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FOLLOWEE RECOMMENDATION BASED FORMAL CONCEPT ANALYSIS IN SOCIAL NETWORK

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Abstract. *We show how Formal Concept Analysis (FCA) can be applied to friends recommender in social network. FCA is a mathematical method for analyzing binary relations. Here we apply it to the relation between users and terms of Micro-blogs text in a friends recommender system. The concept lattice was utilized to store the knowledge context based on the relationship among users and terms in order to guide a recommender for the recommending. By computing the concept similarity and matching visited candidate users with the concept lattice, we obtained the rank values of the candidate users to expand the target users' friend lists. Experimental results show that the proposed method is satisfactory for effective and efficient friends recommendation.*
Keywords: Social network, Followee recommendation, FCA, VSM

1. **Introduction.** With the rapid development of social network, Micro-blogging has become a new form of communication in people's daily life. In China, TENCENT Micro-blog is the most significant Micro-blog platform which has already owned approximately 540 million registered accounts. Active users normally update more than 1 tweet per day [1]. For a normal TENCENT Micro-blog user, he usually receives thousands of new Micro-blogs from his followees each day, most of which are likely to be neglected along with the latest tweets coming to occupy the top positions of his Micro-blog homepage [2]. Therefore, in the constantly increasing TENCENT community, finding high correlated and reliable followees as information source presents a challenging issue. It is evident that the recommending algorithm in the social network is of great importance to expand effectively the target user's friend lists.

Unlike traditional recommendation systems, we do not have any structured information available about the user's interests in the form of ratings on items he/she likes or dislikes. For modeling a target user we need to utilize context that can be derived from user interactions, content streams and the topology of the network [4, 5, 6, 7, 8]. There are also other sources of information about a user, such as his/her own bio, but it has been demonstrated that many users either do not provide a bio or they have a bio which does not provide any topical information. Existent studies have also considered Twitter lists meta-data to derive the topics of interest of a Twitter user [9]. In our paper, we propose FCA-based recommendation method in which we utilize both the structure of the followers/followees network and the Micro-blogs published in this network as a means to recommend people that share the same topic with the target users.

In summary, the contributions of this paper are as follows.

1. A friend recommendation approach based on formal concept analysis. We adopt concept lattice to profile the preference of target users.

2. A matching method based concept similarity. Visited candidate users were recommended to target user by computing the similarity between the concept and the concept lattice.

The rest of this work is organized as follows. We start from existing research efforts related to our work in Section 2. Then, we describe the FCA-based approach to tackle the problem of followee recommendation in Section 3. In Section 4 experiments carried out to validate the approach are reported. Finally, we conclude our findings in Section 5.

2. Related Work.

2.1. Formal concept analysis in information science.

Formal Concept Analysis (FCA) is an important method for data analysis, knowledge representation and information retrieval. In [10], Carpineto and Romano consider that FCA can support query refinement. Because a document/term lattice structures a search space into clusters of related documents, lattices can be used to make suggestions for query refinement in cases where too many documents are retrieved. Boucher-Ryan and Bridge [11] go a step forward using the method of FCA that groups the users and items into concepts, ordered by a concept lattice. They present new algorithms for finding neighbors in a collaborative recommender. The concept lattice was used as an index to the recommender's ratings matrix. Their experimental results show a major decrease in the amount of work needed to find neighbors.

2.2. Recommending users to follow.

There is a wealth of research on recommender systems. Many approaches employ the technique of collaborative filtering, which utilizes similarities of preferences among users to recommend items such as movies for a user to consume. In the field of collaborative filtering, two types of methods are widely studied. Neighborhood-based methods mainly focus on finding the similar users [12] or items [13] for recommendations. The model-based approaches to collaborative filtering use the observed user-item ratings to train a compact model that explains the given data [14].

As regards friends recommendation, one of them is the content matching algorithm, which is based on the intuition that "if we both post content on similar topics, we might be interested in getting to know each other". Armentanon et al. proposed the algorithms for recommending followees in Twitter [14]. Multiple profiling strategies were considered according to how users are represented in a content-based approach (by their own tweets, by the tweets of their followees, by the tweets of their followers, by the combination of the three).

Research has also been done using social network structures for recommendations. For instance, the friend-of-friend algorithm leverages only social network information based on the intuition that "if many of my friends consider Alice a friend, perhaps Alice could be my friend too". Many social network analysis approaches have adopted similar ideas to find neighborhoods and paths within the network [13].

Recommenders usually give a simple model that speeds up the process of finding neighbors. Further speedup may be obtained by building an index to the twitters so that it is no longer necessary to perform an exhaustive online search through all the users. The common approach to this is to use some form of heuristic-based clustering algorithm. In the rest of this paper, we investigate an alternative, which builds an index using the technique of Formal Concept Analysis.

In this paper, aiming to expand effectively the target user's friend lists, based on the intuition that lattices can be employed to make suggestions for query refinement, a method based-FCA recommendation methods was proposed. A concept lattice was utilized to profile target users in order to find mind-like users to recommend. By computing the concept similarity and matching visited candidate users with the concept lattice, we obtained the rank values of the candidate users and it is then applied to generate the ranking of recommendations.

3. **Friend Recommendation in Social Network.** The problem of friend recommendation in social network aims to help target user to identify mind-like users and Micro-blogs that other users post. The matching between the information each user publishes in social network and the user interests needs to be evaluated in order to obtain a ranked list of friend recommendations. The preference of a target user can be described using various content sources as well as following relationships in social network, such as the text of his/her own posts or the posts published by the followees that he/she follows.

In general, target users posted few Micro-blog themselves, but followed active people. Hence, an alternative method to model the preference of a target user is based on who he/she is following. For a target user u_T, let $\mathrm{MB}(u_T)$ be the set of all Micro-blogs that both target user own and their followees post, that is:

$$\mathrm{MB}(u_T) = \{p_1, p_2, \cdots, p_k\} \tag{1}$$

The simplest alternative to build a profile for a target user in Micro-blog network is aggregating all Micro-blogs that both his/her own and their followees post under the assumption that these users are likely to post about information that interests them:

$$\mathrm{Post}(u_T) = \sum_{i=1}^{k} p_i \tag{2}$$

3.1. **Profiling the target users.** Concept lattice is systematically built up by R. Wille in 1982. Concept lattice and corresponding Hasse diagram reflect a conceptual hierarchy (Wille 1982). It is constructed based on formal context [15, 16, 17]. In this section, we propose some notions such as formal context, formal concept, and concept lattice of target user.

A formal context of target user is a tripe $T = (\mathrm{uid}, T, Q)$, where uid is the number of user ID and each $\mathrm{uid} \in \mathrm{UIDs}$ is interpreted to object, each $t \in T$ is interpreted to attribute, and t is the common key term set of Micro-blogs identified by uid in UIDs. UIDs and T cannot be empty sets. $Q \subseteq \mathrm{UIDs} \times T$ is a binary relation, if $(\mathrm{uid}, t) \in Q$, then it means that uid has the attribute t.

A concept can be formalized into a duality (objects, attributes), and it reflects that these objects in duality take on the common attributes and these attributes only are shared by these objects. To introduce the definition of the formal concept of UIDs, we rewrite two set-valued functions, given by the expressions:

$$\uparrow: P(\mathrm{UIDs}) \to P(W), X^{\uparrow} = \{w | w \in W; \forall \mathrm{uid} \in X, (\mathrm{uid}, w) \in Q\} \tag{3a}$$

$$\downarrow: P(W) \to P(\mathrm{UIDs}), Y^{\downarrow} = \{\mathrm{uid} | \mathrm{uid} \in \mathrm{UIDs}; \forall w \in W, (\mathrm{uid}, w) \in Q\} \tag{3b}$$

Definition 3.1. *A concept of* UIDs *is a duality* $(X, Y) \in P(\mathrm{UIDs}) \times P(W)$ *such that* $X^{\uparrow} = Y$ *and* $Y^{\downarrow} = X$. *The set* X *is called extent of the concept, the set* Y *intent of the concept.*

Definition 3.2. *Two concept of* $(X_1, Y_1) \leq (X_2, Y_2)$ *if and only if* $X_1 \subseteq X_2$ *(or equivalently* $Y_2 \subseteq Y_1$*).*

Definition 3.3. *Leting* C *be all concepts of* UIDs, *and* $L(T)$ *be* $(C, O, I, \leq)$, *we denote* $L(T)$ *to a concept lattice of* UIDs.

Example 3.1. *It is supposed that* $Post(u_T)$ *includes terms of Micro-blog posted by* UIDs*: "Social Network, Technology, Flower, Post, Information, Recommendation". Table 1 is the formal context of* UIDs*. From this formal context, we extract some formal concepts as follows:*

1. ({UID1, UID2, UID3, UID5}, {Post});
2. ({UID2, UID3, UID4, UID5}, {Technology});
3. ({UID1, UID4, UID5}, {Information, Recommendation});
4. ({UID1, UID2, UID5}, {Post, Recommendation});
5. ({UID2, UID3, UID4}, {Technology, Flower});
6. ({UID2, UID3, UID5}, {Technology, Post});
7. ({UID1}, {Post, Information, Recommendation});
8. ({UID2, UID4}, {Technology, Flower, Recommendation});
9. ({UID2, UID5}, {Technology, Post, Recommendation});
10. ({UID2, UID3}, {Social Network, Technology, Flower, Post});
11. ({UID4}, {Technology, Flower, Information, Recommendation});
12. ({UID5}, {Technology, Post, Information, Recommendation});
13. ({UID2}, {Social Network, Technology, Flower, Post, Recommendation});
I. ({UID1, UID2, UID3, UID4, UID5}, {ϕ});
O. ({ϕ}, {Social Network, Technology, Flower, Post, Information, Recommendation}).

Definition 3.4. *(The Target Concept Lattice* (TL)*) Consider formal context* $T =$ (UIDs, T, Q)*. It generates the target concept lattice* TL *from the formal context* T*.*

TABLE 1. The terms frequency between 5 user ID and 13 terms

Obj\Att	Social Network	Technology	Flower	Post	Information	Recommendation
User 1				√	√	√
User 2	√	√	√	√		√
User 3	√	√	√	√		
User 4		√	√	√	√	√
User 5		√		√	√	√

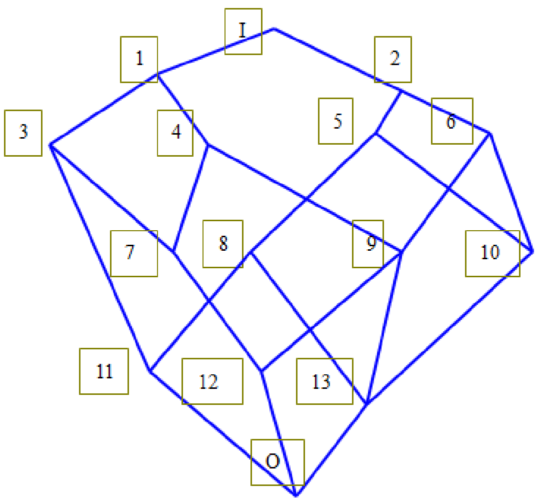

FIGURE 1. Concept latice corresponding to Table 1

3.2. **Extension similarity degree of two concepts.** In social network, A follow, from user A to user B, is supposed as 'users A and B might be on same preference' or 'the user A is interested in user B'. It implies an axiomatic semantic relation between user A and user B.

On the other hand, A forwarding or commenting user B's posts for user A, is supposed as "user A and user B might be of same hobby". A forwarding implies also an axiomatic semantic relation between users A and B. It indicates that the intension of concepts of user A is the similar as one of user B. This semantic relation denotes the ontology similarity relation. The relationships between target user and their followee recorded the abundant history data of user-forward-data, comment-data, etc. In this paper, we defined comment-data and forward-data of the users as the user domain.

3.2.1. *Direct correlation computation.* The weight of correlation is a way to quantify the similarity of a user about another user's behavior, and the greater the weight is, the higher the similarity is. Unlike SNS such as FilmTrust and Epinions, Tencent Weibo does not provide direct correlation weight statements expressed by users. Motivated by the homophily of social networks that users are more likely to be friends with higher frequencies of interactions between them and users are easily influenced by the friends they trust, we define a direct correlation metric based on the forwarding or commenting between the active user and his neighbors in Tencent Weibo.

The direct correlation degree between user u and his neighbor u' is given by

$$Cor(u,u') = \frac{forwarding(u,u')}{\sum_{\mathrm{u'\in Neighbor(u)}} forwarding(u,u')} + \frac{commenting(u,u')}{\sum_{\mathrm{u'\in Neighbor(u)}} commenting(u,u')} \quad (4)$$

3.2.2. *Indirect correlation computation.* Based on the direct correction values between pairs of users in social networks, we can construct the social network graph.

Formally, given the target user u and his social graph G, a social network graph $G_t = (V,E)$ with weights on the edges. The nodes of the graph correspond to the concept in G, and the edges and edge weights correspond to the direct extension correlation and the degree of correlation associated with each relation according to Equation (4).

To compute the indirect correlation on G_t, we define two operators to combine the available direct correlation information as follows.

Definition 3.5. *(Concatenation Operator) Concatenation operator which is denoted with the symbol $\otimes$, is used to combine direct correlation values along a path p_1 from the user u to candidate user u' with distance d.*

$$\begin{aligned} Cor^{p_1}(u,u') &= Cor(u,u_1) \otimes Cor(u_1,u_2), \ldots, \otimes Cor(u_{d-1},u') \\ &= \min\left(Cor(u,u_1), Cor(u_1,u_2), \ldots, Cor(u_{d-1},u')\right) \end{aligned} \quad (5)$$

Definition 3.6. *(Summary Operator) Summary operator which is denoted with the symbol $\oplus$, is used to combine extension correlation values along different path $p_1, p_2, \ldots, p_n$ from the user u to candidate user u'.*

$$\begin{aligned} Cor(u,u') &= Cor^{p_1}(u,u') \oplus Cor^{p_2}(u,u'), \ldots, \oplus Cor^{p_n}(u,u') \\ &= \max\left(Cor^{p_1}(u,u'), Cor^{p_2}(u,u'), \ldots, Cor^{p_n}(u,u')\right) \end{aligned} \quad (6)$$

Given a social network graph G_t, the indirect correlation between the pair of users u and u' is firstly computed by Equation (5) on each path from u to u', and then calculated by Equation (6) to find the maximum correlation value along these paths.

3.2.3. *Extension similarity degree computation.* To consider two concepts (X_i, Y_i) and (X_j, Y_j), the user u in X_i follow user u' in X_j reflects the semantic correlation; the forward-data of user u in X_i and user u' in X_j reflects the semantic relation of their extents too. Because they cannot share objects between concepts, noting that there exist some follow and forward-data among users, they reflect the semantic correlation of extensions of two concepts respectively.

Definition 3.7. *(Extension Similarity Degree) Considering two concepts* (X_i, Y_i) *and* (X_j, Y_j)*, let* $Sim_{\text{extension}}$ *be the extension similarity between* (X_i, Y_i) *and* (X_j, Y_j)*.*

$$Sim_{\text{extension}}((X_i, Y_i), (X_j, Y_j)) = \max Cor(u, u') \tag{7}$$

where u is the member of extension of concept (X_i, Y_i) and u' is the member of extension of concept (X_j, Y_j).

3.3. **Intension similarity degree of two concepts.** In order to compute the semantic similarity of intensions of two concepts in a predefine domain ontology, the similarity degrees for any pair of concept descriptors should be contained. In [18, 19], A. Formica replaces axiomatically the similarity degrees with information content similarity scores that they can be automatically computed by any lexical database (such as WordNet).

There are some methods to determine semantic similarity between terms based on Chinese WordNet: Edge Counting Methods, Information Content Methods, Feature based Methods, Hybrid Methods [20, 21, 22, 23]. In our experiment, we use Lin's theory of similarity between arbitrary objects.

Definition 3.8. *(Information Content Similarity (ics)).*

$$ics(a, b) = \frac{2 \times \log p(lso(a, b))}{\log p(a) + \log p(b)} \tag{8}$$

where $p(a)$ and $p(b)$ are the probability of a concept noun a and b, respectively. $lso(a, b)$ is a concept noun providing the maximum information content shared by a, b.

Definition 3.9. *(Semantic Intension Similarity) Considering two concepts* X_1 *and* X_2*, let* $Sim_{\text{intension}}$ *be the intension similarity between* (X_1, Y_1) *and* (X_2, Y_2)*.*

$$Sim_{\text{intension}}(P, Q) = \frac{\sum_{i=1}^{k} ics(p_i, q_i) \times w(p_i) \times w(q_i)}{\sqrt{\sum_{i=1}^{m} w^2(p_i) \times \sum_{i=1}^{n} w^2(q_i)}} \tag{9}$$

where P and Q are intensions of concepts (X_1, Y_1) and (X_2, Y_2) respectively, $w(p_i)$ is the weight of the i^{th} term in P and $w(q_i)$ is the weight of the i^{th} term in Q. $ics(p_i, q_i)$ is the semantic similarity degree between the terms p_i and q_i in WordNet.

3.4. **Preference similarity degree of CUID.** The concept similarity between (X_1, Y_1) and (X_2, Y_2) includes two parts: the extension similarity and intension similarity. We define it as follows:

$$Sim((X_1, Y_1), (X_2, Y_2)) = Sim_{\text{extension}} \times \mu + Sim_{\text{intension}} \times (1 - \mu) \tag{10}$$

where $\mu \in [0, 1]$ is a weight which is a proportion of the extension in the whole concept. μ is defined as $Sim_{\text{extension}}/(Sim_{\text{extension}} + Sim_{\text{intension}})$.

According to the assumption that followees followed by target users are likely to post about information that interests them, each UID in UIDs can accord with target user's interest. These concepts of target lattice TL are derived from the target users and their followees, step by step.

In order to make conveniently choice of Micro-blogs users for commendation, each candidate user corresponding target user should be assigned a preference score. We take the candidate user ID (CUID) as an object, the key terms vector Y derived from Micro-blogs corresponding to the candidate user as attributes, and the combination of the object and attributes as a virtual concept (CUID, Y). The preference similarity degree of the virtual concept with target lattice (TL) reflects the mind-like relation between the candidate user and target user. It allows us to define the preference similarity degree (namely preference score) between the virtual concept and target lattice as follows.

Definition 3.10. *(Preference Similarity Degree) Let* $PSim((\mathrm{CUID}, Y_1), \mathrm{TL})$ *be the Preference similarity degree between the virtual concept and target lattice.*

$$PSim((\mathrm{CUID}, Y_1), \mathrm{TL}) = \max Sim((\mathrm{CUID}, Y_1), (X, Y)) \tag{11}$$

4. Experimental Evaluation.

4.1. Dataset description. We download Micro-blogs that users post from TENCENT, and record their following relationship as our experiment's dataset. The dataset used in this paper is actually a social graph of 83,541 follower/followee relations between 45,107 users and their corresponding tweets belonging to a time span of 2013.12-2014.03, reaching a total of 1,467,110 tweets. This dataset was created using a Micro-blogs crawler based on TENCENT API. We began with a small seed-set of 20 users and expanded the user-base by following their followees links. Users who posted less than 10 tweets were excluded so that valuable content-based profiles can be extracted for all users involved in the evaluation. The filtered dataset contained 10,727 unique users and 35,495 relationships. In this experiment we evaluate 4 different profiling and recommendation strategies based on the different sources of profile information:

1. (S1) users are represented by their own tweets ($tweets(U_T)$);
2. (S2) users are represented by the tweets of their followees ($followeestweets(U_T)$);
3. (S3) users are represented by the IDs of their followees ($followee(U_T)$);
4. (S4) a strategy based FCA ($FCA(U_T)$).

Table 2. Summary of statistics of the users selected for testing the approach

	Average	Maximum	Minimum
User 1	95.3±52.45	225	1
User 2	0.9±1.95	29	0
User 3	101.23±58.61	300	11

4.2. Experimental results. Figures 2 and 3 show the precision and hit-rate [13] results for followees recommendations using S1-S3 and FCA-based approach, respectively. The number of candidates tested was in average 8651.6±468.57 target users traveled through the user's followee links.

It can be observed that S1-S3 are not satisfactory for identifying potentially mind-like followees. This is probably due to the fact that S1-S3 methods only consider content of Micro-blogs or the relationship among user.

In contrast, S1-S3 were more effective in recognizing interesting users among the candidates visited. In fact, the strategies utilizing a set of concepts for users outperform S1-S3 for the different sizes of the recommendation lists. Utilizing S1-S3, precision diminished slightly but also the complexity of similarity computations is reduced since concept lattices are not necessarily constructed. Further experiments will be conducted to evaluate other settings of the similarity threshold μ, that was assigned to 0.35.

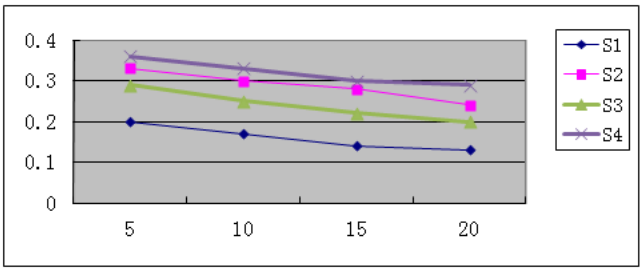

FIGURE 2. Precision of followees recommendation for different methods

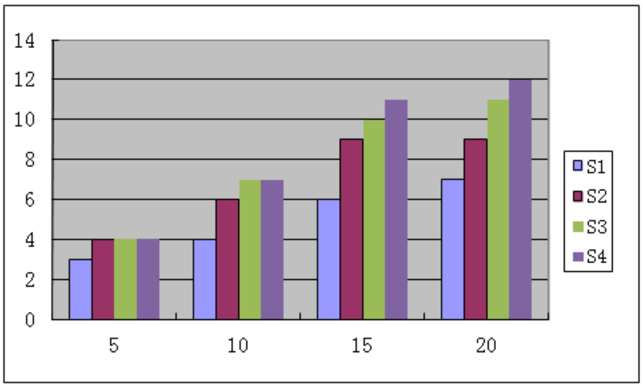

FIGURE 3. Hit-rate of followees recommendation for different methods

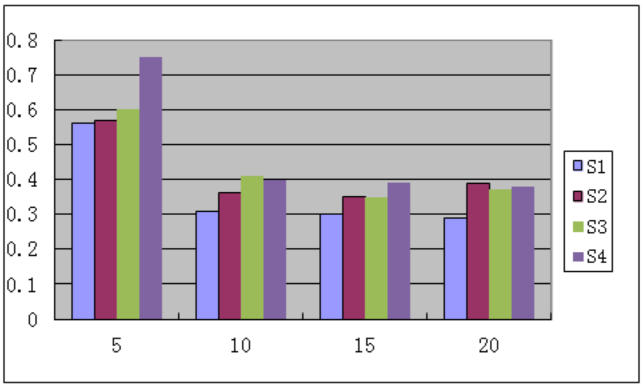

FIGURE 4. ARHR values of followees recommendation for different methods

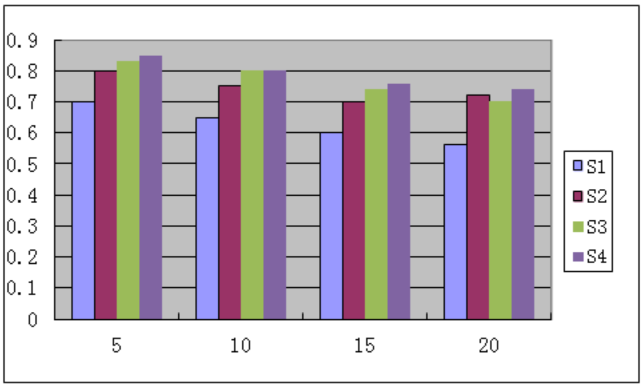

FIGURE 5. Average similarity of the recommended followees with the target users

Interestingly, the ARHR values [14] shown in Figure 4 for the four commendation methods allow to infer that hits are even better positioned in the list generated using S1-S3 than in those produced with FCA-based method. Therefore, the issue of improving the ranking of mind-like recommendations will be a matter of future research, particularly exploiting intension similarity degree as a voting mechanism.

Figure 5 depicts the average similarities between Micro-blog users in the top-N lists with the corresponding S1-S3 and FCA-based strategies. The relatively high similarity between posts published by the recommended users and the target user' posts account for the good results of FCA-based strategies.

5. **Conclusion and Discussion.** Nowadays, personalized recommendation has been widely used in social applications, in which the content-based followee recommendation has become a very significant approach for higher accuracy and lower computational complexity. This paper proposes the FCA-based model considered both the relationships among users and content generated by the target user and their followees. The FCA-based algorithm with S-VSM can better explain user's behaviors and content-oriented recommendation in the social network at: (1) We combine network topology of SNS with content-based recommendations; (2) Topic preference of target users will be adequately profiled via concept lattices; (3) The calculating of similarity between short text is solved well by improved S-VSM. By evaluations of Ranking Score, precision, HR, ARHR, and F-measure, the proposed recommendation algorithm via the FCA-based method and S-VSM can provide a more effective and personalized recommendation with high accuracy in the social network.

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