Demonstration

MINARET: A Recommendation Framework for Scientific Reviewers

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ABSTRACT

We are witnessing a continuous growth in the size of scientific communities and the number of scientific publications. This phenomenon requires a continuous effort for ensuring the quality of publications and a healthy scientific evaluation process. Peer reviewing is the de facto mechanism to assess the quality of scientific work. For journal editors, managing an efficient and effective manuscript peer review process is not a straightforward task. In particular, a main component in the journal editors' role is, for each submitted manuscript, to ensure selecting adequate reviewers who need to be: 1) *Matching* on their research interests with the topic of the submission, 2) *Fair* in their evaluation of the submission, i.e., no conflict of interest with the authors, 3) *Qualified* in terms of various aspects including scientific impact, previous review/authorship experience for the journal, quality of the reviews, etc. Thus, manually selecting and assessing the adequate reviewers is becoming tedious and time consuming task.

We demonstrate MINARET, a recommendation framework for selecting scientific reviewers. The framework facilitates the job of journal editors for conducting an efficient and effective scientific review process. The framework exploits the valuable information available on the modern scholarly Websites (e.g., Google Scholar, ACM DL, DBLP, Publons) for identifying candidate reviewers relevant to the topic of the manuscript, filtering them (e.g. excluding those with potential conflict of interest), and ranking them based on several metrics configured by the editor (user). The framework extracts the required information for the recommendation process from the online resources *on-the-fly* which ensures the output recommendations to be dynamic and based on up-to-date information.

1 INTRODUCTION

The world is witnessing a continuous growth in the size of scientific communities and the number of scientific publications. With the current rates, it is expected that the global scientific output doubles every nine years[1]. For example, Figure 1 shows the statistics of the popular DBLP indexing services for computer science publications[2]. In particular, the DBLP library is currently indexing over 3.8M publications. Out of these publications, the number of journal articles published in 2018 is about 120K articles. In 2017, Elsevier journals received 3919 submissions, out of which 530 were accepted with acceptance rate of 14%[3]. This situation raises a crucial need for continuous efforts to ensure and improve the quality of the scientific publication process.

In general, peer reviewing is a widely accepted practice to assess the quality of scientific publications [5, 9]. In this process, the *selection* of appropriate reviewers for evaluating the submitted manuscript is a significant step. For example, selecting reviewers without adequate knowledge in the topic of the submissions or selecting inexperienced reviewers would lead to poor reviews that harm the quality of the publishing venue, the scientific community, and the authors of the manuscript [3]. In addition, it is crucial to avoid any reviewers with potential conflict of interest [10]. In practice, assigning reviewers for a conference submission is less challenging than assigning a reviewer for a journal submission. In particular, the universe of reviewers is *closed* where it is limited to the program committee (PC) members who are commonly selected based on their experience and reputation in the scientific field of the conference. In addition, accepting the membership for the PC of a scientific conference indicates explicit commitment for the assigned review workload of the conference within the defined review deadline. Moreover, conference management systems provide a bidding process where each PC member should select the submissions that he/she would like to review. Thus, with this setup and conditions, it is possible to automate the paper-reviewer assignment task [2, 3, 8].

The manuscript review process for a journal submission is different. In particular, the universe of reviewers is *open* with various aspects of *uncertainty*. Thus, it depends much on the editor's experience, effort and professional network to select the adequate reviewers for a submitted manuscript. For example, there is no pre-defined agreement or arrangement between the journal and a set of committed reviewers. In particular, the manuscript review is a totally voluntary work with the only incentive of having a mutual benefit when the volunteering reviewer is an author of another manuscript submission that needs to be reviewed in the same or other journals. In addition, reviews' deadlines are soft constraints that are not obligatory for the reviewer. Thus, in order to achieve efficient and effective review process, it is the role of the editor to choose the reviewers that should at least cover the following main criteria: 1) Have matching research interests with the topic of the submitted manuscript, 2) Fair in their evaluation of the manuscript with no potential conflict of interest, 3) Have a good rank according to the editor's preferences in various criteria [4]. In practice, the first point can be managed by the editors' experience with the scholars of the scientific community of the journal and by browsing the profiles for candidate

[1] http://blogs.nature.com/news/2014/05/global-scientific-output-doubles-every-nine-years.html
[2] source: https://dblp.uni-trier.de/statistics/newrecordsperyear
[3] source:https://journalinsights.elsevier.com/journals/0142-9612/acceptance_rate

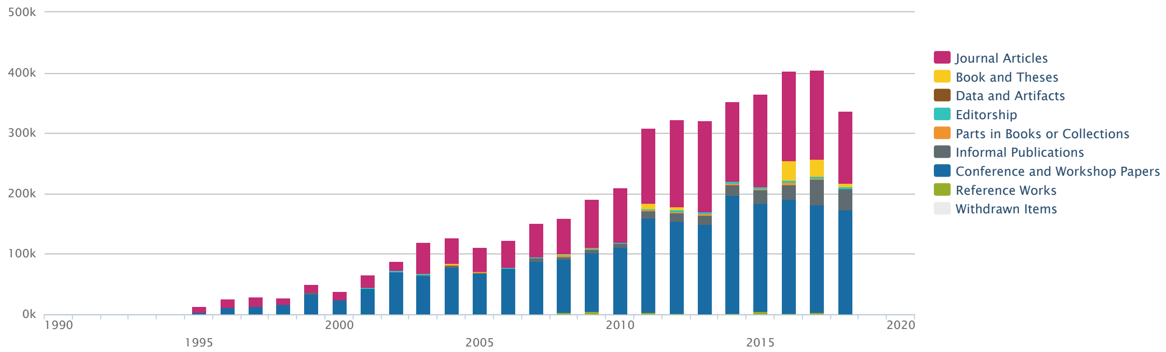

Figure 1: Statistics of DBLP library content

reviewers. However, the second point would require investigating the track record for both the authors and reviewers for discovering any potential for conflict of interest (e.g., co-authorship, having current/previous similar affiliations, ..., etc). Manually exploring and investigating this information would be a tedious and time-consuming task for the editors. The third point involves various aspects that need to be considered. For example, inviting a high-profile reviewer who happens to be quite busy will do nothing but delaying the review process as she might not reply to the invitation in a timely manner, simply reject it or accepting the invite and sending the review very late. Such selections may increase the turnaround time for making the decision on the submitted manuscript. Another aspect that can be considered is the history of review activities of the candidate reviewers and the quality of their reviews. Thus, it is crucially required that the reviewer selection process strikes a balance between these criteria and aspects.

Recently, we have been witnessing a continuous increase in the number of Websites and services that provide comprehensive scholary information. For example, `DBLP` provides the list of publications for a given author, `Google scholar` provides information about important metrics for the scientific impact (e.g., citation count, H-index, i10-index), `Publons`[4] provides information about the reviewing activities that have been conducted by a scholar. In this demonstration, we present `MINARET`, a recommendation framework for choosing scientific reviewers of a given manuscript information. The framework facilitates the job of journal editors for conducting an efficient and effective scientific review process by dynamically exploiting and integrating the available information on scholarly Websites *on-the-fly*. Within the search process, keywords representing the submission are semantically expanded to provide a wider range of related reviewers as candidates. Extracted information about the candidate reviewers are used to automatically exclude those with potential conflict of interests with the authors of the manuscript. Finally, the list of reviewers is ranked based on various criteria including the experience of the reviewer, recency of his familiarity with the topic of the submission, likelihood to accept and timely return his review, h-index, etc. The weight of these criteria is flexible to be configured by the users of the framework (editors).

[4]https://publons.com/

2 REVIEWER RECOMMENDATION

Figure 2 shows the workflow of our recommendation framework. Using the basic information of the submitted manuscript (e.g., keywords, authors list and their current affiliation), the recommendation workflow goes through three main phases: *information extraction*, *filtration*, and *ranking* of the candidate reviewer list.

2.1 Information Extraction

The information extraction phase consists of the following main steps:

- *Verification of authors' identities*: This step is concerned with the disambiguation of authors' names [1, 6, 7]. For example, in the far east, many scholars may share one of the popular names[5]. The identification of the correct author profile is crucial as it influences the accuracy of the collected information. We use various services (e.g., DBLP, Google Scholar, ACM) to gather the information about the author list. In case of multiple matches, the user has to manually identify the correct profiles for the author list among the returned matches.
- *Extracting the track records of the author list*: This step focuses on extracting information about the publications list and affiliation history of the author list using multiple services (e.g., DBLP, Google Scholar, ACM, Publons). Extracting the authors' track record is particulary important to allow discovering any potential for conflict of interest.
- *Retrieval of candidate reviewers' profiles*: The main driver for candidate reviewers search is the list of keywords supplied as part of the manuscript details. Usually, this list contains three to five keywords defined by the authors to describe the research topic of their submission. To widen the search space of candidate reviwers, we employ a semantic keyword expansion. For this purpose, as our demonstration is focusing on the computer science community, we rely on an ontology of computer science topics[6]. Each relevant expanded keyword is assigned a similarity score $sc \in [0, 1]$ that defines the relevance between the returned keyword from the ontology and the original keyword. For example, if one of the manuscript's keywords is "RDF", the expansion module

[5]https://dblp.uni-trier.de/pers/hd/z/Zhou:Lei
[6]https://cso.kmi.open.ac.uk/downloads

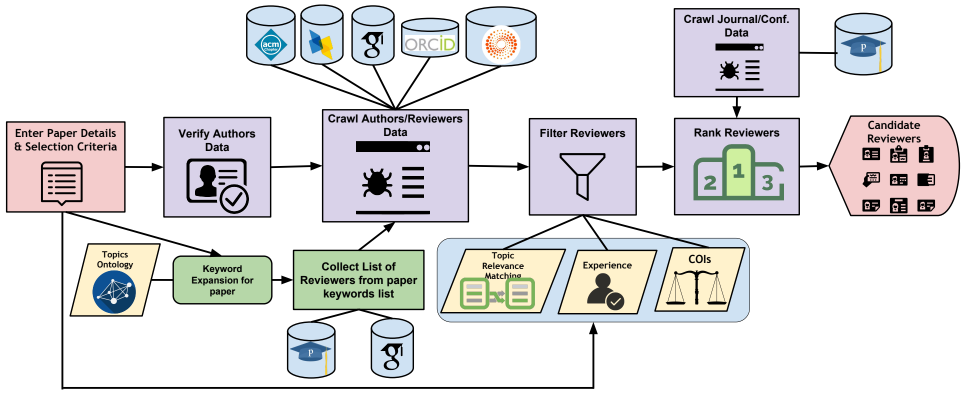

Figure 2: `MINARET` workflow

would return “Semantic Web”, “Linked Open Data”, and “SPARQL” as semantically related keywords among its results. Using the expanded keywords list, we retrieve the scholars who are registering these keywords as research interests by querying multiple services (e.g., Google Scholar and Publons).

`MINARET` is currently implemented to extract the information from six main sources: `Google Scholar`, `DBLP`, `Publons`, `ACM DL`, `ORCID` and `ResearcherID`. However, the framework is flexibly designed to include any further information from any additional scholary resource.

2.2 Filtering

In this phase, the list of candidate reviewers which is returned from the expanded keyword-based reviewer search gets filtered using the following conditions:

- *Conflict of interest*: COI is determined by checking the extracted profile information for both of the author list and candidate reviewers and based on the existence of a previous co-authorship between the candidate reviewer and one of author list or the existence of any shared affiliations on the level of the university or country, as configured by the editor.
- *Keyword matching score*: The editor can specify a threshold on the similarity score between the expanded keywords and those attached to the reviewers' profiles. Candidate reviewers with matching score below the defined threshold are filtered out.
- *A set of expertise constraints defined by the editor*: The user/editor can specify filtering out some of the candidate reviewers based on various user-defined filtering criteria (e.g., the range of number of citations / H-index, the number of previous review activities)

2.3 Ranking

The last phase of our workflow is ranking the candidate reviewers. `MINARET` ranks the list of reviewers by means of a score which is computed as a weighted sum that fuses the following components:

- *Topic coverage*: Represents the reviewer's coverage score for the keywords of the submitted manuscripts. For example, if the paper keywords were “Semantic Web” and “Big Data” and we have two recommended reviewers with fields of interest as “Semantic Web, Ontologies, RDF”and “Semantic Web, Big Data”, respectively. `MINARET` gives the second reviewer a higher rank than the first, because the second reviewer covers more topics/keywords of the paper and therefore is more related to the paper.
- *Scientific impact*: This component is based on the number of citations/H-index of the reviewer, as configured by the user. Clearly, the higher the number of citations/H-index, the higher the rank.
- *Recency*: Reviewers who have recently authored papers in the topic of the reviewed manuscript are ranked higher than others with less recent publications in the topic [5].
- *Experience with manuscript reviewing*: This component is based on the total number of manuscript reviews that is previously conducted by the candidate reviewer. This information is obtained from the `Publons` profile of the candidate reviewer.
- *Familiarity/Activity with the target outlet*: The reviewer's familiarity score is calculated based on two sub-components. The first is the number of previous reviewers that are conducted by the candidate reviewer for the target outlet. The second subcomponent is how many times this reviewer has published papers in this journal.

`MINARET` allows the user to configure the weights of the different components for computing the final ranking score for the candidate reviewers.

3 DEMO SCENARIO

`MINARET` is available both as a Web application[7] as well as RESTful APIs[8]. In this demonstration[9], we will present to the audience the workflow and the phases of the `MINARET` framewrok (Figure 2). We start by introducing to the audience the challenges we tackle, the main goal and the functionalities of our framework. Then, we take the audience through the reviewers recommendation process for sample manuscripts. We start by completing the manuscript details form (Figure 3) with the basic information including authors' names,

[7] https://bigdata.cs.ut.ee/minaret/

[8] The source code of the `MINARET` framework is available on https://github.com/DataSystemsGroupUT/Minaret

[9] A demonstration screencast is available on https://www.youtube.com/watch?time_continue=7&v=rNHTqdY6GuI

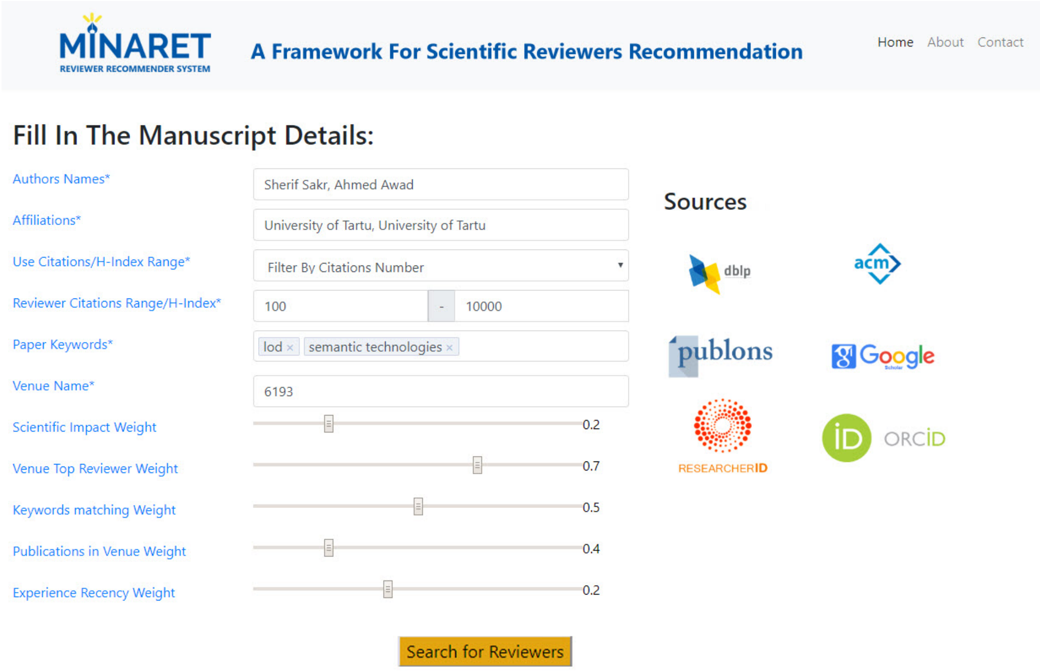

Figure 3: Screenshot of adding paper details page

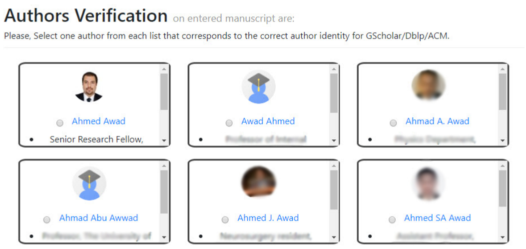

Figure 4: Verification of authors identities

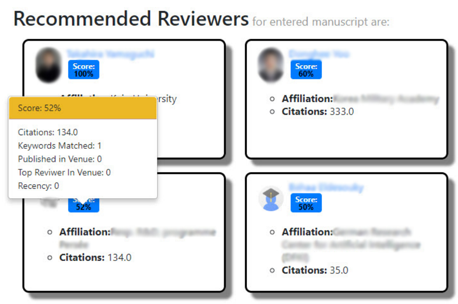

Figure 5: Example recommended reviewers

authors' current affiliations, submission topics/keywords, target journal in addition to any user-defined filters for the target reviewers (e.g, citation range, H-index range). Next, we will show how `MINARET`checks and verifies authors names (Figure 4). After this, we will show how `MINARET` queries the different scholary sites for extracting the required information (Section 2) for candidate reviewers. Next, we will continue with the stage of reviewers' filtration and ranking till returning the final results (Figure 5) where the computed score of each reviewer is shown. By clicking on the total score, score details for each ranking component will be displayed.

While `MINARET` is designed for tackling the more challenging case of recommending reviewer for journal submissions. It can be also integrated with conference management systems to automate the paper-reviewer assignment. In that case, the list of programme committee members can be used as a further filter. Thus, only candidate reviewers who belong to the programme committee are retained.

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