Introduction to Information Retrieval

Lecture 7 Evaluation

How do you evaluate a search engine / algorithm [say for e-commerce]

- How fast does it index?
 - Number of documents/hour
 - Incremental indexing site adds 10K products/day
- How fast does it search?
 - Latency and CPU needs for site's 5 million products
- Does it recommend related products?
- This is all good, but it says nothing about the quality of search
 - You want the users to be happy with the search experience

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
 - But how do you measure relevance?
- Pioneered by Cyril Cleverdon in the Cranfield Experiments



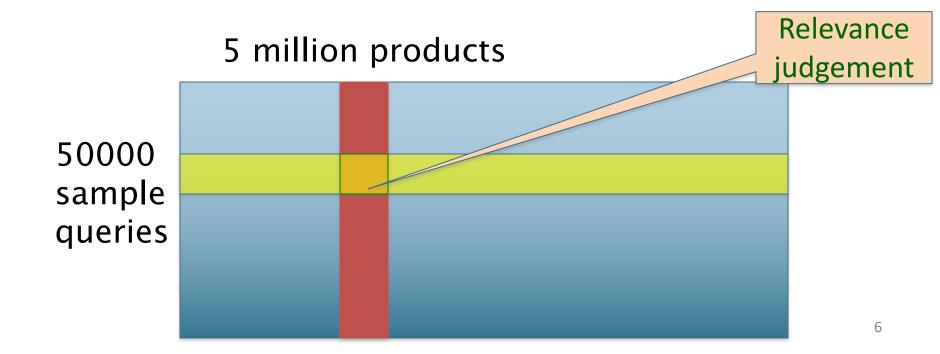
Measuring relevance

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

d₁ 1 23

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

- Benchmark documents the 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 10¹¹ 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 appropriate to docs in corpus
 - 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"

Sec. 8.5

Some public test Collections

			ondition reat	-	
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

TABLE 4.3	Common	Test	Corpora
-----------	--------	------	---------

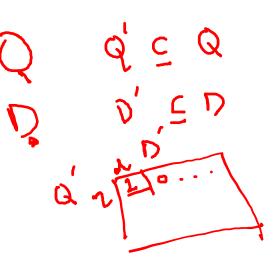
Typical TREC

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

Now we have the basics of a benchmark

- Let's review some evaluation measures
 - Precision
 - Recall
 - DCG
 - •



Unranked retrieval evaluation: Precision and Recall

Binary assessments

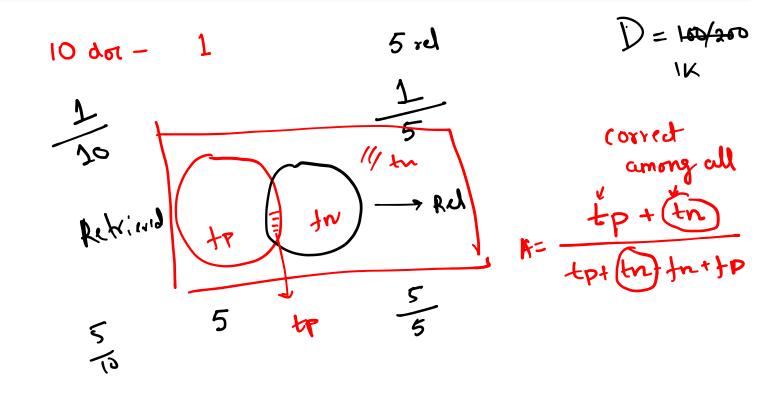
Precision: fraction of retrieved docs that are relevant =
 P(relevant|retrieved)

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)

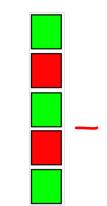


Rank-Based Measures

- 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

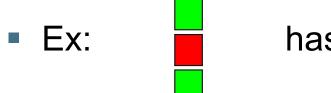
- Set a rank threshold K
- Compute % relevant in top K
- Ignores documents ranked lower than K
- Ex:
 - Prec@3 of ?
 - Prec@4 of ?
 - Prec@5 of ?



In similar fashion we have Recall@K

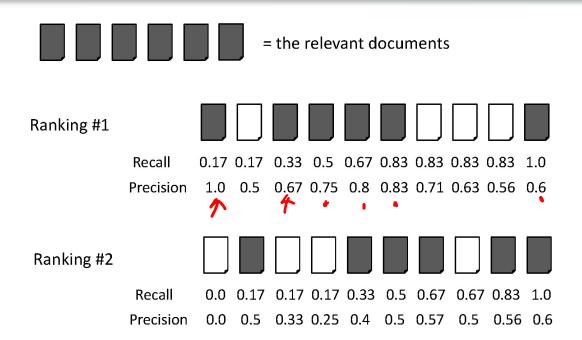
Mean Average Precision

- Consider rank position of each relevant doc
 - K₁, K₂, ... K_R
- Compute Precision@K for each K= K₁, K₂, ... K_R
- Average precision = average of P@K



has AvgPrec of
$$\frac{1}{3} \cdot \left(\frac{1}{1} + \frac{2}{3} + \frac{3}{5}\right) \approx 0.76$$

Average Precision



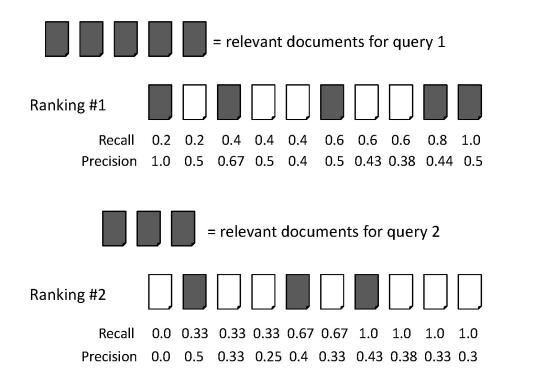
Ranking #1: (1.0 + 0.67 + 0.75 + 0.8 + 0.83 + 0.6)/6 = 0.78

Ranking #2: (0.5 + 0.4 + 0.5 + 0.57 + 0.56 + 0.6)/6 = 0.52

Mean average precision

- MAP is Average Precision across multiple queries/rankings
- MAP is macro-averaging: each query counts equally
- Now perhaps most commonly used measure in research papers

MAP



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

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

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

$$\frac{dm}{2-di} = \frac{dm}{di}$$

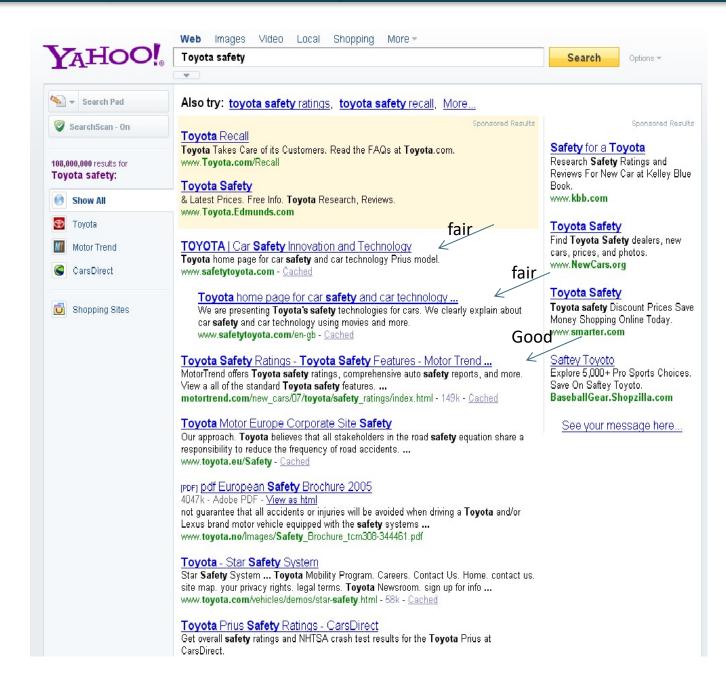
./

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

BEYOND BINARY RELEVANCE



Discounted Cumulative Gain

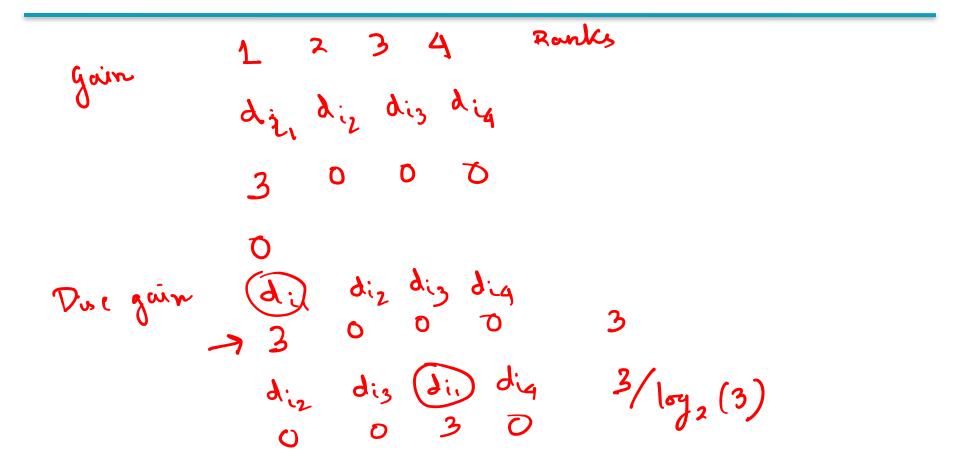
- Popular measure for evaluating web search and related tasks
- Two assumptions:
 - Highly relevant documents are more useful than marginally relevant documents
 - The lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Discounted Cumulative Gain

- Uses graded relevance as a measure of usefulness, or gain, from examining a document
- <u>Gain</u> 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
- Intuition: if a good document is retrieved at rank 4, system gets only half the credit that it would have got if the doc were to be retrieved at rank 1



Summarize a Ranking: DCG

- What if relevance judgments are in a scale of [0,k]? k>=2
- Let the ratings of the n documents be r₁, r₂, ...r_n (in ranked order)
- Cumulative Gain (CG) at rank n
 - CG = $r_1 + r_2 + ... r_n$
- Discounted Cumulative Gain (DCG) at rank n
 - DCG = $r_1 + r_2/\log_2 2 + r_3/\log_2 3 + \dots + r_n/\log_2 n$

We may use any base for the logarithm -> 3 + 0 + 0 + 0

3 + 0 + 0 + 0

Discounted Cumulative Gain

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

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

- 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
- A problem: how to compare DCG for queries having different number of relevant docs?

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 for the same example

- 10 ranked documents judged on 0-3 relevance scale:
 3, 2, 3, 0, 0, 1, 2, 2, 3, 0
- Perfect ranking: 3, 3, 3, 2, 2, 2, 1, 0, 0, 0
- Ideal DCG values:

3/3

- 3, 6, 7.89, 8.89, 9.75, 10.52, 10.88, 10.88, 10.88, 10
- Actual DCG (from two slides back):
 - **3**, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61
- NDCG values (divide actual by ideal):
 - 1, 0.83, 0.87, 0.76, 0.71, 0.69, 0.73, 0.8, 0.88, 0.88
 - NDCG ≤ 1 at any rank position

NDCG – Another 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	

$$DCG_{GT} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$
$$DCG_{RF1} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$
$$DCG_{RF2} = 2 + \left(\frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.2619$$

 $MaxDCG = DCG_{GT} = 4.6309$