Information Retrieval

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(Ranking, Evaluation)

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Overview of this lecture

- Organizational
  - Your experiences with ES1 — Inverted index
  - Requirements for ES2 — Test Cases
- Contents
  - Ranking — tf.idf and BM25
  - Evaluation — Ground truth, Precision, …
  - **Exercise Sheet #2:** implement BM25, tune your ranking, and then evaluate on a small benchmark

    There will be a small competition (table on the Wiki)

Experiences with ES1 1/3

- Summary / excerpts
  - Nice and interesting exercise … most time spent on SVN, Checkstyle, etc. or due to lack of programming practice

    Don't worry, this will get much better soon
  - Some problems understanding Exercise 2

    In case of doubts, always ask on the Forum!
  - Some battles fought with Jenkins / Checkstyle

    Don't worry, you will get used to it quickly
  - Problems with the encoding on some platforms

    One solution: open(file, encoding=utf8)

Experiences with ES1 2/3

- Results
  - Queries that work well:

harry potter	sufficiently specific keywords
columbia pictures 2011	sufficiently specific keywords

  - Queries that don't work well

men in black	words frequent in other docs
the kings speech	apostrophe in doc (king's)
spiderman	two words in doc (spider man)

Experiences with ES1 3/3

- Linear construction time?
  - Quite a few of you implemented something like this:

```
for line in file:
    ...
    if record_id not in self.inverted_lists[word]:
        self.inverted_lists[word].append(record_id)
```

  - Then index construction on movies.txt takes **very** long:

    the "not in" takes linear time, not constant time

    which means the whole loop take **quadratic time**

    Super-important piece of advice: **never** use built-in functions without understanding their time-complexity

Requirements for ES2

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- Test Cases
  - For ES1 you had to write the test cases yourself
  - From now on, we will provide test cases, at least for the central functions of each exercise sheet
  - This should save **you** some work, but also **our tutors**

    Code that does not pass a basic unit test can be very hard and cumbersome to correct (similar to code that doesn't compile or has checkstyle errors)
  - In return, you **have to** implement these unit tests

    You can also extend them, but not restrict them
  - As before, everything must run through on Jenkins without errors, otherwise no correction and no points

Ranking 1/14

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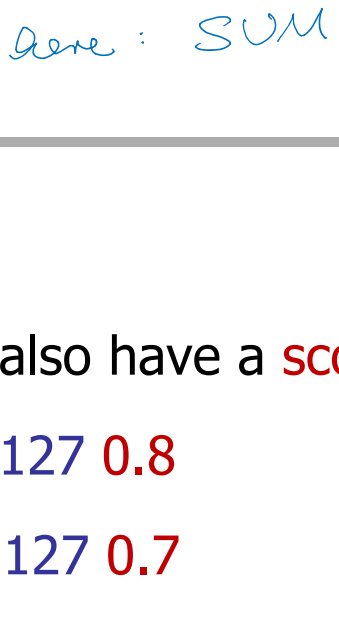
- Motivation
  - Queries often return many hits
  - Typically more than one wants to (or even can) look at

    For web search: often millions of documents

    But even for less hits a proper ranking is **key** to usability
  - So we want to have the most "relevant" hits first
  - **Problem:** how to measure what is how "relevant"

Ranking 2/14



- Basic Idea
  - In the inverted lists, for each doc id also have a score

    university 17 0.5 , 53 0.2 , 97 0.3 , 127 0.8

    freiburg 23 0.1 , 34 0.8 , 53 0.1 , 127 0.7
  - While merging, **aggregate** the scores, then **sort** by score

    MERGED 17 0.5 , 23 0.1 , 34 0.8 , 53 0.3 , 97 0.3 , 127 1.5

    SORTED 127 1.5 , 34 0.8 , 17 0.5 , 53 0.3 , 97 0.3 , 23 0.1
  - The entries in the list are referred to as **postings**

    Above, it's only doc id and score, but a posting can also contain more information, e.g. the position of a word

Ranking 3/14

- Getting the top-k results
  - A full sort of the result list takes time $\Theta(n \cdot \log n)$, where n is the number of postings in the list
  - Typically only the top-k hits need to be displayed
  - Then a **partial sort** is sufficient: get the k largest elements, for a given k

    Can be computed in time $\Theta(n + k \cdot \log k)$

    k rounds of HeapSort yield time $\Theta(n + k \cdot \log n)$

    For constant k these are both $\mathbf{\Theta(n)}$

    For ES2, you can ignore this issue

Ranking 4/14

- Meaningful scores
  - How do we precompute good scores

    university 17 0.5 , 53 0.2 , 97 0.3 , 127 0.8

    freiburg 23 0.1 , 34 0.8 , 53 0.1 , 127 0.7
  - **Goal:** the score for the posting for doc D_i in the inverted list for word w should reflect the **relevance** of w in D_i

    In particular, the larger the score, the more relevant
  - **Problem:** relevance is somewhat subjective

    But it has to be done somehow anyway !

Ranking 5/14

- Term frequency (**tf**)
  - The number of times a word occurs in a document
  - **Problem:** some words are frequent in many documents, regardless of the content

university	… ,	**57**	**5**	, …	…	…	,	**123**	**2**	, …
of	… ,	**57**	**14**	, …	…	…	,	**123**	**23**	, …
freiburg	… ,	**57**	**3**	, …	…	…	,	**123**	**1**	, …
SCORE SUM	… ,	**57**	**22**	, …	…	…	,	**123**	**26**	, …

A word like "of" should not count much for relevance

Some of you observed that already while trying out queries for ES1

Ranking 6/14

- Document frequency (**df**)
  - The number of documents containing a particular word

    $\mathbf{df}_{university}$ = 16.384 , $\mathbf{df}_{of}$ = 524.288 , $\mathbf{df}_{freiburg}$ = 1.024

    For simplicity, number are powers of 2, see below why
  - Inverse document frequency (**idf**)

    idf = $\log_2$ (N / df) N = total number of documents

    For the example df scores above and N = 1.048.576 = 2^{20}

    $\mathbf{idf}_{university}$ = 6 , $\mathbf{idf}_{of}$ = 1, $\mathbf{idf}_{freiburg}$ = 10

    Understand: without the $\mathbf{log_2}$, small differences in **df** would have too much of an effect ; why exactly $\mathbf{log_2}$ → later slide

Ranking 7/14

$df_{university} = 6$
$df_{of} = 1$
$df_{freiburg} = 10$

- Combining the two (**tf.idf**)
  - Reconsider our earlier **tf** only example

university	… ,	**57**	**5** ,	… … … ,	**123**	**2** , …
of	… ,	**57**	**14** ,	… … … ,	**123**	**23** , …
freiburg	… ,	**57**	**3** ,	… … … ,	**123**	**1** , …
SCORE SUM	… ,	**57**	**22** ,	… … … ,	**123**	**26** , …

  - Now combined with **idf** scores from previous slide

university	… ,	**57**	**30** ,	… … … ,	**123**	**12** , …
of	… ,	**57**	**14** ,	… … … ,	**123**	**23** , …
freiburg	… ,	**57**	**30** ,	… … … ,	**123**	**10** , …
SCORE SUM	… ,	**57**	**74** ,	… … … ,	**123**	**45** , …

Ranking 8/14

- Problems with tf.idf in practice
  - The idf part is fine, but the tf part has several problems
  - Let w be a word, and D_1 and D_2 be two documents
  - **Problem 1:** assume that D_1 is longer than D_2

    Then tf for w in D_1 tends to be larger then tf for w in D_2, because D_1 is longer, not because it's more "about" w
  - **Problem 2:** assume that D_1 and D_2 have the same length, and that the tf of w in D_1 is twice the tf of w in D_2

    Then it is reasonable to assume that D_1 is more "about" w than D_2, but just a little more, and not twice more

Ranking 9/14

- The **BM25** (best match) formula
  - This tf.idf style formula has consistently outperformed other formulas in standard benchmarks over the years

    BM25 score = tf* · $\log_2$ (N / df), where

    tf* = tf · (k + 1) / (k · (1 – b + b · DL / AVDL) + tf)

    tf = term frequency, DL = document length, AVDL = average document length
  - Standard setting for **BM25**: k = 1.75 and b = 0.75

    Binary: k = 0, b = 0; Normal tf.idf: k = ∞, b = 0

Ranking 10/14

- Plausibility argument for BM25, part 1
  - Start with the simple formula tf · idf
  - Replace tf by tf* such that the following properties hold:
    - tf* = 0 if and only if tf = 0
    - tf* increases as tf increases
    - tf* → fixed limit as tf → ∞
  - The "simplest" formula with these properties is
    - tf* = tf · (k + 1) / (k + tf)

$$tf = 0 \Rightarrow tf^* = 0 \quad \square$$

$$tf^* = \frac{k+1}{1+k/tf} \quad \square$$

$$tf^* = \frac{k+1}{1+k/tf} \xrightarrow[tf\to\infty]{} k+1$$

$$= \frac{tf\cdot(k+1)}{k+tf} = \frac{k+1}{k/tf+1}$$

Ranking 11/14

- Plausibility argument for BM25, part 2
  - So far, we have $tf^* = tf \cdot (k + 1) / (k + tf)$
  - Normalize by the length of the document
    - Replace tf by tf / α
    - Full normalization: $\alpha = DL / AVDL$ ... too extreme
    - Some normalization: $\alpha = (1 - b) + b \cdot DL / AVDL$
  - This gives us $tf^* = tf / \alpha \cdot (k + 1) / (k + tf / \alpha)$
  - And hence $tf^* = tf \cdot (k + 1) / (k \cdot \alpha + tf)$

$b = 0 \Rightarrow \alpha = 1$

$b = 1 \Rightarrow \alpha = \frac{DL}{AVDL}$

Lots of "theory" behind this formula, but to me not really more convincing than these simple plausibility arguments

Ranking 12/14

- Implementation advice
  - First compute the inverted lists with **tf** scores

    You already did that (implicitly or explicitly) for ES1
  - Along with that compute the document length (DL) for each document, and the average document length (AVDL)

    You can measure DL (and AVDL) via the number of words
  - Make a second pass over the inverted lists and replace the **tf** scores by **tf* · idf** scores

    $tf \cdot (k + 1) / (k \cdot (1 - b + b \cdot DL / AVDL) + tf) \cdot \log_2 (N / df)$

    Note that the **df** of a word is just the length (number of postings) in its inverted list

Ranking 13/14

- Further refinements
  - For ES2, play around with the BM25 parameters **k** and **b**
  - Boost results that match each query word at least once

    Warning: when you **restrict** your results to such matches, you might miss some relevant results

    For example: steven spielberg **movies**
  - Somehow take the popularity of a movie into account

    In the file on the Wiki, movies are sorted by popularity

    Popularity scores also have a Zipf distribution, so you might take $\sim \mathbf{N}^{-\alpha}$ as popularity score for the N-th movie in the list
  - Anything else that comes to your mind and might help …

Ranking 14/14

- Advanced methods
  - There is a multitude of other sources / approaches for improving the quality of the ranking, for example:

    Using query logs and click-through data

    Who searches what and clicked on what … main pillar for the result quality of big search engines like Google

    Learning to rank

    Using machine learning (more about that in a later lecture) to find the best parameter setting

Evaluation 1/6

- Ground truth
  - For a given query, the ids of all documents relevant for that query

    Query: matrix movies

    Relevant: 10, 582, 877, 10003
  - For ES2, we have built a ground truth for 10 queries

    Building a good and large enough ground truth is a common (and time-consuming) part in research in IR

Evaluation 2/6

P@R = P@2, where
2 = # relevant documents
= 4 below

- Precision (**P@k**)
  - The P@k for a given result list for a given query is the percentage of relevant documents among the top-k

Query:	matrix movies
Relevant:	10, 582, 877, 10003
Result list:	582 (REL, 1.), 17 (NOT REL, 2.), 5666 (NOT REL, 3.), 10003 (REL, 4.), 10 (REL, 5.), 37 (NOT REL, 6.), … , 877 (REL)
P@1:	1/1 = 100%
P@2:	1/2 = 50%
P@3:	1/3 = 33%
P@4:	2/4 = 50% ← P@R
P@5:	3/5 = 60%

Evaluation 3/6

- Average Precision (**AP**)
  - Let R_1, …, R_k be the sorted list of positions of the relevant document in the result list of a given query
  - Then AP is the average of the k P@Ri values

Query:	matrix movies
Relevant:	10, 582, 877, 10003
Result list:	582, 17, 5666, 10003, 10, …, 877
R_1, …, R_4:	1, 4, 5, 40
$P@R_1$, …, $P@R_4$:	100%, 50%, 60%, 10%
AP:	55%

REL NOT REL NOT REL REL REL NOT REL REL

1. 2. 3. 4. 5. 40.

Note: for docs not in result list, just take $P@R_i = 0$

Evaluation 4/6

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- Mean Precisions (**MP@k**, **MP@R**, **MAP**)
  - Given a benchmark with several queries + ground truth
  - Then one can capture the quality of a system by taking the **mean** (average) of a given measure over all queries

    MP@k = mean of the P@k values over all queries

    MP@R = mean of the P@R values over all queries

    MAP = mean of the AP values over all queries

    These are very common measures, which you will find in a lot of research papers on information retrieval

Evaluation 5/6

- Other measures
  - There is a BIG variety of other evaluation measures, e.g.
  - **nDCG** = normalized discounted cumulative growth

    Takes into account that documents can have varying degrees of relevance, e.g. "primary" and "secondary"

    Gives credit if "primary" is ranked before "secondary"
  - **BPref** = binary relevance … preference relation

    Takes into accounts that some documents are unjudged

    This is a frequent problem in benchmarks for huge text corpora, where complete judgment is impossible

    E.g. all relevant documents for "tom hanks" on the web

Evaluation 6/6

- Overfitting
  - Tuning parameters / methods to achieve good results on a given benchmark is called **overfitting**

    In an extreme case: for each query from the benchmark, output the list of relevant docs from the ground truth
  - In a realistic environment (real search engine or competition), one is given a **training** set for development

    The actual evaluation is on a **test** set, which must not be used / was not available during development

    For ES2, do the development / tuning on some queries of your choice, then evaluate without further changes

References

- In the Manning/Raghavan/Schütze textbook

  Section 6: Scoring and Term Weighting

  Section 8: Evaluation in Information Retrieval

- Relevant Papers

  Probabilistic Relevance: BM25 and Beyond **FnTIR 2009**

  Test Collection Based Evaluation of IR Systems **FnTIR 2010**

- Relevant Wikipedia articles

  http://en.wikipedia.org/wiki/Okapi_BM25

  https://en.wikipedia.org/wiki/Information_retrieval
  #Performance_and_correctness_measures