A novel personalized academic venue hybrid recommender

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***Abstract*—To see his work accepted and published, a researcher should submit it to the most appropriate conferences or journals. When a researcher schedules to submit his paper, it is generally difficult to him to find an upcoming conference that fits his research topics and also his requirements. To tackle this problem, we propose a personalized academic venue recommendation solution related to venues in the computer science field. Since generally researchers who are cited in the references share the same research interests with a target researcher, our approach is based on bibliographic data augmented by citation relationships between papers. The main idea is to recommend venues on the basis of those of his co-authors, co-citers and co-affiliated. The reliability of each researcher is taken into account to make recommendations. Then, call of papers data are used to recommend personalized upcoming conferences to a given researcher. Our hybrid recommendation system is able to filter out irrelevant conferences that do not respond to the researcher's requirements (ranking, publisher, location). The cold start problem for young researchers is also taken into account. Experiments with the bibliographic citation dataset show that our new approach outperforms the standard collaborative filtering and provides accurate recommendation.**

I. Introduction

The growth of academic venues has had a considerable impact on the choice of the appropriate conference into which research papers should be submitted. Indeed, with information overload, researchers are no more able to be aware of all academic venues and to find the most appropriate conferences that fit their domain of interests and correspond to their needs. In fact, several papers were rejected because they are off-topics. This situation is so-called the academic venue problem.

To cope with the information overload problem, recommender systems have proven to be efficient in several areas (e.g., books [1], movies [2] and web pages [3]). These latter predict user's response on new items on the basis of historical information stored in the system. They filter out irrelevant items and only suggests new items having a high predicted responses. Recent works investigate on recommendation systems to solve problems related to the academic world and more especially to research activities (paper recommendation [4], classification of scientific journals [5], identifying relevant domains of research [6], academic venue problem [7], [8], [9], [10], [11]).

In this work, we present a novel hybrid method to recommend personalized upcoming conferences for researchers in the computer science area. We propose a personalized framework with a personalized web interface for researchers on which they are able to get a list of recommended venues each time they log onto our system. The recommendation process is based on the venues of the co-citers, the co-authors and also those of researchers belonging to the same institution/laboratoy of the target scientist (i.e., co-affiliated). To select the most relevant conferences, the frequency of citing or co-authoring the target researcher's papers is taken into account to model the reliability of co-citers and co-authors. The set of resulting conferences can be refined to fit the target researcher's requirements by dealing with conferences' ranking, publisher and/or location. Our framework also focus on young researchers profiles who who have not published papers yet in order to afford to them some help about potential venues where to submit their works.

This paper is organized as follows: Section 2 recalls basic concepts about recommender systems and presents related works on the academic venue problem recommendation. Our new recommendation engine is detailed in Section 3. Section 4 is dedicated to the experimental study. Section 5 concludes the paper and presents some future works.

II. Background

A. Recommender Systems

To solve decision making problems, people may converse with friends, consult the Internet, trust their gut instinct or follow the crowd. However, good advice is difficult to receive, time-consuming in most cases and of questionable quality often. To overcome these problems, recommender systems [12] are used to support people in their (online) decision making by providing easily accessible, high-quality recommendations for a large user community. Several types of recommenders have been proposed to ensure good recommendations according to the application domain. In what follows, we will detail collaborative, community, utility-based recommenders and hybrid systems.

1) Collaborative recommender: Collaborative filtering recommendation [13] can be either memory-based or model-based. The recommendation process takes as input a matrix of a given user-item ratings and provides as an output either a numerical value indicating the degree of likeliness of a certain item or a list of Top-N liked items. It is based on the past likes of other users having a similar rating history. In the model based recommendation, an offline preprocessing step in which an item-item similarity matrix describing the pairwise similarity of all items is added. This kind of recommendation is more appropriate for large rating matrices since at run time, preferences of the current user are inferred by matching the matrix and user's data [14]. Collaborative filtering recommenders suffer from the so-called *cold-start* problem [15] which corresponds to a situation of lack of information on user or items (e.g, previous user's ratings). To overcome this problem, community-based recommender is used.

2) Community-based recommender: Community-based recommendations suggest that users tend to rely more on recommendations from their friends than on recommendations from anonymous even similar peers [16]. The recommendation is based on ratings that were provided by the user's friends.

3) Utility-recommender: Utility-based recommendations [17] are presented on the basis of a utility operation. This latter is computed as a weighted function of a combination of variables values reflecting the preferences of users to items.

4) Hybrid systems: Hybrid recommendations [18] have been investigated by combining several algorithms implementations or recommendation components. There are *Monolithic*, *Parallelized* and *Pipelined* hybrid architectures [19]. In what follows, we will present parallelized mixed and pipelined cascade recommenders since they will be used in our framework.

- *Parallelized*: Recommendation components work in parallel and produce separate recommendation lists. It is called *mixed* when the results of different recommender systems are combined and presented at the level of the user interface.
- *Pipelined*: The output of one recommender becomes part of the input of the subsequent one. A pipelined hybridization is in *cascade* when each recommender refines the recommendations produced by its predecessor.

B. Academic Venue Recommendation Problem: Related Works

With the huge growth of the number and the type of academic venues these recent years, researchers encounter difficulties to decide where to submit their works. Indeed, the number of venues collected in DBLP (www.informatik.uni-trier.de/ ley/db/) by distinct proceeding has increased from approximately 400 events in 1997 to 2005 events in 2007 [7]. To facilitate this task, some recent works have investigated the recommendation of venues for scientists. These latter can be divided on two groups depending on the way the venue recommendation is defined. Some works [8], [20] are based on the content and thus take as input papers. A combined path constraint random walk-based approach was proposed in [8] where a big edge-weighted graph is constructed. Nodes in this graph represent terms in the paper's title combined with author's and venue's names. In [20], a collaborative filtering recommender based on topic and writing-style information is used. This first category based on content can lead to errors due to mismatches caused by ambiguity in text comparisons [9].

Accordingly, other works [7], [9], [10], [11] aim to predict the publications venues of scientists, and hence their input is researchers. To recommend academic venues, authors in [7] applied collaborative filtering techniques to study how research communities support individual members to find suitable venues. In [10], [11] they used a clustering-based approach to group researchers having similar patterns. In [9], the authors used researcher's publication history network. They took into account information about publications and co-author relationships among the members.

However, existing academic venue frameworks still lack of personalization efficiency. To the best of our knowledge, there are no works that propose for a computer science researcher, personalized upcoming conferences that fulfill his needs. Thus, in the next section we propose a new framework for academic venue personalization able to automatically find the most appropriate "upcoming" venues that fit the researcher's domain and respond to his requirements.

III. Personalized academic venue framework

A. Data sources

To generate personalized upcoming venues, data related to researchers' profiles should be collected and stored for further use. Researcher's personal information is gathered when he makes registration for the first time on our venue recommender system. Indeed, his name, his email address, his institution, his laboratory if any and his country should be provided. These data are stored in the *researchers' profiles database*. Bibliographic data is augmented by the citation relationships between papers (i.e, co-citations) and stored in the *citation database*. Information about call for papers (e.g., topics, deadlines, committees and locations) is extracted from the *call of papers database* while ranking categories and the field of research's code are derived from the *ranking database*.

B. Personalized interface

A customized interface is offered to each registered researcher to ensure his interactions with the system. His connection is made by providing his email and password. Besides, he has the possibility to modify the information related to his profile (e.g., his affiliation). Once logged into the system, the researcher can make customized venues searches. Hence, he is able to filter out conferences that do not correspond to his requirements by refining the list of recommended upcoming venues according to a given ranking, publisher and/or location (e.g., keeping only relevant upcoming conferences taking place in Hungary and published by IEEE).

C. Recommender engine

The proposed recommender engine aims to find the most suitable upcoming academic venues to a computer science researcher on the basis of his domain of interests and eventually his requirements. Two kind of hybridization techniques are used, namely *mixed* and *cascade* hybridization. In fact, to detect conferences that match the target researcher's domain of interests, we will use a new collaborative filtering recommender that exploits his co-citers academic venues. Note that a researcher's co-citers should be different from his co-authors and those belonging to his institution/laboratory. The list of recommended conferences are mixed with those of the community-based recommender, which focus on his co-authors and his co-affiliated. The requirements of the target researcher are then handled with the utility-based recommender which is used in cascade to refine the list of venues obtained from the mixed recommendation result.

1) A new collaborative engine: The standard collaborative based engine recommends items that are not yet being rated by the target user. Thus, if the target likes a given book or a movie, the system will recommend him novel movies that are similar to the ones he has liked.In the academic context, recommended venues are those of researchers participating to the same events as the target researcher, which he has not yet participated. This is a non-realistic and non-personalized recommendation. In fact, if a researcher has published in CINTI conference in 2013, the system may recommend him the CINTI conference in 2014. Furthermore, the researchers, on which the recommendation was held, are not truly similar, especially for multi-topics conferences. To overcome the limitation of standard collaborative recommenders, we propose a new collaborative engine as depicted in Fig. 1. The recommendation process takes as input a matrix where researchers, denoted by Rr_i, are only those who have already cited the works of the target researcher (co-citers). Each entry in the matrix, denoted by P_{ij}, represents a researcher's participation (number of published papers) Nb_{ij} in a particular academic venue V_j.

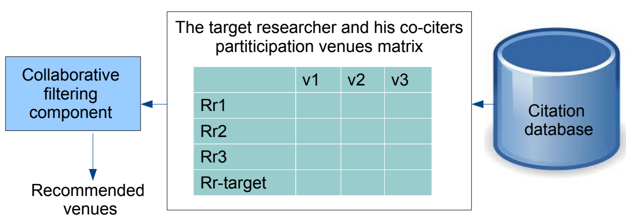

Fig. 1. Collaborative recommender

The collaborative recommendation process is composed of three steps, namely, normalization, discounting and sorting.

a) Normalization: To avoid that researchers who publish a large number of papers skew the recommendation results, we take into account for each researcher Rr_i the total number of his published papers Nb_i as follows:

$$P_{ij} = \frac{Nb_{ij}}{Nb_i} \tag{1}$$

b) Discounting: In this second step, the reliability given to a co-citer Rr_i is taken into consideration by computing the frequency of his citing of the target researcher Rr_t works according to the total number of his published papers Nb_t, denoted by Nb_{it}^C. Thus, the participation entry obtained from the previous step, denoted here by P_{ij}^{old}, is updated by a discount rate α taking values in a range between 0 and 1. The idea is to weight most heavily the venues of the best citers and inversely for the less reliable ones. It is defined by:

$$P_{ij} = \alpha \cdot P_{ij}^{old} \tag{2}$$

where:

$$\alpha = \frac{Nb_{it}^C}{Nb_t} \tag{3}$$

The larger α is, the most reliable the citer is and consequently his venues are relevant. Thus, if $\alpha = 1$, this means that all the target researcher's papers are cited by Rr_i and accordingly this co-citer is fully reliable. In our approach, we consider that the target researcher is fully reliable, i.e., all his previous venues are relevant.

c) Sorting: The collaborative filtering component sorts venues according to a score assigned to each venue V_j, denoted by $S(V_j)$. It is computed as the weighted sum of participation of the n co-citers to V_j, as well as the one of the target researcher.

$$S(V_j) = \sum_{i=1}^{n+1} P_{ij} \tag{4}$$

Example 1. *Let us consider the case of a target researcher John who has 15 publications. His co-citers are Mary, Paul and Peter who have 20, 10 and 50 publications, respectively. These papers are spread over four different conferences as presented on columns (a) of Table I. The normalized participation is given on columns (b).*

TABLE I
PARTICIPATION MATRIX

	conferences											
	CINTI			SAMI			INES			SMC		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
Mary	10	0.5	0.03	2	0.1	0.01	5	0.25	0.01	3	0.15	0.01
Paul	3	0.3	0.16	0	0	0	7	0.7	0.23	0	0	0
Peter	30	0.6	0.4	5	0.1	0.06	10	0.2	0.13	5	0.1	0.06
John	12	0.8	0.8	2	2/15	2/15	1	1/15	1/15	0	0	0

Mary, Paul and Peter have cited John's works but not at the same frequency. Indeed, John's works have been cited in one Mary's paper, five Paul's papers and ten Peter's works. The reliability of each co-citer is computed as shown in Table II. The discounting factor will be then used to update the matrix entries and new results are shown in columns (c) of Table I.

TABLE II
RELIABILITY OF RESEARCHERS

Mary	Paul	Peter	John
0.06	0.33	0.66	1

Finally, the set of conferences will be sorted according to their score such that S(CINTI)=1.39 $>$ S(INES)= 0.44 $>$ S(SAMI)= 0.2 $>$ S(SMC)= 0.07.

2) A community recommender engine: To tackle the cold start problem a community-based recommender is added to the collaborative using a *mixed hybridization*. In literature, the researcher's community corresponds to his co-authors [21], [9]. In our work, we extend communities by incorporating both of co-authors and co-affiliated. Data sources of these researchers are citation database and profile database, respectively as depicted by Fig. 2.

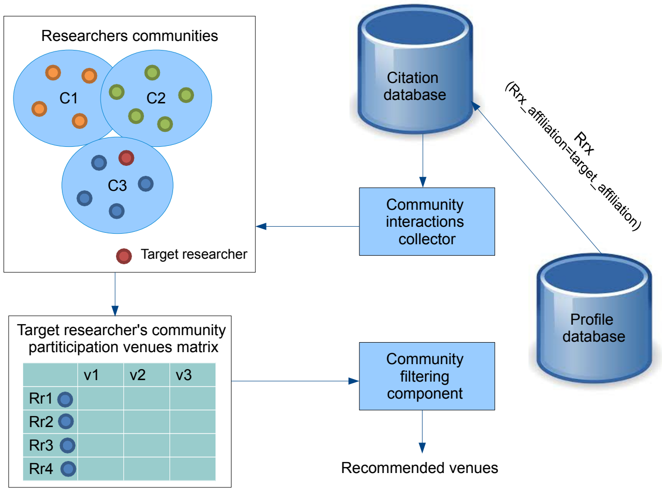

Fig. 2. Community-based recommender

The community recommendation process requires the same steps of normalization and sorting relative to our new collaborative recommender, except for discounting as detailed below:

- *The case of co-authors:* venues of co-authors having an important number of publications shared with the target researcher are considered in the recommendation process. To not aggrieve researchers who do not have many publications the normalization operation of Equation (1) is applied. The participation of each co-author is weakened using its reliability expressed by Equation (2) in which the discounting rate α is computed as follows:

$$\alpha = \frac{Nb_{it}^{A}}{Nb_t} \tag{5}$$

where Nb_{it}^{A} denotes the number of papers of researcher Rr_i co-authored with the target researcher.

- *The case of co-affiliated:* Researchers belonging to the same institution/laboratory as the target researcher may share the same domain of interests. In our case, for caution reasons, we assume that these researchers have one publication whose venue may correspond to the target researcher's venues. Hence, we define the discounting factor α in this case as:

$$\alpha = \frac{1}{Nb_t} \tag{6}$$

The community filtering component scores venues by computing the weighted sum of participation of researchers n' belonging to his community as follows:

$$S^C(V_j) = \sum_{i=1}^{n'} P_{ij} \tag{7}$$

Example 2. *Let us continue with Example 1. We assume that John has written 1 academic paper with Pedro, 7 papers with Marc and 5 with Liu. The number of publications of these co-authors is 5, 7 and 30, respectively. Our target author has the same affiliation as Laura who has 6 published papers as shown in columns (a) of Table III. Normalized participation is presented on columns (b). Pedro, Marc and Liu have collaborated on John's works. The reliability of each one of his co-authors and his co-affiliated is exposed in Table IV. Discounted John's community participation results are shown on columns (c) of Table III.*

TABLE III
JOHN'S COMMUNITY PARTICIPATION MATRIX

	conferences											
	CINTI			SISY			INES			SACI		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
Pedro	3	0.6	0.04	1	0.2	0.01	1	0.2	0.01	0	0	0
Marc	6	0.86	0.4	0	0	0	1	0.14	0.06	0	0	0
Liu	10	0.33	0.11	5	0.17	0.06	14	0.47	0.15	1	0.03	0.01
Laura	0	0	0	3	0.5	0.03	3	0.5	0.03	0	0	0

TABLE IV
RELIABILITY OF RESEARCHERS OF JOHN'S COMMUNITY

Pedro	Marc	Liu	Laura
0.06	0.46	0.33	0.06

The set of conferences from the community based engine will be sorted as: S^C(CINTI)=0.55 $>$ S^C(INES)= 0.25 $>$ S^C(SISY)= 0.1 $>$ S^C(SACI)= 0.01.

Venues obtained from the collaborative and the community-based recommenders present the entries of the mixed hybrid recommender. Once combined, a list of ranked conferences is obtained. The final score $S^F(V_j)$, which reflects the relevance of each venue V_j to the target researcher, is computed as follows:

$$S^F(V_j) = S(V_j) + S^C(V_j) \tag{8}$$

Example 3. *The final score of each venue is therefore computed as: S^F(CINTI)= 1.94 $>$ S^F(INES) = 0.7 $>$ S^F(SAMI) = 0.2 $>$ S^F(SICY)=0.1 $>$ S^F(SMC) = 0.07 $>$ S^F(SACI)= 0.01.*

Given a venue matrix, a matching between the sorted conferences obtained from the mixed hybrid recommender and the upcoming ones of the call of papers database is performed according to the venue name. A list of recommended upcoming venues, whose submission deadlines are not outdated, is therefore obtained.

3) Utility-based recommender: The utility-based recommender is used to refine the list of recommended venues according to target researcher's requirements. Venue features used by this recommender are venue's location, ranking and publisher. The location and the publisher are extracted from the call of papers database while the ranking is obtained from the ranking database as depicted in Fig. 3.

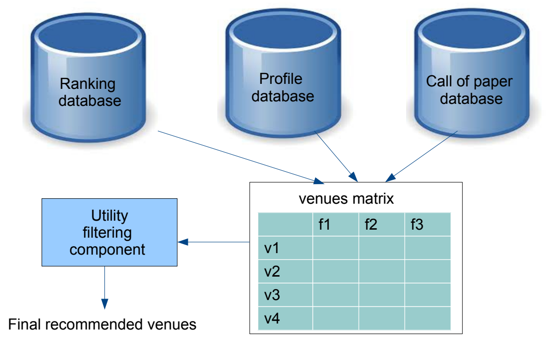

Fig. 3. Utility-based recommender

By default, all locations, rankings and publishers are preferred to a researcher. To refine the set of upcoming venues produced by the mixed hybridization, he may indicate through his personalized web page his preferences by choosing a value v_s per feature x. In such a case, a preference parameter, denoted by λ_x, is computed by:

$$\lambda_x = \begin{cases} 1 \text{ if } v_x = v_s \\ 0 \text{ otherwise} \end{cases} \tag{9}$$

where v_x represents the set of values of feature x.

The refinement process is made using a cascade hybridization technique through a utility-based filtering component. This latter computes the utility of each upcoming venue $U(V_j)$ according to a utility value $u(V_j)$ depicting the combination of the m selected features' weights. Interestingly enough, venues with a utility different from one will be discarded.

$$U(V_j) = u(V_j) \cdot S^F(V_j) \tag{10}$$

where

$$u(V_j) = \prod_{i=1}^{m} \lambda_x \tag{11}$$

Example 4. *Let us consider the case of John who wishes to know if there are relevant upcoming events that will take place in Hungary and published by IEEE. We assume that only CINTI 2014 and SMC 2015 are not outdated according to the call of papers data. The utility operation of each venue is then computed as shown in Table V.*

TABLE V
VENUES' UTILITIES

venue	location	ranking	publisher	u	U
CINTI 2014	Hungary	-	IEEE	1*1=1	1.94
SMC 2015	France	B	IEEE	0*1=0	0

Hence, CINTI 2014 will be recommended to John and its information related to CINTI 2014 will be displayed in John's web page.

IV. Evaluation

A. Data description

The experiments were conducted on the DBLP citation dataset (http://arnetminer.org/DBLP_Citation) which consists of bibliographic data augmented by the citation relations between papers. It contains information about 2,084,055 academic papers with 2,244,018 citation relationships published until September 2013. A set of 1000 target researchers have been chosen randomly, for which a venues recommendation list is presented. The call of papers database contains data relative to topics, deadlines, committees and locations of call of papers from WikiCFP (www.wikicfp.com) and Eventseer (http://eventseer.net/). Information about computer science venues (venue's title, acronym, publisher, previous venue ranking (from CORE 2008, ERA 2010, CORE 2013), and the field of research code) are extracted from the CORE Conference Portal (http://103.1.187.206/core/). In the 2013 list, we can distinguish six ranking categories ranging from A* (flagship conference) to unranked (insufficient information is available to judge ranking).

B. Results

In this section, we will compare the baseline collaborative filtering recommendations and the recommendations obtained from our proposed engine. In order to highlight the extent to which reliability can improve recommendations, we will compares results of both cases with and without reliability of co-citers, co-authors and co-affiliated.

In order to demonstrate the significance of our approach for the task of academic venue recommendation, we compute a measure of quality widely used, namely precision. Indeed, on the basis of research's field code, the precision is defined as the number of true positives TP (i.e., positive recommendations, which we correctly recommend, obtained by the mixed hybrid recommender) divided by the total number of venues labeled as belonging to the positive class (i.e., the sum of true positive TP and false positive FP). It is equal to TP/(TP+FP).

Fig. 4 compares precision of the three methods. We found that considering co-citers, co-authors and co-affiliated improves recommendations given by the baseline method by 15%. By incorporating reliability into the recommendation process, we obtain more accurate results. In fact, there is an improvement of 40% compared to the baseline collaborative filtering method.

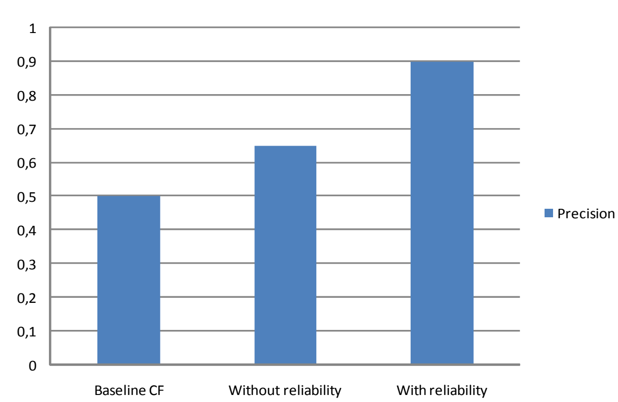

Fig. 4. Effectiveness of our approach

To demonstrate the usefulness of the refinement process, we investigate judgments about the final recommendation results. In fact, a group of 10 young researchers from the Larodec laboratory at the university of Tunis in Tunisia were asked to define their requirements about upcoming venue's location, ranking and/or publisher and then to express their satisfaction regarding recommendation results (i.e., satisfied, moderately satisfied or unsatisfied) in two periods of the year (i.e., June and August). As shown in Fig. 5, most of researchers were satisfied with provided recommendations, especially in June, in which the number of call of papers is greater.

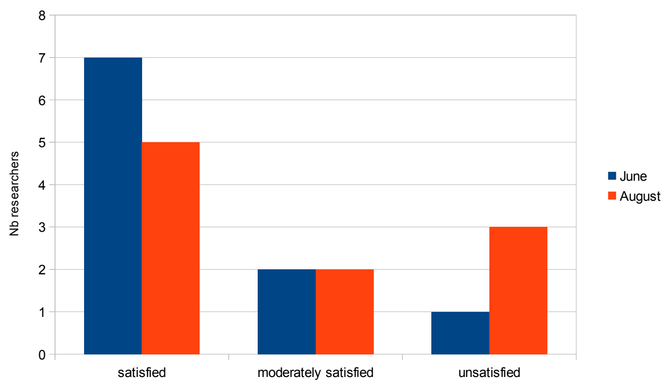

Fig. 5. Researchers' satisfaction

V. CONCLUSION

In this paper, we presented a recommender framework for the academic venue problem. Our proposed engine is based on historical bibliographic data augmented by citation relationships between papers. In fact, an hybrid recommender mixes the recommended venues of a new collaborative recommender relying on the reliability of co-citers and those of a community-based one considering the reliability of co-authors and co-affiliated. Through a personalized page, a target researcher can refine the list of recommended venues by selecting venue's location, publisher and/or ranking. The refinement process is handled by a cascade hybridization using a utility based recommender. Experimental results demonstrate the significance of our approach.

As future work, we plan to investigate how to deal with researchers who have changed their field of researches by integrating some dynamics in our framework. As DBLP data do not contains enough IEEE Xplore publications, we also intend to integrate other bibliographic data sources as in [22].

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