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# A New Recommender System Based in Collaborative Filtering Based on Personal and Group Trust for Offering Significant Suggestions to the Users

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**Abstract:** In recent years, using different trust models in recommender systems based on collaborative filtering, provides a trustable environment for transactions and interactions between vendors and vendees. Several trust based models were created based on rates given by users to different products and items in the past and also based on relational and popularity trust. In this study, a new recommender system is proposed by combining personal and group viewpoints. Personal viewpoints are computed according to rates given by the users. The On the other hand, user whose favorites and priorities are similar for choosing a website items can make a group together. In our method, group trust is computed based on users' weights in a group. Eventually, our recommender system recommends by using personal and group trusts and combining these two viewpoints and adding entropy. The Our experimental results shows that our model increases performance and accuracy of prediction significantly in compare with other collaborative filtering models.

**Key words:** Recommender system, collaborative filtering, personal trust, group trust, entropy, similarity

## INTRODUCTION

Recommender systems are proposed by Tapestry (Goldberg *et al*., 1992). Their goal is helping users choose their favorite items a huge number of data in a particular area and by using information based on user priorities. In other words, a recommender system is personalizing users' suggestions. Thus, three important factors in these systems are user, rating and product which are related in all models.

Collaborative filtering which is one of the most successful and popular subset of recommender systems, could improve quality of the recommend and accuracy of the prediction by employing methods based on users' trust and similarities. In recent years, growth of social networks and E-commerce websites, trust mechanisms are formed to improve collaborative filtering systems and eliminate their limitations. Trust based recommender systems recommends based on trust rates or by combining those rates with similarities. User trust increases when she receives a recommend from those whom she know or from those who are similar to her.

### Fundamental concepts and related works

**Related works:** In many trust based recommender systems, users' trust is merged with filtering techniques to enhance quality of the recommend. These combined models are used in recommender systems to provide a suggestion based on rates users given to different items. Generally, these trust computational model (Hwang and Chen, 2007; Kim *et al*., 2008; O'Donovan and Smyth, 2005) can be categorized into the following classes.

**Relation trust, direct or local:** In this method which is completely related to relations in social networks, user achieves her trust based on knowledge she had gained in her past interactions or determines her relations directly.

**Reputation trust, indirect or global:** Information are collected based on relations and behavior of users in social networks. Reputation trust is a quantitative evaluation which is collected from members of a social and it gives rate to an object or person (Lai *et al*., 2013).

Some researchers believe that real trust is based on a relation between two users. Massa and Avesani (2004) established trust network using epinions.com data. Papagelis (2005) used similarity factor to determine trust level and then he used another method to eliminate dispersion. Afterwards, Weng *et al*. (2006) proved that by decreasing undetermined condition, incorrect predictions

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degree of a new item will be decreased. In the same year, Golbeck and Kuter (2009) designed a new type of trust named Tidal trust which is based on breadth first algorithm and then it finds the shortest path between user and the source user and their weight rate is evaluated using trust level between the source user and other categories.

Mole trust idea which is introduced by Massa and Avesani (2007) is used in Tidal trust model which is similar to it. Mole trust is computed the source user trust according to target user using exploring in social networks which starts from the source vertex and is determined by propagating trust between valid edges.

Ray and Mahanti (1899), after determining similar neighbors and their trusted users and also user rates given to the items, undetermined rates are guessed by similar users. In correctness of recommends is improved by relational or direct trust using reconstruction of social networks (Chen *et al*., 2013).

Bedi and Sharma (2012), proposed trust between users combined with Ant colony theory to create a small and appropriate set of users and a system named Ant proposed. Correctness and covering of social filtering method increased by merging factors of trust, similarity and importance of social networks (Faridani *et al*., 2014). In the suggested combinational trust model (Lai *et al*., 2013), relational and personal trust based on users' rates given to common items from the personal point of view are considered. In the group point of view, most decided recommends in personal trust are enhanced based on users' role weight.

## MATERIALS AND METHODS

**Related computational methods:** Collaborating filtering methods based on user are used to provide appropriate recommendations in two phases.

**Selecting similar users whose interests are close to the target user:** Cosine method, Pearson correlation coefficient and conditional probability are the ways for computing similarity. Pearson correlation coefficient which is used to evaluate correlation between target user and recommender is shown in Eq. 1.

$$W_{t,p}^{Pearson} = \frac{\sum_{i\in (d'_t nd'_p)} (r_{t,i} - \bar{r}_t)(r_{p,i} - \bar{r}_t])}{\sqrt{\sum_{i\in (d'_t nd'_p)} (r_{t,i} - \bar{r}_t)^2} \sqrt{\sum_{i\in (d'_t nd'_p)} (r_{p,i} - \bar{r}_p)^2}} \quad (1)$$

Equation 1, $d'_t$ and $d'_p$ are item sets related to target user$^t$ and recommender p$r^r_{t,i}$ is the rate given by target user to the item i.$\bar{r}_t$ is the average of rates given by the target user in set (d)' tn $d'_p$).

**Predicting rates given by the user to different items:** In prediction phase, Eq. 2 is employed which is named Rsnick prediction. It predicts rates that might be given by the target user$^t$ to item$^i$ based on neighbor set$^{NS}$ (Resnick *et al*., 1994):

$$\bar{p}_{t,i} = \bar{r}_t \frac{\sum_{p\in NS} (r_{p,i} - \bar{r}_p) W_{t,p}^{Wpearson}}{\sum p \in NS \left| W_{t,p}^{pearson} \right|} \quad (2)$$

**Combinational trust models:** One of the other methods employed in this study is combination of personal and group trust. Particularly, when the person has a low rate of data and she is not sure whom she can trust. In this case, personal trust between users are considered less. To solve this problem and exploiting advantages of both methods, value of trust for target user based on recommendation suggested by recommender for item can be computed using Eq. 3:

$$HT_{c,p}^{H,i} = \alpha \times PT_{c,p}^{ra} + (1-\alpha) \times (GT - CF)_{ugip}^{i} \quad (3)$$

Equation 3, $Ht_{cp}^{H,I}$ is the value of trust between target user c and recommender user p for item i. It is calculated using linear combination of personal trust $Pt_{cp}^{ra}$ and group trust $GT\text{-}CF_{Ugp}^{i}$. This values shows level of trust that target user c has to recommender p for item i such that α is the weight given to the value of personal and group trust and its range is between 0 and 1.

If personal trust has more impact in compare with group trust then α will be increased and as a result in this method, Personal Trust model (PT) can assist more than collaborative filtering model which is based on group trust (GT-CF) for determining value of combinational trust. Conversely, by decreasing α value and impact of group trust will be increased. For combining collaborative filtering with different trust models Eq. 4 can be employed.

$$\bar{p}_{t,d} = \bar{r}_t + \frac{\sum_{p\in NS} H(Psim(t,p), TM_{t,p}^{H}) \times (r_{p,d-\bar{r}_p})}{\sum_{p\in NS} H(Psim(t,p), TM_{t,p}^{H})} \quad (4)$$

In this equation $H(P_{sim}$ (t,p) $TM^H_{t,p})$ is weighted arithmetic mean between user similarity Psim (t,p) (It is computed using Pearson correlation coefficient) and trust level $TM^H_{t,p}$ (It can be one of the value of personal trust, group trust or combinational trust (personal and group). Equation 5 shows how this mean is calculated.

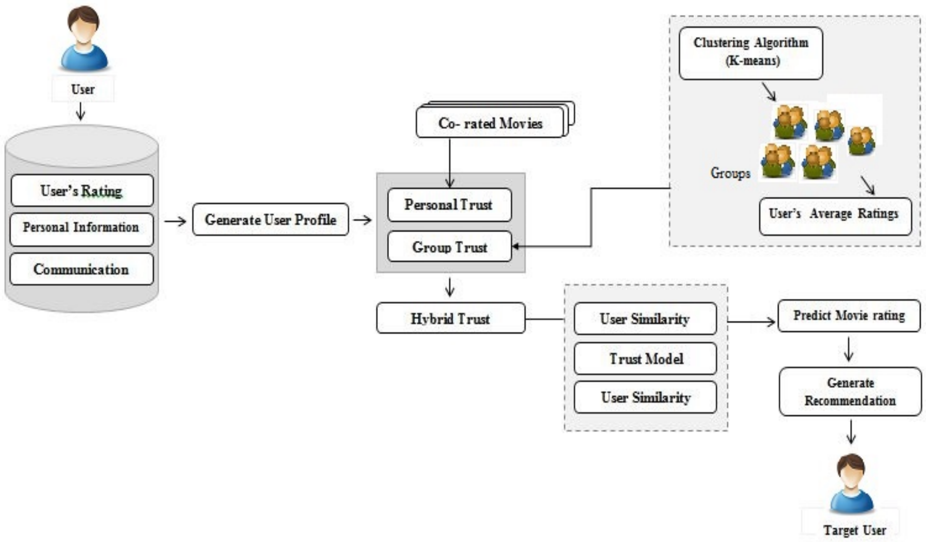


Fig. 1: Architecture of the proposed method

$$(Psim(t,p)TM^{H}_{t,p}) = \beta\times TM^{H}_{t,p} + (1-\beta)\times P_{sim}(t,p) \quad (5)$$

Importance of using weighted arithmetic mean is that it allows us to adjust the level of significance related to user similarity Psim (t,p) and trust level $TM^{H}_{t,p}$. $\beta$ is a parameter that can be achieved using the best experimental results (Lai *et al*., 2013).

**The proposed method:** In this part of the study, a brand new model is presented in recommender systems which is recommending beneficial suggestions to users by combining personal and group point of view and similarity. Also, steps of the proposed method will be explained. Figure 1 shows the architecture of our proposed method.

Firstly, personal trust of a user to another user is calculated based on rates they gave to common items. To this aim, all information of these two users in their items record is analyzed. Then, for grouping different users some clusters, whose users are similar to each other from rating viewpoint, are created using the k-mean algorithm. For computing value of group trust which is given by recommender user to the target user, average value of rates to a particular item of all users in group is calculated and related weight of each cluster to each user is computed.

As shown in Fig. 1. in the next step personal and group trust are combined. Namely, trust value of the target user which is given to recommender user and the groups she belongs to for a particular item is calculated using a linear relation. After this step, users whose trust value is positive are considered as appropriate users for the target user and their ratings are used in producing recommendation. This value of trust is merged with similarity level of the target user and the recommender user in a form of a linear formula. This formula produces a weighted arithmetic mean which is used in Resnick prediction Eq. 5. Finally, entropy value of the studied item is added to this relation by a constant coefficient.

**Computing personal trust:** Computation method of personal trust of the users are based on ratings to common documents. It uses by Hwang And Chen (2007). Consider that  is a recommender user and  is a target user. Rate given to item  by the target user  according to recommender user  whose notation is  is calculated using Eq. 6:

$$\overline{P}^{p}_{t,d} = \overline{r}_{t} + (r_{t,d} - \overline{r}_{t}) \quad (6)$$

In this equation $\overline{r}_{t}$ and $\overline{r}_{p}$ are average rates of target user t and recommender user p, respectively. The closer the value of $p_{ti}^{p}$ to the rate given by target user t to this item namely, $r_{t,i}$ the more similar these users are and so trust value between them is more:

$$T^{d}_{t,p} = \left|\frac{\widehat{P}^{p}_{t,d} - r_{p,d}}{M}\right| \quad (7)$$

In Eq. 7 $T^{d}_{t,p}$ is the value of pure trust between target user$^{t}$ and recommender user$^{p}$ for item$^{i}$ and$^{M}$ is difference between most and least value among rates. Eventually, for computing value of personal trust between target user$^{t}$ and recommender user, p Eq. 8 is used. This formula is based on items that are rated by both users:

$$PT_{t,p}^{ra} = \frac{1}{\left|I_t^d \cap I_p^d\right|} \sum_{d \in (I_t^d \cap I_p^d)} \left(1 - \frac{\left|\hat{P}_{t,d}^{p} - rp,d\right|}{M}\right) \quad (8)$$

In Eq. 8, $Pt_{t,p}^{ra}$ is the personal trust value that shows how much target user t trusts recommender user $PI_p^d$ and $I_t^d$ are sum of rates given by target user t and recommender user p respectively and $^M$ is the difference between most and least value among rates. The $PT_{t,p}^{ra}$ is rates given by target user t to item i according to recommender user p which can be computed using Eq. 7 $r_{t,d}$ is the real value given by target user$^t$ to item.

**Computing group trust:** In this step, k-mean clustering algorithm (Jain *et al*., 1999; Jamali and Ester, 2010) is employed for grouping different users. This algorithm depends on initial centers strictly. In each step, we compute similarity of each cluster to every user using Eq. 9 and 10 and then we update clusters such that similar users are placed in a same cluster again. This step is repeating until clusters become stable:

$$Sim(u_n, c_k) = \frac{\sum_{un,m>0c_{k,m}>0}(un,m - \bar{u}_n) \times (c_{k,m} - \bar{c}_k)}{\sqrt{\sum_{u>m>0,c_km>0}(u_{n,m} - \bar{u}_n)} \times \sqrt{\sum_{u>m>0,c_km>0}(c_{k,m} - \bar{c}_k)^2}} \quad (9)$$

$$\bar{c}_K = \frac{1}{|c_k|} \sum_{u_n \in c_k} \bar{u}_n \quad (10)$$

In Eq. 9 $\bar{u}_n$ and $\bar{c}_k$ are average rates of user $u_n$ and cluster $|c_k|$ and is the number of users in cluster $|c_k|$. These steps are repeating until clusters become stable.

After determining clusters, Eq. 11 is employed for calculating group trust? The method that is used for computing group trust of item level. Group trust of a group (Cluster) related to recommender p is obtained by getting average of pure trust value ratio to created predictions on item i and also of weight similarity of users to each cluster. Group trust $U_g$ to recommender p for item i can be computed using Eq. 11:

$$GT - CF_{Ug,P}^{i} = \frac{\sum_{u \in Ug}\left(1 - \frac{\bar{p}_{u,i}^{p} - r_{u,i}}{M}\right) W_{u,Ug}^{sim}}{\sum_{u \in U_g} W_{u,U_g}^{sim}} \quad (11)$$

Table 1: Characteristics of selected database for this study

| Data set | No. of user | No. of movies | No. of ratings | No. of sparsity |
|---|---|---|---|---|
| Flixter | 6040 | 3706 | 1000209 | 95.53 |

$U_g$ is the group that target user t belongs to and $W_{u,Ug}^{sim}$ is the weight of similarity between user u and group $U_g$.

$$HT_{t,p}^{H,i} = \alpha \times PT_{t,p}^{ra} + (1-\alpha) \times IGT_{U_{g,p}}^{i} \quad (12)$$

In Eq. 12, α is the weight given to each personal and group trust and is between 0 and 1.

**Combining trust model and entropy:** Entropy test is evaluation of random values diversity or dispersion of users' ideas for items. The larger the produced number is the more diverse exists among numbers. So, random generator seed was a better generator.

$$H = -\sum_{1=1}^{n} p_i * \log p_i \quad (13)$$

In Eq. 13, p is probability of the i-th event of selecting the number in a sequence of random numbers or probability of selecting item i is item sets. It is equal to number of items that item i has selected by neighbors of the target user divided by sum of items selected by the neighbors. n is the number of all numbers that should be generated by the generator and i is the number counte . H is the entropy or value of the sequence diversity (diversity of selected items) (O'Donovan and Smyth, 2005):

$$\bar{P}_{t,i} = \bar{r}_t + \frac{\sum_{P \in NS} TM \times (r_{p,i} - \bar{r}_p)}{\sum_{p \in NS} TM} + Y * H_i \quad (14)$$

In Eq. 14, $H_i$ is the entropy of item i. In this equation, the major change is adding entropy of each item with coefficient r to the value of prediction for that item. It has the potential for further researches.

## RESULTS AND DISCUSSION

**Database:** Selected set of data for this study comes from a social website for film named Flixter (Jamali and Ester, 2010) which contains users' identity, film's identity, rates given to the films and timed labels. Rate are real numbers in the range of 0.5 and 5 with the distance of 0.5 between numbers. This database characteristics are shown in Table 1. The 20% of users of this database is considered for evaluation of the quality of the recommends as a training set and 80% of them are used in the training set for producing the list of recommendations.

**Selecting criteria for an appropriate evaluations:** Selecting an appropriate algorithm for designing a recommender system depends on goals that the system has created for them and particular evaluations criteria are selected based on this. In this study, for measuring performance and accuracy of created recommendations we use criteria such as Mean Absolute Error (MAE), coverage and F-measure.

MAE is computing absolute average deviation between predicted rate and real rate that the target user has given to the item. MAE can be calculated using Eq. 15:

$$\mathrm{MAE} = \frac{\Sigma_{i=1}^{N}\left|\hat{P}_{d_i}\right|}{N} \tag{15}$$

In Eq. 15, N is the number of tested data which is considered 20% of the users. $P_{di}$ is predicted rate for item di and rdi is the real rate for item. The less MAE value is the closer prediction value to the real value is. Reversed MAE or iMAE is defined as correctness of prediction by inspiration from (O'Doherty *et al*., 2012) which is normalized by allowed range of value for scores:

$$\mathrm{iMAE} = 1 - \frac{\mathrm{MAE}}{r_{max} - r_{min}} \tag{16}$$

In Eq. 16, $r_{max}$ and $r_{min}$ are most and least value for an item rating, respectively. Higher value of iMAE shows that provided predictions are more accurate.

Rating Coverage (RC) measures percentage of recommended items by an algorithm. If Totallp is the number of created predictions by the algorithm TotallN and is number of users who use this algorithm for prediction, then coverage is computed using Eq. 17:

$$\mathrm{Converage} = \frac{\mathrm{Total\,P}}{\mathrm{Total\,N}} \tag{17}$$

The more coverage value is the more diverse recommendations is by the algorithm. Because recommending favorite items to the user will decrease coverage, it can be used as a criteria for evaluation of accuracy criteria.

F-measure is one the other metrics for evaluation which measures total performance of the system using coverage test and accuracy of the system. Accuracy and coverage are significant criteria for the system. According to (O'Doherty *et al*., 2012), F is computed using Eq. 18:

$$F = \frac{2.\mathrm{iMAE.RC}}{\mathrm{iMAE+RC}} \tag{18}$$

In trust base recommendations, recommenders whose trust are greater than or equal to a threshold are selected for creating collaborative filtering recommendations as neighbors of the target user. Determining value of the threshold has influence on quality of the recommend such that a proper threshold should select trustworthy recommenders. In here, we will consider the threshold equal to 0.

In this part of the study, performance of our method from different points of view is studied and efficiency of this technique is shown using different kinds of test. Also according to experimental results achieved from our tests, the best value for coefficients α, β and y is 0.1 because the system has the least MAE for this value. Coefficient test is done for values such as 0, 0.001, 0.01, 0.1, 0.2 and etc.

**Comparing predicted method based on combinational trust and similarity to combinational entropy method:** Table 2 shows numerical in which Resnick prediction Eq. 5 is extended by getting weighted arithmetic mean (combination of trust and similarity-Eq. 5).

As shown in Table 2, by using combination of trust and similarity, we will have the least value of error. Thus, predictions will be computed by higher accuracies.

If the goal is increasing percentage of recommended items and improving performance of the system, personal trust method is the best option for selecting the algorithm for the system. In comparing with combinational trust methods, we can say adding similarity factor to trust not only decreases the error but also increases performance and coverage. Results of measuring evaluation criteria on Eq. 13 is shown in Table 3. By comparing Table 2 and 3, we can conclude that

Table 2: Numerical value of MAE, Coverage, F-measure in presented methods

| Approaches measured by MAE, RC and F1 (View all users) | | |
|---|---|---|
| P-rate | HT | H |
| 0.668 | 0.6610 | 0.5310 |
| 53.75 (%) | 48.5600 | 48.9300 |
| 0.6590 | 0.6189 | 0.6294 |

Table 3: Numerical value of MAE, Coverage, F-Measure in methods which uses entropy

| Approaches measured by MAE, RC and F1 (View all users) | | |
|---|---|---|
| P-rate | HT | H |
| 0.631 | 0.6240 | 0.5090 |
| 53.75 (%) | 48.6600 | 48.9900 |
| 0.6615 | 0.6211 | 0.6307 |

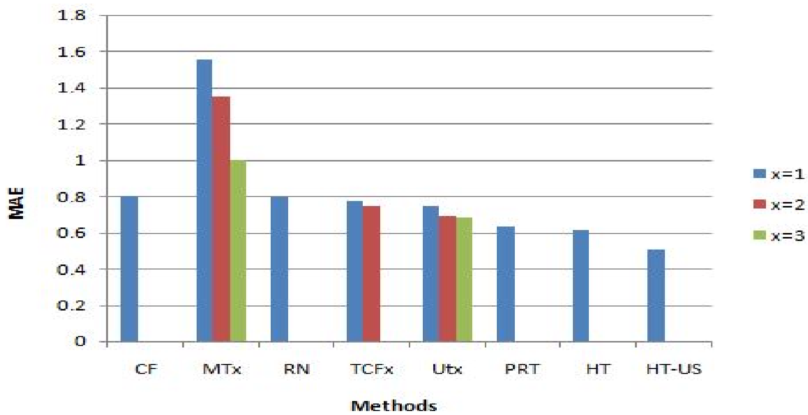


Fig. 2: Comparing prediction accuracy of methods based on MAE criterion

adding entropy to the prediction relation with using weighted arithmetic mean in which trust and similarity are merged in compare with the algorithm which does not consider entropy, contains not only fewer error and rate and more accurate predictions but also has a higher level of performance and coverage. This method can consider as a basis of future works. In the next sections our proposed method is this study will be compared with some other methods.

**Methods that are compared with ours:** In this part of the study, we compare and evaluate our proposed method with some of trust method related to collaborative filtering which is explained as follows.

**Collaborative Filtering (CF):** Computing similarity of users using Pearson Correlation Coefficient in filtering and creating recommendations and predicting users' rates by Resnick standard model in Grouplens (Resnick *et al*., 1994). In here for comparing, value of threshold is considered 0.

**Personal trust based on rating in collaborative filtering (Rating based Personal Trust CF or Personal T-CF):** Personal trust is calculated by the average of prediction error for items with common rates (Mooney and Roy, 2000). In here, it refers as PRT.

**Mole trust algorithm:** This algorithm is for propagating trust with length through the network in which only trusted neighbors are used for items rating prediction. This algorithm refers as MRx (x = 1, 2, 3) (Massa and Avesani, 2007).

**Reconstructed network algorithm:** In this method, prediction of items rate is done by reconstructing the network trust. For similarity equal to 0.5, selecting 5 of the most similar neighbors for predicting rate and length 1 for propagation has the best outcome for this algorithm. This algorithm refers as RN in here (Ray and Mahanti, 2010).

**TCFx (x = 1, 2) algorithm:** In this method for improving collaborative filtering method, items that are not rated with users are predicted based on trusted neighbors' rates. So, more similar neighbors participate in creating recommendations. The best outcome of this algorithm happens when trust propagation distance in the trust network is equal to 2 (Chowdhury *et al*., 2009).

**UTx (x = 1, 2, 3):** In this method, different propagation distances for propagation distance x is computed and impact of propagation on performance is tested (Faridani *et al*., 2014).

**Comparing the proposed method with other methods:** In this part of the study, our method is compared with other methods based on evaluation criteria which are discussed earlier in the study. To this aim, combinational personal and group trust methods are compared based on MAE criterion firstly. Variable x in Fig. 1 shows propagation trust distance. As shown in Fig. 2, in methods that are based on propagation distance, error is decreased by adding distance value. The most error value is for Multrust algorithm in which only trusted neighbors takes part in producing items rate prediction. After this method, CF method has the most error value (MAE = 0.801) which recommends without considering trust. In RN method by reducing error to 0.798, prediction accuracy increases. Relying on only personal trusts based on users' rating to

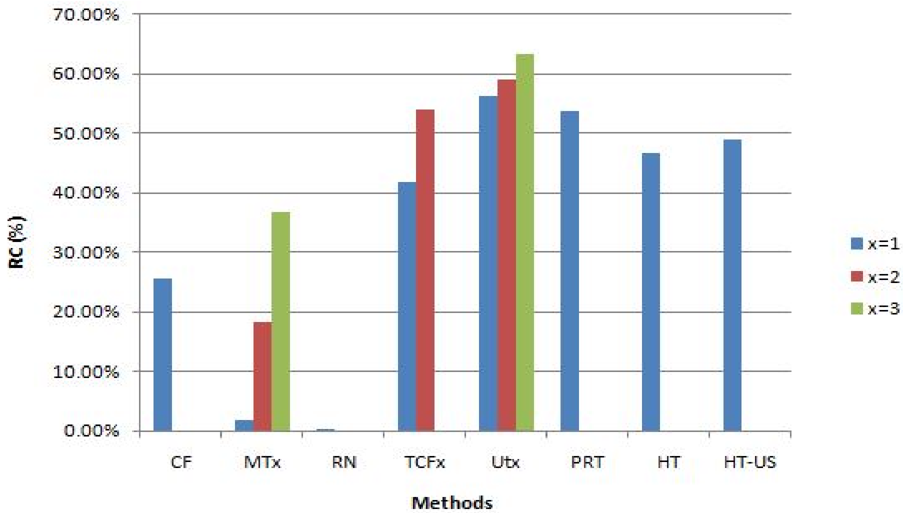


Fig. 3: Comparing coverage of different methods

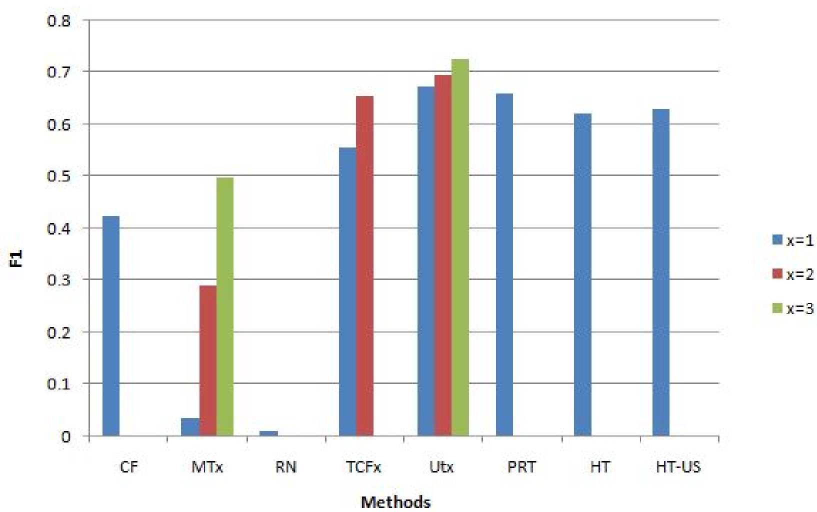


Fig. 4: Comparing F1-score of different methods

common items can reduce error a little bit. Clearly, merging the personal trust with group viewpoint leads to more accurate predictions with better performance (MAE = 0.624). Finally, we add similarity factor to combinational personal and group trust and our evaluation shows that our method has a lower percentage of error (MAE = 0.509) and thus it can propose more accurate recommendations.

In Fig. 3 and 4, methods are compared based on coverage and F-measure for having a more general view of their performance.

In methods which are based on propagation distance, by adding distance length performance percentage and coverage of items is increased. In UTx method that is a combinational of MoleTrust and TidalTrust coverage and performance increase significantly in compare with other methods. After this method, TCFx with 54.01%t has the most coverage and PRT with the value of 0.6310 has the highest performance. As shown in Fig. 3 and 4 this algorithm in the case of using only Personal Trust (PRT) in compare with the case that group trust and similarity are merged, has a better performance and higher coverage percentage. CF covers just a few predictable items because it does not consider trust between users. It does not suggest high quality recommendations and in compare with other methods it is suffering of cold start problems intensively. So, trust models for improving quality of trust are used more. RN method uses only rates given by users who has high number of neighbors and high rate of similarity for creating predictions. Also, it

Table 4: Numerical values of evaluation criteria for different methods

| Approaches measured by MAE, RC and F1 (View all users) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| CF (%) | MT1 (%) | MT2 (%) | MT3 (%) | RN (%) | TCF1 (%) | TCF2 (%) | UT1 (%) | UT2 (%) | UT3 (%) |
| 0.801 | 1.557 | 1.348 | 1.001 | 0.798 | 0.775 | 0.746 | 0.744 | 0.692 | 0.681 |
| 28.53 | 1.81 | 18.33 | 36.71 | 0.21 | 41.85 | 54.01 | 56.34 | 59.22 | 63.37 |
| 0.4236 | 0.0352 | 0.2910 | 0.4987 | 0.0042 | 0.5559 | 0.6557 | 0.6727 | 0.6968 | 0.7256 |

covers a few number of items which according to dispersion of data this method has improper performance and also it is not accurate enough. In compare with direct trust propagation methods such as (MT1 and MT2) in which only direct trusted neighbors are used, UTx method performance is better. Moreover, UTx method has a better performance in all propagation distance of trust in compare with MTx because of combining similarity, trust and importance. TCFx methods perform badly for cold users and this is because of dependency to CD method for finding similar users it has before using trust.

In group trust method presented in this study, value of trust is obtained based on more important (more trusted) members of the group who have higher weights and level of priorities. Thus, group viewpoint can have a great impact on suggesting a trustable recommendation and a providing a proper quality. In here, combining this method with personal trust based on rates given by users to common items has 0.624 for value of error which in compare with personal trust error is only 0.007 lower. By merging these viewpoint together in the form of linear mathematical combination and comparing them based on evaluation criteria, we can conclude that our method has the lowest error value in compare with other methods and thus it improves accuracy of recommender system prediction.

In the case that the goal of the recommender system is more accurate and high quality recommendations, out combinational trust method is recommended. But, in the case that the goal is increasing performance and percentage of recommended items trust method based on propagation distance has a better performance.

**Comparing enhancement of combinational trust method with other methods:** We compute percentage of enhancement of each method in compare with CF method by considering F1 criterion to have a general view of performance of each method. This percentage is computed as shown in Eq. 19:

$$\text{Improvment} = \frac{\text{Methods.F1} - \text{CF.F1}}{\text{CF.F1}} \times 100\% \quad (19)$$

In this Eq. 19, Method. F1 refers to performance of each tested method in evaluation except CF method. Methods in which F1 criterion is considered as reference.

Table 5: Created improvements in all methods in compare with CF method using F1 criterion

| Dataset | View | MTx (%) | RN (%) | TCFx (%) | Utx (%) |
|---|---|---|---|---|---|
| Flixster | All users | 17.73 | -99.01 | 54.79 | 71.29 |
| Dataset | View | PRT (%) | HT (%) | HT-US (%) | |
| Flixster | All users | 56.16 | 46.62 | 48.89 | |

The more positive changes between the method and CF method, the more enhancement occurs. Results are shown in Table 2.

For better perception of these computation, other numerical values related to diagram are shown in Table 4. For example, we compute improved value for HT method. F1 value for HT method is 0.6189 and F1 for CF method is 0.4236. So, improvement is calculated as shown in Eq. 20.

$$\text{Improvment} = \frac{0.6189 - 0.4236}{0}.4236 \times 100\% = 46.10\% \quad (20)$$

Computation is the same for other values. For methods that are based on propagation distance in which propagation length is variable, the best status is chosen from Table 4. Results of these improvements in Table 5 shows that personal trust method has more improvement in compare with combinational trust method. Further more, by adding similarity factor to personal and group trust improvements will be increased and this method outperforms Mtx and RN algorithms. For PRTm HT and HT-US value prediction is computed based on entropy.

In the case that the only goal of the recommender system is improvement without considering prediction accuracy, UTx method is recommended. Our proposed method has a better performance in compare with basic methods such as Mtx and RN. Our method increase accuracy of prediction in compare with all other methods.

## CONCLUSION

By trust based collaborative filtering systems coming into action, produced recommends have higher level of trust ability. Data dispersion problem and information overhead are two sever challenges in the world of the Internet that commercial website and social networks face on. By expanding trust mechanism, costumer trust to suggested recommendations increases and so competition between vendors of different items and other trusted websites are increased.

In this study in personal viewpoint, two users rating to common items is considered. In new group viewpoint, after collecting other individual ideas for a particular item, users of a group will have similar priorities in compare with users in different groups. When a recommender system is trusted for a person then it will be trusted for the group that user belong to as well. In this research, group trust based model has a better performance and higher accuracy in compare with non-grouping trust models.

For employing an appropriate algorithm for the recommender system, its design goal should be considered. In cases that improvement related to performance is the goal in the design of a recommender system, personal trust method have a better performance than combinational method. In cases that increasing accuracy of the system is the goal, coverage and performance are lower and recommendation is recommended based on items with the most rating (favorite items). Experimental results show that our method reduces value of absolute error significantly. Thus, recommendations suggested with this method has higher accuracy.

Because social networks need to recognized trusted users and relations between them. In future, relations of the users can be modeled using combinational trust model. Precises analysis of these relations can increase accuracy of trust computation and recommendation quality which are two main goals of recommender system improvement.

Using some of trust computation methods beside similarity factor to design a social recommender system is a proper subject for future researches. For instance, data dispersion problem in CF environments may occur in social recommender environments too. This subject can be studied and evaluated by checking similarities between users and their selection priorities using users' rates to products and propagating an item (product, description, image, video clip, etc.) by the user herself.

The proposed technique based on group trust in this study, can collect items related to trusted users with the highest level of entropy in the form of a packet or a group of related products instead of presenting an item to a group of users and then suggest that item to a person or a group. Using correlation test for evaluating users' dependency, computing probability of selecting an item by a trusted user and using Bayes probability for recommending are some of suggested research subjects for future works.

According to high number of recommender systems, we can claim that these systems still have great potential to be studied, analyzed and explored in future.

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