Rec4LRW – Scientific Paper Recommender System for Literature Review and Writing

Aravind SESAGIRI RAAMKUMAR[1], Schubert FOO and Natalie PANG
Wee Kim Wee School of Communication and Information,
Nanyang Technological University, Singapore
{aravind002, sfoo, nlspang}@ntu.edu.sg

Abstract. In this paper, we introduce Rec4LRW, a recommender system (RS) for assisting researchers in finding research papers for their literature review and writing purposes. This system focuses on three researcher tasks – (1) Building a reading list of research papers, (2) Finding similar papers based on a set of papers, and (3) Shortlisting papers from the final reading list for inclusion in manuscript based on article type. A set of intermediate criteria are proposed to capture the relations between a research paper and its bibliography. The recommendation techniques for the three tasks in Rec4LRW are specifically devised on top of the intermediate criteria. The Rec4LRW workflow along with the screen designs for the three tasks is provided in this paper. The recommendation techniques in the system will be evaluated with state-of-the-art approaches along with user-based evaluation in subsequent studies.

Keywords. Scientific Paper Recommender Systems, Research Paper Recommender Systems, Recommender Systems

Introduction

Recommender Systems (RS) extend traditional Information Retrieval (IR) systems by providing the capability to include contextual dimensions other than the search keywords, for retrieving relevant resources [1]. Digital footprints of the users can be sufficiently exploited through RS to predict user preferences for unused resources in the system. These characteristics of RS assist the users in effectively finding the required resources in both direct and serendipitous ways. RS have been used for academic use-cases such as identifying conference reviewers [2] and topical experts [3], identifying potential co-authors for a paper [4], recommending similar research papers [5] and reading list of papers [6], to name a few.

Researchers perform a series of search tasks during literature review for collecting research papers [7]. Prior RS studies have mainly pursued an algorithmic approach by directly applying computational techniques for the different search tasks. Basic versions of Collaborative Filtering (CF) and Content-based (CB) recommendation algorithms along with hybrid variations involving techniques such as topic models [8], language models [9], and citation graphs [10] have been used to formulate recommendations. Previous approaches provide relevant resources to the users for the

[1] Corresponding Author.

corresponding researcher tasks, albeit the diversity of the techniques makes it a difficult proposition for replication. Each technique needs to be separately implemented along with the different set of data items for the recommendation formulation process. This scenario creates the need for an intermediate structure for connecting the researchers' search tasks to the RS algorithms. The second drawback of existing approaches is the lack of interconnection between the recommendation formulation processes for literature review search tasks performed in a sequence. Such serial tasks typically include (1) building an initial reading list of research papers, (2) finding topically similar papers, (3) finding relevant citations for specific placeholders in the manuscript and (4) shortlisting papers from reading list for inclusion in manuscript. The researchers' selection of research papers evolves through these tasks in a natural setting. Therefore, RS should be designed with task interconnectivity as a prerequisite during the recommendations formulation process.

An unexplored area in this research area is the use of 'Article Type' as one of the contextual dimensions for formulating recommendations. Article type ranges from journal survey/review papers, journal case studies to conference long papers and short papers. The quantity and nature of literature cited in these article types vary accordingly. RS can be used to provide recommendations based on article type preference of the user during the manuscript writing stage.

In this paper, we address the two aforementioned drawbacks and the article type-based recommendation scenario with a system called as Rec4LRW. This system is currently being developed to provide recommendations for three key researcher tasks: (1) Building a reading list of research papers, (2) Finding similar papers based on a seed set of papers and (3) Shortlisting papers from the final reading list for inclusion in manuscript based on article type. The contributions of this system can be summarized as follows:

- The recommendations formulation in Rec4LRW is based on seven proposed criteria that can be used across different researcher tasks, thereby simplifying the implementation process.
- The recommendation techniques proposed in this paper for the three tasks are hybrid novel combinations of traditional RS algorithms and criteria-based information filtering.
- The third task in Rec4LRW is a novel task in RS studies. It provides recommendations as per the article type selected by the users.

The organization of this paper is as follows: Related works are discussed in section 1. The researcher tasks addressed in Rec4LRW are introduced in section 2. In sections 3 and 4, the recommender criteria along with the recommendation techniques are proposed. The workflow and screen designs of Rec4LRW are presented in section 5. The concluding remarks and future works are presented in section 6.

1. Related Work

One of the earliest RS studies on researcher tasks, McNee et al. [11, 12] introduced a theoretical model referred to as the Human Recommender Interaction (HRI) comprising of multiple aspects based on three pillars: Recommendation Dialogue, Recommender Personality and End User's Information Seeking Tasks. HRI establishes interaction mechanisms between user, tasks and RS. Experience levels of users and facets of seven researcher tasks are linked to RS metrics through aspects. For instance, a task 'Find Starting Point for Research' is subjectively associated with the aspects Correctness, Transparency, Quantity, Usefulness, Usability, Boldness, Affirmation, Pigeonholing and Trust which are then mapped to corresponding RS metrics such as Coverage, Intra-list Similarity and Ratability. The RS techniques applicable for the tasks are subsequently selected based on a performance benchmark with the RS metrics. Evaluation results showed that User-based Collaborative Filtering (UBCF) provided authoritative recommendations for most tasks. The HRI approach is mainly aimed at mapping the bouquet of RS algorithms to the tasks through RS metrics and it does not use the characteristics of the tasks for filtering purpose.

Majority of RS studies have concentrated on specific researcher tasks. Ekstrand et al. [6] used combinations of CF, CB and Hybrid recommenders for building reading lists for researchers who are venturing into new research areas. CF recommender reinforced with graph ranking algorithms, consistently outperformed CB recommenders in both offline and user evaluations. Recent studies have used Latent Dirichlet Allocation (LDA) [8] and hybrid approaches based on multiple similarity measures [13] for building reading lists. Studies related to the important researcher task of finding similar papers based on a seed set of papers, have employed metadata-based similarity [14] and citation-based similarity [5] approaches to identify relevant papers, making use of data items such as title, abstract, keywords, bibliographic references and citation web.

Among the RS studies based on multiple criteria, Matsatsinis et al. [15] used research paper metadata as criteria for an algorithm inspired by decision-making theory. The algorithm balances the criteria values based on user feedback. However, it cannot be used for all researcher tasks. Naak et al. [16] put forth multi-criteria CF techniques for recommending papers based on user ratings in a tool called as Papyres. The techniques' scope is limited as explicit user ratings for research papers are required.

There has been few online stand-alone citation RS put forth in previous studies. RefSeer is a citation RS built on top of CiteSeer digital library data [17]. The system makes use of translation model, a probability distribution method to retrieve relevant citations for a chunk of text provided by the user. The recommendations are provided for two modes: context-based and topic-based. theadvisor is a recent online citation RS that recommends papers based on a seed set of papers [18]. The system makes use of direction-aware random walk to identify important papers in the citation networks. It is one of the few systems incorporating relevance feedback from users. Docear is a reference management tool with an inbuilt recommendation module [19]. The tool provides an innovative mind-map feature for arranging papers. Data from the user's mind-maps are used for generating a user model. A Content-based RS (CB) generates recommendations based on the user model.

The current systems are tailored for specific tasks and the corresponding recommendation techniques make use of different data items that are specific to the data available as part of the systems. This creates a need for research in identifying an intermediate set of criteria for connecting researcher tasks and RS algorithms so that recommendation techniques can be subsequently devised in an environment where all the tasks are interconnected. With Rec4LRW, we address the aforementioned drawbacks with a multi-criteria based recommendation approach. The key characteristics of the research papers and their bibliographies are captured with a set of criteria. These criteria values are subsequently used to formulate recommendations as per the requirements of the researcher tasks. The recommendation techniques employ CB and CF recommender algorithms along with the criteria values based information filtering, to generate recommendations in Rec4LRW.

2. Researcher Tasks addressed in Rec4LRW

The three researcher tasks considered for Rec4LRW are (1) Building a reading list of research papers, (2) Finding similar papers based on a set of papers, and (3) Shortlisting papers from the final reading list for inclusion in manuscript based on article type. The first and second tasks are performed during the searching and reading stages of the literature review [20] while the third task is performed when the researcher intends to publish the results of his/her research study. The three tasks are inter-related as the reading list prepared at the end of the first task becomes the input to the second and third task. The reading list from the first task gets enhanced in the second task after which it gets refined in the third task as only the most relevant and appropriate papers from the final reading list need to be cited in the manuscript. The pictorial representation is provided in Figure 1. Therefore, the research papers from the reading list are the links connecting the three tasks. The research papers are the entities based on which recommendations are to be formulated. Thereby, the tasks in Rec4LRW are interconnected in order to address the connectivity issue in previous studies.

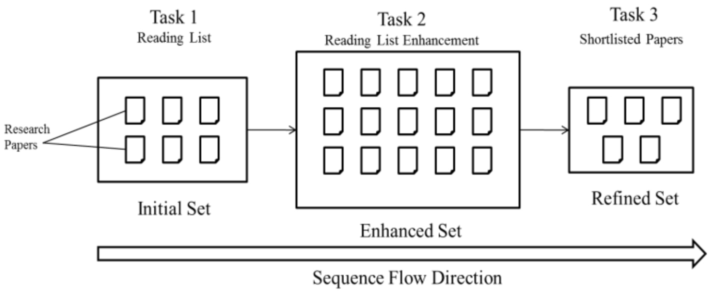

Figure 1. Pictorial representation of the evolution of reading list in the three tasks

3. Recommender Criteria and Techniques for Rec4LRW

The criteria used for filtering and ranking resources along with the recommendation techniques for the three tasks are described in this section. A snapshot of the ACM Digital Library (ACM DL) is used as the base dataset for Rec4LRW. Research papers from conference proceedings and journals for the period 1951 to 2011 form the dataset. The papers from the dataset have been shortlisted based on full text availability in the dataset. The criteria values for all the shortlisted papers in the dataset are measured as a pre-processing step.

3.1. *Criteria for Recommendation Techniques*

One of the drawbacks of existing RS studies is the lack of an intermediate set of criteria for usage across recommendation algorithms for different tasks. Rec4LRW's recommendation mechanisms are based on seven criteria that represent the characteristics of the bibliography and its relationship with the research paper. The rationale for choosing bibliography is its ability in differentiating research papers. The bibliography section comprises of the references cited in the paper, indirectly representing the content of the paper. The high level characteristics of the bibliography are captured using three criteria: References Count, Grey Literature Percentage and Coverage. The next set of criteria is conceptualized for capturing the relations between the research paper and each reference in the bibliography. Three criteria: Recency, Textual Similarity and Specificity are identified for this purpose. An additional criterion Citation Count is included as it has been traditionally used for assessing a paper's popularity. Few of the proposed criteria are novel while others have been adopted from earlier studies Figure 2 provides an illustration on the sequence of activities employed for measuring the criteria values for the shortlisted papers in the ACM dataset.

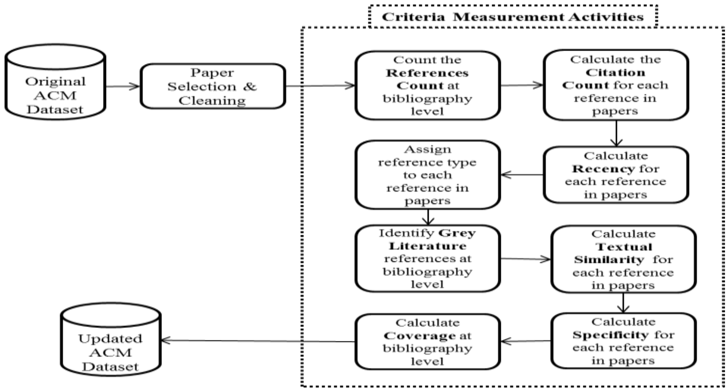

Figure 2. Sequence of activities in criteria measurement exercise for the shortlisted papers in ACM dataset

The definitions and measurement procedures of the criteria are described as follows.

3.1.1. References Count

The basic criterion References Count's value is not meant to be the same in the bibliographies of research papers even though certain publication houses restrict the number of references directly or through page restriction indirectly. This criterion is required to check for commonalities across different article types (e.g., journal review paper, conference short paper). Data from this criterion provides the potential for setting the number of the recommendations in the recommendations list provided to the user for the third task 'Shortlisting articles from reading list for inclusion in manuscript'. Usage of this criterion is novel in both citation analysis and RS studies.

3.1.2. Grey Literature Percentage (GL)

Researchers usually cite references from scientific sources. However, there are situations where non-scientific references such as technical reports and websites are also cited. These non-scientific references that are yet to be formally published are referred to as grey literature [21]. It can be claimed that journal articles tend to have more scientific references in comparison to conference papers. Articles other than conference papers, journal papers, PhD thesis and books are considered as grey literature in the current study. This novel criterion is intended to be used for the purpose of calculating the extent of inclusion of grey literature references in the bibliographies of papers. It will be used in situations where data from external sources could strengthen the recommendation list. The values calculation is performed after the identification of reference type for each reference in the bibliography of research papers in the ACM dataset.

3.1.3. Coverage (C)

The 'Related Work' section of a paper covers the important and relevant prior studies. The bibliography's ability in capturing the important references for the research topic(s) needs to be measured. This characteristic is referred to as Coverage. It is observed that review papers have higher coverage in comparison to other article types. Therefore, it is postulated that this novel coverage criterion will distinguish the different article types in a significant manner as it is a direct indicator of the spread of references in the bibliography. The measurement procedure is as follows: The full list of papers that have been published for the main topic (keywords) of the parent paper is identified as base nodes in a citation web in the first step. The citation web is built by connecting the references and citations of papers. Secondly, the lists of references cited in the parent paper are highlighted as key nodes in the citation web. The key nodes are compared with the base nodes and the number of matches indicates the Coverage value to be set for the parent paper. Coverage values are ordinal. Table 1 provides the proposed mapping between the match percentage and the corresponding Coverage value. The approach followed in [6, 12] for building the citation web will be employed.

Table 1. Proposed mapping between match percentage and coverage values

Match Percentage	Coverage Value
Above 80%	Very High
60%-80%	High
40%-60%	Medium
20-40%	Low
Below 20%	Very Low

3.1.4. Recency (RE)

The temporal aspect of bibliographic references is ignored in most studies, on the basis that it does not affect the citing behavior. Prior studies indicate that new publications take an average of two years to be cited [22]. Therefore, the temporal data is required for recommending recent papers. Recency refers to the characteristic that shows how recent the referenced papers are in the bibliographies of the papers. It is calculated by finding difference in years between the publication date of the parent paper and references in the bibliography. A similar criterion has been used in an earlier study [23]. Values are calculated by subtracting the publication date of the parent paper and the reference, at the year level.

3.1.5. Textual Similarity (TS)

Researchers find relevant papers for their literature review by searching with appropriate keywords in academic databases and search engines. The search keywords are topically related to their search requirement and information need. It is observed that the title of the paper is textually related to the title of the references in most occasions. Therefore, it is imperative to calculate the similarity between the parent paper and references in the bibliography. Textual Similarity is the criterion for calculating the keyword-based similarity of the title section between the parent paper and the references of the bibliography. A similar criterion has been used in [23]. Cosine similarity is the traditional similarity measure used in IR systems. The measure suffers in situations where the textual content is minimal. Therefore, there is a requirement to use hybrid similarity measurement techniques that make use of semantics. One such technique is available in the API [2] provided by UMBC research team. This API calculates textual similarity using a unique hybrid method that combines statistical and semantic methods. This hybrid method is described in [24] and it provides better results than the basic methods such as the Vector Space models and Machine Learning models.

3.1.6. Specificity (S)

The previous criterion Textual Similarity measures the similarity using the text from the title and references. It leads to an apparent gap as certain references are related to the parent paper even though the title may contain dissimilar keywords. A novel criterion called as Specificity is introduced to address this issue. It refers to the nature of the references in being very specific or otherwise to the topic(s) of the parent paper. The broad/narrow relation in a thesaurus is an apt analogy for the different levels of specificity [25]. The measurement makes use of the keywords specified by the author(s). It is postulated that there is a possibility of finding correlation between the values of Textual Similarity and Specificity. The theoretical idea behind the calculation of specificity is the comparison of keywords from the parent paper and reference papers using taxonomy of concepts, similar to that of the ACM taxonomy. This approach is analogous to the similarity calculation used in taxonomies [26]. The proposed approach starts with extraction of author specified keywords from the parent paper followed by the extraction of keywords from the reference papers. The keywords from the parent paper are set at the appropriate nodes in the taxonomy and the keywords from the references are later placed in the taxonomy so that their distance from the keywords of parent paper can be measured. If the keywords from the references are at the same level as the base paper keywords, the references are highly specific and if they are at the different levels (both lower and higher), then the specificity is at the lower end. The criterion has five possible values (Very Low, Low, Medium, High and Very High) for this criterion.

3.1.7. Citation Count (CC)

A common behavior among researchers is to cite popular references since they are widely accepted in the research community. There is a proclivity in citing references based on its citation count. This behavior is common while writing journal papers when compared to conference papers where the most recent works are cited even though they

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[2] UMBC Semantic Similarity http://swoogle.umbc.edu/SimService/index.html

may not have high citation counts. The criterion 'Citation Count' is intended to identify the extent to which citation count of references is given importance. This criterion has been used in [15]. The values are calculated by counting the number of times, the reference paper is cited by other papers in the dataset.

4. Recommendation Techniques for the Three Tasks

The seven criteria introduced in the previous subsection, provide flexibility for usage across the recommendation techniques for the three tasks. The proposed techniques combine traditional RS algorithms along with the criteria for both information filter-ing and resource ranking. The recommendation techniques for the three tasks are described as follows:

4.1.1. Task 1 – Building an initial reading list of research papers

The recommendation technique process flow for this task is displayed in Figure 3. This task has two inputs – search keywords and an optional set of seed papers. These seed papers are papers read by the researcher and they serve as a starting point for building a reading list. Key terms are extracted from the title and keywords metadata fields of the seed papers using the machine learning approach employed in [27] as it has been recognized as the best method for automatic key term extraction. These key terms are passed on to the Content-based (CB) recommender. The CB recommender retrieves the initial set of potential papers. The number of papers to be retrieved is tentatively set as 50. The BM25 retrieval method [28] employed in [6] is used for retrieving the initial set of papers 'R' as it is a probabilistic model that offers better performance than other retrieval models [29]. The next step is the ranking of these articles so that top 20 papers can be shortlisted. The number of recommendations is set as 20 for evaluation purposes. The ranking is performed primarily using the criterion Coverage (C) since it gives an indication of the level of coverage of papers in that particular research topic (e.g., literature review/survey papers will have high coverage value). The initial reading list forms the user profile of the current user and will be used as a reference for the subsequent two tasks.

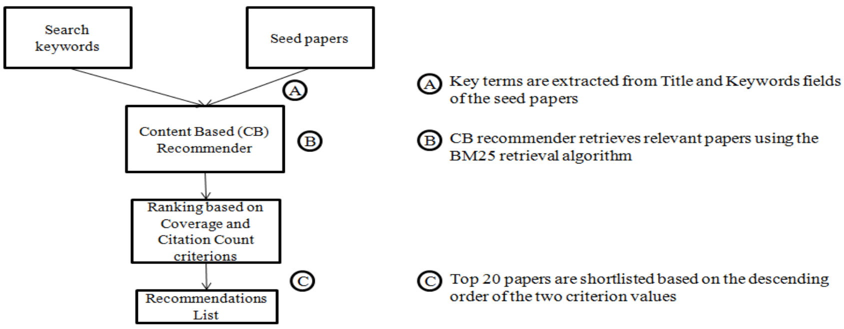

Figure 3. Task 1 recommendation technique process flow

4.1.2. *Task 2 – Finding similar papers based on set of papers*

The process flow of the recommendation technique for this task is displayed in Figure 4. The input is a subset of papers from the initial reading list, chosen by the user. The objective of this task is to identify similar papers from both the citation network of seed papers and find topically similar papers based on content similarity. The criterions Textual Similarity (TS) and Specificity (S) are used for finding relevant papers along with a CB recommender. There are two paths in this technique. In the first path, the initial step is the extraction of key terms from the titles and author specified keywords of the papers in the input basket. The key terms are passed on to a CB recommender to find topically similar papers. In the second path, the initial step is to retrieve the papers that are cited by the seed papers and the papers that cite the seed papers. For these new set of papers, the pre-computed values for the Textual Similarity and Specificity criterions are retrieved from the database. The weighted hybrid recommender method [30] is used for merging the outputs of two paths. Papers from both paths are merged in this step. The papers that are already present in the user's initial reading list are excluded. Top 20 papers from the final list are recommended to the users.

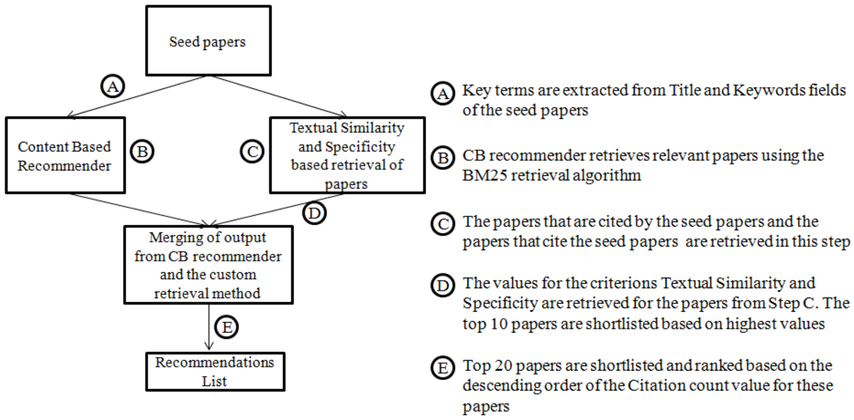

Figure 4. Task 2 recommendation technique process flow

4.1.3. *Task 3 – Shortlisting articles from reading list for inclusion in manuscript*

The process flow of the recommendation technique is displayed in Figure 5.The final reading list of papers collected by the researcher during the LR is input as set R. There are two other inputs provided by the user for this task: Article Type and the Prospective Keywords (PK) that the user plans to add to the manuscript. The criterions used for the shortlisting process are References Count (RC), Coverage (C) and Citation Count (CC). The threshold values for the criterions References Count and Coverage are retrieved for the Article Type preference (e.g., the Coverage value for the article type Literature Review will probably be High). In the next step, the CF matrices are populated with papers from set R along with corresponding co-references for IBCF (Item-based Collaborative Filtering) and co-citations for UBCF (User-based Collaborative Filtering). The variant of IBCF algorithm put forth in [12] is used to identify clusters of co-references. IBCF algorithm simulates the mechanism process of Bibliographic Coupling [31]. Representative papers from each of these clusters are shortlisted based on Coverage criterion value. Papers with the highest Citation Counts are selected from each cluster and added to the final list. Similarly, UBCF is used to identify clusters of co-citations, after which representative papers are selected from each cluster based on higher number of co-citations. The outputs from the CF matrices are merged into the final list. The final list is sorted based on descending order of the Textual Similarity value dynamically calculated between the user specified prospective keywords (PK), title texts and keywords of the papers from the final list. This final list is generated and recommended to the users.

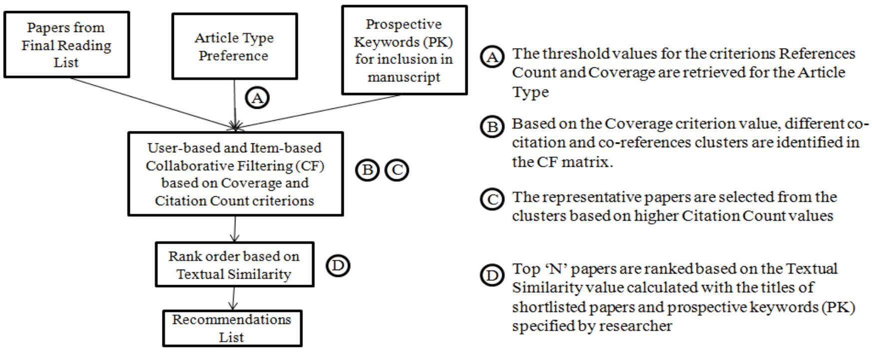

Figure 5. Task 3 recommendation technique process flow

5. Rec4LRW System Design

Rec4LRW is a system meant for usage across the process cycle of literature review and writing as researchers search for research papers at different stages and they tend to write papers intermittently during the entire process. Therefore, continuity is explicitly set between the three tasks in the system. The workflow diagram of Rec4LRW is illustrated in Figure 6. Tasks 1 and 2 are performed during the literature review stage. Task 1 is a one-time task performed at the start of the literature review while Task 2 is performed at different stages whenever the researcher is in need of more researcher papers. Task 3 is mostly performed after data collection and research completion. However, researchers also write papers midway to report ongoing results. The workflow diagram is meant to highlight the sequence of user activities within Rec4LRW.

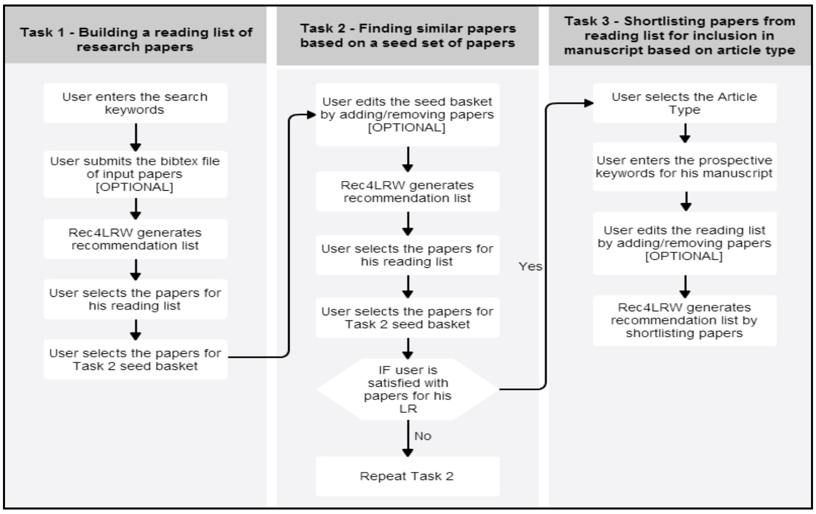

Figure 6. Rec4LRW tasks workflow

The mock screen designs for the three tasks are illustrated in Figure 7, Figure 8 and Figure 9 respectively. Each Rec4LRW user is provided with a unique id for identification purpose as the reading list needs to be tracked based on the id. During the user evaluation of the system, a questionnaire section will be added to the bottom of the screens so that users can conveniently answer the questions by observing the recommendation lists for each task. The recommendation lists generated by Rec4LRW are dynamic as the users are allowed to edit the seed basket bibtex file at any stage during the execution of the three tasks.

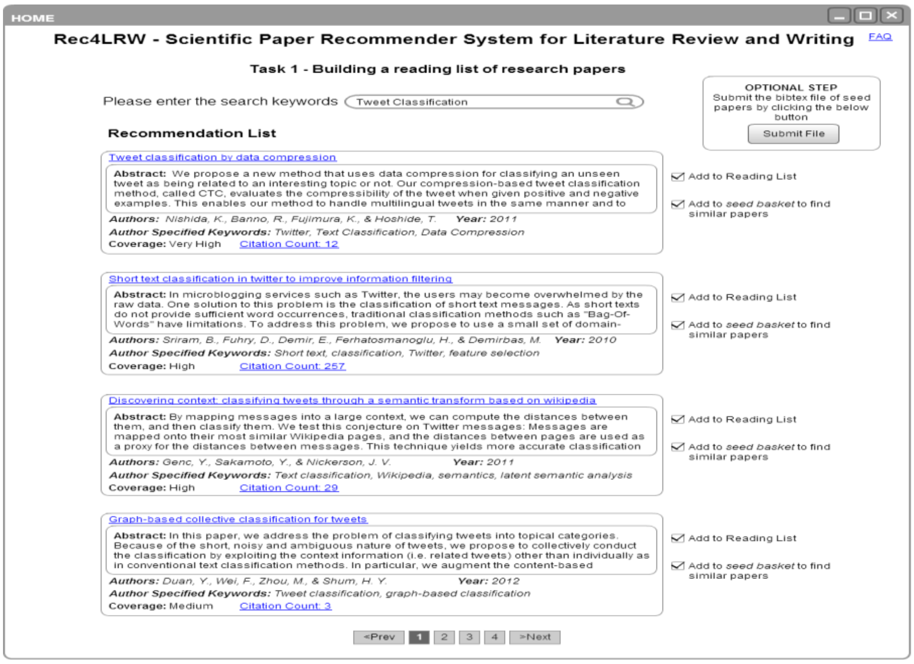

Figure 7. Rec4LRW task 1 screen

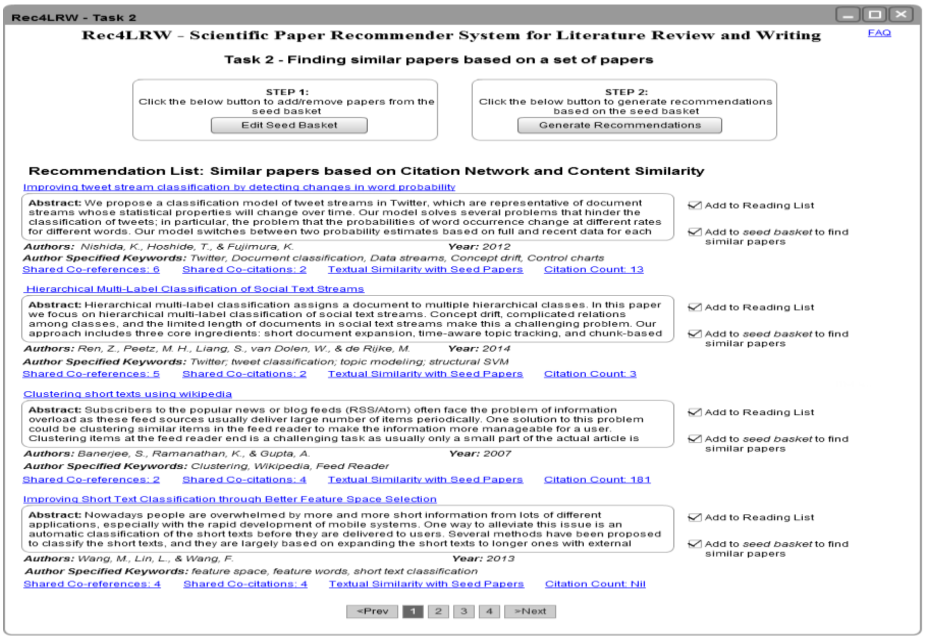

Figure 8. Rec4LRW task 2 screen

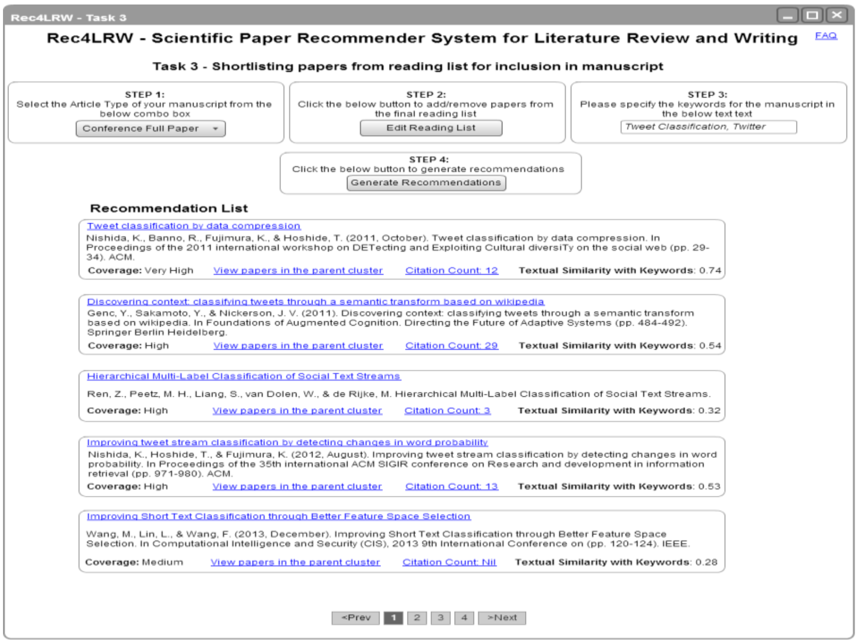

Figure 9. Rec4LRW task 3 screen

6. Conclusions

The application of RS algorithms in academic databases and digital libraries provides benefits for both researchers and system designers as more relevant resources are recommended to the end user, as according to the task in hand. Even though, prior scientific paper RS studies have put forth sophisticated techniques, the cost of replicating these approaches are high due to the different algorithms and corresponding sets of data items. Secondly, there is a lack of interconnection between the recommendation formulation techniques for tasks that are performed in a sequence. The proposed system Rec4LRW is specifically designed to address these drawbacks. The three tasks handled by the system, caters to the researchers' need for recommended research papers during literature review and writing stages. The recommendation techniques in Rec4LRW are based on an intermediate set of criteria that capture the characteristics of a scientific paper since it is the main entity used in recommendations. The seven criteria connect researchers' tasks and RS algorithms by capturing the characteristics of the bibliography and its relations with the parent paper. This approach provides high flexibility since future studies can pick and choose the criteria applicable for the recommender tasks. New criteria can also be appended to the set for addressing new recommender tasks. The third task in Rec4LRW is a novel task that shortlists papers from reading list for inclusion in manuscript based on article type. The system is currently under development with the values for the seven criteria being calculated for the shortlisted papers from the ACM dataset. As a part of future work, offline evaluations (comparison with previous studies) and user evaluations will be conducted to verify the effectiveness of Rec4LRW in performing better than state-of-the-art approaches and more importantly providing expected results in user evaluation.

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