

Extending a Research-Paper Recommendation System with Scientometric Measures

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Abstract. In recent years the number of academic publication increased strongly. As this information flood grows, it becomes more difficult for researchers to find relevant literature effectively. To overcome this difficulty, recommendation systems can be used which often utilize text similarity to find related documents. To improve those systems we add scientometrics as a ranking measure for popularity into these algorithms. In this paper we analyse whether and how scientometrics are useful in a recommender system.

Keywords: research paper recommender system, scientometric, bibliometric, altmetric, citations, readership

1 Introduction

The number of academic publications doubles approximately every ten years [6]. As a result it becomes more difficult for researchers to find relevant literature. It is nearly impossible to read all literature of an academic field, to find the most important and relevant documents. Even if one has profound knowledge about his academic field it is difficult to follow the latest news and filter them for relevance [13].

To handle this information flood, recommender systems come into account. They identify the informational needs of researchers and recommend the best fitting literature. Unfortunately, neither the automatic identification of the informational needs, nor the search for relevant literature are trivial tasks. The extent of this challenge can be derived from the amount of research in this area. In the last sixteen years 90 methods were developed and investigated by around 300 academic researches and published in over 200 publications [2].

Since it is important to recommend papers which are relevant, it is necessary to improve recommender systems. In this paper we focus on the use of scientometrics to rank the recommendations.

Scientometrics are introduced as a 'quantitative study of science and technology' [11]. They are most generally classified into bibliometrics and altmetrics.

Bibliometrics are used for the 'measurement of texts and information' [8]. The term is often used to describe the statistical analysis based on citation data. There are many ways to use citation data to calculate metrics for the popularity of a paper, author or journal. A list of 108 bibliometrics is published by Wildgaard and Schneider [16], which includes normalizations, h-index and many others.

On the contrary, altmetrics, which takes its name from alternative metrics, use information from social media, blogs et cetera [7]. The count of readers is also an altmetric that correlate with bibliometrics [15].

Until now recommendation systems rank their recommendation only with respect to content similarity. The assumption in this paper is that a paper with a good reputation is more worth reading, thus should be recommended. To measure the reputation we will use scientometrics. The scientific question is which scientometrics and their combination with the similarity ranking is most liked by the user and thus the best. To measure how much users like a recommendation the Click-Through-Rate (CTR) will be analyzed.

2 Related work

2.1 How to rank papers

Papers can be ranked by different criteria. Lewandowski and Behnert [4] divided these criteria in six fields: 'text statistics', 'popularity', 'freshness', 'locality and availability', 'content properties' and the 'user's background'.

The text statistics can describe how similar two documents are based on the content. A famous measure is, for example, TF-IDF. Text statistics also can focus on the document length or anchor text and emphasized text. The popularity pays heed to the usage of a document, how often is it read, cited, downloaded or bought, and how highly are they rated. The freshness ensures that one gets recent documents. The locality and availability considers, if the user currently has access to the document, since he would not want to get recommendations he can not read. It also considers costs, since free documents are easier to access. Also one can use content properties to rank papers, which includes the file format, the language and the amount of meta data. People like to read their own language and use common file formats like PDF. The last category is the user's background, where the user is categorized, for example, by his academic background or his field of study. The rationale behind this is that a computer scientist most likely will not read a document related to history [4].

In this paper we focus on the popularity category to rank papers. We use scientometrics which we assume indicate the popularity and rank the paper accordingly.

2.2 Scientometrics in rankings

Scientometrics are used to calculate the reputation of journals, authors, institutions or papers. After that people can for example identify authors with high

or low reputation. Scientometrics can help to identify patterns which are highly cited [8] and thus can be used to optimize further citations.

It is also common to rank results in search engines based on their popularity. This concept is for example used in Google's Page Rank Algorithm, where the popularity is expressed by hyperlinks [12]. Scientometrics are also used in search engines for research paper [14]. Bethard and Jurafsky added citations, h-index and recency into their search engine for research paper. They found pure citations improve the ranking, but h-index and recency impair it [5]. In our work we will use scientometrics to measure popularity and rerank results in a research-paper recommendation system.

3 Methods

3.1 Our system and data

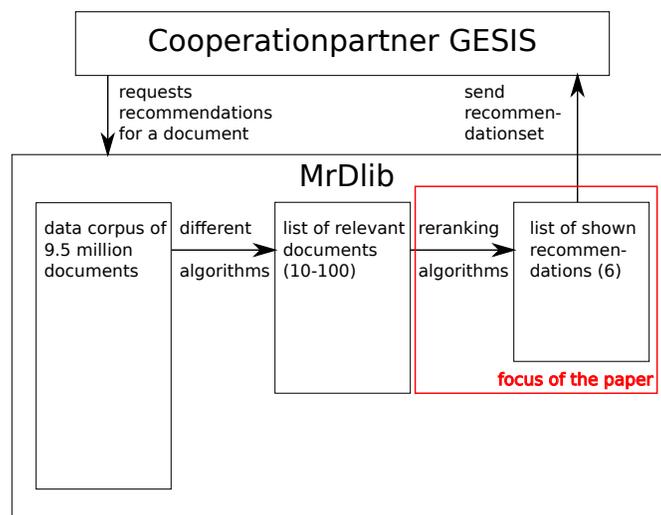


Fig. 1. Simplified visualisation of Mr. DLib and its components.

Mr. DLib (Machine Readable Digital Library, <http://mr-dlib.org/>) is a research-paper recommender system and for academic purposes only [1,3]. It recommends papers similar to a given input paper. Mr. DLib has a database where the data is stored and indexed using Solr. We cooperate with GESIS, that provides a framework for the user, as well as our data [10]. The data consists of 9.5 million documents. From these documents are 5.3 million English and 2 million are German. As soon as a document is requested in GESIS, the request is forwarded to Mr. DLib. Mr. DLib responds with six recommendations which are displayed on the Sowiport website. This communication flow is shown in figure 1. Every

time a user clicks on a recommendation, a click is logged on Mr. DLib's servers, and the user is taken to the corresponding GESIS page for the recommended document. With this procedure we can measure the Click-Through-Rate (**CTR**).

$$CTR = \frac{\text{Number of clicked recommendations}}{\text{Number of delivered recommendations}}$$

We gathered data from 17th October 2016 to 8th February 2017. Currently we display six recommendations for each recommendation request. In total we analysed 38,740,893 recommendations with 53,441 clicks, which corresponds to a CTR of 0.138%.

3.2 Algorithms and ranking approaches

Figure 1 shows how the recommendations are generated. First a relevance algorithm is executed, providing us with a list of at most 100 documents, where each document has an attached relevance score. After this we choose which re-ranking algorithm is executed. It chooses randomly from the following variables: 1) how many documents are considered for the re-ranking, 2) how much influence the relevant score has and 3) which scientometric scheme is applied.

There are currently five different algorithms, which create a list of documents to be re-ranked. Out of this five algorithms only two provide a relevance score we can usefully combine with the scientometrics. Since these two algorithms are more interesting our random generator picks them more often. Roughly 90% of the recommendations are produced by them.

It was already shown that readership usually correlate with citations [15]. Because of this, readership data can be used instead of citation as a base for all presented scientometrics. In this paper we use readership data from Mendeley to rank the documents. We got readership data for 1,694,373 documents, which is a coverage of 17.82%. Currently we use the absolute count of readers, the count of readers normalized by the age of the paper, and the count of readers normalized by the number of authors.

4 Results

In this section we present our test results of the re-ranking approaches. They are split with respect to the three different attributes. All data is available at <http://datasets.mr-dlib.org/>.

4.1 Re-ranking method

The re-ranking method describes how the scientometric data and the text relevance score are combined. We ranked the recommendations considering 'text relevance (**TR**) only' or 'scientometrics only' combined with different weightings. While the text relevance calculated by Solr is within a certain range, the scientometric values can range from 0 to several 1000. To balance the impact

of the text relevance and the scientometrics, root and logarithmic transformation are applied on the scientometrics. Each combination was sorted ascending and descending to ensure there is a difference in sorting them according to the metrics.

As seen in figure 2, the ascending ordered scores are always lower than the descending. This was expected since we assume that scientometrics are a measure for popularity and a popular publication has higher quality or more interesting findings thus is more worth reading. Also the ranking with the scientometrics scores higher than the text relevance only approach. An unclear occasion is the good performance of the ascending ordered 'scientometric only'. Its performance was nearly identical to the descending ordered 'text relevance only'.

The statistical significance is given for the associated descending and ascending orders - except for the 'scientometric only'. There is no statistically significant difference between the descending orders.

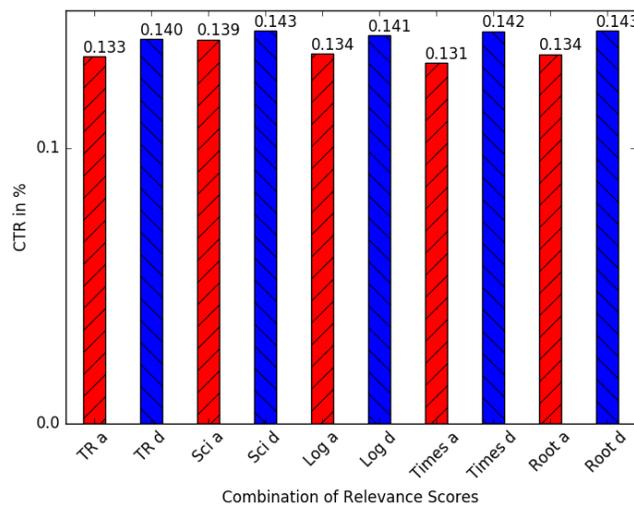


Fig. 2. Visualisation of the Click-Through-Rate (CTR) for different weightings of text relevance and scientometrics. The red bars as well as the letter 'a' indicates ascending order. The blue bars as well as the letter d indicates descending order. TR = Text Relevance, Sci = scientometric, Log = $TR * \log(\text{Sci})$, Times = $TR * \text{Sci}$, Root = $TR * \text{root}(\text{Sci})$.

4.2 Metrics

By metrics, we refer to the scientometric indicator that we used for ranking recommendations. We analysed absolute readership count R_{count} , readership count normalized by the age of the paper in years R_{age} and readership count normal-

ized by the number of authors R_{auth} . The formula for readership normalized by the age of the paper R_{age} is

$$R_{age} = \frac{R_{count}}{Year_{now} - Year_{published} + 1}$$

This is expected to show better performance, since good papers need time to become famous.

The formula for readership normalized by the number of authors R_{auth} is

$$R_{auth} = \frac{R_{count}}{\#authors}$$

This normalization is expected to show also better performance. Paper with many authors are likely to be more famous because they are wider spread.

We considered in our experiments primarily those metrics which were easy to calculate while incorporating as many as possible different aspects of the scientometrics in the literature review. Another important criteria was that the metrics would only use the data that we had. By evaluating this subset of metrics, we will have an idea of which groups of metrics perform best in a real-world setting. With this information we can focus on this group in the future.

Surprisingly the absolute readership count R_{count} scores highest. These results are statistically significant.

The discrepancy of the CTR to the re-ranking method results from not including 'text relevance only' data.

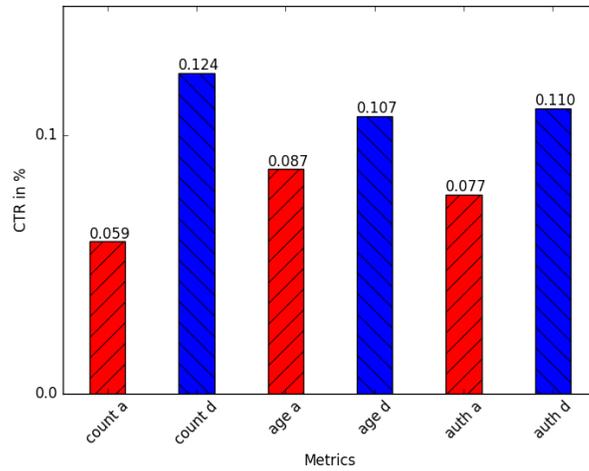


Fig. 3. Visualisation of the Click-Through-Rate (CTR) for different scientometric indicators. The red bars as well as the letter 'a' indicates ascending order. The blue bars as well as the letter d indicates descending order. count = absolute count of readership, age = normalized by the age of the paper, auth = normalized by the number of authors.

4.3 Re-ranked candidates

The re-ranked candidates are the number of candidates which will be picked from an algorithm to re-rank them according to the ranking parameters. The more candidates are considered for re-ranking, the less the text relevance is considered. It seems that more candidates leads to a better performance although a medium sized list decreased it. The statistical significance is given for the associated descending and ascending orders except for 30 and 100 candidates. Between the different descending orders roughly half of the combinations are statistically significant.

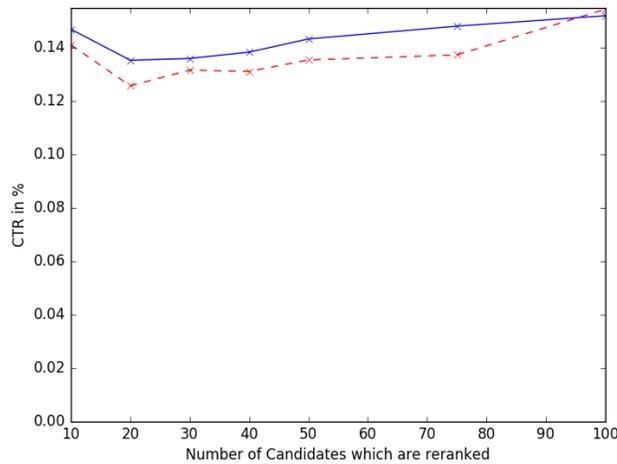


Fig. 4. Visualisation of the Click-Through-Rate (CTR) of the number of received candidates from the algorithm. The red lines indicates ascending order. The blue line indicates descending order.

5 Conclusion and future work

In this paper we evaluated different re-ranking approaches to see whether and how scientometrics can improve academic paper recommendations systems. With our current data we can conclude that scientometrics do improve the ranking of documents in a recommendation system compared to a text relevance only approach. This is shown in figure 2, where the CTR of the descending rankings that include scientometrics score higher than the 'text relevance only' approach. However, this improvement is rather small. Furthermore, a smaller list of re-ranking candidates seem to lead to a better CTR. The metric which achieved the best score is the absolute count without normalization.

However, the good scoring of the 'scientometrics only' with ascending ordering was not expected. This might be due to the low scientometric data coverage of 17.82%. If too many documents of the pre-generated list do not have associated readership data the re-rank will not effect the sorting. Thus, descending and ascending orders will have the same sorting and same performance.

To achieve a better coverage in the future we will calculate author metrics and apply them back to the papers by building a sum or the average. This will lead to a coverage of 46.27%. Furthermore, a fall-back mechanism could be implemented, which will choose a higher coverage metric if the current metric has to less data.

Another reason for the small improvement of the scientometric-including rankings might be the style of the evaluation. When the recommendations are displayed only title and authors are shown. The user decides only based on this

information if the recommendation might be useful. However, our approach takes popularity into account, which is an assumption for quality. To enhance the evaluation we should log if the user used the document after taking a look at it e.g. if he clicked several links like cite, export, favourite or search. This measure might be more suitable for evaluating a popularity approach.

The next step is gathering and calculation of citation metrics. We will soon be able to evaluate the scientometrics in JabRef and collect more data [9]. In addition the scientometric rankings can also be evaluated together with the different algorithms to find out if they are stable and which different combinations of algorithm and ranking approaches work best.

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