A Novel Approach to Trust Based Recommender Systems Leveraged by Context Attributes

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Abstract—Internet has undergone many fold expansion in last couple of decades or so, the pitfall of that is the data overloading problem which has become extremely intricate for retrieving useful information from internet. Users searching for intended contents have endless number of Web pages to navigate and require enormous efforts, requires judgmental aptitude and intuitiveness to extract meaningful information from almost unlimited number of pages and huge content. Recommender systems are meant to be an important solution to the data overload and skewed information problem that persists today in World Wide Web. Very recent research trend in Recommender systems encourages towards consideration of Context awareness along with trust based filtering.One of the major challenges in the context aware recommender system is the selection of relevant contexts and appropriately weighting the relevant contexts for prediction calculations. Also dynamic nature of trust puts practical challenges in using trust based recommender system. The selection of a few most relevant contexts and using them with proper importance factors incorporates aspects of dynamic behaviour of trust and are vital for enhanced accuracy in the recommender output, as irrelevant and inappropriate contexts assimilation decreases the accuracy of recommender output, creates data sparseness and also increases the computational complexity. There are various ways to infuse the weightages of relevant contexts in recommender systems. While doing the neighbourhood formation, trust propagation and predictions, context weighting plays a pivotal role towards increasing the accuracy of Recommender Systems. In this paper, we propose an approach that incorporates the relative weightages of relevant contexts in trust calculations and neighbourhood formation. Trust network thus formed is leveraged by the context attributes. This approach is advantageous in terms of increased recommender accuracy and also overcome data sparseness of hard context filtering methods.

Keyword-Context, Recommender, Trust Neighbourhood, Prediction, Optimization

I. INTRODUCTION

Internet has been perhaps the most outstanding innovation in the field of communication and information technology. In the last two decades or so there had been an unprecedented expansion of internet and web contents. On the flipside, this has created the problem of information overloading. Recommender system aims at solving the problem of information overloading andis emerging as a widely used tool for Web applications. In an environment where there are an infinite number of Web sites for consumers to choose from, the competition is fierce. If a Web site/application can offer a consumer, anvalue added and intelligent system which generates personalized guidance, this would definitely provide a competitive advantage and also ease out the effort required on part of the user to achieve the intended task.There are many different types and uses for recommender systems. Recommender systems use various types of information to generate a recommendation, such as, past purchase records, click stream analysis, user profiles, explicit ratings of items, or social network information. Recommender systems use various methods to process the input data, and output recommendations to the user. Recommender system has been a very active area of research both in industry and academia in the recent years.Recommender systems use various methods to process the input data, &output recommendations to the user; these are broadly categorized in to two types: Content based and collaborative filtering.In Content based recommender systems description of recommendable itemsare compared with the user preferences. This type of recommender system requires detail content description of items those are being recommended. Products or services may be items here. A content-based movie recommender system will typically operate on information such as actors, directors, category of movie (action, drama etc), producers and so on. This information will be compared against the predefined user preferences to determine the movie to be recommended to the user. This type of recommender system requires a lot of information processing pertaining to each item details. Also it presumes the availability of each item description. Incollaborative filtering based recommender system, a different approach is used. Recommendations are generated for a target user by other users who have similar taste or preferences. It is built on the assumption that a possible way to determine interesting content for a user, is to find other users who have similar interest, and then recommend item that those similar users liked. Collaborative filtering also suffers from major shortcomings. A major problem with traditional collaborative filtering based recommender system is data sparseness.

Poor recommendation accuracy has been a major hindrance towards using a Recommender System in practical scenarios. Though there have been many improvements in traditional recommender system, the accuracy of recommender output is still remains below practical useable threshold in many real life scenarios. In a trust based recommender system, in addition to profile to profile similarity matching, trustworthiness of a recommendation partner is also considered for determining recommendation partner. Context based recommender system makes use of context information and context based knowledge in order to determine personalize recommendation to a particular user in a given context. One of the major challenges in trust network based context aware recommender system is the identification of relevant contexts and incorporation of those contexts with appropriate weighting for data processing. In this paper, we propose a novel approach to incorporate weighting of the relevant contexts in trust network based recommender system so that the recommendation accuracy is enhanced and data sparseness can also be tackled.

Trust Network based Context Aware Recommender System:

Trust based recommender system takes into considerations trustworthiness of the recommending partners and neighbours and not just similarity between them and target user. Context aware recommender system takes into consideration contextual information, such as time, place and company of other people (such as watching a movie with friend or family etc) along with user and item. Both trustworthiness and Contextual information plays very key role towards enhancing the accuracy of recommender system.Trust Network based Context Aware Recommender Systemtakes into considerations trust parameters in a given set of relevant contexts to predict the recommended ratings for a target user. That is, they infuse the inherent trust dynamism while doing recommendation. For example, using the relevant contexts and the trust parameters for a given user, a movie recommender system would provide a movie recommendation to the target user in his/her present context from his web of trusted partners. As given in [1], these findings are in line with the findings in behavioural research in consumer decision making. Therefore, accurate prediction of consumer preferences depends on the degree to which the recommender system incorporates the relevant contextual information, this becomes even more important in the context of Trust based recommender system. It has been found that the users that are linked with each other in a social network tend to share similar taste and interests which can help to improve the quality of recommendations and overcome data sparsity issue [12,13,14]. As given in [4], there are various limitations ofsocial recommendation models and these are addressed using relevant rating information from context-aware trust worthy friends. There are various types of contextual information such as time, location, social companion, mood etc. those may be relevant. There are different types of context aware recommender system; these are pre-filtering, post filtering and context modelling. The incorporation of irrelevant context information makes the decision system very inefficient and also inaccurate. That is why, it is extremely important to isolate and find out the relevant context information and ignore the irrelevant ones and apply them appropriately in a trust network. Suppose there are 3 relevant contexts with different weightages, it is evident that not all three of them are equally important towards formation of the neighbourhood and predicting the ratings. For example, in a movie recommendation weightage for company > weightage for Weather > Weightage for Location. If all of these contexts are considered with equal importance, this will eventually create data sparsity and also will reduce the recommendation accuracy. Hence it is extremely important to apply them in the trust network with appropriate importance value.

Relevant Context Selection:

In our previous work [15], we have presented a novel method of selecting relevant contexts for a recommender system, we have used unsupervised feature selection for identification of important features in high-dimensional datasets. The method combines PCA techniques and a weighing method. We first obtained the weighted PC, which can be calculated by the weighted sum of the first *k* PCs of interest. Each of the *k* loading values in the weighted PC reflects the contribution of each individual feature.With minimal loss of information, it is possible to represent original data by using 3 or 4 extracted features. Because it is difficult to visualize multi-dimensional space, principal components analysis (PCA), a multivariate technique, is mainly used to reduce the dimensionality of multi-attributes to three or four dimensions. In PCA, the extractions of PC can be made using either original multivariate datasets or using the covariance or the correlation matrix if the original dataset is not available. PCA summarizes the variation in a correlated multi-attribute to a set of uncorrelated components, each of which is a particular linear combination of the original variables. The extracted uncorrelated components are called principal components (PC) and are estimated from the eigenvectors of the covariance or correlation matrix of the original variables. Therefore, the objective of PCA is to reduce dimensionality by extracting the smallest number components that account for most of the variation in the original multivariate data and to summarize the data with little loss of information Although all of the existing unsupervised feature selection methods performed reasonably well within the limits of the situations for which they were designed, no consensus exists about which of them best satisfies all conditions. Moreover, most of the methods require a high computational load because they involve an extensive search procedure such as the forward selection or the backward elimination. This method using PCA belongs to the filter category and is computationally efficient and easy to implement.Using a real Dataset and applying PCA approach, we have found out 4 most relevant contexts along with their weightages. In this paper, we propose an approach to incorporate these contexts with appropriate importance in a trust network based recommender system.

The paper is organized as follows, section II discuses related works. Our proposed approach on context selection is presented in section III. In Section IV, outline of the experimental setup and results is given. Finally, conclusion of the paper is given in section V.

II. Related work

In recent years, there is lot of reach done in the area of Context Aware Recommender System and Trust Networks, both in the industry and academia. In [1], the concept of Context Aware Recommender System (CARS) is described, various approaches to context information modelling is also outlined. [2] outlines the importance of relevant context information, also describes the relevant context selection using bayes classifiers and SVD. [4] brings out the context aware trust on a social network to handle the heterogeneity and diversity of social relationships. Also importance of relevant context selection along with the usage of statistical method for the same is given in [4]. Relevancy assessment from user survey and the relevancy detection with statistical testing is given in [3]. The same dataset LDOS-CoMoDa is used in our work also. [15] provides PCA based approach for relevant context selection. [16] models trust in recommender system. Context variable weighting is listed in [17]. The literature describes the various concepts associated with CARS and Trust Networks along with the importance of relevant context detection. None of these however explores the context weighting in trust based CARS.

III.Proposed approach

This section presents the proposed method that incorporates weightages of relevant contexts in trust network. One of the major challenges associated with trust based recommender system is the dynamic nature of trust. It has been seen in [18], the trust is not a static parameter and is dynamic in nature. This dynamism of trust needs to be infused in the recommender system to enhance the accuracy. Incorporation of relevant contextparameters in the trust network resolves this issue. If all the relevant contexts are considered as in traditional approaches, these will substantially reduce the data points and hence the neighborhood formation and prediction calculation will become extremely difficult and will eventually result in poor recommendation accuracy. In this paper, we propose an approach that infuses that context sensitiveness and at the same time do away with data sparseness issue. Prediction calculation for trust network based context aware recommender system is shown in figure 1.

Context Weighted Trust Metric:

Trust is defined as the ability of a user to provide accurate recommendations. Trust values are calculated between in pair of users and trust values are asymmetric. Rating prediction is for a target user is generated using target user's neighborhood and applying Resnick formula [11].

$$P_{c,i} = \bar{r}_c + \frac{\sum_{p \in M} sim(c,p)(r_{p,i} - \bar{r}_p)}{\sum_{p \in M} |sim(c,p)|} \text{ ....(i)}$$

Where,

$P_{c,i}$ = Predicted rating for target user c on a specific item i.

$\overline{r_c}$ = Average rating of user c.

$\overline{r_p}$ = Average rating of user p

sim (c,p) = Similarity between user c and p as given by Pearson Correlation.

$r_{p,i}$ = rating user gave to item i

M = the set of all users who belong to target user's neighborhood and rated item i.

This means that all users in the neighborhoodcontribute to the rating prediction.Trust values represent the trust that the target user holds for specific user p. Resnik's formula is modified to generate rating prediction where user p is the sole contributor:

$$P_{c,i} = (\bar{r}_c - \bar{r}_p) + r_{p,i} \text{ ....(ii)}$$

$$T_{c(p,i)} = 1 - \frac{|P_{c,i} - r_{c,i}|}{Z_{\text{MAX}} - Z_{min}} \text{ ....(iii)}$$

$T_{c(p,i)}$ = Trust of target user c for p for a specific item i.

$r_{c,i}$ = Target user's actual rating on item i

Z_{Max} = Top of the rating scale

Z_{Min} = Bottom of the rating scale.
Let $C_1, C_2, C_3, \ldots\ldots, C_r$ be the r most relevant contexts (r is typically 3 or 4) from the set of available contexts with weightages $W_1, W_2, W_3, \ldots\ldots, W_r$ respectively.

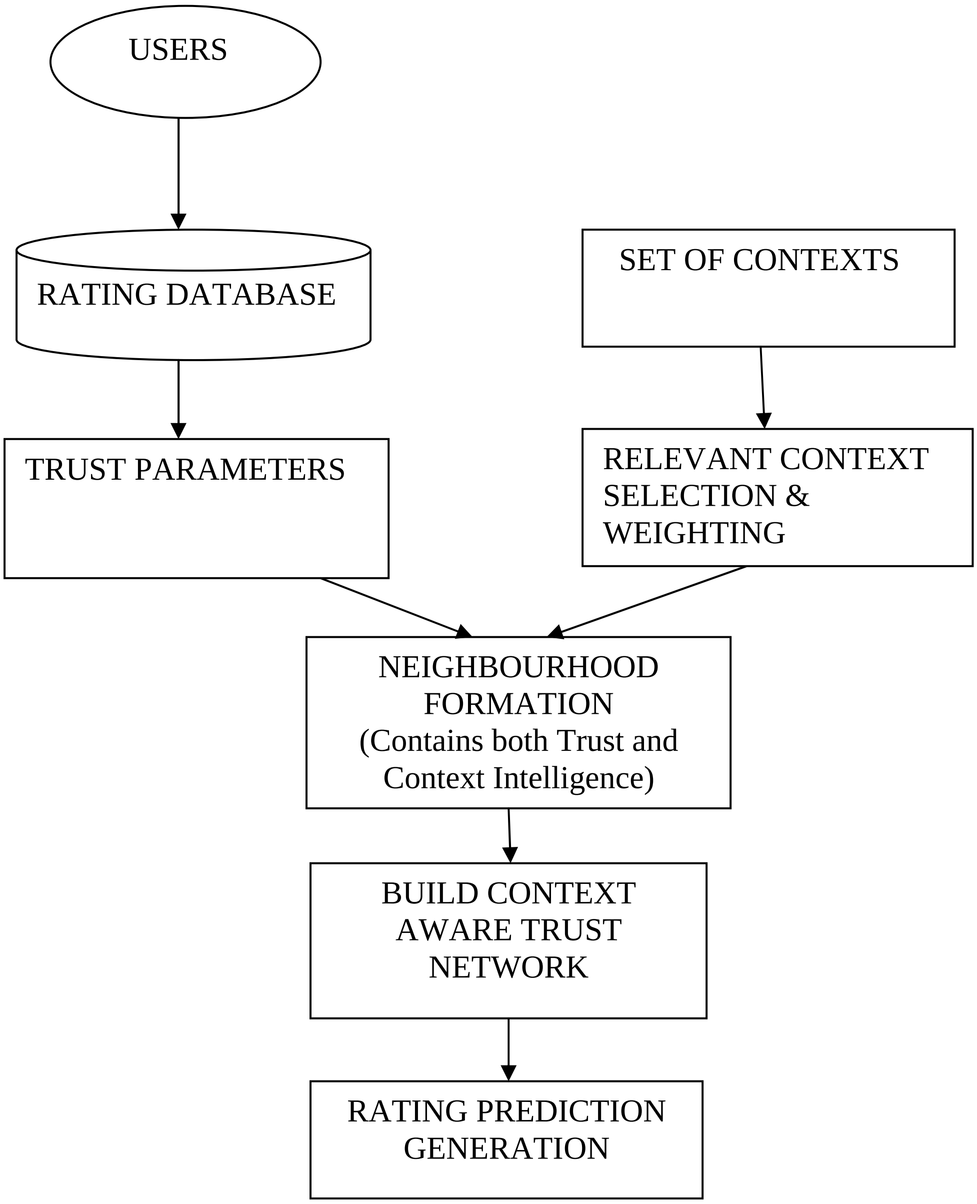

Figure 1: Prediction calculation for trust network based context aware recommender system

In order to take context weightings (importance factors) into consideration, equation (iii) is modified as:

$$WT_{(c,i)} = T_{(c,i)} \left[X + Y . \frac{\sum_{q=1}^{m} W_q}{\sum_{q=1}^{r} W_q} \right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\text{(iv)}$$

where,

$WT_{(c,i)}$ = Context weighted Trust value.

X,Y = Two real numbers such that X+Y = 1

m = number of matching contexts

r= number of relevant contexts selected, r≥m

$$P_{c,i} = \bar{r}_c + \frac{\sum_{p \in N} WT_{c(p)} (r_{p,i} - \bar{r}_p)}{\sum_{p \in N} |WT_{c(p)}|} \ldots\ldots\ldots\ldots\ldots\ldots\text{(v)}$$

Equation (iv) takes into considerations, the effect of relevant contexts on the trust value and derive the context weighted trust value. $WT_{(c)} \leq T_{(c)}$ for all contextual situations. If all the contexts matches, then $WT_{(c)} = T_{(c)}$, i.e.; the context weighted trust value is same as trust value. If none of the contexts matches, then also in this approach, the data point is not altogether discarded, rather it is considered but with a lesser trust score. Depending on the value of X & Y, the weighted trust score varies. We determine the optimum value of X,Y for minimum error in prediction. Thus in this approach, the contextual awareness and sensitivity is induced in a softer way unlike traditional methods of incorporating the context parameters in a hard scale; and there by greatly reducing the data sparseness issue. Hence by implementing the proposed approach, the recommender system becomes more accurate and useful.

Prediction quality:

The usefulness of a recommender system depends on the accuracy of prediction. We will measure the Mean Absolute Error (MAE) after implementing our approach. MAE measures the average absolute deviation between predicted ratings and users true ratings. If MAE is small, it indicates high prediction accuracy. MAE is simple but a very effective measure the accuracy of recommender system. MAE is also most commonly used metric for quantification of recommender system accuracy.

$$MAE = \frac{\sum_{i=1}^{N} |p_i - r_i|}{N} \quad \text{……………………………………….(vi)}$$

Where,

p_i = Predicted rating, $r_i =$ user's actual ratings, N = total number of items for which prediction is made.

IV. EXPERIMENTAL SETUP AND RESULTS

A real dataset is used in the experiment. One of the major challenges of doing any experiment with CARS is to get a real dataset. LDOS-CoMoDa is used as the dataset for our experiment. The Dataset consists of 2296 entries in total. Dataset consists of movie ratings.The following are the context variables used in the dataset:

time : Morning, Afternoon, Evening, Night

daytype : Working day, Weekend, Holiday

season : Spring, Summer, Autumn, Winter

location : Home, Public place, Friend's house

weather : Sunny / clear, Rainy, Stormy, Snowy, Cloudy

social : Alone, My partner, Friends, Colleagues, Parents, Public, My family

endEmo : Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral

dominantEmo : Sad, Happy, Scared, Surprised, Angry, Disgusted, Neutral

mood : Positive, Neutral, Negative

physical : Healthy, Ill

decision : User decided which movie to watch, User was given a movie

interaction : first interaction with a movie, n-th interaction with a movie

The tool used for our work is WEKA v3.6.10. The excel file is converted in to csv format and then WEKA GUI based explorer is used.

By applying PCA and calculating the weightages, we found out in our previous work [15], the following top 4 relevant contexts out of 12 context parameters:

W_1(Social) = 0.2233

W_2(Mood) = 0.2154

W_3(Weather) = 0.1981

W_4(Location) = 0.1944

We calculate trust value using equation (iii) and weighted Trust value using equation (iv).

We use MAE to measure the accuracy of our proposed approach with different parameters.

We calculate MAE with and without considering context weighting.

We also derive context weighted Trust value for different combinations of X,Y in the steps of 0.1 and for each combination, we capture MAE.

We divide the total dataset into training set and Test set. For our experiment, we consider the following splits:

a. 20% Training data and 80% Test data.
b. 50% Training data and 50% Test data.
c. 80% Training data and 20% Test data.

We see improvements in the accuracy when context weighted trust values are considered.

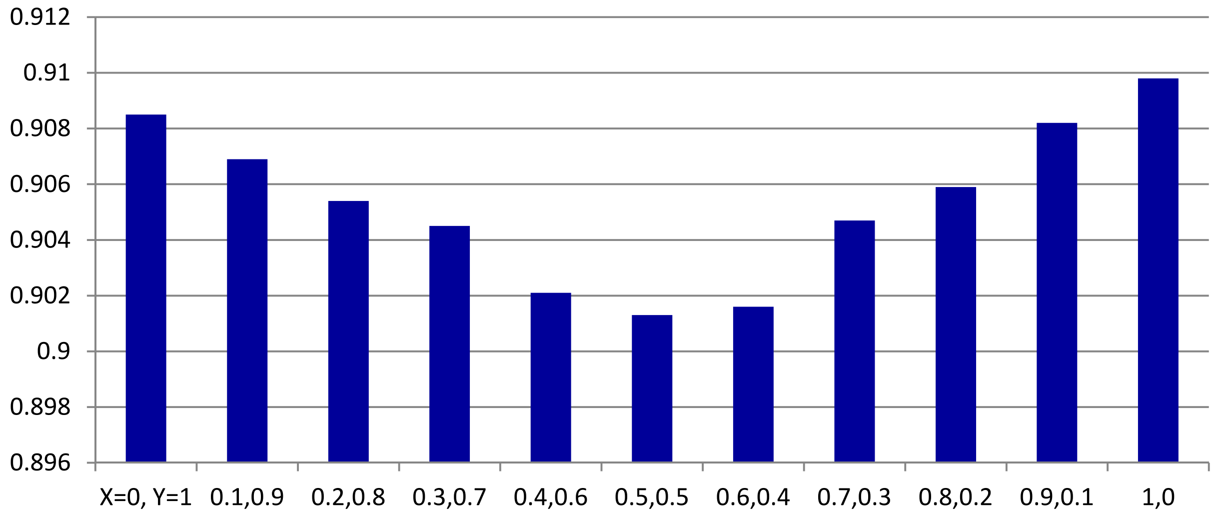

Figure 2: MAE with context weighted Trust value with 80% Training set and 20% Test set.

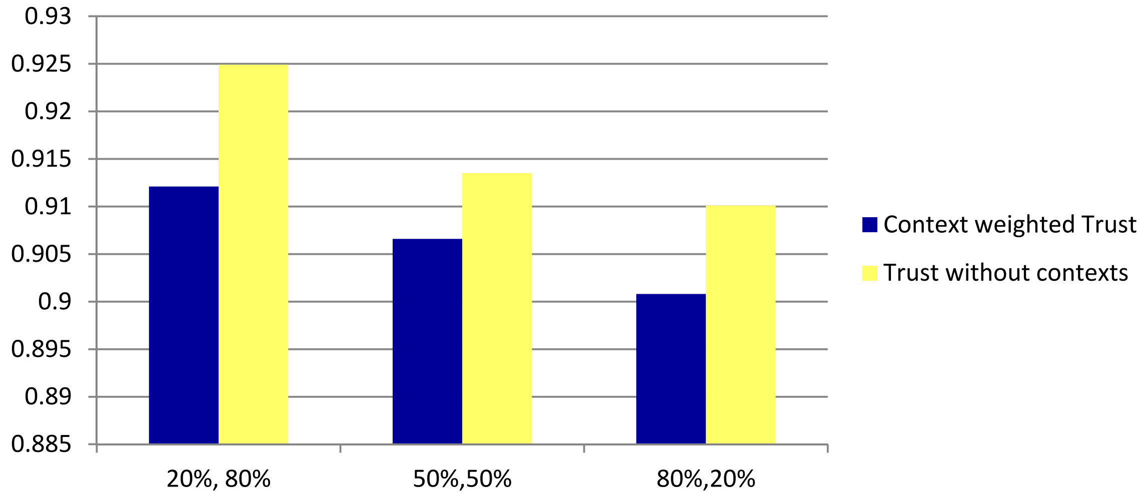

Figure 3: MAE with different ratio of training and test set

V. CONCLUSION

We have presented a new method of infusing context weightages of the relevant contexts in trust network based recommender system. Trust based recommender system has advantages over traditional Collaborative Filtering based Recommender system. When relevant contexts are selected and their weightages are appropriately taken into considerations, this further improves the prediction accuracy. When contexts are considered as hard threshold, it reduces the data points and thus effects the overall usefulness of the recommender system. In our propose approach, data points are not reduced and relevant contextual situations are also factored into and thereby improving the prediction accuracy. In our approach, we have implemented partially the dynamic nature of trust. We have calculated the context weighted trust value, we further plan to incorporate context parameters while calculating reputation, distrust and in trust propagation calculations. Also we plan to analyse the semantics of relevant context variables to enhance the recommender system accuracy in our future work.

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