# CS 172 INFORMATION RETRIEVAL

Search Engine Evaluation

Chapter 8 in the textbook

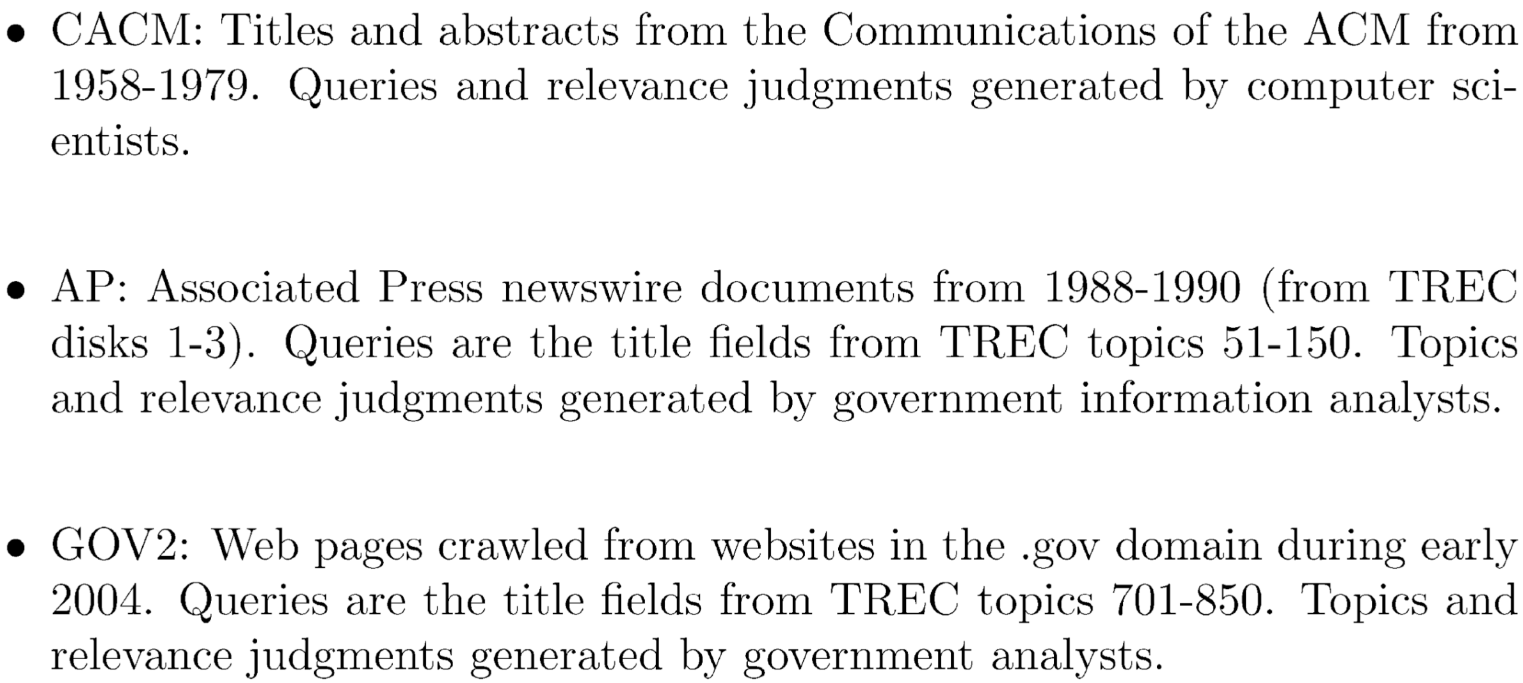
# Evaluation

- Evaluation is key to building *effective* and *efficient* search engines
  - measurement usually carried out in controlled laboratory experiments
  - *online* testing can also be done

- Effectiveness, efficiency and *cost* are related
  - e.g., if we want a particular level of effectiveness and efficiency, this will determine the cost of the system configuration
  - efficiency and cost targets may impact effectiveness

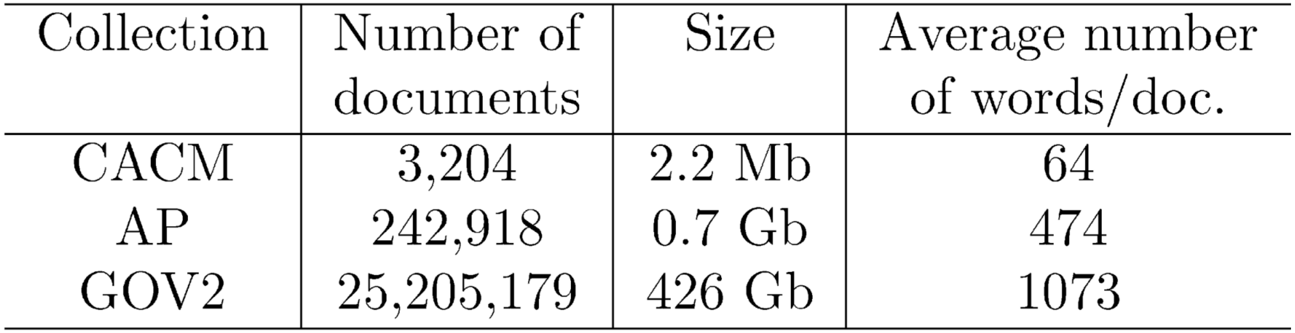
# Evaluation Corpus

- *Test collections* consisting of documents, queries, and relevance judgments, e.g.,

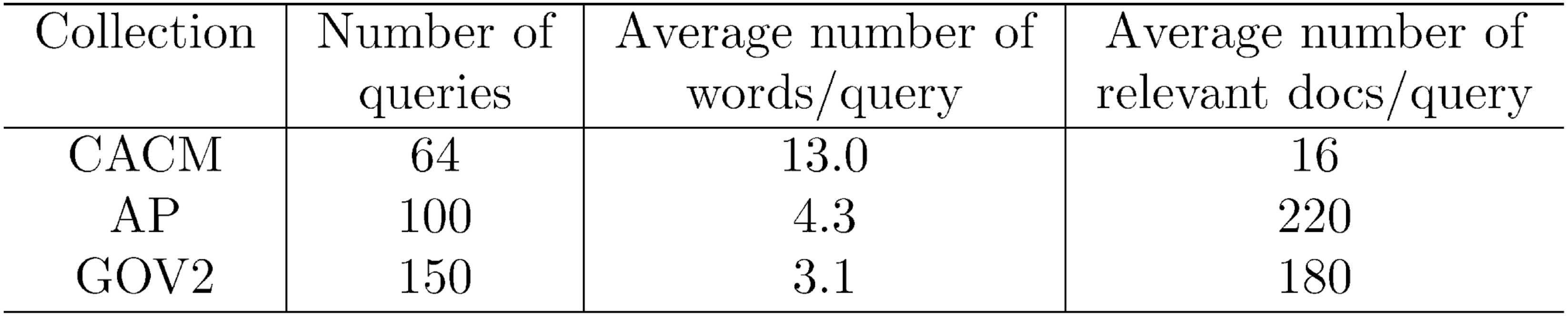


- CACM: Titles and abstracts from the Communications of the ACM from 1958-1979. Queries and relevance judgments generated by computer scientists.
- AP: Associated Press newswire documents from 1988-1990 (from TREC disks 1-3). Queries are the title fields from TREC topics 51-150. Topics and relevance judgments generated by government information analysts.
- GOV2: Web pages crawled from websites in the .gov domain during early 2004. Queries are the title fields from TREC topics 701-850. Topics and relevance judgments generated by government analysts.

# Test Collections

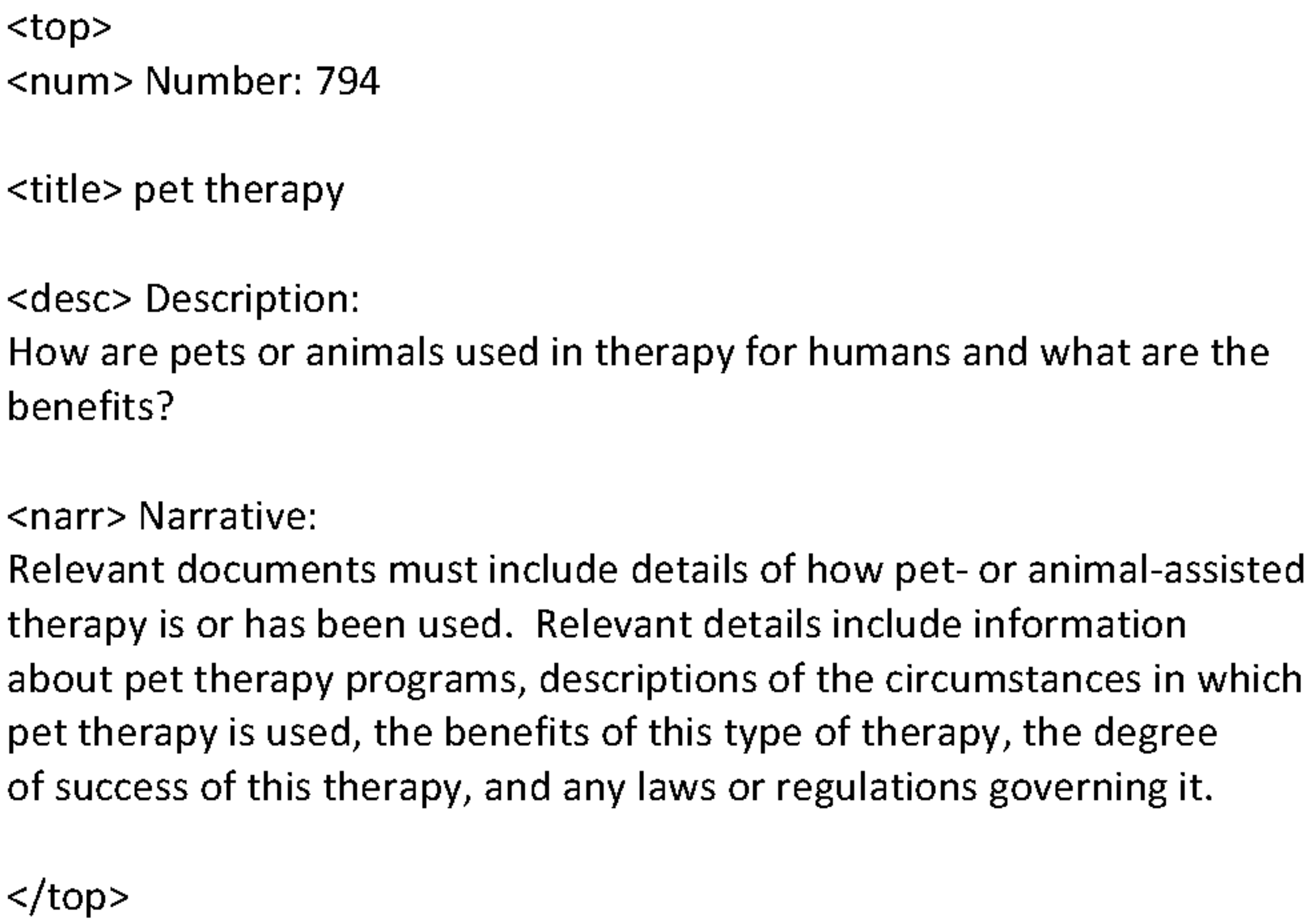


| Collection | Number of documents | Size | Average number of words/doc. |
|---|---|---|---|
| CACM | 3,204 | 2.2 Mb | 64 |
| AP | 242,918 | 0.7 Gb | 474 |
| GOV2 | 25,205,179 | 426 Gb | 1073 |



| Collection | Number of queries | Average number of words/query | Average number of relevant docs/query |
|---|---|---|---|
| CACM | 64 | 13.0 | 16 |
| AP | 100 | 4.3 | 220 |
| GOV2 | 150 | 3.1 | 180 |

# TREC Topic Example



```
<top>
<num> Number: 794

<title> pet therapy

<desc> Description:
How are pets or animals used in therapy for humans and what are the
benefits?

<narr> Narrative:
Relevant documents must include details of how pet- or animal-assisted
therapy is or has been used.  Relevant details include information
about pet therapy programs, descriptions of the circumstances in which
pet therapy is used, the benefits of this type of therapy, the degree
of success of this therapy, and any laws or regulations governing it.

</top>
```

# Relevance Judgments

- Obtaining relevance judgments is an expensive, time-consuming process
  - who does it?
  - what are the instructions?
  - what is the level of agreement?

# Pooling

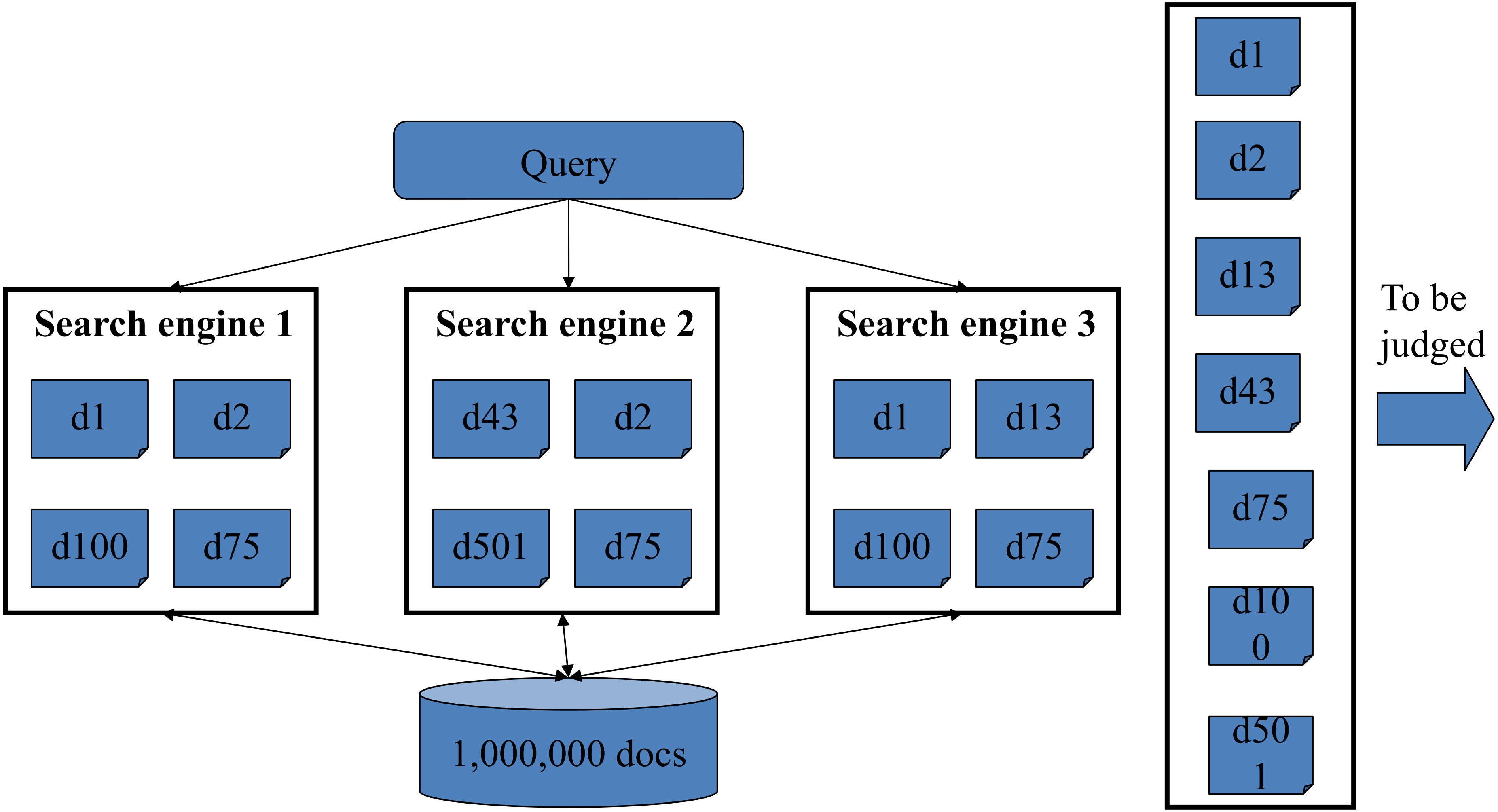
- Exhaustive judgments for all documents in a collection is not practical

- Pooling technique is used in TREC
  - top *k results (for TREC, k varied between 50 and* 200) from the rankings obtained by different search engines (or retrieval algorithms) are merged into a pool.
  - duplicates are removed
  - documents are presented in some random order to the relevance judges

- Produces a large number of relevance judgments for each query, although still incomplete

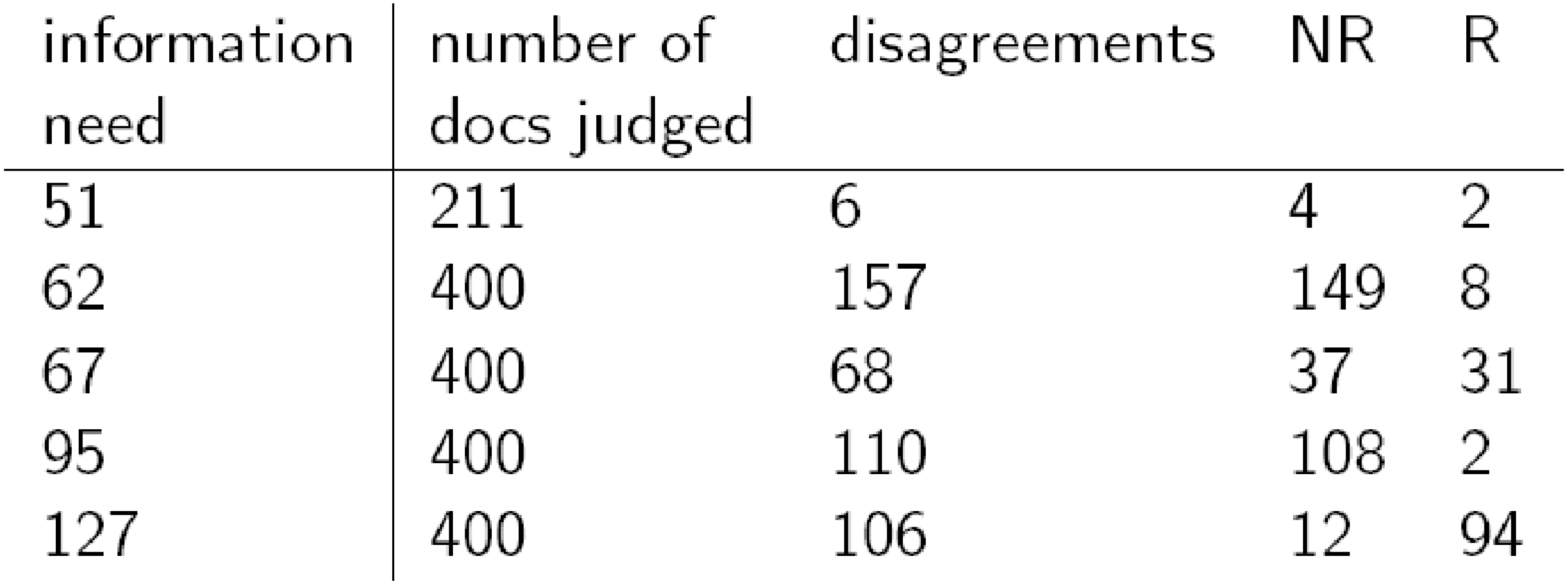
- Issue, if a new ranking algorithm retrieves documents not within the pool, then those will be marked as non-relevant.

# Pooling


Query
Search engine 1
d1
d2
d100
d75
Search engine 2
d43
d2
d501
d75
Search engine 3
d1
d13
d100
d75
1,000,000 docs
d1
d2
d13
d43
d75
d10
0
d50
1
To be
judged

# Bias in Relevance Judgments

- Relevance judgment is subjective
- Disagreement among assessors

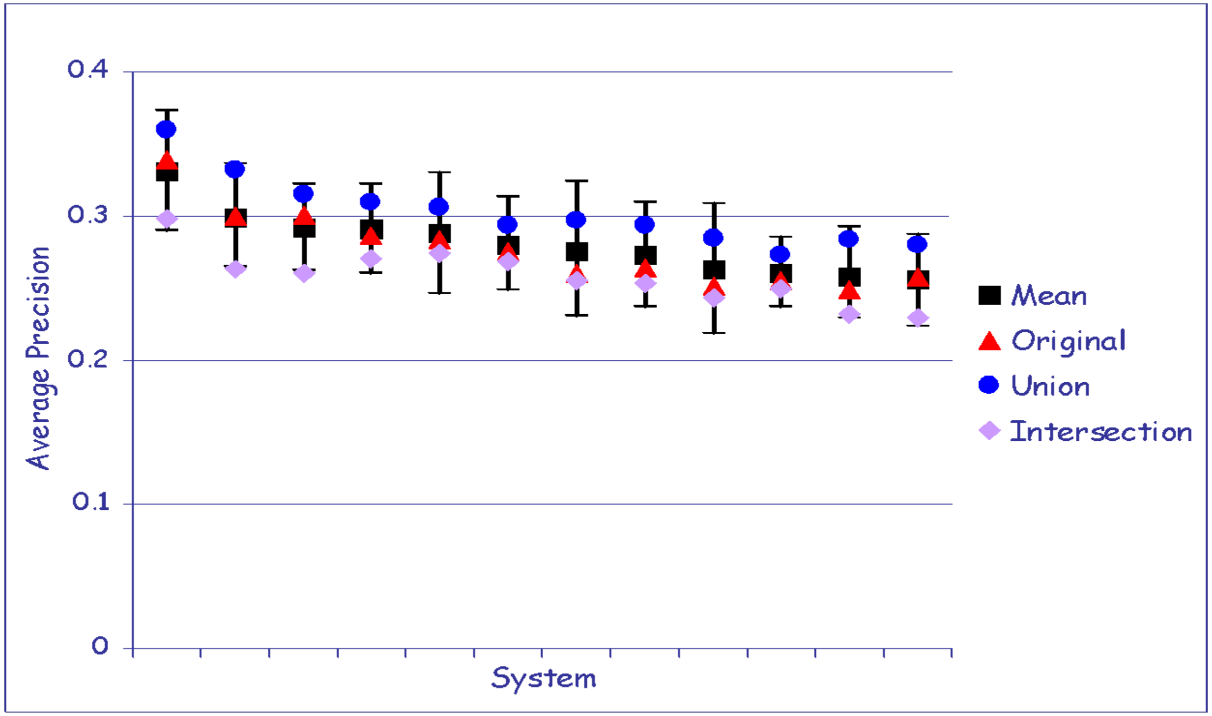


| information need | number of docs judged | disagreements | NR | R |
|---|---|---|---|---|
| 51 | 211 | 6 | 4 | 2 |
| 62 | 400 | 157 | 149 | 8 |
| 67 | 400 | 68 | 37 | 31 |
| 95 | 400 | 110 | 108 | 2 |
| 127 | 400 | 106 | 12 | 94 |

# Combine Multiple Judgments

- Judges disagree a lot. How to combine judgments from multiple reviewers ?
  - Union
  - Intersection
  - Majority vote

# Combine Multiple Judgments



- Large impact on absolute performance numbers
- Virtually no impact on ranking of systems

# Query Logs

- Used for both tuning and evaluating search engines
  - also for various techniques such as query suggestion

- Typical contents
  - User identifier or user session identifier
  - Query terms - stored exactly as user entered
  - List of URLs of results, their ranks on the result list, and whether they were clicked on
  - Timestamp(s) - records the time of user events such as query submission, clicks

# Query Logs

- Clicks are not relevance judgments
  - although they are correlated
  - biased by a number of factors such as rank on result list

- Can use clickthrough data to predict *preferences* between pairs of documents
  - appropriate for tasks with multiple levels of relevance, focused on user relevance
  - various “policies” used to generate preferences

# Example Click Policy

- *Skip Above and Skip Next*
  - click data
  - generated preferences

$$\begin{array}{l} d_1 \\ d_2 \\ d_3 \ \text{(clicked)} \\ d_4 \end{array}$$

$$\begin{array}{l} d_3 > d_2 \\ d_3 > d_1 \\ d_3 > d_4 \end{array}$$

# Query Logs

- Click data can also be aggregated to remove noise

- *Click distribution* information
  - can be used to identify clicks that have a higher frequency than would be expected
  - high correlation with relevance
  - e.g., using *click deviation* to filter clicks for preference-generation policies

# Effectiveness Measures

*A* is set of relevant documents,
*B* is set of retrieved documents

| | Relevant | Non-Relevant |
|---|---|---|
| Retrieved | $A \cap B$ | $\overline{A} \cap B$ |
| Not Retrieved | $A \cap \overline{B}$ | $\overline{A} \cap \overline{B}$ |

$$\begin{aligned} Recall &= \frac{|A \cap B|}{|A|} \\ Precision &= \frac{|A \cap B|}{|B|} \end{aligned}$$

# Classification Errors

- *False Positive* (Type I error)
  - a non-relevant document is retrieved

$$Fallout = \frac{|\overline{A} \cap B|}{|\overline{A}|}$$

- *False Negative* (Type II error)
  - a relevant document is not retrieved
  - 1- *Recall*

- *Precision* is used when probability that a positive result is correct is important

# F Measure

- *Harmonic mean* of recall and precision

$$F = \frac{1}{\frac{1}{2}\left(\frac{1}{R}+\frac{1}{P}\right)} = \frac{2RP}{(R+P)}$$

  - harmonic mean emphasizes the importance of small values, whereas the arithmetic mean is affected more by outliers that are unusually large

- More general form

  - β is a parameter that determines relative importance of recall and precision

$$F_\beta = (\beta^2+1)RP/(R+\beta^2 P)$$

# Ranking Effectiveness

■ ■ ■ ■ ■ ■ = the relevant documents

Ranking #1

|  |  |  |  |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|---|
|  | ■ | □ | ■ | ■ | ■ | ■ | □ | □ | □ | ■ |
| Recall | 0.17 | 0.17 | 0.33 | 0.5 | 0.67 | 0.83 | 0.83 | 0.83 | 0.83 | 1.0 |
| Precision | 1.0 | 0.5 | 0.67 | 0.75 | 0.8 | 0.83 | 0.71 | 0.63 | 0.56 | 0.6 |

Ranking #2

|  |  |  |  |  |  |  |  |  |  |  |
|---|---|---|---|---|---|---|---|---|---|---|
|  | □ | ■ | □ | □ | ■ | ■ | ■ | □ | ■ | ■ |
| Recall | 0.0 | 0.17 | 0.17 | 0.17 | 0.33 | 0.5 | 0.67 | 0.67 | 0.83 | 1.0 |
| Precision | 0.0 | 0.5 | 0.33 | 0.25 | 0.4 | 0.5 | 0.57 | 0.5 | 0.56 | 0.6 |

# Summarizing a Ranking

- Calculating recall and precision at fixed rank positions
- Calculating precision at standard recall levels, from 0.0 to 1.0
  - requires *interpolation*
- Average Precision: Averaging the precision values from the rank positions where a relevant document was retrieved

# Average Precision

■ ■ ■ ■ ■ ■ = the relevant documents

| Ranking #1 | ■ | □ | ■ | ■ | ■ | ■ | □ | □ | □ | ■ |
|---|---|---|---|---|---|---|---|---|---|---|
| Recall | 0.17 | 0.17 | 0.33 | 0.5 | 0.67 | 0.83 | 0.83 | 0.83 | 0.83 | 1.0 |
| Precision | 1.0 | 0.5 | 0.67 | 0.75 | 0.8 | 0.83 | 0.71 | 0.63 | 0.56 | 0.6 |

| Ranking #2 | □ | ■ | □ | □ | ■ | ■ | ■ | □ | ■ | ■ |
|---|---|---|---|---|---|---|---|---|---|---|
| Recall | 0.0 | 0.17 | 0.17 | 0.17 | 0.33 | 0.5 | 0.67 | 0.67 | 0.83 | 1.0 |
| Precision | 0.0 | 0.5 | 0.33 | 0.25 | 0.4 | 0.5 | 0.57 | 0.5 | 0.56 | 0.6 |

$$\text{Ranking } \#1\text{:} \;\; (1.0 + 0.67 + 0.75 + 0.8 + 0.83 + 0.6)/6 = 0.78$$

$$\text{Ranking } \#2\text{:} \;\; (0.5 + 0.4 + 0.5 + 0.57 + 0.56 + 0.6)/6 = 0.52$$

# Averaging Across Queries

■ ■ ■ ■ ■ = 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 |

# Averaging

- *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

- Recall-precision graphs are also useful summaries

# MAP

■ ■ ■ ■ ■ = 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 |

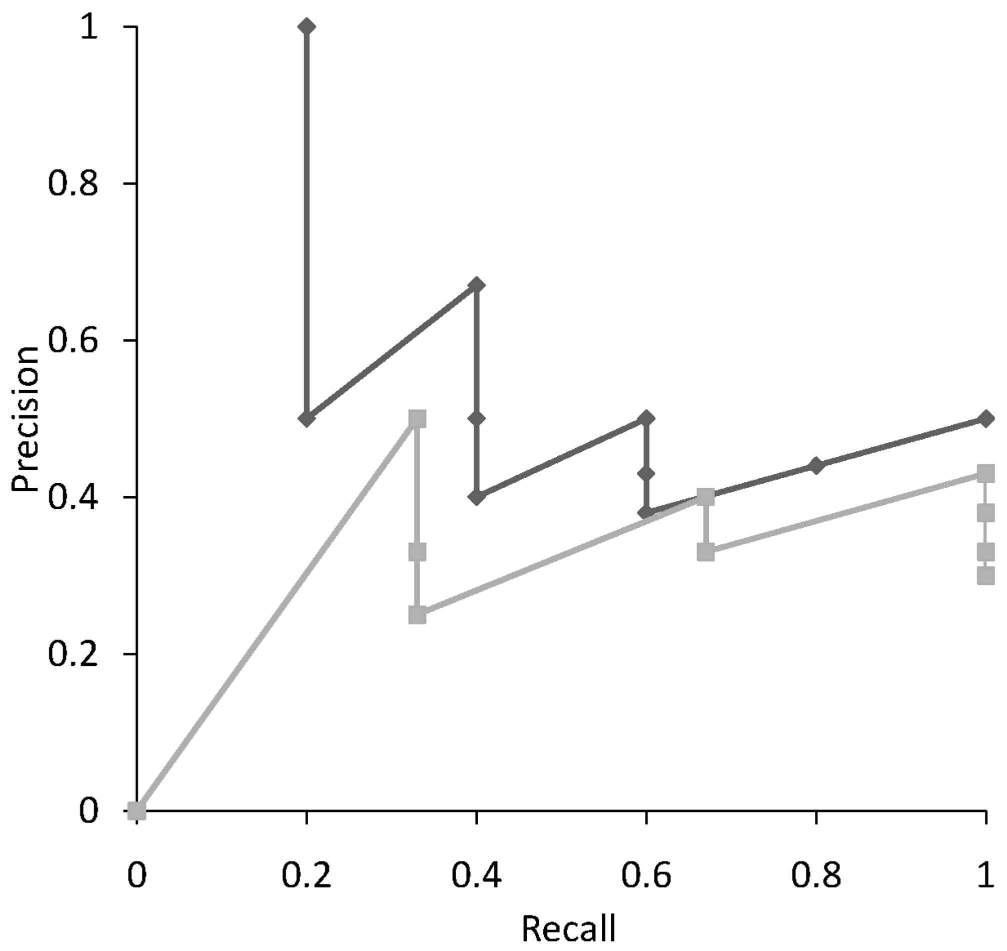
■ ■ ■ = relevant documents for query 2

| 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 |

$$\begin{aligned} \mathit{average\ precision\ query\ 1} &= (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62 \\ \mathit{average\ precision\ query\ 2} &= (0.5 + 0.4 + 0.43)/3 = 0.44 \end{aligned}$$

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

# Recall-Precision Graph



# Interpolation

- To average graphs, calculate precision at standard recall levels:

$$P(R) = \max\{P' : R' \geq R \wedge (R', P') \in S\}$$

  - where *S* is the set of observed (*R*,*P*) points

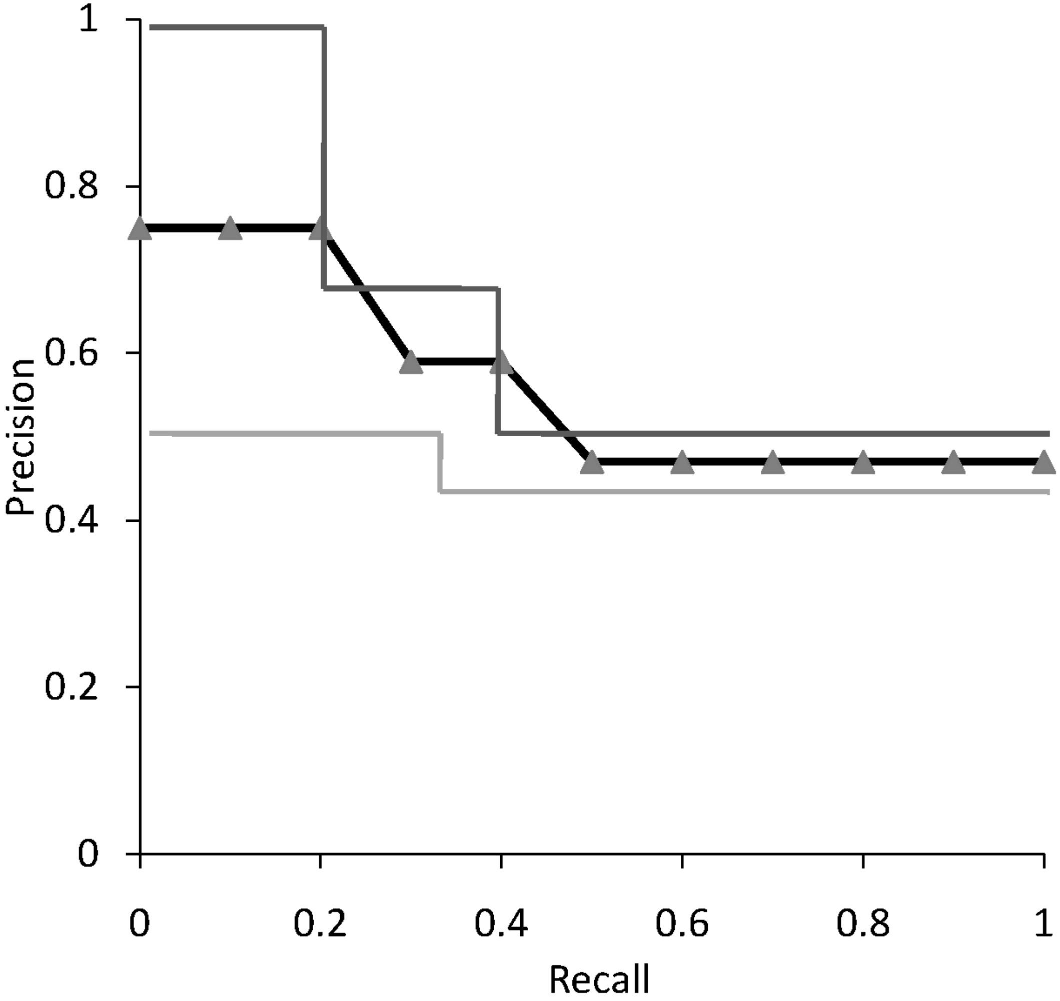
- Defines precision at any recall level as the *maximum* precision observed in any recall-precision point at a higher recall level
  - produces a step function
  - defines precision at recall 0.0

# Average Precision at Standard Recall Levels

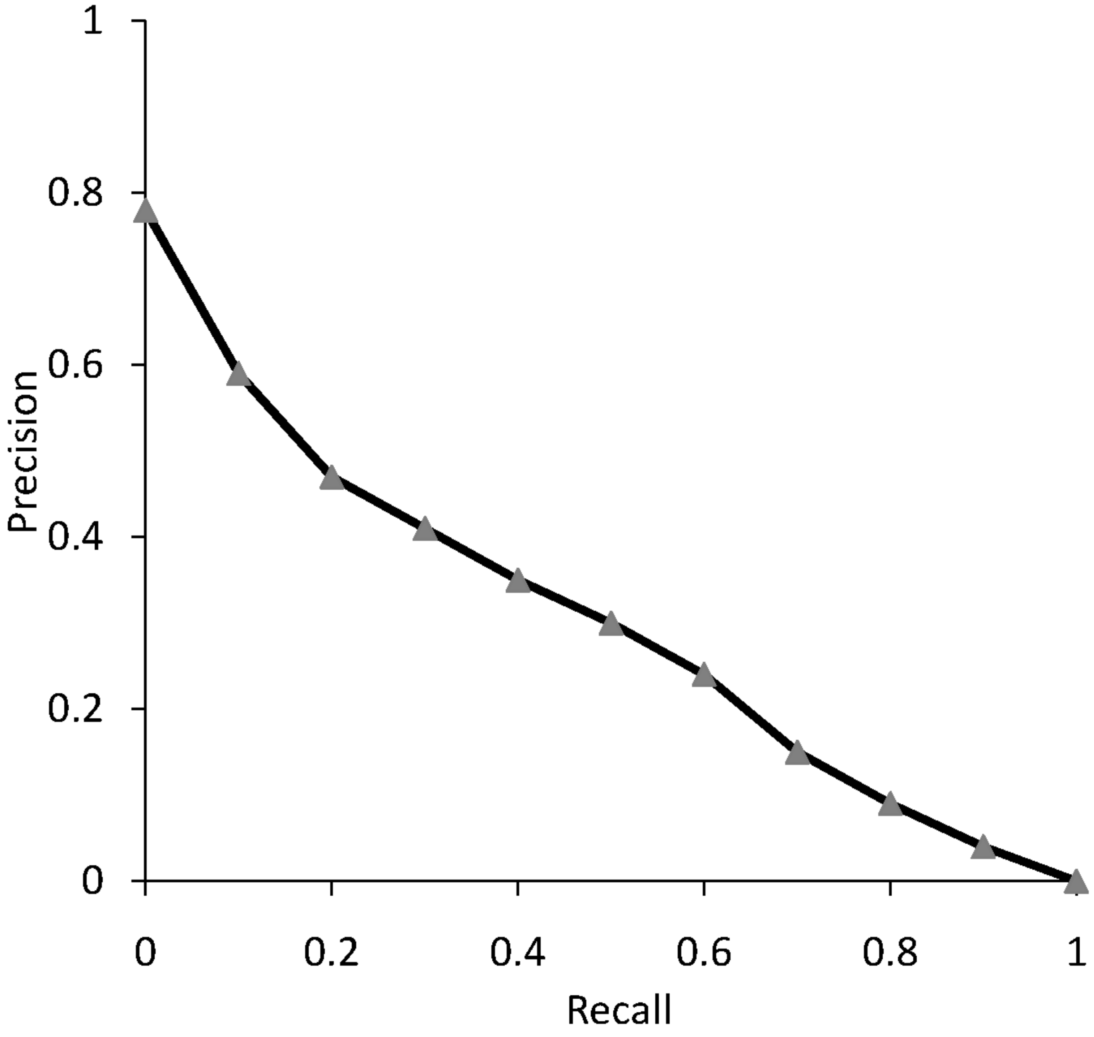
| Recall | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | 1.0 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Ranking 1 | 1.0 | 1.0 | 1.0 | 0.67 | 0.67 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Ranking 2 | 0.5 | 0.5 | 0.5 | 0.5 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 | 0.43 |
| Average | 0.75 | 0.75 | 0.75 | 0.59 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 | 0.47 |

- Recall-precision graph plotted by simply joining the average precision points at the standard recall levels

# Average Recall-Precision Graph



# Graph for 50 Queries



# Focusing on Top Documents

- Users tend to look at only the top part of the ranked result list to find relevant documents

- Some search tasks have only one relevant document
  - e.g., navigational search, question answering

- Recall not appropriate
  - instead need to measure how well the search engine does at retrieving relevant documents at very high ranks

# Focusing on Top Documents

- Precision at Rank R
  - R typically 5, 10, 20
  - easy to compute, average, understand
  - not sensitive to rank positions less than R

- Reciprocal Rank
  - reciprocal of the rank at which the first relevant document is retrieved
  - *Mean Reciprocal Rank (MRR)* is the average of the reciprocal ranks over a set of queries
  - very sensitive to rank position
  - Ex. Retrieving 5 documents
    - $d_n$, $d_r$, $d_n$, $d_n$, $d_n$ the reciprocal rank is ½
    - $d_n$, $d_n$, $d_n$, $d_n$, $d_r$ the reciprocal ranks is 1/5
    - The MRR of these two rankings is (1/2+1/5)/2 = 0.35

# 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

- Uses *graded relevance* as a measure of the 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

# Discounted Cumulative Gain

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

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

rel$_i$: relevance judgment for i-th result. E.g. 0 to 5 (most relevant)

- 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

# Normalized DCG

- DCG numbers are averaged across a set of queries at specific rank values
  - e.g., DCG at rank 5 is 6.89 and at rank 10 is 9.61

- DCG values are often *normalized* by comparing the DCG at each rank with the DCG value for the *perfect ranking*
  - **makes averaging easier for queries with different numbers of relevant documents**

# NDCG Example

- Perfect ranking:
  3, 3, 3, 2, 2, 2, 1, 0, 0, 0

- ideal DCG values:
  3, 6, 7.89, 8.89, 9.75, 10.52, 10.88, 10.88, 10.88, 10

- 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 $\leq$ 1 at any rank position

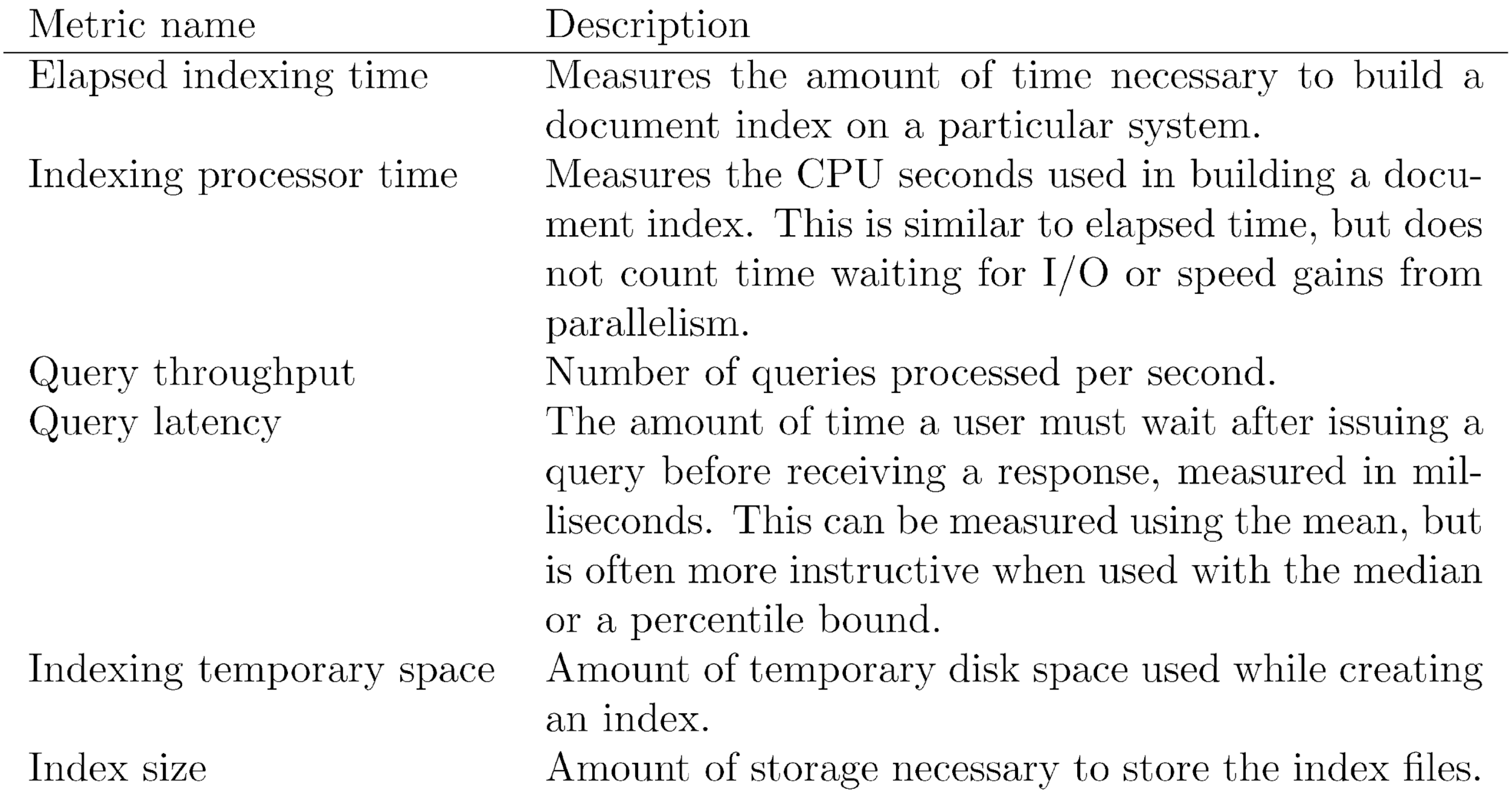
# Using Preferences

- Two rankings described using preferences can be compared using the *Kendall tau coefficient (τ ):*

$$\tau = \frac{P - Q}{P + Q}$$

  - *P* is the number of preferences that agree and *Q* is the number that disagree

# Efficiency Metrics



| Metric name | Description |
|---|---|
| Elapsed indexing time | Measures the amount of time necessary to build a document index on a particular system. |
| Indexing processor time | Measures the CPU seconds used in building a document index. This is similar to elapsed time, but does not count time waiting for I/O or speed gains from parallelism. |
| Query throughput | Number of queries processed per second. |
| Query latency | The amount of time a user must wait after issuing a query before receiving a response, measured in milliseconds. This can be measured using the mean, but is often more instructive when used with the median or a percentile bound. |
| Indexing temporary space | Amount of temporary disk space used while creating an index. |
| Index size | Amount of storage necessary to store the index files. |

# Hypotheses Testing

- Ideally, all our research problems should have a hypotheses that we test to see whether the hypotheses holds.
- A is better than B on task Z along some dimension W
  - Example: For *keyword-based searches in medical databases* Relevance Feedback will provide better search results than Topic Modeling as measured by mean average precision of the ranked list.
  - Suppose we run systems A, B on 5 queries
    - Observe that A has 50% higher MAP compared to B
    - Can I conclude A is better?
  - Well, you will have doubt that differences could be purely accidental
    - Is 5 queries enough to be confident?
    - Is 50% a significant difference?
    - What is a significant difference?
  - In this scenario, statistical hypotheses testing allows you to rule out that the differences between the two systems is coincidental, hence you can be more confident about the results.

# Statistical Hypothesis Testing

| Query | Q1 | Q2 | Q3 | Q4 | Q5 | Mean |
|---|---|---|---|---|---|---|
| System A | 0.61 | 0.52 | 0.12 | 0.73 | 0.22 | 0.44 |
| System B | 0.32 | 0.55 | 0.13 | 0.32 | 0.12 | 0.29 |
| Difference | +0.29 | -0.03 | -0.01 | +0.41 | +0.10 | +0.15 |

- See if differences can be explained by pure chance
- Null Hypothesis ($H_0$) is that A & B are equivalent
  - Natural variation of Average Precision (AP) values across queries … some queries are easier while some are harder
    - $H_0$ assumes that number for A and B are drawn from the distribution of numbers

  - We want to test $H_0$
    - Basically, we want to determine how likely (what is the probability) that these two samples of numbers come from the same distribution
    - If $Pr(H_0) < 5\%$, then its enough for us to reject $H_0$ and conclude A is better

# Significance Tests

- Given the results from a number of queries, how can we conclude that ranking algorithm A is better than algorithm B?

- A significance test enables us to reject the *null hypothesis* (no difference) in favor of the *alternative hypothesis* (B is better than A)
  - the *power* of a test is the probability that the test will reject the null hypothesis correctly
  - increasing the number of queries in the experiment also increases power of test

# Significance Tests

1. Prepare your experiment carefully, with only one difference between the two systems: the change whose effect you wish to measure. Choose a significance level $\alpha$, used to make your decision.
2. Run each system many times (e.g. on many different queries), evaluating each run (e.g. with AP).
3. Calculate a test statistic for each system based on the distributions of evaluation metrics.
4. Use a statistical significance test to compare the test statistics (one for each system). This will give you a p-value: the probability of the null hypothesis producing a difference at least this large.
5. If the p-value is less than $\alpha$, reject the null hypothesis.

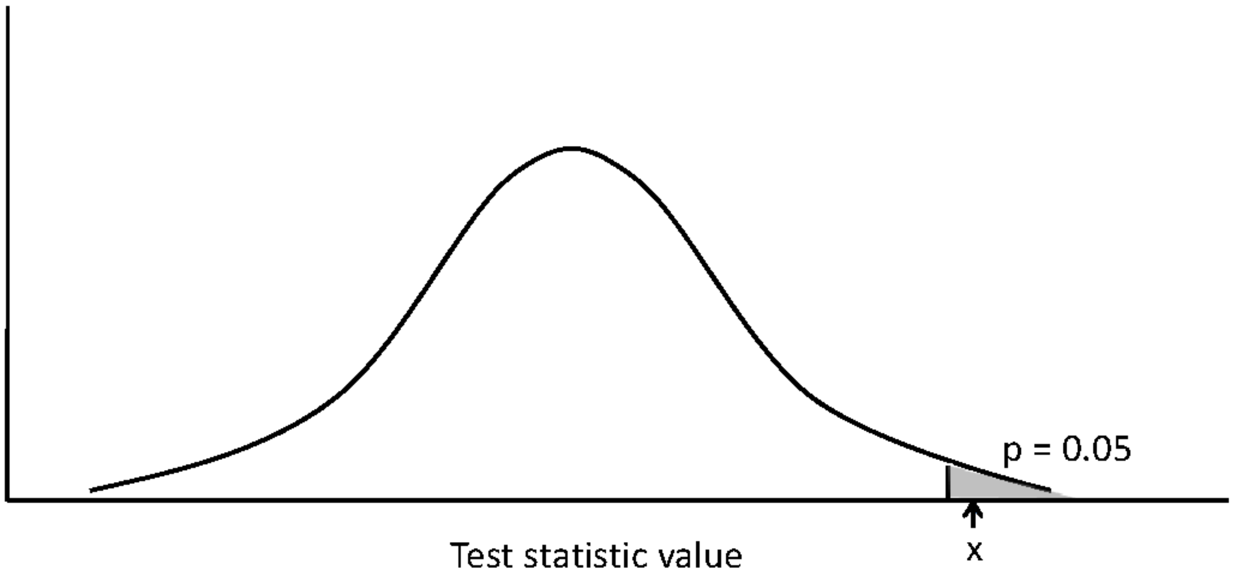
The probability that you will ***correctly*** reject the null hypothesis using a particular statistical test is known as its power.

# Error Types

- Hypothesis testing involves balancing between two types of errors:
  - Type I Errors, or false positives, occur when the null hypothesis is true, but you reject it •
  - Type II Errors, or false negatives, occur when the null hypothesis is false, but you don’t reject it.
- The probability of a type I error is $\alpha$ – the significance level. The probability of a type II error is $\beta = (1 - \text{power})$.

# One-Sided Test

- Distribution for the possible values of a test statistic assuming the null hypothesis



  - shaded area is *region of rejection*

# Example Experimental Results

| Query | A | B | B-A |
|---|---|---|---|
| 1 | 25 | 35 | 10 |
| 2 | 43 | 84 | 41 |
| 3 | 39 | 15 | -24 |
| 4 | 75 | 75 | 0 |
| 5 | 43 | 68 | 25 |
| 6 | 15 | 85 | 70 |
| 7 | 20 | 80 | 60 |
| 8 | 52 | 50 | -2 |
| 9 | 49 | 58 | 9 |
| 10 | 50 | 75 | 25 |

# t-Test

- Assumption is that the difference between the effectiveness values is a sample from a normal distribution
- Null hypothesis is that the mean of the distribution of differences is zero

- Test statistic
  - for the example,

Mean of the difference

$$t = \frac{\overline{B-A}}{\sigma_{B-A}} . \sqrt{N}$$

Sample size

Standard deviation

Get p from the t-test table, for 1-tailed, and degrees of freedom df=18 (20 observations -2)

$$\overline{B-A} = 21.4,\ \sigma_{B-A} = 29.1,\ t = 2.33,\ \text{p-value}{=}.02$$

# Wilcoxon Signed-Ranks Test

- Nonparametric test based on differences between effectiveness scores
- Used when we cannot assume normal distribution (needed in t-test)
- Test statistic

$$w = \sum_{i=1}^{N} R_i$$

$R_i$ is a signed-rank, $N$ is the number of differences $\neq 0$

  - To compute the signed-ranks, the differences are ordered by their absolute values (increasing), and then assigned rank values
  - rank values are then given the sign of the original difference

# Wilcoxon Example

- 9 non-zero differences are (in rank order of absolute value):

  2, 9, 10, 24, 25, 25, 41, 60, 70

- Signed-ranks:

  -1, +2, +3, -4, +5.5, +5.5, +7, +8, +9

- $w$ = 35, p-value = 0.025

# Online Testing

- Test (or even train) using live traffic on a search engine

- Benefits:
  - real users, less biased, large amounts of test data

- Drawbacks:
  - noisy data, can degrade user experience

- Often done on small proportion (1-5%) of live traffic

# Summary

- No single measure is the correct one for any application
  - choose measures appropriate for task
  - use a combination
  - shows different aspects of the system effectiveness
- Use significance tests (t-test)
- Analyze performance of individual queries