

# Search Evaluation

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Slides partially based on text book [CMS]  
[MRS]

# Table of Content

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- **Search Engine Evaluation**
- **Metrics for relevancy**
  - Precision/recall
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# Difficulties in Evaluating IR Systems

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- **Effectiveness is related to the *relevancy* of retrieved items.**
- **Relevancy is not typically binary but continuous. Not easy to judge**
- **Relevancy, from a human standpoint, is:**
  - Subjective/cognitive: Depends upon user's judgment, human perception and behavior
  - Situational and dynamic:
    - Relates to user's current needs. Change over time.
  - E.g.
    - CMU. US Open. Etrade.
    - Red wine or white wine

# Measuring user happiness

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- **Issue: who is the user we are trying to make happy?**
- **Web engine: user finds what they want and return to the engine**
  - Can measure rate of return users
- **eCommerce site: user finds what they want and make a purchase**
  - Is it the end-user, or the eCommerce site, whose happiness we measure?
  - Measure time to purchase, or fraction of searchers who become buyers?

# Aspects of Search Quality

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- **Relevancy**
- **Freshness & coverage**
  - Latency from creation of a document to time in the online index. (Speed of discovery and indexing)
  - Size of database in covering data coverage
- **User effort and result presentation**
  - Work required from the user in formulating queries, conducting the search
  - Expressiveness of query language
  - Influence of search output format on the user's ability to utilize the retrieved materials.

# System Aspects of Evaluation

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- **Response time:**
  - Time interval between receipt of a user query and the presentation of system responses.
  - Average response time
    - at different traffic levels (queries/second)
    - When # of machines changes
    - When the size of database changes
    - When there is a failure of machines
- **Throughputs**
  - Maximum number of queries/second that can be handled
    - without dropping user queries
    - Or meet Service Level Agreement (SLA)
      - For example, 99% of queries need to be completed within a second.
  - How does it vary when the size of database changes

# System Aspects of Evaluation

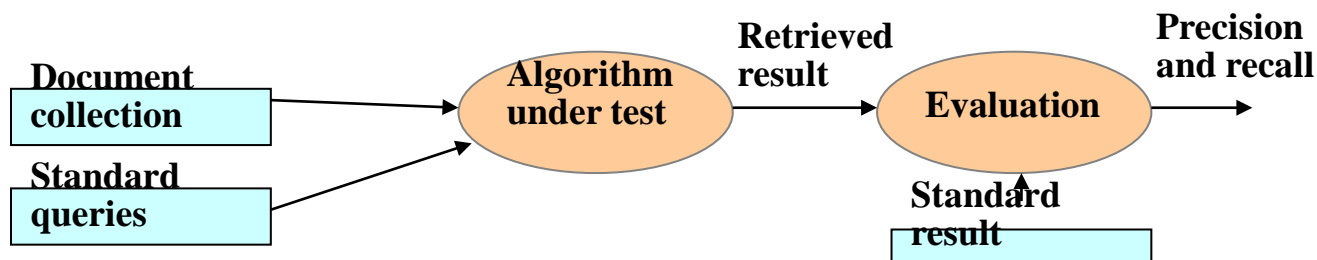
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- **Others**

- Time from crawling to online serving.
- Percentage of results served from cache
- Stability: number of abnormal response spikes per day or per week.
- Fault tolerance: number of failures that can be handled.
- Cost: number of machines needed to handle
  - different traffic levels
  - host a DB with different sizes

# Relevance benchmarks

- **Relevant measurement requires 3 elements:**
  1. A benchmark document collection
  2. A benchmark suite of queries
  3. Editorial assessment of query-doc pairs
    - Relevant vs. non-relevant
    - Multi-level: Perfect, excellent, good, fair, poor, bad



- **Public benchmarks**
  - TREC: <http://trec.nist.gov/>
  - Microsoft/Yahoo published learning benchmarks



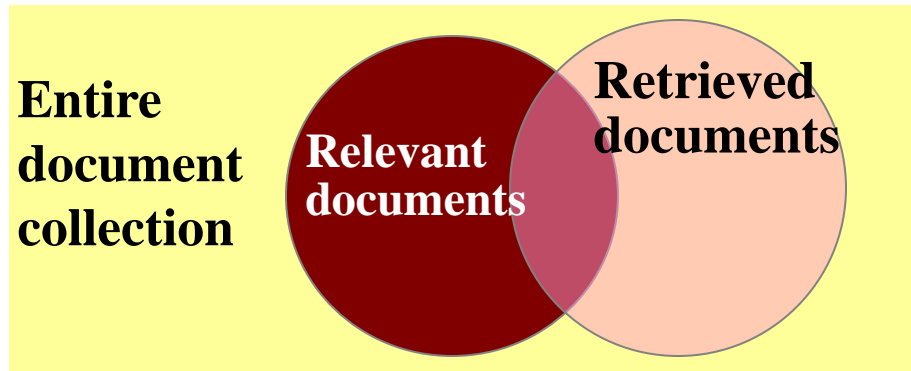
# Unranked retrieval evaluation: Precision and Recall

- **Precision: fraction of retrieved docs that are relevant =  $P(\text{relevant}|\text{retrieved})$**
- **Recall: fraction of relevant docs that are retrieved =  $P(\text{retrieved}|\text{relevant})$**

	Relevant	Not Relevant
Retrieved	tp (True positive)	fp
Not Retrieved	fn	tn

- **Precision  $P = tp/(tp + fp)$**
- **Recall  $R = tp/(tp + fn)$**

# Precision and Recall: Another View



relevant	retrieved & relevant	not retrieved but relevant
	irrelevant	Not retrieved & irrelevant
	retrieved	not retrieved

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

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

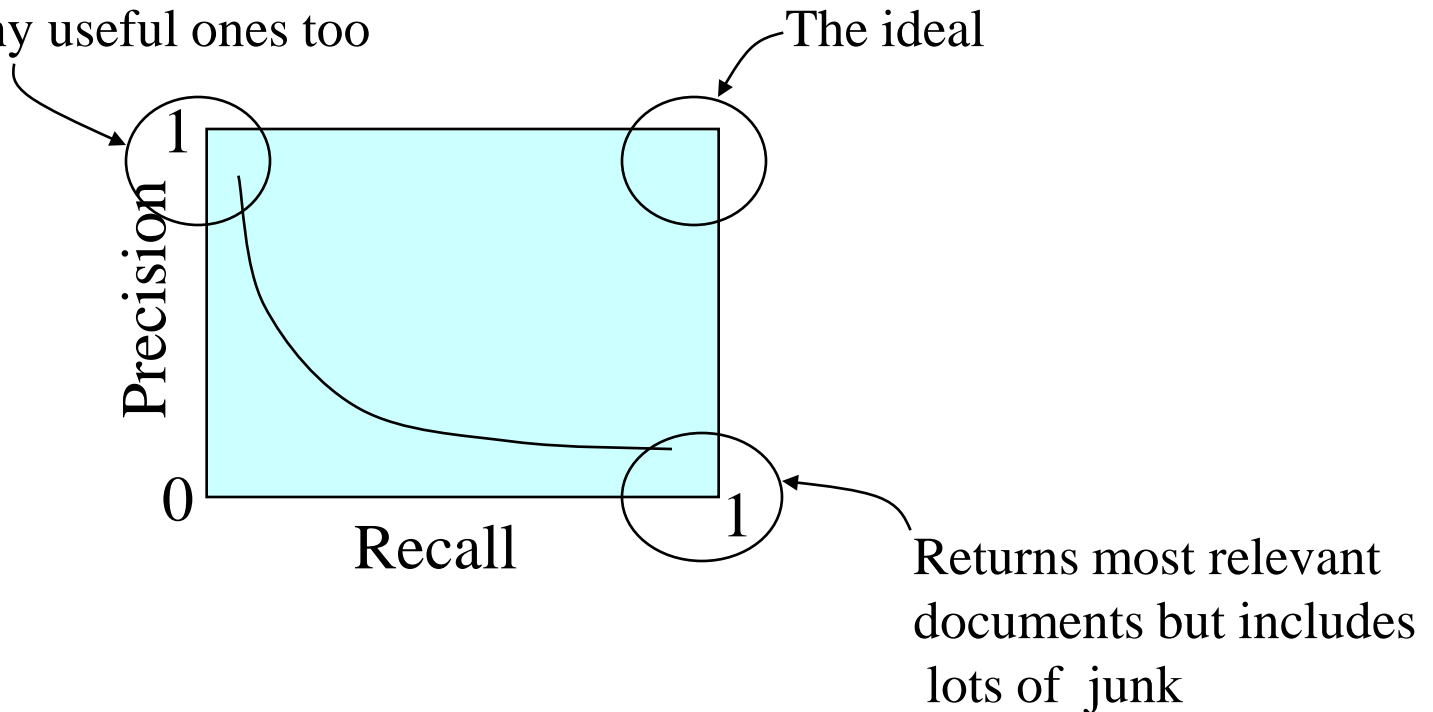
# Determining Recall is Difficult

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- **Total number of relevant items is sometimes not available:**
  - Use queries that only identify few rare documents known to be relevant

# Trade-off between Recall and Precision

Returns relevant documents but misses many useful ones too



# F-Measure

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- **One measure of performance that takes into account both recall and precision.**
- **Harmonic mean of recall and precision:**

$$F = \frac{2PR}{P + R} = \frac{2}{\frac{1}{R} + \frac{1}{P}}$$

# E Measure (parameterized F Measure)

- A variant of F measure that allows weighting emphasis on precision over recall:

$$E = \frac{(1 + \beta^2)PR}{\beta^2 P + R} = \frac{(1 + \beta^2)}{\frac{\beta^2}{R} + \frac{1}{P}}$$

- **Value of  $\beta$  controls trade-off:**
  - $\beta = 1$ : Equally weight precision and recall ( $E=F$ ).
  - $\beta > 1$ : Weight precision more.
  - $\beta < 1$ : Weight recall more.

## Computing Recall/Precision Points for Ranked Results

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- For a given query, produce the ranked list of retrievals.
- Mark each document in the ranked list that is relevant according to the gold standard.
- Compute a recall/precision pair for each position in the ranked list that contains a relevant document.

# R- Precision (at Position R)

- Precision at the R-th position in the ranking of results for a query that has R relevant documents.

n	doc #	relevant
1	588	x
2	589	x
3	576	
4	590	x
5	986	
6	592	x
7	984	
8	988	
9	578	
10	985	
11	103	
12	591	
13	772	x
14	990	

R = # of relevant docs = 6

R-Precision =  $4/6 = 0.67$



# Computing Recall/Precision Points: An Example

n	doc #	relevant
1	588	x
2	589	x
3	576	
4	590	x
5	986	
6	592	x
7	984	
8	988	
9	578	
10	985	
11	103	
12	591	
13	772	x
14	990	

Let total # of relevant docs = 6  
Check each new recall point:

$R=1/6=0.167$ ;  $P=1/1=1$

$R=2/6=0.333$ ;  $P=2/2=1$

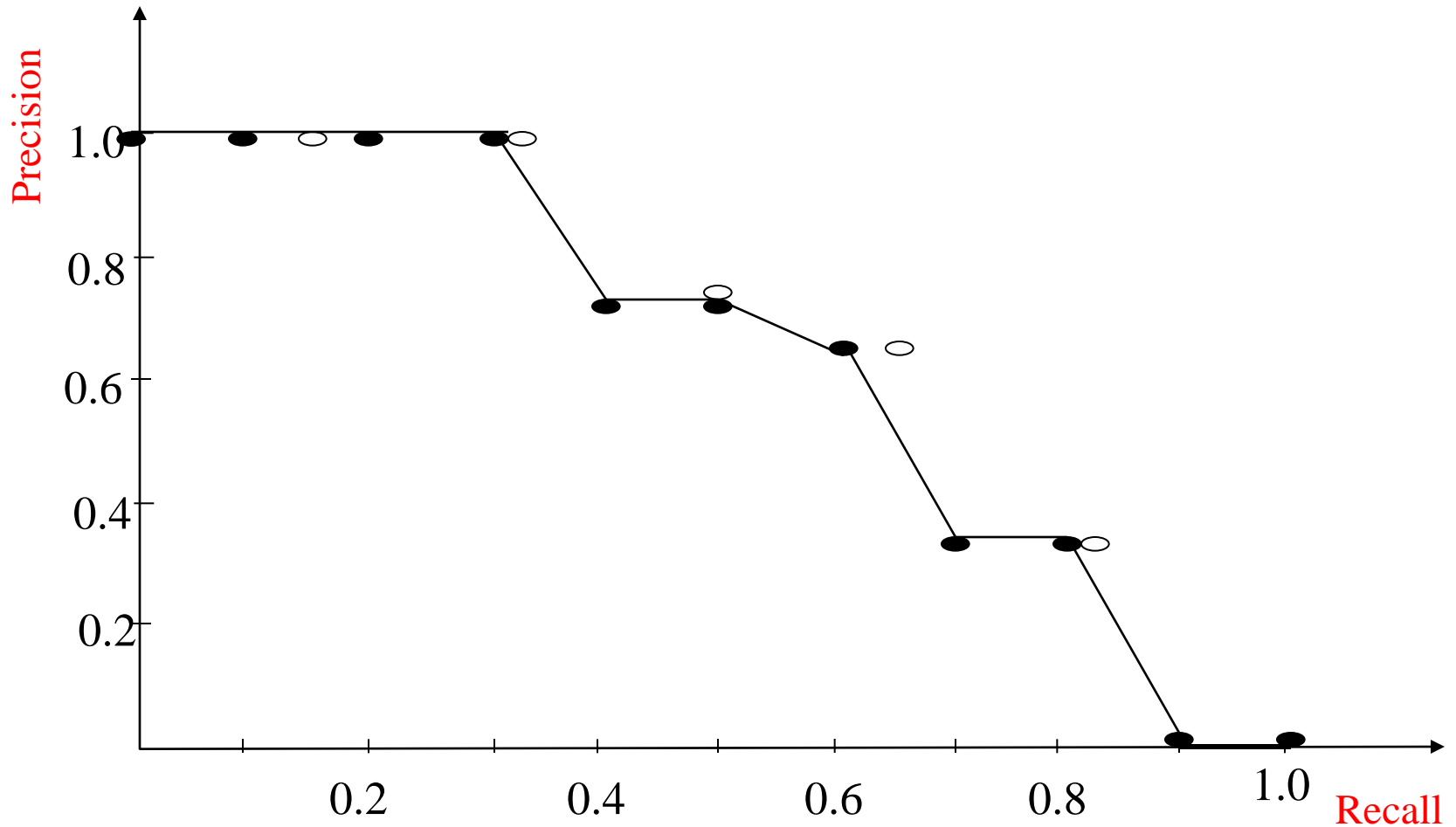
$R=3/6=0.5$ ;  $P=3/4=0.75$

$R=4/6=0.667$ ;  $P=4/6=0.667$

$R=5/6=0.833$ ;  $p=5/13=0.38$

Missing one  
relevant document.  
Never reach  
100% recall

# Interpolating a Recall/Precision Curve: An Example




# Averaging across Queries: MAP











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- ***Mean Average Precision (MAP)***
  - summarize rankings from multiple queries by averaging average precision
  - most commonly used measure in research papers
  - assumes user is interested in finding many relevant documents for each query
  - requires many relevance judgments in text collection

# MAP Example:











 = 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

*average precision query 1* =  $(1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$

*average precision query 2* =  $(0.5 + 0.4 + 0.43)/3 = 0.44$

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

# Discounted Cumulative Gain

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- **Popular measure for evaluating web search and related tasks**
- **Two assumptions:**
  - Highly relevant documents are more useful than marginally relevant document
    - Support relevancy judgment with multiple levels
  - 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
- **Gain is *discounted*, at lower ranks, e.g.  $1/\log(\text{rank})$** 
  - With base 2, the discount at rank 4 is  $1/2$ , and at rank 8 it is  $1/3$

# Discounted Cumulative Gain

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- ***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

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- **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@1, @2, etc:**

3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61

# Normalized DCG

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- DCG values are often *normalized* by comparing the DCG at each rank with the DCG value for the *perfect ranking*
  - *Example:*
    - $DCG @5 = 6.89$
    - Ideal  $DCG @5 = 9.75$
    - $NDCG @5 = 6.89 / 9.75 = 0.71$
- NDCG numbers are averaged across a set of queries at specific rank values



# NDCG Example with Normalization

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- **Perfect ranking:**

3, 3, 3, 2, 2, 2, 1, 0, 0, 0

- **Ideal DCG@1, @2, ...:**

3, 6, 7.89, 8.89, 9.75, 10.52, 10.88, 10.88, 10.88, 10

- **NDCG@1, @2, ...**

- normalized values (divide actual by ideal):

1, 0.83, 0.87, 0.76, 0.71, 0.69, 0.73, 0.8, 0.88, 0.88

- $\text{NDCG} \leq 1$  at any rank position