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Social Behaviour based Metrics to enhance Collaborative Filtering

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***Abstract*: Expeditious growth of Internet and related network technologies has spectacularly increased the popularity of social networking systems such as blogs, forums, reviews sites etc. These systems allow the web users to share and disseminate their experiences and opinions with millions of users across the globe. This collaborative behavior of community can be observed as an electronic word of mouth (e-WOM) and can be utilized by the collaborative filtering systems to enhance the quality of recommendations. Despite of this importance very few studies have considered "social" aspect of user. This paper explores the role of explicit social relationship by presenting two novel similarity metrics. First metric is based on the social behavior (SB) that measures similarity between two users on the basis of "how similar they are in their social relationship". The second metric integrates the (Hybrid) social similarity with the interest similarity between two users. The efficacy of proposed metrics has been evaluated over trust aware SFLA based collaborative filtering recommender system. Experimental study conducted on Epinions datasets indicate that for small set of target users, collaborative filtering (CF) system developed using social behavior metric performed better than Hybrid CF and conventional CF approach. However with the increase in percentage of active users, hybrid approach starts dominating and provides better recommendations.**

***Keywords*: Social networks, Collaborative filtering, Social behavior similarity metric, Social behavior, Trust aware Recommender System**

I. Introduction

Interactions over the Social Web or Web 2.0 in the form of online discussions, expressing opinions, chats, blogs etc have become the key mode of communication among the people. This digital society generates tons of data everyday over the WWW. Analytical studies [1][2] are performed over these databases in order to discover some useful knowledge in terms of users' buying behavior, topic popularity, product popularity, product sales trends etc. Companies utilize this information to design their e-business policies to provide only relevant information/items to the users. Automated information filtering (popularly known as recommender systems) is the most prevalent mechanism being used as an embedded service within the web sites to boost e-commerce e.g. amazon.com [3], ebay [4] and epinions.com [5] etc. Prevalent information filtering techniques include content based filtering and collaborative filtering. Content based filtering approach extracts relevant items based on the correlation between the content of the items and the users' past personal preferences [6]. However, personal preferences change over time with the changing needs of user, thus difficult to capture. Moreover content based approach analyzes the features of each item which is sometimes difficult to obtain. On the contrary, collaborative filtering (CF) technique computes the active users' items of interests based on the preferences of like-minded peer group. These systems are developed as either memory based CF or model based CF. Memory based approach primarily computes the similarity of active user with all other users using some heuristic measure such as the cosine similarity or the Pearson correlation score.

Thereafter preferences of a set of k nearest neighbors are used to compute relevant suggestions for the target user. However, it is difficult to compute the appropriate value of k. Besides, the performance of this approach starts declining with the increase in number of users; the scalability problem. In Model-based CF technique initially a model of the community preferences is prepared and subsequently trained model is used to predict relevant items for the active users. Prevalent techniques to develop the learning model include Bayesian network [7] and clustering algorithms [8]. Among these, clustering techniques are preferred more as they reduce the size of data to be processed online to 1/k times where k is number of clusters. Despite several advantages over content based approach, conventional CF technique [9] suffers from cold start and sparsity problem. In practice, user's rate very few items from the variety of items available and this results in sparse datasets. Increase in sparsity leads to decline in prediction accuracy of the approach. Cold Start problem relates to the situation when a user enters the system and has expressed no ratings. CF approach cannot compute recommendations under such cases and thereby compromises with the quality of recommended items. Therefore the focus of studies related to CF is now shifted towards the solution of these problems.

In reality, users get influenced by either interests/preferences of their friends or colleagues or the extent to which "word of mouth" effects take hold in their social network. A social network on the web is modeled as a directed / undirected graph G(V,E) where V set of vertices represents users in the network and E set of edges represents social relationship and interaction that exists between the users as shown in Figure 1.

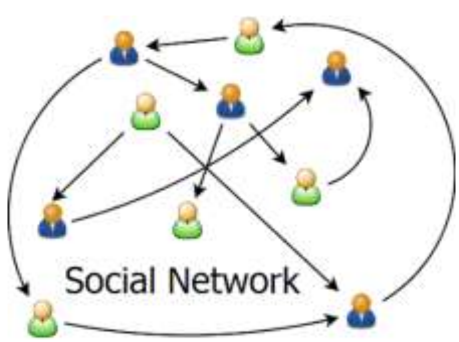

Figure 1. Social Network over Web

Social Network is observed as an ideal platform for interactions and sharing of experiences and recommendation among electronic peers. Sharing of information and relationship over social network provides rich source of information about user interest, preferences and social behavior. This information can be utilized to enhance recommendations. Various CF models have been proposed to compute user interests and preferences by exploiting 'Web of Trust/friendship' of user (i.e. members of the community for whom user expressed trust or friendship). These models are based on the concept that "people who like this also like that." In contrast to this the paper presents distinct concept that is based on the assumption that "people who like me also like this." The presented concept leverages this aspect of human social behavior and enhances the conventional collaborative filtering approach in terms of the prediction accuracy. The paper extends the trust aware SFLA based collaborative filtering model developed in [10]. It explores the role of explicit social relationship in recommender system and presents two novel similarity metrics. First metric is based on social behavior (SBCF) that measures similarity between two users on the bases of "how similar they are in their social relationship". The second metrics integrates the (Hybrid CF) social similarity with the interest similarity between two users to generate the community model. Subsequently only the trustworthy users from the virtual community are considered to compute recommendations. The rest of the paper is organized as follows. Section II presents the work done in literature followed by the proposed approach in section III. Section IV presents experiments and discussion of results. Conclusion is given in section V.

II. Related Work

Over the last decade, researchers have put their efforts to improve the performance of collaborative filtering (CF) systems. The first attempt made by Resnick et al [11] towards the development of automated CF mechanism was GroupLens. Goldberg et al [12] proposed a hybrid recommender system that combines the manual CF with content-based filtering. Aggarwal et al [13] applied the twin concepts of horting and predictability in the CF procedure. Delgado & Ishii [14] employed 'weighted-majority' prediction as an extension to the standard correlation based CF technique. All these approaches used 'user-to-user' similarity for the CF mechanism. In contrast Sarwar et al proposed item-to-item similarity for CF [10]. This approach is popularly known as item based collaborative filtering and has been adopted in several newer CF approaches. Palanivel & Sivakumar [15] focused their study on implicit-multicriteria for music recommendation and conducted experiments for both user-based and item-based collaborative filtering. With the rising popularity of CF systems, trust among the members of virtual communities became another issue.

Shneiderman [16] define trust as "the positive expectation a person has for another person or an organization based on past performance and truthful guarantees". Thus, trust in other people is established on the basis of history of promises kept. People come across large number of persons with similar tastes and preferences but very few are trustworthy and become friends. It has been observed that trust is modeled as either implicit trust or explicit trust in collaborative filtering systems as shown in Figure 2. Donovan and Smyth [17] pointed that trustworthiness of a user may be computed implicitly based on the past rating behavior of individuals. Their approach inferred the degree of trust utilizing user-item rating matrix. Accordingly, trust weight is computed based on the number of true predictions made by the users. This approach does not require any explicit value of trust to be specified by the users.

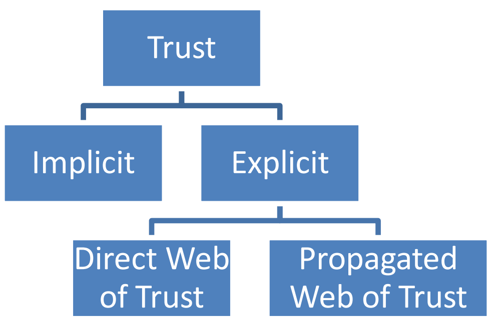

Figure 2. Trust modelling in Collaborative Filtering Systems

Hwang and Chen [18] inferred the trust score from the users' rating data and thereafter exploit the trust propagation in the web of trust. The work investigated the effects of trust propagation using both the local trust metric and the global trust metric in the standard collaborative filtering recommendation. Yahalom, Klein and Beth [19] and Beth, Borcherding and Klein [20] distinguished trust as direct trust and indirect trust. Direct trust refers to the explicit expression of an entity to indicate trust over another entity about a particular subject. Indirect trust is studied as propagated trust that is derived from the trust relationships between multiple entities connected in the network of "Web of Trust". Massa and Bhattacharjee [21] developed a trust model based on user's direct web of trust and propagated trust to recommend the books, movie, music, software etc. to on-line users. Subsequently it was established through experiments that trust metric and similarity metric increased the coverage of recommender systems while maintaining the recommendation accuracy. Avesani, Massa and Tiella, [22] presented "Moleskiing" a trust aware recommender system for the semantic web. The model allows the users to explicitly express their views about trips and trust in other users. Based on this data, system provides only reliable information to the users. Other approaches include probability based approach [23] to compute confidence level of trust in social networks. Adali et al [24] developed algorithmically quantifiable measures of trust which can be determined from the communication behaviour of the actors in a social communication network. Aberer and Despotovic [25] performed their study to manage the trust in p2p networks. Abdul-Rahman and Hailes [26] developed a trust model by adopting the findings of social sciences in distributed computer systems. The model utilizes reputation information and direct experiences to make decisions on the trustworthiness of agents in the virtual community. It was established in the literature that incorporation of trust into social filtering process indeed improves the prediction accuracy of the system.

However it is difficult to formulate the Web of Trust as it requires extra efforts from the users. Direct trust is the best indicator of user's true friend community. One of the prominent sources that provide this information is social networks. It allows the user to indicate whom they trust and distrust, creating links in the network. Several studies have suggested incorporation of direct social relationships in CF systems. Referral Web [2] was one of the first systems to suggest the combination of direct social relations and CF to enhance searching for documents and people. Li et al [27] analyzed the data from the social bookmarking site 'Delicious' and observed a high similarity between the tag vector of a URL and its keyword vector, as extracted from the corresponding web page. Firan et al [28] studied personalized recommendation of tracks within the popular music portal 'Last.Fm' and established that tag-based profiles produce better recommendations than conventional ones based on track usage. Vatturi el al [29] studied personalized bookmark recommendation using a CF approach that leverages tags, assuming that users would be interested in pages annotated with tags similar to ones they have already used. It has been observed that incorporation of explicit social network information in CF systems improves the quality of recommendation in various domains such as music [30], clubs [31], and news stories [20].

The metrics proposed in this paper are different from the metrics used in existing approaches. These metrics consider the "social" aspect of user for product recommendation. The proposed metrics have been evaluated in Collaborative Filtering model. The model works in two phases. First phase develops a social community model that incorporates the social behavior with the past purchase behavior. Previous studies established that model developed using nature inspired algorithms such as memetic algorithm [32][33] and shuffled frog leaping algorithm [34][35] perform better than genetic algorithm and conventional k-means algorithm. Thus, the model is developed using SFLA.

Subsequently trustworthy recommendations are generated in the second phase.

III. Proposed Methodology

In conventional CF approach social communities are formulated on the basis of rating behavior that depicts the interests of the users. However, the social relationship between users can also be utilized for creating the communities. Interest based community represents a group of users having similar rating behavior whereas social relationship based community represents groups of users having common friends. For example the social network shown in Figure 3 consists of eleven users namely $A, B, C, D, E, F, G, H, I, J$ *and* K. Each edge (u, v) represents the social relationship (friendship) between u $(user\ u)$ and $v\ (user\ v)$. In view of this network, F is a common friend between $active\ user$ and B whereas there is no common friend between $active\ user$ and H. Based on this similarity social community for active user consists of B, F *and* K.

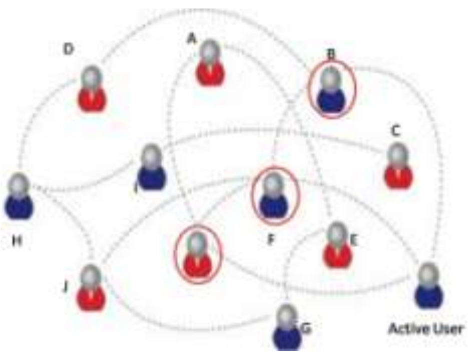

Figure 3. Social Community of Active User

Therefore, the work proposes two novel metrics which incorporate the social behavior for formulating the communities. The various metrics are as follows:

Interest Based Similarity UIsim($w_{i,j}$) : This is the conventional collaborative filtering metric which computes the similarity weight $w_{i,j}$ between user i and user j using adjusted cosine function [36] given in equation 1 as follows-

$$\boldsymbol{UIsim}(w_{i,j}) = \frac{\sum_{n=1}^{n\_items}(U_{in} - \overline{o(n)})(U_{jn} - \overline{o(n)})}{\sqrt{\sum_{n=1}^{no\_items}(U_{in} - \overline{o(n)})^2}\sqrt{\sum_{n=1}^{no\_items}(U_{in} - \overline{o(n)})^2}} \quad \textbf{(1)}$$

In equation 1, $\boldsymbol{U_i}$ and $\boldsymbol{U_j}$ are the vectors containing ratings given by user i and j for item n. $\overline{o(n)}$ refers to the average of the ratings given by all users on the n^{th} item.

Social Behavior Based Similarity SBsim ($w_{i,j}$) : This metric exclusively uses the social behavior of the users to identify the social community. It computes the similarity weight between user i and j, based on their social relationships which is defined as the size of the intersection divide by the size of the union of friend sets as given in equation 2.

$$\boldsymbol{SBsim}(w_{i,j}) = \frac{F(U_i) \cap F(U_j)}{F(U_i) \cup F(U_j)} \quad \textbf{(2)}$$

Hybrid Similarity HBsim ($w_{i,j}$): This approach combines the interests based similarity of users with their social similarity weight to compute the overall similarity between two users as follows:

$$\textbf{HBsim}(w_{i,j}) : \alpha^* \textbf{UIsim}(w_{i,j}) + \beta^* \textbf{SRsim}(w_{i,j}) \quad \textbf{(3)}$$

Where α and β are the weights given to two similarity measures respectively according to the application. In all experiments equal weight is given to both the metrics such that α = β=1.

The efficacy of proposed metrics has been evaluated in trust aware collaborative filtering system developed using Shuffled Frog Leaping Algorithm by Mehta & Banati [35]. The developed collaborative filtering recommender system works in two phases as shown in Figure 4. First phase develops a clustering model of social communities using Shuffled Frog Leaping Algorithm(SFLA). The model integrates the past rating behavior of users with their social relationship among the peer group to formulate the social communities. Users with close similarity are grouped in the same clusters. The subsequent phase primarily identifies the social community of the active user. Thereafter, the recommendations/ preferences are computed by considering only the trusted memebers (as indicated by the web of trust of active user) of the selected community.

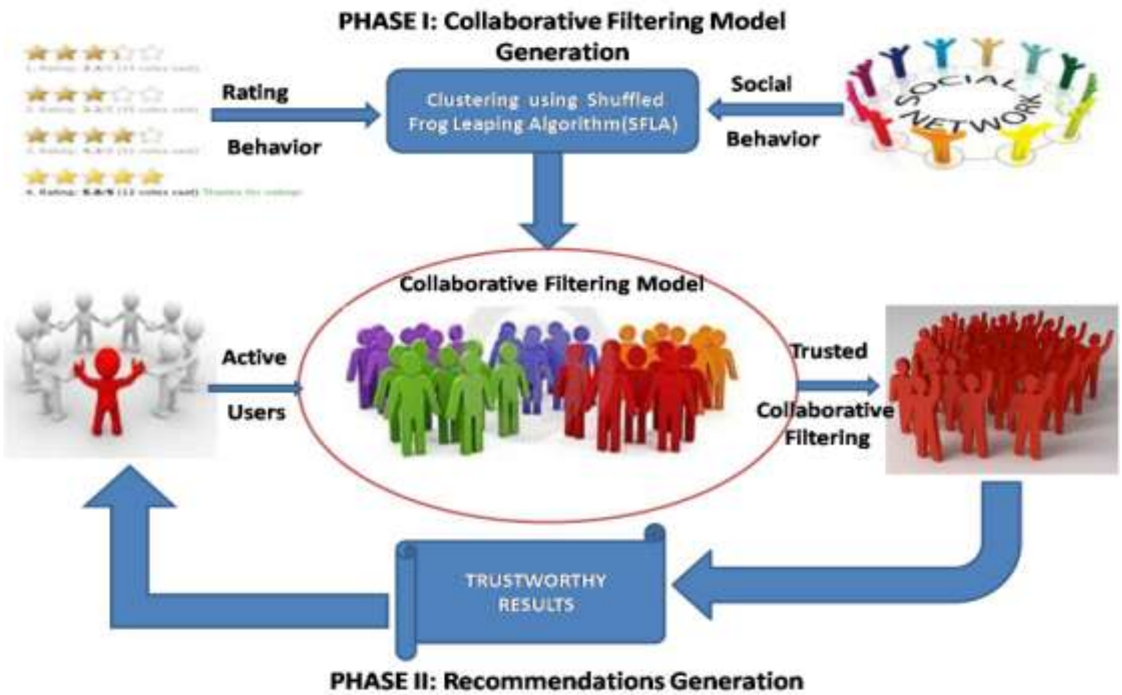

Figure 4. Social Behavior enhanced Collaborative Filtering Model

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This approach strengthens the relevance of predicted items along with handling the cold-start and sparsity problems.The detailed working of the model is as follows:

Phase-1: Develop Collaborative Filtering Model using SFLA based Clustering.
Phase-II: Generate Recommendations using Trusted Social group

3.1 Develop Collaborative Filtering Model using SFLA based Clustering

Shuffled frog leaping algorithm [37] is a population based algorithm that comprises a set of frogs divided into diverse groups known as memeplexes. Each frog in the memeplex represents a viable solution to an optimization problem. All frogs within a memeplex hold ideas that could be shared with each other to evolve themselves. This process of memetic evolution is known as local search. After defined number of memetic evolutionary steps, all the memeplexes are shuffled together for global evolution. The local and global evolution continues until the defined convergence criteria are satisfied as depicted in Table 1. In the Table 1 D_{max} and D_{min} are the maximum allowed changes in the frogs position and *rand ()* is a random function that generates number between 0 and 1.

Table 1. Pseudo code SFLA

```
Begin;
Generate random population of P solutions (frogs);
For each individual i in P: calculate fitness (i);
Sort the population P in descending order of their fitness;
Determine the global best frog Xgb ;
Divide P into m memeplexes;
For each memeplex
    For each memetic iteration
        Determine the local best( Xlb ) and worst( Xw ) frogs;
  // Improve the worst frog position using Eqs. (1) with respect local best frog;
      Change in frog position (Di) = rand (   )x (Xlb − Xw);   (1)
                                                    (Dmax >= Di >= −Dmin)
       If position improves
          New Position Xw = Xw + Di;
      Else
 / Improve the worst frog position using Eqs. (2) with respect global best frog(Xgb);
      Change in frog position (Di ) = rand (   )x (Xgb − Xw);   (2)
                                                    (Dmax >= Di >= −Dmin)
     If position improves
          New Position Xw = Xw + Di;
     Else
        New Position Xw = rand() * Dmax + rand() * (− Dmin );
   End;
End;
 Combine the evolved memeplexes;
Sort the population P in descending order of their fitness;
Check if termination is true;
End;
End;
```

The various parameters of SFLA adapted for collaborative filtering are as follows-

3.1.1 Structure of the Potential Solution: In SFLA, every frog represents a viable solution to the given problem. For clustering, solution consists of N memes/centroids of N respective clusters as shown in Figure 4.

$\boldsymbol{Centroid\ 1}$	$\boldsymbol{Centroid\ 2}$	…… .	$\boldsymbol{Centroid\ N-1}$	$\boldsymbol{Centroid\ N}$

Figure 4. Structure of Frog

3.1.2 Compute weight ($w_{i,j}$) between the users as follows:

To compute the similarity weight $w_{i,j}$ between user i and user j, collaborative filtering model employs the similarity metrics depicted in equation 1, equation 2 and equation 3.

3.1.3 Objective Function: Since the function used to compute the weight between the users is a similarity function, clustering technique groups the users with similar tastes/preferences into the same cluster. Equation 4 depicts the objective function used by SFLA to compute the fitness of a particular solution (Sol) as follows:

$$\text{Fitness (Sol)} = \frac{\sum_{j=1}^{N} C_i}{N} \qquad \textbf{(4)}$$

where C is the cluster and N is the number of clusters in the solution. The fitness of a particular cluster is determined by computing the mean similarity of all users in the cluster with its centroid/meme as given in equation 5.

$$\text{Fitness(C)} = \frac{\sum^{n}_{\substack{i=1 \\ i \neq Cent}} w(i, Cent)}{n} \quad \textbf{(5)}$$

where $Cent$ is the centroid of the respective cluster and n is the number of users in the cluster.

3.1.4 Convergence Criteria: It refers to the measure used to control the algorithm. In the presented model, algorithm was stopped after fixed number of generations.

3.2. Generate Recommendations using Trusted Social Group

Collaborative filtering model developed in previous phase is utilized to generate the recommendations for the active user. Prevalent CF approaches considers the preferences of all users of the community whose profiles match with the active user profile to recommend the items. However, in the real world, people come across large number of persons with similar tastes and preferences but very few are trustworthy and become friends. Inferred relevant items considering all types of users whether friends or not thus compromises with the needs of the users. Therefore, proposed approach considers the preferences of only credible peers / true friends of active user with similar interests and preferences to make recommendations.

Recommendations are generated by predicting the relevant items. Thus, predictive accuracy of the proposed system is computed by estimating the rating score that a target user may assign to an item and then comparing the predicted ratings with the true ratings. Rating scores measure the extent to which a user likes an item. The rating prediction performance of an algorithm reflects its capability to capture user's preference over items. A modified version of Resnick's [11] formula which only allows trusted users of the selected community to participate in the recommendation process is as follows:

$$\boldsymbol{P(i,n) = \bar{p} + \frac{\sum_{j \in N(i)^T} (n(j) - \bar{j}) * w(i,j)}{\sum_{n \in N(i)^T} sw(i,j)}} \quad \textbf{(6)}$$

where $\bar{p}$ is the average rating of the current user *i* over item *n*, *n(j)* represents the rating of trusted user *j* over item *n* and N^T is a set of trusted users and $w(i, j)$ is the similarity weight that may be computed using Equation 1/ Equation 2/ Equation 3. To evaluate the efficacy of proposed similarity metrics, studies are performed as discussed in the next section.

EXPERIMENTS AND DISCUSSION OF RESULTS

Experiments were performed on Core2 Duo 1.67 GHz processor, 3-GB RAM computer using Java1.6 and MYSQL5.1 to evaluate the efficacy of proposed approach. Results were averaged over five independent runs with following initial parameter settings- Training dataset: 80%, Test dataset: 20%. The division of dataset was made on the basis of users such that users of the test dataset did not participate in the training model. Hence, the system generates recommendations for the new users and solves cold-start problem as per the accuracy obtained. After several experiments, it was observed that algorithm worked best for Population Size: 50, Number of Generations: 100, Number of memeplexes: 5 and Number of Memetic iterations: 16.

The studies were performed over Epinions Dataset obtained from [5] epinion website. This website provides an option for the users to express their personal Web of Trust i.e. the people whose reviews/ratings have consistently proved to be useful and their web of distrust i.e. the people whose reviews /ratings do match their preferences. Dataset consists of approximately 50,000 users who rated a total of almost 140,000 different items at least once. The total numbers of reviews are around 660,000 and the total numbers of issued trust statements are about 490,000.

For experiments, all users of the training data were used for developing the clustering model using SFLA while only trusted users were involved in generating the recommendations. In the results, SBCF represents collaborative filtering model developed using social behavior based similarity metric, CCF [35] refers to conventional collaborative filtering model with interests based similarity measure and hybrid refers to the results of hybrid model developed by integrating both the similarity measures. The statistical accuracy of the presented approach was measured using Mean absolute error (MAE) metric. The studies were performed to

- Compare the performance of system developed using social behavior based similarity weight vs. conventional interests based CF approach
- Evaluate the Efficacy of Hybrid approach vs. conventional interests based CF approach
- Assess the Strength of Hybrid approach vs. social behavior based similarity weight approach
- Relative accuracy of all the three approaches.

A. Compare the performance of system developed using social behavior based similarity weight vs. conventional interests based CF approach

This study was performed to evaluate the effect of incorporating social behavior similarity weight in SFLA based social filtering model with respect to conventional CF approach. Figure 5 depicts the mean absolute error obtained by varying the number of active users for whom relevant items are predicted. It can be observed from Table 2 that

SBCF model is able to reduce the mean absolute error by more than 30%. This indicates that social network of users may serve as better medium to compute the friend communities as compared to rating behavior.

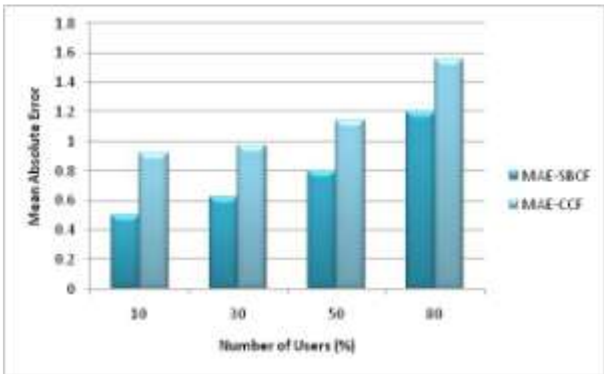

Figure 5. Mean Absolute Error of SBCF vs. CCF

Table 2. Percentage gain in accuracy of SBCF vs. CCF

Number of Users	MAE-Hybrid	MAE-CCF	Gain (%)
10	0.5	0.92	11
30	0.62	0.97	26
50	0.8	1.14	39
80	1.2	1.56	41.2

B. Evaluate the Efficacy of Hybrid approach vs. conventional interests based CF approach

This experiment establishes the effect of integrating both the social behavior and item interests of the users in collaborative filtering model. Fig 6 depicts the MAE obtained by both hybrid and CCF for varying percentage number of users. The results substantiate that hybrid approach brings significant improvement in the accuracy of recommendations as compared to conventional collaborative filtering approach. Table 3 depicts the percentage gain obtained by integrating social behavior of users with personal interests. Results precisely indicate that with the increase in number of users, percentage gain is improving and reaches to more than 40% when recommendations are generated for 80% of the users. This accuracy substantiates the strength of proposed approach. It can be observed from the Table 3 that proposed hybrid approach to compute the relevant items further enhances the accuracy of collaborative filtering recommender systems. This study also establishes that with the increase in number of user's improvement is also enhanced. This trend depicts the potential for scalability of the proposed approach.

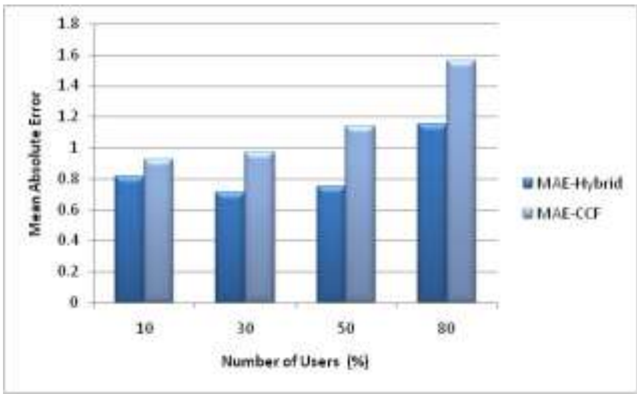

Figure 6. Mean Absolute Error of Hybrid vs. CCF

Table 3. Percentage gain in accuracy of Hybrid vs. CCF

Number of Users	MAE-Hybrid	MAE-CCF	Gain (%)
10	0.81	0.92	11
30	0.71	0.97	26
50	0.75	1.14	39
80	1.148	1.56	41.2

C. Relative accuracy of all the CCF, SBSF and Hybrid approach.

The relative performance of all the three (CCF, SBCF and Hybrid) approaches as shown in Figure 7 illustrates that both the system developed using proposed similarity metrics i.e. social behavior based metric and hybrid metric considerably outperform conventional collaborative filtering system developed using interest based metric. Results (Table 4) also indicate that among the proposed approaches social behavior based approach depict best performance among all for small number of users.

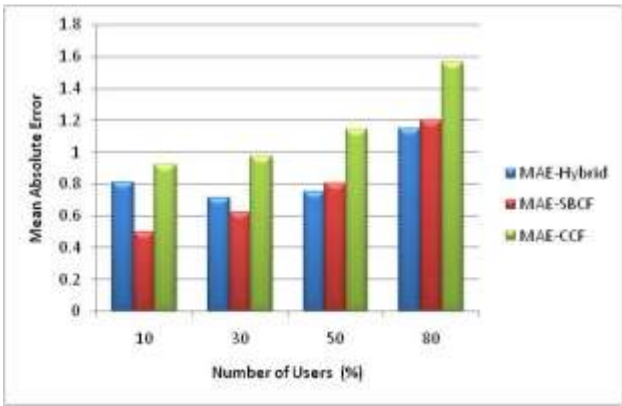

Figure 7. Mean Absolute Error of Hybrid, SBCF vs. CCF

Table 4. Percentage gain in accuracy of Hybrid, SBCF vs. CCF

No. of Users	MAE-Hybrid	MAE-SBCF	MAE-CCF	Gain (SBCF vs.CCF) (%)	Gain (Hybrid vs. CCF) (%)
10	0.81	0.5	0.92	42	11
30	0.71	0.62	0.97	35	26
50	0.75	0.8	1.14	34	39
80	1.148	1.2	1.56	36	41.2

However with the increase in percentage of active users, hybrid approach starts dominating. Thus it may be inferred that for the web systems developed to handle small set of target users, Social behavior approach is more suitable and for large web portals, Hybrid approach may provide better recommendations.

CONCLUSION

With the exponential growth of WWW, information filtering systems have gained edge over other applications. These systems generate recommendations for the active in order to ease their decision making. The paper presented two novel similarity metrics to improve the accuracy of recommendations generated by collaborative filtering systems. The proposed metrics are evaluated in trust aware collaborative filtering model developed using Shuffled Frog Leaping algorithm. The first metric utilizes social behavior (SBCF) of the active user with other members of community, to predict recommendations. The second metrics combines (Hybrid CF) the social network information of target users with the interest behavior, to compute relevant items for the user. Both collaborative filtering systems developed using proposed metrics were evaluated with respect to conventional collaborative filtering technique. Results indicated that both the presented metrics performed better than conventional approach and improved the accuracy by upto 40%. These results establish the efficacy of proposed metrics and their potential to generate more accurate recommendations.

References

[1]. K. Lerman, “Social Networks and Social Information Filtering on Digg”, Proc. ICWSM ’07, 2007.

[2]. Kautz, B. Selman, and M. Shah, “ReferralWeb: Combining Social Networks and Collaborative Filtering”, Commun. ACM 40(3), pp. 63-65, 1997.

[3]. http://www.amazon.com

[4]. http://www.ebay.com

[5]. http://www.epinions.com

[6]. M. Ferman, J. H. Errico, P. van Beek, and M. I. Sezan “Content-based filtering and personalization using structured metadata”, In JCDL '02: Proceedings of the 2nd ACM/IEEE-CS joint conference on Digital libraries, pp. 393-393, 2002.

[7]. Jin and L. Si, "A Bayesian Approach toward Active Learning for Collaborative Filtering", Proceedings of the 20th conference on Uncertainty in artificial intelligence, pp.278 – 285, 2005

[8]. Kohrs and B. Merialdo, "Clustering for Collaborative Filtering Applications", In Proceedings of CIMCA'99, pp. 1-5, 1999.

[9]. P. Massa and P. Avesani, “Trust-aware collaborative filtering for recommender systems”. Proceedings of International Conference on Cooperative Information Systems, LNCS 3290, pp. 492-508, 2004.

[10]. Sarwar, G. Karypis, J. Konstan, and J. Riedl, “Item-Based Collaborative Filtering Recommendation Algorithms,” Proceedings of the 10th International Conference on World Wide Web, pp. 285-295, 2001.

[11]. P. Resnick, N. Iakovou, M. Sushak, P. Bergstrom, and J. Riedl, “GroupLens: An Open Architecture for Collaborative Filtering of Netnews,” Proceedings of the 1994 Computer Supported Cooperative Work Conference, pp. 175-186, 1994.

[12]. Goldberg, D. Nichols, B.M. Oki, and D. Terry, “Using Collaborative Filtering to Weave an Information Tapestry,” Communications of ACM, 35(12), pp. 61-70, 1992.

[13]. C.C. Aggarwal, J. L. Wolf, K-L.Wu, and P.S. Yu, “Horting Hatches an Egg: A New Graph-Theoretic Approach to Collaborative Filtering,” Proceedings of the fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 201-212, 1999.

[14]. Delgado and N. Ishii, “Memory-Based Weighted-Majority Prediction for Recommender Systems,” Proc. ACM SIGIR ’99, Workshop Recommender Systems: Algorithms and Evaluation, 1999.

[15]. K. Palanivel, and R. Sivakumar, “A Study on Implicit Feedback in Multicriteria E-Commerce Recommender System,” Journal of Electronic Commerce Research, 11(2), pp.140-156, 2010.

[16]. Shneiderman, “Designing trust into online experiences.” Communications of the ACM, 43, pp. 57-59, 2000.

[17]. Donovan and B. Smyth, “Trust in Recommender Systems", IUI’05, ACM, pp-167-174, 2005.

[18]. Hwang and Y. Chen , "Using Trust in Collaborative Filtering Recommendation", IEA/AIE 2007, LNAI 4570, pp. 1052–1060, 2007.

[19]. Yahalom, B. Klein, T. Beth, ”Trust relationships in secure systems – A Distributed authentication perspective”, In Proc. of the 1993 IEEE Symposium on Research in Security and Privacy, pp. 202-209, 1993.

[20]. Beth T., Borcherding M. and Klein B., “Valuation of trust in open networks,” in Proceedings of ESORICS, Lecture Notes in Computer Science, 875, pp. 1-18, 1994.

[21]. P. Massa and B. Bhattacharjee, “Using trust in recommender systems: an experimental analysis”, Proceedings of 2nd International Conference on Trust Managment, Lecture Notes in Computer Science, 2995, pp. 221-235, 2004.

[22]. Avesani, P. Massa and R. Tiella, "Moleskiing: A Trust-Aware Decentralized Recommender System", Proceedings of the First Workshop on Friend of a Friend Social Networking and the Semantic Web, Galway, Ireland, 2004.

[23]. Kuter and J. Golbeck, “Sunny: A new algorithm for trust inference in social networks using probabilistic confidence models,” in AAAI, pp. 1377–1382, 2007.
[24]. Adali, R. Escriva, M. K. Goldberg, M. Hayvanovych, M. Magdon-Ismail, “Measuring Behavioral Trust in Social Networks”, International conference on Intelligence and Security Informatics(ISI), IEEE, pp. 150-152, 2010.
[25]. Aberer K. and Z. Despotovic, “Managing trust in a peer-2-peer information system,” in Proc. 10th Int. Conf. on Information and Knowledge Management(CIKM01), pp. 310–317, 2001.
[26]. A. Abdul-Rahman and S. Hailes, “Supporting trust in virtual communities,” in Proceedings of the 33rd Hawaii International Conference on System Sciences, pp. 1-9, 2000.
[27]. L. Li Guo, and Y.E. Zhao, Tag-based Social Interest Discovery. Proc. WWW '08, pp. 675-684, 2008.
[28]. C.S. Firan, W. Nejdl, W., and R. Paiu, “The Benefit of Using Tag-Based Profiles”, Proc. LA-WEB ’07, pp. 32-41, 2007.
[29]. P.K. Vatturi, W. Geyer, C. Dugan, M. Muller, and B. Brownholtz, “Tag-based filtering for personalized bookmark recommendations”, Proc. CIKM ’08, pp.1395-1396, 2008.
[30]. Konstas, V. Stathopoulos, and J. M. Jose, “On social networks and collaborative recommendation”, Proc. SIGIR '09, pp. 195-202, 2009.
[31]. Groh, and C. Ehmig, “Recommendations in Taste Related Domains: Collaborative Filtering vs. Social Filtering”, Proc.GROUP ’07, pp. 127-136, 2007.
[32]. Banati H. and S. Mehta , "Memetic Collaborative filtering based Recommender System", 2nd Vaagdevi International Conference on Information Technology for Real World Problems, IEEE, pp.102-107, 2010.
[33]. H. Banati and S. Mehta, "A Multi-Perspective Evaluation of MA and GA for Collaborative Filtering Recommender System", International journal of computer science & information Technology (IJCSIT), .2(5), pp.103-122, 2010.
[34]. H. Banati and S. Mehta, "Evolution of Contextual Queries Using Shuffled Frog Leaping Algorithm", Proceedings of the 2010 International Conference on Advances in Communication, Network, and Computing, IEEE Computer Society, USA, pp. 360-365, 2010.
[35]. S. Mehta and H. Banati, Trust aware social context filtering using Shuffled Frog Leaping Algorithm, International conference on Hybrid Intelligent Systems (HIS), pp. 342-347, 2012.
[36]. M.M. Eusuff, and K.E. Lansey, "Optimization of water distribution network design using the shuffled frog leaping algorithm", Journal of Water Resources Planning and Management, 129(3), pp.210-225, 2003.
[37]. U. Shardanand, and P. Maes, "Social Information Filtering: Algorithms for Automating “Word of Mouth”", Proceedings of the SIGCHI conference on Human factors in computing systems, pp. 210-217, 2005.