Introduction to Information Retrieval

Evaluation

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)

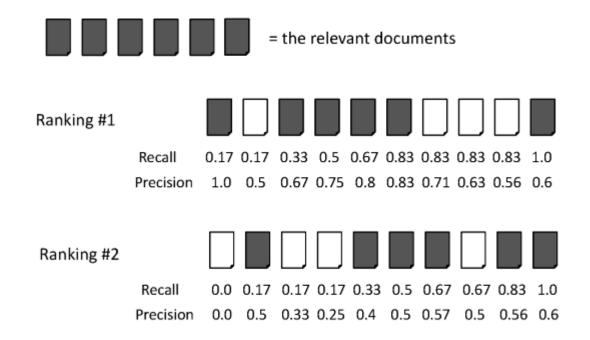
Precision@K

- 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

Mean Average Precision

- Consider rank position of each relevant doc
 - K₁, K₂, ... K_R
- Compute Precision@K for each K₁, K₂, ... 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

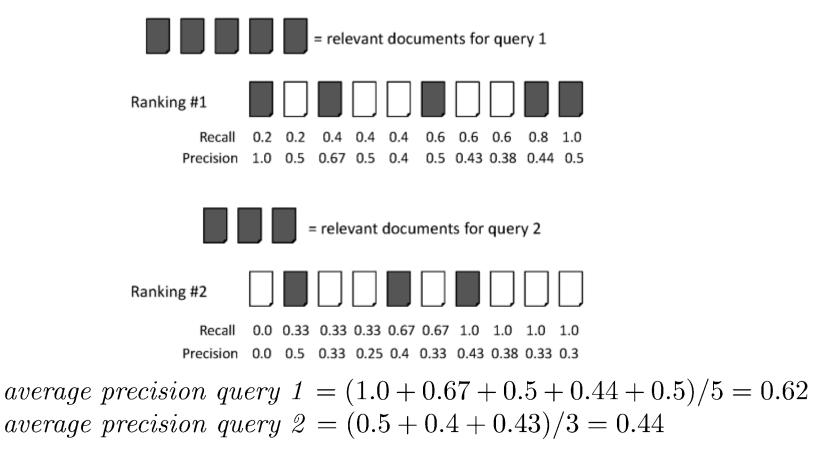
Average Precision



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

MAP



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

When There's only 1 Relevant Document

- Scenarios:
 - known-item search
 - navigational queries
 - looking for a fact
- Search Length = Rank of the answer
 - measures a user's effort

Mean Reciprocal Rank

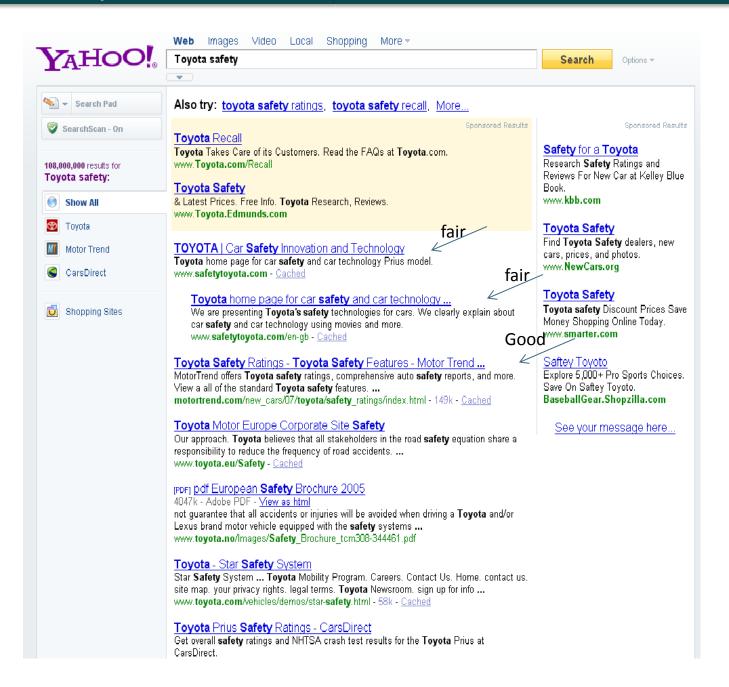
Consider rank position, K, of first relevant doc

Reciprocal Rank score =
$$\frac{1}{K}$$

MRR is the mean RR across multiple queries

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
 - But harder to create evaluation set
 - See Carbonell and Goldstein (1998)
- Using facts/entities as evaluation unit can more directly measure true recall
- Also related is seeking diversity in first page results
 - See <u>Diversity in Document Retrieval</u> workshops



Discounted Cumulative Gain

Popular measure for evaluating web search and related tasks

- Two assumptions:
 - Highly relevant documents are more useful than marginally relevant document
 - 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 r₁, r₂, ...r_n (in ranked order)
 - $CG = r_1 + r_2 + ... r_n$
- Discounted Cumulative Gain (DCG) at rank n
 - DCG = $r_1 + r_2/\log_2 2 + r_3/\log_2 3 + \dots + r_n/\log_2 n$
 - We may use any base for the logarithm, e.g., base=b

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 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
 - Compute the precision (at rank) where each (new) relevant document is retrieved => p(1),...,p(k), if we have k rel. docs
- NDCG is now quite popular in evaluating Web search

NDCG - Example

4 documents: d₁, d₂, d₃, d₄

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	

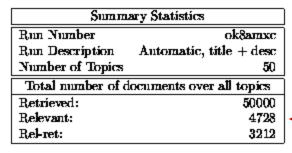
$$DCG_{GT} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$

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

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

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

Precion-Recall Curve



Out of 4728 rel docs, we've got 3212

Recall=3212/4728

0docs

e got 3212	0.8
I=3212/4728 E	0.6
docs	
about 5.5 docs in the top 10 docs are relevant	Q.2 Q.4 Q.6 Q.8 Q.0 Recall Recall-Precision Cutve

Recall Level Precision Averages				
Recall	Precision			
0.00	0.8190			
0.10	0.5975			
0.20	0.5032			
0.30	0.4372			
0.40	0.3561			
0.50	0.2936			
0.60	0.2511			
0.70	0.1941			
0.80	0.1257			
0.90	0.0696			
1.00	0.0296			
Average precision over all				

relevant docs

non-interpolated

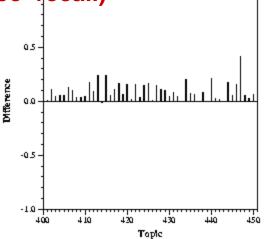
Document Level Averages					
Dro	Precision				
At 5 does	cışı<u>an</u>@				
At 10 does	0.5500				
At 15 docs	0.4987				
At 20 docs	0.4650				
At 30 does	0.4253				
At 100 does	0.2680				
At 200 does	0.1921				
At 500 does	0.1085				
At $1000 \operatorname{docs}$	0.0642				
D Droginian /	anadician after				

R-Precision (precision after R docs retrieved (where R is the number of relevant documents))

0.3470 Exact

(prec=recall)

Breakeven Point



Difference from Median in Average Precision per Topic

Mean Avg. Precision (MAP)

0.3169

What Query Averaging Hides

