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LITERATURE REVIEW FOR ACADEMIC RESEARCH RECOMMENDATION

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ABSTRACT

Recommender systems are now being used in many areas around the world. Recommender systems appears in every field, from movie, music recommendation to paper recommendation. The number of papers published is increasing day by day and it is increasingly difficult for researchers to find reliable sources that match what they are looking for. Researchers waste far too much time seeking for the right article. The goal of an academic research recommendation system is to save time and introduce them to articles that are related to what they are reading. It is a software tool and approaches that filter tailored information based on the user's preferences from a big volume of data to give suggestions based on the customer's taste in order to discover new relevant things for them. This literature review aims to find the best methodologies to create well-functioning recommendation platform for academic research.

Keywords: recommender system, paper recommendation, recommendation algorithms

1.INTRODUCTION

Nowadays, recommender systems are commonly utilized in ecommerce for the purpose of targeted advertising. They propose items that each user is likely to enjoy based on their profile, prior purchase history, and online activities. Amazon.com, for example, suggests comparable goods such as books, while Netflix suggests movies based on a user's preferences. The rapid development of information technology has led to a rapid increase within the volume of digital information. Researchers sharing their research with the aim of exchanging information on a digital platform can lead to information overload. Thus, information pollution also arises, making it difficult for users to be sure of the accuracy of the information. In academic research, recommender systems can provide researchers with accurate and relevant papers in no time.

2.PAPER RECOMMENDATION METHODS

The recommendation techniques can be divided into four main categories.

2.1 Content-Based Filtering (CBF)

Content-based filtering (CBF) attempts to recommend items to active users based on the similarity count of the users' past positive reviews. For instance, if users like web pages with the words "cast list", "trailer" and "scene", Content-based filtering will recommend pages related to the movies. Content-based filtering relies heavily on item descriptions and user orientation profiles. There are a lot of ways to building profile. First of all, a researcher's papers collected. For instance, using keywords that the user has already searched for, the user profile can be predictable. Content-based filtering algorithms try to recommend items based on similarity count. Recommend the most matching item by comparing various candidate items with items previously rated by the user. Also, the academic research recommendation systems take keywords from paper's title and parts of paper like abstract and content. It recommends an article from the database by matching the keyword of the user's profile and the keyword from the papers. [1]

Item Representation, Profile Learning, and Recommendation Generation are the three important processes of CBF.

Item Representation: To comprehend how items differ from one another, special attributes are required. These attributes are examined in two categories: Structured attribute and Unstructured attribute. Structured and Unstructured attribute difference is the value of attribute. For the structured attribute, the value of attribute is limited and specific but for the unstructured attribute, it is the opposite. As a result, unstructured attribute can't be utilized for analysis. There is an item representation method which name is TF-IDF model. TF-IDF model (term frequency inverse document frequency) is widely used method in the fields of information retrieval and text mining. DF returns a statistical result based on how often a keyword occurs in the text. This method is a useful way to present similar papers to the user. Also, there is a method which is for create a description of the content of the papers. This method is Key phrase (typically constituted by one to three words) Extraction Model. If the paper has not the keyword session, analysis system finds the most appropriate words from the paper. The key phrase list is a list that helps to understand the main idea, subject of the paper. In contrast to CBF, keyword-based search only focuses on the searched word and doesn't care about the user's other interests. Also, some researchers cannot choose their keywords correctly. Therefore, they cannot get efficient results. That's why it's important to personalize recommendation results. For the CBF, if researcher's interests change, recommendations are formed accordingly. Consequently, the importance of a profile cannot be overstated. [2][3][4]

Profile Learning: CBF recommender system builds a profile according to the interests and tastes of the researcher. So, it can determine whether this profile likes the new recommendation or not. Building user profiles may be done in a variety of ways. For example, the LDA method is used to create a profile based on the researcher's previous publications. The researcher profile is organized according to users newly publish papers. In order to make recommendation systems and user profiles more personal, researchers are divided into senior and junior researchers according to the number of papers they publish. All the profile learning methods mentioned are based on researchers' previous publications and activities. For example, the user's interests are discovered from the title or references section of the papers. The system can divide the abstract into two parts to suggest papers from two aspects and to make more specific suggestions to the user: problem description and solution description. In addition, there is another form to represent user profile. Docear arranges users' data in a tree before creating a user model from the user's mind map collection. [4][5][6][7][8]

Recommendation Generation: To display the most relevant papers to researchers, user profiles and representations of candidate papers have been constructed. A user profile is also builds for these random results. There are two recommendation lists: related papers and unrelated papers. The result list is sorted by the similarity of the user profile and the candidate paper. Sometimes, in order to have a broader perspective and gain new information, researchers can be presented with paper recommendations from more distant topics. There are some disadvantages in the CBF system. For example, it may not detect insufficient information in junior researchers' paper because it relies on the word analysis technique. Therefore, it cannot provide fully guaranteed information. [9]

2.2 Collaborative Filtering (CF)

CF, just like CBF, makes recommendations on the user's interests. So, it needs to know these interests. CF considers that if two different users are rating on the same common items, those users have similar interests. So, it can be recommended if one user saves something the other user does not. User opinions can be obtained through a survey. CF finds similar user by looking at rating history and uses neighborhood. Compared to the Content-Based Filtering method, CF has some advantages: evaluated based on user ratings, regardless of recommended paper content. Also, since only cross-user similarity is considered, recommendations may be independent of the user's current research. CF mainly contains the two categories of methods: **User-based approach:** Users are the main subject of the system. Similar users are found, and recommendations are made according to their common interests. **Item-based approach:** Relationships between papers are the main subject of the system. Recommendations are made according to the ratings made by the user, assuming that the interests of the user will not be variable. In the user-based filtering, candidate papers are found based on the past preferences of the neighboring user. In the item-based filtering, papers are found based on the user's past preferences. [10][11][12][13][14]

Although CF is a common method of recommendation, it does have certain drawbacks. The most evident flaw is the cold start problem. Papers that haven't been rated yet aren't recommended till they have Because new users with few ratings on any papers have an empty history, the algorithm will not be able to discover a neighborhood until they have enough ratings.

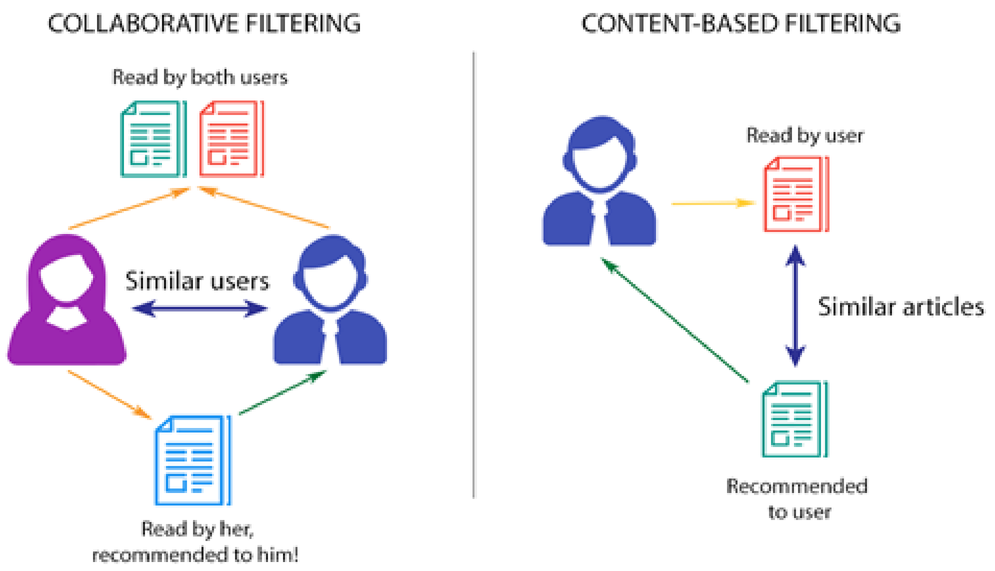

Figure 1: Collaborative Filtering and Content-Based Filtering [15]

2.3 Graph-Based Method (GB)

Graphs are made of nodes and edges; they can be made of several categories of data such as researchers and their social relationships and their papers which involves their citations and list goes on. Recommendation systems use algorithms to look over the graph to find useful data. Graph-Based Method uses more than one source of information to better its accuracy when other methods stick with one or two sources only.

Every graph starts showing its collected data in a mixed form consists of researchers and papers. For example, if certain researchers publish about the same topic and if every researcher and their papers are shown in a graph-based model, we can see a pattern that would be helpful for an algorithm. [16]

The progress of recommending based of GB recommender systems follow two processes which are Graph Construction and Recommendation Generation.

Graph Constructing uses digital information mostly nowadays because most researchers choose to publish and read papers for sharing precious data, with that data graphs can be made. Matrices can be made with knowledge of a researcher and his interest in a paper, with that confirmation papers' coauthors if there are any might publish similar papers with that probability accuracy of recommendation can be increased. [16][17]

Bi-Relational Graph (BG) is an alternative graph for RSs. BG includes subgraphs of paper similarities, researcher similarities and graph of researchers and papers conjoined together. [18]

Citation Graph (Network) consists of papers and their citation correlations among each other. If papers have mutual references or they use citation to point one another, they are considered alike and that's how RSs use structure of the network. Co-authors connections can be used as an asset to a Citation Graph, and it's called as citation-collaborative network which contains citations, collaborative and author, paper relationships. [19][20][21]

Graph based methods doesn't use the content of the paper and the profiles of researchers because their data is not appropriate for using as nodes.

Basic random walk algorithm can't be said as the best method because it jumps to another different vertex for traversing a graph and jumping randomly.[22] Random walk with restart method walks among the neighbor knowing where its base of movement is and that helps with ranking articles such as bipartite network. [16]

Random walk model can be used for cross-domain recommender systems. Such as recommending a certain user their friend candidates with the data of their social relations between each other. Random walk is used on the network of similar candidates. Cross-domain systems use all of these find relations between source domain and a certain domain. [23]

PaperRank is used for computing relations between papers in citation network, it's also used for evaluating papers which don't have anything in common. [24]

In the end Graph-Based method mostly makes use of correlation among nodes.

2.4 Hybrid Method (HM)

Using a few methods is proven to be better choice in couple of areas such as accuracy and performance. Different methods provide more analysis techniques. [25]

Combining Content-Based and Collaborative-Filtering resulted in a mixed bag of advantages and disadvantages for first-rater and sparsity issues. CB methods can be used to setting up the researchers' profiles then CF is used to finding out the potential citation papers. Building up a profile requires TF-IDF scheme and finding papers with the highest cosine similarities. Then CF comes into play, paper-citation matrix is used for calculating similarities and the most similar ones are called neighbors in the end. [26][27][28][29]

Other algorithms have risen from combining methods such as CBF Separated which is an algorithm based on CBF difference is it additionally recommends similar lists for its references, and it combines the previous list with the new one and presents only the combined one; CF-CBF Separated algorithm requires CF method to run first then CBF; CBF-CF Parallel algorithm makes use of both CF and CBF in parallel and it combines lists from both in a right order. These HM's are verified to be better than a single method running and other special methods exist and they are better as well, they are CF with latent factor, probabilistic topic, spreading activation etc. [30]

CF with latent factor works with other users' past interests then calculating similarity with targets' interests and this is mostly used for known papers. Spread activation method is used in CB and user-based CF to find targets similarities. EIHI algorithm is suitable for dynamic datasets such as modern world digital papers, this one can be personalized to guarantee quality of the content. [31][32]

CB and GB combination performs better than usual methods, CB digs the profiles of its users' interest, and the GB uses citations to find similar papers form the graph. CB with citation network can be used to show most related papers from digital datasets. [33]

2.5 Others

Long Short-Term Memory finds out a semantic representation of the papers after CBF is used.[34]

Comparisons of Common Techniques

CB Filtering has advantages such as: Every paper is individually handled for similarity; results are based on users' personal preferences.
Disadvantages: Word relevance quality is uncertain, new users cause problems.
CF has advantages such as: Results might be from by coincidence, quality is assured.
Disadvantages: Cold start problem, sparsity problem.
GB has advantages such as: Uses different sources.
Disadvantages: Doesn't use papers' content or users' interests.

Open Issues and Challenges

Cold Start

When a newly introduced paper or a user pops up in the algorithm, it can cause issues. New user means no back story to compliment the accuracy of algorithm. New papers disappear among popular ones. CB filtering analyses the papers' content so that solves the issue. [35]

Sparsity

It's a common misconception to assume users and the papers are in the same amount or the users are more than papers. The truth in the situation is that papers are a lot more than users and not every paper is rated for users by users. CF method takes a toll with sparsity, not enough sparsity, and similarity among users. [36]

Scalability

Scalability is for a system to work efficiently in an environment. CBF and CF uses static datasets, but datasets grow each moment so it's an issue. EIHI is a newly developed algorithm and its efficient with dynamic datasets. [32][37]

Privacy

Datasets require users' data and that involves personal information as well. That causes privacy concerned issues, so algorithms need to be developed without invading someone's privacy. [5][37][38]

Serendipity

This helps users to find papers with their interests such as younger researchers need to know more about their profession so meanwhile senior researchers need newer data. CF offers serendipity because it doesn't consider the contents but the neighbors while offering papers. [7]

Unified Scholarly Data Standard

There are different sources of academic data. Most of them have their own characters and causes issues.

All these issues with static datasets also have an impact on ever-expanding datasets. This situation is called incremental dataset problem. There are studies developed for this problem, such as the EIHI algorithm and the EIHI-based technique.

3.INCREMENTAL DATASET

The Efficient Incremental High-Utility Itemset Mining method (EIHI), which is designed to operate with dynamic datasets, was utilized. The EIHI algorithm is used in this proposed solution because it is compatible with dynamic datasets. The tree-based algorithm makes it easier to update the dataset than other algorithms. Academic literature is incremental. When it comes to the continuous update process, it becomes difficult to scan the entire article, so the EIHI algorithm does not rescan the previous dataset. [39]

3.1 Related Work

One of the bases of the research paper is makes recommendations based on the citation frequency of an article or the relevance of its content to the user. The method of using semantic data to improve the quality of the recommendation and using the concepts of co-authors and different users to encourage diversity was used. To boost the quality of suggestions even further, a research paper recommender system supporting diversity has been built, which makes recommendations based on the notions of co-authors and dissimilar users. To better respond to the user's personal searches, a recommendation system was created by considering the user's recent searches or interests. To create this system, the user's inputs, or the published article that the user needs can be used. [40][41]

3.2 Proposed Approach

The datasets are based on a two-stage algorithm that limits the efficient use of the incremental nature of the research report pool. To overcome this limitation, the dynamically assisted EIHI-based recommendation approach is preferred. EIHI is used to suggest the most appropriate result for user searches regardless of the increase in articles. The technique performs the overall recommendation process in two steps. 1) To select the publications that are suitable for the researcher's interest. 2) Suggest to researchers with extremely useful articles. They used EIHI to extract HURs to keep it running efficiently even as the amount of research publications in the repository increased (as EIHI can handle dynamic datasets). [42]

3.3 Working

The proposed approach works as a two-stage method:

Stage I. Finding papers that are relevant to the user based on their contents: [42]

The dataset is partitioned into 'k' clusters using the PLSA algorithm based on the word distributions of publications and their chances of fitting into a specific cluster in this phase. Each cluster is assigned a distinct subject implicitly and then based on their word distribution.

Following the formation of the clusters, the closeness of each cluster to the user's topic of interest is assessed using similarity metrics.

The PLSA algorithm determines which cluster of papers has the most affinity for the user's topic of interest. When a new paper is added to the repository, the algorithm is rerun to allocate the newly added papers to their corresponding clusters. Only the cluster with the highest relevance to the users' issue is given to the next phase.

Stage II. Identifying Reference-sets of high benefit to the user based on the user's customized requirements: [42][43]

We may use the date of publication, the publishing authority, and other factors to determine the value of a reference-set. EIHI is a HUIM technique that extracts the most suitable reference sets for user requirements.

The internal utility(i) of a reference can take values of 1 or 0, indicating whether the reference is referenced by a work. The researcher provides the external utility(e) depending on his preferences (which in the presented approach is publishing date). The utility of a reference (r) in any paper (P) is *u(r, P) = i*e*, where I and e are the internal and external utilities, and the utility of a reference-set (R) is the sum of the utilities of all the references in that set. Usually, all reference sets with minimal benefit are collected for inclusion in the recommendation list. The first 10 reference sets are selected and recommended to the user. In case more articles are added to the repository, the EIHI is applied again to the newly added articles. EIHI is capable to deal with dynamic datasets as one can discover new HURs only by judging newly added articles together pre-found HURs.

3.4 Dataset

Network ACL Anthology (a real-world dataset) collects research articles from many places and displays them in the form of a citation network.[41] Because of the consistency of the dataset's focus on computational linguistics, they had to execute the second step of mining HURs from the research paper repository directly. There is no need for clustering to discover research papers that are relevant to the user. Each paper Pi in the citation network is considered a transaction, with its references signifying the objects in the transaction. They must have a network of the "transaction-itemset" type to utilize HUIM techniques. IDs (unique) must be assigned to the papers, and the output only represents the papers with these IDs. Pre-processing of raw data is performed. [42]

3.5 The Result of an Exemplary Study

In the case of the Two-Phase approach, if the dataset is increased, the entire operation for generating HURs must be restarted. When updates (increments) are applied to the dataset, the graph that they created shows that the EIHI-based technique is always faster than the Two-phase based approach. As a result, their suggested method can work efficiently even with dynamic datasets. [42]

4.CONCLUSION

Today, recommendation systems have an important place in obtaining information over the internet. There are four groups for paper recommender systems: content-based filtering, collaborative filtering, graph-based method and hybrid method. If the hybrid recommendation system is compared with a collaborative or content-based system, the recommendation accuracy of the hybrid system is generally higher. This happens because of the absence of understanding of domain dependencies in collaborative filtering and people's preferences in content-based systems. The combination of the two leads to an increase in common knowledge, which contributes to better recommendations. The increase in knowledge makes it especially promising to explore new methods of using content data to extend the underlying collaborative filtering algorithm and using user behavior data to extend content-based algorithms.

In this review, initially, there is an explanation of the logic, advantages, and disadvantages of each technique. To assess the performance of paper recommender systems, the following measures are introduced: Precision, Recall, F-measure, NDCG, MAP, MRR, MAE, and UCOV. This review summarizes the open issues. And then, we explain compatibility of the EIHI method with dynamic datasets. After that, we talked about the feature and convenience of the tree-based algorithm, why they chose the ACL dataset. Also, we talked about the result obtained after the study on these.

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