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Text Technologies for Data Science

INFR11145

IR Evaluation (2)

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Lecture Objectives

- Learn about how to evaluate IR
  - How to create a test collection?
  - Topic vs. query
  - Relevance judgements
  - Pooling

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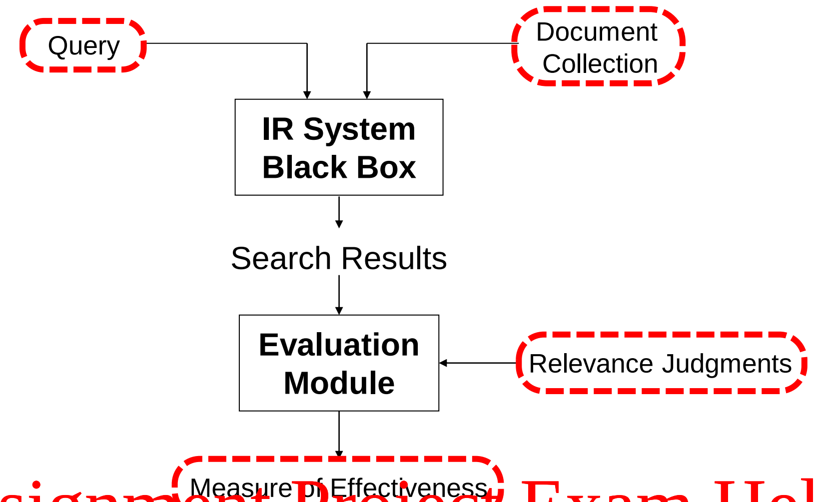
Cranfield Paradigm



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Reusable IR Test Collection

- **Collection of Documents**
  - Should be “representative” to a given IR task
  - Things to consider: size, sources, genre, topics, …
- **Sample of information need**
  - Should be “randomized” and “representative”
  - Usually formalized **topic** statements (query + description)
- **Known relevance judgments**
  - Assessed by humans, for each topic-document pair
  - Binary/Graded
- **Evaluation measure**

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Where Do Test Collections Come From?

- For web search, companies apply their own studies to assess the performance of their search engine.
- Web-search performance is monitored by:
  - Traffic
  - User clicks and session logs
  - Labelling results for selected users' queries
- For other search tasks:
  - Someone goes out and builds them (expensive)
  - As the by-product of large scale evaluations
- IR Evaluation Campaigns are created for this reason

IR Evaluation Campaigns

- IR test collections are provided for scientific communities to develop best IR methods
- Collections and queries are provided, relevance judgements are built during the campaign
- TREC = Text REtrieval Conferences
  - Main IR eval campaign. Sponsored by NIST (US gov)
  - Series of annual evaluations, started in 1992
  - Organized into "tracks"
- Other evaluation campaigns
  - CLEF: European version (since 2000)
  - NTCIR: Asian version (since 1999)
  - FIRE: Indian version (since 2008)

TREC Task

- It is a task for search a set of documents of given genre and domain.
- TREC (or other IR eval campaigns) are formed of a set of tracks, each track has a set of search tasks.
- Example
  - TREC Medical track
  - TREC Legal track → CLEF-IP track → NTCIR patent mining track
  - TREC Microblog track
  - Different CLIR tracks in all campaigns

TREC Collection

- 100's of collections were released in the different evaluation campaigns covering most of the domains in life
- A set of hundreds of thousands of docs
  - 1B in case of web search (TREC ClueWeb09)
- The typical format:

```
<DOC>
<DOCNO> 1234 </DOCNO>
<TEXT>
Multilines of plain text of the document
</TEXT>
</DOC>
```

TREC Topic

- Query sets are provided for each collection. Generated by experts and is associated with additional details. It is called **Topics**, and contains:
  - Query: the query text
  - Description: description of what is meant by the query
  - Narrative: what should be considered relevant

<num>189</num>
<title>Health and Computer Terminals</title>
<desc>Is it hazardous to the health of individuals to work with computer terminals on a daily basis?</desc>
<narr>Relevant documents would contain any information that expands on any physical disorder/problems that may be associated with the daily working with computer terminals. Such things as carpel tunnel, cataracts, and fatigue have been said to be associated, but how widespread are these or other problems and what is being done to alleviate any health problems</narr>

Relevance Judgements

- For each topic, set of relevant docs is required to be known for an effective evaluation!
- **Exhaustive assessment** is usually impractical
  - TREC usually has 50 topics
  - Collection usually has >1 million documents
- **Random sampling** won't work
  - If relevant docs are rare, none may be found!
- **IR systems** can help focus the sample (**Pooling**)
  - Each system finds some relevant documents
  - Different systems find different relevant documents
  - Together, enough systems will find most of them
  - Leverages cooperative evaluations

Pooling

1. Systems submit top **1000** documents per topic
2. Top **100** documents from each are judged
   - Single pool, duplicates removed, random ranking
   - Judged by the person who developed the topic
3. Treat unevaluated documents as irrelevant
4. Compute MAP (or others) down to **1000** documents

- To make pooling work:
  - Large number of reasonable systems participating
  - Systems must not all "do the same thing"

Pooling, does it work?

- Judgments can't possibly be exhaustive!
  It doesn't matter: relative rankings of different systems remain the same!
  Chris Buckley and Ellen M. Voorhees. (2004) Retrieval Evaluation with Incomplete Information. SIGIR 2004.
- This is only one person's opinion about relevance
  It doesn't matter: relative rankings remain the same!
  Ellen Voorhees. (1998) Variations in Relevance Judgments and the Measurement of Retrieval Effectiveness. SIGIR 1998.
- What about hits 101 to 1000?
  It doesn't matter: relative rankings remain the same!
- We can't possibly use judgments to evaluate a system that didn't participate in the evaluation!
  Actually, we can!
  Justin Zobel. (1998) How Reliable Are the Results of Large-Scale Information Retrieval Experiments? SIGIR 1998.

Who decides a doc is relevant or not?

- The same doc can be seen relevant by me, but not you
- Sometimes, it would be useful to have multiple judgements on relevance on the same document
- How to measure agreement among different assessors?
- Cohen's *kappa*

$$\varkappa = \frac{P(A) - P(E)}{1 - P(E)}$$

$P(A)$ – proportion of time judges agree (*inter-annotator agreement*)
$P(E)$ – what agreement would be by chance

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Cohen's *kappa*

- Two judges (J_1 & J_2) annotating 50 docs for relevance
- $P(A) = \frac{20+15}{50} = 0.7$
- $P(E) = P(J_1, J_2|rel) + P(J_1, J_2|irrel)$
  - $P(rel) = P(J_1|rel) \cdot P(J_2|rel) = \frac{20+10}{50} \cdot \frac{20+5}{50} = 0.6 \times 0.5 = 0.3$
  - $P(irrel) = P(J_1|irrel) \cdot P(J_2|irrel) = \frac{20}{50} \cdot \frac{25}{50} = 0.4 \times 0.5 = 0.2$
- $\varkappa = \frac{P(A)-P(E)}{1-P(E)}$
- $= \frac{0.7-0.5}{1-0.5} = \frac{0.2}{0.5} = 0.4$

		J_1	
		Relevant	Irrelevant
J_2	Relevant	20	5
	Irrelevant	10	15

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Cohen's *kappa* - meaning

- Kappa = 0, for chance agreement,
  = 1, for total agreement.
  < 0, for worse than random!
- Kappa > 0.8 ➔
  good agreement
- 0.67 < Kappa < 0.8 ➔
  "fair" agreement
- Kappa < 0.67 ➔
  seen as data providing a suspicious basis for an evaluation

Web Search Engines Evaluation

- Search engines have test collections of queries and hand-ranked results
- Recall is difficult to measure on the web – why?
- Search engines often use
  - precision at top k, e.g., k = 10
  - measures that reward you more for getting rank 1 right than for getting rank 10 right (nDCG)
  - non-relevance-based measures:
    - Clickthrough on first result
      not very reliable if you look at a single clickthrough … but pretty reliable in the aggregate.
    - Studies of user behaviour in the lab
    - A/B testing

Web Search Engines: A/B testing

- Purpose: Test a single innovation
- Prerequisite: You have a large search engine up & running.
- Have most users use old system
- Divert a small proportion of traffic (e.g., 1%) to the new system that includes the innovation
- Evaluate with an "automatic" measure like clickthrough on first result
- Now we can directly see if the innovation does improve user satisfaction.
- Probably the evaluation methodology that large search engines trust most

Is system B really better than A?

- Given the results from a number of queries, B achieved better score than A. How can we conclude that ranking algorithm B is really better than algorithm A?

Experiment 1

Query	System A	System B
1	0.20	0.40
2	0.21	0.41
3	0.22	0.42
4	0.19	0.39
5	0.17	0.37
6	0.20	0.40
7	0.21	0.41
Average	0.20	0.40

Experiment 2

Query	System A	System B
1	0.02	0.76
2	0.39	0.07
3	0.16	0.37
4	0.58	0.21
5	0.04	0.02
6	0.09	0.91
7	0.12	0.46
Average	0.20	0.40

Significance Test

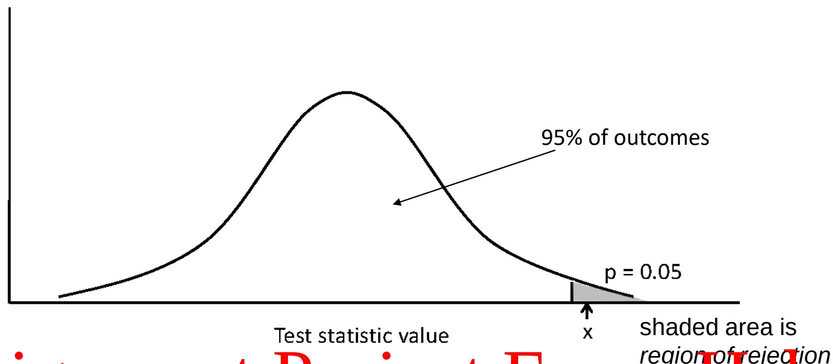
- **Null Hypothesis**:
  No relationship between two observed phenomena
  - Rejecting null hypothesis: observation has a meaning
- A **significance test** enables the rejection of *null hypothesis* (no difference) in favor of the *alternative hypothesis* (B is better than A).
- The power of a test is the probability that the test will reject the *null hypothesis* correctly.
  - increasing the number of queries in the experiment increases the power of test.

Significance Test: Steps

- Compute the effectiveness measure for every query for both retrieval systems (note: AP not MAP).
- Compute a **test statistic** based on a comparison of the effectiveness measures for each query.
  - depends on the significance test
- Test statistic is used to compute a ***p-value***: reflects the probability that the *null hypothesis* is true.
  - Small p-values suggest that the null hypothesis may be false.
- The null hypothesis (no difference) is rejected in favor of the alternate hypothesis (B is more effective than A) if **p-value ≤ α**, where **α** is the significance level.
  - Values for **α** are small, typically **0.05** or less, to reduce the chance of incorrect rejection.

One-sided Test Static

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



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

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

- t-value to *p*-value
  http://www.socscistatistics.com/pvalues/tdistribution.aspx

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

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

Significance Test

- It is not enough to show that system B achieves better score than system A
  - Significance test is essential
- Two-tailed t-test is highly accepted, with α=0.05
  - Sometimes it is required to use others
    Wilcoxon test: does not assume normal distribution
- Meaning of significance test for IR system
  - When a user uses system B that is significantly better than system A, he/she will feel the difference in performance
  - If system B is better than A but not significantly, the user won't notice a difference between the two systems

Now, is system B better than A?

Experiment 1

Query	System A	System B
1	0.20	0.40
2	0.21	0.41
3	0.22	0.42
4	0.19	0.39
5	0.17	0.37
6	0.20	0.40
7	0.21	0.41
Average	0.20	0.40

t-test p-value = 0

B is statistically significantly better than A

Experiment 2

Query	System A	System B
1	0.02	0.76
2	0.39	0.07
3	0.16	0.37
4	0.58	0.21
5	0.04	0.02
6	0.09	0.91
7	0.12	0.46
Average	0.20	0.40

t-test p-value = 0.306

B and A are statistically indistinguishable

Summary

- IR test-collection for automatic evaluation
  - Collection of documents
  - Set of topics
    - Topic = query + details on what is meant and what is relevant
    - Recommended minimum number of **25** topics
  - Relevance judgements
    - Pooling is the most common approach for creating judgements
    - Large number of diverse systems are required
  - Evaluation measure
    - Select the proper measure according to the IR task
    - Significance test is essential to confirm that improvement has real meaning
- Web-search uses different evaluation methods that relies on user experience and click-through data

Resources

- Text book 1: Intro to IR, Chapter 8
- Text book 2: IR in Practice, Chapter 8
- Pooling:
  Chris Buckley and Ellen M. Voorhees. (2004) Retrieval Evaluation with Incomplete Information. SIGIR 2004