An Adaptive Social Influence Propagation Model Based on Local Network Topology

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Abstract. With the wide application of all kinds of social network services, social recommendation has attracted many attentions from academia and industry. Different from traditional recommender systems, social influence plays a significant role in social recommendation. However, many existing approaches cannot effectively simulate the influence propagation and the computation of social influence is complex. This leads to the low prediction accuracy. Hence, this paper proposes an adaptive social influence propagation model to address this problem. Moreover, we present a simple and fast social influence computation method according to the local network topology, which can provide distinguishing influences for one user depending on its neighbors. To demonstrate the performance, we design the shortest path with maximum propagation strategy and experiments are conducted to compare our model with other social influence propagation approaches on the real data set. Empirical results show that both the quality of prediction and coverage have remarkable improvement, especially with few ratings.

Keywords: Social Influence, Propagation Model, Local Network Topology, Social Recommendation.

1 Introduction

With the development of the Internet, the Internet of Things and the extensive application of all kinds of intelligent terminals, common people can generate, share and propagate any contents at any time and any place. People can also express their thoughts or ideas freely. The collective wisdom has been widely demonstrated and utilization, such as Wikipedia[1]. However, there are huge amount of contents on the Web, which make more difficult for users to obtain their required information. Traditional search engine fails to meet requirements on convenience and efficiency, especially when users do not know how to describe their demands by only a few search terms. In this case, the recommender system (RS)[2] has been presented and applied widely[3][4].

However, the traditional recommendation approaches have faced many challenges, such as data sparsity, cold start, scalability and so on. In recent years, all kinds of social network services have been widely applied in many domains[5],

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such as Facebook, Twitter, LinkedIn, Instagram, Flickr etc. Social network can provide more information about users, especially social relationships. Researchers have demonstrated that the network can propagate many things, for instance, information, disease, emotion and even fat. At the same time, the decisions of user are also affected by their social relationships. Hence, social recommendation emerges and it is the use of social relationships as well as the contents on the social network to mine user's interest, preferences, and thus to recommend appropriate objects for the user.

Social influence and its propagation is very important to the performance of social recommendation. While the existing social influence propagation models and the computations of social influence generate low prediction accuracy. Hence, this paper focuses on social influence propagation on social network. We research and analyze the existing social influence propagation models and the computational methods of social influence. Then, we propose an adaptive social influence propagation model, in which the computation of social influence of one node is based on its local network topology.

The contributions of the paper are as follows:

1) We propose an adaptive social influence propagation model. In our model, social relationships and social influence will be propagated through the network. Especially, social influence is dynamic with the change of network topology.

2) We design a simple and fast method to compute social influence of user. It relies on the network topology related to each user. It assigns different social influence measures depending on the user's neighbor in bounded computational time.

3) We adopt the shortest path with maximum social influence propagation strategy and compare our model with other two social influence propagation approaches on the real data set. The experimental results demonstrate that the proposed model can improve the prediction accuracy effectively.

The rest of this paper is organized as follows. In section 2, related research work is introduced. The proposed social influence propagation model and the computation of social influence is formulated in section 3 and empirical results are reported in section 4. Finally, we provide some final remarks and a conclusion in section 5.

2 Related Work

Since the abundant and huge amount of social network data can provide more information about users and alleviate many problems with which the traditional recommender systems encounter, such as cold start, data sparsity and so on. Social recommendation has been presented and applied widely. Sigrubjörnsson *et al.*[6] proposed a tag recommendation method based on the collective knowledge. The tags described the contents of the photo and provided additional contextual and semantical information. The paper firstly analyzed the tag characteristic, that is, how users tag photos and what kind of tags the users provide. Then, they presented four different tag recommendation strategies to help users annotate photos. Tan *et al.*[7] built a hypergraph model for music recommendation by using the rich social media information (such as user, music, tag, relation etc.). The model includes more sophisticated relations than pairwise relation. They proposed a novel music recommendation algorithm which used both multiple kinds of social media information and music acoustic-based content.

Social relationships are the most important information in social network. The behavior of user is influenced by its social relationships and the influence is not only from the direct friends, but also from indirect friends. Christakis and Fowler[8] indicates that the behavior, interest and decision of the user is influenced by users who are in your three degree distance. The influence becomes very small, when the distance is more than three. The innovation, disease, idea, trust, social influence and even fat can be propagated along with the social relationships. Yang *et al.*[9] researched the interest propagation in social networks. They presented a friendship-interest propagation model which was used to predict friendship. Trust propagation has also used in social recommendation. Massa and Avesani[10] proposed a trust-aware recommender system. They proposed to replace the finding similar user with the use of a trust metric, which can propagate trust over the trust network. This system can alleviate the sparsity of the rating matrix. In social network, not only the trust can be propagated, but also the distrust. Guha *et al.* [11] developed a framework of trust and distrust propagation schemes. In this framework, it was first to incorporate distrust in the computational trust propagation setting.

Many propagation models have also been proposed. The Linear Threshold Model and Independent Cascade Model[12] are two most widely used propagation models. The former assumes that each node has a threshold. The node becomes the active state (i.e. it is influenced) when the sum of influence of its neighbors exceeds this threshold. While, the latter assumes that each neighbor of one node has some probability to activate the node. Moreover, epidemic model[13] and probabilistic generative model[14] are also proposed. In social influence propagation model, the key is to compute the social influence. Social influence is a measure which denotes the degree of affecting the behavior of others. Generally, influence metrics may basically be subdivided into global and local. The global influence is based upon complete social network information. PageRank[15] is a global influence metric. However, it is too time consuming and the influence of one node is equal to its neighbors. While, local influence is able to operate on partial social network information. Sun *et al.*[16] presented a fixed decay factor method to transfer the similarity in network. They assume that the influence is proportional to the distance. The greater the distance is, the smaller the influence is. Massa and Avesani[17] presented a linear distance propagation method. They evaluate every user's trust based on its minimum distance from the source user. If the user is not reachable within the maximum propagation distance, it has not predicted trust value.

3 Proposed Social Influence Propagation Model

3.1 Motivations

All kinds of social relationships, such as friendship, colleagues, schoolmate etc., can influence user's behavior, decision, thought. For example, if your friends recommend a movie to you, you probably will watch it on Sunday. However, users do not usually follow each recommendation provided by their friends. That is, different friends may generate different trusts and influences to you.

However, many existing influence propagation models and computation methods cannot obey the principle. Sun *et al.*[16] assumes that the influence decreases as a fixed decay factor with the increase of propagation distance. In [17], the author defines a linear function, the influence decreases linearly with the increase of propagation distance. In both methods, the direct neighbors of node have not influence decay, that is, each direct neighbors will generate same influence. This is not reasonable obviously.

The motivations of this paper are as follows:

1) Influence does not only from our direct friends. In practice, our behaviors will be influenced not only from our direct friends, but also from the indirect friends. However, not all other users on social network can influence our behaviors. According to [8], our behaviors will be influenced from the users who are within our three degree distance. The influence is very small if the distance is more than three.

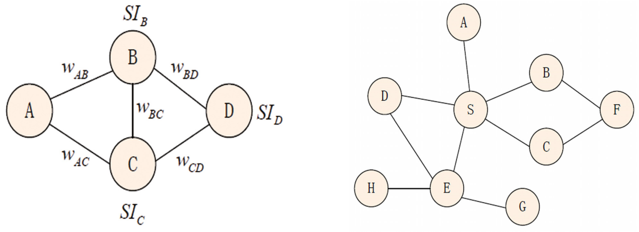
2) Your social influence is dynamic with your friends. In fact, every person has many friends, however, your social influence is not equal to all your friends. Your influence is larger to your good friends than to the common friends.

3) The local network topology of the node can affect its size of social influence. That is, the social influence is local, which is related to its local friends, is not very relevant to other nodes of the network.

3.2 Adaptive Social Influence Propagation Model

A social network can be denoted as $G = (V, E, W)$. V is the user set. E represents the social relationships, such as $(u, v) \in E, u, v \in V$. W is the weight matrix between each pair of users. For example, it is the similarity matrix if G is a user similarity network. If G is undirected network, the matrix is symmetric and each element $w \in W$ is set 1. In directed network, W is a non-symmetric matrix, that is, $w = (u, v) \neq w' = (v, u)$.

In this section, we present an adaptive social influence propagation model. Fig. 1(a) shows the illustration of the model. w denotes the weight between two nodes and SI represents the social influence (SI) of the node. In our propagation model, different neighbors of one node have different social influences, which is determined by its local network topology (it will be introduced in section 3.3). Assume that $P_{u,v}$ represents the path set between node u and v. $P_{u,v}^k \in P_{u,v}$ denotes the k path and $P_{u,v}^k = \{(v_1, v_2), ..., (v_{n-1}, v_n)\}$. The formalization of the proposed social influence propagation model is as follows:



(a) Illustration of the presented social influence propagation model

(b) An example of computation of social influence based on local network topology.

Fig. 1. The illustration of the proposed social influence propagation model and the computation of the social influence

$$SI_{u,v} = \prod_{(v_i,v_j)\in P_{u,v}^k} \left(w_{v_iv_j} \cdot SI_i\right) \tag{1}$$

Where, $SI_{u,v}$ represents the influence of node u to node v. Take the $SI_{D,A}$ for example, one of the path between node D and node A is $P_{D,A}^1 = \{(v_D, v_B), (v_B, v_A)\}$. The influence of node D to node A is $SI_{D,A} = (w_{DB} \cdot SI_D) \cdot (w_{BA} \cdot SI_B)$.

In fact, there are many paths between two nodes. Hence, we should aggregate all path to obtain the final social influence from one node to another. In [18], the author intruduces two aggregation methods. One of the methods considers only the best propagation path between two nodes, i.e., the path where the influence propagation is maximum. Another considers all possible paths between two nodes and the social influence is computed by weighted all paths. Golbeck *et al.*[19] introduces the maximum and minimum length path strategies. These path length functions can return the full chains of weighted edges which make up the maximum and minimum length paths.

In this paper, we design the shortest path with maximum propagation methods(SPMPM) by aggregating the previous two methods. We first find all the shortest path between two nodes. Then, the social influence propagation of each path will be computed. The maximum propagation path is selected as the final result. Assume $SP_{u,v}$ represents the shortest path set between node u and v. The formalization is defined as follows:

$$SI_{u,v} = \max\left\{\prod_{(v_i,v_j)\in SP_{u,v}^k} \left(w_{v_iv_j} \cdot SI_i\right), k = 1, 2, ..., m\right\} \tag{2}$$

Where, m denotes the number of the shortest path between node u and v. $SP_{u,v}^k$ is the k shortest path.

Take the influence of $SI_{D,A}$ for example in Fig. 1(a), there are two shortest paths between node D and A. That is $SP_{D,A}^1 = \{(v_D, v_B), (v_B, v_A)\}$ and

$SP^2_{D,A} = \{(v_D, v_C), (v_C, v_A)\}$. $SI^1_{D,A} = (w_{DB} \cdot SI_D) \cdot (w_{BA} \cdot SI_B)$, $SI^2_{D,A} = (w_{DC} \cdot SI_D) \cdot (w_{CA} \cdot SI_C)$. The maximum propagation value between $SI^1{}_{D,A}$ and $SI^2{}_{D,A}$ will be selected as the final social influence between node D and A.

3.3 Computation of Node Social Influence

Social influence is an intuitive concept. It refers to the behavioral change of individuals affected by others in the social network. The strength of social influence depends on many factors, such as node attribution, the strength of relationships between users, the distance between users, temporal effects and so on. It is difficult to measure the social influence, but the social influence has been accepted in social network.

Granovetter[20] states that the more common neighbors a pair of nodes may have, the stronger the tie between them, further, the stronger the mutual influence will be. The disadvantage is that it cannot compute the social influence if they don't have any common neighbors. However, any pair of nodes has some influence so long as they are connected. Node centrality[21] can measure the importance of one node in social network and it can also be used to represent the social influence of one node, such as degree centrality, closeness centrality, betweenness centrality, Katz centrality. However, the computation of node centrality need the global network topology and it is time consuming.

In this section, we introduce a simple and fast method to compute the social influence based on the local network topology of the node which is called local node centrality (LNC) method. The social influence of one node to another is related to the local information, and is irrespective with other nodes. The formalization can be defined as follows:

$$SI_{v_k,u} = \frac{degree\left(v_k\right)}{\max\left\{degree\left(v_i\right), i = 1, ..., n\right\}} \tag{3}$$

Where, $SI_{v_k,u}$ is the social influence of node v_k to node u. $degree\left(v_i\right)$ represents the node degree of v_i. n is the number of neighbors of the node u. The formula indicates that the social influence $SI_{v_k,u}$ is only related to the neighbors of the node u. This method doesn't need the global information of network.

Fig. 1(b) gives an example of the computation of social influence based on the local network topology. The node S has five neighbors. The maximum degree of the neighbor is the neighbor $E(degree(E) = 4)$. Hence, the social influence of each neighbor is:

$SI_{A,S} = degree(A)/degree(E) = 1/4 = 0.25$
$SI_{E,S} = degree(E)/degree(E) = 1/1 = 1$
$SI_{B,S} = SI_{C,S} = SI_{D,S} = degree(B)/degree(E) = 2/4 = 0.5$

There are three advantages of this methods. First, it can generate different social influences for each neighbor of one user when their degrees are different. In practice, your friends will impact you in varying degree. Second, for the same node, its social influence is varying depending on its neighbors. This reflect the adaptiveness of our model. Third, it does't need the global network information, hence its computation is simple and fast.

4 Experiments and Analysis

4.1 Data Set

In our experiments, we adopt the most widely used Epinions (http://www.epinions.com/) data set. It is collected from epinions.com. Epinions founded in 1999 is a product and shop review site where users can review items (such as movies, books, software, etc.) And users can also assign items numeric ratings in the range 1 to 5. Moreover, users can express their trust to other users, i.e. reviewers whose reviews and ratings are helpful and valuable to me.

The Epinions data set consists of 49289 users who have rated a total of 139738 different items at least once. There are 40163 users who have rated at least one item. The total number of reviews is 664824. The sparseness of the data set is hence more than 99.99%. The total number of trust statements is 486985. The number of users who have rated items less than 5 is more than 52.8%. For example, the number of users who have rated three and four items is 2917 and 2317 respectively.

4.2 Evaluation Measures

The MAE (Mean Absolute Error)[22] and RMSE (Rooted Mean Squared Error) [23] are the two most widely used metrics to measure the performance of algorithm.

However, MAE and RMSE are not always informative about the quality of an recommender systems[17]. Usually, in the computations of MAE and RMSE, for the users who have rated many items (called heavy rater), the results will have small errors; for the users who have rated little (called cold user), the results will have big errors. But, since heavy raters provide many ratings, these small errors will be counted many times, while the few big errors made for cold users count few times. For this reason, we need adopt other two measures: Mean Absolute User Error (MAUE) and Rooted Mean Squared User Error (RMSUE). Take the MAUE for example, we first compute the mean error for each user and then these user errors are averaged over all the users. In this case, every user is taken into account only once and the cold users are influenced as much as the heavy raters. The MAUE and RMSUE can be defined as follows:

$$\begin{aligned} \mathrm{MAUE} &= \tfrac{1}{N_T} \sum_{k=1}^{N_T} \mathrm{MAE}(u_k)' \\ \mathrm{MAE}(u_k)' &= \tfrac{1}{R_N(u_k)} \sum_{i=1}^{R_N(u_k)} \left| r_i - r_i' \right| \end{aligned} \tag{4}$$

$$\begin{aligned} \mathrm{RMSUE} &= \tfrac{1}{N_T} \sum_{k=1}^{N_T} \mathrm{RMSE}(u_k)' \\ \mathrm{RMSE}(u_k)' &= \tfrac{1}{R_N(u_k)} \sum_{i=1}^{R_N(u_k)} \left(r_i - r_i' \right)^2 \end{aligned} \tag{5}$$

Where, N_T is the testing user number. MAE$(u_k)'$ and RMSE$(u_k)'$ denotes the mean absolute error and rooted mean squared error of user u_k respectively. $R_N(u_k)$ represents the number of ratings by user u_k. r_i is the real rating of item i and $r_i{}'$ is the predicted value.

In practice, it is often the case that the recommender systems can give a good performance in predicting all the ratings for a user who gave many ratings and provide a worse predicting to a user who has rated few items. Hence, except the MAUE and RMSUE, we should measure how many users can be predicted(*user coverage*) and how many ratings are able to be predicted among all the ratings (*item coverage*). The *user coverage* can be defined as the portion of users for which the system is able to predict at least one rating. The *item coverage* is defined as the portion of items for which the system can predict. The formalization of the user coverage (UC) and the item coverage (IC) can be defined as follows:

$$UC = \frac{N_T{}'}{N_T}, IC = \frac{R_N{}'}{R_N} \tag{6}$$

Where, $N_T{}'$ denotes the number of users who can be predicted at least one rating by the system. $R_N{}'$ represents the number of items which can be predicted.

4.3 Compared Methods

In order to demonstrate the performance of the proposed social influence propagation model, we compare our model with three other approaches.

Collaborative filtering (CF) is the traditional prediction approach. The user-based nearest neighbor algorithm is used in this paper. It includes two steps: the computation of each pair of users and recommendation according to the nearest neighbors. Pearson's correlation coefficient[4] is the most used similarity measure. The formula is as follows:

$$sim(u,v) = \frac{\sum_{p \in I} (r_{u,p} - \bar{r}_u) \cdot (r_{v,p} - \bar{r}_v)}{\sqrt{\sum_{p \in I} (r_{u,p} - \bar{r}_u)^2 \cdot (r_{v,p} - \bar{r}_v)^2}} \tag{7}$$

Where, I is the common rating set between user u and v. $\bar{r}_u$ and $\bar{r}_v$ is the average rating of user u and v respectively. The similarity will be sorted according to descending order and the M most similar users are selected as the nearest neighbors. The prediction of item p by user u can be obtained by aggregating the rating of nearest neighbors.

$$pre(u,p) = \bar{r}_u + \frac{\sum_{i \in M} (w_{u,i} \cdot r_{i,p})}{\sum_{i \in M} w_{u,i}} \tag{8}$$

Another benchmark is the method which is proposed in [16]. It assumes that the propagation of social influence decreases as a fixed decay factor. This method is named decay factor (DF). Assume $SP_{u,v}^k$ is the k shortest path from node u to

v except the last hop. According the shortest path with maximum propagation strategy, the formalization the social influence from u to v is as follows:

$$SI_{u,v} = \max \left\{ \varepsilon \cdot \prod_{(i,j) \in SP_{u,v}^{k}} w_{i,j}, k = 1, ..., m \right\} \tag{9}$$

The third benchmark is proposed in [17], the author defines a linear function according to the maximum propagation distance, the social influence decreases linearly with the increase of propagation distance. We call this method as linear decrease (LD) method. Assume the maximum propagation distance is d, user u at distance n from the user v. The social influence from u to v can have a predicted value:

$$SI_{u,v} = \frac{d - n + 1}{d} \tag{10}$$

From equation 9 and 10, we note that the direct neighbors of node v have the same and maximum social influence. However, our approach (equation 3) can make up this drawback.

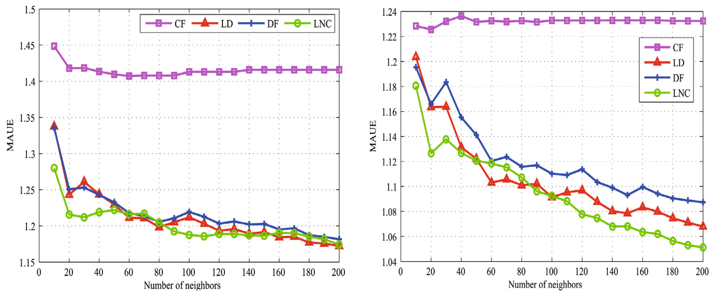
4.4 Performance Comparison

In this section, we compare the performance between our model and the benchmarks. We choose the Leave One Out evaluation technique to measure the performance. Leave one out technique involves hiding each rating and trying to predict them successively. We compare the predicted rating with the real rating and the difference (such as absolute value and rooted squared value) is the prediction error. Averaging the error over every prediction gives the overall MAUE and RMSUE respectively. Moreover, we also compute the user coverage (UC) and item coverage (IC) to compare these methods comprehensively.

According to [8], the behavior of user will be influenced within three degree distance, that is, your behavior is influenced by your friends of friends of friends. The influence is very small if the users are more than three degree and it can be ignored. Hence, in our experiments, the social influence propagation is limited within three degree distance. Moreover, since the optimal performance of fixed decay factor method can be obtained when the decay factor ε is set 0.006 in [16], we also set this value in our experiments.

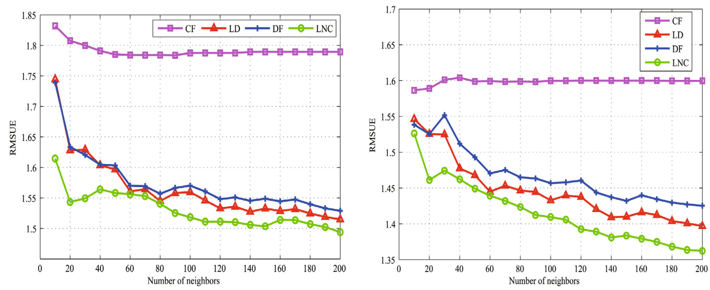
In order to predict one rating, we first compute the user similarity matrix after hiding the rating. Then the social similarity network can be built according to the similarity matrix. The network is weighted and undirected in our experiments. Moreover, we make the comparison for the users who only give three and four ratings(because user similarity cannot be computed when rating number is two) in our experiments.

Fig. 2 shows the comparisons between our model and the benchmarks when the users only give three and four ratings. We can see that the approaches based on social influence propagation are better than the traditional collaborative filtering (CF). In Fig. 2(a), the performance of our model (LNC) is better than



(a) Rating number:3 (b) Rating number:4

Fig. 2. The comparison on mean absolute user error (MAUE) between our model (LNC) and collaborative filtering(CF), linear decrease (LD), decay factor (DF) with the condition of users only give three and four ratings respectively

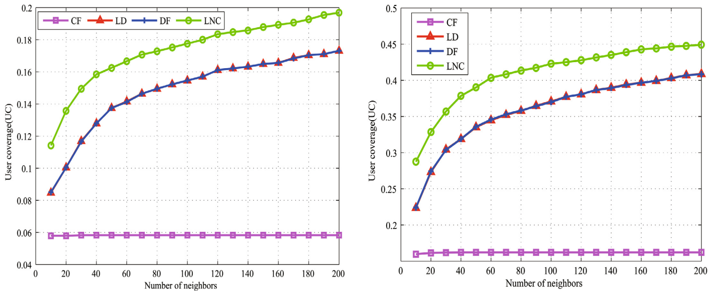


(a) Rating number:3 (b) Rating number:4

Fig. 3. The comparison on rooted mean squared user error (RMSUE) between our model (LNC) and collaborative filtering(CF), linear decrease (LD), decay factor (DF) with the condition of users only give three and four ratings respectively

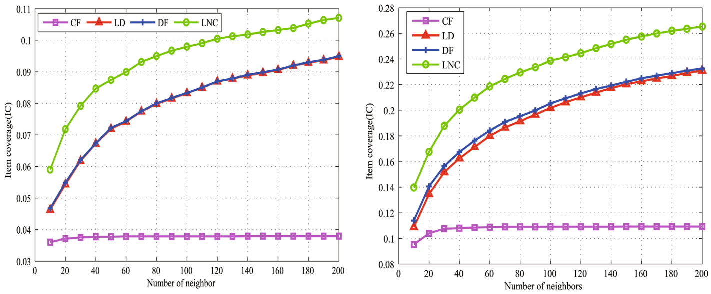
the linear decrease (LD) and decay factor (DF) methods when the number of neighbors is less than 50 and it is between 90 and 170. When the number of neighbors is more than 40, the LD will be better than DF. While in Fig. 2(b), the performance of our model is not better than LD only when the number of neighbors is between 50 and 80. The LD can surpass DF except when the number of neighbors is less 20. From the Fig. 2, we also can see that the mean absolute user error (MAUE) of the social influence propagation approaches is less when the rating number given by users is more(the maximum MAUE is less than 1.21 in Fig. 2(b) and the best MAUE is more than 1.18 in Fig. 2(a)).

The performance on rooted mean squared user error (RMSUE) between our model and other approaches is given in Fig. 3. We also see that the RMSUE of the social influence propagation approaches is more small than the collaborative filtering. We can note that our model (LNC) can obtain the best performance within the range of entire neighbors. The linear decrease (LD) method is also better than decay factor (DF) method except when the number of neighbors



(a) Rating number:3 (b) Rating number:4

Fig. 4. The comparison on user coverage (UC) between our model (LNC) and collaborative filtering(CF), linear decrease (LD), decay factor (DF) with the condition of users only give three and four ratings respectively



(a) Rating number:3 (b) Rating number:4

Fig. 5. The comparison on item coverage (IC) between our model (LNC) and collaborative filtering(CF), linear decrease (LD), decay factor (DF) with the condition of users only give three and four ratings respectively

is small, such as 10. In Fig. 2, the advantage of our model is not obviously. However, it is very notable in Fig. 3. This phenomenon explains that our model can produce many small error data and other two methods generate more large error data. Since the rooted mean squared user error (RMSUE) can magnify those large errors, our model is more accurate and stable than the benchmarks.

Moveover, we also compare the user coverage (UC) and item coverage (IC) except the MAUE and RMSUE. Fig. 4 shows the comparison results on the user coverage evaluation measure between our model and other three methods. We can see that the three social influence propagation methods can give better UC than the traditional collaborative filtering (CF). Moveover, the linear decrease (LD) and the decay factor (DF) methods have the same performance. We note that our model can give better results than LD and DF methods evidently. It obtains the best performance. We also see that the performance is better when users give more ratings. For example, the optimal user coverage is less than 0.2 in Fig. 4(a), while the worst result is more than 0.2 in Fig. 4(b).

Fig. 5 presents the comparison results on the item coverage evaluation measure between our model and the benchmarks. Just like the Fig. 4, the three social influence propagation approaches obtain better item coverage (IC) than the traditional collaborative filtering (CF) and our model can also achieve the best performance. The decay factor (DF) method obtain better item coverage than the linear decrease method and the users give more ratings, the distinction is larger. Similarly, the three social influence propagation approaches can give better item coverage if the users provide more ratings. For instance, the optimal item coverage is less than 0.11 in Fig. 5(a), while the worst performance is more than 0.11 in Fig. 5(b).

From Fig. 2 to Fig. 5, we can conclude that our model is not only able to obtain the less prediction error, but also it can have the best user coverage and item coverage. This demonstrates that the proposed model can improve the prediction performance effectively.

5 Conclusions

In order to improve the prediction performance in social recommendation, this paper proposes an adaptive social influence propagation model in which the computation of social influence of one node is based on its local network topology. There are three advantages of this method. First, different neighbors of nodes can generate different social influences. Second, one node can produce different social influences depending on its neighbors. Third, it does't need the global information about social network, hence its computation is very fast. We conduct experiments on Epinions data set and compare our model with other methods. The experimental results show that the proposed model can obtain the least prediction error and largest coverage. The performance of social recommendation is able to be improved effectively.

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