Introduction to

Information Retrieval

Evaluation

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CS276 – Information Retrieval and Web Search

Revised by

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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/… ?

Happiness: elusive to measure

- Most common proxy: relevance of search results
  - Pioneered by Cyril Cleverdon in the Cranfield Experiments

- But how do you measure relevance?

Measuring relevance

- Three elements:
  1. A benchmark document collection
  2. A benchmark suite of queries
  3. An assessment of either Relevant or Nonrelevant for each query and each document

Early public test Collections (20^{th} C)

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

Recent datasets: 100s of million web pages (GOV, ClueWeb, …)

Evaluating an IR system

- Note: **user need** is translated into a **query**
- Relevance is assessed relative to the **user need,** *not* the **query**
- E.g., Information need: *My swimming pool bottom is becoming black and needs to be cleaned.*
- Query: ***pool cleaner***
- Assess whether the doc addresses the underlying need, not whether it has these words

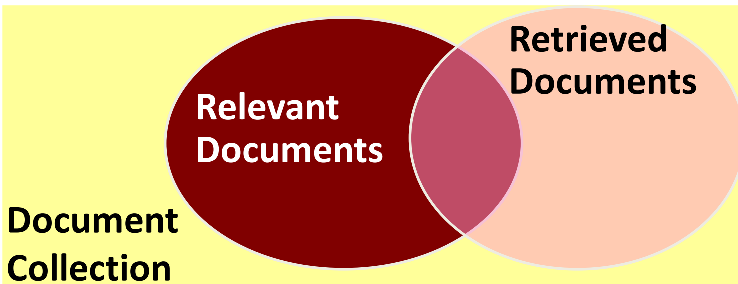
Motivations

- Among different IR systems/models/algorithms which one is the best ?
- What's the best component for :
  - ranking (inner product, cosine, …)
  - Term Selection (stopword, stemming…)
  - Term weighting (TF, TF-IDF,…)
- When to stop (cut) the ranked list of retrieved documents?

Labeled Document Collections (Gold Standard)

- Given a target Document Collection:
- STEP 1. Develop a set of representative queries.
- STEP 2. Use a basic IR technology with wide coverage (see later about recall) to gather all relevant candidate document
- STEP 3. For each query, one or more experts establish the relevance of the different documents of the collection selected at STEP 2.
  - Typically the decision is categorical (i.e. binary)
- The overall process is quite costly in terms of involved human resources as document collections should be representative (i.e. very large)

Precision & *Recall*



	returned	Not returned
irrelevant	retrieved& irrelevant	not retrieved & irrelevant
relevant	retrieved & relevant	not retrieved & relevant

$$recall = \frac{Number\ of\ relevant\ documents\ retrieved}{Total\ number\ of\ relevant\ documents}$$

$$precision = \frac{Number\ of\ relevant\ documents\ retrieved}{Total\ number\ of\ documents\ retrieved}$$

Precision & *Recall*

	retrieved	not retrieved
relevant	tp (true positive)	fn (false negative)
irrelevant	fp (false positive)	tn (true negative)

$$recall = \frac{tp}{tp + fn}$$

$$precision = \frac{tp}{tp + fp}$$

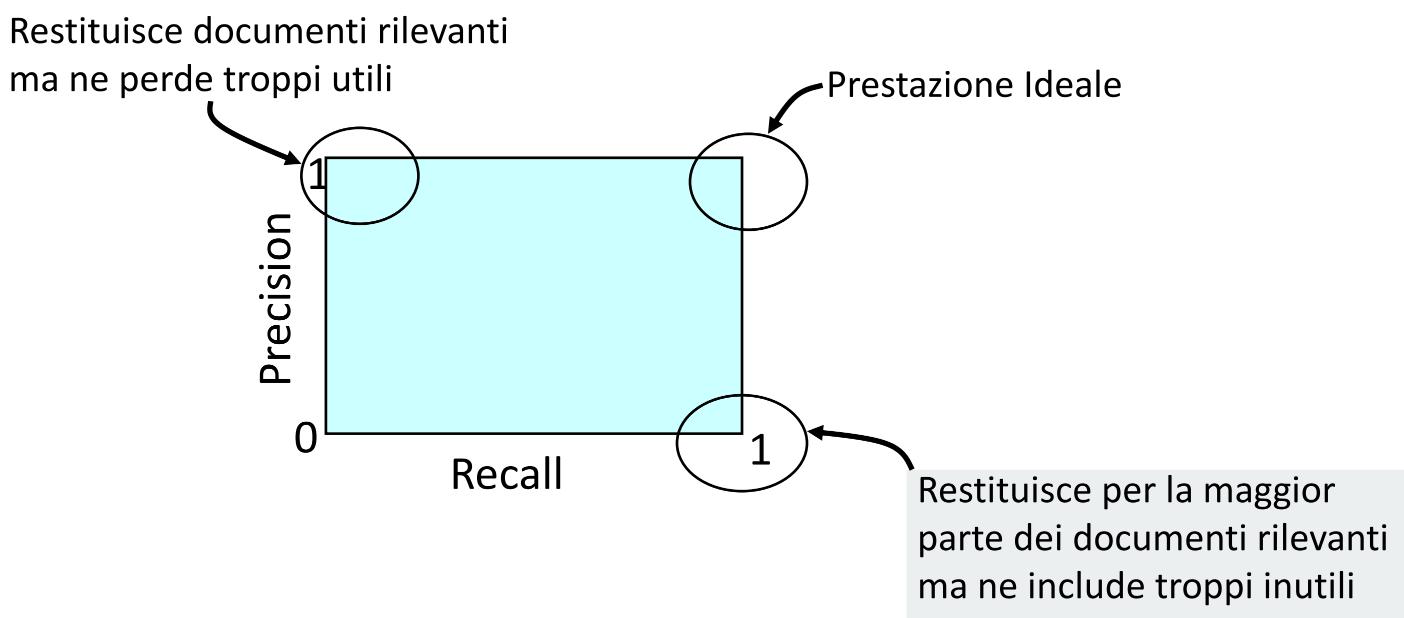
Accuracy and *Error rate*

	retrieved	not retrieved
relevant	tp (true positive)	fn (false negative)
irrelevant	fp (false positive)	tn (true negative)

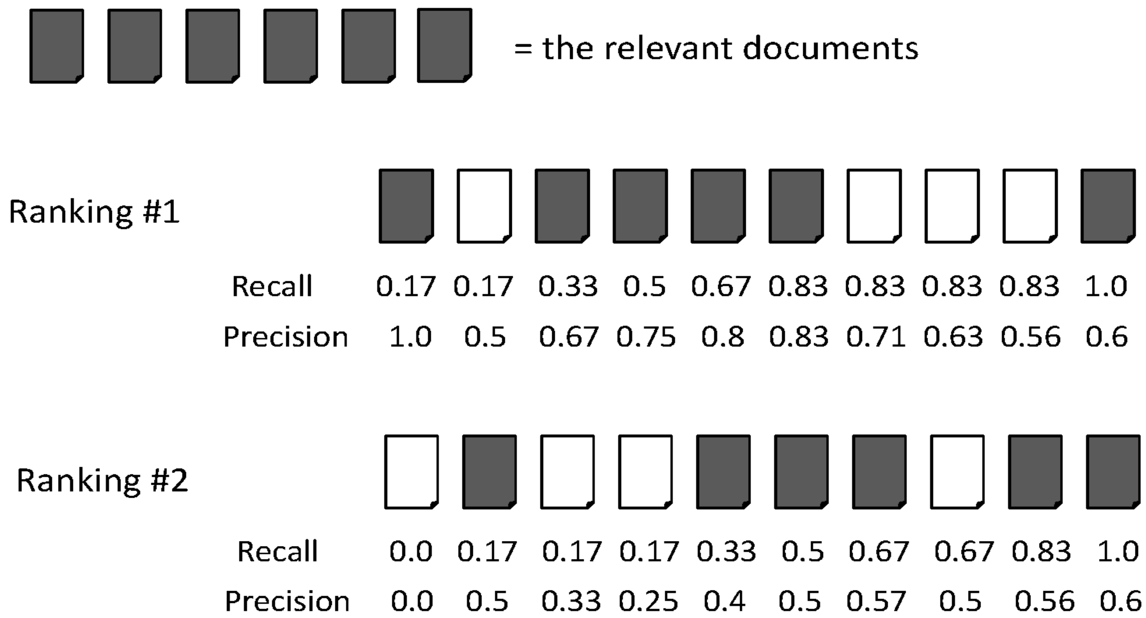
$$acc = \frac{tp + tn}{tp + tn + fn + fp}$$

$$err = \frac{fp + fn}{tp + tn + fn + fp}$$

Recall vs. Precision



Evaluation Metrics: Examples



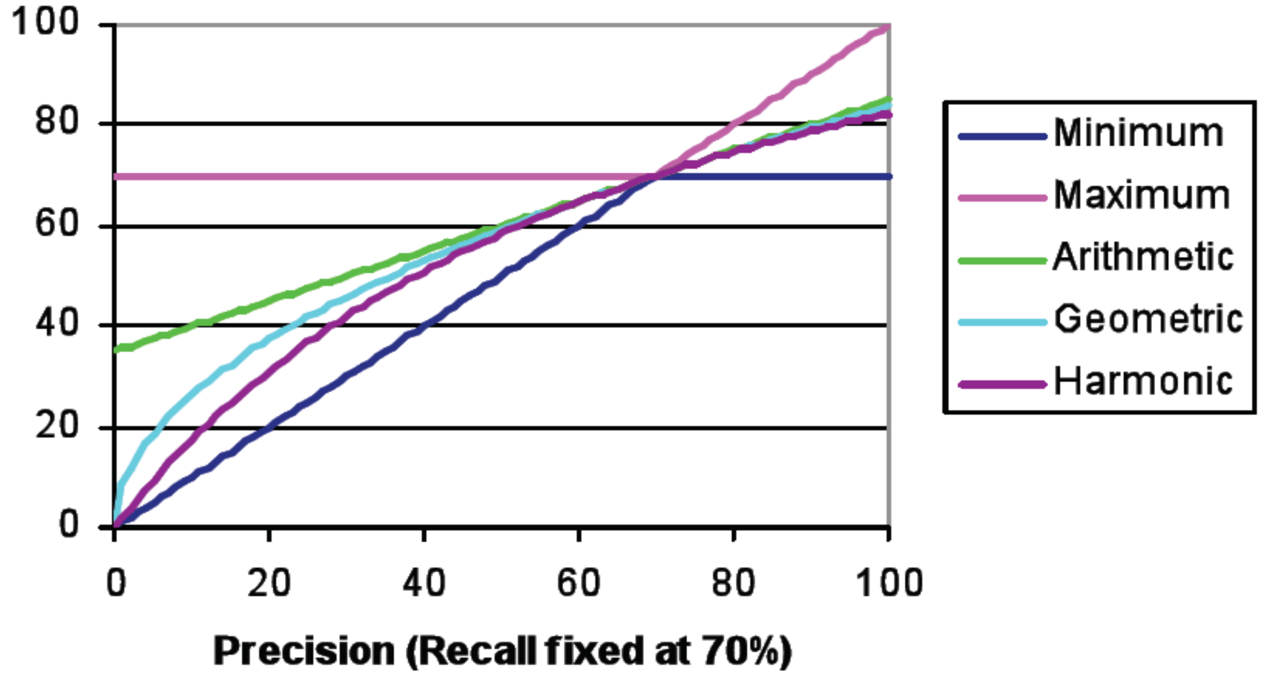
F Measure

- Harmonic mean of recall and precision

$$F = \frac{1}{\frac{1}{2}(\frac{1}{R}+\frac{1}{P})} = \frac{2RP}{(R+P)}$$

  - Why harmonic mean?
  - harmonic mean emphasizes the importance of small values, whereas the arithmetic mean is affected more by outliers that are unusually large

Different Combinations of *precision & recall*

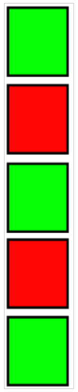


Rank-Based Measures

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

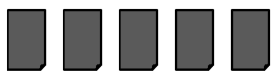
Precision@K

- 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

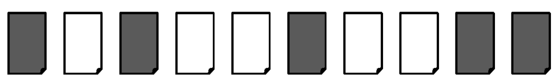


- In similar fashion we have Recall@K

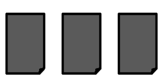
Recall-Precision Graph


= relevant documents for query 1

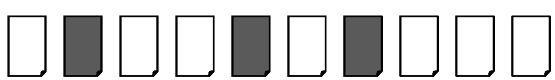
Ranking #1



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

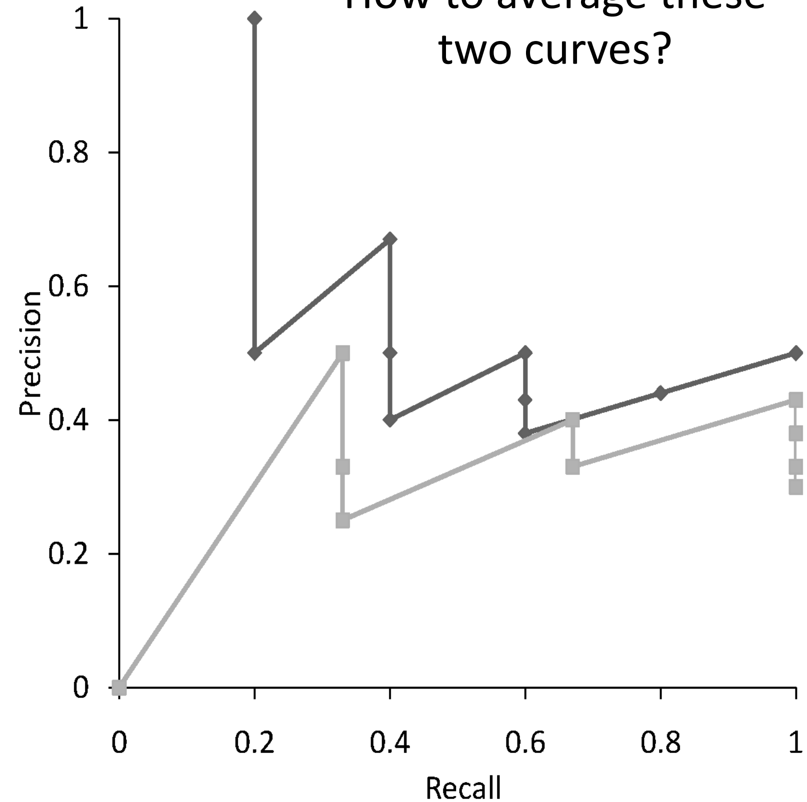

= relevant documents for query 2

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

How to average these two curves?

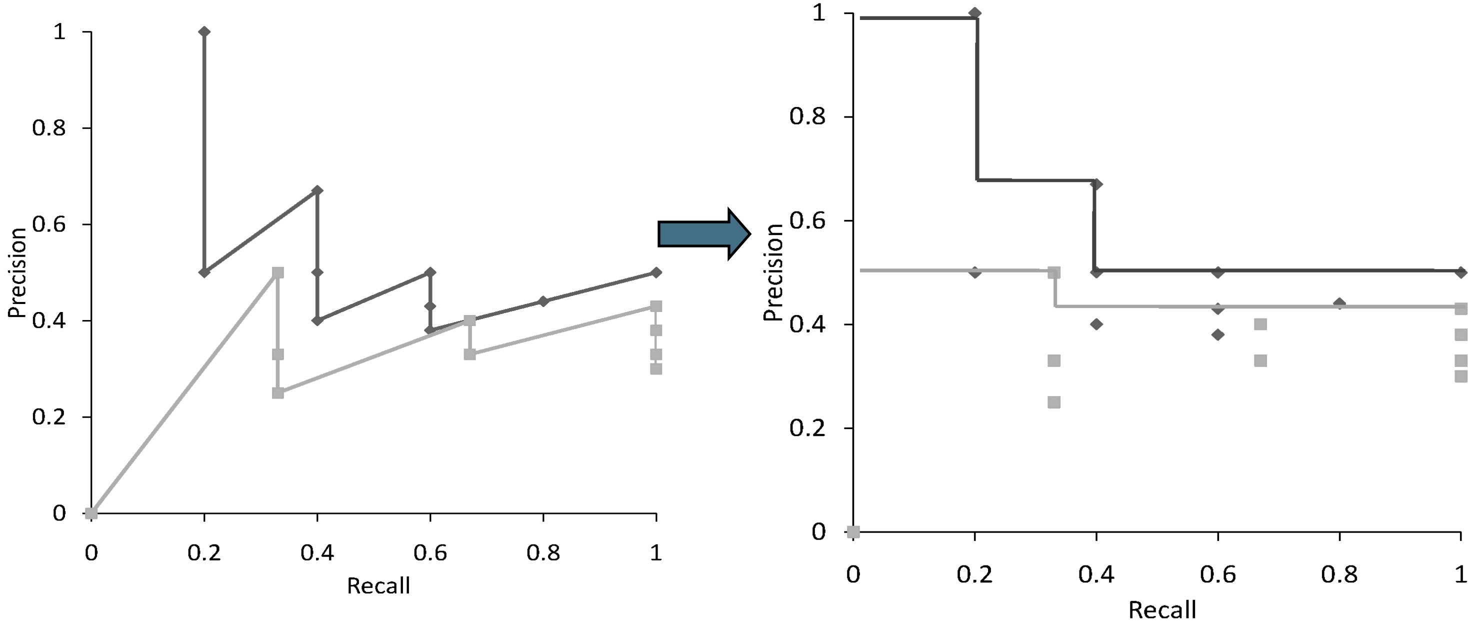


Interpolation

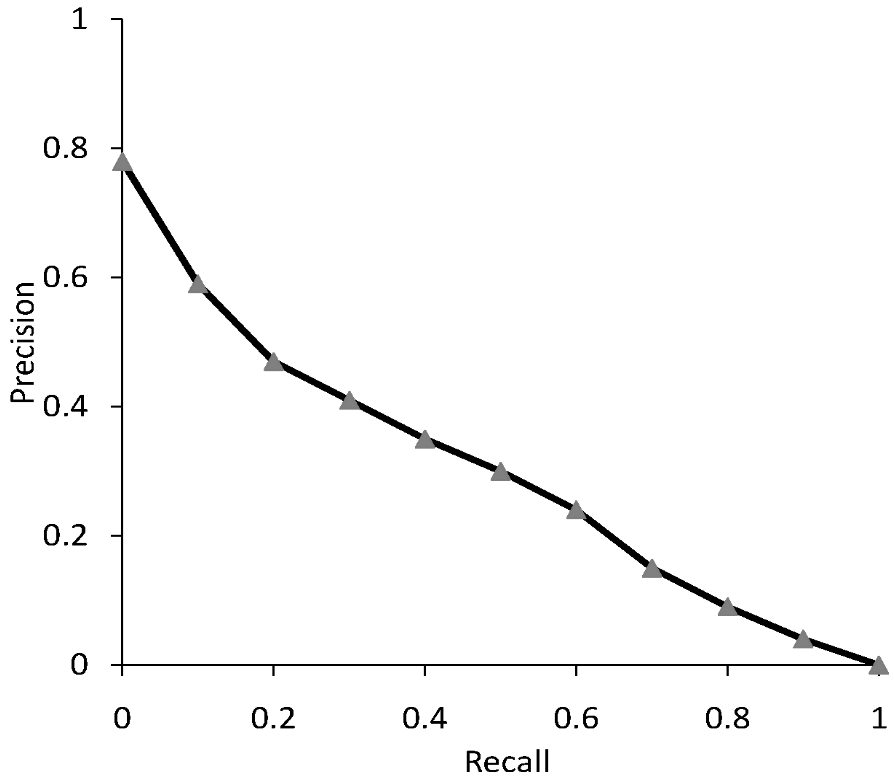
$$P(R) = \max\{P' : R' \geq R \wedge (R', P') \in S\}$$

  - where S is the set of observed (R,P) points
- Defines precision at any recall level as the maximum precision observed in any recall-precision point at a higher recall level
  - produces a step function
  - defines precision at recall 0.0

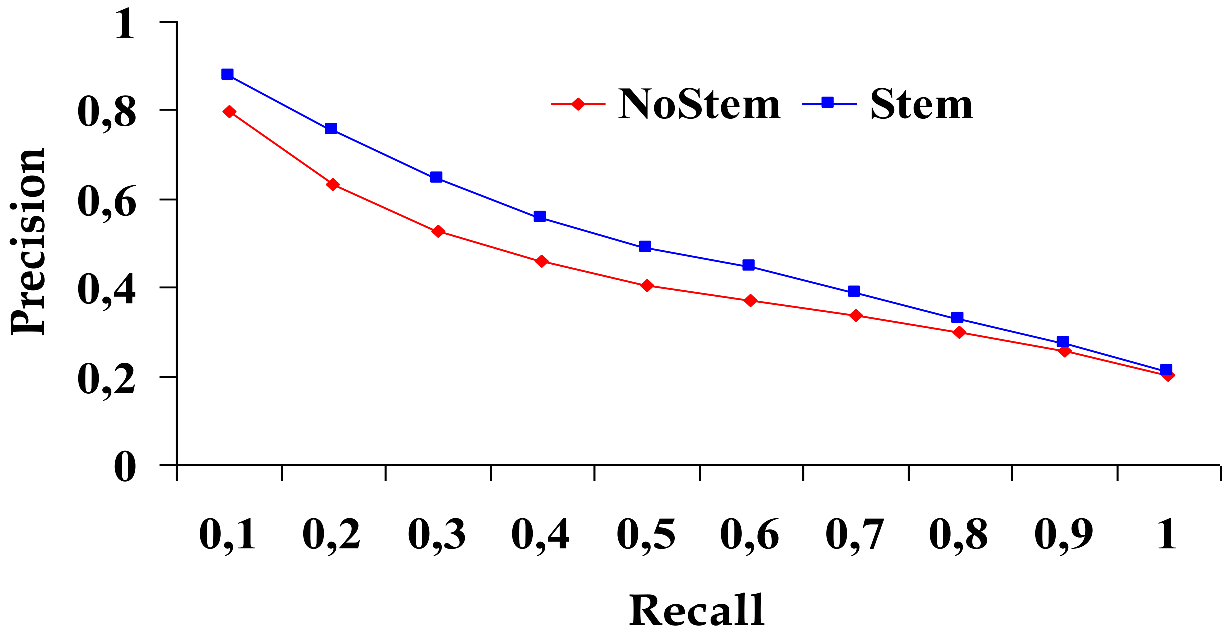
Interpolation



Graph for 50 Queries

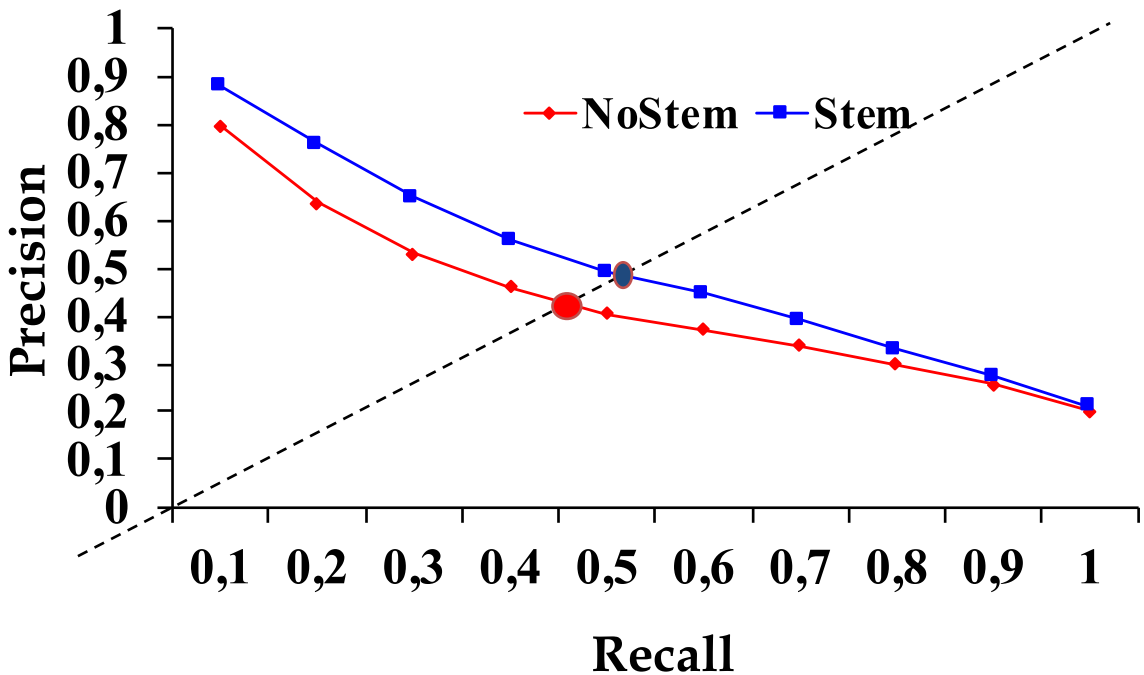


Comparison among different IR Systems

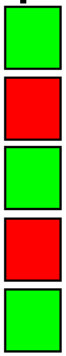


Breakeven point

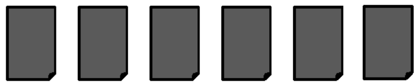
Is the interpolated value for which *precision* **equals** *recall*



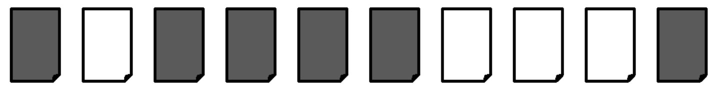
Mean Average Precision

- 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

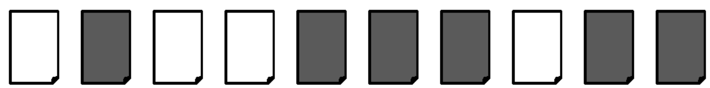
 = the relevant documents

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

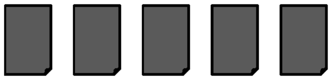


Recall	0.0	0.17	0.17	0.17	0.33	0.5	0.67	0.67	0.83	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.5	0.56	0.6

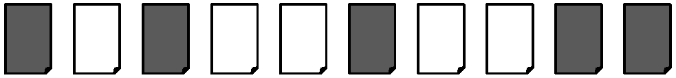
$$\text{Ranking \#1: } (1.0 + 0.67 + 0.75 + 0.8 + 0.83 + 0.6)/6 = 0.78$$

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

MAP

 = relevant documents for query 1

Ranking #1



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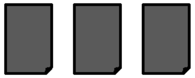
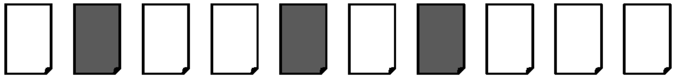
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

 = 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

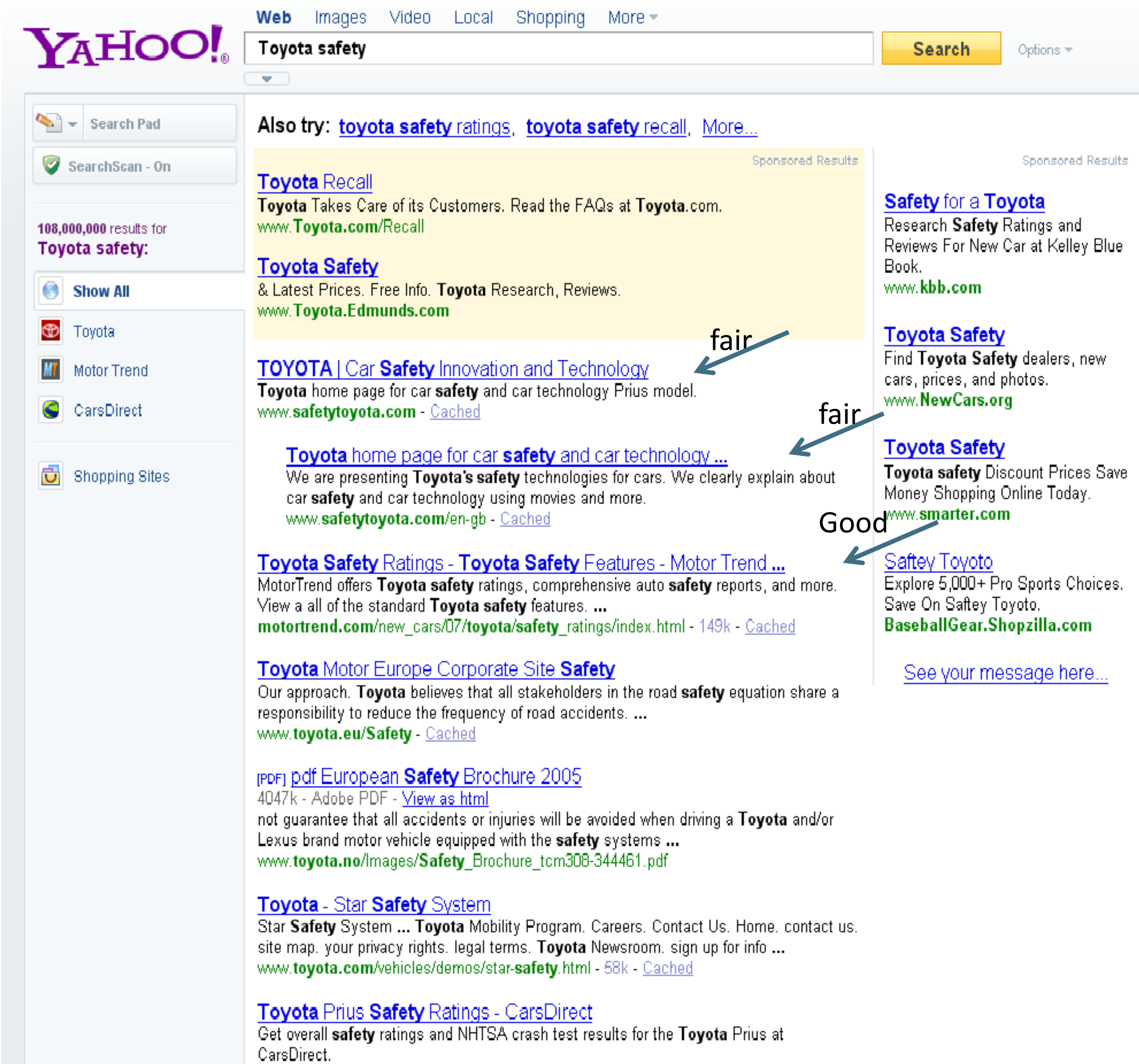
$$\textit{average precision query 1} = (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$$
$$\textit{average precision query 2} = (0.5 + 0.4 + 0.43)/3 = 0.44$$

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

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

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
CarsDirect
Shopping Sites
Also try: toyota safety ratings, toyota safety recall, More...
Sponsored Results
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Toyota Takes Care of its Customers. Read the FAQs at Toyota.com.
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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)
    - $CG = r_1+r_2+\ldots r_n$
- 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

NDCG for summarizing rankings

- 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 = $\dfrac{1}{K}$
- MRR is the mean RR across multiple queries

Human judgments are

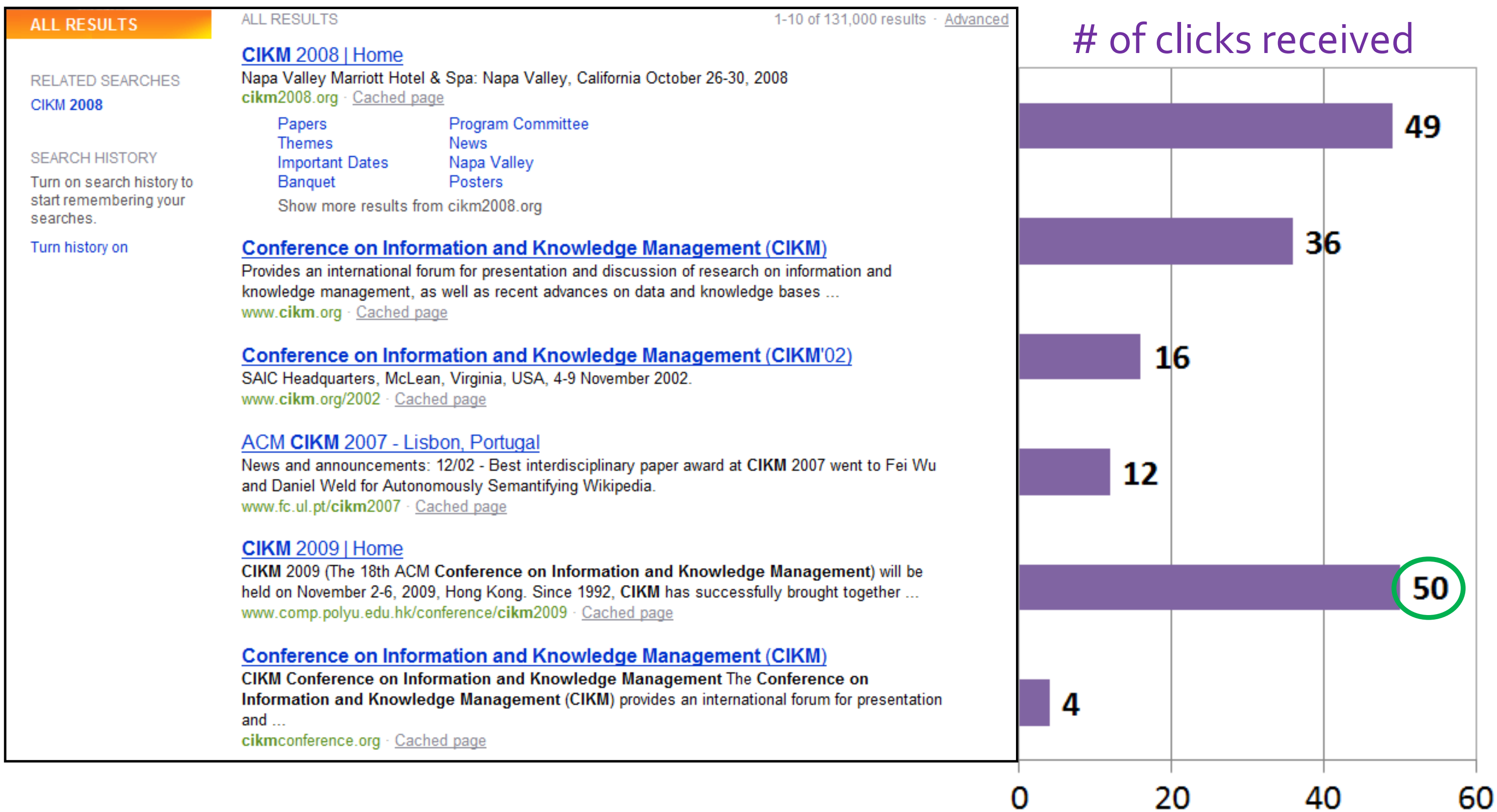
- Expensive
- Inconsistent
  - Between raters
  - Over time
- Decay in value as documents/query mix evolves
- Not always representative of “real users”
  - Rating vis-à-vis query, don’t know underlying need
  - May not understand meaning of terms, etc.
- So – what alternatives do we have?

USING USER CLICKS

User Behavior

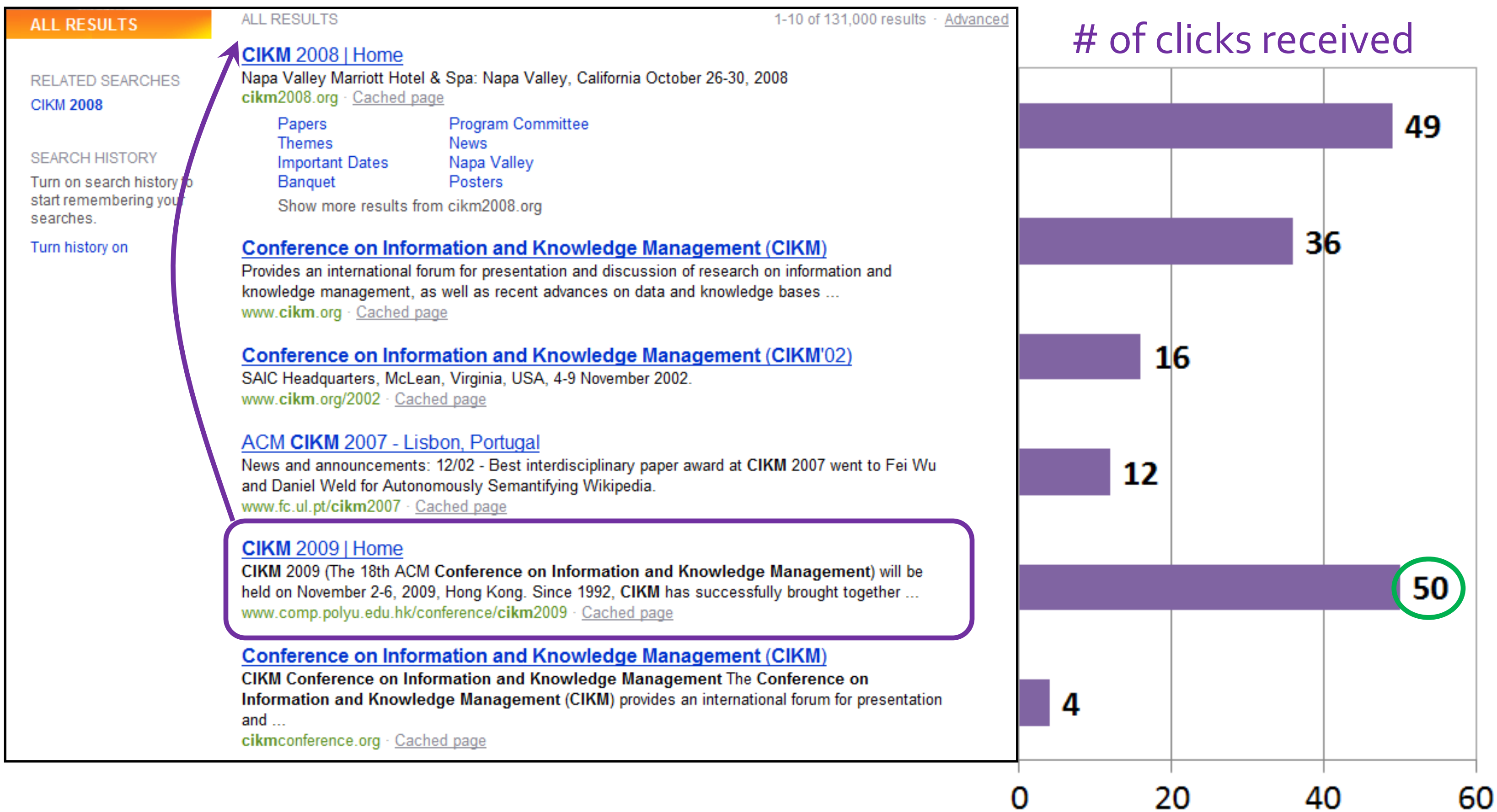
Taken with slight adaptation from Fan Guo and Chao Liu's 2009/2010 CIKM tutorial: Statistical Models for Web Search: Click Log Analysis

- Search Results for "CIKM" (in 2009!)



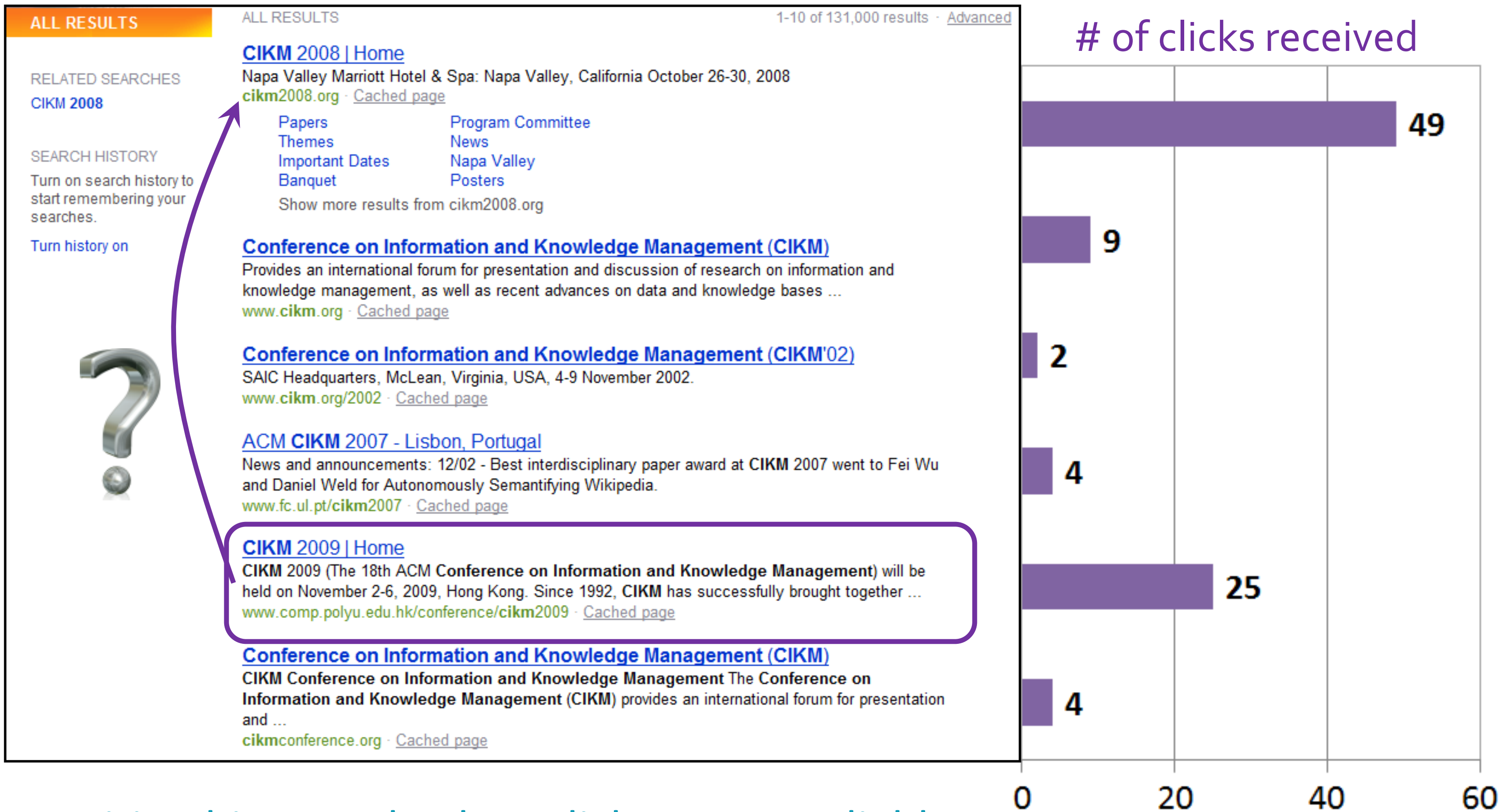
User Behavior

- Adapt ranking to user clicks?



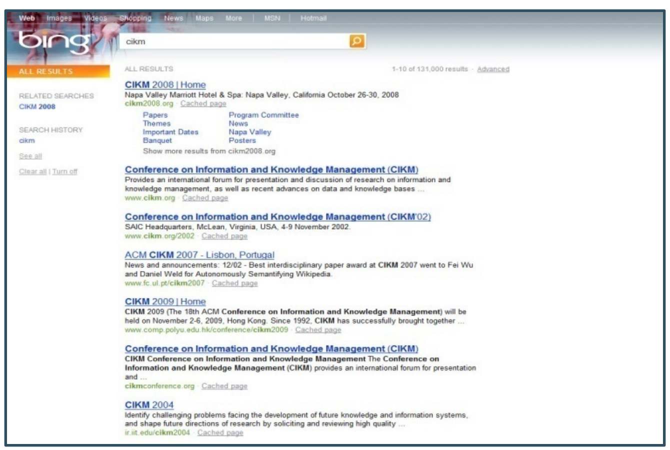
What do clicks tell us?

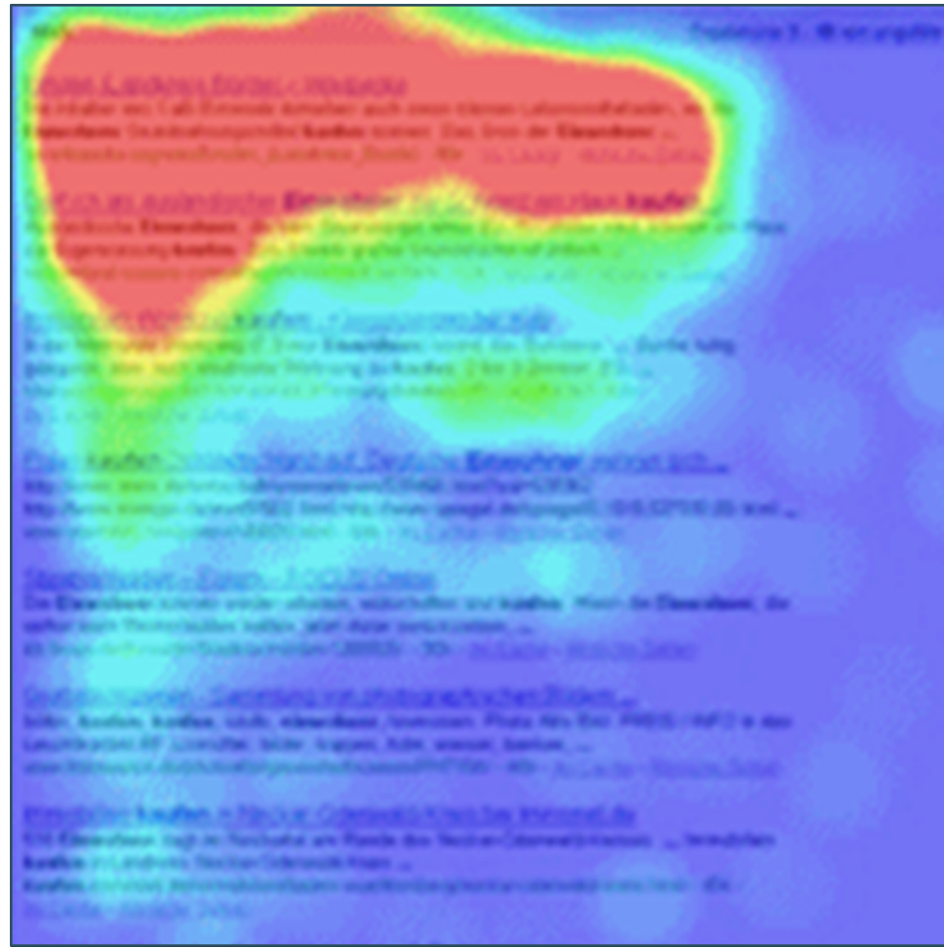
- Tools needed for non-trivial cases



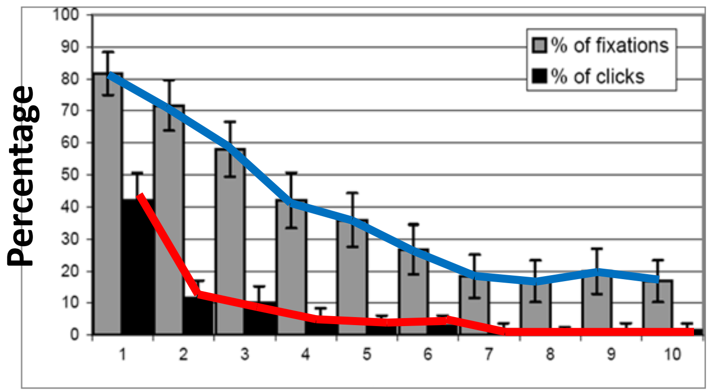
Strong position bias, so absolute click rates unreliable

Eye-tracking User Study

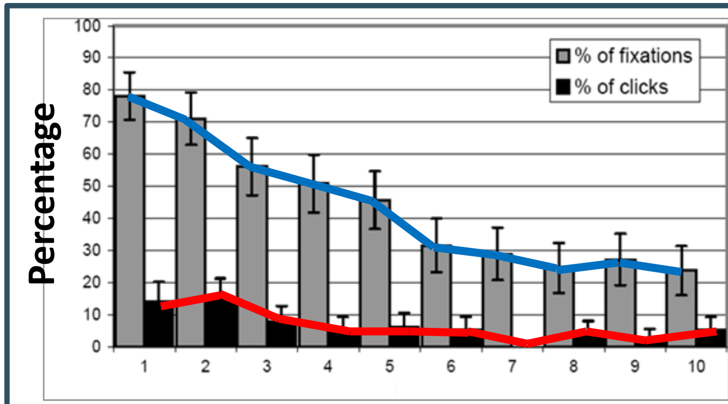




Click Position-bias



Normal Position

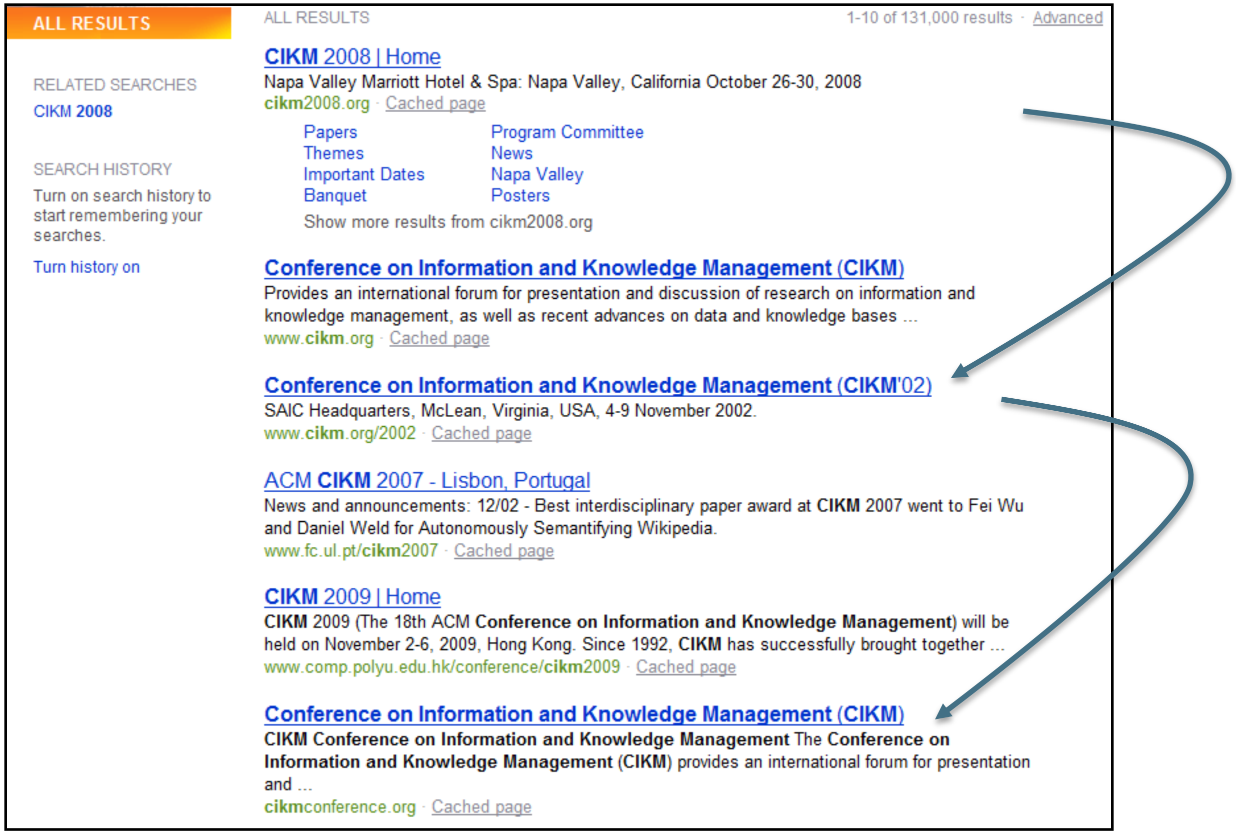


Reversed Impression

- Higher positions receive more user attention (eye fixation) and clicks than lower positions.
- This is true even in the extreme setting where the order of positions is reversed.
- "Clicks are informative but biased".

[Joachims+07]

Relative vs absolute ratings



User's click sequence

Hard to conclude <u>Result1 > Result3</u>
Probably can conclude <u>Result3 > Result2</u>

Evaluating pairwise relative ratings

- Pairs of the form: DocA <u>better than</u> DocB for a query
  - Doesn't mean that DocA <u>relevant</u> 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

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
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SVM-light

…

Remove duplicate results

Kernel machines
Kernel machines
SVMs
SVM-light
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SVM-light

…

Count user clicks

Ranking A: 3
Ranking B: 1

Kernel machines
Kernel machines
SVMs
SVM-light
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…

Clicks

- Kernel machines ← A, B
- SVM-light ← A
- Lucent SVM demo ← A

Interleaved ranking

- Present interleaved ranking to users
  - Start randomly with ranking A or ranking B to even 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., 0.1%) to an experiment to evaluate an innovation
  - Interleaved experiment
  - Full page experiment

Recap

- Benchmarks consist of
  - Document collection
  - Query set
  - Assessment methodology
- Assessment methodology can use raters, user clicks, or a combination
  - These get quantized into a *goodness measure* – Precision/NDCG etc.
  - Different engines/algorithms compared on a <u>benchmark</u> together with a <u>goodness measure</u>

User behavior

- User behavior is an intriguing source of relevance data
  - Users make (somewhat) informed choices when they interact with search engines
  - Potentially a lot of data available in search logs

- But there are significant caveats
  - User behavior data can be very noisy
  - Interpreting user behavior can be tricky
  - Spam can be a significant problem
  - Not all queries will have user behavior

Incorporating user behavior into ranking algorithm

- Incorporate user behavior features into a ranking function like BM25F
  - But requires an understanding of user behavior features so that appropriate V_j functions are used
- Incorporate user behavior features into *learned* ranking function
- Either of these ways of incorporating user behavior signals improve ranking