A Survey on Recommender Systems Regularized with User Trust and Item Ratings

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ABSTRACT*:* With the drastic increase in number of users and contents available across the internet users are often overloaded with irrelevant content. As it has become increasingly challenging to deliver meaningful content to users, various recommender systems have been developed to try and address this issue. Recommender systems typically search through huge volumes of data dynamically to mine information that is most likely to be relevant and appealing to the user. These techniques use various informations related to users such as history of their actions, interests, geography, gender, age, etc. to deliver personalized services and content. This information is often combined with user trust information and item ratings information by several state of the art models to show better recommendations. This paper studies and presents various recommendation techniques with their characteristics and the impacts of user trust information and item ratings information on recommendation.

KEYWORDS: Recommender systems, user trust, item ratings,Contentfiltering, Collaborative filtering, Hybrid filtering technique.

I. INTRODUCTION

Recommender systems help users by improving discoverability of items. Advanced recommender systems can potentially reduce the reliance on search algorithms since they connect relevant information to users which might be difficult to find. Recommender systems are primarily used across many fields such as e-commerce, marketing, financial services and personalized vacations to improve user experience by presenting personalized recommendations focusing on user tastes and wants thus improving profitability. Recommendation Techniques are broadly categorized as: Content-based filtering technique, Collaborative filtering technique and Hybrid recommender systems.
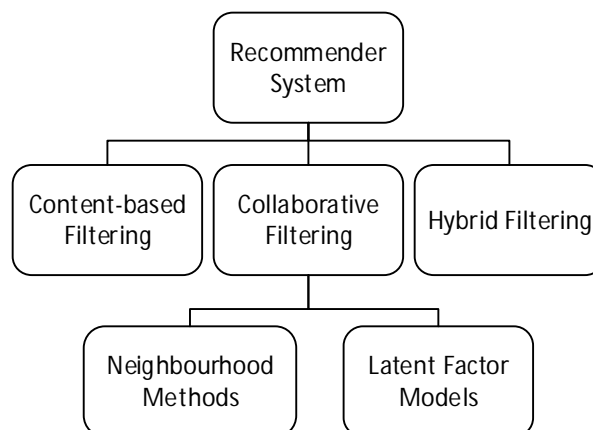
Figure 1. Types of recommender systems

Content-based filtering strategy uses information on users' preference profile and item description about historic transactions. For instance, a content filtering music recommender system may consider using attributes such as music genre, singers, musicians, beats, etc. of the songs that users like based on which they may recommend further songs that may interest users. Data collection from external sources is necessary for these systems which may present challenges.

Collaborative filtering (CF) strategy on the other hand solely relies on past behavior exhibited by the users. CF often outperforms content-based filtering approach in terms of accuracy with the exception of cold start scenarios, wherein a product or user is relatively new and hence CF fails to provide meaningful recommendations. Second problem faced by CF is of data sparsity as users typically rate only small subset of items from the millions of items available. Third, these systems are difficult to scale as there are millions of users and millions of product which makes the task of computations very expensive.

CF techniques are further classified into neighborhood methods and latent factor models. As described by Yehuda et all in [1], neighborhood methods compute item to item relations or user to user relations to make recommendations while latent factor models characterizes items and users on multiple factors determined using rating patterns.

Users relations can be described in terms of social trust networks which are based on online (i.e. trust) relationships and offline (trust-alike) relationships between users. These relations can respectively strongly and weakly influence the opinions of users.
Research has also been done on Hybrid recommender models which combine content-based filtering and CF techniques sequentially or together.

II. RECOMMENDATION TECHNIQUES

A. CONTENT-BASED FILTERING TECHNIQUES:
For point of interest recommender systems are personalized by mining user preferences in [7] to understand user preferences transition patterns to improve accuracy of POI recommendation systems but users textual comments are not considered for making predictions.This paper helps study users preference transition across categories of point of interest and further predictions are done based on this analysis.

B. NEIGHBORHOOD TECHNIQUES:
Recommender systems can use trusted neighbors as shown in [4] which improves accuracy, coverage, system performance of recommender systems. This works well in case of sparse data availability of sparse distribution ratings but majority strategy used in this paper doesn't work well when there is diversity in ratings. It shows us how for generating recommendation, ratings of trusted neighbors are merged.

C. MATRIX FACTORIZATION TECHNIQUES:
Researchon matrix factorization techniques done in [1] shows how they are better than classic nearest neighbor technique. It shows us matrix factorization model that incorporates implicit feedback, confidence levels and temporal effects.

D. HYBRID FACTORIZATION TECHNIQUES USING NEIGHBORHOOD AND LATENT FACTORIZATION METHODS:
Neighborhood and latent factorization models are merged in [3] to provide improved accuracy and thus improve system performance by using neighborhood and latent factor models at different levels to complement each other. It also provides efficient global optimization scheme but it is not tested with large datasets related to implicit feedback. It integrates implicit user feedback in neighborhood model and latent factor model (SVD).

E. MATRIX FACTORIZATION USING USER TRUST INFORMATION:

User trust applied to social collaborative filtering techniques in [2] show how trust based social collaborative filtering techniques work well in case of cold start and integrates item ratings and user trust to improve predictive accuracy but it is inferior to latest state of the art ratings only model. It creates hybrid model by integrating item rating with user trust based on truster and trustee model to compute influence on item ratings.

Probabilistic matrix factorization is used with social recommendation in [5] to demonstrate how social recommendations can be scalable to even very large datasets as it scales linearly with number of observations.In case of few or no ratings, this system performs better than other state of the art systems but distrust information is not accounted for in this system.Problems of poor prediction accuracy and data sparsity are solved by employed rating records and user social network information.

Recommender systems with social regularization [6] provide solution which is generic and easily extensible but it may have adverse impact in case of some social connections. It shows ways wherein recommendation systems are benefitted by social trust.

Better quality trust information is derived by using decomposed trust in matrix factorization [10], but they do not consider trust transitivity of the trust networks. Trust information is able to explain user similarity only up to some extent. This information can be combined with truster and trustee information to improve prediction accuracy.

F. UNRATED ITEM RECOMMENDATION TECHNIQUES:

Unrated tail items recommendation system in [8] improves rating diversity and accuracy and recommends better products to users by proposing novel approach for recommending tail products. This system works better than most system but PureSVD is more useful for preferences especially for short head data.

G. ITEM TO ITEM COMPARISON TOP-N RECOMMENDATION TECHNIQUE:

Item to item recommendation models using top N recommendation [9] elaborate on how influence of local and global preference weights can determine the top N item recommendation output list but like other top N algorithms, this can capture just pairwise item-item relations but no higher order relations. This paper demonstrates improved performance of top N recommendation algorithm by using combination of local and global SLIM models instead of single point models.

III. COMPARISON OF EXISTING RECOMMENDER SYSTEMS

Content based filtering techniques can recommend new items even if there are no ratings provided by users. So even if absence of user preference information, recommendation accuracy is maintained. Secondly, it can adjust its recommendations quickly with changing user preferences. It enables users to get good recommendations even though their profile information is not shared and hence improves privacy. This technique can clearly explain the basis of generated recommendations.

However, content based recommendation techniques are dependent on metadata for items. In absence of detailed description of items or extensive user profile information they cannot make good recommendations. This system also tends to over-specialized recommendations and hence they do not get recommendations outside of pre-defined categories of items.

Collaborative Filtering on the other hand performswell even in domains without much content and where content is considered difficult to analyze. Additionally, it is capable of recommending items that are nowhere related to user profile but are highly likely to be relevant to the user.

CF system cannot work well in case of new item or new user which is referred as cold start problem. Secondly, since the database contain millions of items and millions of users and only few items are ever rated even by the most active

users, it leads to problem of data sparsity. Third challenge is of scalability since the with the users and items, the computation grows linearly

IV. CONCLUSION

Several state of the art recommender systems have been developed over past few years most of which work on collaborative filtering techniques. These systems face problems such as data sparsity, scalability and cold start.Several systems studied in this paper propose different ways to solve some or all of these problems. They are faced with unique challenges in the process. These systems can be further extended to solve these problems better which forms the basis of our research.

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