ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Website: www.ijircce.com

Vol. 5, Issue 8, August 2017

An Improvised Recommendation System on Top-N, Unrated and Point of Interest Recommendations Regularized with User Trust and Item Ratings

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ABSTRACT*:* Data availability is not a primary concern of this age, but using that data to make meaningful decisions is. Recommendation systems search through huge volumes of data dynamically to mine information that is both relevant and appealing to the targeted user. The recommender systems use various information related to users such as history of their actions, interests, geography, gender, age, etc. to deliver personalized services and content. This information when combined with user trust information and item ratings information improves quality of recommendations drastically. User trust in recommender systems is incorporation of impacts of social relations between users while item ratings are the ratings values currently associated with various items. Some of the most exciting features associated with recommendations are identification of interest points of user, identification of Top-N most appealing items for the users and developing ability to recommend even the unrated tail items that have management costs associated with them but are not sold well due to lack of ratings information. There are several techniques developed that do these recommendations but they do not consider the combined effects of user trust and item ratings for generating these recommendations. In my system, I propose an enhanced recommender system that applies techniques of point of interest recommendation, recommendation of unrated items and Top N recommendation on user trust and item ratings to further improve quality of recommendation results.

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.

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

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that may interest users. Data collection from external sources is necessary for these systems which may present challenges.

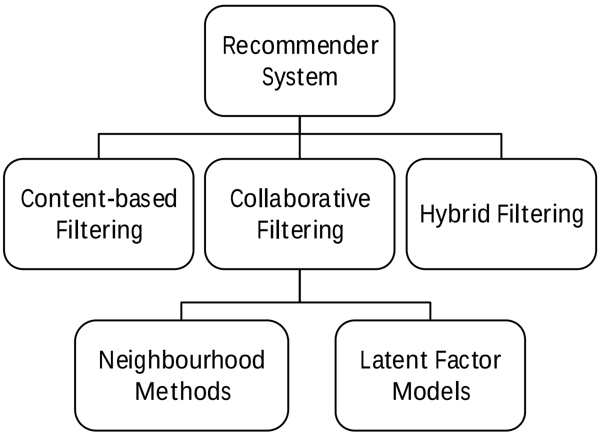

Figure 1. Types of recommender systems

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

2.1 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.

2.2 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.

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2.3 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.

2.4 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).

2.5 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.

2.6 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.

2.7 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.

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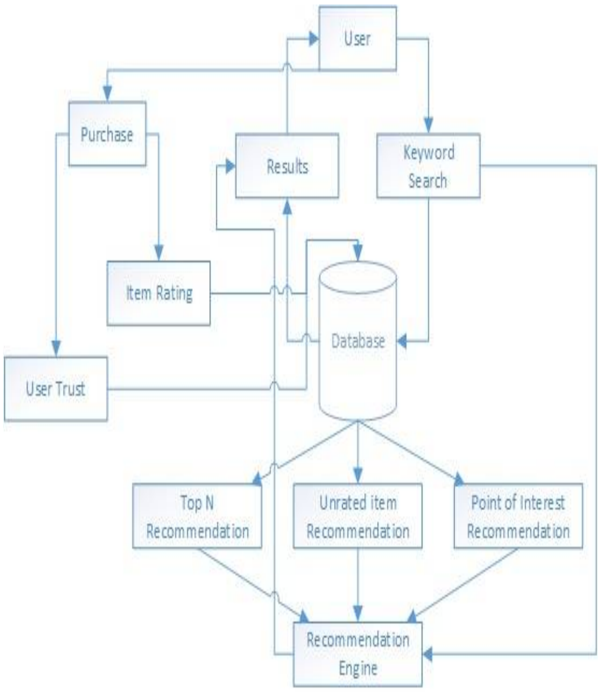
However, content based recommendation techniques are dependent on metadata for items. In absence of detailed description of items or extensive user profile information they cannot make good recommendations. This system also tends to over-specialized recommendations and hence they do not get recommendations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

Existing state of the art collaborative filtering systems face cold start and data sparsity problems. In our recommender system, we propose to further reduce the impact of these issues by applying point of interest recommendation technique, unrated item recommendation technique and top-N recommendation technique on top of user trust and item ratings. A high level system architecture diagram is shown in Fig.



V. ALGORITHMS

5.1 Top-N Recommendation:

5.1.1 Using K-means clustering on implicit and explicit values of user trust, products are filtered.
5.1.2 Implicit and explicit item ratings information is applied to order the products.
5.1.3 Top-N products are recommended.

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5.2 Unrated Items Recommendation.

5.2.1 Unrated items are filtered from all items.
5.2.2 K-means clustering is applied on implicit values of user trust, since explicitvalues won't be available.
5.2.3 Implicit item ratings information is applied to order the product.
5.2.4 Unrated items are recommended.

5.3 Point of Interest Recommendation:

5.3.1 Using K-means clustering on implicit and explicit values of user trust, products are filtered.
5.3.2 Implicit and explicit item ratings information is applied to order the products.
5.3.3 Products are filtered based on point of interest attributes such as author,title, etc.
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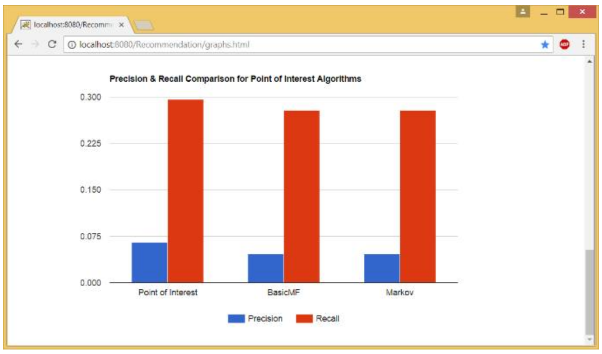
VI. EXPERIMENTATION RESULTS

Accuracy of recommendation systems is evaluated in terms of precision and recall.Precision can be viewed as percentage of recommendations that are considered goodwhile recall can be viewed as percentage of good recommendations that are also part of recommended items. They are computed as:

Precision = Correctly recommended items / Total recommended items

Recall = Correctly recommended items / Total useful recommended items

The results from our algorithms are shown in below graphs:



DOI: 10.15680/IJIRCCE.2017. 0508036

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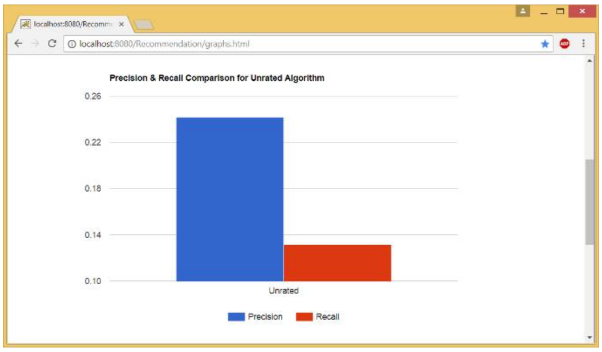

VII. CONCLUSION

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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