Introduction to Information Retrieval

Lecture 6

Evaluation

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

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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
 - But how do you measure relevance?

Pioneered by Cyril Cleverdon in the

Cranfield Ex

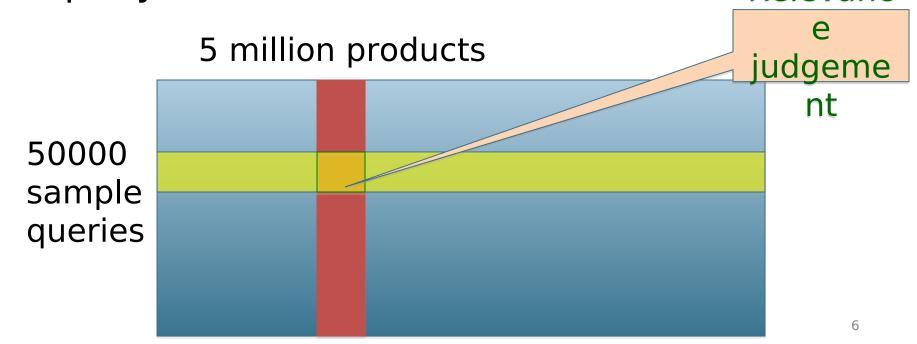
Measuring relevance

- 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

Retrieval

quality of a new search algorithm

- Benchmark documents the products
- Benchmark query suite more on this
- Judgments of document relevance for each query
 Relevance



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

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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"

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 |



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Now we have the basics of a benchmark

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

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., <u>Information need</u>: 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

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 Retrievecision P = tp/(tp ^{tn} + 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 2/3
 - Prec@4 of 2/4
 - Prec@5 of 3/5



In similar fashion we have Recall@K

Mean Average Precision

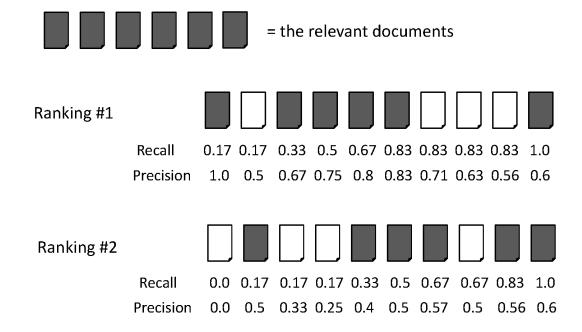
- Consider rank position of each relevant doc
 - K₁, K₂, ... K_R
- Compute Precision@K for each $K = K_1, K_2, ... K_R$
- Average recision = average of P@K

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

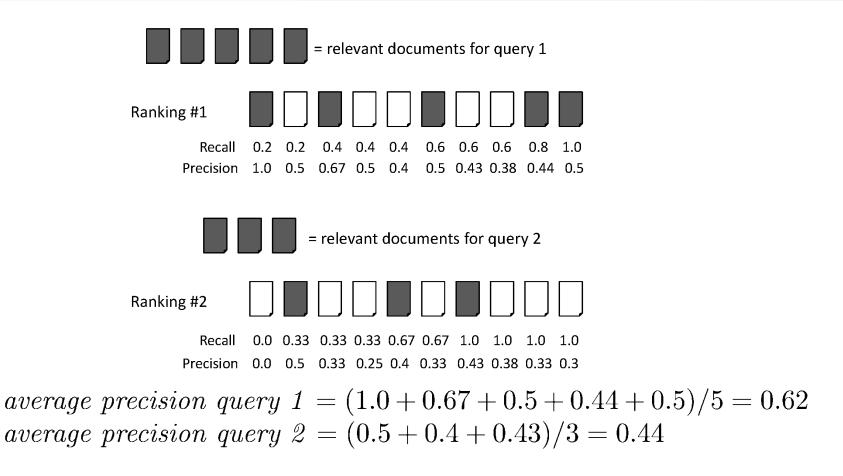
Average Precision



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

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

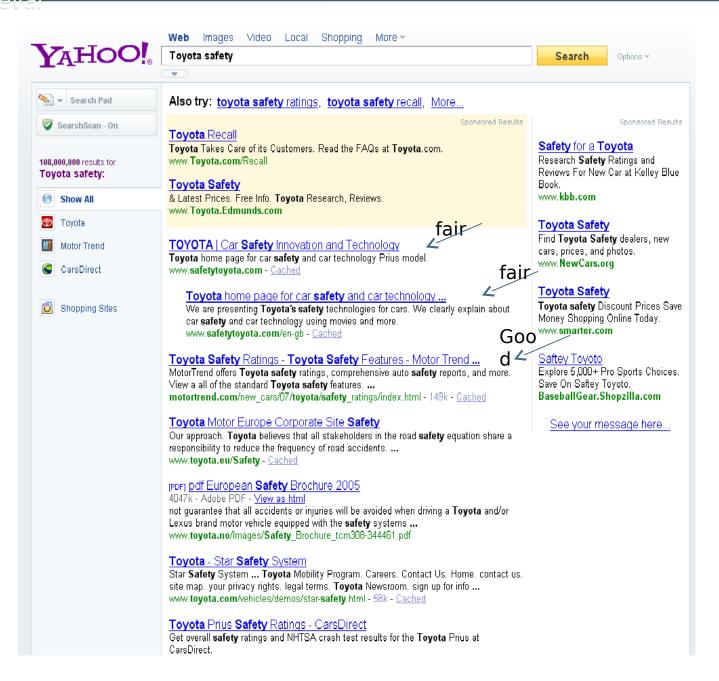
- Consider rank position, K, of first relevant doc
 - Could be only clicked doc

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

MRR is the mean RR across multiple queries

Beyond binary relevance

Potrioval



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
 - 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,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

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
- Ideal DCG values:
 - 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: d₁, d₂, d₃, d₄

| i | Ground Truth | | Ranking Function ₁ | | Ranking Function ₂ | |
|---|--------------------------|----------------|-------------------------------|----------------|-------------------------------|----------------|
| | Docume nt Order | r _i | Docume nt Order | r _i | Docume nt 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 | |

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

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

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

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