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Article

Semantic Interest Modeling and Content-Based Scientific Publication Recommendation Using Word Embeddings and Sentence Encoders

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Abstract: The fast growth of data in the academic field has contributed to making recommendation systems for scientific papers more popular. Content-based filtering (CBF), a pivotal technique in recommender systems (RS), holds particular significance in the realm of scientific publication recommendations. In a content-based scientific publication RS, recommendations are composed by observing the features of users and papers. Content-based recommendation encompasses three primary steps, namely, item representation, user modeling, and recommendation generation. A crucial part of generating recommendations is the user modeling process. Nevertheless, this step is often neglected in existing content-based scientific publication RS. Moreover, most existing approaches do not capture the semantics of user models and papers. To address these limitations, in this paper we present a transparent Recommendation and Interest Modeling Application (RIMA), a content-based scientific publication RS that implicitly derives user interest models from their authored papers. To address the semantic issues, RIMA combines word embedding-based keyphrase extraction techniques with knowledge bases to generate semantically-enriched user interest models, and additionally leverages pretrained transformer sentence encoders to represent user models and papers and compute their similarities. The effectiveness of our approach was assessed through an offline evaluation by conducting extensive experiments on various datasets along with user study (N = 22), demonstrating that (a) combining *SIFRank* and *SqueezeBERT* as an embedding-based keyphrase extraction method with *DBpedia* as a knowledge base improved the quality of the user interest modeling step, and (b) using the *msmarco-distilbert-base-tas-b* sentence transformer model achieved better results in the recommendation generation step.

Keywords: semantic user modeling; content-based recommender system; word embedding; sentence encoder

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1. Introduction

Every year, thousands of papers are published in journals and conferences by researchers in many different fields. The increasing amount of digital data resulting from the development of information technologies means that literature search is becoming a challenging and time-consuming task in which it is more difficult to reach the desired information. With the constantly increasing amount of papers, users frequently utilize the current academic paper search engines (e.g., Google Scholar and Semantic Scholar) to search for relevant papers based on a set of keywords. The existing search engines often fail to satisfy users' demands efficiently because they do not take individual user profiles into account. In fact, for a given search query, a search engine provides the same information to all users even though individual users may have their own interests and information needs. This drawback necessitates a personalized information system, such as a scientific publication recommendation system (RS) (sometimes denoted in the literature as paper RS, research paper RS, academic paper RS, scientific paper RS, article RS, scholar RS, etc.) to automatically present the most relevant papers to researchers based on their interests and information needs while minimizing the time they spent in searching [1,2].

The field of recommending scientific publications has been extensively researched [3–6]. Common approaches for scientific publication recommendation include collaborative filtering (CF) (e.g., [7,8]), content-based filtering (CBF) (e.g., [9–11]), graph-based methods (e.g., [12,13]), and hybrid approaches (e.g., [14–17]), each of which attempts to measure relevance among research papers using different methods. CBF methods have been widely used in the literature [3,18,19]. Their popularity can be attributed to their effectiveness in comprehending the content of items, particularly textual ones, which leads to recommendations that are highly aligned with user interests. In addition, they are able to mitigate cold start and data sparsity issues, and are inherently transparent [3,4,20].

A fundamental part of generating recommendations is the user modeling process that identifies a user's information needs [3,21]. CBF relies on inferring the interests of users, which can be explicitly provided by users as input queries (e.g., paper, keywords) or implicitly inferred from the items that users have interacted with in the past (e.g., papers that the user authored, cited, tagged, browsed, or downloaded). These interests are then used to build user models, which are utilized to find relevant recommendations based on matching features between user models and papers [3,4,6,22]. Thus, a good user model plays an important role in enhancing the performance of the RS by providing more accurate recommendations [3,6,23]. Nevertheless, the majority of existing scientific RS publications neglect the user modeling process. In their literature survey of scientific RS publications between 1998 and 2013, Beel et al. [3] observed that many authors neglected the user modeling process. According the the authors, the majority (81%) of the surveyed approaches made their users provide a keyword, text snippets, or a single input paper to represent their information needs. Only few approaches automatically inferred information needs from the user's historical item interactions. In their comprehensive literature review of scientific RS publications between 2019 and 2021, Kreutz and Schenkel [6] found that the problem of neglecting user modeling continues to hold.

Another major issue in current content-based scientific RS publications is related to capturing the semantics of user models and papers, which is essential to developing more accurate and effective RS [19]. Most of the current content-based scientific RS publications use the classical bag-of-words method, which represents the number of times each word occurs in a document. These methods do not consider the context of the words or the semantic similarity between words during the extraction and representation of the paper and user model features [6,9,19]. Recently, text and sentence embedding techniques have gained more and more attention due to the good performance they have shown in a broad range of NLP-related scenarios. By examining how words are used in large corpora of textual data, word embedding algorithms generate a low-dimensional vector space representation of words in an entirely unsupervised manner, enabling machines to understand and process textual information more effectively. This approach serves to capture the semantic meaning of the words or documents and contextual relationships between them, which can be effectively used to extract meaningful data representations, obtain a semantic and relational understanding of the data, and measure semantic similarities between words or documents [6,9,24,25].

To address these limitations, in this paper we propose the transparent Recommendation and Interest Modeling Application (RIMA), a content-based scientific publication RS that leverages word embeddings and sentence encoders to improve the accuracy and effectiveness of the user modeling and recommendation generation tasks. Concretely, RIMA implicitly infers semantically enriched user interest models from users' past publications by combining embedding-based keyphrase extraction techniques with knowledge bases, then utilizes pretrained transformer sentence encoders to encode semantic information of user models and papers and compute their similarities. We conducted extensive experiments on different datasets to evaluate our approach, along with an online user study (N = 22). Our results revealed that combining *SIFRank* [26] and *SqueezeBERT* [27] as an embedding-based keyphrase extraction method with *DBpedia* [28] as a knowledge base can improve the quality of the interest model generation task. For recommendation generation, we were able to generate a more accurate and better-ranked recommendation using the sentence transformer model *msmarco-distilbert-base-tas-b* (https://huggingface.co/sentence-transformers/msmarco-distilbert-base-tas-b, accessed on 18 September 2022) to extract semantic representations of user models and papers in order to capture semantic similarity between them.

The rest of this paper is organized as follows. Section 2 reviews related works on different methods of user interest model generation and content-based scientific publication recommendation. Section 3 presents the two pipelines related to user model construction and recommendation generation in RIMA. Section 4 presents the results of the offline evaluations and the user study. Finally, Sections 5 and 6 point out limitations, summarize the work, and outline our future research plans.

2. Related Work

In this section, we provide an overview of the literature addressing different methods of interest model generation and scientific publication recommendation, with a focus on content-based approaches and NLP techniques.

2.1. Interest Model Generation

User modeling is a crucial task to achieve personalized services such as recommendation. The main aim of the user modeling process is to build a user profile by analyzing users' shared information. User interests are one of the most critical pieces of information in the user model [29]. The process of automatically acquiring the user's interests is known as interest modeling [30]. "User interest modeling", "interest mining", and "interest profiling" are all synonyms for "interest modeling" in the academic literature on user modeling. Interest modeling can be seen as the process of constructing a model to represent individual user interests based on their long-term and/or short-term information. User interest models can be generated through various approaches, including explicit user interest detection and implicit user interest mining [22]. Data in a user interest model are acquired through different methods, either manually, in which the user explicitly provides information about their interests and preferences, or implicitly, by analyzing user data such as behaviors, preferences, and other contextual information [31]. The widespread use of social media and digital publications has led researchers to focus on generating user interest models based on textual content containing keyphrases, which can be self-annotated by the user or automatically extracted using keyphrase extraction algorithms.

Several text mining methods have been used to generate user interest models. Text classification [32–34], named-entity recognition [35,36], and keyphrase extraction are popular techniques that are commonly used to construct interest models from text-based and social media-based data sources [22]. In this work, we focus on user interest modeling based on keyphrase extraction approaches. Keyphrase extraction plays a vital role in creating user interest models by uncovering meaningful patterns and insights from textual data. There are various categories that keyphrase extraction falls under, with the two most common being supervised and unsupervised. In supervised approaches, classification algorithms are commonly used to allocate users into predefined interest classes based on their data. Supervised approaches are relatively simple and easy to apply; however, they are domain-dependent and limited to identifying only predefined interests which were used to train the prediction model [37]. Unsupervised approaches, on the other hand, can be applied in various domains and are not dependent on any predefined prediction model. Thus, they can generate a more diverse set of user interests. Moreover, they are able to automatically identify and capture user interests without relying on labeled training data, which necessitates a lot of human labor [38,39]. In this work, we focus on unsupervised keyphrase extraction methods. These can be broken down into statistical-based, graph-based, and embedding-based approaches. Statistical models such as Latent Dirichlet Allocation (LDA), Term Frequency–Inverse Document Frequency (TF-IDF) [40], Rapid Automatic Keyword Extraction (RAKE) [41], and YAKE! [42] often include features such as word frequency, n-gram feature, location, and document grammar. Graph-based methods such as TextRank [43], SingleRank [44], ExpandRank [45], PositionRank [46], TopicalPageRank [39], TopicRank [47], and MultipartitieRank [48] attempt to model the relationships between words or phrases in the text.

Both statistical-based and graph-based methods are widely used for keyphrase extraction. However, neither approach considers the semantic issues during the keyphrase extraction task. A disadvantage of these approaches is that they cannot provide additional information about the semantic relationships of the entities or concepts present in the text [30,49]. In the user interest modeling task, user models might contain similar interests represented in the form of acronyms (e.g., MOOC and massive open online course), synonyms (e.g., technology enhanced learning and elearning), and lexical variants (e.g., elearning and E-learning). In addition, there may be overgeneration problems (e.g., the keyphrases open learning analytics and learning analytics represent the same interest, namely, learning analytics) [29]. Due to the lack of semantic knowledge, traditional statistical-based and graph-based keyphrase extraction methods can identify semantically similar interests as different, which might influence RS accuracy. To address semantic problems in the keyphrase extraction task, word and sentence embeddings are increasingly used as embedding-based keyphrase extraction techniques. Large corpora are utilized to train models for word and sentence embeddings into a vector space [50]. Pretrained language model encoders are commonly used, and have greatly improved the challenge of extracting keyphrases from textual data. Using sentence embedding techniques, Bennani-Smires et al. [38] developed the EmbedRank model for extracting keyphrases. To determine the document's sentence embedding and the possible keyphrases, the model employs two pretrained embedding models, Doc2Vec [51] and Sent2Vec [52]. The cosine similarity between the document embedding and candidate keyphrases embeddings determines which keyphrases are chosen. As a result of EmbedRank's embedding-based Mean Reciprocal Rank (MMR), keyphrase coverage and diversity are increased among the selected keyphrases. A more recent keyphrase extraction model utilizing ELMo [53] and SIF [54] was proposed by [26]. Noun phrases are extracted using tokenization and Part-of-Speech (POS) tagging, and their embeddings are calculated together with the document embedding. Then, the cosine similarity is used to pick the keyphrases. Due to SIFRank's limitations on longer texts, the authors created SIFRankPlus, an extension of SIFRank that incorporates a position-biased weighting scheme to increase extraction accuracy.

In order to address the semantic issues, research works have incorporated knowledge bases such as Wikipedia [29,55–61], DBPedia [57,62–64], WordNet [65–67], Freebase [68], Linked Open Data (LOD) cloud [49,69,70], and YAGO [71] to semantically represent user models. Semantic enrichment in the user modeling process is motivated by the need to enhance the accuracy of user models [22], increase the breadth of the keyphrases used to represent the users' interests [22,49], gather additional contextual knowledge about the entities and the relationships between them [30,49], infer more transparent and serendipitous user models [56], and bypass the problems of acronyms, synonyms, lexical variants [29], and polysemy, i.e., when a word may have multiple meanings which cannot be distinguished using keyword-based representation [30].

Our approach for interest model generation moves beyond existing works by combining word embedding-based keyphrase extraction techniques with Wikipedia/DBPedia as a knowledge base to generate semantically-enriched user interest models in order to improve the quality of keyword extraction and user modeling by considering the semantic meanings of words.

2.2. Content-Based Scientific Publication Recommendation

Scientific publication RS are well studied in the literature. We refer the interested reader to four comprehensive literature reviews in this area [3,4,6,20]. The four predominant categories are content-based filtering (CBF), collaborative filtering, graph-based, and hybrid systems. In this work, we are interested in a scientific publication RS based on CBF. The key procedure in a content-based scientific publication RS is to match information between users (i.e., researchers) and items (i.e., publications). In general, recommendations in CBF methods are generated by observing features of users and publications. CBF mainly considers the users' historical preferences and personal library to build the user interest model (i.e., the user profile). Then, CBF extracts keywords from the candidate publications and calculates the similarity of the keywords extracted from user profiles and candidate publications. Finally, publications with high similarity are recommended to users [4]. CBF includes three main steps: item representation, user modeling, and recommendation generation [4].

2.2.1. Item Representation

The appropriate item representation is very important, and is closely related to the performance of the RS [20]. In content-based scientific publication RS, items are represented by a content model containing the items' features, which are typically word-based, i.e., single words, phrases, or n-grams [3]. Publications are mostly represented as TF-IDF vectors or based on keyphrase extraction models [4,6]. For example, Renuka et al. [72] used TF-IDF representations of automatically extracted keywords and key phrases. Few approaches have used a topic modeling component mostly based on LDA to represent publications' content. For example, Subathra and Kumar [73] used LDA on publications to find their top n words, then used LDA again on these words' Wikipedia articles. To counter the semantic problem in content-based approaches that rely on basic TF-IDF representations of publications, recent research on content-based scientific publication recommendation increasingly adopts text embedding methods based on different parts of a publication (i.e., titles, abstracts, keywords, and bodies) [6]. The most common embedding methods used to represent the content of scientific publications include Word2Vec [9,23,74], Doc2Vec [2,74,75], Glove [10], and SciBERT [11]. However, while widely used in graph-based and hybrid scientific publication RS (e.g., [76–79]), transformer-based embedding techniques, e.g., BERT, SBERT, and DistilBERT, remain under-investigated in content-based scientific publication RS.

2.2.2. User Modeling

One central component of a content-based scientific publication RS is the user modeling process. The user model typically consists of the features of a user's publications [3]. The literature on scientific publication RS distinguishes between two ways to capture user preferences, implicitly and explicitly [19,23]. Implicit user modeling identifies needs automatically by inferring them from the user's item interactions. Concretely, the interests of users are automatically inferred from the publications that users have authored or interacted with through actions such as reading, citing, tagging, browsing, or downloading [9,18,23,25,80,81]. In the explicit user modeling approach, the RS asks users to specify their preferences by explicitly providing a list of keywords or an input paper [9,82–88]. However, in this case an RS behaves similarly to a search engine, and loses the capability to recommend publications even if users do not know exactly what they need [3]. In our work, we focus on content-based scientific publication recommendation approaches that implicitly derive user interest models from their authored papers. Only few works exist that follow this approach [2,89–97]. These works have built user models with keyphrases, concepts, or topics extracted from the researcher's past publications using a bag-of-word (BoW) model, TF-IDF, topic modeling, keyphrase extraction, or embedding techniques. For example, Lee et al. [89] modeled researchers using a BoW model based on their papers retrieved from different digital libraries. Sugiyama and Kan [90] noted that an author's published works constitute a clean signal of the latent interests of a researcher, and constructed researcher profiles using a feature vector comprising unique terms obtained from their list of previous publications based on TF. Nishioka et al. [91,92,93] constructed user models from research papers and tweets based on different variants of TF-IDF. To generate user models, Bulut et al. [94,95] considered a user's past publications and represented users as the sum of the features of their publications. All the required metadata, such as the title, year, author, abstract, and keyword of each publication, were extracted and merged together in a profile represented by TF-IDF. Chen and Ban [96] used LDA as a topic modeling technique to topically cluster user interests mined from their published papers. First, a user's publications were divided into different interest points by clustering technologies. Then, the user's interests were represented in terms of pattern equivalence classes. Similarly, Amami et al. [97] constructed a user profile based on LDA-generated topics from the users's publications corpus. Bulut et al. [2] used the Doc2vec embedding method to construct user models while taking the user's past articles into consideration. They found that the Doc2vec-based representation of the user model achieved better results than TF-IDF. While keyphrase extraction techniques have been used to infer user models from users' interactions with publications (e.g., in [80]), to the best of our knowledge there are no works that have utilized keyphrase extraction to implicitly derive user interest models from their authored publications.

In summary, while various methods have been utilized for building user interest models from researchers' authored papers, approaches relying on keyphrase extraction or embedding techniques are lacking. Moreover, these methods do not consider the semantic issues in the user interest modeling task. In order to fill these research gaps, we combine keyphrase extraction, word embeddings, and knowledge bases to build semantically-enriched user interest models to be used as input for our content-based scientific publication RS.

2.2.3. Recommendation Generation

To generate a recommendation list, the similarity between user interest models and recommendation candidates is calculated using a vector space model and a similarity measure to ensure that candidate publications with high similarity are recommended to the researcher [3,4]. In most content-based scientific publication RS, cosine similarity is often applied between papers or between users and papers [6]. For application between papers, similarity is computed between the feature vectors of the input paper on the one hand and the set of the candidate papers to recommend on the other hand [11,24,72–75,98–101]. For application between users and papers, similarity is computed using the constructed user profile and the feature vectors of the set of the candidate papers to recommend [2,9,25,80,82–84,87–95]. Most of the similarity computation is based on papers and users represented by TF-IDF [72,80,83,84,87,88,90–95,99–101]. We found that whereas embedding techniques are often applied to compute similarities between papers (e.g., [11,24,74,75]), approaches utilizing embedding of user models and papers remain scarce in the literature on content-based scientific publication recommendation [2,9,25].

Overall, our investigation reveals limited previous research utilizing embedding-based approaches to compute similarities between vector representations of the constructed user models and candidate papers to be recommended in the context of content-based scientific literature recommendation. Our work aims to fill this gap by adopting pretrained transformer sentence encoders in a scientific literature RS for embedding users and papers as well as for similarity computation.

3. RIMA Application

The transparent Recommendation and Interest Modeling Application (RIMA) serves as a content-based recommendation system for scientific publications [102–110]. RIMA was designed to automatically extract users' interests from their past scientific publications and then utilize them to provide relevant publication recommendations. In this work, we focus on the generation process of interest models and recommendations. Each process is elaborated through a conceptual pipeline, where the methodology is explained, and a technical pipeline, where the implementation details are presented.

3.1. Interest Model Generation

3.1.1. Conceptual Pipeline

The pipeline for generating the interest model is depicted in Figure 1. The first step involves collecting all publications authored by a user in the last five years. Next, an unsupervised keyphrase extraction method is applied on the publications to obtain keyphrase-based interests. Subsequently, a knowledge base is utilized to semantically enrich the keyphrase-based interests. To introduce dynamism to the interest model, the interests are periodically updated over time using a forgetting function. In the following sections, we discuss these steps in detail.

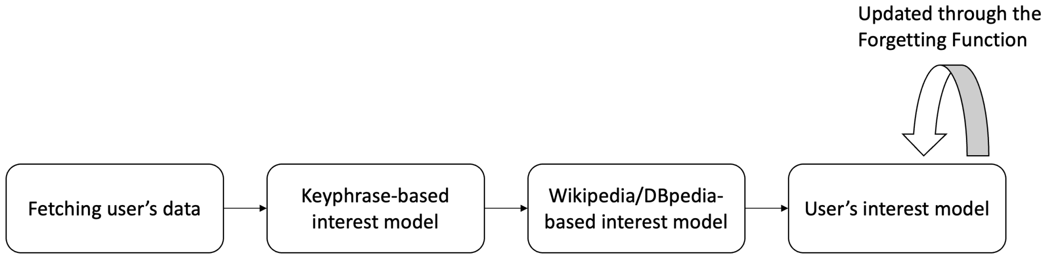

Figure 1. Interest model generation pipeline

Keyphrase-based interest model. In this work, our focus is on embedding-based keyphrase extraction techniques in comparison to other statistical- and graph-based approaches. To achieve this, we initially assessed the performance of various statistical- and graph-based keyword extraction algorithms to select the best-performing one as a baseline based on the Precision, Recall, and F-measure metrics. We chose exact matching to compute these metrics. The performance measures for the different keyword extraction algorithms, namely, TextRank [43], SingleRank [44], TopicRank [111], TopicalPageRank [112], PostionRank [46], MultipartitieRank [113], Rake [41], and YAKE! [114], were benchmarked using the Inspec dataset [115]. The Inspec dataset is designed for benchmarking keyphrase extraction and generation techniques from abstracts of English scientific papers. It comprises a document collection of 2000 scientific abstracts with sets of keyphrases identified by expert annotators. The results of the computation are summarized in Table 1, which indicates that SingleRank outperforms all other selected algorithms when extracting the top ten and top fifteen keywords. In particular, SingleRank (marked bold in Table 1) improves upon the strongest baseline, TopicalPageRank (underlined in Table 1), with respect to precision by 2.4%, recall by 2.7%, and F1-score by 2.4% for extracting ten keyphrases. For extracting fifteen keyphrases, the improvement is 0.9% in precision, 2.1% in recall, and 1.4% in F1-score. Therefore, we selected and implemented SingleRank as the baseline for our work.

We employed SIFRank [26] as an embedding-based keyphrase extraction method to extract keyphrases from an author's publications for the purpose of generating the interest model. SIFRank presents a method for unsupervised keyphrase extraction based on a pretrained language model. It combines the sentence embedding model SIF [54] and the autoregressive pretrained language model ELMo [53]. The selection of SIFRank was based on its performance, as it achieved state-of-the-art results on short documents compared to other unsupervised keyphrase extraction techniques based on pretrained language models [26]. When compared to SIFRank's performance with core transformer models such as BERT [116], RoBERTa [117], and XLNet [118], the evaluation conducted by the authors of SIFRank showed that SIFRank's performance was better when employing ELMo as a word embedding approach [26]. However, LSTM-based approaches such as ELMo can be time-consuming [116]. Therefore, we substituted the ELMo word embedding method in SIFRank with the pretrained model SqueezeBERT [27]. SqueezBERT presents a novel neural architecture which uses grouped convolutions. It runs 4.3x faster than BERT-base on the Google Pixel 3 smartphone while achieving competitive accuracy on the General Language Understanding Evaluation (GLUE) set of tasks, which is a standard evaluation benchmark for NLP research [27]. In addition to its speed, SqueezeBERT was chosen because of the increased information flow between its layers and the fact that its transformer design is lightweight. Henceforth, we refer to this method as $SIFRank_{SqueezeBERT}$.

Table 1. Keyword extraction algorithm performance measures on the Inspec dataset.

Algorithm	K = 5			K = 10			K = 15		
	P	R	F	P	R	F	P	R	F
TextRank	18.15	7.10	9.79	16.15	9.58	11.51	14.88	10.15	11.48
SingleRank	30.96	13.60	17.99	**26.95**	**22.04**	**23.02**	**23.57**	**27.01**	**24.03**
TopicRank	26.97	11.52	15.38	21.86	17.31	18.41	19.53	21.24	19.51
TopicalPageRank	30.36	13.37	17.67	<u>26.31</u>	<u>21.44</u>	<u>22.47</u>	<u>23.34</u>	<u>26.43</u>	<u>23.69</u>
PositionRank	**32.12**	**13.82**	**18.38**	25.45	20.79	21.77	22.79	25.80	23.15
MultipartitieRank	28.60	12.11	16.20	21.99	17.83	18.70	19.76	22.75	20.20
Rake	20.02	9.13	11.87	21.54	18.27	18.75	18.42	21.57	18.97
YAKE!	24.80	11.14	14.59	20.32	17.70	17.88	17.86	22.78	18.96
Percentage Improvement (%)	-	-	-	2.4	2.7	2.4	0.9	2.1	1.4

P—precision, R—recall, F—F-measure, K—number of keywords.

Wikipedia/DBpedia-based interest model. The use of a knowledge base to infer interest models has the potential to resolve several semantic-related problems, including the merging of synonym interests, the reduction of acronym interests, and the elimination of noise caused by irrelevant keyphrases. Consequently, knowledge-based interest models should be more comprehensive and precise than keyphrase-based models. In this work, we employed two distinct knowledge bases, namely, Wikipedia and DBpedia, to construct semantically-enriched user interest models. Wikipedia is used to map the generated keyphrases to entities/concepts in the knowledge base. If a matching Wikipedia article's title could be found, the term was included in the interest model; otherwise, it was removed. To connect keyphrases to concepts in the DBpedia knowledge base [28], we utilized DBpedia Spotlight [119] as an entity linking service.

Dynamic interest model. It was realized that if interests were not constantly updated, they could lose their significance; hence, a forgetting function was deemed necessary. The weight of an interest diminishes depending on the time elapsed since the user last generated it and the current date. Cheng et al. [120] proposed a forgetting function to characterize the diminishment of human interests. By adjusting the half-life hl, they represented the gradual loss of interest in things that had not been recently updated:

$$F(t) = e^{-\frac{ln(2)*(t-est)}{hl}} \tag{1}$$

where the forgetting coefficient $F(t)$ represents the percentage of the original interests that have declined, t represents the current date, and est represents the date when the original model was constructed. Here, hl represents the half-life (in days) that regulates the forgetting rate. A larger hl value results in a slower decline of interest. The update periods for the interest models for publications were set at 365 days (one year). Assuming $t - est = hl$, we have $F(t) = 1/2$, which suggests that the interest weight for publication data decreased by half per year.

3.1.2. Technical Pipeline

Figure 2 illustrates the steps to generate the user interest model in the RIMA application. Users sign up using their Semantic Scholar ID information, initiating an API request to the Django server. This request is then forwarded to the Celery worker, which triggers three tasks: (a) collecting user data, (b) generating short-term interest models, and (c) creating long-term interest models. The first task sends an HTTP request to the Semantic Scholar API to collect the user's publications, including titles and abstracts, from the last five years. Upon receiving the API response with the requested publications, they are forwarded to the second Celery task, where keyphrases are extracted along with their corresponding weights. After this is the weight normalization step, in which the weights for the extracted keyphrases, which range from 0–1, are normalized and mapped to a range from 1–5. Further, the extracted keyphrases with the normalized weights are semantically enriched using either the Wikipedia or DBpedia APIs. The short-term interests are then stored in the database and scheduled for regeneration by the second Celery task on an annual basis. The third task takes the short-term interests as input and utilizes the forgetting function to generate the long-term interest model, which is subsequently stored in the database. When users log into their accounts, a request is sent to the Django server, which requests the long-term interests from the Django model. The Django Model communicates with the database to retrieve the long-term interests. The response with the long-term interests is sent to the front-end through Django View to be visualized.

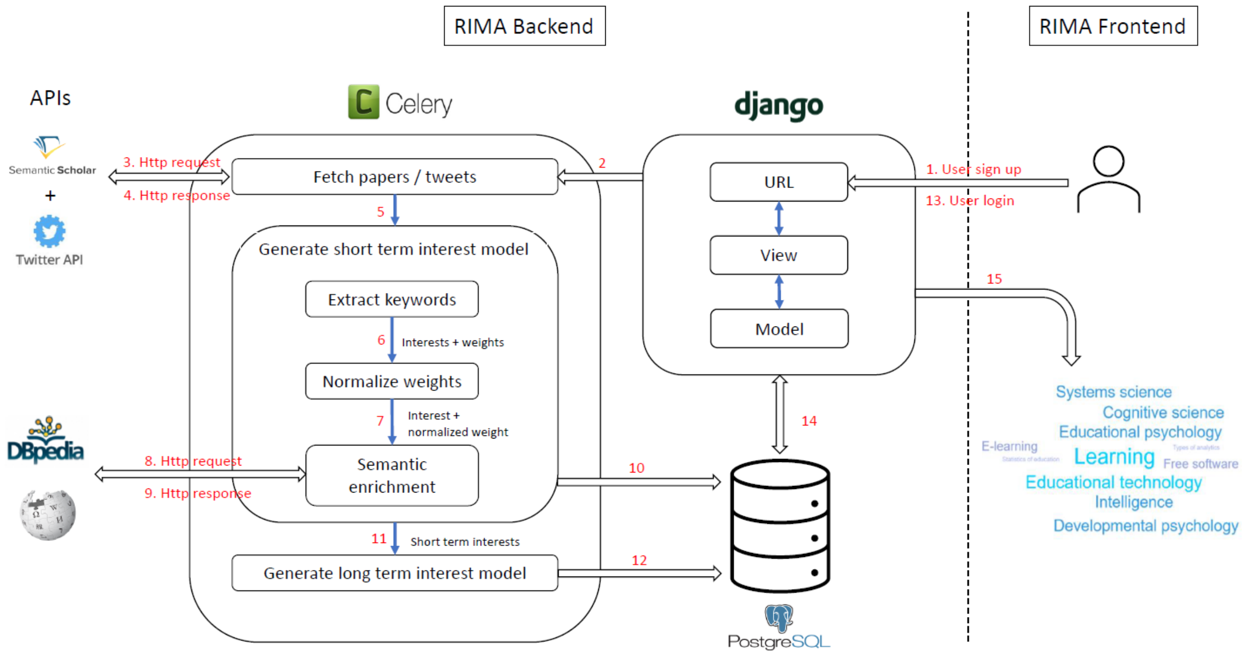

Figure 2. Interest model generation pipeline.

3.2. Recommendation Generation

3.2.1. Conceptual Pipeline

The pipeline for generating the publication recommendations is depicted in Figure 3. It begins with the collection of the most similar publications to the user's interest model using the Semantic Scholar API. Subsequently, keyphrases are extracted from the collected publications. After that, we represent the user's interest model and the keyphrases extracted from the collected publications as embedding vectors. To calculate the weighted average embedding vector of the interest model, we multiply each interest's embedding vector by its weight and then sum these vectors. Finally, we divide this sum by the total sum of all interest weights. Similarly, we compute a weighted average embedding vector for each publication, based on its extracted keyphrases. Finally, we calculate the cosine similarity between the average weighted vector of the interest model and the average weighted vector of each collected publication. The top ten most similar publications are then recommended to the user.

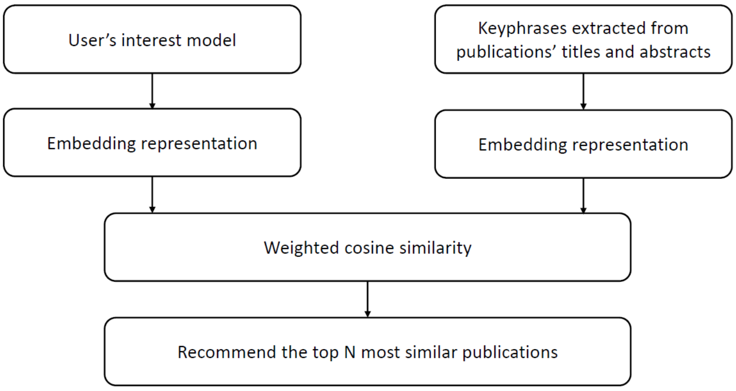

Figure 3. Recommendation generation pipeline

3.2.2. Technical Pipeline

Figure 4 illustrates the steps to generate the top ten scientific publications to be recommended to the user. Initially, a request containing the user's top five interests and their corresponding weights is sent to the Django server, which in turn communicates with the Semantic Scholar API to retrieve the most relevant publications based on the user's interests. Keyphrases are extracted from each obtained publication and their weights are calculated by considering the frequency of these keyphrases in the publication's title and abstract. Subsequently, the resulting weights are normalized to a scale ranging from 1 to 5. After that, a pretrained transformer language model encoder is used to generate the weighted embedding vectors for the user interest model and each publication. Following that, the cosine similarity function is used to determine the similarity between the user's interest model and each of the obtained publications. Finally, the top ten most relevant publications with the highest similarity score are recommended to the user.

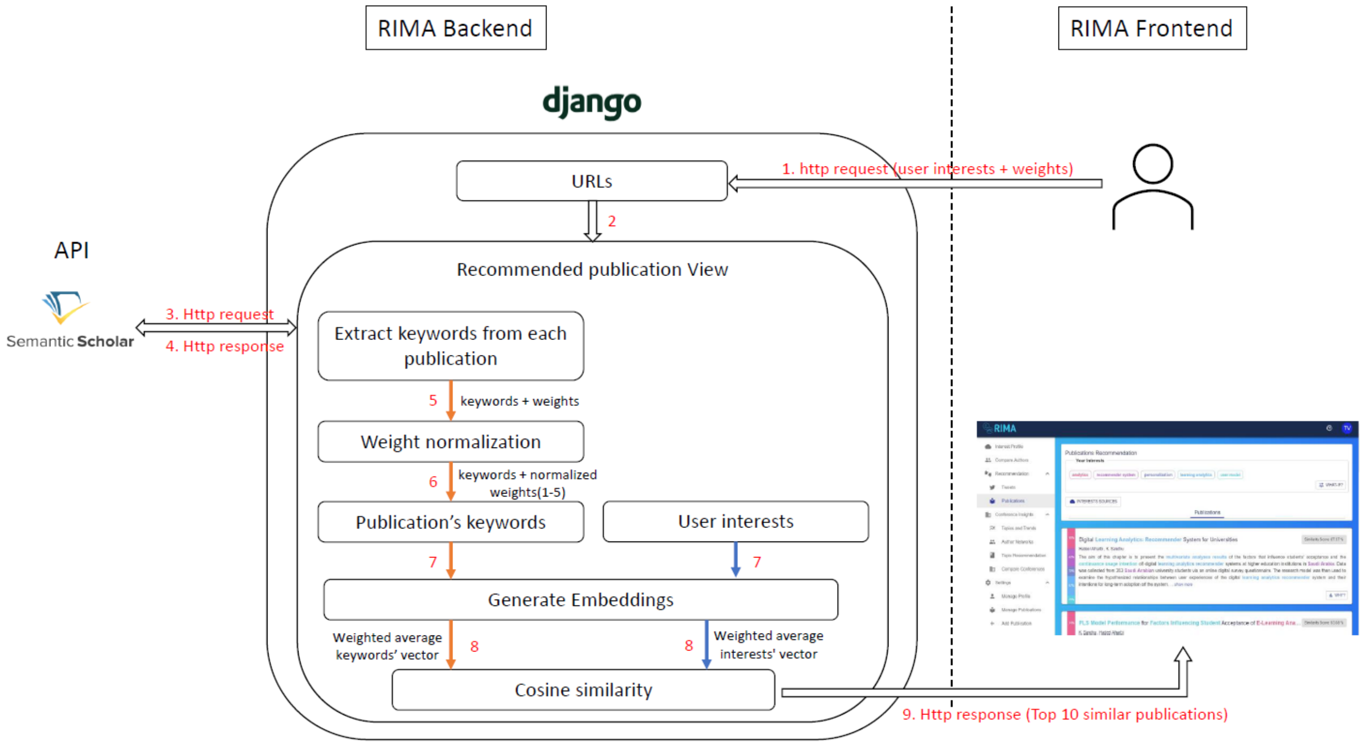

Figure 4. Recommendation generation pipeline

4. Evaluation

The overall goal of this work was to improve the interest modeling and recommendation mechanisms in a content-based RS by leveraging word embedding techniques. In this section, we first present the results of the evaluation conducted to gauge the quality of the generated interest models through a user study. The best performing approach was then selected to generate user interest models to be used as input for publication recommendation generation. Finally, we present the offline and user study evaluation results related to the quality of the generated recommendations. For the user study evaluations, we used the statistical measurements Precision at K (Precision@K), Mean Reciprocal Rank (MRR), and Mean Average Precision (MAP).

4.1. Interest Model Generation

4.1.1. Participants

The target group for our study consisted of researchers and students. Participants were recruited via e-mail, word-of-mouth, and groups in social media networks, and had to fulfill two participation requirements, namely, having at least one scientific publication, and possessing a Semantic Scholar ID, which is necessary for the interest model generation step. A total of 43 people were contacted, of whom 22 (9 males and 13 females) participants completed the study, including PhD students and professors from various countries and ages and with different backgrounds.

4.1.2. Procedure

We conducted an online user study using a questionnaire to assess the quality of the generated interest models. User information was anonymized and all participants provided their informed consent for study participation. Our goal was to investigate the best approach among three different combinations for generating an accurate interest model: (a) *SingleRank* as a keyphrase extraction method with *Wikipedia* as a knowledge base for semantic enrichment; (b) $SIFRank_{SqueezeBERT}$ as a keyphrase extraction method with *Wikipedia* for semantic enrichment; and (c) $SIFRank_{SqueezeBERT}$ as a keyphrase extraction method with *DBpedia* as a knowledge base. The average time taken to complete the questionnaire was seven minutes. The questionnaire consisted of two questions for each of the three generated interest models: *(1) "Please rate the relevance of the following interests which were extracted from your publications"* and *(2) "Are any of your top five interests not represented in this interest model? If yes, how many?"*. Additionally, there was one general question: *"Which interest model, in your opinion, most accurately represents your interests?"*.

For each generated interest model, users were provided with a list of the top k interests sorted by weight and were asked to assign a relevance value to each interest (1: not at all relevant, 2: low relevance, 3: relevant, and 4: high relevance). Later in the calculations, we considered ranks 1 and 2 to indicate non-relevant interests and ranks 3 and 4 to indicate relevant interests. With the first question, we were able to calculate how many relevant interests were found at the top k interests (Precision@K), how early in the ranked list of generated interests a relevant interest could be found (MRR), and the accuracy with which the interests were ranked and how early relevant interests appear (MAP). The K in Precision@K is the total number of extracted interests. In our case, it is different from one user to another because our approaches generate a different number of interests for each user, with a maximum of fifteen interests depending on the number of publications per user and the number of keyphrases per publication. With the second question, we were able to gain a subjective perspective on the completeness of each interest model by estimating how many interests were missing.

4.1.3. Analysis and Results

Table 2 shows the results for Precision@k, MRR, and MAP. It can be seen that Model 3 generated by ($SIFRank_{SqueezeBERT}$ + *DBpedia*) has the highest precision@k value at 0.73, which indicates that it is the most accurate interest model. However, Model

2 ($SIFRank_{SqueezeBERT}$ + *Wikipedia*) has the highest MRR value at 0.86, meaning that this interest model provides a better ranking for the highest-ranked relevant interests. Both of these interest models share a similar MAP value of 0.78. In contrast, Model 1 (*SingleRank* + *Wikipedia*), which served as the baseline, yields the lowest results across all three metrics. Overall, these results demonstrate that the utilization of word embedding techniques can enhance the quality of interest model generation.

Table 2. Interest modeling evaluation results using statistical metrics.

	Precision@k	MRR	MAP
Interest model 1 (*SingleRank* + *Wikipedia*)	0.62	0.64	0.65
Interest model 2 ($SIFRank_{SqueezeBERT}$ + *Wikipedia*)	0.69	0.86	0.78
Interest model 3 ($SIFRank_{SqueezeBERT}$ + *DBpedia*)	0.73	0.81	0.78

Because the results based on Precision@k, MRR, and MAP were close to each other regarding Models 2 and 3, we relied on the subjective opinions of the users to decide which model to use in order to generate the recommendations. As can be seen in Figure 5, 59% of the users selected Model 3 ($SIFRank_{SqueezeBERT}$ + *DBpedia*) as the best interest model. This suggests that they considered it the most complete model, covering most of their interests. Furthermore, Model 3 had the lowest percentage of missing interests at 40%, followed by Model 2 ($SIFRank_{SqueezeBERT}$ + *Wikipedia*) at 44%, while Model 1 (*SingleRank* + *Wikipedia*) had the highest percentage of missing interests at 53%. In summary, the offline and user evaluation showed that combining $SIFRank_{SqueezeBERT}$ as a keyphrase extraction method with *DBpedia* as a knowledge base can improve the quality of the interest model generation task.

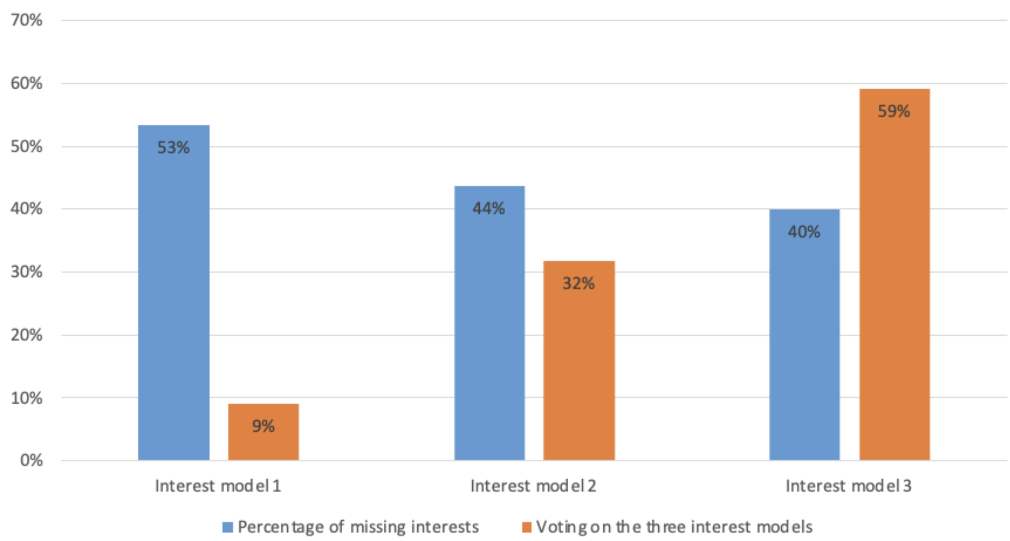

Figure 5. Interest modeling evaluation results using subjective opinions of users.

4.2. Recommendation Generation

4.2.1. Offline Evaluation

We conducted an offline experiment with the goal of identifying the best approaches for delivering accurate and relevant scientific publication recommendations. Initially, we tested various keyphrase extraction methods, then subsequently evaluated different embedding models.

Keyphrase extraction from publications. To determine the keyphrase extraction approach for publications, we conducted an experiment comparing the accuracy and performance of *SingleRank* and $SIFRank_{SqueezeBERT}$ when extracting keyphrases from publication titles and abstracts. Using various user interest models, we sent requests to the Semantic

Scholar API to obtain lists of publications relevant to each interest model. Assuming that the publications should have high semantic similarity to the interest model used to find them, we computed semantic similarities between the interest model and the publication's keyphrases extracted using both *SingleRank* and $SIFRank_{SqueezeBERT}$. Figures 6 and 7 show the distribution of semantic similarity scores calculated between an example interest model and the publications' keyphrases. The x-axis represents the similarity scores and the y-axis represents the number of publications which have these similarity scores. For brevity, we selected only one example for presentation here. Overall, we observed no significant difference in accuracy, between the two keyphrase extraction methods as indicated by the distributions of semantic similarity scores. However, it is worth noting that *SingleRank* consistently outperformed $SIFRank_{SqueezeBERT}$ in terms of extraction speed. Consequently, we decided to use *SingleRank* to extract keywords from publications.

Embedding representation. Different models were selected for testing on the embedding step of the recommendation generation pipeline. We compared different pretrained transformer sentence embedding techniques. These included the *USE* sentence encoder, which has been shown to outperform the BERT [116], ELMo [53], and InferSent [121] models [24]. In addition, we included the *SciBERT* [122] model, as it was trained on publications. Furthermore, Hugging Face documentation includes a list of models for the sentence embedding task. Among these models, we selected *all-mpnet-base-v2* (https://huggingface.co/sentence-transformers/all-mpnet-base-v2, accessed on 18 September 2022), which has the average highest performance in the Hugging Face documentation, *all-distilroberta-large-v1* (https://huggingface.co/roberta-base, accessed on 18 September 2022), which has the highest performance in the sentence embedding task, *all-MiniLM-L12-v2* (https://huggingface.co/sentence-transformers/all-MiniLM-L12-v2, accessed on 18 September 2022), which is smaller than the other selected models in terms of size and the model is faster, and *msmarco-distilbert-base-tas-b*, which achieved the highest performance regarding the asymetric semantic search task. Asymmetric semantic search means that we have a short query (in our case, the user's interest model) and that we want to find a longer paragraph answering the query (in our case, the publications).

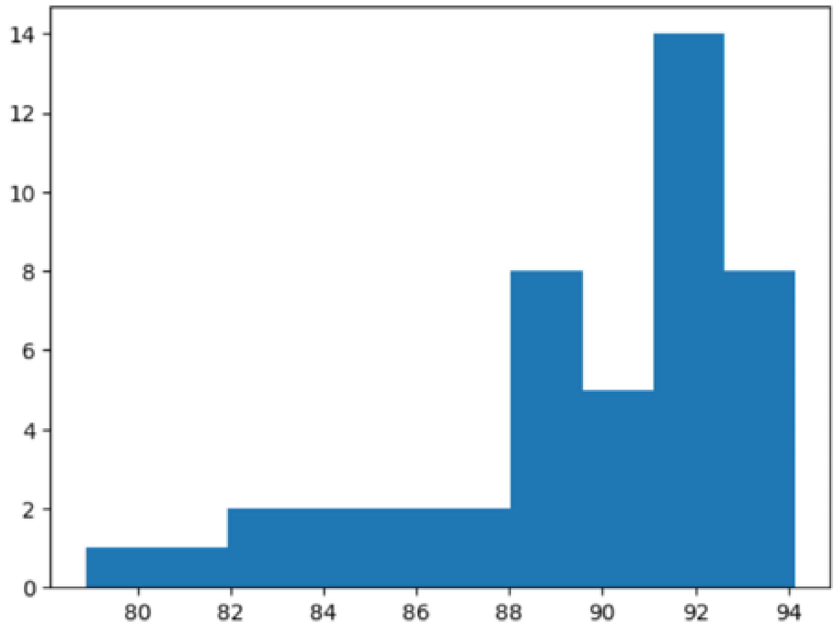

Figure 6. Semantic similarity score distributions with *SingleRank*.

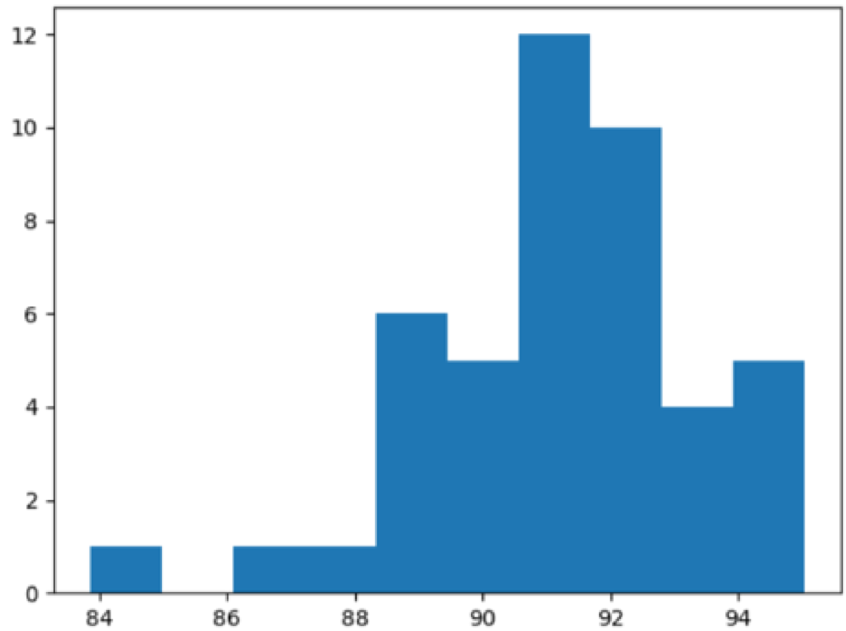

Figure 7. Semantic similarity score distributions with $SIFRank_{SqueezeBERT}$.

4.2.2. Analysis and Results

To determine the optimal model, the embedding performance for uni-grams, bi-grams, and sentences was tested using three benchmarks. First, we used the SimLex999 dataset [123], which is a benchmark dataset for evaluating the performance of semantic models. It consists of 999 pairs of words with human-annotated similarity ratings. The ratings are based on the genuine similarity of the words, which is the degree to which the words are semantically related. Second, we used the BiRD dataset [124], which is another benchmark dataset for evaluating the performance of semantic composition models. This dataset consists of 3345 fine-grained relatedness ratings for 3345 bi-gram pairs. The ratings are based on the comparative annotation technique, which asks human annotators to compare the relatedness of two bi-grams. The last dataset was the the STS Benchmark [125], which is a benchmark for evaluating the performance of semantic textual similarity (STS) systems. The task is divided into two subtasks, multilingual STS and cross-lingual STS. We used Pearson correlation to compare the quality of machine similarity scores to the quality of human judgments for the six selected models. The Pearson correlation test evaluates the strength and the directional association between two continuous variables. We used the r-value, often known as the Pearson correlation coefficient, in our analysis to determine the direction and strength of the correlation. The greater the proximity to 1 (-1), the stronger the positive (negative) correlation. A value of 0 indicates that there is no correlation. Table 3 shows that the *all-mpnet-base-v2* model achieved the best performance at the bi-gram and sentence levels, while *msmarco-distilbert-base-tas-b* achieved the highest performance at the word level and the *USE* model was the fastest. It is apparent that model performance improves as the length of the grams increases. This makes sense, as these embedding models are context-dependent.

Further, we investigated the performance of these models in our context to obtain the embeddings of the interest models and the publications. For the publication embedding, we compared the embedding performance at the document level, which means representing the titles and abstracts of publications as a whole, and at the keyphrase level, where we extracted the important keyphrases first.

Table 3. Comparison of the selected embedding techniques using Pearson correlation.

Models	SimLex999		BiRD		STS	
	Pearson Correlation	Time	Pearson Correlation	Time	Pearson Correlation	Time
USE	0.51	**396 ms**	0.61	**2.27 s**	0.78	**1.12 s**
SciBERT	0.07	33.7 s	0.45	2 min 10 s	0.44	2 min 59 s
all-mpnet-base-v2	0.54	34.1 s	**0.67**	1 min 52 s	**0.84**	2 min 52 s
all-distilroberta-v1	0.31	26.1 s	0.63	1 min 9 s	0.83	1 min 23 s
all-MiniLM-L12-v2	0.51	14.9 s	0.64	36.8 s	0.83	51.3 s
msmarco-distilbert-base-tas-b	**0.55**	25.1 s	0.59	1 min 16 s	0.79	1 min 23 s

Tables 4 and 5 show the results of calculating the similarity between a user's interest model and fifty related relevant publications from the Semantic Scholar API at the keyphrase level and document level, respectively. The similarity scores presented in the tables correspond to the range between the maximum and minimum scores achieved within the list of candidate publications. The results show that the keyphrase level achieves higher similarity scores compared to the document level. However, the keyphrase level is slower, as keyphrases need to be extracted first. It can be seen that *SciBERT* and *msmarco-distilbert-base-tas-b* were the best performing models in terms of similarity score. We believe that the good performance of *SciBERT* in this context is due to the fact that it was trained on publications. However, *msmarco-distilbert-base-tas-b* was faster. Based on these results, we decided to compute embeddings of the publications at the keyword level and use *msmarco-distilbert-base-tas-b* in the embedding step of the recommendation generation pipeline in order to obtain embeddings of both interest models and publications before computing their similarities.

Table 4. Comparison of embedding techniques at the keyphrase level.

Model	Time	Similarity Scores
USE	24 s	62–53%
SciBERT	**1 m 8 s**	**95–80%**
all-mpnet-base-v2	1 m 11 s	76–40%
all-distilroberta-v1	56 s	80–41%
all-MiniLM-L12-v2	45 s	81–41%
msmarco-distilbert-base-tas-b	**47 s**	**95–81%**

Table 5. Comparison of embedding techniques at the document level.

Model	Time	Similarity Scores
USE	3 s	59–53%
SciBERT	**24 s**	**72–53%**
all-mpnet-base-v2	22 s	70–41%
all-distilroberta-v1	13 s	66–40%
all-MiniLM-L12-v2	6 s	71–41%
msmarco-distilbert-base-tas-b	**12 s**	**89–70%**

4.2.3. Online Evaluation

We conducted an online user study to evaluate the accuracy and ranking of the recommended publications. These recommendations were generated based on the most accurate interest model (i.e., $SIFRank_{SqueezeBERT}$ + *DBpedia*), which we selected based on the results of the user study related to interest model generation (see Section 4.1.3). We invited the same 22 participants from the previous user study, of whom 16 responded. All participants provide their informed consent for study participation. Our goal was to compare the accuracy and ranking performance of our generated recommendation list with the list provided by the Semantic Scholar API, with the assumption that while the list from the Semantic Scholar API is relevant, the ranking could be improved. The questionnaire we used in this study was comprised of a question per recommendation: *"Please rate the relevance of the following publications suggested based on your interest model"*, and a general question: *"According to you, which recommendation list best reflects your preferences?"*. The average time to complete the questionnaire was 10 minutes. In the first question, users were asked to assign a relevance score to each of the top ten recommendations for each list. Users could rate the recommendations using one of four options (1: not at all relevant, 2: low relevance, 3: relevant, and 4: high relevance). Later in the calculations, we considered ranks 1 and 2 to be non-relevant recommendations and ranks 3 and 4 to be relevant. We calculated the statistical measures of Precision@k (how many relevant publications are in the top k extracted publications), MRR (the position of the highest-ranked relevant item), and MAP (the accuracy with which the top k publications are ranked and how early relevant results appear), where k is the total number of recommendations, which was ten in our case, as shown in Table 6.

The results show that recommendation list 1 (our approach) outscored the recommendation list provided by Semantic Scholar (recommendation list 2) in all three metrics, indicating that our approach was able to generate a more accurate and better-ranked recommendation list. In addition, 63% of the participants found that our recommendation list better reflected their interests.

Table 6. Evaluation result for recommendation generation.

	Precision@k	**MRR**	**MAP**	**Voting on the Better List**
Recommendation list 1 (Our approach)	0.42	0.72	0.60	63%
Recommendation list 2 (Semantic Scholar)	0.39	0.63	0.58	38%

5. Limitations

As a first analysis of the benefits of the application of word/sentence embedding techniques for user modeling and recommendation generation tasks in a content-based RS, this study is not without limitations. First, we performed this analysis in a single domain. It must be verified whether our findings transfer to domains beyond the recommendation of scientific publications. In addition, it must be assessed whether the results generalize to recommendations made by another publication RS as a baseline. Moreover, the proposed pipelines were evaluated with PhD students and professors from various backgrounds. While we achieved a diverse user group, a user study with a larger sample would probably have yielded more significant and reliable results.

6. Conclusions and Future Work

In this paper, we aimed to shed light on neglecting user modeling and capturing the semantics of user models and papers in content-based scientific publication recommender systems (RS). To address these research gaps, we have presented a transparent Recommendation and Interest Modeling Application (RIMA) that leverages word embeddings and sentence encoders to improve the quality of the user modeling and recommendation generation tasks. Moreover, we conducted extensive experiments on different datasets to evaluate our approach, as well as an online user study. The results of our study demonstrate that pretrained transformer word embeddings and sentence enocoders can provide a simple, yet powerful method to improve the accuracy and performance of the user modeling and recommendation generation processes in content-based scientific publication RS. While we are aware that our results are based on one particular RS and that the results cannot be generalized, we are confident that they represent valuable anchor points for the implementation of effective future content-based RS based on embedding techniques.

As future work related to this research, we plan to validate our findings through a quantitative and qualitative user study with a larger sample. Additionally, we aim to enhance the publication extraction process in terms of both time and accuracy, as our current approach can be time-consuming and occasionally extracts sections of the publication beyond the abstract. Further, we intend to explore and compare other approaches, e.g., graph-based and hybrid ones, for scientific publication recommendation.

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