Social Recommendation Based on Multi-relational Analysis

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***Abstract*—Social recommendation methods, often taking only one kind of relationship in social network into consideration, still faces the data sparsity and cold-start user problems. This paper presents a novel recommendation method based on multi-relational analysis: first, combine different relation networks by applying optimal linear regression analysis; and then, based on the optimal network combination, put forward a recommendation algorithm combined with multi-relational social network. The experimental results on Epinions dataset indicate that, compared with existing algorithms, can effectively alleviate data sparsity as well as cold-start issues, and achieve better performance.**

Keywords-social recommendation; multi-relation social network; regression analysis

I. INTRODUCTION

A social networking service is an online service, platform, or site that focuses on facilitating the building of social networks or social relations among people who, for example, share interests, activities, backgrounds, or real-life connections [1]. Social networks usually hold large quantities of users' information and activities data, which results in severe information overloading. Social recommendation, which emphasizes utilizing both users' individual interest information and relations in social networks to assist recommendation systems, has been regarded as an important tool to recommend useful information to people and deal with information overloading.

In recent years, researches on social recommendation mainly focus on uni-relational social network. According to whether considering the similarities of recommended items, social recommendation can be categorized into recommendation based on uni-relational social network and recommendation based on uni-relational social network and CF.

Recommendation based on uni-relational social network lays emphasis on ratings from users trusted directly or indirectly by the target user. TidalTrust [2] performs a modified breadth first search in the trust network to find all users who have rated the recommended item with shortest path distance from the target user, and then aggregates their ratings weighted by the trust value between target user and these users so as to compute a prediction. MoleTrust [3] shares similar idea with TidalTrust, but MoleTrust considers all users who have rated the recommended item up to a maximum-depth given as an input. Maximum-depth is independent of any specific user and item. Besides, in comparison with TidalTrust, MoleTrust must perform a backward exploration to compute the trust value between two users.

Recommendation based on uni-relational social network and CF insists that both relations in social networks and similarity between items should be taken into account. TrustWalker [4] has been put forward as a random walk model that combines the uni-relational social network and item-based CF. TrustWalker performs random walks on the trust network to find ratings for the recommended items or similar items, and then compute a prediction. The stop criteria for a single random walk at a certain user depend on the similarity of items rated by the user, the recommended item, and the current steps of the random walk. DCMR [5] claims that different recommendation methods should be applied to different users, like cold-start users and noncold-start users. DCMR performs breadth first search in the trust network to find users who have rated the recommended item and distributes weights to these users based on their confidence, and then collects all the predictions with their weights to generate the final result. DCMR presents that prediction confidence and trust attenuation as the two factors that affect the weight gained by users. Besides, a MTD (maximum trust distance) is required as stop criteria for every search. While there is no users meeting the needs, recommendation systems apply user-based CF to calculate the prediction.

To some extent, methods mentioned above can improve performance of recommendation systems; however, they postulate that there is only one kind of relationship between users, which is not the case. In social networks, there may exist many relations: some people live in the same city, some share interest, some join to the same club, etc. The postulation held by the above methods interfere researchers from revealing users interests accurately and solving data sparsity and cold-start user problems properly. In fact, more and more researchers have propose methods to analyze multi-relational social network, and apply the analysis results to community mining [6,7], link prediction, etc.

We presents a recommendation algorithm based on multi-relational analysis: first, according the needs of recommendation, we combine different relation networks by applying optimal linear regression analysis; and put forward a recommendation algorithm based on the optimal network combination. The experimental results on real dataset indicate that, compared with existing algorithms, our method can alleviate data sparsity and cold-start issues effectively.

978-0-7695-4880-7/12 $26.00 © 2012 IEEE
DOI 10.1109/WI-IAT.2012.222

II. Optimal Relation Network Analysis

Let $G\langle U, E\rangle$ donate a social network, where $U = \{u_x, u_y, \ldots\}$ is a set of nodes and $E = \{(u_x, u_y) | u_x \in U,\ u_y \in U,\ u_x \neq u_y\}$ is a set of edges between nodes, and weights on the edges indicate the relation strength.

A typical social network may contain many relations, and each of them can be treated as a relation network, represented as $G_k\langle U, E_k\rangle$, $k = 1,2,\cdots,K, K > 2$, where E_k is the set of edges associated with the corresponding relation network. Such kind of social network can be called multi-relational social network. To improve performance of recommendation systems, we need to identify which relation networks plays dominating roles in recommendation.

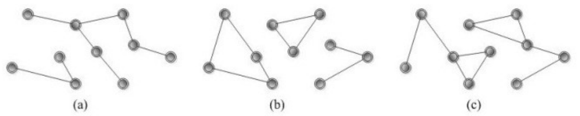

Figure 1. Relation Networks between Researchers coauthored in KDD, SIGMOD, VLDB conferences

For instance, three different relation networks (a), (b) and (c) exist in the social network in Figure 1, represent relations between researchers who have coauthored papers in KDD, SIGMOD and VLDB conference, respectively. The nodes represent researchers and the edges between nodes represent relations, which mean the researchers connected by an edge have coauthored at least one paper in the corresponding conference. Three relation networks play different roles in different recommendation tasks. That means (a) should gain more attention in comparison with (b) and (c) while systems are recommending information related with data mining, and in reverse while recommending information related with database.

Thus, utilization of multi-relational social network should depend on the recommendation requirement. This paper focuses on how to apply recommendation requirement as prior knowledge in analyzing the importance of different relation networks, and then gain an optimal network combination, which reflects the needs to the maximum degree.

Given a multi-relational social network $G_k\langle U, E_k\rangle$, $k = 1,2,\cdots,K, K > 2$, we use M_k to donate the weight matrix associated with G_k. Suppose there exists an optimal relation network $\hat{G}\langle U, \hat{E}\rangle$, the weights on the edges in $\hat{G}$ reveals the interest similarity between users, and $\hat{M}$ donates the weight matrix associated with $\hat{G}$. Now our task is to learn a linear combination of the weight matrices $M_1, M_2, \ldots, M_K$ which gives the best estimation of the optimal weight matrix $\hat{M}$.

In essence, this can be regarded as relation extraction and selection problem. Relation extraction problem could be related with feature extraction problem on the basic of machine learning. In the realm of machine learning and data mining, feature extraction, aiming at discovering the intrinsic characteristic of dataset, is usually applied in classification and clustering. It is similar to relation extraction, but used in different scenarios. Feature extraction is used when the objects have explicit vector representation, while relation extraction is used when only relationships between objects are available. Many typical feature extraction methods originate from regression analysis, including Principle Component Analysis, Ridge Regression Analysis and Linear Discriminant Analysis, etc. The following deduction will present how to apply regression analysis to solve relation extraction problem.

Each relation can be normalized to make the biggest strength (weight on the edge) be 1. Since the weights on the edges in optimal relation network $\hat{G}$ indicate the interest similarity between users, we can apply the following method to construct $\hat{G}$: for user u_x and u_y, compute the Pearson Correlation of ratings expressed by both users:

$$\mathrm{corr}(x, y) = \frac{\sum_{i \in CI_{x,y}} (r_{u_x,i} - \bar{r}_{u_x})(r_{u_y,i} - \bar{r}_{u_y})}{\sqrt{\sum_{i \in CI_{x,y}} (r_{u_x,i} - \bar{r}_{u_x})^2} \sqrt{\sum_{i \in CI_{x,y}} (r_{u_y,i} - \bar{r}_{u_y})^2}}$$

Here $CI_{x,y}$ is the set of common items rated by both user u_x and u_y, $r_{u_x,i}$ and $r_{u_y,i}$ donates the rating of u_x and u_y on item i, respectively. Besides, $\bar{r}_{u_x}$ and $\bar{r}_{u_y}$ donates the average of ratings expressed by u_x and u_y. Thus $\mathrm{corr}(x, y) \in [-1,1]$, -1 means the two users share completely opposite interests and in reverse 1 means completely same interests. As negative correlations mean that the two users are in opposite directions, these user pairs are not useful for our purpose. Therefore, we only consider user pairs with positive correlations.

Note that the size of the set of common items is also important in computing similarity. For example, if $\mathrm{corr}(x, y) = \mathrm{corr}(x, z)$, but $|CI_{x,y}| > |CI_{x,z}|$, since u_x and u_y have rated more common items, the correlation between them is stronger and the interest similarity between u_x and u_y should be greater than that between u_x and u_z, which means $\hat{M}_{x,y}$ can be defined as:

$$\hat{M}_{x,y} = \frac{1}{1 + e^{-\frac{|CI_{x,y}|}{2}}} \times \mathrm{corr}(x, y)$$

Sigmoid function used here is to avoid favoring the size of $CI_{x,y}$ too much and to keep the similarity value in the range $[0,1]$. As for the number 2 in the denominator of the exponent, it is used to gain a factor of greater than 0.9 if the size is greater than 5.

Once the target relation matrix is built, we aim at finding a linear combination of the existing relations to optimally approximate the target relation in the sense of L_2 norm.

Let $\boldsymbol{a^{opt}} = [a_1, a_2, \cdots, a_K]^T \in R^K$ denote the combination coefficients for different relations. The approximation problem can be characterized by solving the following optimization problem:

$$\boldsymbol{a^{opt}} = arg\, min_a \left\| \hat{M} - \sum_{k=1}^{K} a_k M_k \right\|^2 \quad (1)$$

Since $\hat{M}$ is a $N \times N$ symmetric matrix (N refers to the number of nodes in social network), it can be represented as a $N(N-1)/2$ dimentional vector $\mathbf{X}$:

$$\boldsymbol{a^{opt}} = arg\, min_a \left\| \hat{\boldsymbol{X}} - \sum_{k=1}^{K} a_k \boldsymbol{X_k} \right\|^2 \quad (2)$$

In fact, (2) is a linear regression problem. Therefore, the relation extraction problem is interpreted as a prediction problem. Once the combination coefficients are computed, the hidden interest similarity between any user pair can be predicted.

In real applications, when performing recommendation, the systems do not need to specify the relationships between any pair of users, which means the vector $\mathbf{X}$ need not to be $N(N-1)/2$ dimensional. We assume that $\mathbf{X}$ is m-dimentional in the following. In order to obtain the solution to the problem, let us first consider the simplest case:

$$\sum_{k=1}^{K} a_k \boldsymbol{X_k} = \widehat{\boldsymbol{X}} \qquad (3)$$

And define $\boldsymbol{Y}$ as:

$$\boldsymbol{Y} = [\boldsymbol{X_1}, \boldsymbol{X_2}, \cdots, \boldsymbol{X_K}]$$

Hence, (3) can be rewritten as follows:

$$\boldsymbol{Y}a = \widehat{\boldsymbol{X}} \qquad (4)$$

Supposed the rank of $\boldsymbol{Y}$ is $min(m, K)$, we have following facts:

- When $m < K$, there are many solutions to (4);
- When $m = K$, there is a unique solution to (4);
- When $m > K$, there is no solution to (4).

In the first two cases, a solution with perfect match (The minimization error is zero) could be easily calculated. However, in some circumstances, m can be larger than K. In these cases, the optimal solution to (4) is obtained when the derivative of this objective function with respect to $\boldsymbol{a}$ is zero, i.e.

$$\frac{\partial \left\| \widehat{\boldsymbol{X}} - \sum_k^K a_k \boldsymbol{X_k} \right\|^2}{\partial a_k} = 0, k = 1,2, \cdots, K$$

By some algebraic steps, we have:

$$\boldsymbol{Y^T Y a} = \boldsymbol{Y^T} \widehat{\boldsymbol{X}}$$

Since the matrix $\boldsymbol{Y}$ has full rank as postulated, i.e. $\text{rank}(\boldsymbol{Y}) = min(m, K)$, the matrix $\boldsymbol{Y^T Y}$ is invertible and the optimal solution to (4) is $\boldsymbol{a^{opt}} = (\boldsymbol{Y^T Y})^{-1} \boldsymbol{Y^T} \widehat{\boldsymbol{X}}$.

When the matrix $\boldsymbol{Y}$ is rank deficiency, i.e. $rank(\boldsymbol{Y}) < min(m, K)$, there will be multiple solutions with the same minimization value. In such case, the $\boldsymbol{a}$ with minimum norm can be chose as our solution.

The objective function, (2), models the relation extraction problem as an unconstrained linear regression problem. One of the advantages of unconstrained linear regression is that, it has a close form solution which is easy to compute. However, large quantities of researches on linear regression problems show that in many cases, such unconstrained least squares solution might not be a satisfactory solution for reasons like low prediction accuracy and difficulty of interpreting results.

Hence, we apply Principal Component Analysis to solve these problems. Principal Component Analysis is a technique used for dimensionality reductions, it produces a small number of linear variable combinations $\boldsymbol{Z_p}$ ($p = 1, \cdots, P, P > 2$) of the original variables $\boldsymbol{X_k}$, and the $\boldsymbol{Z_p}$ are then used in place of the $\boldsymbol{X_k}$ as inputs in the regression. $\boldsymbol{Z_p}$ is also called principal components, P donates the number of principal components, and it is less than or equal to the number of original variables, i.e. $\text{P} \leq K$.

In order to construct $\mathbf{Z_p}$, singular value decomposition (SVD) is applied to the input matrix $\boldsymbol{Y}$:

$$\boldsymbol{Y} = UDV^T \qquad (5)$$

U and V are $1 \times \text{K}$ and $\text{K} \times \text{K}$ orthogonal matrices, D is $\text{K} \times \text{K}$ diagonal matrix. The covariance matrix of original input matrix X is given by $S = \boldsymbol{Y^T Y}$, and from (5) we have:

$$S = VD^2V^T \qquad (6)$$

Equation (6) is the eigen decomposition of S, the eigenvectors $\boldsymbol{v_j}$ (columns of V) are also called the principal components directions of $\mathbf{Y}$, they meet: the principal component direction $\boldsymbol{v_j}$ has the property that $\boldsymbol{Z_p} = \boldsymbol{Y v_j}$ has the corresponding sample variance. Thus the intrinsic characteristic of original dataset can be maintain by selecting P principal component $\boldsymbol{Z_p}$ with biggest sample variance. And then regress $\widehat{\boldsymbol{X}}$ on $\boldsymbol{Z_1}, \cdots, \boldsymbol{Z_p}$ in place of $\boldsymbol{X_1}, \cdots, \boldsymbol{X_K}$:

$$\boldsymbol{a^{pcr}} = \arg\min_a \left\| \widehat{\boldsymbol{X}} - \sum_{p=1}^{P} \theta_p \boldsymbol{Z_p} \right\|^2$$

Here $\theta_P = \langle \boldsymbol{Z_p}, \widehat{\boldsymbol{X}} \rangle / \langle \boldsymbol{Z_p}, \boldsymbol{Z_p} \rangle$, since the $\mathbf{Z_p}$ are each linear combinations of the original $\boldsymbol{X_k}$, the solution can be expressed in terms of coefficients of the $\boldsymbol{X_k}$:

$$\boldsymbol{a^{pcr}} = \sum_{p=1}^{P} \theta_p \boldsymbol{v_p}$$

III. Recommendation Algorithm Based on Multi-relational Social Network

By employing regression analysis, an optimal relation network can be conducted from multi-relational social network. Weights on the edges in the optimal relation network reflects the relation strength between users; in other words, elements $\widehat{M}_{x,y}$ in the Matrix $\widehat{M}$ represent the interest similarity between user u_x and u_y. When recommending an item to u_x, the recommendation system can decide whose rating data should be considered by finding top Q users with largest interest value through $\widehat{M}$.

Reference [5] claims ratings expressed by strongly trusted users on similar items are more reliable than ratings expressed by weakly trusted users on the extract item. Similarly, ratings expressed by users who share highly similar interest on similar items are more reliable than ratings expressed by users who share hardly similar interest on the exact item. This motivates us to combine the multi-relational social network and item-base collaborative filtering (CF) approach. To compute the similarity of item i and j, we use the Pearson Correlation of ratings expressed for both items, similar to compute the correlation of two users:

$$\text{corr}(i,j) = \frac{\sum_{u_x \in UC_{i,j}} (r_{u_x,i} - \bar{r}_{u_x})(r_{u_x,j} - \bar{r}_{u_x})}{\sqrt{\sum_{u_x \in UC_{i,j}} (r_{u_x,i} - \bar{r}_{u_x})^2} \sqrt{\sum_{u_x \in UC_{i,j}} (r_{u_x,j} - \bar{r}_{u_x})^2}}$$

Here, $UC_{i,j}$ is the set of common users who have rated both item i and j, and $\text{corr}(i,j)$ donates the correlation of item i and j. Similar to construct optimal relation network, we only consider items with positive correlation and take the size of the set of common users into consideration, $\text{sim}(i,j)$ can be defined as:

$$\text{sim}(i,j) = \frac{1}{1 + e^{-\frac{|UC_{i,j}|}{2}}} \times \text{corr}(i, \text{j})$$

We propose a Recommendation Algorithm based on Multi-relational Social Network (RAMSN) in Algotithm.1.

Algotithm.1： Recommendation Algorithm based on Multi-relational Social Network

Input:
1. $\widehat{M}$: Weighted matrix associated with optimal relation network;
2. Q: Number of users to be found;
3. u_x: Target user;
4. $\tilde{\iota}$: Recommended item;

OutPut:
1. $\overline{r_{u_x,\tilde{\iota}}}$: Prediction of $r_{u_x,i}$

Algotithm:

```
Find Q users who have largest interest similarity M_{x,y}(y ≤ Q) with u_x in M̂
for y→ 1 to Q do
  if u_y has rated ĩ
    r_{temp,y} ← r_{u_y,ĩ}
    S_y ← 1
  Else
    for each item i rated by user u_y do
      compute sim(ĩ, i), select the one which has largest value
      S_y ← sim_max(ĩ, i)
      r_{temp,y} ← r_{u_y,i}
    end for
  end if
end for
```

$$\overline{r_{u_x,\tilde{\iota}}} \leftarrow \frac{\sum_{y=1}^{Q} r_{temp,y} \cdot M_{x,y} \cdot S_y}{\sum_{y=1}^{Q} M_{x,y} \cdot S_y}$$

IV. EXPERIMENT

A. Dataset

We use the version of the Epinions' dataset by the authors of [8]. Note that it is not a typical collaborative dataset, since the ratings are about the reviews associated with items instead of about the items, which contains 132000 users, 1560144 reviews and 13668319 ratings. Besides, this dataset include not only the trust statement with positive values but also the ones with negative values, which means users are distrusted by the user who makes the statement.

First, we construct the multi-relational social network based on Epinions; and then apply the proposed method to extract the optimal relation network; finally compare the results by using RAMSN and other state of art methods for social recommendation.

The method used to analyze multi-relational social network requires of storing weight matrix associated with different relation networks in memory. Suppose we have constructed 3 different relation networks that contain 100000 users respectively, and assume each cell of the weight matrix occupies just one byte, then each weighted matrix would occupy almost 9.3 GB, and need almost 38GB to store all matrices, which is not feasible. This issue motivates performing our method on a smaller extracted dataset. We pick 5643 users and related data to form a smaller dataset. It Contains 248639 reviews and 433084 ratings on reviews. Table 1 shows comparison between original social network and the smaller social network formed by the extracted dataset on some structure characteristic metric.

TABLE I. COMPARISON BETWEEN ORIGINAL SOCIAL NETWORK AND THE SMALLER EXTRACTED SOCIAL NETWORK

Metric	Original Social Network	Smaller Extracted Social Network
Average Weighted Degree	4.506	4.168
Average Clustering Coefficient	0.092	0.11
Average Path Length	7.934	6.144

Table 1 shows that, the smaller extracted social network nearly maintains its original intrinsic structure characteristic. Besides, the average rating value of original dataset is 4.67 and the average rating value of extracted dataset is 4.59. Therefore, we firmly believe that results on the extracted dataset are reliable.

B. Multi-relational Social Network Based on Epinions

In Epinions, if users share friends or interested items, perform similar rating behavior or interact with each other frequently, we believe there exists some kind of hidden relationship between them. Thus, we construct the relation network based on writing reviews on items in common, sharing friends, rating reviews in common and interaction frequency. Meanwhile, in order to depict the relationship strength between users, we adopt Jaccard coefficient to define the weight on the edges in relation networks.

- Relation network based on writing reviews on items in common

Let $G_1\langle U, E_1\rangle$ donates this relation network, M_1 is the weighted matrix associated with G_1, if user u_x and u_y write reviews on items in common, $M_{1,x,y}$ can be defined as:

$$M_{1,x,y} = \frac{\left|WI_{u_x} \cap WI_{u_y}\right|}{\left|WI_{u_x} \cup WI_{u_y}\right|}$$

Here WI_{u_x} and WI_{u_y} donate the set of items received reviews from user u_x and u_y.

- Relation network based on sharing friends

Let $G_2\langle U, E_2\rangle$ donates this relation network, M_2 is the weighted matrix associated with G_2, if user u_x and u_y trust or distrust friends in common, $M_{2,x,y}$ can be defined as:

$$M_{2,x,y} = \frac{\left|TU_{u_x} \cap TU_{u_y}\right| + \left|\widehat{TU_{u_x}} \cap \widehat{TU_{u_y}}\right|}{\left|TU_{u_x} \cup TU_{u_y}\right| + \left|\widehat{TU_{u_x}} \cup \widehat{TU_{u_y}}\right|}$$

Here TU_{u_x} and TU_{u_y} donate the set of friends trusted by u_x and u_y, while $\widehat{TU_{u_x}}$ and $\widehat{TU_{u_y}}$ donate the set of friends distrusted by user u_x and u_y.

- Relation network based on rating reviews in common

Let $G_3\langle U, E_3\rangle$ donates this relation network, M_3 is the weighted matrix associated with G_3, if user u_x and u_y rate reviews in common, $M_{3,x,y}$ can be defined as:

$$M_{3,x,y} = \frac{|RR_{u_x} \cap RR_{u_y}|}{|RR_{u_x} \cup RR_{u_y}|}$$

Here RR_{u_x} and RR_{u_y} donate the set of reviews rated by user u_x and u_y.

- Relation network based on interaction frequency

Let $G_4\langle U, E_4\rangle$ donates this relation network, M_4 is the weighted matrix associated with G_4, if user u_x or u_y rate reviews written by each other, $M_{4,x,y}$ can be defined as:

$$M_{4,x,y} = \frac{|WI_{u_x} \cap RR_{u_y}| + |WI_{u_y} \cap RR_{u_x}|}{|WI_{u_x} \cup WI_{u_y}|}$$

C. Experiment Design and Evaluation Metric

We implement various versions of RAMSN and other methods for recommendation. Their labels and described as follows:

TABLE II. LABELS AND DESCRIPTIONS OF RECOMMENDATION METHODS

Labels	Description
UB - CF	User-based CF with Pearson correlation as similarity metric
IB - CF	Item-based CF with Pearson correlation as similarity metric
MoleTrust	Typical method based on uni-relational social network used in [3], with the maximum-depth 4
TrustWalker	Typical method based on uni-relational social network and CF used in [4]
RAMSN – G1/G2/G3/G4	Apply RAMSN in the G1, G2, G3 and G4 resprectively, with $Q = 6$
RAMSN - Equal	Treat G1, G2, G3 and G4 as equal, aggregate them with no difference and apply RAMSN in this network combination, with $Q = 6$
RAMSN - PCA	Apply RAMSN in the extracted optimal network conducted from applying Principal Component Analysis, with $Q = 6$

Noting that, people usually interact frequently with a few friends in social network, which indicates 4 to 6 [9], hence we choose $Q = 6$ when applying RAMSN.

Besides, the extracted dataset contains 353 users (6.3%) who expressed less than 5 ratings, who can be regarded as cold-start users. It is very important to consider the performance of the recommendation for cold-start users. We will present the results of our experiments, first for cold-start users and then for all users.

Typically, the Leave-one-out method is used to evaluate recommendation systems; it requires withholding a rating and trying to predict it by using the relation network and the remaining ratings.

Root Mean Square Error (RMSE) is a metric frequently used to measure the error in recommendation:

$$RMSE = \sqrt{\frac{\sum_{(u_x,i)|R_{u_x,i}} (r_{u_x,i} - \overline{r_{u_x,i}})^2}{|(u_x,i)|R_{u_x,i}|}}$$

In the above equation, $R_{u_x,i}$ is a Boolean showing whether u_x has a rating on i in our dataset, $r_{u_x,i}$ and $\overline{r_{u_x,i}}$ denote the actual and predicted rating respectively. The smaller the value of RMSE is, the more precise a recommendation is. Besides, the percentage of pairs of <user, item> which we can predict a rating (Coverage) is also an important metric to measure the performance of recommendation systems.

According to [4], we combine RMSE and Coverage into a single evaluation metric by computing FMeasure. For this purpose, we have to convert RMSE into a precision metric in the range $[0,1]$. So precision can be defined as follows:

$$Precision = 1 - \frac{RMSE}{4}$$

In this equation, 4 is the maximum possible error since the values of ratings are in the range $[1,5]$. So FMeasure can be defined as follows:

$$FMeasure = \frac{2 \times Precision \times Coverage}{Precision + Coverage}$$

D. Experimental Results

For the recommendation tasks in Epinions, we randomly select 100 users in the dataset, and compute the interest similarity between every pair of them so as to construct the optimal relation network. By applying Principal Component Analysis, we have the combination coefficient as follows:

TABLE III. COMBINATION COEFFICIENT OF RELATION NETWORKS

Relation Networks	G1	G2	G3	G4
a_k	0.00537	0.01464	0.07110	0.05142

- Comparison of evaluation between RAMSN and other methods.

Table 4 shows the RMSE, Coverage and FMeasure for all comparison partners on cold-start users and all users.

Table 4 shows us that, for cold-start users, RAMSN – PCA has higher error than all the other methods in measuring error of recommendation. However, RAMSN – PCA outperforms all the other methods in Coverage, it predicts more 12% <user, item> pairs than TrustWalker. According to the combination of Precision and Coverage, RAMSN – PCA obviously has better performance than all the other methods. Especially, compared with the MoleTrust and TrustWalker, methods based on uni-relational social network, RAMSN – PCA' FMeasure is 0.0664 more than that of TrustWalker and 0.3031 more than that of MoleTrust.

TABLE IV. COMPARISON OF EVALUATION BETWEEN RAMSN AND OTHER METHODS

	Cold-start users			All users		
Metric	RMSE	Coverage	FMeasure	RMSE	Coverage	FMeasure

UB - CF	0.7115	14.94%	0.2528	***0.4956***	34.06%	0.4906
IB - CF	***0.6735***	7.23%	0.1331	0.5064	27.18%	0.4146
MoleTrust	0.9561	31.74%	0.4479	0.7428	41.52%	0.55
TrustWalker	0.9843	40.26%	0.5249	0.8309	78.13%	0.7867
RAMSN - PCA	1.2179	***50.29%***	***0.5837***	0.768	***90.35%***	***0.8531***

By analyzing the results for all users, we can make similar conclusion. RAMSN – PCA' error is only lower than that of TrustWalker, but still achieves highest Coverage. In terms of FMeasure, RAMSN – PCA gives best performance.

The above experimental results show that, compared with traditional recommendation methods based on uni-relational social network; recommendation methods based on multi-relational social network give better depiction of users' need and improve the performance of recommendation systems.

- Comparison of evaluation between RAMSN based on uni-relational social network and RAMSN based on multi-relational social network.

Table 5 shows the results of RAMSN – PCA, RAMSN – G1, RAMSN – G2, RAMSN – G3 and RAMSN – G4 according to each of the three evaluation measures for cold-start users and all users.

TABLE V. COMPARISON OF EVALUATION BETWEEN RAMSN – PCA, RAMSN – G1, RAMSN – G2, RAMSN – G3 AND RAMSN – G4

	Cold-start users			All users		
Metric	**RMSE**	**Coverage**	**FMeasure**	**RMSE**	**Coverage**	**FMeasure**
UB - CF	1.2953	25.90%	0.3746	0.8478	54.36%	0.6434
IB - CF	***1.089***	24.50%	0.3666	***0.7038***	59.61%	0.6918
MoleTrust	1.2966	***63.24%***	***0.6534***	0.7571	***96.42%***	***0.8808***
TrustWalker	1.2715	31.51%	0.431	0.775	83.76%	0.8216
RAMSN - PCA	1.2179	50.29%	0.5837	0.768	90.35%	0.8531

In both cases, RAMSN – PCA has higher FMeasure than all the other methods, except RAMSN – G3. It is reasonable that RAMSN – G3 gives better performance than RAMSN – PCA since relation network G3 is constructed based on rating reviews in common. By utilizing G3, users with valuable ratings could be easily decided; in other words, RAMSN – G3 can achieve high Coverage than other relation networks. In fact, RAMSN – G3 has the highest Coverage 96.42% (for all users) and 63.24% (for Cold-start users), which are nearly 6% and 13% higher than that of RAMSN – PCA. But RAMSN – G3 and RAMSN – PCA have similar error for both all users and Cold-start users. Hence we can still conclude that utilization of more information from multi-relational social network will assist recommendation systems.

- Necessity of identifying the importance of different relation networks**.**

Table 6 shows the FMeasure together with RMSE and Coverage for RAMSN – PCA and RAMSN – Equal for cold-start users and all users.

TABLE VI. COMPARISON OF EVALUATION BETWEEN RAMSN – PCA AND RAMSN – EQUAL

	Cold-start users			All users		
Metric	**RMSE**	**Coverage**	**FMeasure**	**RMSE**	**Coverage**	**FMeasure**
RAMSN - Equal	***1.1316***	37.22%	0.4901	0.8478	***0.7471***	81.02%
RAMSN - PCA	1.2179	***50.29%***	***0.5837***	***0.7038***	0.7680	***90.35%***

From the above tables, we obverse that for both Cold-start users and all users, RAMSN – PCA is a little higher than RAMSN – Equal in terms of RMSE, but RAMSN – PCA obviously achieves much higher Coverage. For Cold-start users RAMSN – PCA is nearly 13% higher than that of RAMSN – Equal while for all users is nearly 10%. Hence, RAMSN – PCA outperforms RAMSN – Equal in terms of FMeasure, especially for Cold-start users, RAMSN – PCA is nearly 0.1 more than that of RAMSN – Equal. It proves that optimal relation network analysis is necessary in improving performance of recommendation systems.

- Selection of Q in RAMSN**.**

We also conducted research on the selection of Q in RAMSN. Table 10 shows the results of RAMSN – PCA with different values of Q according to each of the three evaluation measures for all users and Figure 2 depicts the trends of these metrics. Similar results are obtained for Cold-start users.

TABLE VII. RESULTS OF RAMSN – PCA WITH DIFFERENT VALUES OF Q FOR ALL USERS

	RMSE	**Coverage**	**FMeasure**
Q =3	0.7658	81.78%	0.8131
Q =4	0.7744	85.84%	0.8316
Q =5	0.7771	88.52%	0.8436
Q =6	0.7680	90.35%	0.8531
Q =7	0.7650	91.36%	0.8580
Q =8	0.7563	92.33%	0.8635
Q =9	0.7505	93.07%	0.8675
Q =10	0.7479	93.60%	0.8702

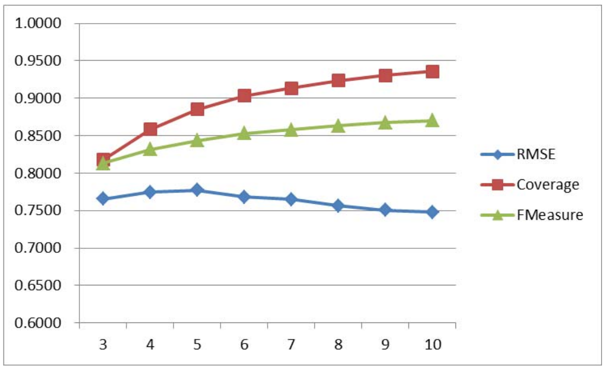

Figure 2. Trends of metrics of RAMSN – PCA with different values of Q

Figure 2 shows that when $Q > 6$, RAMSN – PCA only achieves little improvement in field of RMSE, Coverage and FMeasure in comparison with that of RAMSN – PCA with $Q = 6$, which proves that it is reasonable to choose $Q = 6$.

V. Conclusion

Considering that the state of art methods of social recommendation often only take one kind of social relation into consideration, we propose a recommendation algorithm based on multi-relational analysis. By applying regression analysis to identify the importance of different network relations, we can combine theses networks to obtain an optimal relation network, and employ the recommendation algorithm based on multi-relational social network RAMSN to perform recommendation. Since it takes more advantages of information from multi-relational social network, our method can discover the hidden relationship strength between users and assist in finding useful ratings to compute a prediction, thus achieving better performance.

Acknowledgement

The work was supported in part by the Fundamental Research Funds for the National Natural Science of China (Grant No. 61272065, No.60736020, No.60970044, No.61272067,), the Fundamental Research Funds for the Central Universities, SCUT (Grant No. 2012ZZ0088), the Science and Technology Planning Project of Guangdong Province, China (Grant No. 2011A091000036), China State Key Lab of Software Engineering (Grant No. SKLSE2010-08-22), Guangdong-HK Research Fund (Grant No. 20100101-5), Guangdong-Science Academy Cooperation Research Fund (Grant No. 2011A090100003), Zhujiang Science Star (Grant No. 2011J2200089).

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