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Review Paper on Efficient Approach for Context Aware Recommendation System

Prof. M. K. Sadar*1, Ankita N. Kharche2, Aparna P. Morey3
*123Computer Science and Engineering, Amravati, Anuradha Engineering College/Chikhali, Maharashtra, India

ABSTRACT

Context-Aware Recommender Systems (CARSs) have to face the cold-start problem, that is, there is no possibility to provide proper recommendations for the new users, items or contextual situations. In this paper, the methods proposed for solving cold start problem by exploiting various hybridization techniques, in order to take advantage of the strengths of different CARS algorithms while removing their weaknesses in a given (cold start) situation. The initial analysis has shown that basic CARS algorithms are used and hybridized to achieve an overall optimal performance. Here, combined multiple pre-filters (Combining Multiple approaches) are used with Hybridization to solve the cold-start problem. It is used to generate accurate ratings and better performance of CARS.
Keywords : Context-Aware Recommender Systems(CARs); Cold-Start Problem; Hybrid System

I. INTRODUCTION

Today, the use of internet by the people increases, and the number of people using the web application is also increases. People make internet is a popular and excellent page that stores the data about a specific object in a specific domain, which is visited and explain their opinion and evaluations by the people. The products and services sponsor by the social web site is offered by the reviews of people that is user generated reviews, which can be helpful for the user in making decision. The Recommendation systems have generates to fill up the need of sellers and buyers by automating recommendations according to the data analysis. Innumerable products information about stores have the challenge for customers and also online business in distinguish the products which are best according to their need. As we know the buyers searching the product according to our need, but in that searching lots of time spend. As a solution generate recommendations as a meaningful recommendation to the collection for products of user. The decision making is useful to take in decision in specific domain. This recommendation system is moreover accepted and defaulted to naturally different area and carry out Domain Sensitive CF for the recommender system. Most of the attempts are occur in two stage of sequential process i.e. first detect domain by congregate and then the rating approximation with regular CF within the cluster. The cold start problem is occur, when the user or item is new for that e commerce platform.

In this paper hybridization technique is used to deal with the cold start problem occur in context aware recommendation system, particularly deals with; 1.new user problem, that it does not provide proper rating history of the relevant recommendation; 2.the new item problem, the new items on that system is difficult to reach which is recommend; 3.new context problem, this problem is carried out when we have to produce recommendation by following new situation of context that the system is requested; 4.the mixture(possible mixture of previously mentioned problems. We used combing multiple pre-filtering Other than of post filtering, contextual modelling and simple pre filtering.

The Hybrid RSs techniques are best to deal with the cold start problem in traditional recommender systems (RSs) that is concern many CARS method this are contextual post filtering, contextual pre-filtering and contextual modelling. CARS may be partitioned into the classified as contextual pre-filtering, contextual post-filtering and contextual modelling, the store information is take which is depending upon the recommendation stage.

II. METHODS AND MATERIAL

2.1 Literature Review

In 1992, John Riedl and Paul Resnick attended the CSCW conference together. After they heard keynote speaker Shumpei Kumon talk about his vision for an information economy, [2]they began working on a collaborative filtering system for Usenet news. The system collected ratings from Usenet readers and used those ratings to predict how much other readers would like an article before they read it. This recommendation engine was one of the first automated collaborative filtering systems in which algorithms were used to automatically form predictions based on historical patterns of ratings.

Matthias Braunhoferet al. (2014) proposed the idea is using hybridization techniques to deal with cold-start situations occurring in CARSs. It deal with few problems which are: (i) the new user problem, which refers to the problem of providing relevant recommendations to new users with no rating history; (ii) the new item problem, which denotes the difficulty of accurately recommending items that are new to the system; (iii) the new context problem, which has not been explored in detail so far, and occurs when the system is requested to produce recommendations under new contextual situations; and finally (iv) the possible mixtures of the aforementioned problems.[1]

Memory-based methods focus on finding similar users or items for recommendation. These algorithms generally comply with the following steps: 1) calculate the similarity which reflects correlation between two users or two items. Popular similarity measures include Pearson correlation, vector similarity and various extensions of them; 2) produce a prediction for the active user based on the ratings of similar users found, or based on the computed information of items similar to those chosen by the active user. Such recommender systems are easy-to-implement and highly effective. However, there are several limitations for the memory-based CF techniques, such as sparsity and scalability [2].

Contextual information has been proved to be useful for recommender systems, and various context aware recommendation methods have been developed. According to the survey of, these methods can be categorized into pre-filtering, post-filtering and context modelling. Employing the pre-filtering or postfiltering strategy, conventional methods utilize the contextual information to drive data selection or adjust the resulting set. Baltrunas et al. use the item-splitting for the contextual pre-filtering process. Li et al. view the context as a dynamic feature of items and the items that do not match a specific context that filter out. Some works have applied tree-based partition with matrix factorization, which also fall into the pre-filtering category. Zhong et al. propose RPMF, which applies tree based random partition to split the user-item-rating matrix by grouping users and items with similar contexts, and then applies matrix factorization on each node of the tree. To deal with social network and context, Liu et al. propose SoCo, which has the similar idea with RPMF but applies matrix factorization only on the leaf nodes. These pre-filtering and post-filtering methods may work in practice, but they require supervision and fine-tuning in all steps of recommendation [3].

2.2 Architecture

To accomplish higher execution and overcome the difficulty of traditional recommendation techniques, a hybrid recommendation technique that joins the good and best features of two or more recommendation techniques in hybrid technique has been proposed. According to Burke, there are seven basic hybridization mechanisms of merger used in recommender systems to build hybrids: first is weighted, second is mixed, third is switching, fourth is feature combination, fifth is feature augmentation, sixth is cascade and the last one is meta-level. The accepted practice in the existing hybrid recommendation techniques is to merge the CF recommendation techniques with the other recommendation techniques in an attempt to avoid cold-start, sparseness and/or scalability problems.

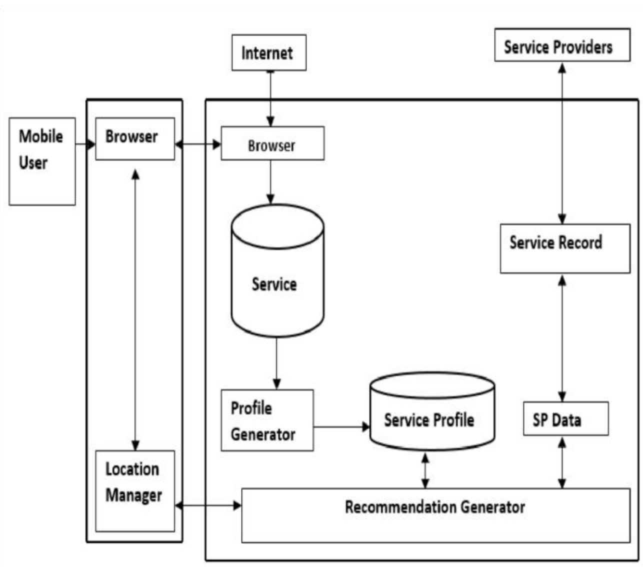

Fig.1: Recommendation system architecture

i) Hybridisation Techniques for Cold-Start Problem

In this method, the idea of using hybridisation techniques to deal with cold-start situations occurring in CARS is used. Hybrid RSs are a well-accepted technique to deal with cold-start issues in traditional Recommender Systems (RSs), they have not yet systematically been applied to CARSs. Hybrid RSs combine in different ways several recommendation techniques, each of which has its own strengths and weaknesses, to achieve overall peak performance. This method is used to deal with: (i) the new user problem, (ii) the new item problem, (iii) the new context problem,(iv) the possible mixtures of the aforementioned problems. The result of this method is able to produce meaningful recommendations also in cold-start situations. The first technique, called Heuristic Switching, uses a stable heuristic in order to switch between the various basic algorithms depending on the encountered cold-start situation. Content-based CAMF-CC is selected when requested to predict a rating for a new item, while it selects demographics-based CAMF-CC when predicting a rating for a new user or a new contextual situation. When a mixture of elementary cold-start cases is detected, it computes the predicted rating by averaging the predictions of the two constituent algorithms. The second one, Adaptive Weighted refers to a novel adaptive weighted hybrid CARS algorithm. It extends the two dimensional adaptive RS and builds for each basic CARS algorithm a new user-item-context error tensor whose entries are the known deviations (errors) of the CARS predictions from the true ratings [1].

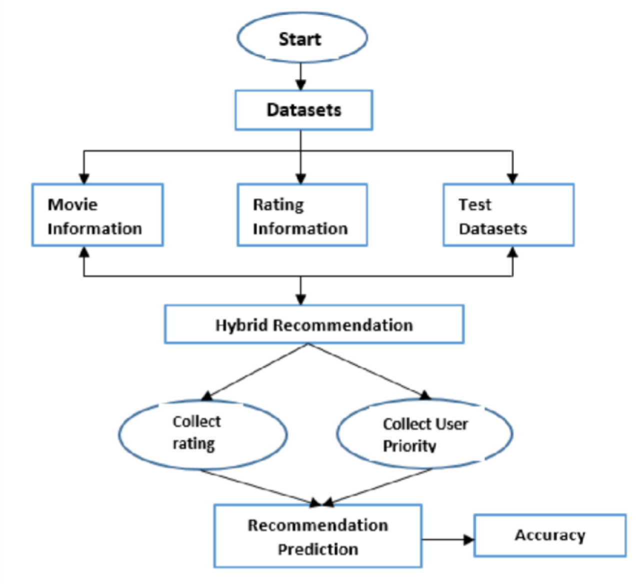

Fig. 2: Flow Diagram of Hybrid Recommendation

ii) Combined Multiple Approach

In this method, combining multiple pre-filtering, post-filtering, and contextual modelling methods is analysed to generate better predictions. It is well documented in recommender systems previous work; often a combination of several solutions provides significant performance improvements over the individual approaches. The three categories of context-aware recommender systems offer several different opportunities for employing combined approaches. One possibility is to develop and combine several models of the same type [1].

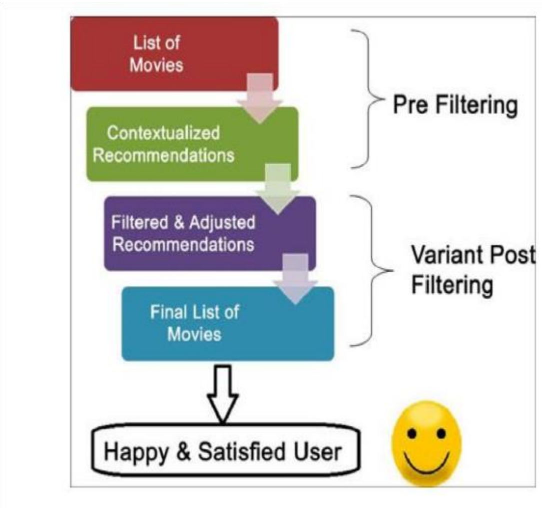

Fig. 3: Combined multiple approach

Different periods of the year or different purchasing intents may lead to different types of behaviour. For instance, a customer may spend more in winter during Christmas and less during the rest of the year or change the product categories and the frequency of purchase. We used user-based collaborative filtering for the standard (2D) rating estimation purposes before (after) the contextual pre- (post-) filtering methods are applied due to its popularity. According to the pre-filtering approach, the contextual information is used as a label for filtering out those ratings that do not correspond to the specified contextual information. This is done before the main recommendation method is launched on the remaining selected data. There are different types of pre-filtering, such as exact pre-filtering (EPF) and generalized pre-filtering. EPF selects all the transactions referred to the exactly specified context (e.g., purchase made in winter 2008), while generalized pre-filtering selects all the transactions referred to a specific context based on the generalization of the contextual information. Note that the EPF is uniquely defined by context k. According to the post filtering approach, we have used the contextual information after the main 2D recommendation method is launched [4]. Once the unknown ratings are estimated and the recommendations are produced, the system analyses data for a given user in a given context to find specific item usage patterns and uses them to "contextualize" the recommendations obtained using the 2D recommendation method, such as collaborative filtering.

The experimental comparisons of the pre- and post-filtering methods were performed on two different datasets. The first dataset (DB1) comes from an e-commerce portal which sells electronic products to approximately 120,000 users and contains about 220,000 transactions. For this dataset, we selected Time of the Year as a contextual variable. We excluded the customers having few transactions and exhibiting abnormal behaviour. The final dataset had about 1,500 users and 10,000 transactions. The second dataset (DB2) contains purchasing transactions performed by students on an Amazon website in a controlled environment that also recorded the contextual information of the purchases via a special-purpose browser developed by us for the project [4]. Once a product was selected, the browser recorded the transaction together with the context specified by the student via an API. The key contextual information to get from some the students by our web browser was the intent for purchase. We excluded the students from DB2 who made less than 40 transactions and who had any kind of misleading or abnormal behaviour. The resulting number of students was 556, and the total number of transactions was 31,925[5].

iii) Semantically-Enhanced Pre-Filtering

A pre-filtering path is planned that is depend on the inspiration that ratings gain in contextual conditions, it is like the tagged o may at rest be handling to progress in the rating prediction accuracy. It also think about context dependent rating by degenerate predictions enumerate in contextual situations like the target. A generic contextual modelling structure for CARSs is to generate, hence that analyser and planner can be used the model that is already used, their code, parameters so to increase the mode to construct their own operation driven modes[8].

iv) Contextual modelling

Context-aware recommender systems (CARS) develop more applicable recommendations by adapting them to the specific contextual situation of the user. But this Context-Aware Recommender Systems (CARSs) suffer from the cold-start problem, that is, the inability to provide accurate recommendations for new users, items or contextual situations. Hybrid RSs are a well-accepted technique to deal with cold start issues. Hybrid RSs combine in different ways several recommendation techniques, each of which has its own strengths and weaknesses, to achieve overall peak performance [10].

III. ADVANTAGES AND LIMITATIONS

- **Advantages:**

1. Time required by the proposed method is less as compared to the existing methods.
2. The performance is better than others in terms of quality and time.
3. It provides the better use of database which store user and product history.
4. Quality prediction, scalability, prediction speed are the main advantages of the proposed scheme.

3.2 Limitations:

Hybridisation Techniques for Cold Start Problem

Contextual situations are made up of only one contextual condition, thus making it impossible for SPF to correctly calculate similarities between contextual situations. Thus, SPF gives a poor performance.

Combined Multiple Approach

Combined multiple approach can be time consuming in some recommendation processes.
Contextual Operation for Recommendation Systems
To obtain the best performance COT depends on the stable result of matrix diversity.
Semantically-Enhanced pre-Filtering
Depends on Matrix Factorization and its performance.
Contextual Modelling
The model has to be generic enough to be able to describe any contextual definition related to CARS. User preferences (and hence ratings) on items depends

on the context, therefore context dependent rating data on items should be available.

IV. APPLICATIONS

Google

• Many applications including:
 -Google Search
 -Google now
 -Google news

Music

• Pandora uses properties of a song or we can say that artist to create a “radio-station” that plays the music with similar properties.

E commerce applications

• Online shopping
• Video on demand
- Subscription based service
- Video rental service
• Online marketing

V. CONCLUSION

In this paper, a proposed method includes the use of combining multiple approaches i.e. combining multiple pre-filters with hybridisation techniques to avoid the problem of cold-start i.e. (i.e., new user problem, new item problem and new context problem) that exploit different CARS algorithms, and adaptively use these algorithms for rating prediction depending on their strengths and weaknesses in a given (cold-start) situation.

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