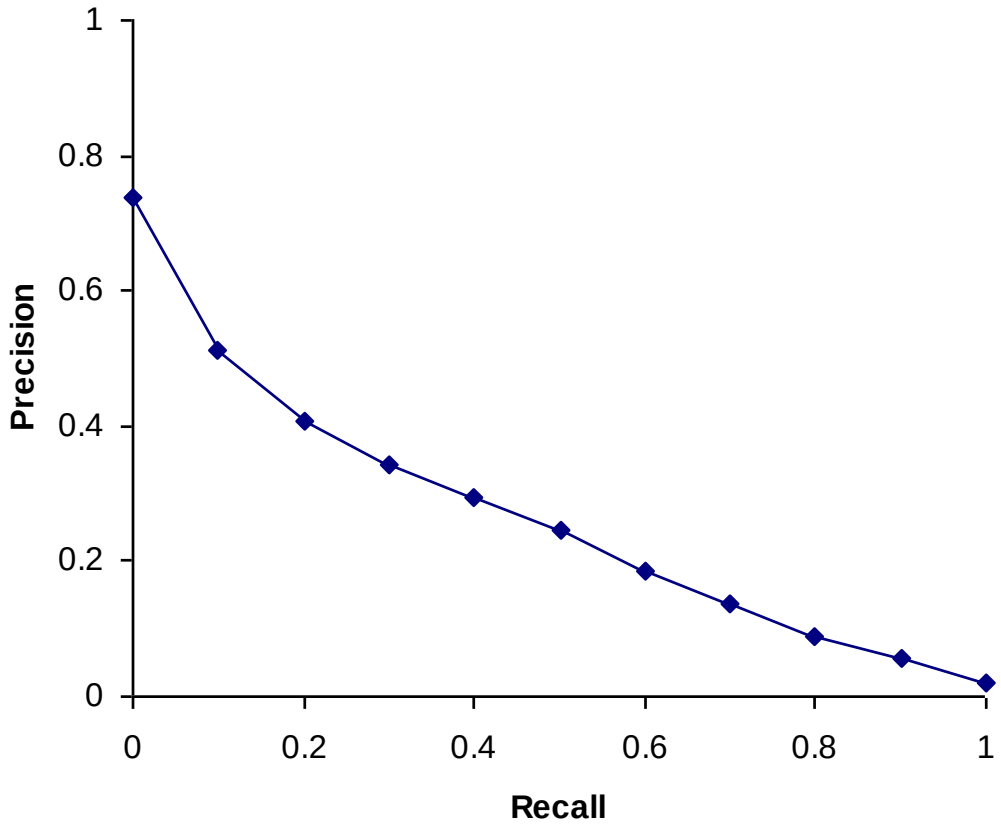


Evaluation

- 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

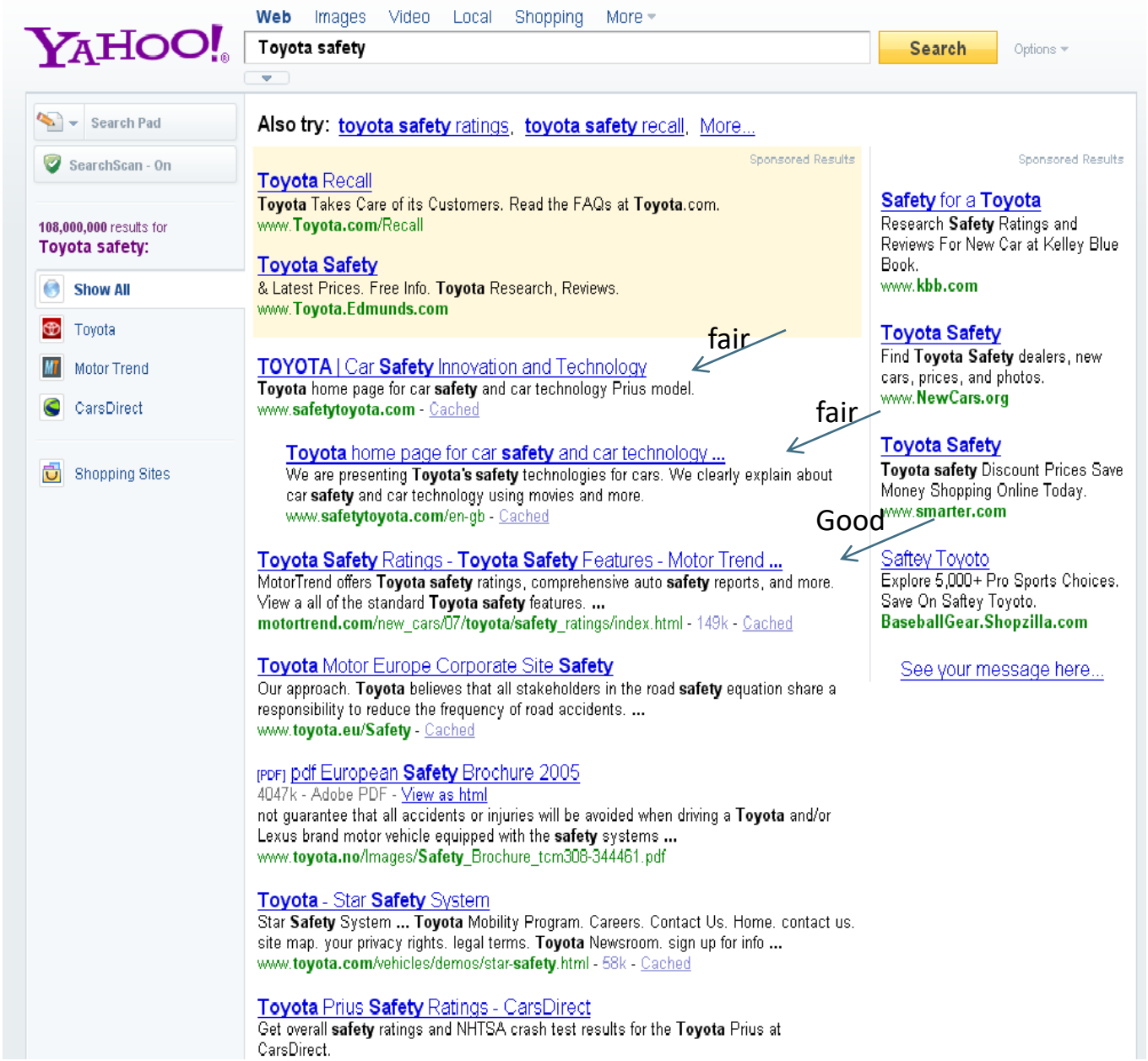
- SabIR/Cornell 8A1 11pt precision from TREC 8 (1999)



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 we have a known (though perhaps incomplete) set of relevant documents of size *Rel,* then calculate precision of the top *Rel* docs returned
  - Perfect system could score 1.0.

BEYOND BINARY RELEVANCE


YAHOO!
Web Images Video Local Shopping More
Toyota safety
Search
Options
Search Pad
SearchScan - On
108,000,000 results for
Toyota safety:
Show All
Toyota
Motor Trend
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Shopping Sites
Also try: toyota safety ratings, toyota safety recall, More...
Sponsored Results
Toyota Recall
Toyota Takes Care of its Customers. Read the FAQs at Toyota.com.
www.Toyota.com/Recall
Toyota Safety
& Latest Prices. Free Info. Toyota Research, Reviews.
www.Toyota.Edmunds.com
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TOYOTA | Car Safety Innovation and Technology
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www.safetytoyota.com - Cached
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Toyota home page for car safety and car technology ...
We are presenting Toyota's safety technologies for cars. We clearly explain about car safety and car technology using movies and more.
www.safetytoyota.com/en-gb - Cached
Good
Toyota Safety Ratings - Toyota Safety Features - Motor Trend ...
MotorTrend offers Toyota safety ratings, comprehensive auto safety reports, and more. View a all of the standard Toyota safety features. ...
motortrend.com/new_cars/07/toyota/safety_ratings/index.html - 149k - Cached
Toyota Motor Europe Corporate Site Safety
Our approach. Toyota believes that all stakeholders in the road safety equation share a responsibility to reduce the frequency of road accidents. ...
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not guarantee that all accidents or injuries will be avoided when driving a Toyota and/or Lexus brand motor vehicle equipped with the safety systems ...
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Star Safety System ... Toyota Mobility Program. Careers. Contact Us. Home. contact us. site map. your privacy rights. legal terms. Toyota Newsroom. sign up for info ...
www.toyota.com/vehicles/demos/star-safety.html - 58k - Cached
Toyota Prius Safety Ratings - CarsDirect
Get overall safety ratings and NHTSA crash test results for the Toyota Prius at CarsDirect.
Sponsored Results
Safety for a Toyota
Research Safety Ratings and Reviews For New Car at Kelley Blue Book.
www.kbb.com
Toyota Safety
Find Toyota Safety dealers, new cars, prices, and photos.
www.NewCars.org
Toyota Safety
Toyota safety Discount Prices Save Money Shopping Online Today.
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Saftey Toyoto
Explore 5,000+ Pro Sports Choices. Save On Saftey Toyoto.
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Discounted Cumulative Gain

- Popular measure for evaluating web search and related tasks

- Two assumptions:
  - Highly relevant documents are more useful than marginally relevant documents
  - the lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Discounted Cumulative Gain

- Uses *graded relevance* as a measure of usefulness, or *gain,* from examining a document
- Gain is accumulated starting at the top of the ranking and may be reduced, or *discounted*, at lower ranks
- Typical discount is 1/log *(rank)*
  - With base 2, the discount at rank 4 is 1/2, and at rank 8 it is 1/3

Summarize a Ranking: DCG

- What if relevance judgments are in a scale of [0,r]? r>2
- Cumulative Gain (CG) at rank n
  - Let the ratings of the n documents be r_1, r_2, …r_n (in ranked order)
  - CG = r_1+r_2+…r_n
- Discounted Cumulative Gain (DCG) at rank n
  - DCG = $r_1 + r_2/\log_2 2 + r_3/\log_2 3 + \ldots r_n/\log_2 n$
    - We may use any base for the logarithm

Discounted Cumulative Gain

- *DCG* is the total gain accumulated at a particular rank *p*:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}$$

- Alternative formulation:

$$DCG_p = \sum_{i=1}^{p} \frac{2^{rel_i} - 1}{log(1+i)}$$

  - used by some web search companies
  - emphasis on retrieving highly relevant documents

DCG Example

- 10 ranked documents judged on 0-3 relevance scale:

  3, 2, 3, 0, 0, 1, 2, 2, 3, 0

- discounted gain:

  3, 2/1, 3/1.59, 0, 0, 1/2.59, 2/2.81, 2/3, 3/3.17, 0

  = 3, 2, 1.89, 0, 0, 0.39, 0.71, 0.67, 0.95, 0

- DCG:

  3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61

Summarize a Ranking: NDCG

- Normalized Discounted Cumulative Gain (NDCG) at rank *n*
  - Normalize DCG at rank *n* by the DCG value at rank *n* of the ideal ranking
  - The ideal ranking would first return the documents with the highest relevance level, then the next highest relevance level, etc
- Normalization useful for contrasting queries with varying numbers of relevant results
- NDCG is now quite popular in evaluating Web search

NDCG - Example

4 documents: d_1, d_2, d_3, d_4

i	Ground Truth		Ranking Function$_1$		Ranking Function$_2$	
	Document Order	r_i	Document Order	r_i	Document Order	r_i
1	d4	2	d3	2	d3	2
2	d3	2	d4	2	d2	1
3	d2	1	d2	1	d4	2
4	d1	0	d1	0	d1	0
	$NDCG_{GT}$=1.00		$NDCG_{RF1}$=1.00		$NDCG_{RF2}$=0.9203	

$$DCG_{GT} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.6309$$

$$DCG_{RF1} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.6309$$

$$DCG_{RF2} = 2 + \left(\frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.2619$$

$$MaxDCG = DCG_{GT} = 4.6309$$

What if the results are not in a list?

- Suppose there's only one Relevant Document
- Scenarios:
  - known-item search
  - navigational queries
  - looking for a fact
- Search duration ~ Rank of the answer
  - measures a user's effort

Mean Reciprocal Rank

- Consider rank position, K, of first relevant doc
  - Could be – only clicked doc
- Reciprocal Rank score = $\frac{1}{K}$
- MRR is the mean RR across multiple queries

Human judgments are

- Expensive
- Inconsistent
  - Between raters
  - Over time
- Decay in value as documents/query mix evolves
- Not always representative of "real users"
  - Rating vis-à-vis query, vs underlying need
- So – what alternatives do we have?

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

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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?

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.

P(A)? P(E)?

Kappa Measure: Example

Number of docs	Judge 1	Judge 2
300	Relevant	Relevant
70	Nonrelevant	Nonrelevant
20	Relevant	Nonrelevant
10	Nonrelevant	Relevant

Kappa Example

- P(A) = 370/400 = 0.925
- P(nonrelevant) = (10+20+70+70)/800 = 0.2125
- P(relevant) = (10+20+300+300)/800 = 0.7878
- P(E) = 0.2125^2 + 0.7878^2 = 0.665
- Kappa = (0.925 – 0.665)/(1-0.665) = 0.776

- 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

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
- See Carbonell reference

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

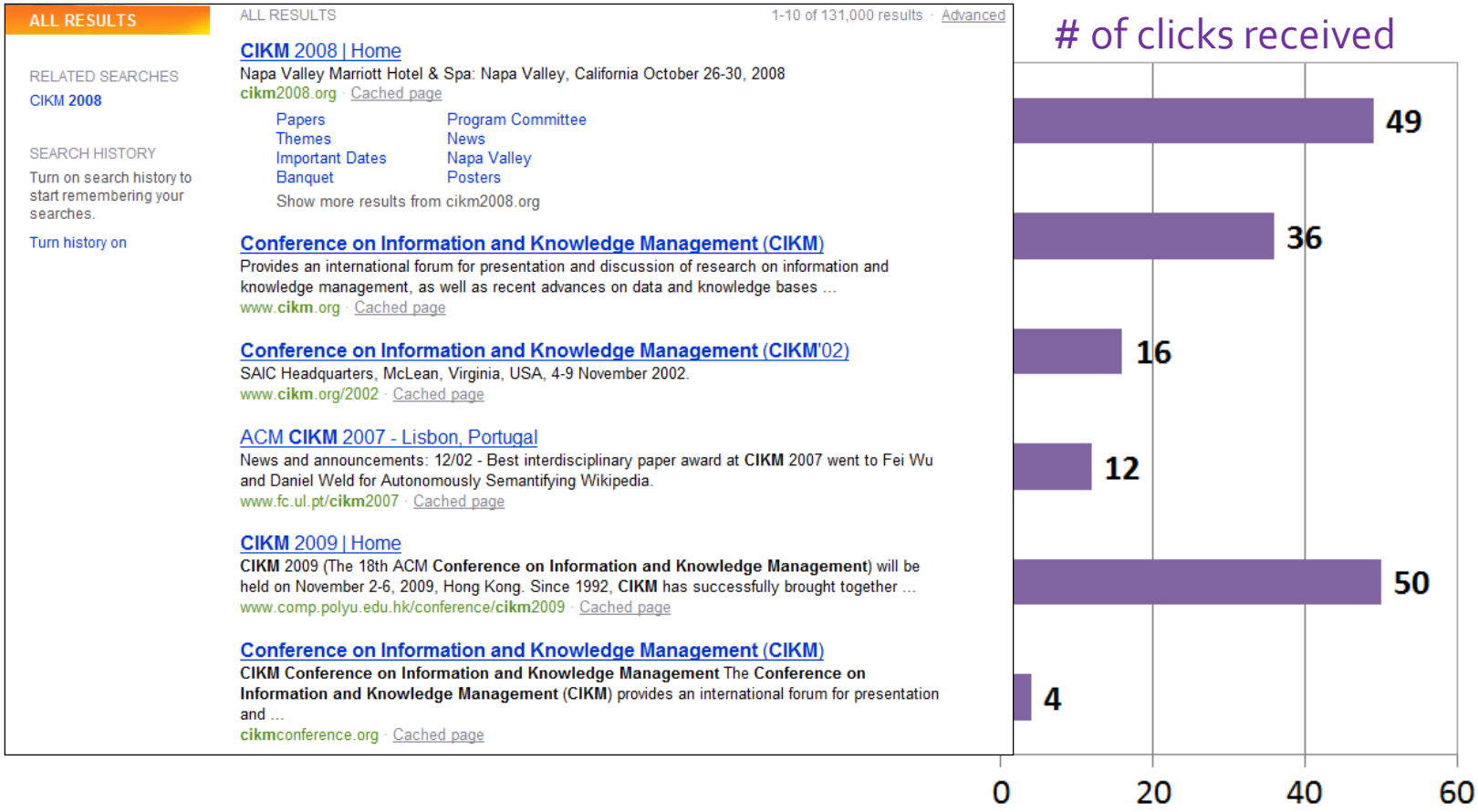
- Search engines have test collections of queries and hand-ranked results
- Recall is difficult to measure on the web
- Search engines often use precision at top k, e.g., k = 10
- . . . or measures that reward you more for getting rank 1 right than for getting rank 10 right.
  - NDCG (Normalized Cumulative 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

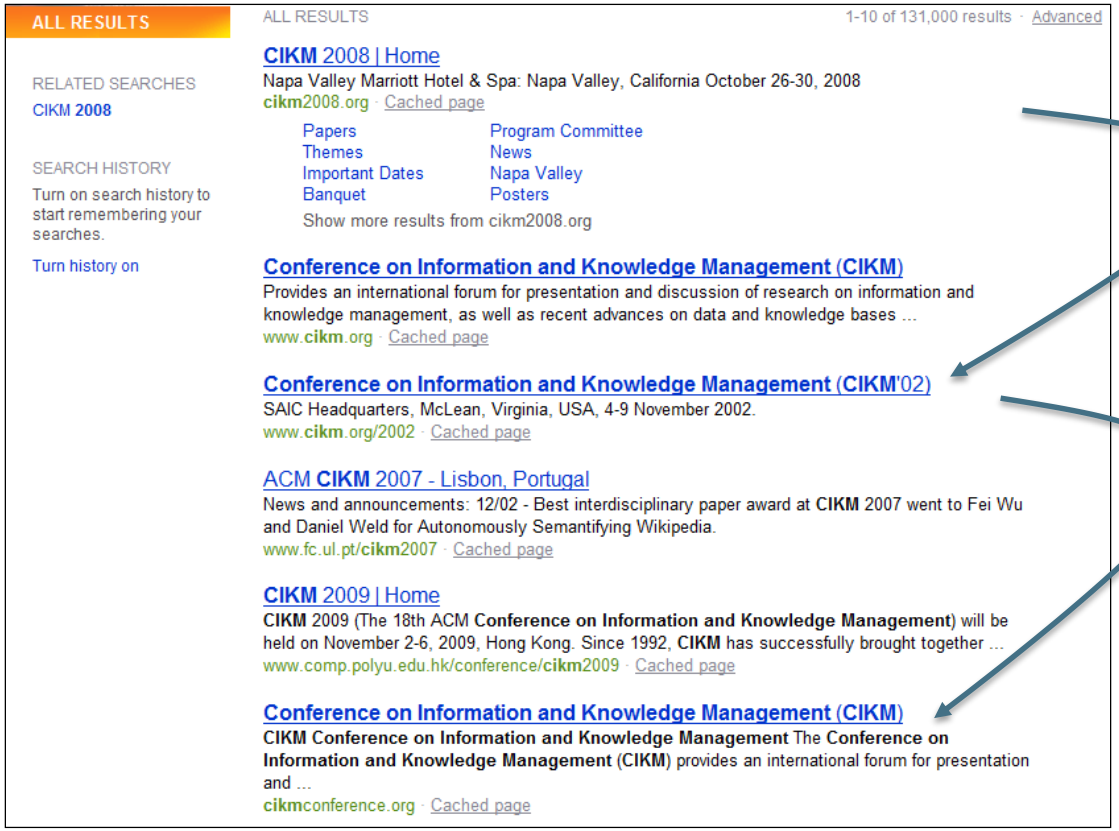
USING USER CLICKS

What do clicks tell us?



Strong position bias, so absolute click rates unreliable

Relative vs absolute ratings



User's click sequence

Hard to conclude Result1 > Result3
Probably can conclude Result3 > Result2

Pairwise relative ratings

- Pairs of the form: DocA better than DocB for a query
  - Doesn't mean that DocA relevant to query
- Now, rather than assess a rank-ordering wrt per-doc relevance assessments
- Assess in terms of conformance with historical pairwise preferences recorded from user clicks
- BUT!
- Don't learn and test on the same ranking algorithm
  - I.e., if you learn historical clicks from nozama and compare Sergey vs nozama on this history …

Comparing two rankings via clicks (Joachims 2002)

Query: [support vector machines]

Ranking A	Ranking B
Kernel machines	Kernel machines
SVM-light	SVMs
Lucent SVM demo	Intro to SVMs
Royal Holl. SVM	Archives of SVM
SVM software	SVM-light
SVM tutorial	SVM software

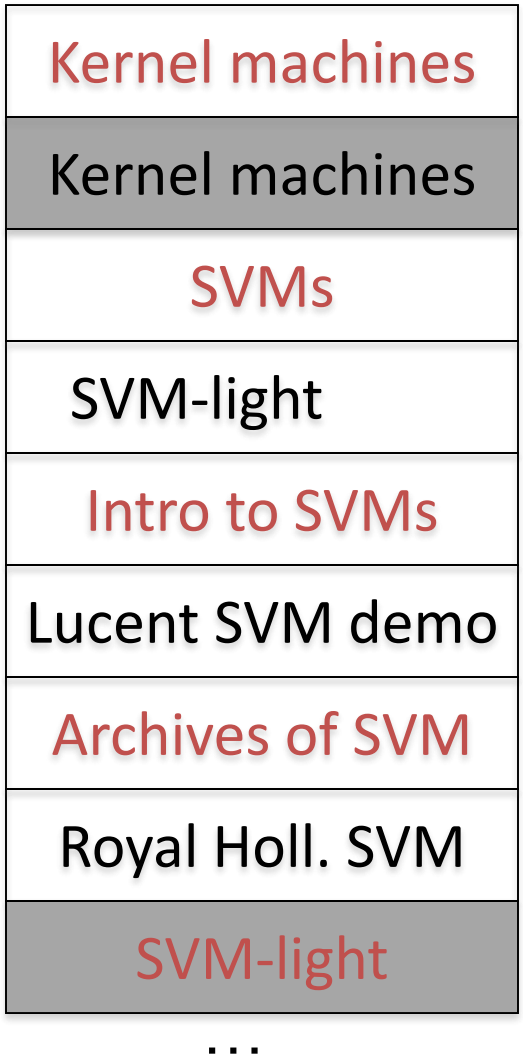
Interleave the two rankings

This interleaving starts with B

Kernel machines
Kernel machines
SVMs
SVM-light
Intro to SVMs
Lucent SVM demo
Archives of SVM
Royal Holl. SVM
SVM-light

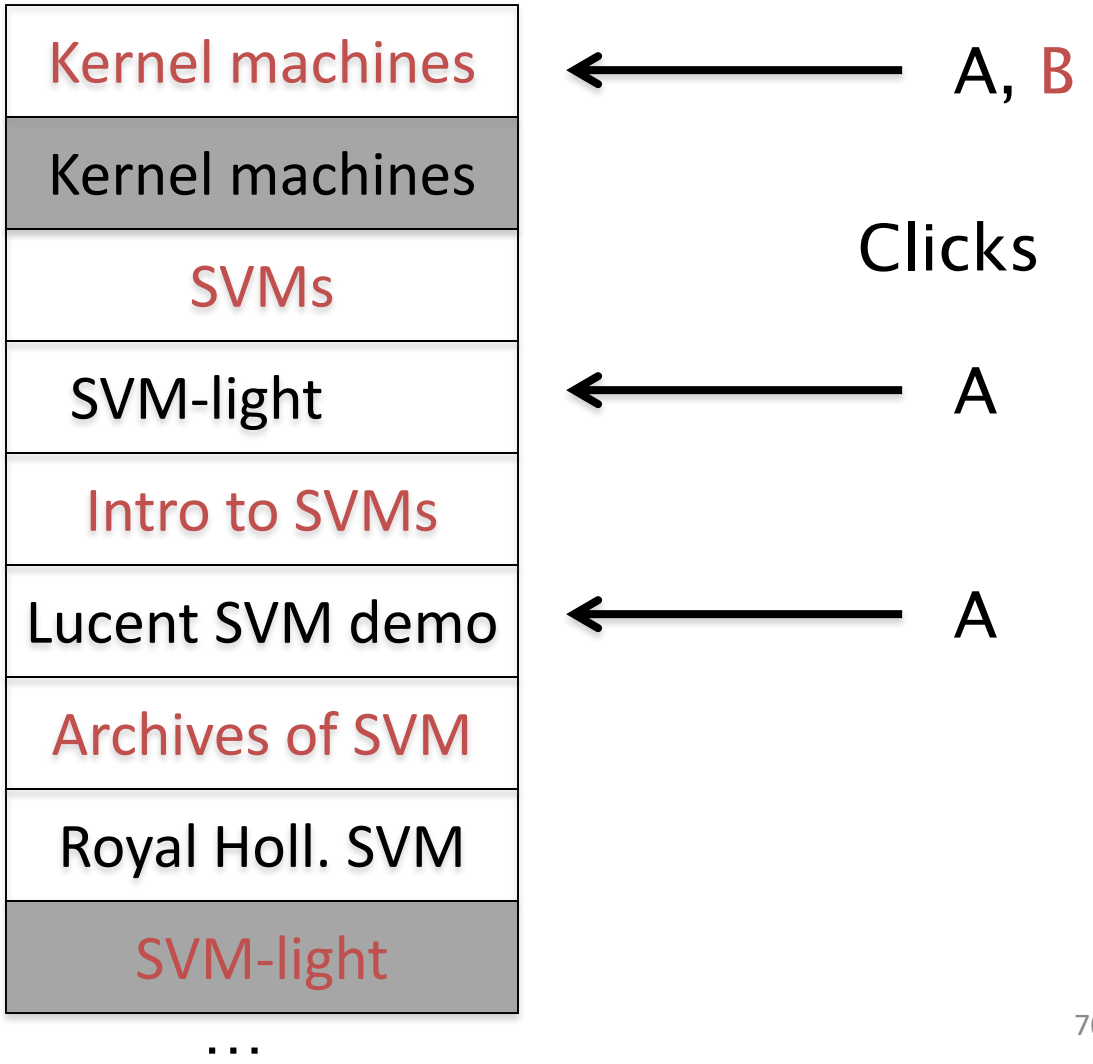
…

Remove duplicate results



Count user clicks

Ranking A: 3
Ranking B: 1



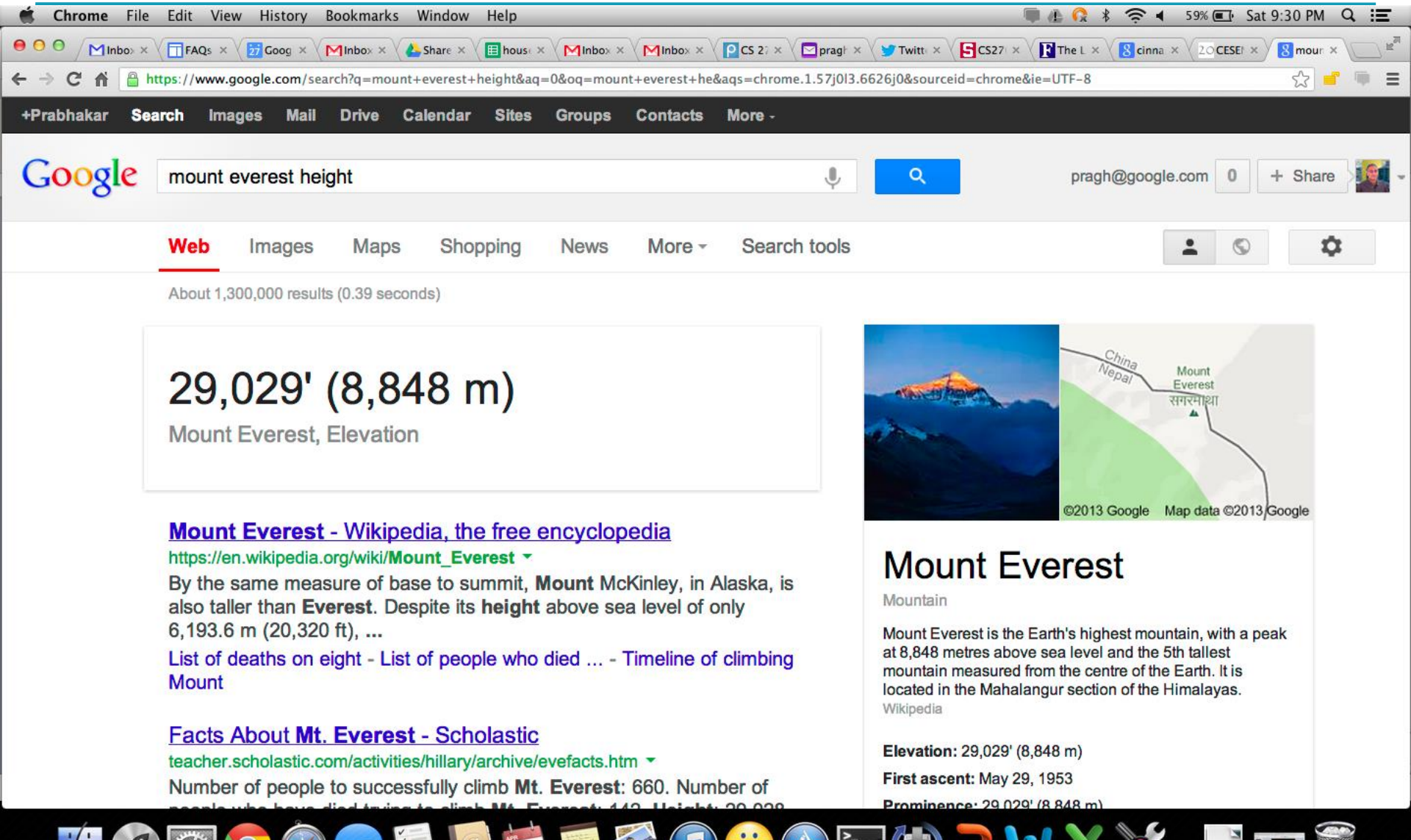
Interleaved ranking

- Present interleaved ranking to users
  - Start randomly with ranking A or ranking B to evens out presentation bias
- Count clicks on results from A versus results from B
- Better ranking will (on average) get more clicks

A/B testing at web search engines

- 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 an experiment to evaluate an innovation
  - Interleaved experiment
  - Full page experiment

Facts/entities (what happens to clicks?)



Comparing two rankings to a baseline ranking

- Given a set of pairwise preferences *P*
- We want to measure two rankings *A* and *B*
- Define a proximity measure between *A* and *P*
  - And likewise, between *B* and *P*
- Want to declare the ranking with better proximity to be the winner
- Proximity measure should reward agreements with *P* and penalize disagreements

Kendall tau distance

- Let X be the number of agreements between a ranking (say *A*) and *P*
- Let Y be the number of disagreements
- Then the Kendall tau distance between *A* and *P* is (X-Y)/(X+Y)
- Say P = {(1,2), (1,3), (1,4), (2,3), (2,4), (3,4))} and A=(1,3,2,4)
- Then X=5, Y=1 …
- (What are the minimum and maximum possible values of the Kendall tau distance?)

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

Summaries

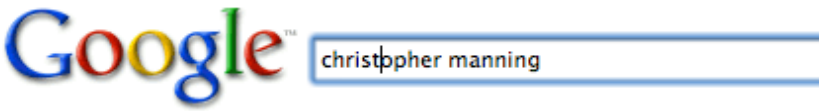
- The title is often automatically extracted from document metadata. What about the summaries?
  - This description is crucial.
  - User can identify good/relevant hits based on description.
- Two basic kinds:
  - Static
  - Dynamic
- A **static summary** of a document is always the same, regardless of the query that hit the doc
- A **dynamic summary** is a *query-dependent* attempt to explain why the document was retrieved for the query at hand

Static summaries

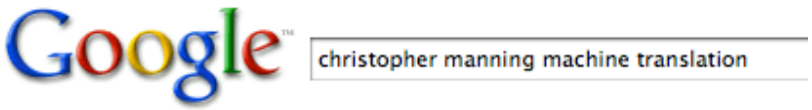
- In typical systems, the static summary is a subset of the document
- Simplest heuristic: the first 50 (or so – this can be varied) words of the document
  - Summary cached at indexing time
- More sophisticated: extract from each document a set of "key" sentences
  - Simple NLP heuristics to score each sentence
  - Summary is made up of top-scoring sentences.
- Most sophisticated: NLP used to synthesize a summary
  - Seldom used in IR; cf. text summarization work

Dynamic summaries

- Present one or more "windows" within the document that contain several of the query terms
  - "KWIC" snippets: Keyword in Context presentation



Christopher Manning, Stanford NLP
Christopher Manning, Associate Professor of Computer Science and Linguistics, Stanford University.
nlp.stanford.edu/~**manning**/ - 12k - Cached - Similar pages



Christopher Manning, Stanford NLP
Christopher Manning, Associate Professor of Computer Science and Linguistics, ...
computational semantics, **machine translation**, grammar induction, ...
nlp.stanford.edu/~**manning**/ - 12k - Cached - Similar pages

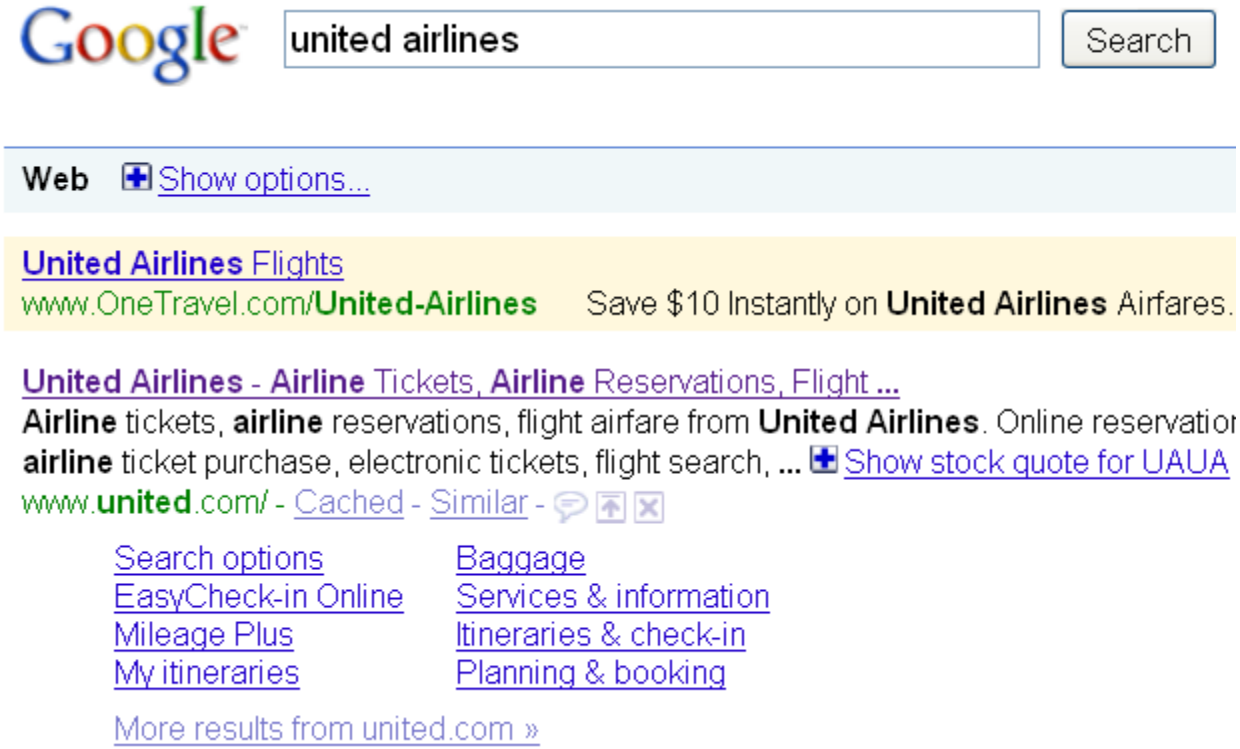
Christopher Manning, Stanford NLP
Christopher Manning, Associate Professor of Computer Science and Linguistics, Stanford University ... **Chris Manning** works on systems and formalisms that can ...
nlp.stanford.edu/~manning - Cached

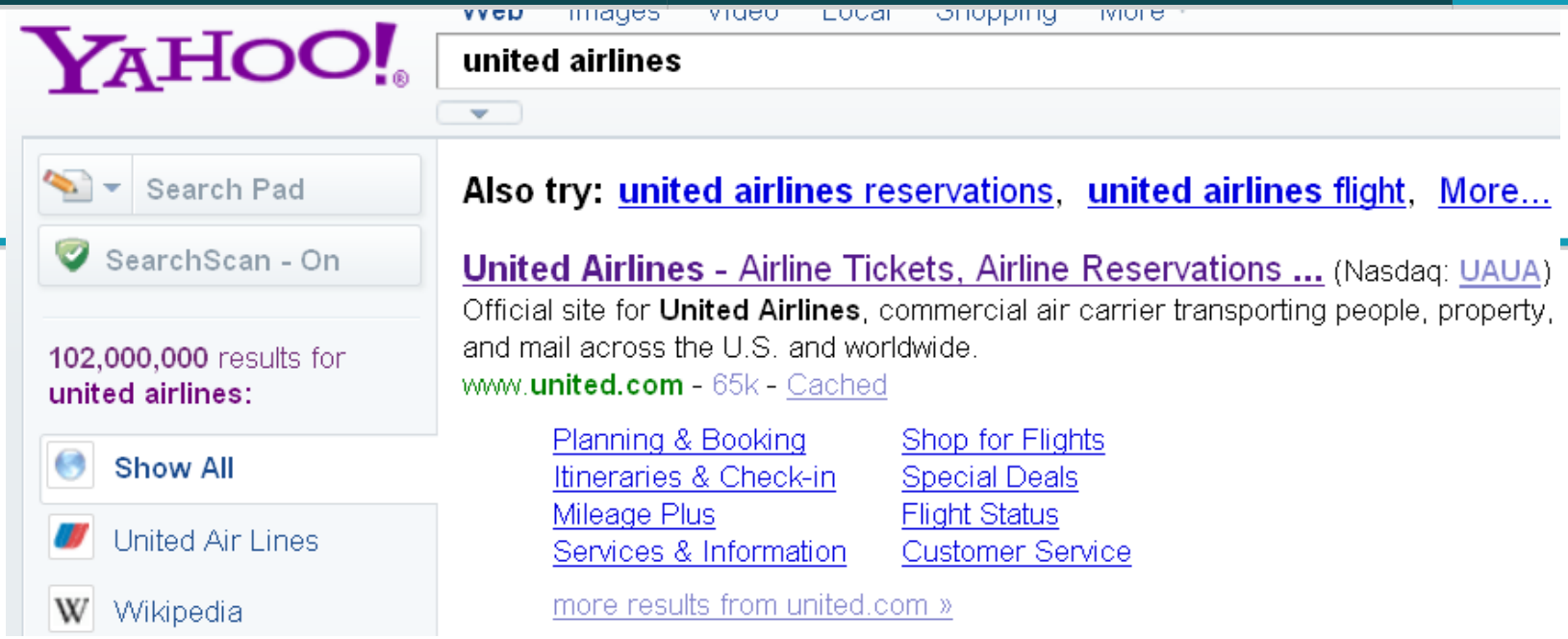
Techniques for dynamic summaries

- Find small windows in doc that contain query terms
  - Requires fast window lookup in a document cache
- Score each window wrt query
  - Use various features such as window width, position in document, etc.
  - Combine features through a scoring function – methodology to be covered Nov 12th
- Challenges in evaluation: judging summaries
  - Easier to do pairwise comparisons rather than binary relevance assessments

Quicklinks

- For a *navigational query* such as ***united airlines*** user's need likely satisfied on www.united.com
- Quicklinks provide navigational cues on that home page

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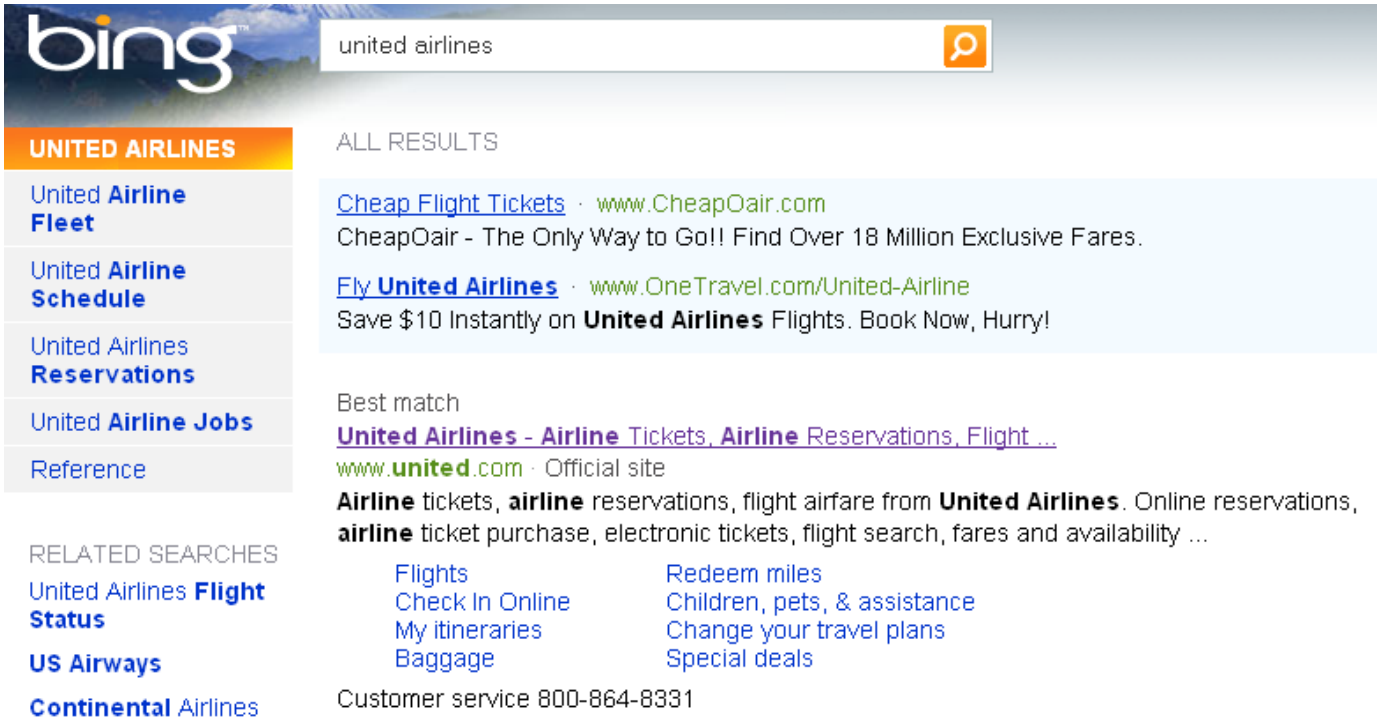
Services & Information
Shop for Flights
Special Deals
Flight Status
Customer Service
more results from united.com »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ALL RESULTS
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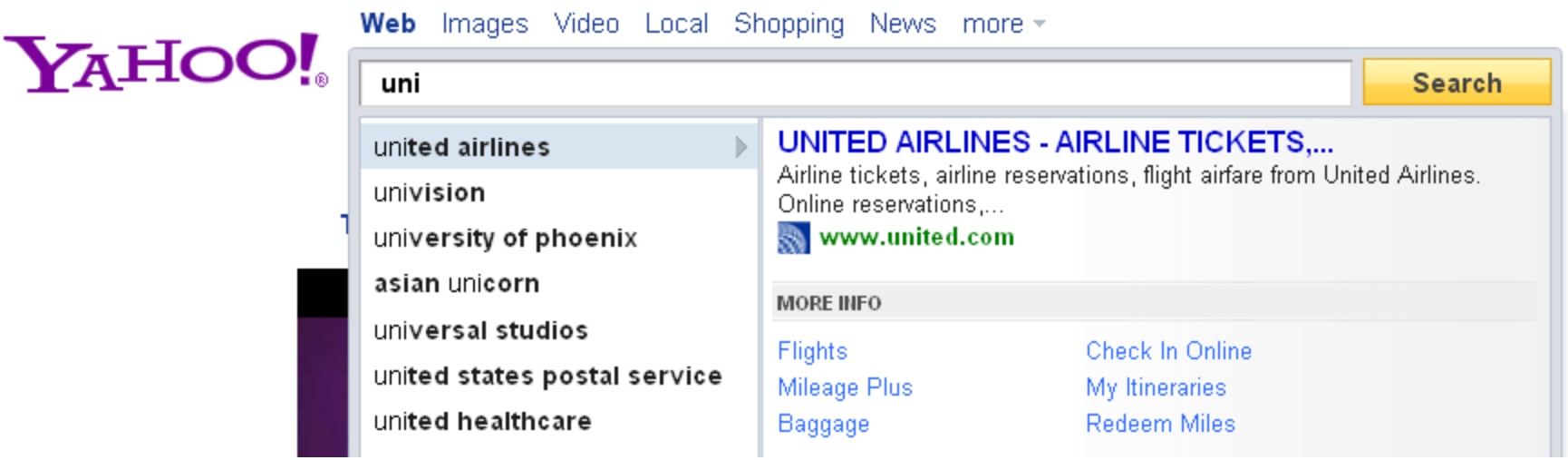
CheapOair - The Only Way to Go!! Find Over 18 Million Exclusive Fares.
Fly United Airlines · www.OneTravel.com/United-Airline
Save $10 Instantly on United Airlines Flights. Book Now, Hurry!
Best match
United Airlines - Airline Tickets, Airline Reservations, Flight ...
www.united.com · Official site
Airline tickets, airline reservations, flight airfare from United Airlines. Online reservations, airline ticket purchase, electronic tickets, flight search, fares and availability ...
Flights
Check In Online
My itineraries
Baggage
Redeem miles
Children, pets, & assistance
Change your travel plans
Special deals
Customer service 800-864-8331

Alternative results presentations?



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.