Privacy Preserving Profile Matching System for Trust-Aware Personalized User Recommendations in Social Networks

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ABSTRACT
Trust is becoming a very important part of social network from the security point of view. In the proposed system, a framework is introduced for handling trust in social networks, which is based on reputation mechanism. The reputation mechanism captures the implicit and explicit connections between the network members, analyses the semantics and dynamics of these connections, and provides personalized user recommendations to another network members. Based on the trust semantics, the system will provide the positive recommendations i.e. list of trustworthy users and the negative recommendations i.e. list of untrustworthy users. Along with this, the proposed system provides one more interesting mode i.e. public profile matching that preserves privacy on social networks. This profile matching contributes in reputation ratings required for suggestions of friend list. The main focus is on providing negative recommendations. In order to compute the reputation of each member, we adopt several other properties of trust such as, transitivity, personalization, and context, and draw ideas from sociology axioms. Trust is not perfectly transitive in social networks, in that trust decays along the transition path, but it is generally agreed that it can be communicated between people. Along with trust generation percentile of profile matching is also considered for personal recommendation.

Keywords
Social Networks; Reputation; Personalisation; Trust; Recommendation; Profile Matching.

1. INTRODUCTION
Social network analysis has been a major area of research for sociologists for many years. Recently, it has gained a lot of interest with the advent of Web 2.0 and the enormous increase in the use of social networking applications, customer review sites, blogs, wikis, etc. By using Recommender Systems, people can find the resources they need by making use of the experience and opinions of their nearest neighbours. [20]

In a nutshell, our contribution is a system for providing personalized user recommendations. The proposed system gives positive and negative, time-dependent trust-related information, represented either explicitly or implicitly [1]. Using collaborative reputation mechanism, the system provides new trust/distrust connections to the network's members. The system can be applied to any type of social network, even in the absence of explicit trust connections, since in such cases only the implicit expressions of trust will be considered for giving ranks and recommendations of the users. Also, before providing recommendations to the user, one more concept of profile matching [2] of users under consideration, will be added. This will help users of social network, to increase the number of best matching and trustworthy connections.

Unlike the initial works on user recommender systems for social networks that do not consider trust [5],[8], and following the paradigm of more recent research works [4],[5],[6],[7], the proposed system uses trust (and distrust) between people in order to assist members of the community to make decisions regarding other members of the same community.

In next section II we are presenting the related work for the proposed system. In section III, the proposed approach and its system architecture is depicted. And next sections cover mathematical model, implementation strategy, dataset information, results, conclusion and future work of system.

2. LITERATURE SURVEY
The content and links analysis in social networks has gained a lot of momentum, increasing the research in the related fields [1]. The largest body of work having positive trust and/or trust propagation in the context of recommender systems mainly focused on item recommendations [9], [14], [15], [16]. Walter et al has introduced Time dynamics. The trust propagation is employed through transitivity, and, similarly to this proposed recommender system, discounting takes place by multiplying trust values along paths.

Making new connections, according to personalized preferences is a crucial service in mobile social networking, where an initiating user can find matching users within physical proximity of the user. According to the work in [2], FindU, a set of privacy-preserving profile matching schemes for proximity-based mobile social networks, is proposed. In FindU, an initiating user can find the one whose profile best matches with user, from a group of users; to limit the risk of privacy exposure, only necessary and minimal information regarding the private attributes of the participating users is exchanged, by preserving privacy of users.

The task of personalized recommendation requires the ability to predict the items, which will be considered interesting by the user. Such a prediction is typically based on (1) content - recommending items with content that is "similar "to the content of the items already consumed by the users; (2) social networks - providing items related to people who are related to the user, either by explicit familiarity connection, or by some kind of similarity. The system refers to social networks in their broad definition, i.e., networks of people; where connecting edges may represent any type of relationship, not only direct familiarity. Content-based recommendation relies on the assumption that user interests and likes are reflected by previous items they have consumed. The above mentioned assumption has several drawbacks, among them the changes in user interests over time and the typical restriction to items similar to those already consumed. [20]

It has been shown that considering social network relationships and respective opinions/ratings improve the prediction, and in turn the recommendation process [3], [6]. A similar kind of work focuses on content ranking, which is consequently employed to recommend the top-ranked items to users. It is particularly important because the rapid increase in terms of content and users of social media shifts the problem of information search to that of information discovery.

A more generic model, can be readily applied to any social medium, has been presented in the previous work [7]. The work defined both local and global metrics for user recommendations in social media that could be applied to any social media. However, in that work, the notion of negative trust among users was not incorporated. Negative trust, previously introduced in different contexts, such as peer-to-peer networks, web recommender systems, and community discovery, has recently been introduced in the context of user recommendations in social networks [4], [11]. In this model, the trust of a user to another user is based on a personalized reputation rating, which quantifies explicit connections among users and implicit connections inferred from the interactions among users of the social network. Social networking sites help users to articulate their social networks by adding other users to their "friend lists "[6].

Leskovecet al. [5] who tries to predict positive and negative links in social networks using a machine-learning framework and ideas, which are drawn from sociology, have derived opposite results. Recommendations are based on aggregated social network information from various sources across the organization [8].

Trust is often defined as the belief of an entity in the benevolence of another entity to act honestly and reliably in opposition to distrust [10].

3. PROPOSED SYSTEM

The proposed trust aware recommender system is based on reputation mechanism that rates participants using observations, past experiences, and other user's view / opinion. Additionally, in order to address the social network dynamics, the element of time has been incorporated in the proposed system. To this direction, suggestion is given that reputation fades by time; thus, the positive (negative) reputation value of a user tends to zero unless new explicit or implicit trust (distrust) and liking (disliking) statements are added frequently. Finally, we assume that the context of trust is the same among community members. We exploit positive and negative, time-dependent trust-related information, expressed either explicitly or implicitly. We propose a collaborative reputation mechanism that captures and quantifies the user's connections and capitalizes on trust propagation and on the dynamics of the social network to propose new trust/distrust connections to the network's members. Specifically, after processing information published on the network, connections (both explicit and implicit) that bear trust semantics between members are formed (phase 1), reputation ratings are estimated (phase 2), and personalized recommendations (both positive and negative) are generated (phase 3). [20]

3.1 Phase 1: User connection formation

The proposed trust aware recommender system differentiates between explicit trust/distrust bonds amongst users that carry strong trust semantics and implicit trust statements that form more transient user connections in the network. These user connection formation or trust bonds can be categorized as follows –

Explicit user to user connection: A user may explicitly relate to another user by forming trust or distrust connections. Such connections represent more permanent bonds between users.

Explicit user to item connection: In this type of connection, the user provides a like or dislike type of comment to a specific item published by another user.

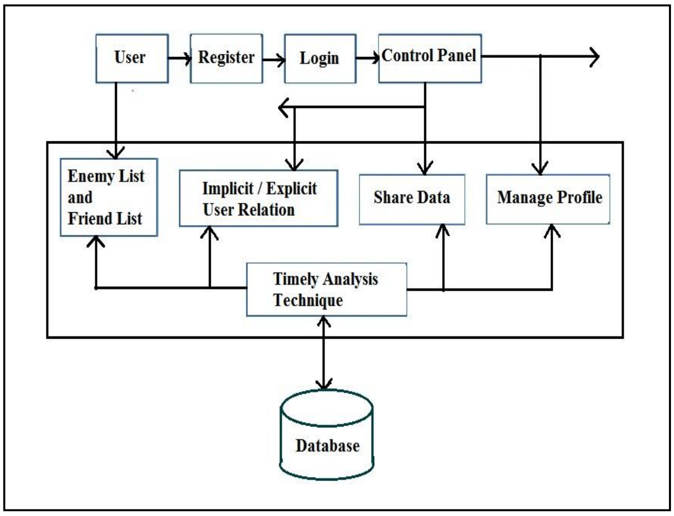

Fig. 1: System Architecture

The semantics of opinion expression differ among applications.

Implicit user to item connection: In this, each content item published by a user, has a unique identifier and a timestamp, and may contain one or more hyperlinks that point to other content items inside the social network or items (URLs) on the web. Preference to an item is shown implicitly, for example, by sharing an article in Reddit or Facebook.

Implicit user to user connection: In this connection the user-to-item information is mapped to the user-to-user level and is aggregated in order to provide a single implicit user-to-user connection.

3.2 Phase 2: Reputation Rating Estimation

The proposed reputation rating mechanism captures the effect of time (e.g., freshness of links) by modelling the fact that more recent events [i.e., newly added explicit or implicit trust (distrust) and like (dislike) statements] should weigh more in the evaluation of the target user's overall reputation rating by the evaluator. The use of time information allows us to distinguish between users who attain a high reputation for a short time period and users who manage to maintain their reputation at a constantly high level.

Following are the reputation rating systems A] Local Rating B] Collaborative Rating C] Transitivity of Trust D] Trust aware personalized recommendations: This is the last step in which personalized collaborative reputation ratings for all users who are connected directly / indirectly with the evaluator up to specific transitivity horizon considered. [20]

User Reputation Rating Algorithm:

Input
This algorithm initially only considers user to user explicit and implicit connection and user to item implicit and explicit connection.

Output
This algorithm gives final collaborative rating of particular user.

Let us assume the presence of N users U = {u1, u2, …, uN} in a social network. Every member uj ϵ U, publishes several content items while in the network. Additionally, F (uj) and E (uj) denote the friend list and the enemy list maintained by user uj, respectively.

Step 1
Calculate explicit user to user trust / distrust i.e.
UserConn(Uj → Ui, Tk) (1)

It has been assumed that UserConn(Uj → Ui, Tk) lies within the [- 1, 1] range, where a value close to 1(1) indicates that the target ui is a friend(enemy) of the evaluator user uj.

Step 2
Calculate explicit user to item connection

It corresponds to the explicit user-to-item connections as expressed by comments of user Uj to content items published by Ui at time period Tk. This factor has been assumed to lie within the [-1, 1] range and is defined as follows.

$$ExplConn(Uj \rightarrow Ui, Tk) = \frac{PosExpl(Uj \rightarrow Ui, Tk) - NegExpl(Uj \rightarrow Ui, Tk)}{PosExpl(Uj \rightarrow Ui, Tk) + NegExpl(Uj \rightarrow Ui, Tk)} \quad (2)$$

Where, PosExpl(Uj → Ui, Tk) and NegExpl(Uj → Ui, Tk) denote the number of positive and negative user-to-item explicit opinions, respectively (i.e., like and dislike) as expressed by user Uj, at time period Tk on the content items published by user ui. The denominator denotes the total number of opinions expressed by user Uj in time period Tk on any published content item.

Step 3
Calculate implicit user to item connection
ImplConn(Uj → Ui, Tk) It corresponds to the implicit user-to-item connections and depends on the number of links from the content items published by user Uj at time period Tk on the content items published by user ui. A link from a content item published by user uj at time period tk on a content item published by user ui denotes the temporary of user uj to the ideas of user ui. This interest may be positive, meaning that user uj supports the idea expressed, or negative, meaning that user uj disagrees with the published content item. This factor also lies within the [-1, 1] range and is given by the following equation

$$ImplConn(Uj \rightarrow Ui, Tk) = \frac{PosImpl(Uj \rightarrow Ui, Tk) - NegImpl(Uj \rightarrow Ui, Tk)}{PosImpl(Uj \rightarrow Ui, Tk) + NegImpl(Uj \rightarrow Ui, Tk)} \quad (3)$$

where, PosImpl(Uj → Ui, Tk) and NegImpl(Uj → Ui, Tk) denote the number of positive and negative user-to-item implicit connections, as expressed by links from the content items published by user Uj at time period Tk on the content items published by user Ui, respectively the denominator denotes the total number of links from the content items published by user Uj in time period Tk on any published content item.

Step 4
Calculate Local Rating of User based on explicit user to user, explicit user to item and implicit user to item connection.

Here the suggested model assumes that the local rating estimation takes place at consecutive, equally distributed time intervals denoted henceforth as Tk, k ϵ N. For this first we have to calculate the user reputation rating Rating(Uj → Ui, Tk) of Ui from Uj at time period Tk is given by the following formula,

$$Rating(Uj \rightarrow Ui, Tk) = Wuser.UserConn\,(Uj \rightarrow Ui, Tk) + Wexpl.ExplConn\,(Uj \rightarrow Ui, \quad Tk) + Wimpl.ImplConn\,(Uj \rightarrow Ui, Tk) \quad (4)$$

Where, Wuser + Wexpl + Wimpl = 1

Weights Wuser; Wexpl and Wimpl provide the relative significance of the three factors user-to-user connections, user-to-item explicit connections, and user-to-item implicit connections, respectively. From the aforementioned analysis, it is obvious that Rating (Uj → Ui, Tk) lies within the [-1, 1] range. Using Rating (Uj → Ui, Tk) we can calculate LocalRating (Uj → Ui, Tc). For the formation of the local user reputation rating at the current time period Tc, the evaluator considers only the r more recent ratings formed by the user. The value of r determines the memory of the system. Small values of r mean that the memory of the system is short, whereas large values consider a longer memory for the system. The local reputation rating LocalRating (Uj → Ui, Tc) of user Ui, as estimated by Uj at time period Tc, is defined as follows:

$$LocalRating(uj \rightarrow ui, tc) = \sum_{k=c-r+1, k>0}^{c} dfk.Rating(uj \rightarrow ui, tk) \quad (5)$$

Step 5: Calculate collaborative rating using Local rating

$$CollRating(uj \rightarrow ui, tc) = cred(uj \rightarrow uj, tc).LocalRating(uj \rightarrow ui, tc) + \sum_{q=1, q\neq i,j}^{Q} cred(uj \rightarrow uq, tc)\,.LocalRating\,(uj \rightarrow ui, tc) \quad (6)$$

Here, the weight cred (Uj → Ui, Tc) is a measure of the credibility of witness Uq and the respective rating of Ui in the eyes of the evaluator Uj.

Our Contribution
The proposed system considers the negative trust between users to help them getting connected to another trustworthy user and to alert them from getting connected to such untrustworthy user. Before providing the list, apart from these filters, we can contribute one more step which is mode of filter i.e. profile matching of the users. In this mode the proposed system can provide list of friends or enemies using set of privacy - preserving profile matching schemes. In this step, the initiating user can find from group of users the one, whose profile best matches with user [12]. Active user in social network will get suggestions of active users matching profile with each other. In profile matching there are following phases as in [12].

1) Profile Generator
It is used to generate random social network profiles with different or similar attributes' values of system users. To simplify this process, a "word generator" is used to generate random words with a similarity measure higher than a chosen threshold. When generating a dataset of profiles, it is possible

to define the percentage of the (1) Profiles created with the same IFP value, (2) Similar profiles referring to the same user but having different IFPs, (3) Number of common attributes between two similar profiles.

2) Profile Retriever
Set of profile is required to get the profile corpus.

3) Weight Assignment
It is used to assign weight to each attribute in the user profile using weight assignment algorithm. The profiles of users are matched using multiple attributes and weight is assigned to each attribute. If the two profiles are similar in particular attribute, the corresponding weight is assigned to the considered attribute of the respective profiles.

4) Profile Matcher
It returns the decision about two compared profile similarity. This decision, done via a decision making algorithm, is computed using the weighted similarity scores. Here similarity is achieved if similarity score is higher than a threshold called the profile matching threshold.

Following are steps for profile matching:

A] Computing profile threshold matching
It means that the minimal similarity value required for matching two profiles. This threshold is computed using the weights assigned to each attribute. These weights are reliable for measures and are important for computing a profile matching threshold.

Threshold calculation

$$\text{th} = f_{decision}\ (\text{w}(\boldsymbol{a_0})\ ,\ \text{w}(\boldsymbol{a_1})\ ,\ \ldots\ \text{w}(\boldsymbol{a_n})) \qquad (7)$$

Where, 'th' is the profile matching threshold to compute, '$f_{decision}$' is the decision making algorithm used, 'a' is the attributes used to describe a user profile, 'n' is the number of available attributes, 'w' is the weight assigned to each attribute.

B] Computing similarity scores between two profiles
For the similarity score, the values of common attributes in both profiles are extracted and their similarity scores are computed. In order to get more realistic score, the obtained similarities are tuned. With the help of tuning new similarity value will tend to increase or decrease depending on the importance of each attribute. This tuning is an attribute based operation that outputs a new similarity score to each attribute by applying a weight to the computed similarity scores. The similarity of users' profiles is checked by matching various attributes of their profile.

3.3 Phase 3 Recommendations Generations

Based on the overall reputation ratings of the social network members as assessed by the evaluator user, the proposed system generates personalized positive and/or negative user recommendations, which can be used to form new trust and/or distrust connections. Positive recommendations can be used from the members in order to connect to new people, subscribe to new blogs and share resources. On the other hand, in the case of negative recommendations, the model in essence generates a list of untrustworthy users. This personalized blacklist can be exploited by the recommender system in order to alert users when content items are published from such untrustworthy users and discourage them from linking or browsing such content, or filter it out from their content feed. Both types of recommendations could be exploited in order for a user to update his/her trust and distrust connections in the social network. In order to provide separate positive and negative recommendations, the proposed system analyses the comments of the user by using content filtering. Stemmer Algorithm is used for Content Filtering. This algorithm takes user comments, posts as input and gives basic words from various forms of particular word as an output. To classify these generated recommendations as positive and/or negative, the Naive Bays Classifier is used.

Naive bays Classifier
Bayes theorem is used to calculate the posterior probability, P (c|x), from P (c), P (x), and P (x|c). Naive Bayes classifier assumes that the effect of the value of a predictor (x) on a given class (c) is independent of the values of other predictors. It is known as class conditional independence.

$$P(c|x) = \frac{P(x|c) * P(c)}{P(x)} \qquad (8)$$

$$P(c|X) = P(x1|c) * P(x2|c) \ldots * P(xn|c) * P(c) \qquad (9)$$

Where, P (c|x) is the posterior probability of class (target) given predictor (attribute), P(c) is the prior probability of class, P(x|c) is the likelihood which is the probability of predictor given class, P(x) is the prior probability of predictor.

4. MATHEMATICAL MODEL

Mathematical model of the proposed system describes basic input, output and process along with algorithms. This model divides input, process and output into sub parts. This gives us an idea of dependencies of processed and output.

Let S = {I, O, T, Sc}

Where,

S= Alpha System Model for user testing and before launching,

I = Input, O = Output, T = Test cases, Sc = Time scheduler

FS= {S, UI, O, Pr}

Where,

FS = Final System Model for User,

UI = User Input, O = Output, Pr = Process,

UI = {C, Tg, P, Pr}

Where,

C = Comments of user to another user's post/tags,

Tg = Tags shared by / with user, P = Posts of user, Pr = Profile Of user

O = {FL, EL}

Where,

FL = Friend List suggested by the user, EL = Enemy List suggested by the user

Pr = {UC, RR, UR}

Where,

UC=User Connection, RR=Reputation Rating, UR=User Recommendation

UC = {EUU, EUI, IUU, IUI}

Where,

EUU = While calculating user behavior Explicit User to user connection is calculated,

EUI = While calculating user behavior Explicit User to Item connection is calculated,

IUU = While calculating user behavior Implicit User to User connection is calculated,

IUI = While calculating user behavior Implicit User to Item connection is calculated.

RR = {LoR, CoR, TT, PeR}

Where,

LoR = Local Rating of User, CoR = Collaborative Rating of User,

TT = Transitivity of Trust, PeR = Personalized Recommendations

5. IMPLEMENTATION STRATEGY

User communicates with the server through browser. User has to register and login to the system to access his control panel. Using this control panel user can fulfill basic requirement of communication i.e. he can send friend request to other user and then he can start communication with him after acceptance of friend request. User will get separate featured options using which he can view his friend list and enemy list. This is calculated with the reputation calculation mechanism adopted by the system at back end. This reputation mechanism considers local rating and collaborative rating of particular user explained in proposed system. User to user explicit / implicit communication and User to item explicit / implicit communication are input to this mechanism. After this input, implemented system generates recommendations list of system users to the end user. The proposed system is implemented using divide and conquers method.

6. DATASET INFORMATION

Epinions is a large product review community that supports various types of interactions between users, such as explicit user-to-user trust statements and product reviews written by the community members and rated by other members. The dataset that we used contains information about product reviews written by the members of the Epinions community. [13] From this dataset following information can be obtained:

Trust/distrust information:

< MY_ID, OTHER_ID, VALUE, CREATION>

Rating information in the form of:

<OBJECT_ID, MEMBER_ID, RATING, STATUS, CREATION, LAST_MODIFIED, TYPE, VERTICAL_ID>

The dataset contains

- ~132,000 users, who issued
- 841,372 statements (717,667 trusts and 123,705 distrusts)
- 1,560,144 articles
- 13,668,319 article ratings.

For Profile dataset we have used online fake profile generator [17]. Using this generator we have generated 50000 records with multiple attributes like: <name, age, gender, city, occupation, company name, favorite color etc.>

7. EXPERIMENTAL SETUP

For experimental purpose we have used systems that act as client and server. This proposed system is implemented using JAVA environment. HTML, CSS and JavaScript technologies are used for front end development. This system is client – server architecture. At the server end apache tomcat container is used. For database MySQL is used. We have setup jdk-7, apache tomcat-7 and mysql-5.3 on this system. To test our system functionality we have built experimental setup. In this we use already existing dataset as previous user input to the system. This ready dataset helps us to test algorithms required for reputation calculation mechanism. Also the dataset is modified as per the proposed system's requirement. For experiment purpose we introduce administrator panel. After successful login with administrator's credential, we can access his control panel using which we can see various reports generated with the help of Epinions dataset. Administrator can generate report by selecting particular user.

8. RESULTS

The results of the system are categorized in 2 sections:

1. Current end user scenario
2. Backend business logic testing

For explicit user to user recommendation we have checked user to user trust and distrust statements. For these testing opinions Trust/distrust information is used. From this we have evaluated top k recommendations as friend and bottom k recommendations as enemy. We have evaluated user list that have only positive user recommendation and user having only negative user recommendation.

The profiles of users under consideration are matched using different attributes in order to provide either positive or negative recommendations of the similar users. For example, the skills of users are taken into consideration for matching profiles of users.

The system will find similarity between user and top k recommendations using

1. Article rating.
2. Profile fields like city, country, gender, occupation, company, color, vehicle

To generate refined result, we compare result of two cases and by combining those results. we have generated top k recommendations by rearranging the result records.

According to Shani and Gunawardana [18], it is unclear how to measure trust in an offline experiment, since trust is build through an interaction between the user and the system. However, according to the same work, it may be beneficial for the system to recommend a few items that the user already knows and likes. In this direction, we capitalize on the similarity of interests between a user and the users recommended by our model and use cosine similarity which is widely used in collaborative filtering to measure the similarity of interests between users [19].

As per the experimental set up, we have used 50,000 users records belong to Epinion dataset. As per our set up user can become the part of our system and send friend request to each other. After establishment of relationship between them user can send comments to each other, user can explicit like and dislike the comments. User can rate for particular comment. All these data transactions are considered to calculate the local rating; collaborative rating which forms the trust about the user and it is helpful for us to recommend the friends. As part of contribution user profiles are also matched from the list recommended on the basis of collaborative rating.

Following Figures show the ability of the system to recommend the friend list. Graph shows that collaborative recommendations are proper and provides desired set of friends. Along with this user profile matching drags user more closely towards the desired ones.

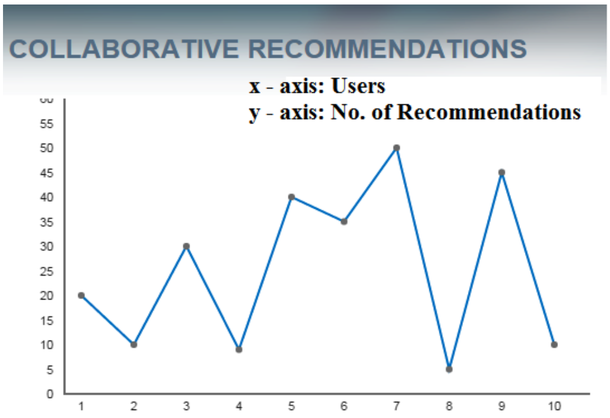

Fig 2: Collaborative Recommendations

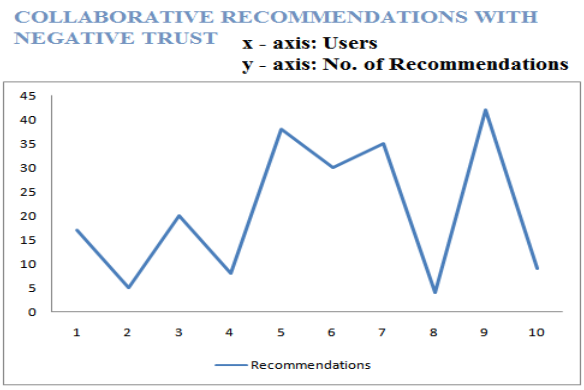

Fig 3: Collaborative Recommendations with Negative Trust

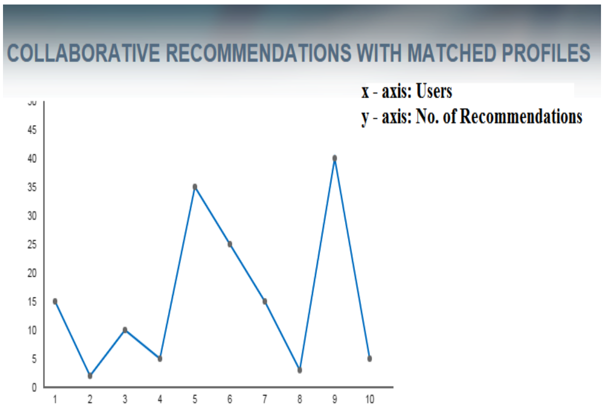

Fig 4: Collaborative Recommendations with Profile Matching

Figure 2 shows the graph having user belongs to X-axis and Number of user recommended in Y-axis. This is result of collaborative recommendations. Figure 3 shows collaborative recommendations when negative trust is considered. The results we get are filtered results. When we apply profile matching filter to it then recommendations becomes less in count and becomes more accurate. Profile matching is done on the basis of gender, city and occupation of user. Figure 4 shows the recommendation result when user profile matching applied to collaborative recommendations. This figure infers that recommendation count is affected and data is filtered.

9. CONCLUSION

The previous work done mainly focused on the item and user recommendation without considering the trust relationship between them. Because of this, the security of user connection might be disturbed. Thus, we propose a trust aware user recommender system to make connections of social network trustworthy by giving positive and negative recommendations to the users while matching their profiles for strong connection. So that, positive recommendations will help in connecting trustworthy users while negative recommendations will alert users not to connect to the untrustworthy users and also making aware of the contents published by such user.

10. REFERENCES

[1] Magdalini Eirinaki, Malamati D. Louta,Member, IEEE,and Iraklis Varlamis,Member, IEEE. "A Trust-Aware System for Personalized User Recommendations in Social Networks" IEEE Trans. Systems, Man, And Cybernetics: Systems, Vol. 44, No. 4, pp. 409 – 421 APRIL 2014

[2] Ming Li, Member, IEEE, Shucheng Yu, Member, IEEE, Ning Cao, Student Member, IEEE, and Wenjing Lou, Senior Member, IEEE. "Privacy-Preserving Distributed Profile Matching in Proximity-based Mobile Social Networks" IEEE Trans. Wireless Communications Vol.: 12 No.: 5 pp. 2024 - 2033 Year 2013

[3] I. Guy, N. Zwerdling, D. Carmel, I. Ronen, E. Uziel, S. Yogev, and S. Ofek-Koifman, "Personalized recommendation of social software items based on social relations," in Proc. 3rd ACM Conf. Recommender Syst., 2009, pp. 53-60.

[4] J. Leskovec, D. P. Huttenlocher, and J. M. Kleinberg, "Predicting positive and negative links in online social networks," inProc. 19th Int. Conf. World Wide Web, 2010, pp. 641-650.

[5] J. Chen, W. Geyer, C. Dugan, M. J. Muller, and I. Guy, "Make new friends, but keep the old: Recommending people on social networking sites," in Proc. SIGCHI Conf. Human Factors Comput. Syst., 2009, pp. 201-210.

[6] I. Konstas, V. Stathopoulos, and J. M. Jose, "On social networks and collaborative recommendation," in Proc. 32nd Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 2009, pp. 195-202.

[7] I. Varlamis, M. Eirinaki, and M. D. Louta, "Application of social network metrics to a trust-aware collaborative model for generating personalized user recommendations," in The Influence of Technology on Social Network Analysis and Mining(Lecture Notes in Social Networks Series), vol. 6, T. Ozyer, J. G. Rokne, G. Wagner, and A. H. P. Reuser, Eds. Berlin, Germany: Springer, 2013, pp. 49-74.

[8] I. Guy, I. Ronen, and E. Wilcox, "Do you know? : Recommending people to invite into your social network," in Proc. 14th Int. Conf. Intell. User Interfaces, 2009, pp. 77-86.

[9] J. Golbeck, “Trust and nuanced profile similarity in online social networks,”J. ACM Trans. Web, vol. 3, no. 4, pp. 1–33, 2009.

[10] T. Grandison and M. Sloman, “A survey of trust in internet applications,” IEEE Commun. Surveys Tuts., vol. 3, no. 4, pp. 2–16, Oct. 2000.

[11] J. Kunegis, A. Lommatzsch, and C. Bauckhage, “The slashdot zoo: Mining a social network with negative edges,” inProc. 18th Int. Conf. World Wide Web, 2009, pp. 741–750.

[12] Elie Raad, Richard Chbeir, Albert Dipanda. “User profile matching in social networks. Network-Based Information Systems (NBiS), Sep 2010, Japan. pp.297-304. <hal-00643509>

[13] For System Dataset - http://www.trustlet.org/wiki/Extended_Epinions_dataset

[14] R. V. Guha, R. Kumar, P. Raghavan, and A. Tomkins, “Propagation of trust and distrust,” inProc. 13th Int. Conf. World Wide Web, 2004, pp. 403–412.

[15] P. Massa and P. Avesani, “Trust-aware recommender systems,” inProc. ACM Conf. Recommender Syst., 2007, pp. 17–24.

[16] C.-N. Ziegler, “On propagating interpersonal trust in social networks,” in Computing With Social Trust, J. Golbeck, Ed. London, U.K.: Springer, 2009, ch. 6.

[17] For Profile Dataset - http://www.fakenamegenerator.com/order.php.

[18] J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, “An algorithmic framework for performing collaborative filtering,” in Proc. 22nd Annu. Int. ACM SIGIR Conf. Res. Develop. Inf. Retrieval, 1999, pp. 230–237.

[19] G. Shani and A. Gunawardana, “Evaluating recommendation systems,” in Recommender Systems Handbook. Berlin, Germany: Springer, 2011, pp. 257–297.

[20] Kulkarni Vaishnavi Shripad and Prof. Archana S. Vaidya, “A Review on Trust-Aware and Privacy Preserving Profile Matching System for Personalized User Recommendations in Social networks”, International Journal of Computer Applications, October 2014, Vol - 104, No. 12.

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