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AN ANALYSIS OF DIFFERENT TECHNIQUES FOR EFFECTIVE RETRIEVAL OF INFORMATION IN SOCIAL NETWORKING SITES

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ABSTRACT

Social Networking Sites (SNS) like Facebook, Twitter, Amazon, Movie Lens etc are those sites which are able to connect different kinds of people. Those sites predict the taste of different users over different item that changes over time. Users may upload media, share information and they can make comment within social circles. It is difficult to derive the exact information on the item which they surf over social sites. Such difficulty is termed as cold start. It is overcomed by several techniques for retrieving exact information. In this paper, an survey or analysis is done on different techniques for drawing exact data in SNS.

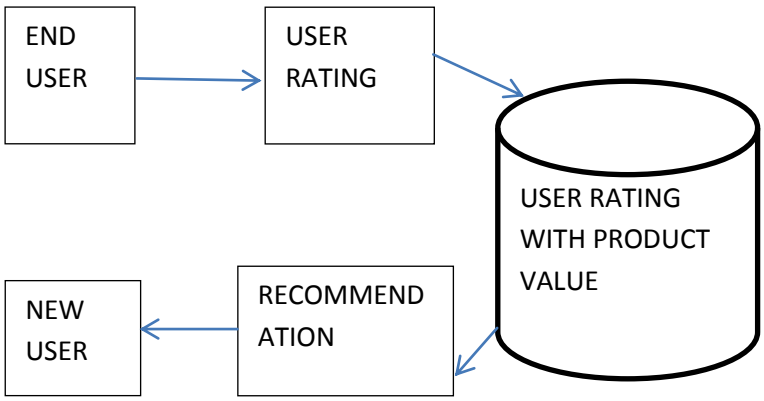
Keywords: Social Networking Sites, Cold Start, survey, Techniques

1. INTRODUCTION

Web Mining is the process of extracting information over the web. Social sites are the one where it is necessary to retrieve the information about the user's interests over different items. Social sites help to analyse the profile of different users. They can add any kind of Medias, comments over the social circles. By this sharing of information any kind of product or item which is popular in the society where its name and fame can be identified.

Fig 1: Architecture Diagram of Social Recommender System

The abundancy of information in the world made it difficult to mine the data due to very storage of information. Hence the retrieval of information such large database is very tedious. Information, redundant data, incomplete information make the retrieval complicated. To make the effective and exact data to be pulled out from the database server several techniques are used. In this paper, some of the techniques are discussed to overcome the cold start problem.



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2. SOCIAL RECOMMENDER SYSTEM TECHNIQUES

2.1CRUC: Cold-start recommendations Using Collaborative Filtering in Internet of Things

In the paper, authors applied collaborative filtering in Internet of Things which aims at interconnecting everyday objects(including things and user).CRUC consist of formulation, filtering and prediction steps. CRUC formulates the cold start problem in IOT as a surmise of user preferences. Then, it picks the most important users and their information by introducing significant users. Finally, CRUC comes up with a fusion policy to predict user preferences. Some basic steps involved are:

A) Identifying significant users

B) Clustering significant users

C) Smoothing user ratings

D) Fusing predictions

2.2 A Scalable Collaborative Filtering Framework based on Co-clustering

Co-clustering is a novel collaborative filtering technique which involves the simultaneous clustering of user and items. It is a weighted co-clustering algorithm for incremental and parallel versions to build an efficient approach for cold start. Performance is evaluated based on metrics corresponding to prediction accuracy, static training time and prediction time. Accuracy is calculated by mean absolute error (MAE) which is the absolute values of errors over all predictions. The static training time was estimated in terms of CPU time taken for core training routines while the prediction time was estimated by averaging over response time taken for all predictions. It is found to be efficient by these merics tested by experimental results.

2.3 Personalized Recommendation on Dynamic Content Using Predictive Bilinear Models

A predictive bilinear model [12] for recommendations was proposed which is feature-based machine learning approach to personalized recommendation that is capable of handling the cold-start issue effectively and maintain profiles of content of interest, in which temporal, characteristics of the content. Based on all features in user and content profiles, developed predictive bilinear regression models to provide accurate personalized recommendations of new items for both existing and new users. This approach results in an offline model with light computational overhead compared with other recommender systems that require online re-training. This framework is general and flexible for other personalized tasks and performance found to be better. Hypothesis testing results shows that improvement is significant. Combination of content based filtering and aggregate level (users are served with the same content at the same time stamp) performs better results.

2.4 Yahoo Music Recommendations: Modelling Music Ratings with Temporal Dynamics and Item Taxonomy Recommendations for music are done using temporal and item taxonomy [4] of data in the Yahoo! Music dataset. It is characterized by three unique features: First, rated items are multi-typed, including tracks, albums, artists and genres; Second, items are arranged within a four level taxonomy, proving itself effective in coping with a severe sparsity problem that originates from the unusually large number of items (compared to, e.g., movie ratings datasets). Finally, fine resolution timestamps associated with the ratings enable a comprehensive temporal and session analysis and further presented a matrix factorization model exploiting the special characteristics of this dataset. The modelling corporate a rich bias model with terms that capture information from the taxonomy of items and different temporal dynamics of music ratings.

2.5Cold-start recommendation using Bi-clustering and Fusion for large scale social recommender system

Cold Start is a problem which reduces the efficiency of the Social Recommendation system. To overcome this problem Bi-Clustering and Fusion was introduced. It clusters both item and users at the same time. Rating is determined by the frequent raters and popular items. To overcome the data sparsity smoothing and fusion was introduced.

2.6 Google news personalization scalable online collaborative filtering

A technique of scalable online [2] collaborative filtering for Google News Personalization was

generated and recommendations were made using three approaches: collaborative filtering using Min Hash clustering, Probabilistic Latent Semantic Indexing (PLSI), and co visitation counts and combined recommendations from different algorithms using a linear model. The approach is content agnostic and consequently domain independent, making it easily adaptable for other applications and languages with minimal effort.

2.7 Whom Should I Trust? The Impact of Key Figures on Cold Start Recommendations

Recommendations are made for cold start using the Key Figures[9] by generating adequate recommendations for newcomers which is award problem for a Recommender System (RS) due to lack of detailed user profiles and social preference data. New users should be encouraged to connect to the network as soon as possible. However, it is critical to guide newcomers through this early stage connection process and identify key figures in the trust network (in particular mavens, connectors and frequent ratters)

Some of the basic notations used in some papers for identifying the user preferences over the item are as follows:

Notation	Explanation
|I |	Number of items in the item-user matrix
|U|	Number of users in the item-user matrix
I_U	The set of items rated by the user u
U_i	The set of users who rated the item i
$r_{u,i}$	The rating that the user u takes the item i
r_i	Average rating of the item i
r_u	Average rating of the user u
$P_{u,i}$	The predicted rating on the item I by the user u
S_i	The set of the item i's similar items
S_u	The set of the user u's like-minded users
$\underline{Y}$	The low bound of the rating on a given item
$\bar{y}$	The upper bound of the rating on a given item

CONCLUSION

In this paper, analysis on different techniques is done to retrieve the exact information in social networking sites .These methods helps to give us an idea to overcome the cold start scalability and create an efficient search for fast retrieval of data. The table and notations described above helps for easy predictions of user over an item. Hence, In this paper, an analysis is done on different papers to overcome some of the issues like cold start using

different techniques in social recommendation system is done.

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