Recommender Systems Based on Doubly Structural Network

Na Chang, Takao Terano
Department of Computational Intelligence and Systems Science, Tokyo Institute of Technology, Tokyo, Japan, 2268502
(E-mail: bacenana@gmail.com, terano@plum.plala.or.jp)

Abstract: In the context of recommender systems, there are two important entities: users and items, and three relationships: users' relationship, items' connection and interactions between users and items. In most literature, one or more of these entities and relationships are used to predict users' preference. In this paper, we proposed a novel approach which incorporates these two entities and three relationships into one framework based on doubly structural network (DSN) and built a dynamic prediction model for users' preference over time. And we have proved that the new approach can give a good performance for recommender systems through experiment.
Key words: Recommender system; Doubly structural network; Dynamic prediction model

1 Introduction

With the development of E-commerce, personalized recommendation service is one of the most important needs for users. Recommender systems are information filtering systems which use users' individual information such as histories of purchasing and items' contents to predict users' preferences[1]. And based on this idea, recommender systems will then recommend the most favorite products or information that are most likely to be interested by users.

In the area of research of recommender systems, most of literatures are around with recommendation approaches and the main aim is to improve the performance of recommender systems. The basic approaches for recommender systems are content-based approach (CB approach), collaborative filtering approach and hybrid approach. Content-based approach has its roots in information retrieval and recommends the right items to users through matching users' profile with items' features[2][3]. The main weak point of the CB approach is that it just predicts users' preference based on the past history and can't predict users' latent preference. Collaborative filtering approach (CF approach) predicts user's rating for item based on his/her nearest neighbors' rating for that item[4]. The CF approach often suffers from data sparse problem because of it just based on the user-item rating matrix which is often very sparse. And both CB and CF methods confront from cold-start problem when a new item of a new user comes to recommender system. And hybrid approach is used to integrate content-based approaches and collaborative filtering approaches together to solve these problems.

By using CB, CF or hybrid methods, most recommendation approaches treat users or items as a collection of entities that are similar to each other and use this information to predict the target user's preference. So from the perspective of a recommender system itself, there are some relationships among users or items. In fact, there really exist some explicit and implicit connections among different users or items. Explicit connections are social relationships that indicate friendships, family relationships, colleagues, classmates and so on. And implicit connections are some implying relationships, for example, if two users major in the same department then they may be interested in the same books even though they don't know each other. As well as users, there are connections among objects. These connections are mostly the natural features among different items, for example, items belong to the same categories. And finally, items' preferences to items indicate that there are interactions between users and items.

Summarily speaking, in the field of recommender system there are two main entities and three main relationships. The two main entities are respectively users, indicating people who use the recommender system, and items, indicating products or information which are provided for users. And three main relationships mean that there are some specific relationships between users or items and there are also interactions between users and items based on the users' preferences. When we descript this phenomenon of recommender systems, we can integrate users, items, and the three types of relationships into one model, which is a doubly structural network which consists of three networks: user-network, item-network and cross-network[5].

Besides the new framework mentioned above, we also build a dynamic prediction model for users' latent preference. From recommender systems' perspective, we assume that recommender system is a dynamic system and if one node or edge in it changes, and then the other part of the system will change too. According to this idea, we use the dynamics of the DSN model to descript the movement of users' latent preference over time.

2 Related Researches

2.1 About doubly structural network

There are a lot of lectures about complex network and these researches are mostly focusing on one mode network such as small-world networks[6][7], scale-free networks and random networks[8]. These complex network are mainly used to descript the connections among entities belongs to one categories. For example, the social network is used to descript the relationship between different human beings and the protein interactions network is made up of a lot of proteins. In recent years, there are also some literatures about two- mode network which treat two types/classes of entities such as literature citation network, co-authorship networks and so on. And most of researchers also use one-mode methods to solve the problem of two-mode network.

In[5],[9],[10],[11], the authors proposed a doubly structural network model which is can be seen a two-mode network model. The DSN Model consists of two levels of networks: one is inner agent-model which represents agents' beliefs or knowledge about the world and the other is inter agent-model which represents a social network among agents. The DSN model can be used to analyze some social phenomenon.

2.2 About recommender systems

In the field of recommender system, there are a few of precedent researches using the similar approaches of our approach.

[12] introduced a recommendation model based on a directed graph of users. In their model, a directed link starting from one user and ending at another user indicates that the later user's behavior is strongly predictive of the former user's behavior. Recommendations are made by exploring short paths joining multiple users.

[13] proposed a graph-theoretic model for collaborative filtering, in which items and users are both represented as nodes and the edges represent interaction between users and items. Edges in this social network graph are induced by hammock jumps. A social network graph of users is then created based on the original graph, and recommendations are generated by navigating the combination of the original graph and the social network graph.

[14] proposed a two-layer graph model for recommender system. The two layers of nodes represent items and users, respectively. Three types of links between nodes capture the input information: the items' information, users' information, and transaction information. Each link between two items captures similarity between them. Each link between two users captures the similarity between them. And Interlayer links are formed based on the transaction information that captures the associations between users and items. In Huang's study, they give three approaches to get the prediction for items' preference based on the two-layer graph mode: direct retrieval, association mining and high-degree association retrieval.

[15] proposed to deal with the sparsity problem by applying an associative retrieval framework and related spreading activation algorithms to explore transitive associations among agents through their past transactions and feedback based on the bipartite graphs. One set of nodes represents products, services, and information objects for potential consumption. The other set represents agents. The transactions and feedback are modeled as links connecting nodes between these two sets.

[16] proposed an integrated-graph model for users' interests in personalized recommendation, which is based on Small-World network and Bayesian network. The Integrated-Graph model also consists of two layers. One is user's layer for representing users and the other is merchandise's layer for representing goods or produce. The relationships among users are described by Small-World network at lower layer. The implications among merchandises are represented by Bayesian network at higher layer. Directed arcs denote the interests and tendency between user's layer and merchandise's layer. Several algorithms for clustering and interest analysis based on Small-World network are introduced.

3 Proposed Approaches

3.1 DSN model for recommender systems

In our DSN model for recommender systems, it consists of three types of network: user-network, item-network and cross-network. Specifically speaking, we use nodes to denote users or items and edges to denote the relationships among them. The item-network consists of items and connections between them, the user-network consists of users and the relationship between them and the cross-network means users' preference for items (in our research, we use the term preference to represent user's real taste or rating to items and use the term latent preference represent the prediction value of preference). The concept graph of this model is as Figure 1 has shown us.

3.1.1 User - network

User - network is a social network which represents the relationships between different users [17]. As we know, the relationships in social network could be defined into two types: explicit and implicit [18]. The explicit relationship means people who know each other or they have trade or other explicit connections with each other. And the implicit relationship means that people have not direct connections but they may have the same tastes to one or more items. For example, people have the same interest on TV/films watching or people have the work of the same type or they are in the same age and so on. In our research, we define the relationship among users as their implicit relationships which we call it latent relationship.

The definition for user - network is as follows (see Figure 2):

$$G^U = (U, E^U, W^U), U = \{u_1, \cdots, u_i, \cdots u_j, \cdots u_n\}, E^U = \{e_{ij}^U \mid 1 \le i \le n, 1 \le j \le n\}, W^U = \{w_{ij}^U \mid 1 \le i \le n, 1 \le j \le n\}$$

Where U is the set of nodes which represent users and E^U is the set of edges which represent the relationship between users and W^U is the weight of E^U. So user - network is a weighted graph. In this paper we define users' similarity as the basic criteria to measure the relationship between them and furthermore we set a threshold θ for user-network's construction as follows:

$$w_{ij}^U = \begin{cases} sim(u_i, u_j), if\ sim(u_i, u_j) \ge \theta \\ 0 \qquad\qquad ,if\ sim(u_i, u_j) < \theta \end{cases} \text{of}\, i = j$$

Where $sim(u_i, u_j)$ is the similarity between user i and j based on any similarity computations.

3.1.2 Item - network

Item - network represents the connection between different items. Items may be in the same category or be liked by users at the same degree .In recommender systems; we also define items' similarity as the criteria to measure the connection between them. The definition for item-network is as follows:

$$G^I = (I, E^I, W^I), I = \{i_1, \cdots, i_p, \cdots i_q, \cdots i_m\}, E^I = \{e_{pq}^I \mid 1 \le p \le m, 1 \le q \le m\}, W^I = \{w_{pq}^i \mid 1 \le p \le m, 1 \le q \le m\}$$

Where I is the set of nodes which represent items and E^I is the set of edges which represent the connections between items and W^I is the weight of E^I. So item – network is also a weighted graph. And the definition for W^I is as follows:

$$w_{pq}^I = \begin{cases} sim(i_p, i_q), if\ sim(i_p, i_q) \ge \pi \\ 0 \qquad\qquad ,if\ sim(i_p, i_q) < \pi \end{cases} \text{of}\, p = q$$

Where $sim(i_p, i_q)$ means the similarity between item p and q based on any similarity computations.

3.1.3 Cross – network

In recommender systems, users giving rating to an item represents the degree of their preferences for the item. We define users' preference for items connect the two networks together. We also call the interaction between user-network and item-network cross links/edges. The definition for cross-network is as follows:

$$G^C = (G^U, G^I, R\ , P\ ), R\ \in \{U \times I\}, P\ \in \{U \times I\}$$

Where R means the relationship between users and items and in our research we define R as the ratings to items given by users and we also define it is users' preference for items, which we denote it in solid line. And with respect to P, we define it as users' latent preference for items， which we denote it in dashed line . The aim of recommender systems is to predict users' latent preference and make it close to users' real preference.

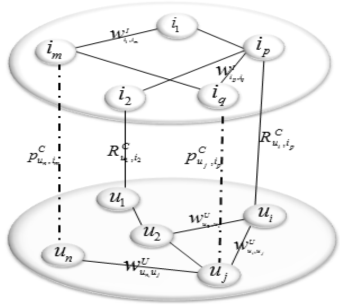

Figure 1 The Concept Graph of Doubly Structural Network for Recommender Systems

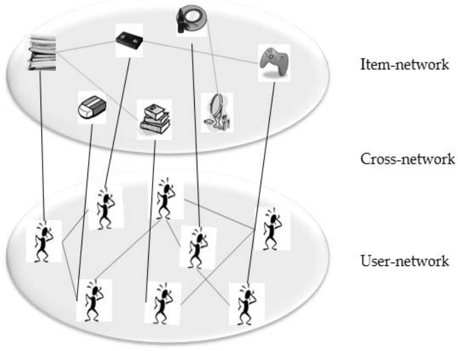

Figure 2 The Definition of Doubly Structural Network for Recommender Systems

3.2 A dynamic prediction model for recommender systems

In order to build the dynamic prediction model for recommender systems, we firstly define the sub-network of DCN as a user together with his neighbors and an item together with its neighbors and the interactions between the user or his neighbors and the item or its neighbors (see Figure 3). And if two users and two items are neighbors respectively, then we call the cross links between them are neighbor cross link.

Secondly, we take time step into account in our research. Just like a real recommender system, after a user came to the system, bought or rated an item, another user comes to the system and repeats the same action (in this paper, we don't consider about the simultaneous actions). When a user buys or rates an item, we call the action one time step and the user active user and in each time step there will be a new cross link between item – network and user – network. Traditional recommendation approaches predict a user' preference just based on the current state of the whole user or item when the user comes to the system and most recommendation methods do not take into account users' local movement. For example, in the sub-network of item i_m and user u_n, at time step t we get u_n's latent preference for i_m is equal to 3.5 and then at time step t+1 the user a_n gives rating 5 to item i_m. Because of user u_n's action, the relationship between u_n and his neighbors may change and the cross link p_{u_j,i_q} 's neighbor cross links such as p_{u_j,i_q} may have the similar trend.

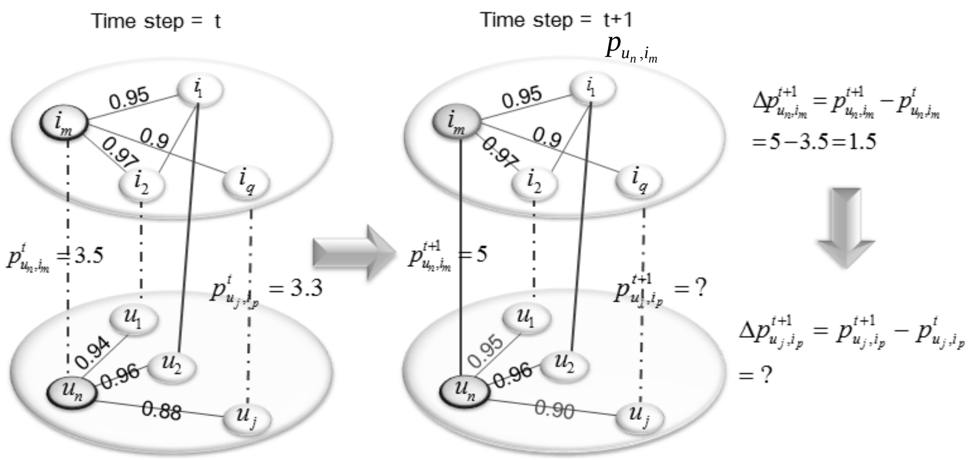

Figure 3 A Sub-network and the Local Movement of it

In addition, we assume some rules for our research as follows:

1. A cross link is similar to its neighbor cross links;
2. The more closer of users or items' relationship are, then the more similar of their cross links are;
3. When a user rates an item, which means there is a new solid cross link between the user-network and item-network, the neighbor cross links of the new cross link will be influenced.

In our dynamic prediction model for recommender systems, we defined two important components: one is expected value of users' latent preference (we'll use expected preference for short in the following parts) which indicates users' average preference for items and this component is relative stable and the other component is predictive value of users' latent preference (we'll use latent preference for short in the following parts) which is our aim and is based on the expected value of users' latent preference and the local movement of sub-networks.

3.2.1 Expected value of users' latent preference

Users' expected preference indicates the average preference of a user for an item. This process is similar to traditional collaborative methods. We use the direct interaction and indirect interaction based on DCN to get users' expected preference for items (see Figure 4).

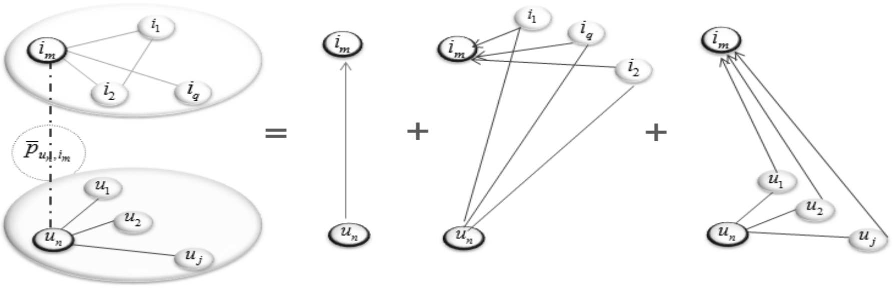

Figure 4 Users' Expected Preference

In this paper, we define the direct interactions between users and items as the overall average preference (rating) of users for items and this value is the same for all user-item pair. And the indirect interactions between users and items consist of two types: one type is user-item-item connection which means that a user' preference to an item's neighbors can be used to descript the user's preference for the item and one type is user-user-item connection which means that a user's neighbors' preference to an item can be used to descript the user's preference for the item.

The specific definition for users' expected preference is as follows:

$$\overline{p}_{u_n,i_m} = \alpha \cdot g^{ui}(u_n,i_m) + \beta \cdot g^{uii}(u_n,i_m) + \gamma \cdot g^{uui}(u_n,i_m)$$

$$= \alpha \cdot \frac{\sum_{j=1}^{n}\sum_{p=1}^{m} r_{u_j,i_p}}{\sum_{r_{u_j,i_p}!=0} 1} + \beta \cdot \frac{\sum_{q \neq m}^{m} r_{u_n,i_q} \cdot w^{I}_{i_q,i_m}}{\sum_{r_{u_n,i_q}!=0}^{m} w^{I}_{i_q,i_m}} + \gamma \cdot \frac{\sum_{j \neq n}^{n} r_{u_j,i_m} \cdot w^{U}_{u_n,u_j}}{\sum_{r_{u_j,i_m}!=0}^{n} w^{U}_{u_n,u_j}}$$

Where α,β,γ are parameters which are used to regulate the weight of three types of interaction and r_{u_j,i_p} means user u_j' s rating to item i_q.

3.2.2 Prediction value of users' latent preference

As talked above, when taking into account time step in recommender systems, we can explore the local movement of DCN model and the local movement of sub-network may influence the whole state of recommender systems. In this paper, we assume local movement is only within the scope of sub-network. This means that when a user rated an item then there will be a cross link between the user and the item and the relationship between the user and his neighbors may change as well as the item and its neighbors and furthermore the cross links inside the sub-network will also change.

$$p^{t+1}_{u_n,i_m} = \begin{cases} (1-\lambda)p^{t}_{u_n,i_m} + \lambda\left(\dfrac{\delta^{t+1}\varepsilon^{t+1}}{1+\left|\overline{p}^{t+1}_{u_n,i_m} - \overline{p}^{t+1}_{u_i,i_p}\right|} + (p^{t}_{a_n,o_m} + r^{t+1}_{a_i,o_p})/2\right) & ,\text{where } \overline{p}^{t+1}_{u_n,i_m} - \overline{p}^{t+1}_{u_i,i_p} \le \eta \text{ and } \delta^{t+1} \neq 0 \\ p^{t}_{u_n,i_m} & ,\text{where } \overline{p}^{t+1}_{u_n,i_m} - \overline{p}^{t+1}_{u_i,i_p} > \eta \text{ or } \delta^{t+1} = 0 \end{cases}$$

Where λ,η are parameters and $\varepsilon^{t+1} = \Delta p^{t+1}_{u_i,i_p} = p^{t+1}_{u_i,i_p} - p^{t}_{u_i,i_p}, \delta^{t+1} = w^{U(t+1)}_{u_n,u_i} \cdot w^{I(t+1)}_{i_m,i_p}$

ε^{t+1} indicates the deviation of user u_i' s real preference (rating) and predictive value in time step t for item i_p, and δ^{t+1} is used to make sure the local movement within the scope of sub-network.

The core issue of our dynamic prediction model for recommender systems is: when a user rated an item at time step t and his rating for the item is different from the latent preference we predicted at time step t-1, which means the previous prediction deviates from the real preference of the user, and after we gain the deviation of the prediction, how to revise the latent preferences inside the sub-network? Take Figure 3 for example, user u_n's rating (real preference) for item is 5 which is higher than the prediction value at time step t and so we can speculate that u_n' neighbors' preference for item i_m or its neighbors may also higher than the prediction at time step t.

According to the research talked above, the definition for dynamic prediction model for recommender systems based on DCN is as follows (we assume that active user u_i rates item i_p in time step t+1):

In the dynamic prediction formula, we define that only the cross links which is closer to the active cross link and within the scope of active user and item's sub-network could be influenced by the local movement. In order to make sure the prediction value of latent preference change smoothly, parameter are supposed to be small enough. The dynamic model has some adaptive characteristic that adjust users' latent preference based on the active user's action.

4 Experimental Analyses

In this paper, we use the data set from GroupLens to verify our research. The data set has 100000 records (user-item-rating) and contains 943 users and 1682 movies. We use 50% of the data set as initial data which is used to get the initial DSN model and 30% as train data which means that in each time step we use one record to get the local movement of DSN through the proposed dynamic prediction model. And we adopted MAE (Mean Absolute Error) as the basic metric in our experiment.

The basic results of this experiment are as Figure 5 has shown us. From the MAE trend line we can see that the value of MAE keeps on decreasing, which means that the prediction of our dynamic model is more close to users' real preference for items. And we notice that the value of MAE decreases very quickly at the beginning and then the change is slower.

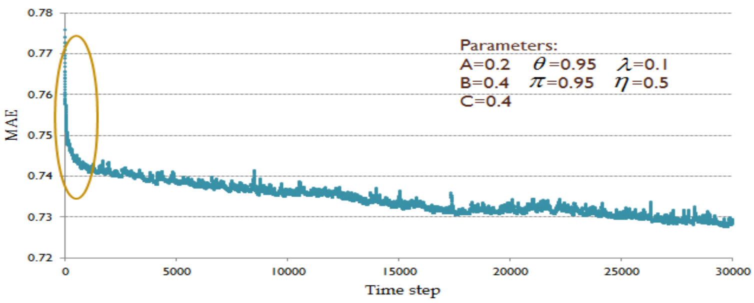

Figure 5 The MAE over Time Step

Besides the MAE results, we also get some interesting results such as users' degree distribution (see Figure 5) and items' degree distribution (see Figure 6). And we can see that the user-network has some characteristics of scale-free network and item-network has the some characteristics of random network.

5 Conclusions

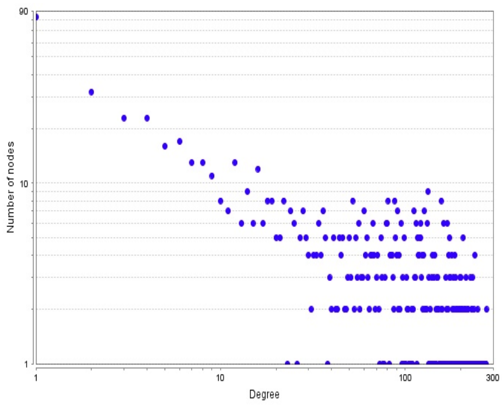

Figure 6 Users' Degree Distribution

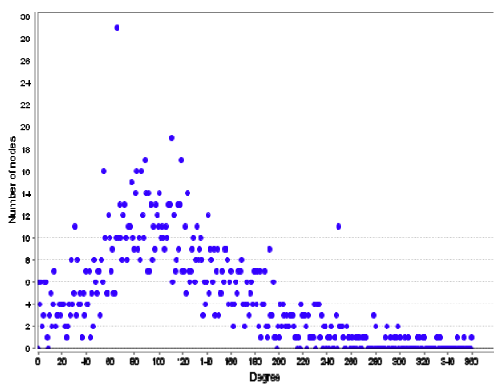

Figure 7 Items' Degree Distribution

In this paper, we proposed a novel approach for recommender systems, which incorporates users, items and the relationships between them into one framework based on doubly structural network, and built a dynamic prediction model for users' latent preference over time. From the experiment we can see that the novel method can give a good performance for recommender systems. In the future we'll keep on studying the proposed dynamic prediction model for recommender systems and use other data sets and more evaluation metrics to verify our idea.

References

[1] Ansari A., Essegaier S., Kohli R. Internet Recommendations Systems[J]. J. Marketing Research, 2000, 363-375

[2] Balabanovic M., Shoham Y.F. Content-based Recommendation[J]. Communication of the ACM, 1997, 40(3): 66-72

[3] Sarwar B., Kar Ypis G., Konstan J., et al. Item-based Collaborative Filtering Recommendation Algorithms[C]. Proceedings of the 10th International World Wide Web Conference, New York, USA: ACM ,2001

[4] Adomavicius G., Tuzhili A. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions[J]. IEEE Transaction on Knowledge and Data Engineering, 2005, 17(6): 734-749

[5] M. Kunigami, M. Kobayashi, et al. On the Emergence of Money through a Complex Doubly Structural Network Model[C]. The 22nd Annual Conference of the Japanese Society for Artificial Intelligence, 2008

[6] Adamic L. A. The Small World Web, in Lecture Notes in Computer Science, Springer, New York, 1999(1696): 443-454

[7] Almaas E., Kulkarn, R. V., and Strou, D, Characterizing the Structure of Small-World Networks, Phys. Rev Lett. 88, 098101, 2002

[8] S. Boccalettia, V. Latora. Complex Networks: Structure and Dynamics[J]. Physics Reports, 2006 (424):175 – 308

[9] M. Kunigami, M. Kobayashi, S. Yamadera, T. Terano. On Emergence of Money in Self-organizing Micro-macro Network Model[C]. Proceedings of ESSA'07, 2007: 417–425

[10] M. Kunigami, M. Kobayashi, S. Yamadera, T. Yamada, T. Terano. A Doubly Structural Network Model and Analysis on Emergence of Money[C]. World Congress on Social Simulation, (WCSS-08), 2008

[11] M. Kunigami, M. Kobayashi, et al. A Doubly Structural Network Model and Analysis on the Emergence of Money, Agent-Based Social Systems, 2010, 7(2):137-149, DOI: 10.1007/978-4-431-99781-8-10

[12] C. Aggarwal. Horting Hatches an Egg: A New Graph-theoretic Approach to Collaborative Filtering. In Proceedings of the 5th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD'99) (San Diego, Calif.), ACM, New York, 1999:201–212

[13] J. Batul. Jumping Connections: A Graph-Theoretic Model for Recommender Systems[EB/OL]. Retrieved February 1, 2003, http://scholar-.lib.vt.edu/theses/available/etd-02282001-175040/unrestricted/etd.pdf

[14] Z. Huang, W. Chung, and H. Chen. A Graph Model for E-Commerce Recommender Systems[J]. Journal of the American Society for Information Science and Technology, 2004,55(3):259–274

[15] Z. Hhuang, H. Chen, and D. Zeng. Applying Associative Retrieval Technique to Alleviate the Sparsity Problem in Collaborative Filtering[J]. ACM Transactions on Information Systems, 2004,22(1):116–142

[16] S. Zhang, D. Chen. Analysis of User Interests Based on Integrated-Graph Model[C]. The Sixth International Conference on Fuzzy Systems and Knowledge Discovery, 2009

[17] B. J. Miraza, B. J. Keller, and N. Ramkrishnana. Studying Recommendation Algorithms by Graph Analysis[J]. J. Intel. Inf. Syst. 2003,20(2): 131–160

[18] D. Frey, A. Jegou, and A.M. Kermarrec. Social Market: Combining Explicit and Implicit Social Networks[C]. International Symposium on Stabilization, Safety, and Security of Distributed Systems, 2011