Towards Explainable Scientific Venue Recommendations

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Abstract Selecting the best scientific venue (i.e., conference/journal) for the submission of a research article constitutes a multifaceted challenge. Important aspects to consider are the suitability of research topics, a venue’s prestige, and the probability of acceptance. The selection problem is exacerbated through the continuous emergence of additional venues. Previously proposed approaches for supporting authors in this process rely on complex recommender systems, e.g., based on Word2Vec or TextCNN. These, however, often elude an explanation for their recommendations. In this work, we propose an unsophisticated method that advances the state-of-the-art in two aspects: First, we enhance the interpretability of recommendations through non-negative matrix factorization based topic models; Second, we surprisingly can obtain competitive recommendation performance while using simpler learning methods.

Keywords: topic models, recommender systems, matrix factorization

1 Introduction

An essential part of the scientific research process is the publication of the obtained results at a suitable venue, i.e., a particular conference, workshop, or journal. The related selection problem for the best fitting scientific venue has many different aspects, such as the fit of the research topics, the prospects of acceptance, and the prestige of the venue. The complexity of the selection is further exacerbated by the growing number of publication venues, the increasing granularity of research topics, and the exponentially surging number of publications.

To support researchers with this task, different methods have been proposed, e.g., based on Latent Dirichlet Allocation [9], hybrid approaches incorporating social networks [14, 13], or procedures that draw from background ontologies [20]. Moreover, recent approaches based on deep learning methods achieved high accuracy in recommendations [6]. All these methods have in common that their recommendations are insufficiently explained. For example, Kobs et al. [6] solely highlight words from the input article that were essential for a recommendation.

With the present work we show a new approach for recommending venues that improves on explainability. From the information a scientist provides, such as paper title, abstract and, possibly, a list of keywords, our method creates a ranking over \( k \) thematically fitting venues. Our method further generates a list
of the most important research topics found in the input article. We provide a contrasting juxtaposition to the venues by generating a similar list of research topics for each recommended venue. The research topics are found automatically through a topic model, specifically a non-negative matrix factorization (NMF), that is precomputed on a corpus of suitable research articles. The thereof resulting recommendations entail two major advantages. First, they are more comprehensible due to their annotations using research topics. Second, their explanations go beyond the mere occurrence of certain terms in the input article.

From a procedural point of view, through NMF, we identify research topics in a corpus and represent venues as a combination of these topics. This approach has been used successfully before to map trajectories of venues within thematic spaces \[17\] in an interpretable manner. Based on that our specific contribution with the present work is threefold. First, we present a simple yet effective recommendation procedure based on tf-idf, logistic regression and non-negative matrix factorization. Second, we demonstrate that our setup can achieve competitive or even better results with respect to the state-of-the-art in venue recommendation. We base this claim on the comparability accomplished by using the data from Kobs et al. \[6\]. Third, we show how the human interpretability of venue recommendations may be enhanced using research topics discovered by NMF.

2 Problem Description

When researchers are looking for a publishing venue for their recent research work \(d\), they encounter an increasing number of conferences and journals. Each of said venues \(v \in V\) has properties \(p \in P\), such as prestige, acceptance rate, and emphasized research topics, to be considered for submission.

Problem 1 (General Submission Problem).
Given paper (document) \(d\), generate a relevance ranking over a set \(V\) of venues.

The order of this ranking should reflect the similarity between elements of \(V\) and the input paper (document) \(d\) in terms of their respective research topics. Furthermore, other properties of \(P\) may be reflected with different levels of importance. The resulting top-\(k\) ranked venues can be viewed as individual venue recommendations for paper \(d\). In order to cover the thematic aspect of the submission problem we resort to a paper corpus \(C\) over a research domain. This corpus is constituted by a set of papers labeled with their publishing venues \(v \in V\). In the following, we consider the aspect of finding good topical fits as the submission problem. We require that all venues \(V\) are represented by the papers in \(C\), i.e., for any \(v\) there is a sufficient number of papers in \(C\). Moreover, the topics of \(d\) must be from the same particular research domain as the corpus \(C\).

Polonioli \[12\] pointed out that transparency is a necessary feature of search engines for research. The most prominent reasons are accountability of the search results and the disclosure of possible biases (e.g., in algorithms or data). In our work, we hence do rather not focus on outperforming previous benchmarks, but on advancing methods that are intrinsically comprehensible. Hence, our
approach is based on a *topic model* that is derived from non-negative matrix factorization (NMF). This method has been used in previous works to gain explainable insights into research topics [17]. Using NMF we annotate venues, i.e., conferences and journals, with their respective topics. Furthermore, we attempt to use the discovered topics as an input to the ranking method. What is more, our method, as presented in this work, is useful to find similar research for a given piece of work, although our focus here is with the first application in mind.

### 3 Related Work

Yang and Davison [21] recommend venues from ACM digital library using a collaborative filtering approach incorporating topics and writing style. Medvet, Bartoli, and Piccinin [9] test three different methods based on n-grams and Latent Dirichlet Allocation. More complex, hybrid methods integrate social network analysis [14, 13]. All of the above do not add explanations to recommendations.

Smart Book Recommender (SBR) represents books, journals and conference proceedings as vectors of topic counts extracted through the *Computer Science Ontology* (CSO) [20, 16]. Due to the dependence on CSO, SBR is not directly applicable to other research domains. Recommendations are only available for items in a pre-computed database. Iana et al. [4] develop a conference recommender based on SciGraph, a taxonomy by Springer Nature. The authors experiment with author information, paper abstracts and paper keywords. For abstracts, different representations are evaluated, such as TF-IDF, Latent Semantic Analysis (LSA), probabilistic LSA and different embedding methods (Word2Vec [10], GloVe and FastText). For keywords, SciGraph marketing codes are used, categories defined by Springer. The best performing method is based on these marketing codes, which, however, may not be available from other than the used data sources.

In “Where To Submit” (WTS, Kobs et al. [6]) self-trained Word2Vec embeddings and TextCNN [5] are employed. Enhancements are made by incorporating paper titles and keywords and applying convolutions separately to them. Explanations through the *integrated gradients method* are added [19]. This computes words influential for the classifier, which are visually highlighted. These, however, do not necessarily improve the interpretability. For example, often, only few words are highlighted. Examples for non-interpretable black-box recommenders can be found online. These are often restricted to journals or specific publishers.

### 4 Method

We approach the submission problem as a supervised learning task. For every paper \( c \) in a corpus \( C \), we use its publication venue \( v \in V \) as its ground truth label. Based on that we train a supervised classifier to predict the venue. The output of such classifiers are probabilities for, or fractions of, class membership, which impose a linear order on \( V \).

[1] <https://journalsuggester.springer.com>
Our aim is to generate both, recommendations and explanations comprised of interpretable, automatically derived research topics. Our reasoning is that research topics provide more informative explanations for venue recommendations than single words [17]. In short, the envisioned NMF approach allows for incorporating words that are not part of the input document $d$ (i.e., the paper title, abstract and keywords) into the explanation. This additional information is pre-extracted from co-occurrences in a paper corpus of the research domain. The research topics allow for a unified view on venues as well as documents.

For the rest of this work, a document is comprised of the following features: a title; an abstract; a set of keywords. Each of these attributes is a string (or set of strings). Every document is labeled with its publication venue $v \in V$.

Definition 1 (Paper Corpus). A paper corpus is a set $C \subseteq T \times A \times 2^S \times V$. A (research) paper $c := (t, a, s, v) \in C$ consists of a title $t \in T$, an abstract $a \in A$, a set of keywords $s \subseteq S$ and is labeled with a venue name $v \in V$.

4.1 Non-negative Matrix Factorization

We use non-negative matrix factorization [8] to create a topic model from a corpus of papers and to obtain a lower-dimensional representation of the papers in topic space. It has previously been shown that NMF is able to reconstruct research topics that are similar to research categories produced by human experts [17]. For an input matrix $U \in \mathbb{R}^{u \times n}_{\geq 0}$ containing document representations (e.g., as tf-idf vectors), NMF finds an approximate factorization $U \approx WH$. The output matrices $W \in \mathbb{R}^{u \times l}_{\geq 0}$ and $H \in \mathbb{R}^{l \times n}_{\geq 0}$ contain a set of basis vectors as well as the desired lower-dimensional representation of the input documents (represented as a weighted sum of the basis vectors). The $l$ basis vectors can be interpreted as vectors of term importances, i.e. topics. The lower-dimensional document representations can be interpreted as proportions of topics in a document. We may stress that NMF, due to its additive nature, allows for human interpretable topics as well as document representations as vectors. We will use research topics calculated through NMF as an attempt towards recommendation explanations.

4.2 Classification Methods

The proposed approach for creating explanations is independent from the concrete choice of the classification method. Hence, we are able to evaluate a multitude of procedures. We also evaluate different methods for feature extraction and paper representation. In particular, we use tf-idf vectors [15] as well as the aforementioned NMF topics as features. This being said, we emphasize in our investigation the logistic regression approach, since this has already been successful in previous work [6, 4]. Additionally, logistic regression is a robust procedure that does not require a large number of parameter values to be identified. Furthermore, the resulting classification function can be computed fast, unlike e.g., similarity-based approaches [20]. Ultimately, linear models such as logistic regression are already interpretable to some extent [2]. In contrast to [6], we prefer tf-idf over tf (i.e.,
term frequencies), because we assume, as being one de-facto standard in text representation, it may enable better classification results. In our experiments we compare our results to Kobs et al. [6].

We use the following methods: \textbullet~**Uniform Random** – we predict venues in random order. \textbullet~**Most Frequent** – we predict venues in the order of their prevalence in the data set. \textbullet~**Logistic Regression ("Logit")** – we employ multi-class logistic regression from \texttt{scikit-learn} [22, 11]. We apply these classifiers to different document representations. For every $c \in C$, we concatenate the title, abstract and keywords before calculating the representations: \textbullet~**NMF** – we use the representation calculated through NMF [8] using a reasonable topic number. We adapt the choice for \texttt{kappa} (learning rate) and \texttt{w_max_iter} and \texttt{h_max_iter}, the maximum training iterations per batch for matrices $W$ and $H$. We report their values in Section 5. \textbullet~**tf-idf** – we use term-frequency (tf) as well as tf-idf [15], i.e., the product of tf and inverted document frequency (idf). \textbullet~**NMF + tf-idf** – we concatenate both of the above representations to a single vector.

5 Experimental Evaluation

We evaluate our methods on two different domains: Artificial intelligence (AI) and medicine (MED). More specifically, we use the data set \footnote{https://github.com/konstantinkobs/wts} compiled and described by Kobs et al. [6], which are based on Semantic Scholar [1]. Each data set is comprised of papers from 78 non-uniformly distributed classes (i.e., venues). The AI corpus contains 245,573 papers; the MED corpus 2,924,609 papers.

To facilitate comparability we calculate the accuracy, the accuracy@$k$ and the mean reciprocal rank (MRR) on a test data set of papers. For accuracy@$k$, a ranking for a tested paper is counted as correct, when its true label is contained in the top $k$ ranked venues. This count is divided by the total size of the test set. Iana et al. [4] used the term \texttt{recall}@$k$, which, due to the single ground truth label, calculates the same. MRR is calculated from a test set $T \subset C$ as follows: Let $\text{rank}(x, C) \in \mathbb{N}_{>0}$ be the rank of the true label of publication $x \in T$ in a ranking generated by algorithm $C$. Then MRR is the average of the inverse ranks, i.e., $\frac{1}{|T|} \sum_{x \in T} \frac{1}{\text{rank}(x, C)}$. For NMF, we use 100 topics for AI and 500 topics for MED to account for its larger size. We set \texttt{kappa} to 1 and the values of \texttt{w_max_iter} to 300 and \texttt{h_max_iter} to 100. This led to better training convergence.

5.1 Results and Discussion

Table 1 (left) depicts our scores in comparison to the state-of-the-art WTS. Notably, on AI, we find that logistic regression achieves higher values for all performance measures. This is remarkable, given the simplicity of logistic regression and the complexity of WTS. Kobs et al. [6] also evaluated logistic regression, however, using mere term frequencies instead of tf-idf. We hence added an experiment on AI to confirm that tf-idf is favorable. On the larger MED corpus, WTS
Table 1: *Left:* Results of different recommendation methods. Results for WTS are taken from Kobs et al. [6]. *Right:* Top 3 recommendations and top 3 topics for the BERT paper [3]. Our recommendation NAACL is the true publication venue.

| Method                  | Acc | Acc@5 | MRR |
|-------------------------|-----|-------|-----|
| Uniform Random (avg)    | 0.012 | 0.067 | 0.063 |
| Most Frequent           | 0.086 | 0.319 | 0.212 |
| WTS                     | 0.503 | 0.831 | 0.645 |
| Logit (NMF)             | 0.397 | 0.744 | 0.550 |
| Logit (tf)              | 0.464 | 0.787 | 0.605 |
| Logit (tf-idf)          | 0.509 | 0.841 | 0.651 |
| Logit (tf-idf + NMF)    | 0.510 | 0.843 | 0.652 |

Input Paper
Title: BERT: Pre-training of Deep Bidirectional (...)
Abstract: We introduce a new language (...)
Keywords: <None>

Found Topics (in rank order)
1) question, answering, questions, answer, answers
2) language, natural, processing, parsing, dialog
3) deep, convolutional, neural, network, cnn

Recommendations (in rank order)
1) EMNLP
   a) translation, machine, statistical, bleu
   b) parsing, grammar, parser, dependency
   c) corpus, text, corpora, news
2) NAACL
   a) translation, machine, statistical, bleu
   b) corpus, text, corpora, news
   c) word, dictionary, sense, disambiguation
3) AAAI
   a) reasoning, representation, knowledge, case
   b) optimization, problem, constraint, constraints
   c) agent, agents, multi, multiagent

exhibits the best performance scores. This shows that the employed TextCNN and Word2Vec profit from large amounts of training data, a fact that has been frequently stated for neural networks before. MED is a very diverse data set covering venues from the fields chemistry, medicine, physics and more. In practice, the domain-focussed AI corpus is a more realistic recommendation scenario.

Adding NMF-topics to tf-idf vectors led to slightly higher scores for AI and MED. The effect might be larger when NMF is trained on an additional corpus or when NMF variants incorporating class information are used [18]. Pure NMF representations led to lower scores than tf-idf. Yet, despite their few vector components they are in the range of the tf representations. To a certain degree, NMF topics allow for an interpretation and assessment of recommendations. Table 1 (right) depicts recommendations and topics for an example paper d [3]. The true venue is ranked second. The identified topics of d, represented by their top-weighted terms, are interpretable as question answering, natural language processing and neural networks. The venue topics are often strongly related and, where not, may give a hint for further recommendation assessment.

6 Conclusion and Outlook

We presented methods towards explainable scientific venue recommendations[^3]. First, we showed that logistic regression with tf-idf is a competitive recommendation setup. Second, we illustrated a principled approach for annotating recommendations with topics derived from a research corpus. The so-provided contrasting juxtaposition using topics allows for explanations that exceed the

[^3]: Demonstration available at [https://sci-rec.org](https://sci-rec.org)
content of the input paper (i.e., query). We envision that future work should target automated topic labeling \cite{Lau2011} to further increase topic comprehensibility.

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