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Social Trust Based Recommendation System for OSN Users

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ABSTRACT: Recommendation systems (RSs) are the most important part of Online Social Networks (OSNs) now a days. The main reason for the need of recommendation system is the exponential popularity of OSN. Although social media provides a good and ease platform to share data and to communicate with friends, they also challenges its users. The challenge that OSN users face is "Information Overload". The RS's can be modelled in such a way that, they can recommend items/users to a target user based on the social data. Thus they will get personalized recommendations. The best way to get this type of recommendation is to incorporate trust information between the users. Most of the existing models work well with internet and computer based OSNs. But they will fail when used for mobile devices. The hindrance to the performance of mobile OSN's are small screen, poor input, poor computational capabilities of mobile devices, and user inconveniences to give feedback values. A better solution to these issues are an automated recommendation system for both mobile based and non-mobile based OSNs. So this work focuses to propose an automated RS to recommend items/users based on social interaction data for both mobile and non-mobile based OSNs.

KEYWORDS: Recommendation systems, Social trust, Collaborative filtering. Online Social Networks.

I. INTRODUCTION

At present, mobile based and computer based social networks are gaining prominence. We all are familiar with the astonishing capabilities of some of the social networks like Facebook and Whatsapp. But the social activities causes some difficulties to the users. The main cause is the overwhelming nature of social data. Users are not getting enough time and not getting relevant recommendations from the network. We have already discussed such issues in the works [1] and [2]. The same works have mentioned about the solution to the problem. That is a personalized recommendation system.

These systems have the capability to automatically recommend contents to the users and [3] these contents will be highly trusted ones. Existing techniques used in RSs are content-based, collaborative filtering (CF) and hybrid approaches [4]. The hybrid approaches take concepts from both content-based and CF based methods. The next question in this context is "What is trust?" Trust in social network refers the feedback value or interaction score among the users. Greater the trust value, more will be the trustworthiness among users.

But the case is not same for mobile based OSNs. Mobile based recommendation systems faces more limitations of mobile devices such as small screen, poor input etc. [5]. Also the users may feel uncomforted by giving regularly rating to each users and activities.

So, in total we need an automated, efficient and user-friendly recommendation system which can perform well in computer based and mobile based OSNs. A social RS improves the accuracy of the existing system by taking social interest and social trust between users of OSN [2].

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II. Related work

The main components of a RS in social context are users, items and interactions [2]. There are different methodologies to calculate trust value among users. Kahanda et al. [6] takes the interaction data among the users to calculate communication link strength. Arnab et al. [7] finds out the existence of dynamic relationship values among the Facebook users.

But a better model is proposed by Xiang [8] in his work. According to Xiang, social trust among users are calculated based on social activities like “commenting”, “sharing”, “liking”, “tagging” and the “number of mutual friends” among a selected pair of friends. He used auxiliary variables to increase the accuracy of the model. It is worth important to mention about the propagation of trust in the network. For that some of the works [8] introduced the concept of trust transitivity. If a user “A” trusts user ”B” and “B” trusts another user “C”, then there can be a trust path among the users “A” and “C”. For that the trust value about “C” from “B” can be inferred by user “A” to make an estimated trust value about “C”.

Adali et al. [9] finds out another relation among trust and conversations. He found that longer conversations will contribute to higher trust and more number of conversations will contribute to higher trust. All the above discussed RS's are for non-mobile based OSNs.

But for the case of mobile based OSN, the same method for recommendations can't be used. In [5], the similarity among users are found out during the time of registration and this similarity value is used to recommend other users.

III. Proposed MODEL

By studying and comparing about various RS's and different domains, we have proposed a model in our previous paper [1]. The important modules in our model are – user registration, user interaction, similarity calculation, social module, request manager, trust calculation and recommendation. But from the point of view of social network, the recommendations can be considered as the search result about a specific user name, which is done by another user. Figure 1 shows the architecture diagram.

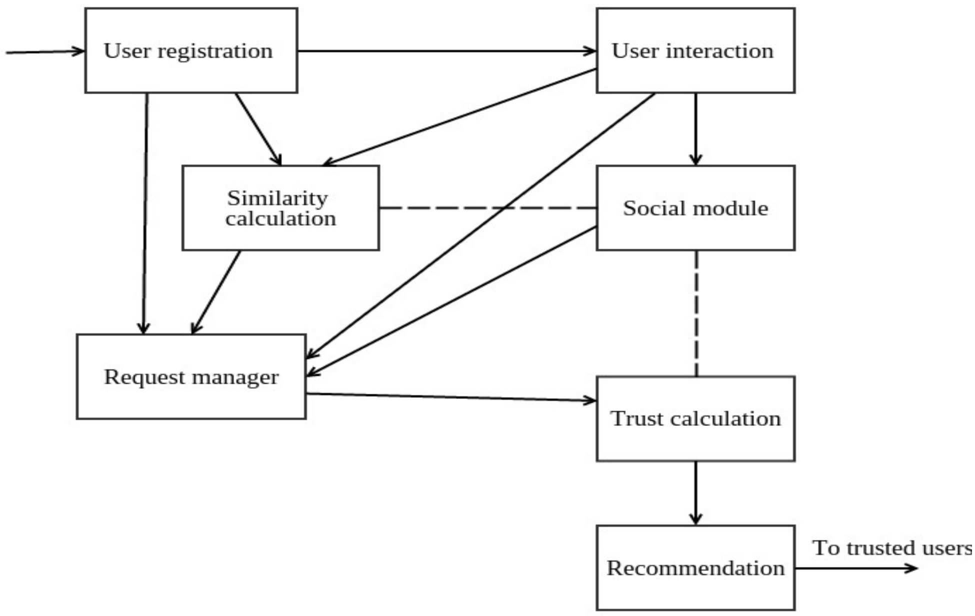

Fig.1. Architecture diagram of proposed model

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User registration module is concerned with the registration/signing up of users. Users have to give details like name, date of birth, sex, education. Work, location and so on. It is based on these details, the user similarities are calculated. Similarity calculation module calculates the similarity among each pair of users. User interaction module keeps track of the interactions taking place among the users and the type and number of each interaction. Social module gives users, the provision to do social activities like liking, commenting, sharing, chatting etc. Semantic value of each conversation in the chat is calculated in the social module. Request manager module helps users to manage the incoming requests. When a request comes, the mutual friends among the requested user and the target user is found. Then trust value is estimated about the requested user based on the mutual friend and inferred trust value. Trust calculation module calculates trust value among the users after each social interaction. Count of social interactions, each type and its count/duration is considered to calculate trust value. Since the social interactions are dynamic, so the trust value will be. Based on the updated trust value, recommendations about unknown users and activities of trusted users are listed according to the need of recommendations.

IV. TRUST MODEL

Trust model in this work is similar to that used in [3]. The trust values are calculated as directed, asymmetric and dynamic. ie. If there are two social friends "A" and "B", then trust value about "B" by "A" and vice versa may not be same. Trust in this work is calculated as:

$$\begin{aligned} Direct\ trust(u,v,d) &= w_1(u) * a_1(u,d) * C(u,v,d) + w_2(u) * a_2(u,d) * L(u,v,d) + w_3(u) * a_3(u,d) * S(u,v,d) \\ &+ w_4(u) * a_4(u,d) * M(u,v,d) + w_5(u) * a_5(u,d) * Call(u,v,d) + a_6(u,v) * N(u,v) \\ &+ a_7(u) * T(u,v) \end{aligned} \qquad \text{eq. (1)}$$

The parameters are:

- Direct Trust(u,v,d) – represents the trust value from user u to user v on a certain date d.
- C(u,v,d) – number of comments posted by user u on user v's posts before the date d.
- L(u,v,d) – number of likes made by user u on user v's posts before the date d.
- S(u,v,d) – number of shares made by user u on user v's posts before the date d.
- M(u,v,d) – number of messages sent by user u to user v before the date d.
- Call(u,v,d) – number of calls made by user u to user v before the date d.
- N(u,v) – Number of mutual friends between user u and v.
- T(u,v) – Total call duration between the users u and v

The term a_i in the direct trust equation refers to auxiliary variables. It shows the auxiliary causes of user behaviors which are independent of the trust towards a specific user [3].

$$a_1(u,d) = \frac{1}{\text{total comments posted by user u before date d}}$$

$$a_2(u,d) = \frac{1}{\text{total likes posted by user u before date d}}$$

$$a_3(u,d) = \frac{1}{\text{total shares posted by user u before date d}}$$

$$a_4(u,d) = \frac{1}{\text{total messages sent by user u before date d}}$$

$$a_5(u,d) = \frac{1}{\text{total callsmade by user u before date d}}$$

$$a_6(u,v) = \frac{1}{\text{at least the neighbour of user u or user v}}$$

$$a_7(u,d) = \frac{1}{\text{total comments talk time of user u before date d}}$$

eq. (2)

The term w_i represents the weight factors. Each weight factor of the parameter shows the weight of that parameter in calculating direct trust value.

$$w_1(u) = \frac{\text{total comments (by user u)}}{\text{total comments + total likes + total shares + total messages + total calls (by user u)}}$$

$$w_2(u) = \frac{\text{total likes (by user u)}}{\text{total comments + total likes + total shares + total messages + total calls (by user u)}}$$

$$w_3(u) = \frac{\text{total shares (by user u)}}{\text{total comments + total likes + total shares + total messages + total calls (by user u)}}$$

$$w_4(u) = \frac{\text{total messages (by user u)}}{\text{total comments + total likes + total shares + total messages + total calls (by user u)}}$$

$$w_5(u) = \frac{\text{total calls (by user u)}}{\text{total comments + total likes + total shares + total messages + total calls (by user u)}}$$

eq. (3)

And in calculating estimated trust value about an unknown user, the harmonic mean of direct trust towards the mutual friend and direct trust between the mutual friend and unknown user is taken.

V. APACHE MAHOUT

Apache mahout's machine learning libraries are used to find out the user similarities.

1) Data model

The data model used in this work is GenericDataModel using java codes. Each record in the data model contains user id, category id, value. Here category id represents each categories like education, job, location etc. Each category will be having different values. So a mapping is done for the value. A numeric unique value is assigned for each possible value of a category. Similarity among the users are found out using this.

2) Similarity Measurement

There are many measures to find out user similarities. We used Pearson Correlation Coefficient (PCC) to find out user similarity. PCC gives a correlation between two variables in the range [-1, 1]. PCC between variable x and y is measured as the ratio of covariance of two variables to the product of their standard deviations.

$$P_{x,y} = \frac{Cov(x,y)}{\sigma_x \sigma_y}$$

eq. (4)

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VI. EVALUATION

In order to understand the result of the project, we have to know about the dataset used, the methodologies implemented and the evaluation metrics and their importance. We implemented the work as a server application using JSP. Proper user interfaces were used to make the work attractive. Trust calculation methodology is implemented. And all those implementation details are kept hidden from users. So the users are free to use the application like that of existing ones without concerning about the implementation part. Then a basic version of the recommendation system is implemented to evaluate the model.

To evaluate the model, we need an authentic dataset. So we utilized the 2009 and 2010 Friendfeed dataset. Actually the dataset is collected by the Special Interest Group on Social Network Analysis (SIGSNA). But it was not available in their website. Since the dataset includes the user details, on grounds of user security and privacy, all the dataset copies were removed from different sources. We contacted the authors of [3], but the result was negative. And at last a dataset is obtained from [10]. The dataset includes two columns – follower id and followed id. Follower ID is the ID of the user following Followed ID. And Followed ID is the ID of users followed by Follower ID. The dataset contains 1048576 users. Out of 1048576 users, 87 user-friend pairs are selected at random. And a friend network is made to understand the friendship among users. This network includes users who are having at least one friend. Some pair of users have mutual friends. It is observed that out of 87 user-friend pair, there are 42 users in total.

Unique names were given to the users and numeric value as ID in order to calculate user similarity. User details like Date of Birth, sex, education, work and location are given randomly in order to maintain the credibility of the system. As mentioned earlier, each user detail is assigned numeric values to find out PCC similarity. Next, we needed <user,friend,trust_value>. Trust and trust value details like number of comments, likes, shares, tags etc. were not there in the Friendsfeed dataset. So direct trust is calculated by considering the similarity value. Further Movielens dataset is collected from [11]. It includes three columns – user id, movie id, and rating. And 87 user ratings are selected at random and is mapped for the 87 user-friend pair of Friendfeed dataset. And thus we got user, friend, trust details.

Further user recommendations and suggestions are made by considering trust value calculated based up on these user, friend and trust values.

EVALAUTION CRITERIA

To evaluate the proposed model, we implemented a small model of existing recommendation system namely – user based recommendation system. And then we compared both the models. Existing model is evaluated using prediction based measures which are Mean Average Error (MAE) and Root Mean Square Error(RMSE) and using IR-based measures which are Precision, Recall and F1 measure. The same IR based measures are used to evaluate proposed model.

MAE computes the deviation between predicted ratings (p_i) and actual ratings (r_i).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|p_i - r_i| \qquad \text{eq. (5)}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|p_i - r_i|} \qquad \text{eq. (6)}$$

Precision is a measure of exactness, determines the fraction of relevant items retrieved out of all items retrieved.

$$Precision = \frac{Number\ of\ positive\ recommendations}{Total\ number\ of\ recommendations} \qquad \text{eq. (7)}$$

Recall is a measure of completeness, determines the fraction of relevant items retrieved out of all relevant items.

$$Recall = \frac{Number\ of\ recommendations\ having\ maximum\ value}{Number\ of\ positive\ recommendations} \qquad \text{eq. (8)}$$

F1 measure attempts to combine precision and recall into a single value for comparison purposes. It gives equal weightage to Precision and Recall by finding Harmonic Mean of both.

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$$F1 = 2\frac{Precision*Recall}{Precision+Recall} \qquad \text{eq. (9)}$$

VII. EVALUATION RESULTS

To evaluate the model using Precision, we need to find the number of positive recommendations. The value of number of positive recommendations varies from domain to domain and user to user. So as a generalized approach, we considered the estimated trust value which are having values greater than 70% of the maximum estimated trust among the recommendations as positive recommendations. And to calculate Recall, the users having maximum trusted values among the positive recommendations are considered.

From the work [1], we came to know that trust incorporated RSs are more efficient than normal RSs. Out of 42 users, only 10 users got recommendations through existing user based RS and recommendation ratio was calculated as 0.238 and percentage of recommendation is 23.8%. While the proposed model have recommendation rate as 1 and 100% of recommendation percentage. The main advantage of proposed model is that, there will be at least one user recommendation for a target user, if he is having at least one Social friend.

For the purpose of evaluation, we just considered user trust values and not semantic information from their conversations or comments. But we implemented the semantic analysis part in server based application. Semantic trust among users will be displayed in the application.

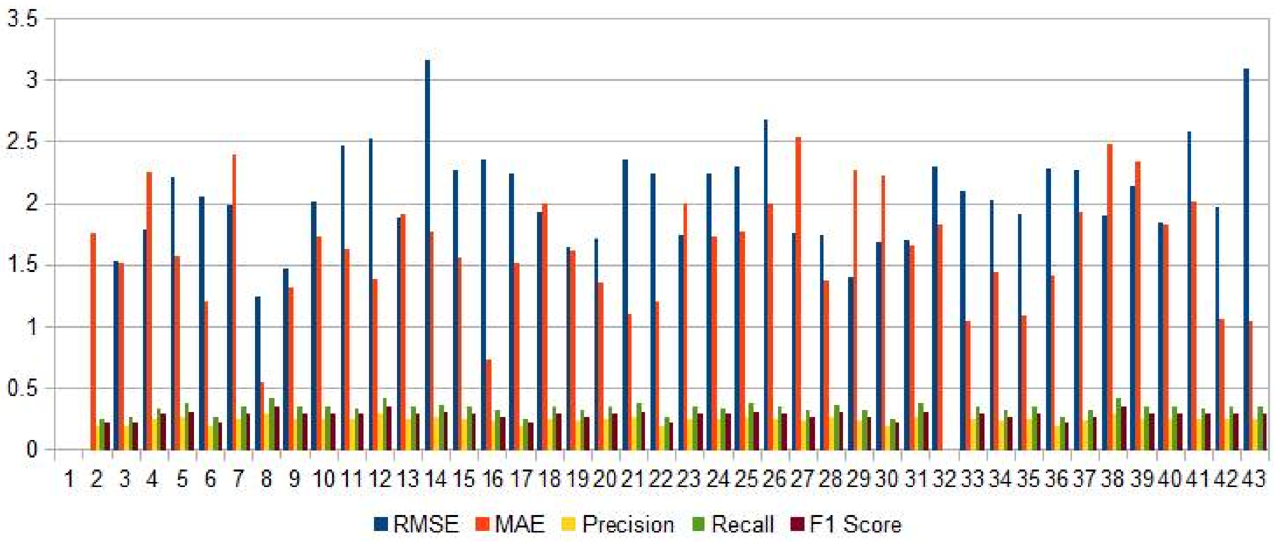

Fig.2. Results of user based recommendation.

The figure 2 shows the RMSE, MAE, Precision, Recall and F1 measure of proposed model. Here we can see the user32 has got no recommendations and Precision, Recall, F1 values are equal to zero. Also the Precision values are not unity. The value of precision and recall shows the exactness and correctness of the system. The Precision and Recall values evaluated using the existing model are less than 0.5. But in the figure 3, the same user has got recommendations with precision =1, Recall = 0.1667 and F1 score = 0.285. Figure 3 shows that the Precision value of proposed model is almost unity. Which implies that the ratio of positive and relevant recommendations are high and almost same.On comparing the two graphs it can be seen that the proposed model have higher precision and recall values. So by analysing the all results, it is clear that trust calculation and propagation is an efficient way to filter out unwanted recommendations and newsfeeds in social networks. Since the semantic trust value and interaction trust values are in two different domains, the user can make an idea about a specific user on grounds of the two values. The same approach used for user recommendation is used for giving notifications also.

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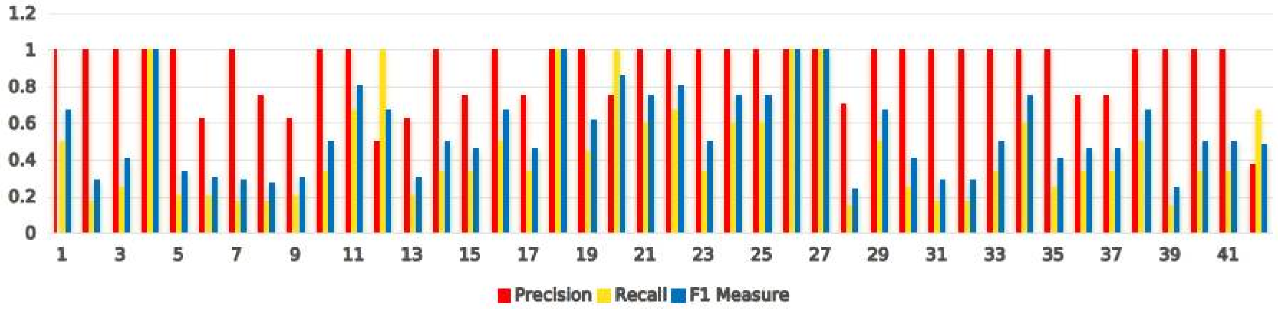

Fig.3. Results of proposed recommendation model.

VIII. CONCLUSION AND FUTURE WORK

In this paper, we propose a new recommendation model for mobile and non-mobile based OSN users. Since the trust value is not calculated separately by the users, this model provides user friendliness and accuracy. The behaviour of each user towards each social activity is considered to calculate trust value. This model makes recommendations to users based on the concept of friends of friend. But the estimated trust value will be listed along with. Total number of calls made, and call duration is also used to make an estimated trust value. This model also shows semantic trust value. The semantic trust is calculated from the chat interactions among a pair of users and from commented text of the target user. The trust value is dynamic in nature.

However, this paper still have modifications and scope of study. First one, the semantic information of comments for a post can be used to get a clear image about the type of post made. That means, a post having many negative comments may imply that the post is having a negative impact or intention, and the source of such posts can be isolated. Second one, instead of recommending friends based on friends of friend concepts, go forward with other users without incurring much cost. Third, interaction time can be considered to calculate trust value. Very past interaction can't be used to calculate present interaction trust. And the concept of recommendation based on trust can be used in other domains like P2P file sharing so that malicious peers can be isolated.

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