International Conference on Computing, Communication and Automation (ICCCA2017)

Open Problems in Recommender Systems Diversity

Akshi Kumar
Dept. of Computer Sc. &Engg.
Delhi Technological University
New Delhi, India
akshikumar@dce.ac.in

Nitin Sodera
Dept. of Computer Sc. &Engg.
Delhi Technological University
New Delhi, India
nitinsodera17@gmail.com

***Abstract*—With increasing information available online, requirement for accurate information filtering tools/ information retrieval have become necessary. Recommender systems have been a crucial research subject after the inclusion of the very first paper on filtering. Recommender Systems is a tool that provides recommendations for products/services which maybe of liking to a particular consumer. Despite the fact that research on recommender systems has extended extensively over the last decades, there's still requirement in the complete literature evaluation of the research made till date and classification of Recommender Systems. This paper presents a categorical review and provides a survey on the diversity & techniques of Recommender systems. The open problems in the area are pinpointed and mapped to the respective recommendation paradigm type thus giving an insight to the research trends in the field of recommender system. The intent of this work is to serve as a base literature review to beginners and at the same time aid as an important pertinent survey for identifying the opportunities in thearea.**

Keywords— Recommender Systems; Types; Issues

I. INTRODUCTION

The improvement in Information Technology has increased the inflow of products in every domain via E-market by many folds. Although it's easier for a consumer to choose from small set items but when the item set increases, it is cumbersome and difficult for user to consider various properties of alternate product. Following these conditions, user wants recommendations from the known users who have information regarding the product. We currently live in an era where there is overload of information. We are surrounded by a plethora of information in the form of papers, reviews, blogs and comments on various social networking websites. The number of people who use the Internet witnessed the increase of approximately 40% since 1995 and reached a net count of 3.2 billion in such a short span of time. Such increase in data leads to information overload, thus creating a high level of stress and chaos [4]. Thus, in order to save a person from this confusion and make the surfing experience on the Internet better, Recommender Systems (RS) were introduced. Recommendation system is defined as the software technology/tool that makes relevant suggestions to a user. Usually, RS suggests products that a user might find valuable, thus helping both the recipient and the seller. Approximately a decade has passed since the first ever paper on Recommender system but till date there is a void when it comes to a state-of-art survey of Recommender Systems. Hence it provides perfect motivation, to the work to resolve this issue and provides researchers interested in Recommender system with an all-in-one study focusing on all its types, approaches and challenges. The mapping between different types of Recommender Systems and the challenges have never been covered before, thereby adding more credibility and importance to this work. The idea is to get a clear picture about the limits of each type of RecommenderSystem.

The rest of the paper is organized as follows: the next section expounds the types of Recommender Systems followed by a discussion of the challenges within the domain of RS. Finally a mapping of the open problems in respective recommender system type is uncovered to determine the research gaps in the field of RecommenderSystems.

II. TYPES OF RECOMMENDER SYSTEMS

Recommender Systems (RS) are primarily directed towards a class of individuals who lack sufficient Experience/Information or competence, resulting in poor evaluation of high number of alternative items provided by the seller/websites. Literature review suggests that categorization to identify the types of RS can primarily be either on the basis of User's aspect (Personalized & Non-Personalized) or approaches used (Collaborative, Content-based, Demographic, Hybrid). Novel categories, such as Knowledge-based RS & Domain-Specific RS (context/location-based) have also been identified in many relevant studies. The details of these types of RS are discussed in the following sub-sections and are pictorially depicted in fig 1:

A. BASED ON USER'SASPECT

In this section we will categorize Recommender system based on the user it will be dealt with. If it is made for a particular type of users then it is PersonalisedRS otherwise it is Non-PersonalisedRS.

1) PERSONALISEDRECOMMENDATIONS

These types of recommendations are given as lists of ranked products. During this task the system tries to recommend/suggest the best matching items/services, depending on recipient's choices [1]. The products can be suggested depending on its visibility & ranking (appearance onthe top) of a website, past analysis of user's behavior or demographics of a user as a suggestion for next recommendations for thecustomer.

2) NON- PERSONALISEDRECOMMENDATIONS

These types of recommendations are easier to generate as compared to the personalized recommendations and are usually used in newspapers and academic journals. The suggestions are independent of the user, therefore everyone tends to get same suggestions. They are automatically generated on the grounds that they require little client effort to create the suggestions and are transient. These proposals are totally independent of the specific client focused by the RS or newspapers/Magazines.

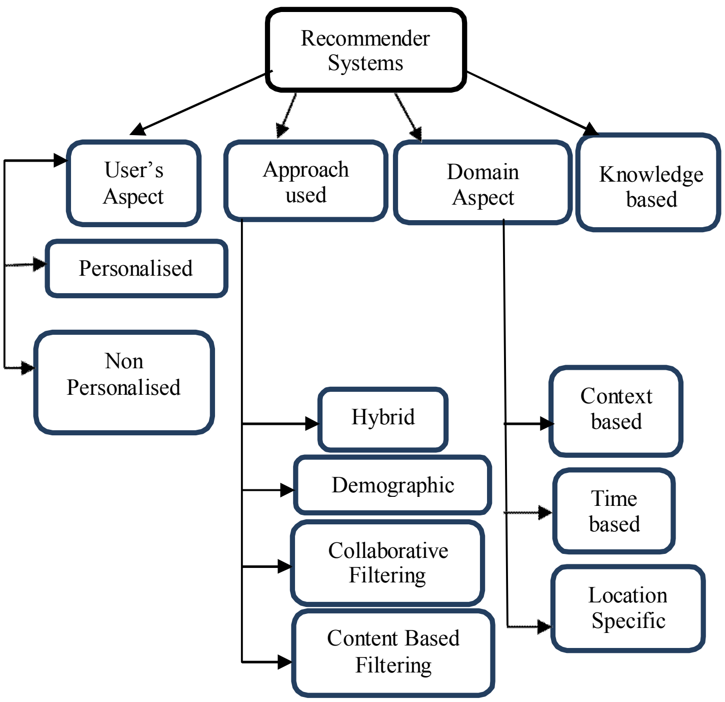

Fig.1. Types of RecommenderSystems

B. BASED ON RECOMMENDATION APPROACHESUSED

Recommender systems facilitate users as a tool for finding items of interest. In this section we expound the basic algorithmic approaches used describing the criteria for recommendation. These include collaborative filtering, content-based filtering, demographic filtering, hybrid & knowledge based recommendation approaches which combine basic variants. The following sub-sections discuss the details of these recommendation approaches enlisting their advantages, disadvantages, prominent techniques used and specific applicationareas.

1) COLLABORATIVE RECOMMENDERSYSTEM

Collaborative filtering (CF) uses the numerical reviews given by the consumers and is based mainly upon the historical data of the user available to the system. It makes suggestions to all dynamic consumers with data about group of consumers and their connection with the item set. Both the consumer profile and the item profile are used to make a recommendation system. It is considered one of the most basic and the easiest method to give suggestions and make predictions regarding a product depending on consumer's previous behavior and the consumer's behavior of other likeminded consumers. Collaborating Filtering based techniques can further be categorized asfollows:

(i) *User-based collaborative Filtering:* Correlation is computed between one user and others user. Also for every data-item we calculate the ratings of the consumers that are heavily related with each consumer [7]. Common problems with these types include data sparsity, bad correlation & ease of gettingattacked.

(ii) *Item-based collaborative Filtering:* Correlation is computed between one item and every item set. Most commonly used are the cosine and Pearson correlation similarity approach. Also for every consumer we calculate the consumer's ratings of products that are heavily related with each data-item. Therefore there is less sparsity and at the same time cold start is less influential and so is any type of Attacks [8].

There are three main algorithmic categorization of collaborative filtering:

<u>Memory based</u>: Users and dataset with similar interest are combined

<u>Model based:</u> different techniques involving data mining and machine learning are used to determine complex patterns.

<u>Hybrid CF</u>: Different CF techniques and other RS's techniques are combined

- *Advantages:* These kinds of filtering approaches don't require representation of data in dataset of data-properties but is only based on precision of active consumer's group. Database's scalability is large as it doesn't require manual involvement.
- *Disadvantages:* The products can't be suggested to any consumer until the data/item is either ranked/rated by any another consumer/users or correlated with data-items of same kind from the item set. Usually the persistent consumer's rate very less number of items even tough, there is very large number of products database thus leading to very sparse results. Because of changes in opinions of many of the users finds this approach expensively costly and it also requires a lot of time. One other issue that is predominant with collaborative filtering is sparsity issue and the measures taken to resolve it includes: implicit rating, dimensionality reduction and contentdescription.
- *Techniques:* Unified relevance model, Hybrid CF model, Fuzzy Association Rules and Multilevel Similarity (FARAMS), Flexible mixture model (FMM), Maximum entropyapproach
- *Applications:* Collaborative filtering application is used to recommend befitting information as judged by the community. Collaborative filtering is usually set to work upon very large data sets. It is also used in solving the nearest neighborproblem.

2) CONTENT BASED RECOMMENDERSYSTEM

It focuses on the features of the items. The goal is to create a user profile depending on the previous reviews of the users and also a profile of the item in accordance with the features it provides and the reviews that has been received for that particular item from the item set [9]. It uses information from the item set and knowledge from the dynamic consumer's .This technique is made from the structural information of properties/content of product/item instead of description of consumer's ratings of the particular dataset. Since it provides suggestions according to user's field of interest and adapts according to user's likes and dislikes, therefore [11], it is also known as adaptive filtering. It compares the content of items of user's interest with the content in the item list. It helps overcome sparsity problem that is faced in collaborative filtering based recommendationsystem.

- *Techniques:* Content-Boosted Collaborative Filtering, FAB Technique, Bayesian hierarchical model (BHM)
- *Advantages*: This approach recommend items from the dataset to the consumer and thereby don't require data of other users and also it don't faces first rater problem i.e., It is can recommend new items/products and rare items for each and every consumer. i.e. helpful in both cold start problem and long tail problem
- *Disadvantages*: In these types of techniques products knowledge is restricted to the initial descriptions/features i.e. explicit specifications of its properties is done[12] i.e. it depends on the information provided explicitly and that too manually.
- *Applications:* Used in situations to deal with cold start problem as it is capable of recommending rare data from the item set. Also, used in confidential places like banking etc.

3) DEMOGRAPHIC FILTERINGSYSTEM

This type of RS uses previous information of demographic knowledge regarding consumers and their views for items that were recommended as a criteria base for suggestions, classifier based on demographic data can be obtained by Machine learning techniques [13]. The display of such info in a consumer's model varies to a large extent.

- *Advantages*: It doesn't require knowledge of ratings given by consumer, which were required by the other main techniques (Content based and collaborative). Demographic approach is fast, simple and straight forward for making depending on fewdataset.
- *Disadvantages*: Compilation of full consumer info is required to get good recommendations which can't be possible [10]. As these types of RS are dependent on consumer's field of interest, it generally results in, recommending the usual data to consumers having same field of demographic interest, thus resulting in too general recommendations. There are security and privacyissues.
- *Applications*: This technique is very well utilized in formulating the recommender system such as trip adviser or a party planner where the demographic information is taken into consideration [14] and so a new user can also be recommended as it does not requires the user's previous information.

4) HYBRID RECOMMENDERSYSTEM

Hybrid RS is type of RS, efficiently overcomes the limitations of other recommendations approaches. This type of techniques uses the good features of two or more approaches to gain stable and robust system and to have a robust recommender system [15].Collaborative and content-based filtering are the most common hybrid approaches. Mostly, this type of approaches uses both ratings of all users and items as attributes [16]. Usually, such RS adapts Heuristic mixture of collaborative filtering and content based filteringmethods.

- *Techniques:* Weighted, Switching, Mixed, Feature combination, Cascade, Feature augmentation, Meta-level [3]
- *Applications:* As it takes into consideration the best aspect of multiple Recommender system that can practically be used to implement any type of Recommender system eg. Movie data, cab, travel advisor, Website Recommender systemetc.

C. KNOWLEDGE BASED RECOMMENDERSYSTEM:

Knowledge based recommender systems tackle almost all the challenges that were cited in other types. The benefit of such knowledge based recommender systems is that no cold start/ramp up issue persists, as no rating information is required. Recommendations are computed exclusively for every consumer's ratings: either on the basis of explicit recommendation rules or based on the common expects between user needs and product [17]. This type of RS can be categorized in two different categories: constraint based and case-based systems. The way in which they use the knowledge provided is the main difference between the two: case-based recommenders focus on the retrieval of similar items on the basis of different types of similarity measures, whereas constraint-based recommenders rely on an explicitly defined set of recommendation rules [5].

- *Advantages*: One of the biggest benefits of such a Recommender system is that cold-start (ramp-up) problems don't exist in it. The main setback is that, there are potential information extraction bottlenecks, initiated by the necessity of defining information of suggestions in an explicit way [18].Deterministic recommendations can be extracted from knowledge based recommender system as we have assured quality. Also it can resemble salesdialogue
- *Disadvantages:* Cost of knowledge acquisition is very high from domain experts/consumers and from web resources.Knowledge engineering effort to bootstrap is quiet high. This approach is basically static and it does not react to short-term trends.Independence assumption can be challenged as preferences are not always independent from eachother

- *Applications:* This technique can be used to deal with long tail data set such as Recommending exotic villas to users, Poker Recommendationsystem.

D. DOMAIN SPECIFIC CONTEXT-BASED / TIME SPECIFIC/LOCATION BASED RECOMMENDER SYSTEM

Contextual information in a recommender system helps to get a clear view of the situation of any person, place or object which is of relevance to the system for suggestions and anything that can be incorporated. In this kind of Recommender system the contextual knowledge of consumers is also taken into consideration while designing a recommender system [10]. Context refers to the location, time, area and environment of the Consumer which define a user's state. RS requires situational information of the user and context based RS accesses the information directly using various techniques (such as GPS) .The user's location data, social data, current time, weather data are also taken into consideration as the contextual data[19].Contextual factors are of two types: Dynamic and static, depending on whether they change with time or not..

- *Techniques:* Hidden Markov Model, Multidimensional approach, Fuzzy Bayesian Networks, Human memory model, Matrix-factorization Predictive Context Based Model
- *Applications:* Used for recommending the cab or the hotel to the user based on its currentlocation.

III. CHALLENGES IN RECOMMENDER SYSTEMS

Perhaps the biggest issue in having a good RS is that they requires big item set to effectively make suggestions. As a result the companies with a lot of consumer data have excellent and accurate recommendations: Google, Amazon, Netflix, Last.fm [2] .An efficient RS firstly needs item set (from a catalog or by any other way), then it needs to incorporate and analyze consumer dataset (behavioral events), after that the recommender system is implemented on the analyzed dataset. The larger item and user dataset to work with better are the chances of having effective and accurate suggestions/recommendations. The issues in the research domain of RS which have been identified across pertinent literatureare:

- Cold startproblem
- Scalability of theapproach.
- Accuracy of theSuggestions
- Changing dataset
- Impact ofcontext-awareness
- Loss of neighbourtransitivity
- Sparsity
- Privacyconcerns.
- Recommending the items in the Longtail

Also it may lead to chicken and egg problem i.e. for efficient suggestions, we requires a lot of consumers, so that we get adequate amount of information for the recommendations there's the requirement of large number of consumers which in turn requires a good and accurate recommender system so as to attract and extract large numbers of users.

1) COLD START PROBLEM

This problem appears at early stages of a recommender system's lifecycle or when a new or rare item/product is added to the dataset. When there is a little knowledge available on a particular item or dataset, ontologies are a proven tool for knowledge extension and extraction [20]. This problem affects every recommender system: the content-based filtering will behave poorly, if there is a little information about the item set. The collaborative filtering also leads to the same result [21]. If the recommender system has no information by using the content-based methods, and there is no user's behavior history in the database/item set, the hybrid approach will produce nearly random recommendations aswell.

B. SCALABILITY AND BIGDATA

This is another important issue in RSs. As ratings database increases, the performance declines exponentially. Systems which can handle large dataset and produce accurate suggestions quickly are required. Trade-off between performance and the prediction accuracy is very common [22]. For example, clustering technique increases performance, but decrease the accuracy. Matrix factorization methods are also not suited for online recommendations with big item sets. This algorithm run on the Netflix Prize competition dataset takes 8 hours to complete the process. Algorithm "Gellyfish", which uses parallelization techniques, reduced computation time of 3 minutes for the Netflix Prize competition dataset. Algorithms' parallelization is a way to solve this problem.

C. ACCURACY OFSUGGESTIONS

Among other details, the user is sensible for false negatives (incorrect recommendations, which the user does not like) which leads to low accuracy in the recommender system. In such cases users lose trust in the RS and stop using it [23]. Therefore, it is important to keep recommendation quality and accuracy at itsbest.

D. CHANGING DATASET

With increase in amount of items and dataset day by day, there is a constant change in the structure of the item set by the constant inclusion of new data in the previous defined item set. Usually an algorithmic approach finds it hard if not impossible to maintain the accuracy with the changing dataset. Most users that are not active face a great issue. They rely on trusted user and groups to recommend and suggest them the new items from the given dataset. This issue can be stated as, biased towards the old and difficult to incorporatenew.

E. CHANGING USER PREFERENCE (CONTEXT AWARNESS)

A user being the in taker needs to get details about differenttypes of data from the single contiguous dataset [24]. A classic scenario: sometimes a user will be browsing flipkart for gadgets, but next moment the same user will be on Amazon searching for a gym kit[25].

F. LOSS OF NEIGHBORTRANSITIVITY

Situations with the Transitive nature are usually not taken into consideration in the Recommender system. Assume that user 1 is highly correlated with user 2, which in turn is highly correlated with user 3.Also user 3 can in turn be highly correlated with user 1. Such relationships are not captured by recommender systems, but can be done with knowledge of users from, for instance, ontology [26]. For example, user aggregating 75-100 are correlated as intelligent ones, whereas users aggregating 35-50 as average one.

G. SPARSITY

It's very usual that user usually purchase or rate relatively few items compared with the total item set which in turns leads to a sparse users-items represented with matrix and, thereby making it difficult to locate neighbors or derive common behavior patterns resulting in low accuracy system[27]. Latent factor models algorithms can be used to address this issue, which utilizes dimensionality reduction of various users and items resulting in finding patterns in reduced dimensional space, which in turn is not sparse. Matrix factorization methods were good during the Netflix Prize competition they were applied to a 99% sparse matrix with 8.4 billion values missing in the competitions[28].

H. PRIVACY

Personal data collected by RS should be kept safe and piracy must be neglected and should be uninfluenced and unmodified. There are three aspects to be taken care of:-

- Value and risk of personalinformation
- Shilling
- Distributed RecommenderSystem

In value and risk of personal information we need to determine when to stop collecting the info to balance the privacy and to intelligently choose which info is to be discarded and which to keep. Techniques such as Cryptosystem and zero knowledge are to be used to counter different security and privacy attacks[29].

I. LONGTAIL

About the $1 Million prize offered by Netflix for a third party to deliver a collaborative filtering algorithm that will improve Netflix's own recommendations algorithm by 10%, we noted that there was an issue with eccentric movies[6].Long-tail phenomena are ubiquitous in real world applications, challenging the task of information trustworthiness estimation. Sources with very few suggestions and items in the dataset are common in applications [30]. Such low number of items (rare items) and suggestions exhibited by user typically exhibits long-tail phenomenon, i.e., most of the users only provide data about one or two items, and there are only a few users that make lots of suggestions [31]. For example, There are numerous sites containing info/knowledge about one or many celebrities, there are few sites which, like Amazon, Wikipedia, provide extensive coverage for thousands of celebrities. Also low number of user participation in survey, review or other activities. On average, participants shows suggestions to few items whereas very few users cover most of the items. ZiedZaier et al. introduced long tail issue and its effects on RS. That provides a review of the different item sets which were used to examine and check collaborative filtering RS algorithms and techniques. Also the effects of various RS techniques depending on different item set were also compared. The study details and covers a single-criterion item set's rating similar to almost all of current collaborative filtering RS. The Table 1 depicts the mapping between different types of Recommender systems and the challenges thus providing an insight to the open problems within the recommender systemdiversity.

TABLEI. MAPPING RS TYPES TOISSUES

	Types of Recommender Systems					
Challenges	Collaborative RS	Content based RS	Demographic RS	Hybrid RS	Domain Based	Knowledge based
• Cold start problem	?	✓	✓	✓	?	✓
• Scalability of the approach.	✓	✓	✓	?	X	X
• Big-data	✓	✓	✓	?	X	X
• Privacy concerns.	✓	X	✓	✓	✓	✓
• Sparsity	X	✓	X	✓	?	?
• Recommending the items in the Long tail	?	✓	✓	✓	?	✓
• Accuracy of the Suggestions	?	✓	X	?	X	X
• Changing data set	✓	✓	X	✓	✓	?
• Impact of context-awareness	?	✓	?	✓	✓	?

IV. CONCLUSION

This study investigated the diversity in Recommender Systems discussing the scope and practical use of each. The existent challenges within the research domain of recommender system are ascertained from pertinent literature and finally a mapping of the open problems to the type of recommendation system is given. The idea was to probe issues that were valid for specific type of RS and which spanned across types. The findings clearly suggest the challenges as opportunities within the research area.

REFERENCES

[1] Gurpreetsingh ,Rajdavindersinghboparai, “A survey on recommendation system”, IOSR Journal of Computer Engineering (IOSR-JCE), e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 17, Issue 6, Ver. V (Nov – Dec. 2015), PP 46-51, :10.9790/0661-17654651, January 20, 2017.

[2] Soanpet .Sree Lakshmi, Dr.T.Adi Lakshmi, “Recommendation Systems:Issues and challenges”, (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 5 (4) , 2014, 5771-5772,ISSN :0975-9646,11,January 2015

[3] RVVSV Prasad and V ValliKumari, “A CATEGORICAL REVIEW OF RECOMMENDER SYSTEMS”, International Journal of Distributed and Parallel Systems (IJDPS) Vol.3, No.5, September 2012 : 10.5121/ijdps.2012.3507.5september,2015.

[4] ShraddhaShinde, Mrs. M. A. Potey, “Survey on Evaluation of Recommender Systems”, International Journal Of Engineering And Computer Science ISSN:2319-7242 Volume 4 Issue 2 February 2015, Page No. 10351-10355, e-ISSN: 2319-7242, 2 February 2015

[5] DietmarJannach, Markus Zanker, Alexander Felfernig, Gerhard Friedrich,” Recommender Systems – An Introduction”, https://pdfs.semanticscholar.org/5d1d/d378962c7601526f65f69e408f8800a0d3c4.pdf, 21 ,januaray 2014.

[6] Richard Macmanus,”5 problems on Recommender systems ,a web article”, http://readwrite.com/2009/01/28/5_problems_of_recommender_systems/ ,January 28, 2009

[7] Zhi-Dan Zhao,Ming-sheng Shang,”User-Based Collaborative-Filtering Recommendation Algorithms on Hadoop”,Scholar of Computer Scence&Eng, University of Electron Science & Technology of China, 10 Jan. 2010.

[8] BadrulSarwar, George Karypis, Joseph Konstan, and John Riedl,”Item-Based Collaborative Filtering Recommendation Algorithms”, GroupLens Research Group/Army HPC Research Center Department of Computer Science and Engineering University of Minnesota, Minneapolis, ACM 1-58113-348-0/01/0005, May 1-5, 2001.

[9] Pasquale Lops,Marco de Gemmis,GiovanniSemeraro,” Content-based Recommender Systems: State of the Art and Trends, pp 73-105 , 10.1007/978-0-387-85820-3_3, 05 October 2010.

[10] HongzhiYin,YizhouSun,BinCui,ZhitingHu,LingChen,”a location-content-aware recommender system”, KDD '13 Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining Pages 221-229,10.1145/2487575.2487608 ,August 14, 2013.

[11] Tommaso Di Noia,RobertoMirizzi,Vito Claudio Ostuni,DavideRomito,MarkusZanker,”Linked open data to support content-based recommender systems”, I-SEMANTICS '12 Proceedings of the 8th International Conference on Semantic Systems, Pages 1-8, 10.1145/2362499.2362501, September 06, 2012.

[12] IvánCantador,AlejandroBellogín,DavidVallet,”Content-based recommendation in social tagging systems”, RecSys '10 Proceedings of the fourth ACM conference on Recommender systems ,Pages 237 -240, 10.1145/1864708.1864756, September 30, 2010.

[13] JoeranBeel,StefanLanger,AndreasNürnberger,MarcelGenzmehr,” The Impact of Demographics (Age and Gender) and Other User-Characteristics on Evaluating Recommender Systems”, Research andAdvanced Technology for Digital LibrariesVolume 8092 of the series Lecture Notes in Computer Sciencepp 396-400, 10.1007/978-3-642-40501-3_45, September 26,2013

[14] Grace Ngai,Stephen Chi-Fai Chan,YuanyuanWang,”Applicability of Demographic Recommender System to Tourist Attractions: A Case Study on Trip Advisor”, WI-IAT '12 Proceedings of the The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology - Volume 03, Pages 97-101 ,10.1109/WI-IAT.2012.133, December 07,2012

[15] Mustansar Ali Ghazanfar,Adam Prugel-Bennett,” A Scalable, Accurate Hybrid Recommender System”, 2010 Third International Conference on Knowledge Discovery and Data Mining, Phuket, 2010, pp. 94-98.: 10.1109/WKDD.2010.117, 10 Jan. 2010.

[16] Luis M. de Campos,Juan M. Fernández-Luna , Juan F. Huete , Miguel A. Rueda-Morales,” Combining content-based and collaborative recommendations: A hybrid approach based on Bayesian networks ”, International Journal of Approximate ReasoningVolume 51,Issue 7, September 2010, Pages 785-799,:10.1016/j.ijar.2010.04.001,11 April2010.

[17] Porcel,E. Herrera-Viedma,” Dealing with incomplete information in a fuzzy linguistic recommender system to disseminate information in university digital libraries”, Published on: Knowledge-BasedSystemsVolume 23, Issue 1, February 2010, Pages 32–39Special Issue on Intelligent Decision Support and Warning Systems, 10.1016/j.knosys.2009.07.007, 5 August 2009

[18] Walter Carrer-Neto , María Luisa Hernández-Alcaraz , Rafael Valencia-García , Francisco García-Sánchez,” Social knowledge-based recommender system. Application to the movies domain”,\ExpertSystems with Applications,Volume 39, Issue 12, 15 September 2012, Pages 10990–11000, 10 March 2012

[19] GediminasAdomavicius,AlexanderTuzhilin,” Context-Aware Recommender Systems”, pp 217-253, 10.1007/978-0-387-85820-3_7, 05 October2010.

[20] BlerinaLika , Kostas Kolomvatsos, , StathesHadjiefthymiades,” Facing the cold start problem in recommender systems”,Expert Systems withApplicationsVolume 41, Issue 4, Part 2,March2014, Pages 2065–2073, 10.1016/j.eswa.2013.09.005, 16 September 2013

[21] Jesús Bobadilla, , Fernando Ortega,Antonio Hernando,Jesús Bernal,” A collaborative filtering approach to mitigate the new user cold start problem”, Knowledge-Based SystemsVolume 26, February 2012, Pages 225–238, : 10.1016/j.knosys.2011.07.021, 30 August 2011

[22] I. Dhillon,Si Si,Cho-Jui Hsieh,Hsiang-Fu Yu,” Scalable Coordinate Descent Approaches to Parallel Matrix Factorization for Recommender Systems”, Data Mining (ICDM), 2012 IEEE 12th InternationalConference on, : 10.1109/ICDM.2012.168, 13 Dec. 2012.

[23] Pearl Pu,LiChen,Rong Hu,” Evaluating recommender systems from the user’s perspective: survey of the state of the art”, User Modeling and User-Adapted Interaction,The Journal of Personalization Research, Journal no. 11257,: 10.1007/s11257-011-9115-7,10 March 2012

[24] GediminasAdomavicius,YoungOk Kwon,” Improving Aggregate Recommendation Diversity Using Ranking-Based Techniques”,IEEETransactions on Knowledge and Data Engineering (Volume: 24, Issue:5, May 2012),: 10.1109/TKDE.2011.15, 06 January 2011.

[25] KatrienVerbert,Nikos Manouselis,Xavier Ochoa,” Context-Aware Recommender Systems for Learning: A Survey and Future Challenges”,IEEE Transactions on Learning Technologies (Volume: 5, Issue: 4, Oct.-Dec. 2012),: 10.1109/TLT.2012.11, 24 April2012

[26] XujuanZhou,YueXu,YuefengLi,AudunJosang,Clive Cox,” The state- of-the-art in personalized recommender systems for social networking”,Artificial Intelligence ReviewFebruary 2012, Volume 37, Issue 2,pp 119–132, : 10.1007/s10462-011-9222-1, 12 May2011.

[27] GeorgiosPitsilis, Svein J. Knapskog,” Social Trust as a solution to address sparsity-inherent problems of Recommender systems”, ACM RecSys 2009, Workshop on Recommender Systems &The Social Web, Oct. 2009, ISSN:1613-0073, New York, USA,Cite as:arXiv:1208.1004 [cs.SI], 5 Aug 2012

[28] Athanasios N. Nikolakopoulos,Marianna A. Kouneli,John D.Garofalakis,” sparsity in ranking-based recommendation”, : 10.1016/j.neucom.2014.09.082, 24 February 2015.

[29] EranToch,YangWang,Lorrie Faith Cranor,” Personalization and privacy: a survey of privacy risks and remedies in personalization-based systems“,Cited as: Toch, E., Wang, Y. &Cranor, L.F. User Model User-Adap Inter (2012) 22: 203,: 10.1007/s11257-011-9110-z,10 March 2012.

[30] Neil Hunt,,Carlos A. Gomez-Uribe,”The Netflix Recommender System: Algorithms, Business Value, and Innovation”, journal , ACM Transactions on Management Information Systems (TMIS), Volume 6 Issue 4, January 2016,Article No. 13, 10.1145/2843948, 4, January 2016.

[31] Kumar, A. & Sharma, A. (2012). Alleviating Sparsity& Scalability Issues in Collaborative filtering based Recommender System .Proceedings of International Conference on Frontiers of Intelligent Computing: Theory and applications (FICTA), Springer AISC, pp. 103-112