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)

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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

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Mean Average Precision

- Consider rank position of each ***relevant*** doc
  - $K_1, K_2, \ldots K_R$
- Compute Precision@K for each $K_1, K_2, \ldots K_R$
- 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

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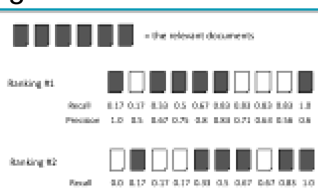
Average Precision



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

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

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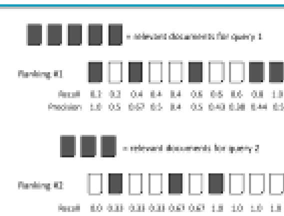
MAP



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

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

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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

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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

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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

Introduction to Information Retrieval Sec. 8.5.1

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 **Diversity in Document Retrieval** workshops

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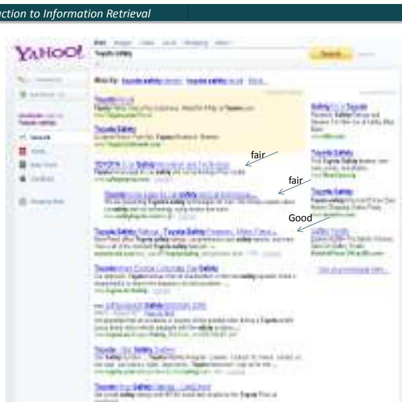

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Discounted Cumulative Gain

- Popular measure for evaluating web search and related tasks
- Two assumptions:
  - Highly relevant documents are more useful than marginally relevant 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 $r_1, r_2, \ldots r_n$ (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, 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: d_1, d_2, d_3, d_4

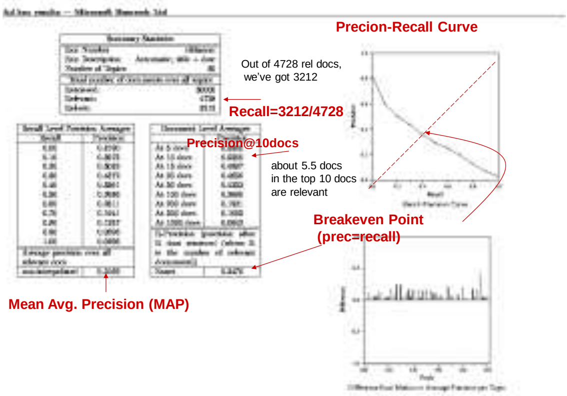
i	Ground Truth		Ranking Function$_1$		Ranking Function$_2$	
	Document Order	r_i	Document Order	r_i	Document Order	r_i
1	d4	2	d3	2	d3	2
2	d3	2	d4	2	d2	1
3	d2	1	d2	1	d4	2
4	d1	0	d1	0	d1	0
	$NDCG_{GT}$=1.00		$NDCG_{RF1}$=1.00		$NDCG_{RF2}$=0.9203	

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

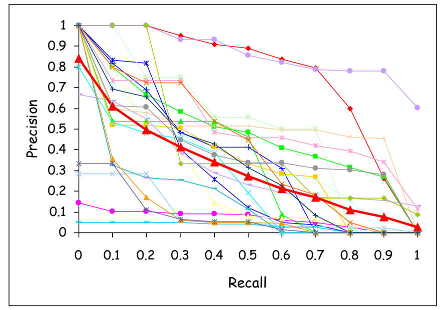
$$DCG_{RF1} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.6309$$

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

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



What Query Averaging Hides



Slide from Doug Oard's presentation, originally from Ellen Voorhees' presentation