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A Hybrid Personalized Scientific Paper Recommendation Approach Integrating Public Contextual Metadata

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ABSTRACT Rapid increase in scholarly publications on the web has posed a new challenge to the researchers in finding highly relevant and important research articles associated with a particular area of interest. Even a highly relevant paper is sometimes missed especially for novice researchers due to lack of knowledge and experience in finding and accessing the most suitable articles. Scholarly recommender system is a very appropriate tool for this purpose that can enable researchers to locate relevant publications easily and quickly. However, the main downside of the existing approaches is that their effectiveness is dependent on priori user profiles and thus, they cannot recommend papers to the new users. Furthermore, the system uses both public and non-public metadata and therefore, the system is unable to find similarities between papers efficiently due to copyright restrictions. Considering the above challenges, in this research work, a novel hybrid approach is proposed that separately combines a Content Based Filtering (CBF) recommender module and a Collaborative Filtering (CF) recommender module. Unlike previous CBF and CF approaches, public contextual metadata and paper-citation relationship information are effectively incorporated into these two approaches separately to enhance the recommendation accuracy. In order to verify the effectiveness of the proposed approach, publicly available datasets were employed. Experimental results demonstrate that the proposed approach outperforms the baseline approaches in terms of standard metrics (precision, recall, F1-measure, mean average precision, and mean reciprocal rank), indicating that the proposed approach is more efficient in recommending scholarly publications.

INDEX TERMS Scientific paper recommendation, public contextual metadata, content-based filtering, collaborative filtering, hybrid approach.

I. INTRODUCTION

Searching related information over the internet using generic search engines is the most common and convenient method among the researchers [1]. Using this traditional method, the researchers need to filter huge number of information and it is a time-consuming task. Furthermore, a reasonable level of expertise needs to be achieved for finding and keeping track of relevant information efficiently. In this regard, developing a recommender system capable of reducing irrelevant data processing and providing the researchers with sufficient relevant data has become an essential tool in the recent years. [2].

The scholarly recommender systems that help in finding papers of interest without much effort from a vast resource collection have attracted many researchers as a highly important and challenging research field [3]. Different scientific paper recommendation approaches have been proposed in the literature [4]–[9]. In general, there exists three forms of current scholarly recommendation approaches: CBF

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(Content-Based Filtering), CF (Collaborative Filtering), and a Hybrid approach. The CBF approach analyzes the content of a scientific paper (e.g., abstract, keywords, introduction, and conclusion) in order to construct a researcher's profile and then recommends papers that are similar to the profile. For example, Sugiyama and Kan [10] proposed a framework that recommends papers to researchers by building researchers profile from the whole content of their previous publications. Nascimento *et al.* [11] suggested a source-independent method for determining paper similarity using metadata such as title and abstract, and then using the similarity to produce recommendations. Kaya [12] proposed a recommendation model that builds a user profile using meta-data from the researcher's previous publications. However, due to the complexity of natural language, the CBF method often fails to produce correct recommendations. Furthermore, the user profiling and feature extraction based on both public and non-public metadata, and the new researchers (users) are the major problems emerged in the CBF approach.

In order to address the shortcomings of the CBF approach, another conventional recommendation approach, CF, has received significant attention in the recent decade [13], [14]. For instance, McNee *et al.* [15] used collaborative filtering to produce different rating matrices from a scientific paper's citation network. Sugiyama and Kan [16] applied collaborative filtering method to identify potential citation papers from researchers' previous publications. To find secret associations between articles, Liu *et al.* [17] proposed a neighbor-based collaborative filtering method. However, the CF approach, like the CBF approach, has a number of drawbacks. One of them is to find a suitable paper rating matrix for the new user (researchers).

In recent years, a hybrid recommendation approach has been suggested to address the above-mentioned problems by combining the CBF and CF approaches [18], [19]. For instance, Sun *et al.* [20] recommended articles by analyzing the semantic content of the article and extracting online users' connection. Zhao *et al.* [21] introduced a graph-based hybrid recommendation model that created a user profile based on the information gaps of the researchers. To build a definition map, the authors look into the context information and goal knowledge of the researchers. Wang *et al.* [22] proposed a hybrid article recommendation approach by incorporating social tag and friend information in scientific social network. Unfortunately, these approaches fail to fully utilize the abundant public contextual metadata that normally existed in the scientific paper. For example, the researchers usually use metadata in a scholarly article that best reflects the overview of the article. Since metadata defines an article's content, it has an obvious effect on the article's latent features. Therefore, considering metadata information while recommending papers can not only provide additional textual information but also help in making the preferences of the researchers. On the other hand, publicly available contextual citation relations information also can play an important role in personalized article recommendation. Despite these advantages of public contextual metadata, there has been little analysis on metadata knowledge mining to solve challenges such as priori user profile, non-public contextual metadata, and new users in conventional CBF and CF scientific paper recommendation approaches available in the current literature of scholarly recommender systems.

As a result, in order to resolve the aforementioned issues and to enhance recommendation accuracy, this study proposes a novel hybrid scholarly recommendation approach that integrates public contextual metadata in scientific papers. Firstly, the contextual metadata, i.e., title, keywords, and abstract are incorporated into the traditional CBF approach to find content-based similarity. Secondly, the contextual citation relations information, i.e., citation context is incorporated into the traditional CF approach to find the collaborative similarity. Finally, the two separate similarity scores from the CBF and CF methods are combined in constructing a hybrid approach.

The key contributions in this research can be summarized as follows:

1. A novel hybrid scholarly article recommendation approach is proposed that does not depend on priori user profiles and utilizes only public contextual metadata information.
2. A scholarly knowledge application in which researchers may use the web to find appropriate and useful research publications regardless of their previous research experience or research field.

The rest of the article is organized as follows. Section II examines similar studies on current scientific paper recommendation methods. The proposed approach is introduced in Section III. Section IV describes the experimental set-up and evaluation procedure. The results are analyzed and discussed in Section V. Finally, the concluding remarks is presented in Section VI.

II. RELATED WORK

Related work has been presented based on three aspects: Content Based Filtering (CBF), Collaborative Filtering (CF), and Hybrid approach. Several existing literatures are identified and reviewed based on their strengths and weaknesses in the above fields. Table 1 shows the selected previous studies in the domain of scholarly recommendation.

A. CONTENT BASED FILTERING APPROACH IN SCHOLARLY RECOMMENDATION

The CBF approach usually extracts content (e.g., text data) from scientific papers to create a relationship between the papers [23]. In this approach, different inherent features are collected to generate an article profile. Different researchers utilized different contents in the literature. Sugiyama and Kan [10] proposed a framework that utilizes whole content of researchers' previous publication list to construct the researchers' profiles. The approach recommends papers by computing similarity between the researchers' profile and

TABLE 1. Selected previous studies.

Study	Recommendation Approach	Contextual Metadata	Publicly Available	Drawbacks
McNee et al. [15]	Collaborative Filtering	Citation context	Yes	• Purely collaborative filtering • Direct citation relation
Sugiyama and Kan [10]	Content Based Filtering	Whole content	No	• Priori user profile • Non-public metadata
Nascimento et al. [11]	Content Based Filtering	Title and Abstract	Yes	• Purely content based
Sugiyama and Kan [16]	Collaborative Filtering	List of researchers' previous publications	No	• Priori user profile • Non-public metadata
Sugiyama and Kan [24]	Content Based Filtering	Whole content	No	• Priori user profile • Non-public metadata
Sun et al. [20]	Hybrid Approach	Online social connection	No	• Priori user profile • Non-public metadata
Liu et al. [17]	Collaborative Filtering	Citation context	Yes	• Purely collaborative filtering • Single level citation relation
Zhao et al. [21]	Hybrid Approach	Researcher's background knowledge	No	• Priori user profile • Non-public metadata
Haruna et al., [33]	Collaborative Filtering	Citation context	Yes	• Purely collaborative filtering • Single level citation relation
Wang et al. [22]	Hybrid Approach	Social tag and neighbor information	No	• Priori user profile • Non-public metadata
Ma et al. [30]	Content Based Filtering	Title, Keywords, Abstract	Yes	• Priori user profile
Sakib et al. [35]	Collaborative Filtering	Citation context	Yes	• Purely collaborative filtering
Haruna et al. [42]	Hybrid Approach	Title, Abstract, Citation context	Yes	• Limited features extraction (only title and abstract) • Single level citation relation

target papers. Sugiyama and Kan [24] extended their work further by investigating different sections of the articles to solve multidisciplinary problems. Nascimento *et al.* [11] proposed a new approach that utilized public contextual metadata. It extracted title and abstract from the researchers' target paper and applied a content-based filtering to find similarity between the target paper and candidate papers.

Meng *et al.* [25] proposed a unified graph-based model by incorporating both public and non-public metadata (e.g., authorship, content, citation and collaboration network). They employed a random-walk algorithm to calculate similarity. To produce recommendations, Guo *et al.* [26] proposed a multi-layered graph-based recommendation model that included the co-authorship graph, paper-citation graph, paper-author graph, and paper-keyword graph. The approach utilized both the public and non-public metadata to find similarity between the papers. Mu *et al.* [27] introduced a method for generating query-focused personalized recommendations by integrating personalized query details into a multi-layered graph. Bhagavatula *et al.*, [23] proposed a model that embedded articles into a vector space by encoding the textual content of each article. Authors utilize the title, abstract, authors and keywords fields of an article to build a user profile. Kaya [12] introduced a recommendation model that builds a user profile based on contextual data such as the number of researchers' published articles, the number of citations of the paper, the year of publication, and the keywords of the article. Yang *et al.* [28] proposed a Convolutional Neural Network (CNN) based context-aware citation recommendation model. The model utilized non-public contextual information to find similarities between the papers. Dai *et al.* [29] introduced a global citation recommendation model that used a citation network to extract different text content and citation features. To learn the process of feature regression, different citation features (e.g., title, abstract, keywords, citation count, author history) were extracted and incorporated with a topic model. A customized recommendation method based on heterogeneous graph was proposed by Ma *et al.*, [30]. Based on the content of the articles, a user and a paper profiles were created (i.e., title, keywords, abstract).

The approaches presented in [10]–[12], [23]–[30] depend on priori user profile to generate recommendation. As a result, they are unable to make suggestions to the new user. Furthermore, they utilize both the public and non-public metadata, therefore, the system cannot find similarities between the papers accurately due to copyright restrictions.

B. COLLABORATIVE FILTERING APPROACH IN SCHOLARLY RECOMMENDATION

The CF approach proposes items (paper) to users based on previous preferences of other users with similar tastes [15]. It finds similarity based on rating history of items and recommends further based on the ratings of the items. Different researchers have suggested various other methods in previous studies. McNee *et al.* [15] proposed a method that explored citation network of a scientific article. As a ranking matrix, they implemented a paper-citation relation matrix. To compute their similarity, the method counted the number of times papers were co-cited with a target paper and recommended papers with the highest total co-citation count. Agarwal *et al.* [31] proposed a subspace clustering model that used previous reading habits of the researchers to construct matrix of the researchers and the papers. It identified like-minded researchers by identifying groups of researchers who expressed an interest in papers that are close to their own. Sugiyama and Kan [16] proposed an alternative approach by extending their previous work to solve the sparsity problem. The authors used the collaborative filtering approach to distinguish possible citation papers from a researchers' previous publications list, in addition to content-based filtering. For citation recommendation, Liu *et al.* [17] proposed a neighbor-based collaborative filtering system. The hidden association that existed between a target paper and its referenced papers were mined to make a personalized recommendation. Xia *et al.* [32] proposed an author-based collaborative filtering approach that took into account common author relationships as well as historical preferences. In order to produce recommendations, a random walk algorithm was used to create a user profile. Haruna *et al.*, [33] proposed a collaborative approach that mined hidden associations between a target paper and its citations. To identify similar neighbors, authors employed a single level paper-citation relationship. To overcome the sparsity problem of conventional collaborative filtering, Dai *et al.* [34] proposed an alternative method that combined low-rank sparse matrix with a fine-grained paper and an author affinity matrix. Sakib *et al.* [35] proposed a collaborative scientific paper recommender framework in which 2-level paper-citation relationships were mined separately using citation context to find related neighbors. Wang *et al.* [36] proposed an alternative hybrid collaborative filtering approach by considering both the paper content and network topology. It produced a paper rating matrix based on the paper text (e.g., title and abstract).

As shown in Table 1, it is clear that the CF approach, as a successful and popular approach, was utilized in scholarly recommendation and it can provide useful recommendations. However, these approaches [15]–[17], [31]–[36] only measure the collaborative similarities to find similar neighbors.

C. HYBRID APPROACH IN SCHOLARLY RECOMMENDATION

The hybrid approach is a special kind of recommendation approach where the CBF and the CF approaches are combined to take advantage of their individual benefits. The motivation behind the hybrid recommendation approach is the opportunity to achieve an improved accuracy. This is because each recommendation approach has drawbacks which can be overcome by combining them [3]. Kim *et al.* [37] proposed a hybrid approach that constructed user profiles with the help of a collaborative filtering to enhance the content recommendation process. It first defined useful user trends, then adds to the user profile by enlisting the support of other users with common interests. Sun *et al.* [20] proposed a hybrid scientific paper recommendation approach that took into account various forms of online social interactions between the researchers in order to find like-minded neighbors, and then combined this with the CBF approach to suggest research articles. Raamkumar *et al.*, [38] proposed an alternative recommendation approach that utilized author-specified keywords of a target paper to generate recommendations. Zhao *et al.* [21] proposed a hybrid recommendation model that generated a user profile based on the information gaps found by the researchers. In order to produce a recommendation list, the authors looked at the context information and goal knowledge of the researchers. By integrating social tag and neighbor knowledge in scientific social networks, Wang *et al.* [22] proposed a hybrid article recommendations model. Waheed *et al.* [39] proposed a hybrid approach by integrating multilevel citation networks and author relationship networks to produce recommendations, where the authors classified key authors from their relationship networks. Khan *et al.* [40] proposed an alternative approach that investigated different logical sections of the papers' content to identify in-text citation pattern while ranking the articles. Zhao *et al.* [41] proposed a hybrid neural network model for recommending the research papers by incorporating researchers' historical behaviors (favorites records) and the information about paper content. Haruna *et al.* [42] proposed a recommendation framework that employed the contextual metadata collecting from the scientific article rather than the researchers' priori profiles.

The approaches presented in the papers [20]–[22] and [37]–[41] either constructed priori user profiles or utilized non-public contextual metadata information to generate the recommendations. Apart from them, a novel hybrid approach has been proposed in this work for recommending scientific paper that does not rely on priori user profiles and only uses publicly available contextual metadata. In addition,

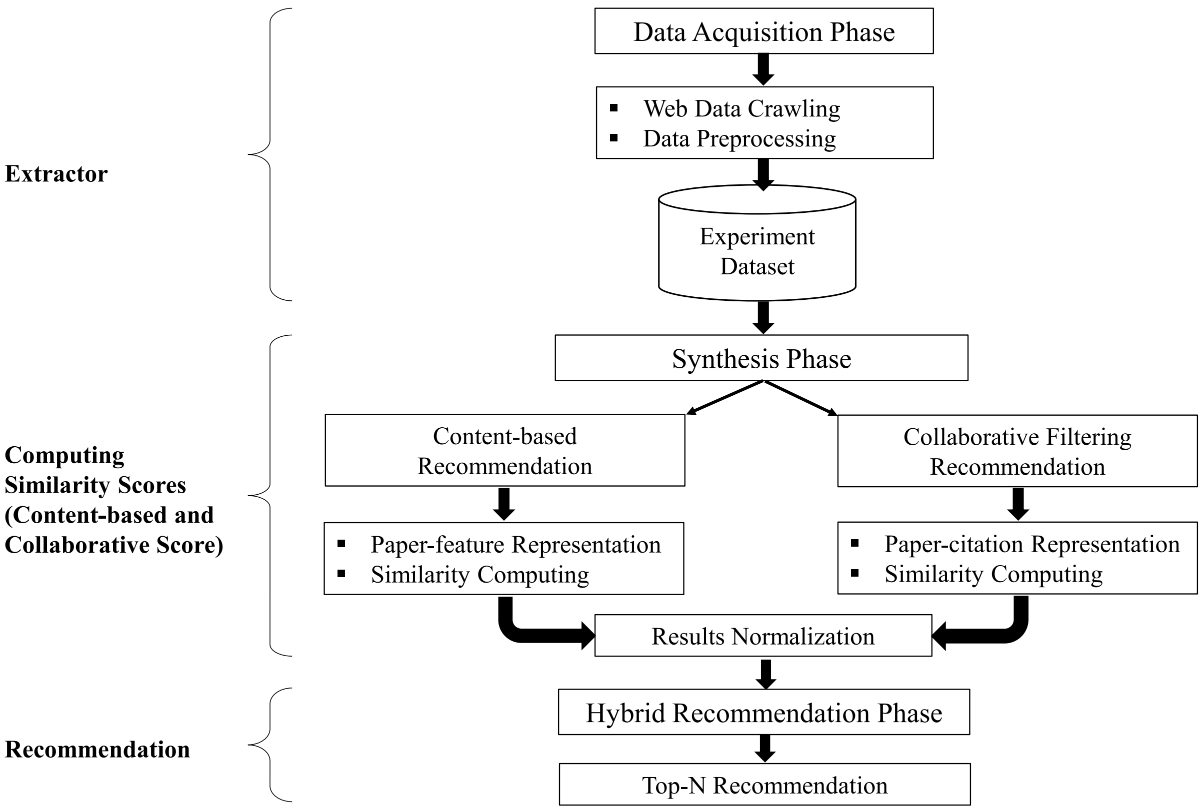


FIGURE 1. Overview of the proposed hybrid approach of scholarly article recommendation.

unlike the work in [42] that mined single level paper-citation relation with public metadata (i.e., title and abstract) of a target paper, in this work, a 2-level paper-citation relation with public contextual metadata (i.e., title, keywords, abstract) of a papers of interest (POI) is employed in order to find similar neighbors. Experimental results of this work have demonstrated the effectiveness of the proposed approach in recommending scholarly publications.

III. PROPOSED METHODOLOGY

Contextual metadata of a scholarly article can be used to characterize the scientific paper. The researcher usually uses metadata in a scientific article that best reflects the overview of the article. Hence, a novel hybrid scholarly recommendation approach is proposed to assist the researchers in identifying the appropriate scholarly articles for their research interests, considering the metadata of a scientific paper. The reason for the proposed approach is that the researchers' contextual metadata can represent and be used to produce useful recommendations. The proposed hybrid approach is illustrated in Fig. 1. The framework of the proposed approach includes the following stages: (a) Data Acquisition phase: web data crawling and data preprocessing, (b) Synthesis phase: Content Based Recommendation (CBR) model and Collaborative Filtering Recommendation (CFR) model, and (c) Hybrid recommendation phase. The CBR model and the CFR model utilize public metadata such as, title, keywords and abstract and public contextual paper-citation relational information of a scholarly article separately to find similarities. The results from these two models are combined further by the hybrid model to increase the recommendation accuracy. A brief summary of each stage has been presented in the following sections.

A. DATA ACQUISITION PHASE

The web crawler is used to scan the web for all the information required to address a user query (POI). The web crawler extracts a full technical experimental dataset for each POI given by researcher. Once the POI is received from a user as an input, the web crawler extracts all the public contextual metadata of the given POI from the web (Google Scholar to be precise) that includes citations, references, title, keywords, and abstract. The algorithm employed in web data crawling stage is shown in Algorithm 1. The data extracted from the web by web data crawling is further analyzed and preprocessed in order to make them clean. Stop words, which are often meaningless have been eliminated during the cleaning process. Prepositions such as "with", "in", "by", and others are examples of these terms. Python, a high-level programming language, is used to delete them from the extracted

Algorithm 1 Extraction of Candidate Papers and Their Public Contextual Metadata

Input Paper of Interest (POI)
Output Candidate Papers and their public metadata
Received a query message (POI) from a user,
(1) Retrieve all papers Ci which cites POI
For each of the citation papers Ci, extract all other papers Pi that appearing at the end of Ci as references
(2) Retrieve all papers Rfi that appearing at the end of POI as references
For each of the reference papers Rfi, extract all other papers Pj that cited Rfi
(3) Select all the candidate papers CP from Pi and Pj which are co-cited with the POI and which has been referenced by at least any of the POI references
(4) Extract the content of the Title, Keywords, and Abstract from POI and each of the qualified candidate papers

data. The result of preprocessed data is further used as the experimental dataset.

B. SYNTHESIS PHASE (THE CBR MODEL INTEGRATING WITH PUBLIC CONTEXTUAL METADATA)

The CBR model computes similarities between POI and each of the qualified candidate papers based on their public contextual metadata that includes title, keywords, and abstract. The approach consists of three steps:

Step 1: Compute feature vector F^{POI} for researcher's Paper of Interest (POI).

A researcher's Paper of Interest (POI) is represented as a feature vector F^{POI} using Equation 1 and Equation 2. Term frequency (TF) scheme has been employed in Equation 3 in order to find content similarity between each vector representation.

$$F^{POI} = T_{Title} + T_{Keywords} + T_{Abstract} \tag{1}$$
$$= \left(W_{t_1}^{POI}, W_{t_2}^{POI}, W_{t_3}^{POI}, \ldots\ldots, W_{t_r}^{POI}\right) \tag{2}$$

where, r represents the number of distinct terms in the content of the title, keywords and abstract of a POI. Also t_s represents the each term, where s = 1,2,…,r.

Using a term frequency (TF), each term W_{t1}^{POI} of F^{POI} from Equation 2 is further defined by Equation 3.

$$W_{t_s}^{POI} = \frac{tf\,(t_S, POI)}{\sum_{y=1}^{Z} tf\,(t_y, POI)} \tag{3}$$

where $f(t_s, POI)$ represents the frequency of each term t_s for a given POI.

Step 2: Compute feature vector F^{Ci} (i = 1, 2,…,j) for each of the qualified candidate papers.

Each of the candidate paper to recommend C_i (i = 1,2,3,…,j) is represented as a feature vector F^{Ci} using Equation 4 and Equation 5.

$$F^{C} = \sum_{k=1}^{m} T_{Title} + \sum_{l=1}^{n} T_{Keywords} + \sum_{q=1}^{o} T_{Abstract} \tag{4}$$
$$= \left(W_{t_1}^{C}, W_{t_2}^{C}, W_{t_3}^{C}, \ldots\ldots, W_{t_r}^{C}\right) \tag{5}$$

where r represents the number of distinct terms in the content of the title, keywords and abstract of a candidate paper. In addition, t_s represents the each term, where s = 1,2,…,r.

The term frequency (TF) scheme is employed in order to find content similarity between each vector representation. Using term frequency (TF), each term W_{t1}^{C} of F^{C} from Equation 5 is further defined by Equation 6.

$$W_{t_s}^{C} = \frac{tf\,(t_s, C)}{\sum_{y=1}^{Z} tf\,(t_y, C)} \tag{6}$$

where $f(t_s,C)$ represents the frequency of each term t_s for a qualified candidate paper.

Step 3: Compute the cosine similarity SIMI (F^{POI}, F^{Ci}) between Paper of Interest F^{POI} and each of the candidate papers F^{Ci} (i = 1,2,…,j).

With the feature vectors already constructed, similarity between a POI and each of the candidate papers is obtained. The cosine similarity measure is used and defined by equation 7:

$$SIMI\left(F^{POI}, F^{C}\right) = \frac{f^{POI} \cdot f^{C}}{\left|f^{POI}\right| \cdot \left|f^{C}\right|} \tag{7}$$

where f^{POI} and f^{C} represent feature vectors of a researcher's POI and a qualified candidate paper.

C. SYNTHESIS PHASE (THE CFR MODEL INTEGRATING WITH PUBLIC CONTEXTUAL PAPER-CITATION RELATIONAL INFORMATION)

Unlike the CBR model, the CFR model searches for secret correlations between POI and each of the candidate papers using paper-citation relationships. It does not need the content of scientific papers to work, and it can find interesting connections that the CBR model is unable to do. The proposed approach consists of four steps:

Step 1: Identify hidden associations between POI and candidate papers using citation context

Citing papers (citation papers) with common cited papers (referenced papers) can be considered to be similar. The similarity between these two citing papers are determined using the cited papers they have in common. In Fig. 2(a), two citing papers c1 and c2 cited the same paper r2 simultaneously, therefore, they are similar to some extent. The proposed approach converts this direct citation relation into hidden associations. It is considered while two papers are co-occurred with same cited paper(s) (as shown in Fig. 2(b)) and two papers are co-occurring with the same citing paper(s) (as shown in Fig. 2(c)) are significantly similar to some extent.

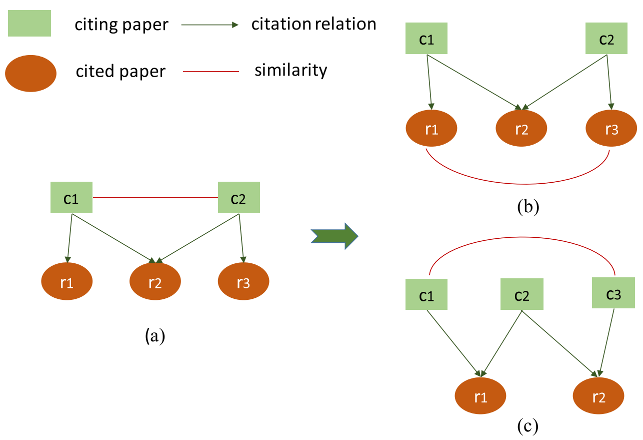


FIGURE 2. Paper-citation relation based on (a) direct relation (b) co-occurred (c) co-occurring.

TABLE 2. Paper-citation relation matrix based on co- occurred.

Citing papers/cited papers	c1	c2
r1	1	-
r2	1	1
r3	-	1

TABLE 3. Single role association matrix.

	r1	r2	r3
r1	1	1	0
r2	1	1	1
r3	0	1	1

Step 2: Measure the extent of similarity between POI and candidate papers based on co- occurred

Based on Fig. 2(b), Table 2 depicts a paper-citation relation matrix. Here, rows represent cited papers, and columns represent citing papers. If a paper i cites a paper j, $C_{i,j}=1$ in the citation relation matrix C; otherwise, $C_{i,j}=0$.

Table 3 represents the transformation of Table 2 into single role association matrix in order to find hidden associations that exits between these two citing and cited papers. If two papers have at least one citing paper in common, they were considered to be substantially co-occurred. A binary value of 1 or 0 is used to indicate whether two papers co-occurred or not.

Then, using the Jaccard coefficient from Equation 8, the pairwise collaborative similarity between POI and each of the candidate papers based on the hidden association matrix is computed.

$$J_{\text{co-occurred}} = \frac{Z_{11}}{Z_{01}+Z_{10}+Z_{11}} \tag{8}$$

where Z_{11} denotes the total number of attributes with values of 1 for both A and B. Z_{01} denotes the total number of attributes in which A's attribute is 0 and B's attribute is 1, while Z_{10} denotes the total number of attributes in which A's attribute is 1 and B's attribute is 0.

Step 3: Measure the extent of similarity between POI and candidate papers based on co- occurring

Based on Fig. 2(c), Table 4 depicts a paper-citation relation matrix. Here, the rows represent cited papers, and the columns represent citing papers. If a paper i cites a paper j, $C_{i,j}=1$ in the citation relation matrix C; otherwise, $C_{i,j}=0$.

TABLE 4. Paper-citation relation matrix based on co- occurring.

Citing papers/cited papers	c1	c2	c3
r1	1	1	-
r2	-	1	1

TABLE 5. Single role association matrix.

	c1	c2	c3
c1	1	1	0
c2	1	1	1
c3	0	1	1

Table 5 represents transformation of Table 4 into a single role association matrix in order to find hidden associations that exits between these two citing and cited papers. If two papers have at least one cited paper in common, it is considered to be substantially co-occurring. A binary value of 1 or 0 is used to indicate whether two papers co-occurring or not.

Then, using the Jaccard coefficient in Equation 9, the pairwise collaborative similarity has been computed between POI and each of the candidate papers based on the hidden association matrix.

$$J_{co-occurring} = \frac{M_{11}}{M_{01}+M_{10}+M_{11}} \tag{9}$$

M_{11} denotes the total number of attributes, with A and B having the same value of 1. M_{01} denotes the total number of attributes in which A's attribute is 0 and B's attribute is 1, while M_{10} denotes the total number of attributes in which A's attribute is 1 and B's attribute is 0.

Step 4: Normalising results by combing similarities scores (co-occurred score and co- occurring score)

To measure collaborative similarity, both Jco-occurred and Jco-occurring scores are used, which provide the relevancy of each candidate paper to the POI. Equation 10 is used to average these two ratings.

$$\begin{aligned} &\textit{collaborative Similarity} \\ &\quad = \frac{\sum_{i=1}^{n}\left(J_{\text{co-occurred}} + J_{\text{co-occurring}}\right)}{2} \end{aligned} \tag{10}$$

D. SYNTHESIS PHASE (HYBRID RECOMMENDATION PHASE)

Although both the CBR and CFR models are widely used separately in order to generate recommendations but due to their individual limitations they are unable to prepare best recommendation results. The novel hybrid approach in this study can provide more precise recommendations than a single approach. Equation 11 incorporates the two separate similarity scores into a hybrid recommendation, which offers more accurate relevancy between POI and each of the candidate articles.

$$Hybrid\_Recommendation = \frac{Content\ Based\ Scores + Collaborative\ Scores}{2} \quad (11)$$

IV. EXPERIMENTS

A. DATASET

The experimental set-up for the proposed hybrid approach to test its efficacy is discussed in this section. In this research, publicly available dataset was used provided by Sugiyama and Kan [24]. The dataset included a list of 50 researchers' publications in the fields including software engineering, programming languages, security, operating systems, networks, information retrieval, graphics, and user interface design. The proposed approach gathered public metadata for each of their publications including title, keywords, abstract, citations and references and extracts all references from each of the POI's citations as well as any other papers that cited any of the POI's referenced papers from the web (Google Scholar). Table 6 shows information about the dataset that was used in this study.

TABLE 6. Statistics of the utilized dataset.

Number of researchers	50
Number of publications on average	10
Each publication's average number of citations	14.8 (max. 169)
Average number of references to each publication	15.0 (max. 58)
Number of candidate papers/total number of papers	100,351
The candidate papers' average number of citations	17.9 (max. 175)
Number of references to the candidate papers on average	15.5 (max. 53)

B. BASELINE METHODS

To demonstrate the efficacy of the proposed hybrid approach, the experimental results were compared to the following four baselines:

1) BASELINE 1: CCF

Liu *et al.* [17] presented a Context-based Collaborative Filtering (CCF) method that used an association matrix based on a single level paper-citation relation matrix. By converting the paper-citation relation matrix into an association matrix and computing pairwise paper similarity, it uncovered the secret relationship between POI and its reference papers.

2) BASELINE 2: CCA

Another method named as Contextual Collaborative Approach (CCA) proposed by Haruna *et al.* [33] employed a single role association matrix to mine the secret relationship between the POI and its citation papers. It measured pairwise similarity based on these paper representations.

3) BASELINE 3: SPR

Sakib *et al.* [35] proposed a Scientific Paper Recommendation (SPR) method which implemented a collaborative filtering approach to expose the secret relationships between a POI and its citations and reference papers. In order to compute similarities between the POI and each of the candidate papers, it made use of 2-level paper-citation relations to mine secret associations of these two paper-citation relations.

4) BASELINE 4: RPRS

Furthermore, Haruna *et al.* [42] presented a Research Paper Recommender System (RPRS) that utilized a hybrid concept by combining both the content and collaborative filtering to calculate similarities between the papers. The authors extracted public metadata (title and abstract) as the papers' content, and fit into with collaborative filtering to generate a recommendation.

In the proposed approach, the concept of hybrid recommendation was also applied since it could provide more reliable suggestions rather than a single approach. It could also address the drawbacks of a single approach. In addition, unlike the work presented in [42], that combined papers' metadata with single level collaborative filtering, in this work, the paper's metadata was employed using a 2-level paper-citation relation with the help of collaborative filtering to find similarities between the POI and each of the candidate papers. Furthermore, unlike the works presented in [17], [33] and [35], that used only collaborative similarity, whereas in this work, both content and collaborative similarity was employed by creating a hybrid approach to make better recommendation.

C. EVALUATION METRICS

The following technique was used to divide the dataset into a training set and a test set in order to assess the accuracy of recommendation. A 5-fold cross validation was conducted for each POI by choosing 20% of the data as a test set. In addition, the three most commonly used measurement metrics were utilized for the evaluation purpose as defined by Equation 12, Equation 13, and Equation 14. (a) Precision assesses the system's accuracy by recommending related documents, (b) Recall calculates the proportion of relevant papers in the Top-N recommendation list to the total number of papers in the collection, and (c) F1 measures, a harmonic mean of precision and recall assess the overall performance of the proposed approach.

$$Precision = \frac{Number\ of\ relevant\ papers}{Total\ mumber\ of\ recommended\ papers} \tag{12}$$

$$Recall = \frac{Number\ of\ relevant\ papers}{Total\ number\ of\ relevant\ papers} \tag{13}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{14}$$

Two other metrics were also used in this study including Mean Average Precision (MAP) and Mean Reciprocal Rank (MRR) to determine the system's ability to return relevant papers at the top of the recommendation list. Average Precision (AP) is the average of precision values of related papers for all rank positions, and MAP calculates the average of all AP (Equation 15). MRR measures the first ranking position of the relevant papers in the recommendation list averaged over all researchers (Equation 16).

$$MAP = \frac{1}{I} \sum_{i \in I} \frac{1}{ni} \sum_{k=1}^{n} P(R_{ik}) \tag{15}$$

$$MRR = \frac{1}{I} \sum_{i \in I} \frac{1}{rank(i)} \tag{16}$$

where I represents a set of papers. The number of relevant papers in the recommendation list is denoted by *ni*. The length of the recommendation list is N. $P(R_{ik})$ represents the precision of retrieved papers from the top until paper k is reached, and rank(i) represents the rank of the first relevant paper in the recommendation list.

V. RESULTS AND DISCUSSIONS

The results of the proposed approach versus the Baseline approaches are presented in this section. Aggregated results obtained by the proposed approach across all 50 researchers who contributed to the dataset have been presented. Fig. 3 depicts the performance improvement of the proposed approach based on precision, recall and F1 evaluation matrices. It was clear from Fig. 3(a) that the proposed approach significantly outperformed the Baseline approaches in terms of precision. However, the RPRS approach slightly outperformed the proposed approach when N = 5(N @ 5), but with an increase in the value of N, it was evident that precision of RPRS reduced significantly while precision of the proposed approach was rising. Besides, for all N recommendation values, the proposed approach significantly outperformed the other Baseline approaches. Thus, it demonstrated the effectiveness of the approach in returning relevant papers than others.

The recall results are shown in Figure 3(b). The proposed approach significantly outperformed the Baseline approaches in terms of recall. However, the RPRS approach slightly outperformed the proposed approach when N = 5(N @ 5), but with an increase in the value of N, it was evident that recall of RPRS was reducing significantly while recall of the proposed

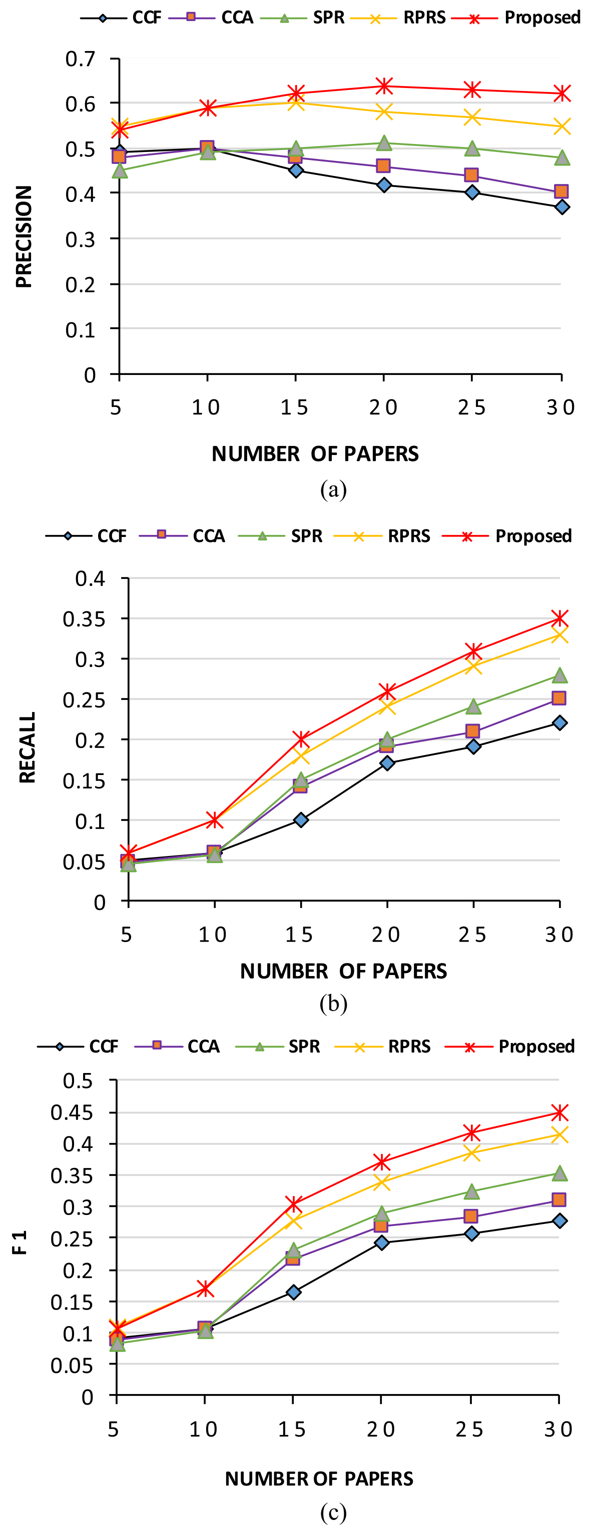
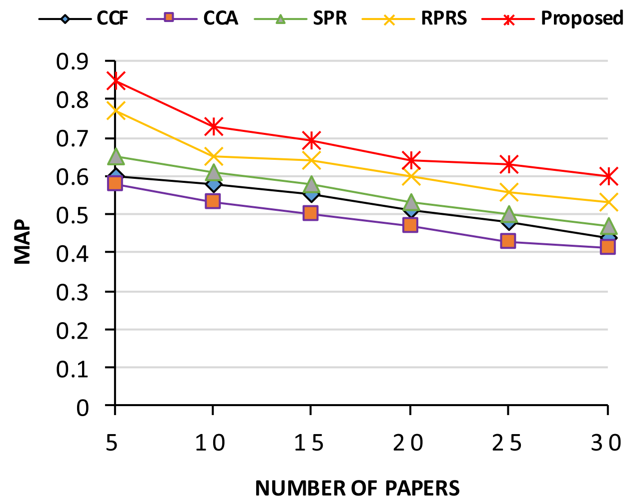
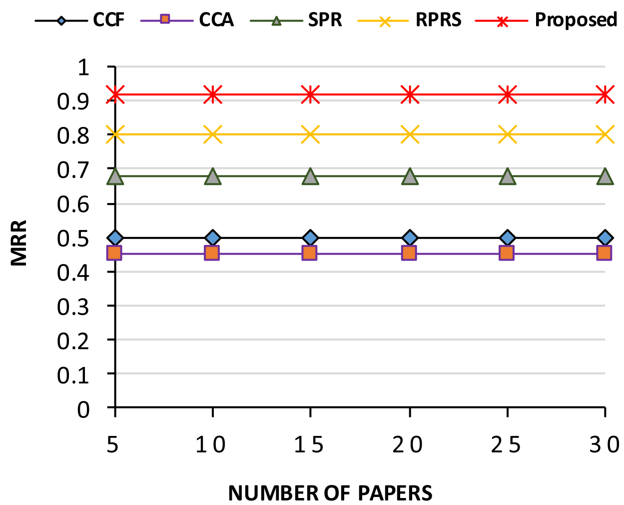


FIGURE 3. Performance comparison of the proposed approach with the baselines (Context-based Collaborative Filtering (CCF), Contextual Collaborative Approach (CCA), Scientific Paper Recommendation (SPR), Research Paper Recommender System (RPRS)) in terms of Precision, Recall and F1.

approach was rising. Besides, for all N recommendation values, the proposed approach significantly outperformed the other Baseline approaches. Thus, it proved the effectiveness



(a)



(b)

FIGURE 4. Performance comparison of (a) MAP and (b) MRR for baselines.

of the proposed approach in removing less relevant papers than the others.

It was clear from the Fig. 3(c) that similar to the experimental results of precision and recall presented in Fig. 3(a) and Fig. 3(b), the proposed approach also significantly outperformed the Baseline approaches in terms of F1 measure. RPRS approach slightly outperformed the proposed approach when N = 5(N @ 5), but with an increase in the value of N, the results of F1 measure of RPRS was reducing significantly while the results of F1 measure of the proposed approach was rising. Besides, for all N recommendation values, the proposed approach also significantly outperformed the other Baseline approaches.

Based on the results shown in Fig. 3, it was clearly presented that the proposed approach outperformed the baseline approaches on all three metrics. However, when N was less than 15, the approach does not show significant differences compared to the Baseline approaches due to strict rules applied in selecting eligible candidate papers for recommendation. However, as the N increased, the current approach started providing significantly better results. This demonstrated the usefulness of public contextual metadata in the proposed novel hybrid approach for providing researchers with more precise recommendations.

Figure 4 shows the results comparisons based on the MAP and MRR evaluation metrics, which reflect the recommendation's rank details. It could be observed from Fig. 4(a) that the proposed approach significantly outperformed the Baseline approaches for all recommendation values (N) based on MAP. However, the best results based on MAP was obtained when N = 5 (N@5).

On the other hand, the comparison of results based on MRR presented in Fig. 4(b) showed that, the proposed approach highly outperformed the baseline approaches for all recommendation values (N) similar to the MAP metric. Furthermore, the proposed approach showed the potential to recommend related papers in the first rank of the recommendation list. This further demonstrated that public contextual metadata found in the scientific papers was extremely useful in improving the efficiency of recommendation algorithms. In addition, combining the CBF and CF into a hybrid approach to improve recommendation accuracy was very effective.

VI. CONCLUSION

A novel hybrid approach for incorporating public contextual metadata in scientific papers is successfully proposed in this study. The public contextual metadata, i.e., title, keywords, and abstract have been used into the CBF to find content similarities between the papers. Simultaneously, the CF is used to find collaborative similarities by using 2-level citation relations between the papers based on citation context. The results of these two methods are then combined to form a hybrid approach that generates recommendations regardless of the researchers' previous research experience or research field. Compared to the baseline methods (CCF, CCA, SPR and RPRS), the experimental findings indicate that the proposed hybrid approach produces the best recommendation results.

The main advantage of this research is that it can use publicly available contextual metadata for recommending research papers. In future, the research work can be further extended by incorporating other available additional information such as co-authorship to further improve the recommendation performance.

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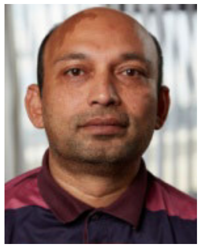

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