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A Survey of Imperfection of Existing Recommender Systems for AcademicFraternity

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Abstract:*The gigantic growth of information on the Internet makes discovery information challenging and time consuming. We are encircledby a plethora of data in the form of blogs, papers, reviews, and comments on different websites. Recommender systems endow a solution to this situation by automatically capturing user interests and recommending respective information the user may also find relevant. The purpose of developing recommender systems is to detract information overload by retrieving the most pertinent knowledge and services from anenormousamount of data, thereby providing personalized services. The most vital feature of a recommender system is its proficiency to "supposition" a user's preferences and interests by examiningthe behavior of this user and/or the behavior of other users to originate personalized recommendations. So several research works have been done in this area, but nothing consolidated has been appraised. In this paper, we are going to discuss a brief summary of imperfection in the available recommender system. We are also trying to figure out theseshortcomingsofthe available recommender system to generate a new method that improves these shortcomings.*

Keywords:*Recommender Systems, Information Extraction, Stereotyping, Semantic Similarity, Content-Based Filtering, Concept Mining.*

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I. Introduction

A recommender system is a subclass of the information filtering system that seeks to forecast the "rating" or "choice" a user would give to an item [1]. Recommender systems are one of the most common and comfortably conceivable applications of big data [2].In the current era of intense growth in the amount of information, it takes much more time for us to explore the information of great value from mass information [3]. This incidence is called "Information Overload". The information overloadin fact impliesthe availability of too much data or information that is beyond the manageable limits of the user and underlay a big nodusin all sorts of decision makings. This arduous occurs mainly when the system is unable to manage and process this enormous amount of information in anorderlymanner. Consequently, in many e-commerce applications, generally the user has a plenty of options, but with a very limited time to unearth them all.

A recommendation system, the most impressive mechanism in this direction, effort to tackle the information overload problem. Recommender systems are a subclass of information filtering system [4] that try to find to prophecy 'assessment' or 'precedence' [1] that a user would give to an item (such asaresearch paper, music, books or movies) or social element they had not yet considered, using a model built from the characteristics of an item in content based approaches or the user's social environment in collaborative filtering approaches. A recommender system is a system which provides recommendations to a user [5]. The Recommender system is to originate expressive recommendations to a set of users for products or items that might inquisitiveness them. Recommendation systems have been in general divided into many varieties[6]. These varieties are, Content-based Filtering, Stereotyping, Collaborative Filtering, Graph-based, Co-Occurrence, Hybrid recommendation, Global Relevance, [1].

II. The Taxonomy Of The Recommender System

Over the past two decades, the Internet has emerged as the mainstream medium for online shopping, searching research paper, social networking, chatting, e-mail and more. Conventional search engines require the user to manually enter keywords in order to finding for relevant data collections or web pages. The outcome of the finding query is displayed to the user based on the order of relevance to the keywords. One of the main issueswithconventional keyword based finding engines is that the user may find it arduous to find the search keywords which will return the optimal outcome [1], in particular if the user is exploringfor information in a new domain. Recommender systems endow a [7] solution to this arduous by automatically capturing user interests &choice and recommending related information the user may also find interesting [6]. There are two ways in which recommender systems are able to [8] capture user choice: explicitly, by enabling the user to enter their choice, or implicitly, by monitoring the user's activities such as browsing the web or reading research papers. We are contemplatingthe following classes to be most appropriate for distinguishing the viewpoint in the field of research-paper recommender systems[9][1].

2.1. Content-Based Filtering

The Content-based filtering, also designated to as cognitive filtering, recommends items based on a compare between thearesearcherprofile and content of the items. In content of every item is represented as a set of the expositor, generally the words that occur in a research paper [10]. The researcher profile is represented by the same terms and built up by examine the content of items which have been seen by the user. Content-based filtering (CBF) is one of the most widely used and researched recommendation viewpoint[1]. The various difficultyhas to be considered when implementing a content-based filtering system. Firstly, the terms can either be entrusted automatically or manually. When terms are entrusted automatically a method has to be selectedthat can extract these terms from items. Secondly, the terms have to be represented like that both the user profile and the items can be compared in a significant way. Thirdly, a learning algorithm has to be selectedthat is able to learn the user profile based on seen items and can make recommendations based on this user profile [1].

The Content-based filtering has a number of benefitscompared to the stereotypes. The Content-based filtering permit a user-based personalization so the recommender system can determine the optimal recommendations for every user individually, rather than being limited by stereotypes.The Content-based filtering also requires less up-front classification work, since user models can be created automatically. Every item must be examinedfor its features, user models must be built, and equality calculations must be performed [11]. If there are many users and many items, these calculations require expressive resources. The frailty of content-based filtering is its low serendipity and overspecialization leading it to recommend items as similar as possible to the ones a user previously be aware [1]. Content-based filtering also disregardquality and prominence of items [10]. For example, two research papers may be considered equally relevant by a Content-based filtering recommender system if the papers share the same terms with the user model. This relevance might not always be appropriate, for instance,if one research paper was written by an authority in the field and presents the genuine outcome, while other research paper was written by a student who paraphrases the outcome of other research papers. Preferably, a recommender system should recommend only the first research paper, but a Content-based filtering system would lapse to do so.

2.2. Stereotyping

The Stereotyping is one of the preliminary user modeling and recommendation classes. It was introduced by Richin the recommender system Grundy, which recommended novels to its users. Rich was inspired by stereotypes from psychology that allowed psychologists to immediately judge people based on a few features [12]. Rich defined stereotypes which she called facets as collections of features.Stereotypingtechniquespermit the definition of a set of differentiating featuresfor a group of users, when a new user is introduced into the system, [13] they can be allocatedto a predefined stereotype, based on their respective data, which permit the activation of a set of default choice that may be further refined over time thanks to user profile adaptation techniques [1].In the domain of research-paper recommender systems, only Beel et al. applied stereotypes. The authors acknowledge that all users of their reference-management software Docearrarestudents or researchers. Consequently, research papers and other itemsrelated to students or researchers are recommended that are potentially interesting for students or researchers (for instance, research papers about ameliorate scholarly literature for Google Scholar [14]. Beel et al. [12]used stereotypes as a retreat model when various recommendation approaches couldn‟t deliver recommendations.

2.3. Collaborative Filtering

The Collaborative filtering recommendation depictsuser specific recommendations ofitems based on patterns of ratings or usage without necessity for exogenous information about either items or users [1]. The term collaborative filtering was coined in 1992 by Goldberg et al., Who proposed that information filtering can be more dominant when humans are involved in the filtering process. Collaborative filtering, also designated to as social filtering, filters information by using the recommendations of another user. It is based on the opinion that people who agreed with their evaluation of certain items in the past are likely to agree again in the ensuing. A person who wants to see a movie for example, might ask for recommendations from a buddy [15]. The recommendations [16] of some buddy who have similar interests are trusted more than recommendations from others [17]. This information is used in the decision on which movie to see. Most collaborative filtering systems apply the so called neighborhood-based technique. In the neighborhood-based approach a number of users areselected based on their similarity to the effectual user. A forecast for the effectual user is made by calculating a weighted average of the ratings of the selected users [18].

A common issue of collaborative filtering in the domain of research-paper recommender systems is sparsity. It is often assumed that data sparsity may cause a small number of co-rated items or no like ones between two users, outcome in irresponsible or unavailable similarity information, and ahead incurring lousy recommendation quality.Thecircumstance is different in the domain of research papers. There are typically few users but millions of research papers, and very few users have rated the same research papers [18]. Quest like-minded users are often not feasible. Therewith, many research papers are not rated by any users and therefore cannot be recommended. Finally Collaborative filtering is normally less scalable and requires more offline data processing than Content-based filtering [19].

2.4. Graph Based

In Graph-based recommendation technique producestheassociation between users and items as a bipartite graph in which there is a weighted or unweightedconcatenationbetween a user and each item he has rated [20]. The data sparsity, that is a common issue in neighbor-based collaborative filtering domain, normally complicates the process of item recommendation. This issue is more significant in the collaborative ranking domain, in which calculating the users' similarities and recommending items are based on ranking data. Roughly graph-based approaches have been proposed to address the data sparsityissue, but they endure from two flaws [21]. The first issue is that current graph-based approaches are unable to capture the preference order of users. The secondissueshortcoming of current graph-based approaches have been proposed for binary implicit feedback and that they cannot capture the pairwise choice of user that is generated by different implicit feedbacks. It is clear that the preference context is a valuable piece of information that can be used to ameliorate the recommendation perfection.

2.5. Co-occurrence recommendations

In co-occurrencerecommendationstechnique produce the, those items are recommended that repeatedly co-occur with some source items. One of the first applications of co-occurrence was co-citation analysis introduced by Smallin 1973 [22].The main benefit of co-occurrence recommendations is the focus on relatedness instead of similarity. The similarity expresses how many features two items have in congruent. Recommending almost identical items, as Content-based filtering is doing, is often not perfect because almost identical items are not serendipitous [23]. In contrast, relatedness express how near coupled two items are, not inevitably dependent on their features. For example, two research papers sharing the same features (words) are congruent. In averse, research paper and pen are not congruent [24] but associated, because both are required for writing letters. For this cause, co-occurrence recommendations technique endowsmore serendipitous recommendations, and in this way are comparable to collaborative filtering and calculating co-occurrence recommendations is not always practicable.

2.6. Hybrid Recommendation

The Hybrid recommendation systems are technique produce the mixture of single recommendation systems as sub-components. This hybrid approach was introduced to cope with anissueof traditional recommendation systems. Two main controversieshave been addressed by researchers in this field, cold-start problem and stability versus plasticity issue. The cold-start issue occurs when the acquisition of knowledge based techniques like collaborative, content-based, and demographic recommendation algorithms are used [25]. Theirthe acquisition of knowledge stages is based on users' information, in most cases a user has to input their ratings or choice manually and therefore the collection of this kind of informationis hard to be achieved. Stability/plasticity issue means that it is sometimes hard to transform established users' profiles which have been established after a given moment of time using the systems as well as prior issue can be solved with the hybrid approach because different type of recommendation technique like knowledge based algorithm can be less affected by the arduous. The Hybrid recommendation systems can produce outputs which checkmate single component systems by combining these multiple techniques [26]. The most congruenthybridizing methodology is combining dissimilar techniques of dissimilar types, for example, put together Collaborative filtering and Content-based filtering. However, it is also possible to mixture dissimilar techniques of the same type, such as KNN based Content-based plus naïve Bayes based Content-based filtering. Additionally, mixing the same type of techniques with different datasets can be possible.

2.7. Global Relevance

In its straightforward form, a recommender system adopts a one-fits-all approach and recommends items that have the highest global relevance. In this case, the relevance is not calculated distinguished to a user, for example based on the similarity of user models and recommendation user. Alternatively, some global measures are used, such as overall prominence. For example, a movie-rental system could recommend those movies that were most often rented or that had the highest average rating over all users.

III. The Related Works

Recommender systems are increasingly used on the Web to assistance users discover material relevant to their interests. The first paper on recommender system was published in the year 1998. Since then a considerable number of papers had been published. The various factors have been explained to risethecredibility of recommender system.Recommendation systems endow a promising approach to ranking scholarly papers according to a user's choice [27]. Such systems are classified by their underlying method of recommendation.We now calibrate recommendation systems in the field of scholarlydigital libraries [28].McNee et al. [29] proposed an approach to Collaborativefiltering to recommend papers that would be appropriate additional references for a target research paper. They createa rating matrix where citing research papers correspond to users andcitations correspond to items. The experiments show Collaborative filtering couldgenerate high quality recommendations. Torres et al. [30] proposed a technique forrecommending research papers by mixture of content-based filtering and collaborative filtering. In spite of, the final ranking schemeacquireby merging the output from content-based filtering andcollaborative filtering is not performed as the authors claim thatpure recommendation algorithms are not designed to receive inputfromdifferent recommender algorithm.However, offline experiments show thosehybrid algorithms did not carry out well. In their belief,the sequential nature of these hybrid algorithms the secondmodule is only able to make recommendations seeded by theoutcome of the first module. Yang et al. [31] presented a recommendation system for scholarly papers that used a ranking-oriented collaborative filtering method. In spite of the fact that, their system overcomes the cold-start issue by utilizing implicit behaviors extracted from a user's access log, Web usage data are noisy and not authentic generally as pointed out in.

Ekstrandet al. [32] introduced the two steps by running a Content-based filteringand a Collaborative filtering recommender in parallel and blending the resultingranked lists. The first items on the amalgamate recommendationlist are those items which appeared on both lists, ordered bythe sum of their ranks. Amazingly, Collaborative filteringoutperforms all hybrid algorithms in their experiments.Gori and Pucci [33] devised a Pagerank-based technique for recommending research papers. But in their technique, a user has to prepare the initial set of pertinent research articles to get better recommendation, and the damping factor that affects the score of Pagerank is not ameliorated.MKu¨cu¨ktuncet al. [34] evolved a personalizedpaper recommendation service, called theAdvisor3,whichpermit a user to specify her search toward recentdevelopments or conventional research papers using a direction-awareunsystematicwalk with restart algorithm. The recommendedpapers returned by theAdvisor are diversified by parameterizedrelaxed local maxima.Wang et al. [35] proposes to include textual information tobuilda topic model of the research papers and adds an additionalimperceptiblevariable to distinguish between the focus of a research paper andthe area it just talks about.A typical related research paper search scenario is that a user startswith a seed of one or moreresearch papers, by reading the availabletext and searching related cited references. Caragea et al. [36] introduced the issue of citation recommendation using singular value decomposition of the adjacency matrix related to the citation graph to construct a latent semantic space a lower-dimensional space where correlated research papers can be more comfortably identified. Their experiments on Citeseer digital library show this approach achieves significant success compared with Collaborative filtering technique. K. El-Ariniet al. [37] proposed by returns a set of advisable research articles by optimizing an objective function based on a finegrainednotion of influence between research papers. K. El-Arinietal.Also claim that, for the research paper's recommendation, defining a queryas a small set of known-to-be-pertinent research papers are better than astring of keywords. B. Golshanet al. [38] proposed to Sofia is a system that automates this recursive process.Stohmanetal. [39] evolvedthe dominance of different citation-based andtext-based features on citation recommendation, they search that neither citation-based nor text-based features performedvery well in isolation, while text similarity alone achievesanastonishingly lousy performance at this job.

W. Huang et al. [40] introduced the vocabulary used in the citation context and in thecontent of research papers isabsolutelydifferent. To address thisissue, some works propose to use translation model, whichcan bridge the gap between two diverse languages. X. Liu et al. [41] proposed citation recommendation from the diverse network mining perspective has attracted more observation. In addition to research papers, metadata such as authors or keywords are also considered as entities in the graph schema. The two entities can be connected through dissimilar paths, called meta-paths, which usually carry dissimilar semantic meanings. Promiscuous work build discriminative models for citation prophecy and recommendation based on meta-paths. K. Sugiyama et al. [42] introduced the hypothesis that an author's published worksconstitute a clean signal of the latent interests of a researcher,investigatethe effect of modeling a researcher's past workin recommending research papers. In particular, they first construct auser profile based on her/his recent works, then rank candidateresearchpapersas stated by the content similarity between the candidateand the user profile.In 2013, SiwipaPruitikaneeet al. [43] researchers proposed a global and soft approach to a research paper recommender system. They introduced a recent approach that embeds the whole process for selecting research papers of interest given some keywords, and their approach is based on a workflow integrating fuzzy clustering of the research papers, the computation of arepresentativecompendium research paper per cluster using OWA operators, and ranking, in order toanswer user queries adequately. Abbreviate sets of papers into a single representativeone promotes the procedure make easy when users interact with enormous number of research papers from the literature.

IV. The Proposed Study and System

The introduced approach reckons in two substructures targeting researcher consideration and analysis of specifiedcontent.Each of these substructures is used to endow a consolidated recommendation. The concern of the presented work is to find out the researcher considerations and collected content explication[44] which certainconsequencesin improved recommendations. In previoussegments introduction regarding recommender system and concerned studyhave been prefabricated.This segment gives pervasive understanding about theintroduced approach considering research paperrecommendation system. Formarly, it has been mentioned that there are manyresearches that have been conductedforresearchpaperrecommendationkeepingin mind severaltenors like matching the keywords of the research papers, [45]profile matching, and access permission, etc.

4.1. Substructure for Researcher Consideration Analysis

In figure 1, a hypothetical substructure is presented to analyze researcher consideration. Primarily, the data are collected from the researcher by using a sampleabstract of research paper in which researcherpresented an opinion about his experience with the research paper. Now the collected data aredisorganized and needed some refinement before it can be

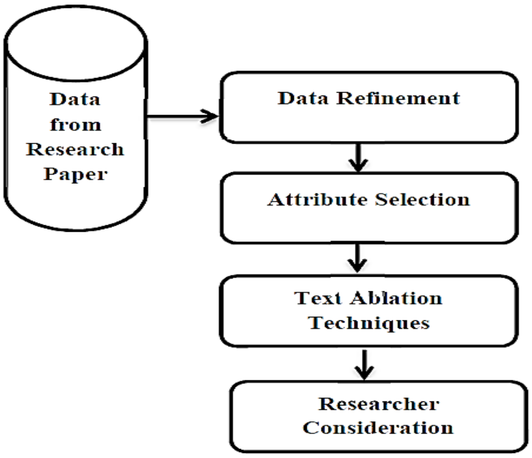

Figure 1. The Substructure for Researcher Consideration Analysis

evaluated. Refinement phase is a dominant challenge and enormous time is exhausted during this phase. aforementioned textual refinement comprises purification steps, such as eliminate redundant characters, supersede special characters with spaces, eliminate stop words and word derive. From the purification data, attribute chosen is made and separated into numerical/categorical and textual attributes [46]. Certainly, by treating several text ablation techniques it is analyzed that though the researcher confers a propitious or unassertive consideration. The figure 1 a hypothetical substructure for researcher consideration, analysis. Researcher consideration analyzed in this segment is anticidently used in the next substructure to confer recommendations.

4.2. Substructure for Concept ClusteringBased Approach

In figure 2, a hypothetical substructure for Concept clustering based approach is provided. For recommendations, another data set is gathered based on the sample abstract of research paper collected in the above-mentioned steps.In text mining, Concept dependant clustering intentions the sense of words/ phrase. It has prescribedprominentamendmentupon traditional term frequency. Concept mining particularizestherole of words in the sense of the sentence, which indicates a copiousadroit and sapient clustering [47]. Concept probably a phrase or a conglomeration of a word which provides an evincive contribution to the text yet we can establish the variant concept in selfsame or other document, which provides identical or almostidentical meaning. This similar meaning concept exigency be considered as lonesomecontent while

Enumerationgparticipation to text. In this method,theidentical meaning concept is classifiedat one time, termed ascollectionof concept. A collection of concept can be perceived as identical meaning, but varied word tokens. The clustering will be constituted based meaning of collection of concept [48]. Aninstinctive language phrasecomprisesvariegated words, some of the phrasesmayprovide a major contribution to phrase meaning than other words. Infrequentlygroupism of words [49] contributemuch better than the single words.Excerpting text contents which depict the meaning of the text is termed as concept forming and these excerpedcontents are called concepts. Concepts may be words or a significant collection of words which comes conglomerately in the text more oftentimes [50].

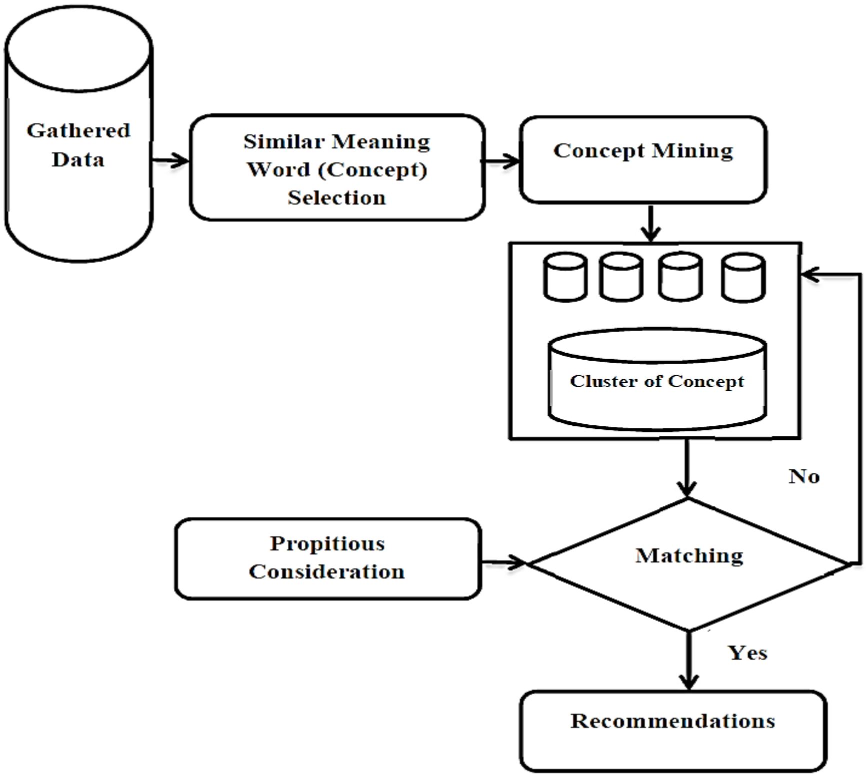

Figure 2. The Substructure for Concept Clustering Based Approach

V. Conclusions

After surveying so many research papers on recommender systems, following difficulties are concluded. Availability of the whole content of recommending paper to be freely accessible, which is not always true due to copyright restriction. Most of the existing recommendation systems work on keyword matching. Some of them are based on citation count, which is not always required. The arduous of common citation recommendation is that, real world citation pattern are not as obvious to explore, since about 50% co-cited papers do not have a direct connection. A lot of systemsare based on collaborative filtering, so they suffer from a cold start problem for new researcher. The profile based recommender system has the hazardof security. Some non-profile based Recommender system works well, but there is the need of query generator. There is a lack of proper modeling in this field. So there is a need of the proper user modeling method. The Concept mining performs well in all applications in which it has been applied, so it will also provide better outcomesinthe research paper recommendation. In our proposed method we are using abstract of the recommending research paper as primary selection which is always freely available without payment restriction.

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