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A Collaborative Approach Toward Scientific Paper Recommendation Using Citation Context

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ABSTRACT Researchers face difficulties in finding relevant papers to their research interest as the number of scientific publication is rapidly increasing on the web. Scientific paper recommenders have emerged as a leading solution to help researchers by automatically suggesting relevant and useful publications. Several approaches have been proposed on improving recommender systems. However, most existing approaches depend on priori user profiles, and thus they cannot recommend papers to new user. Furthermore, the existing approaches utilize non-public contextual information, and thus it cannot adequately find similarities between papers due to copyright restrictions. Also, the existing approaches consider only single level paper-citation relation to identify similarities between papers. Considering the above challenges, this paper presents a collaborative filtering based recommendation approach for scientific papers that does not depend on priori user profiles and which utilizes only public contextual information. Using citation context, we utilized 2-level paper-citation relations to find hidden associations between papers. The rational underlying this approach is that, two papers are co-occurred with same cited paper(s) and two papers are co-occurring with same citing paper(s) are significantly similar to some extent. To evaluate the performance of the proposed approach, publicly available datasets are used to conduct extensive experiments. The experimental results demonstrate that the proposed approach has significantly outperforms the baseline approaches in terms of precision, recall, F1, mean average precision, and mean reciprocal rank, which are commonly used information retrieval metrics. The novelty of this study is that, with the proposed approach, researchers are able to find relevant and useful publications over the internet regardless of their previous research experiences and research area.

INDEX TERMS Scientific paper recommendation systems, collaborative filtering, contextual information, citation context, 2-level paper-citation relation matrix.

I. INTRODUCTION

The number of freely available scientific papers on the web has increased, thus recommender systems have become popular for not only industry but also academia [1]. Unfortunately, fewer studies have examined scientific paper recommender systems in comparison with other recommender systems domains, such as movie and music. Researchers usually perform bibliographical search daily to find relevant scientific papers to their research interest. However, they typically need to filter huge number of scientific papers to find those relevant papers. This is a time consuming and difficult task. Moreover, it becomes worse in finding and keeping track relevant papers for the novice researchers and who do not have sufficient knowledge in the research area. Hence, an efficient scientific papers recommender system that can generate high quality recommendations is essentially needed [2].

Previous studies have utilized different recommendation techniques to provide personalized recommendations for scientific papers. Most commonly used technique is content based filtering. Content based filtering approaches usually extract contents to create relationships between items (e.g., scientific papers). Different contents have been used in the literature. Some of them are, authors [3] extract title and abstract from a single paper, authors [4] extract whole contents of a list of papers authored by an author, authors [5] extract papers' keywords and so on to provide recommendation. Most of these approaches extract various contents

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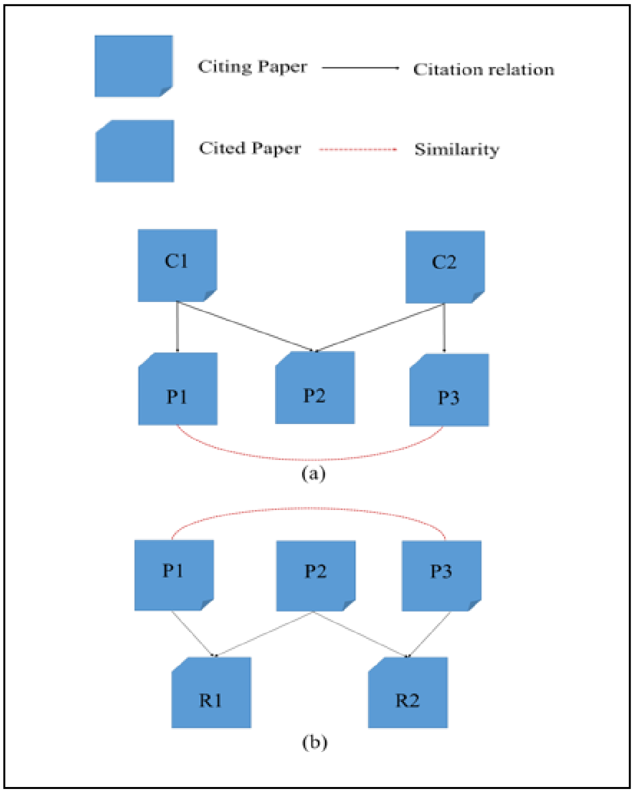

FIGURE 1. Paper's similarity based on (a) co-occurred (b) co-occurring.

from the scientific papers to build user profile to provide recommendations. These priori user profile based approaches cannot work well for new recommender systems. Also, all the contents of the scientific papers cannot be freely accessible due to copyright restrictions. Moreover, content based filtering cannot capture user interests properly due to ambiguity of natural language [6].

Collaborative filtering is a classical recommendation approach that is exploited in scientific paper recommender systems [7]. It creates paper-citation matrix to find relationships between scientific papers. Here, citing papers are represented as users and cited papers are represented as items. Two citing papers (users) can be similar if they have common cited papers (items). In this research, we consider two papers are significantly similar to some extent if they are co-occurred with the same cited paper(s) and are co-occurring with the same citing paper(s) respectively. As can be seen from Fig. 1(a), C1 and C2 are two citing papers and P1, P2 and P3 are three cited papers. Papers P1 and P2 are being cited simultaneously by the citing paper C1, and papers P2 and P3 are being cited simultaneously by the citing paper C2. There is no paper that cited both papers P1 and P3. Despite this, P1 and P3 papers are similar to some extend because P1 and P3 are co-occurred with the same cited paper P2. Aa can be seen form Fig. 1(b), P1, P2 and P3 are three citing papers and R1 and R2 are two cited papers. P1 and P2 papers cited the same paper R1, and P2 and P3 papers cited the same paper R2. There is no common paper that cited by both the papers P1 and P3. Despite this, P1 and P3 are similar to some extend because P1 and P3 are co-occurring with the same citing paper P2.

This paper proposes a collaborative approach for scientific paper recommendation that utilizes citation context. Using citation context, 2-level paper-citation relations (i.e., two papers with the same citing paper(s) and two papers with the same cited paper(s)) are generated to find similar papers. The proposed approach mines hidden associations between scientific papers separately based on these paper-citation relations and later combines to compute similarities between paper of interest and candidate papers.

The main contribution in our work is, proposing a novel approach towards scientific paper recommendation that combines 2-level paper-citation relations based on citation context to recommend papers as paper references to user.

The rest of the paper is structured as follows. Some related works on existing recommendation approaches is presented in Section II. Section III introduces the proposed methodology. Experimental setup and evaluation are presented in Section IV. Section V discusses our results in detail. Finally, Section VI concludes the paper.

II. RELATED WORK

The recommender systems are introduced to solve the information overload problem by suggesting items of interest to user. Since emerged as effective tools, several recommendation algorithms have been successfully applied in many fields such as e-commerce [8, 9], movie [10, 11], music [12, 13], news [14], e-learning [15, 16] and so on [17, 18]. As aforementioned, due to the increase of scientific articles publications in recent years, it is becoming notably popular and challenging to apply recommendation techniques in scientific community. This section presents some related works on scientific papers recommender systems. There is two classes of recommendation techniques in this domain: priori user profile based and non priori user profile based recommendation technique.

A. PRIORI USER PROFILE BASED TECHNIQUE

A priori user profile based technique is a recommendation technique that creates user profiles based on users' previous research interests and their paper access history [5]. Different researchers have constructed different profiles using different contextual information. Agarwal *et al.* [19] proposed a subspace clustering approach with the help of collaborative filtering. The model utilizes researchers' previous reading habits to build user profile. Sugiyama and Kan [20] introduced a citation network based user profile creation model to understand researchers' interests clearly. The contents of researchers' previous publications were used to construct user profile. And, papers are recommended to user by comparing the profile with the content of the candidate papers. Authors extended their work [4] to solve the sparsity problem. They apply collaborative filtering method to identify potential citation papers from researcher's previous publications. Later, authors again extended their work [21] to solve the multidisciplinary problems. Authors investigate different sections of the scientific papers to find better paper presentations. Different from above the studies, Xia *et al.* [22] proposed an author based recommendation approach by considering common authors relations and their historical preferences. Using these information, a graph based article ranking algorithm was used to build user profile and later based on profile, new recommendation lists were generated. Zhao *et al.* [23] proposed a graph based recommendation model that constructs user profile based on researchers' knowledge gaps. Authors investigate researchers' background knowledge and target knowledge, and later create a concept map. Guo *et al.* [24] proposed a fine-grained approach that uses co-authorship, author-paper, paper-citation, and paper-keyword relations to construct multi-relations graph. The approach employs a topic cluster model and a random walk model to produce recommendations. Kaya [5] proposed a score based recommendation model that constructs user profile based on different contextual information such as the number of users' published publications, the number of citations of the publications, year of publications, and articles keywords. Scores are calculated based on these information and later top-n papers are recommended to a researcher. Ma and Wang [25] proposed a personalized recommendation method based on heterogeneous graph. User and paper profiles were created based on contents of papers (i.e., title, keywords, abstract). Later, two meta-path based proximity measures were employed to find similarity of neighbors, and recommendation was generated based on user feature vector and paper feature vector. Bulut *et al.* [26] proposed a deep learning based paper recommendation system by considering user's previous research interests. User profile was created based on different contextual information (i.e., title, year, authors, abstract, and keywords) of each publication previously written by researcher.

Most of these works [4], [5], [19]-[26] do not use publicly available contextual information to build user profile. Thus, these approaches cannot adequately find similarities between papers due to copyright restrictions. Also, the recommendations are fully depended on priori user profiles, hence as said before, it cannot provide useful recommendations for new users.

B. NON PRIORI USER PROFILE BASED TECHNIQUE

A non priori user profile based technique is a recommendation technique that does not require any information stored a priori [3]. In existing studies, different researchers have proposed different approaches. McNee *et al.* [7] explored citation network of the scientific paper using collaborative filtering. The aim was to utilize the neighbor-based collaborative filtering to recommend citations. Gori and Pucci [27] proposed a graph model based approach that creates a citation graph based on paper citation relations. A random-walk algorithm was employed to the citation graph to compute similarity scores. Meng *et al.* [28] proposed a unified graph-based model with random walk using various types of information (e.g., authorship, content, citation and collaboration network). They incorporated information into the model to generate recommendations. Liu *et al.* [29] proposed a pseudo relevance feedback based graph model that extracts various meta paths from heterogeneous bibliographic graph to find important seed nodes. Later, a random walk algorithm on heterogeneous bibliographic graph was employed to compute the papers' ranking. Different from the above studies, Nascimento *et al.* [3] proposed a source independent framework that utilizes only publicly available contextual information. Title and abstract were extracted from the paper of interest to apply content based recommendation method to generate top-n recommendations. Raamkumar *et al.* [30] proposed a recommendation model that utilizes publicly available contextual author-specified keywords from papers. The model creates a citation network based on these keywords to apply two coverage measure techniques to build a reading list of scientific papers. Liu *et al.* [31] proposed a neighbor-based collaborative filtering for citation recommendation. Using citation context, a single level paper-citation relation was exploited to find similar neighbors. They mined hidden associations between paper of interest and its references to recommend citations. Haruna *et al.* [32] also exploited single level paper-citation relation by mining hidden associations between paper of interest and its citations to find similar neighbors. Son and Kim [33] proposed a recommendation model that utilizes multilevel citation networks to find relevant papers. They considered both 'cites' and 'cited by' relationships between scientific papers beyond a single level to recommend high quality papers. Waheed *et al.* [34] proposed a hybrid approach that combines multilevel citation networks and authors relationship networks. They identified key authors from their relationship networks to recommend papers to user. Mu *et al.* [35] proposed a multi-layered mutual reinforcement rules based citation recommendation framework. A multi-layered graph was constructed based on multiple types of relations between authors, papers, and keywords. Further, authors incorporated personalized query information into this multi-layered graph to achieve query-focused personalized recommendation. Dai *et al.* [36] proposed a recommendation method that combines low-rank sparse matrix with fine-grained paper and author affinity matrix to alleviate the sparsity problem of traditional collaborative filtering. Firstly, fine-grained paper and author affinity matrix were extracted from heterogeneous bibliographic network, and then integrated these matrices into low-rank and sparse matrix factorization. Dai *et al.* [37] proposed a global citation recommendation model using topic learning and joint feature regression that extracts various text content and citation features from citation network. Different citation features (i.e., title, abstract, keywords, citation count, author history, and meta-path) were extracted and integrated with topic model to learn the process of feature regression. Yang *et al.* [38] proposed a context-aware citation

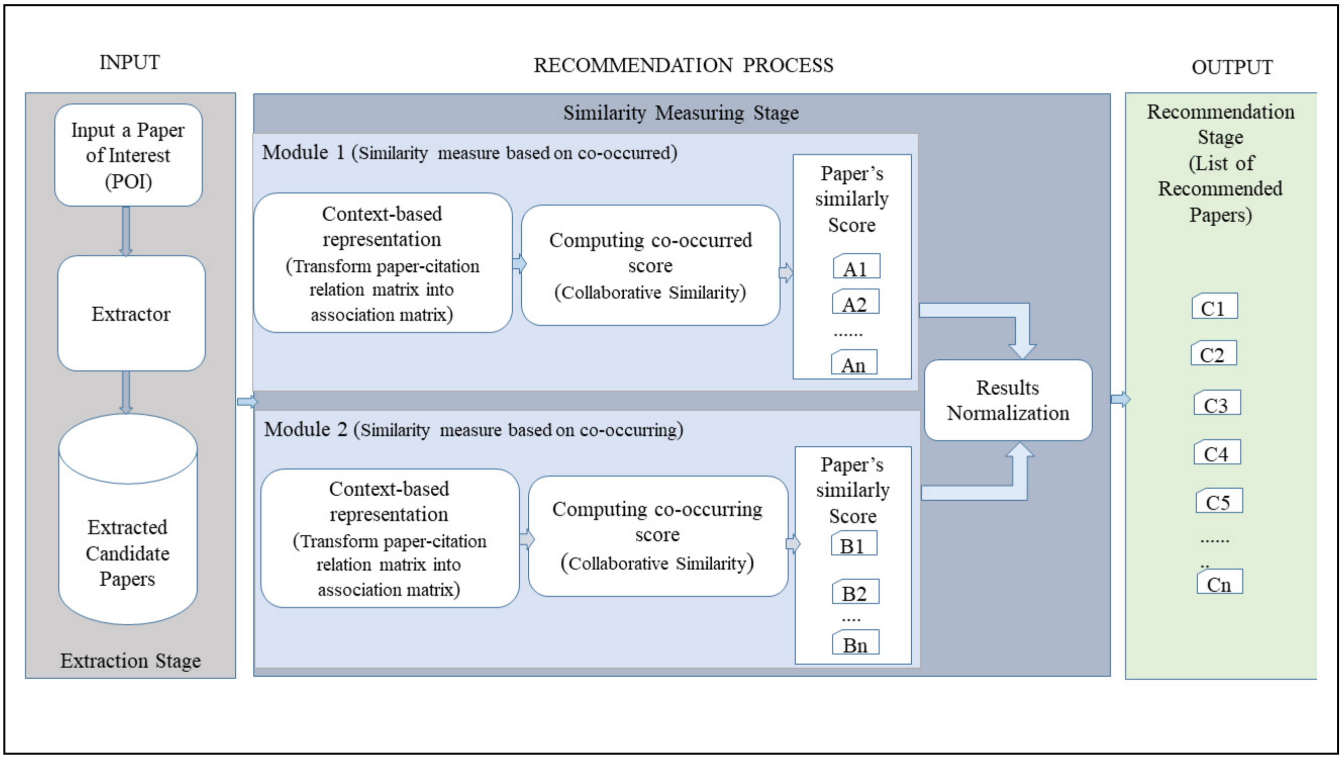

FIGURE 2. Overview of the proposed recommendation approach.

recommendation model using convolutional neural networks (CNN). A Long-Short-Term Memory (LSTM) model was created based on citation context vectors and scientific paper vectors to measure the relevancy. Later, papers with high relevancy scores were recommended as recommendation list. Khan *et al.* [39] proposed a recommendation approach that utilizes in-text citation frequencies and in-text citation patterns to find most relevant scientific articles. The authors investigated different logical sections of papers to identify in-text citation pattern and, then based on these patterns, relevancy score is calculated to rank the articles.

Most of these works [3], [27]-[30], [33]-[39] either extract some paper contents or utilize graph model-based techniques for recommending papers. Apart from them, in this work we propose a neighbor-based collaborative approach for scientific paper recommendation that utilizes only easily obtained publicly available contextual citation relations information. In addition, unlike some works [7], [31]-[32] that utilize single level paper-citation relation, we employ 2-level paper-citation relationships with the help of citation context to find similar neighbors. The experimental results have been shown to verify the effectiveness of the proposed approach.

III. PROPOSED METHODOLOGY

Our proposed approach starts by accepting user's query from a user as Paper of Interest (POI) to which a user wants to get other recommendations similar to it. Once the POI is received, the extraction stage starts and the extractor extracts all the candidate papers. Next, our proposed approach analyses extracted candidate papers by several computations of the recommendation process stage, and finally presents Top-N recommendations to the user. Fig. 2 shows the overview of our proposed approach. It mainly includes the following several stages: (1) data extraction and selection of candidate papers, (2) measuring similarity score of each candidate paper for 2-level paper citation relations (module 1 and module 2), and (3) Normalizing results by combining obtained similarity scores from 2-level paper-citation relations, and sorting scores to recommend Top-N papers to user. The brief description of each stage is provided below:

A. DATA EXTRACTION AND SELECTION OF CANDIDATE PAPERS

In the first stage, candidate papers are selected based on citation papers and reference papers of Paper of Interest (POI). Citation papers are a list of papers which cites POI and reference papers are a list of papers appearing at the end of POI. The relations between POI and these papers are "cited" and conversely, "cites". The algorithm for selection of the candidate papers is given below in Algorithm 1.

B. MODULE 1 (SIMILARITY MEASURE BASED ON CO-OCCURRED)

The extracted set of candidate papers is represented as a paper-citation relational matrix. Table 1 shows the representation of the matrix. Here, rows denote candidate papers, and

Algorithm 1 Selection Of Candidate Papers

Input: Paper of Interest (POI)
Output: Candidate Papers
Received a POI from user as a query message,

1. Retrieve all papers C_i which cites POI
   For each of the citation papers C_i, extract all other papers
   P_i that appearing at the end of C_i as references
2. Retrieve all papers Rf_i that appearing at the end of POI as references
   For each of the reference papers Rf_i, extract all other papers P_j that cited Rf_i
3. Select all the candidate papers CP from P_i and P_j which are co-cited with the POI and which has been referenced by at least any of the POI references

TABLE 1. Paper-citation relation matrix based on co-occurred.

Candidate paper/Citation paper	c1	c2	c3	c4	c5
POI	1	1	1	1	1
cp1	1	-	-	-	-
cp2	-	-	1	1	-
cp3	1	1	-	-	1
cp4	1	-	-	1	-

TABLE 2. Single role association matrix based on co-occurred.

	POI	cp1	cp2	cp3	cp4
POI	1	1	1	1	1
cp1	1	1	0	1	1
cp2	1	0	1	0	1
cp3	1	1	0	1	1
cp4	1	1	1	1	1

columns denote citation papers of POI. In citation relation matrix C, if a paper i cites a paper j, $C_{i,j} = 1$; conversely, $C_{i,j} = 0$. The representation of the matrix can be viewed as a binary rating matrix.

In order to get relationship between POI and each candidate paper, the original double-role relational matrix C is transformed into a single-role association matrix as presented in Table 2. Here, we consider two papers to be significantly co-occurred if both have at least a common citation paper. Additionally, a binary value of 1 or 0 is used for stating whether two papers are co-occurred or not. Furthermore, based on obtained association matrix we compute the collaborative similarity to measure pairwise similarities between POI and each candidate papers using Jaccard similarity coefficient given by Equation 1.

$$J_{co-occurred} = Score^{POI \to cp_n} = \frac{Z_{11}}{Z_{01} + Z_{10} + Z_{11}} \quad (1)$$

TABLE 3. Paper-citation relation matrix based on co-occurring.

Referenced paper/Candidate paper	cp1	cp2	cp3	cp4	cp5
POI	1	1	1	1	1
rf1	1	-	-	-	-
rf2	-	-	1	1	-
rf3	1	1	-	-	1
rf4	1	-	-	1	-

TABLE 4. Single role association matrix based on co-occurring.

	POI	cp1	cp2	cp3	cp4
POI	1	1	1	1	1
cp1	1	1	0	1	1
cp2	1	0	1	0	0
cp3	1	1	0	1	0
cp4	1	1	0	0	1

where, Z_{11} represents the total number of attributes where A and B both having a value of 1. Z_{01} represents the total number of attributes where the attribute of A is 0 and the attribute of B is 1 and Z_{10} represents the total number of attributes where the attribute of A is 1 and the attribute of B is 0.

C. MODULE 2 (SIMILARITY MEASURE BASED ON CO-OCCURRING)

The set of candidate papers is represented as a paper-citation relational matrix. Table 3 shows the representation of the matrix. Here, rows denote the referenced papers of POI, and columns denote candidate papers of POI. In citation relation matrix C, if a paper i cites a paper j, $C_{i,j} = 1$; conversely, $C_{i,j} = 0$. The representation of the matrix can be viewed as a binary rating matrix.

In order to get relationship between POI and each candidate paper, the original double-role relational matrix C is then transformed into a single-role association matrix as presented in Table 4. Here, we consider two papers to be significantly co-occurring if both have at least a common referenced paper that appearing at the end of scientific papers. Additionally, a binary value of 1 or 0 is used for stating whether two papers are co-occurring or not. Furthermore, based on obtained association matrix we compute the collaborative similarity to measure pairwise similarities between POI and each candidate papers using Jaccard similarity coefficient given by Equation 2.

$$J_{co-occurring} = Score^{POI \to cp_n} = \frac{M_{11}}{M_{01} + M_{10} + M_{11}} \quad (2)$$

where, M_{11} represents the total number of attributes where A and B both having a value of 1. M_{01} represents the total number of attributes where the attribute of A is 0 and the attribute of B is 1 and M_{10} represents the total number of

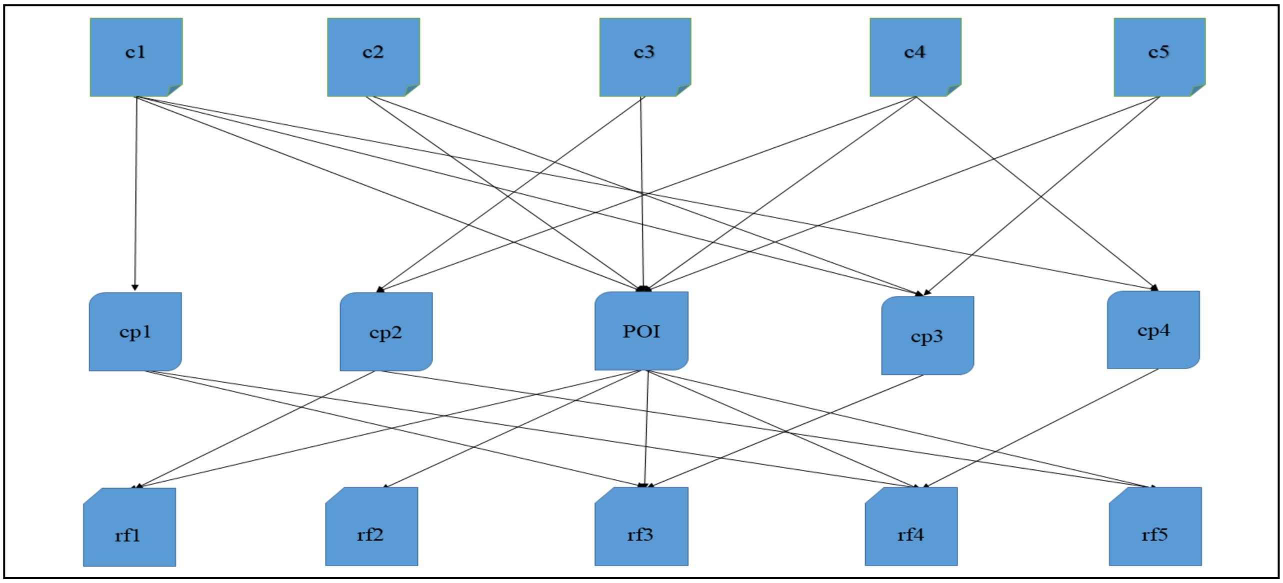

FIGURE 3. Scenario of our proposed recommendation approach.

attributes where the attribute of A is 1 and the attribute of B is 0.

D. RESULTS NORMALIZATION

The two different similarity scores from $J_{co-occurred}$ and $J_{co-occurring}$ are then normalized to get a final score, which gives the relevancy of each candidate papers to POI. We combine these two scores using Equation 3.

$$ResultsNormalization = \frac{\sum_{n=1}^{N}((J_{co\text{-}occurred}(POI, cp_n)) + (J_{co\text{-}occurring}(POI, cp_n)))}{2} \quad (3)$$

E. RECOMMENDATION STAGE

The results obtained from Equation 3 is then ranked and presents the Top-N most similar papers to the user as a set of recommendations list.

Fig. 3 represents a scenario of our proposed approach. For example, c1, c2, c3, c4 and c5, are citation papers and rf1, rf2, rf3, rf4, and rf5 are referenced papers for POI. Candidate papers (cp1, cp2, cp3 and cp4) are papers that are co-cited with POI and which has been referenced by at least any of the POI referenced paper. Table 5 shows an example of how final scores for candidate papers are calculated.

For example, the collaborative similarity score of cp1 for co-occurred relationship is 0.8 (using Equation 1 from Table 2) and the collaborative similarity score of cp1 for co-occurring relationship is 0.8 (using Equation 2 from Table 4).

TABLE 5. The calculation of final scores for candidate papers.

Candidate papers	Jacard similarity scores for co-occurred, $J_{co\text{-}occurred}$	Jaccard similarity scores for co-occurring, $J_{co\text{-}occurring}$	Normalizing results (Final Score)
cp1	0.8	0.8	0.8
cp2	0.6	0.4	0.5
cp3	0.8	0.6	0.7
cp4	1.0	0.6	0.8

TABLE 6. Data statistics.

Number of researchers	50
Average number of publications	10
Average number of citations of each publications	14.8 (max. 169)
Average number of references to each publications	15.0 (max. 58)
Number of candidate papers	100,351
Average number of citations of the candidate papers	17.9 (max. 175)
Average number of references to the candidate papers	15.5 (max. 53)

IV. EXPERIMENTS

A. DATASET

We utilized publicly available dataset provided by Sugiyama and Kan [21] in our experiment. The dataset presented publication list of 50 researchers from various field of computer science such as software engineering, programming language, security, operating system, networks, information retrieval, graphics and user interface. We collected citation and reference papers for every one of researchers' publications and used Google Scholar to extract all the references of each of the POI's citations and all other papers that cited any of the referenced paper of POI. Table 6 presents some statistics about our utilized dataset.

B. BASELINE METHODS

To demonstrate the effectiveness of our proposed approach, we compare the experimental results with three baselines explained bellow:

The method presented by McNee *et al.* [7] firstly introduces the paper-citation relation matrix as rating matrix and generates recommendation based on direct citation-relation. It counts the number of times papers are co-cited with a given POI to compute their similarities and recommends papers based on highest total co-citation count.

Another method presented by Liu *et al.* [31] introduces the use of association matrix in citation recommendation based on single level paper-citation relation matrix. It mines the hidden relation between POI and its reference papers by transforming paper-citation relation matrix into single role association matrix and computes pairwise papers' similarity.

Another method presented by Haruna *et al.* [32] mines the hidden relation between POI and its citation papers by transforming single level paper-citation relation matrix into single role association matrix. Further, based on these paper representations, it calculates pairwise papers' similarity for recommending papers.

In this research, we have also utilized the advantages of neighbor-based collaborative approach for scientific paper recommendation similar to these three baseline methods. In addition, unlike the work presented in [7] that firstly introduces paper-citation relation matrix as rating matrix and utilizes only direct citation-relation between papers, we employ hidden associations between scientific papers to find similar papers. Also, unlike the works presented in [31] and [32] that utilize only single level paper-citation relation, we employ 2-level paper-citation relationships to find similar neighbors.

C. EVALUATION METRICS

To evaluate the quality of our proposed approach, we divided dataset into a training set and a test set using the following procedure. For each of the POI paper, we performed 5-fold cross validation by selecting 20% as a test set. Then, we employed three most commonly used evaluation metrics in our experiments to assess the general performance: (a) Precision: it measures the accuracy of the system by recommending relevant papers to researcher; (b) Recall: it measures the ratio of relevant papers in the Top-N recommendation list to the whole set of papers; (c) F1: it is a harmonic mean of precision and recall.

$$\Pr ecision = \frac{Number\ of\ relevantpapers}{Total\ number\ of\ recommended\ papers} \tag{4}$$

$$Recall = \frac{Number\ of\ relevat\ papers}{Total\ number\ of\ relevant\ papers} \tag{5}$$

$$F1 = \frac{2 \times \Pr ecision \times Recall}{\Pr ecision + Recall} \tag{6}$$

Besides three commonly used metrics, we also employed two other metrics: Mean average precision (MAP) and Mean Reciprocal Rank (MRR). Unlike previous three metrics, these two metrics consider the rank information of the relevant papers to evaluate the ability of the system in providing useful recommendations. Mean average precision (MAP) measures the average of all AP, where Average Precision (AP) is the average of precision values of the relevant papers for all rank position and Mean Reciprocal Rank (MRR) measures the first ranking position of the relevant papers in the recommendation list averaged over all researchers.

$$MAP = \frac{1}{I} \sum\nolimits_{i \in I} \frac{1}{ni} \sum_{k=1}^{n} P(R_{ik}) \tag{7}$$

$$MRR = \frac{1}{I} \sum_{i \in I} \frac{1}{rank(i)} \tag{8}$$

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

V. RESULTS AND ANALYSIS

This section represents the experimental results of our proposed approach against Baseline approaches in term of scientific paper recommendation. We present aggregated results obtained by the proposed approach over all the 50 researchers of our dataset. Fig. 4 demonstrates the results comparisons based on precision, recall and F1 evaluation metrics respectively. As can be seen from the Fig. 4(a), our proposed approach achieves larger values of precision over the Baseline approaches for different N recommendation values. However, the results of the co-citation approach outperformed the proposed approach when N = 5 (N @ 5). But the results become less significant when the number of recommendation values (N) increases. Besides that, the results of our proposed model has significantly outperformed the other Baseline approaches for all N recommendation values. Thus, the experimental results demonstrate that our proposed approach is significantly able to return relevant papers to the user than others.

Fig. 4(b), demonstrates the results comparison based on recall. As can be seen from this figure, the proposed approach achieves larger values of recall as the value of recommendation (N) is increasing. However, the co-citation method outperformed the proposed approach when N = 5 (N @ 5). But the result of co-citation method becomes less significant as the number of recommendation values (N) increases. In addition, the experimental results of our proposed approach has significantly outperformed the other Baseline methods for all N recommendation values. Hence, this indicates, our proposed approach is significantly able to remove less related papers before recommending to the user than others.

The experimental results comparisons based on F1 measure is depicted in Fig. 4(c). As can be seen, similar to the experimental results of recall presented in Fig. 4(b), our proposed approach achieves almost same values of F1 measure to the co-citation method when N is less than 15, but the

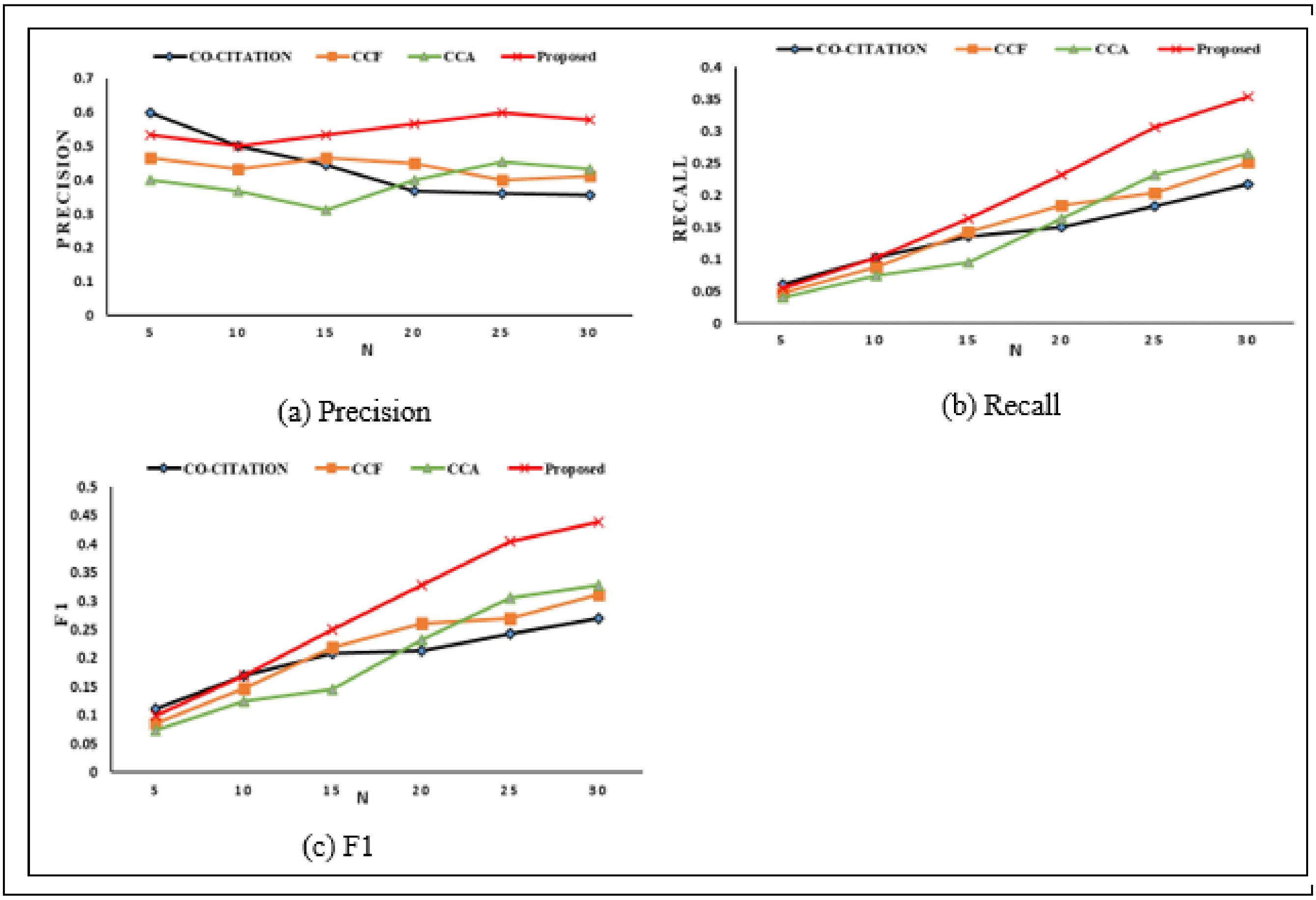

FIGURE 4. Performance comparison of Precision, Recall, and F1 for baselines.

results of our proposed approach achieves the larger values of F1 measure to all the Baselines when N is larger than 10.

From these experimental results comparisons presented in Fig. 4, it can easily be seen that, our proposed approach has significantly outperformed the Baseline approaches in terms of three evaluation metrics. To be very specific, although the performance difference between our proposed approach and the Baselines methods is not much significant when N is less than 10, but as the value of N is increasing, specifically when N is larger than 10, the performance of our proposed approach starts to show the significant differences to the Baseline approaches. However, due to strict rules applied in selecting candidate papers, our proposed appraoch shows insignificant performances to the Baselines when N is below 10. Furthermore, these results also indicate that, the proposed approach is able to generate more accurate recommendations.

In order to measure the performances of our proposed approach against other Baseline methods in term of the ability of returning relevant papers at the top of the recommendation list, we compare experimental results based on Mean average precision (MAP) and Mean Reciprocal Rank (MRR) respectively. Fig. 5 demonstrates the comparison results of Mean average precision (MAP) and Mean Reciprocal Rank (MRR) to the Baselines. As can be seen form Fig. 5(a), our proposed approach has significantly outperformed the Baseline methods for all recommendation values (N). The results of the CCA method performs worst in this case. However, our proposed approach achieves the highest value of MAP when N = 5 (N @ 5).

On the other hand, the experimental results presented in Fig. 5(b) has shown that, our proposed approach has outstandingly outperformed the baseline methods for all recommendation values (N). The CCA method performs worst in this case also. In addition, this result indicates that, relevant papers appear at either rank 1 or rank 2 position in the recommendation list.

However, the main reason behind the outstanding performances provided by the proposed approach based on these two evaluation metrics to the Baseline methods is the strict rules in selecting candidate papers. Due to this strictness, large number of irrelevant papers are removed which increased the performance of the systems by returning relevant papers at the top of the recommendation list.

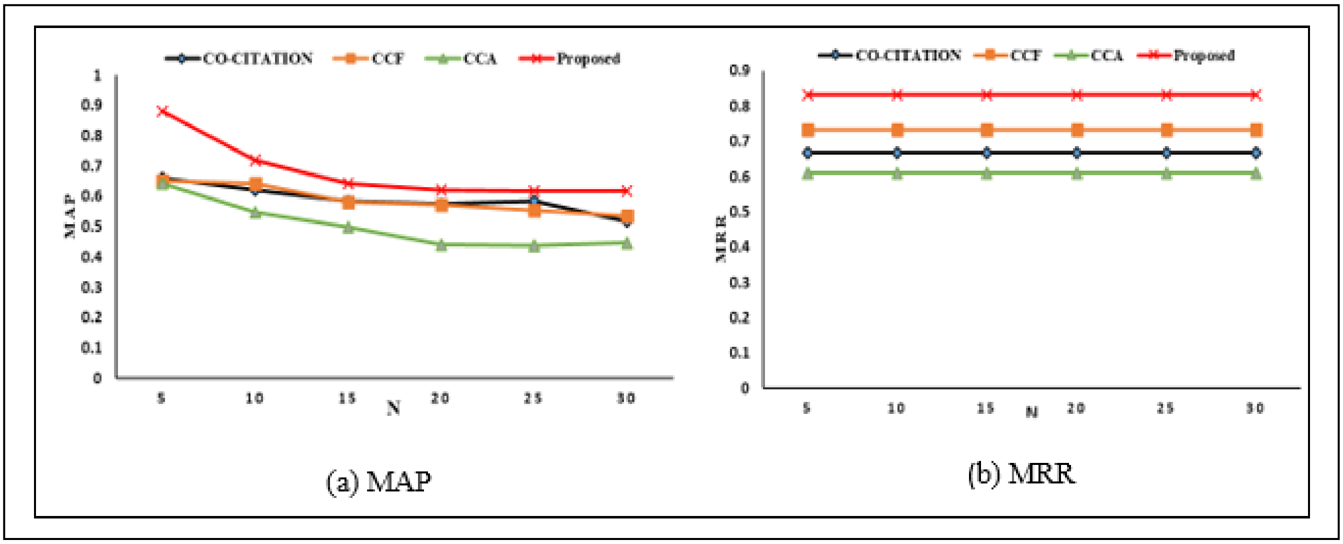

FIGURE 5. Performance comparison of MAP and MRR for baselines.

VI. CONCLUSION

The enormous amount of information over the internet makes it difficult for researchers to locate the most important scientific papers for their current work or study. Considering this situation, this study has successfully proposed a personalized scientific paper recommendation approach for recommending relevant scientific papers as paper references to users. Unlike traditional collaborative filtering applied in scholarly recommender systems, we utilize 2-level contextual citation relations based on citation context to find collaborative similarities. Also different from others, this study separately mines hidden associations that exit between POI and candidate papers to provide closely related and useful list of papers as recommendations. Experimental results on publicly available dataset demonstrate that, our proposed approach outperforms the Baseline approaches in term of precision, recall, F1, MAP, and MRR. This indicates that, mining latent associations separately in calculating collaborative similarities generate better recommendations than others.

One big advantage of the proposed approach is that it only utilizes easily obtained citation relations information for recommending papers. For further work, we hope to include additional features such as authors and journals information to improve our recommendation approach for improved performances.

REFERENCES

[1] F. Xia, W. Wang, T. M. Bekele, and H. Liu, "Big scholarly data: A survey," *IEEE Trans. Big Data*, vol. 3, no. 1, pp. 18–35, Mar. 2017.

[2] X. Bai, M. Wang, I. Lee, Z. Yang, X. Kong, and F. Xia, "Scientific paper recommendation: A survey," *IEEE Access*, vol. 7, pp. 9324–9339, 2019.

[3] C. Nascimento, A. H. F. Laender, A. S. da Silva, and M. A. Gonçalves, "A source independent framework for research paper recommendation," in *Proc. 11th Annu. Int. ACM/IEEE Joint Conf. Digit. Libraries (JCDL)*, 2011, pp. 297–306.

[4] K. Sugiyama and M.-Y. Kan, "Exploiting potential citation papers in scholarly paper recommendation," in *Proc. 13th ACM/IEEE-CS Joint Conf. Digit. Libraries (JCDL)*, 2013, pp. 153–162.

[5] B. Kaya, "User profile based paper recommendation system," *Int. J. Intell. Syst. Appl. Eng.*, vol. 2, no. 6, pp. 151–157, Jun. 2018.

[6] C. Bhagavatula, S. Feldman, R. Power, and W. Ammar, "Content-based citation recommendation," 2018, *arXiv:1802.08301*. [Online]. Available: http://arxiv.org/abs/1802.08301

[7] S. M. McNee, I. Albert, D. Cosley, P. Gopalkrishnan, S. K. Lam, A. M. Rashid, J. A. Konstan, and J. Riedl, "On the recommending of citations for research papers," in *Proc. ACM Conf. Comput. Supported Cooperat. Work (CSCW)*, 2002, pp. 116–125.

[8] J. Wang and Y. Zhang, "Opportunity model for e-commerce recommendation: Right product; right time," in *Proc. 36th Int. ACM SIGIR Conf. Res. Develop. Inf. Retr. (SIGIR)*, 2013, pp. 303–312.

[9] Z. Wu, J. Wu, J. Cao, and D. Tao, "HySAD: A semi-supervised hybrid shilling attack detector for trustworthy product recommendation," in *Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2012, pp. 985–993.

[10] L. O. Colombo-Mendoza, R. Valencia-García, A. Rodríguez-González, G. Alor-Hernández, and J. J. Samper-Zapater, "RecomMetz: A context-aware knowledge-based mobile recommender system for movie showtimes," *Expert Syst. Appl.*, vol. 42, no. 3, pp. 1202–1222, Feb. 2015.

[11] Y. Shi, M. Larson, and A. Hanjalic, "Mining mood-specific movie similarity with matrix factorization for context-aware recommendation," in *Proc. Workshop Context-Aware Movie Recommendation (CAMRa)*, 2010, pp. 34–40.

[12] N. Hariri, B. Mobasher, and R. Burke, "Context-aware music recommendation based on latenttopic sequential patterns," in *Proc. 6th ACM Conf. Recommender Syst. (RecSys)*, 2012, pp. 131–138.

[13] Q. Li, S. H. Myaeng, and B. M. Kim, "A probabilistic music recommender considering user opinions and audio features," *Inf. Process. Manage.*, vol. 43, no. 2, pp. 473–487, Mar. 2007.

[14] F. Garcin, C. Dimitrakakis, and B. Faltings, "Personalized news recommendation with context trees," 2013, *arXiv:1303.0665*. [Online]. Available: http://arxiv.org/abs/1303.0665

[15] J. Bobadilla, F. Serradilla, and A. Hernando, "Collaborative filtering adapted to recommender systems of e-learning," *Knowl.-Based Syst.*, vol. 22, no. 4, pp. 261–265, May 2009.

[16] W. Chen, Z. Niu, X. Zhao, and Y. Li, "A hybrid recommendation algorithm adapted in e-learning environments," *World Wide Web*, vol. 17, no. 2, pp. 271–284, Mar. 2014.

[17] E. Medvet, A. Bartoli, and G. Piccinin, "Publication venue recommendation based on paper abstract," in *Proc. IEEE 26th Int. Conf. Tools Artif. Intell.*, Nov. 2014, pp. 1004–1010.

[18] J. Tang, S. Wu, J. Sun, and H. Su, "Cross-domain collaboration recommendation," in *Proc. 18th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining (KDD)*, 2012, pp. 1285–1293.

[19] N. Agarwal, E. Haque, H. Liu, and L. Parsons, "Research paper recommender systems: A subspace clustering approach," in *Proc. Int. Conf. Web-Age Inf. Manage.* Berlin, Germany: Springer, 2005, pp. 475–491.
[20] K. Sugiyama and M.-Y. Kan, "Scholarly paper recommendation via user's recent research interests," in *Proc. 10th Annu. Joint Conf. Digit. Libraries (JCDL)*, 2010, pp. 29–38.
[21] K. Sugiyama and M.-Y. Kan, "A comprehensive evaluation of scholarly paper recommendation using potential citation papers," *Int. J. Digit. Libraries*, vol. 16, no. 2, pp. 91–109, Jun. 2015.
[22] F. Xia, H. Liu, I. Lee, and L. Cao, "Scientific article recommendation: Exploiting common author relations and historical preferences," *IEEE Trans. Big Data*, vol. 2, no. 2, pp. 101–112, Jun. 2016.
[23] W. Zhao, R. Wu, and H. Liu, "Paper recommendation based on the knowledge gap between a researcher's background knowledge and research target," *Inf. Process. Manage.*, vol. 52, no. 5, pp. 976–988, Sep. 2016.
[24] L. Guo, X. Cai, F. Hao, D. Mu, C. Fang, and L. Yang, "Exploiting fine-grained co-authorship for personalized citation recommendation," *IEEE Access*, vol. 5, pp. 12714–12725, 2017.
[25] X. Ma and R. Wang, "Personalized scientific paper recommendation based on heterogeneous graph representation," *IEEE Access*, vol. 7, pp. 79887–79894, 2019.
[26] B. Bulut, E. Gündoğan, B. Kaya, R. Alhajj, and M. Kaya, "User's research interests based paper recommendation system: A deep learning approach," in *Putting Social Media and Networking Data in Practice for Education, Planning, Prediction and Recommendation*. Cham, Switzerland: Springer, 2020, pp. 117–130.
[27] M. Gori and A. Pucci, "Research paper recommender systems: A random-walk based approach," in *Proc. IEEE/WIC/ACM Int. Conf. Web Intell. (WI Main Conf.)(WI)*, Dec. 2006, pp. 778–781.
[28] F. Meng, D. Gao, W. Li, X. Sun, and Y. Hou, "A unified graph model for personalized query-oriented reference paper recommendation," in *Proc. 22nd ACM Int. Conf. Conf. Inf. Knowl. Manage. (CIKM)*, 2013, pp. 1509–1512.
[29] X. Liu, Y. Yu, C. Guo, and Y. Sun, "Meta-path-based ranking with pseudo relevance feedback on heterogeneous graph for citation recommendation," in *Proc. 23rd ACM Int. Conf. Conf. Inf. Knowl. Manage. (CIKM)*, 2014, pp. 121–130.
[30] A. S. Raamkumar, S. Foo, and N. Pang, "Using author-specified keywords in building an initial reading list of research papers in scientific paper retrieval and recommender systems," *Inf. Process. Manage.*, vol. 53, no. 3, pp. 577–594, May 2017.
[31] H. Liu, X. Kong, X. Bai, W. Wang, T. M. Bekele, and F. Xia, "Context-based collaborative filtering for citation recommendation," *IEEE Access*, vol. 3, pp. 1695–1703, 2015.
[32] K. Haruna, M. Akmar Ismail, D. Damiasih, J. Sutopo, and T. Herawan, "A collaborative approach for research paper recommender system," *PLoS ONE*, vol. 12, no. 10, 2017, Art. no. e0184516.
[33] J. Son and S. B. Kim, "Academic paper recommender system using multilevel simultaneous citation networks," *Decis. Support Syst.*, vol. 105, pp. 24–33, Jan. 2018.
[34] W. Waheed, M. Imran, B. Raza, A. K. Malik, and H. A. Khattak, "A hybrid approach toward research paper recommendation using centrality measures and author ranking," *IEEE Access*, vol. 7, pp. 33145–33158, 2019.
[35] D. Mu, L. Guo, X. Cai, and F. Hao, "Query-focused personalized citation recommendation with mutually reinforced ranking," *IEEE Access*, vol. 6, pp. 3107–3119, 2018.
[36] T. Dai, T. Gao, L. Zhu, X. Cai, and S. Pan, "Low-rank and sparse matrix factorization for scientific paper recommendation in heterogeneous network," *IEEE Access*, vol. 6, pp. 59015–59030, 2018.
[37] T. Dai, L. Zhu, Y. Wang, H. Zhang, X. Cai, and Y. Zheng, "Joint model feature regression and topic learning for global citation recommendation," *IEEE Access*, vol. 7, pp. 1706–1720, 2019.
[38] L. Yang, Y. Zheng, X. Cai, H. Dai, D. Mu, L. Guo, and T. Dai, "A LSTM based model for personalized context-aware citation recommendation," *IEEE Access*, vol. 6, pp. 59618–59627, 2018.
[39] A. Mehmood Khan, A. Shahid, M. Tanvir Afzal, F. Nazar, F. S. Alotaibi, and K. H. Alyoubi, "SwICS: Section-wise in-text citation score," *IEEE Access*, vol. 7, pp. 137090–137102, 2019.

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