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A Context-Awareness Dynamic Friend Recommendation Approach for Mobile Social Network Users

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Mobile SNS (Social Networking Services) is a hotspot in the current mobile Internet field. Based on the user's context information like location and surrounding users, it has an important practical significance to dynamically recommend friends for mobile SNS users by mining the potential social relations. By combining the context-awareness, community division and ontology modeling, this paper presented a context-awareness dynamic friend recommendation approach for mobile SNS users, and the evaluation criterion of community division precision was given. This approach successfully addressed the user's dynamic feature and the sparseness of the existing social relations in the current mobile social networking sites. It has a positive significance to the development of the mobile social networking services. Finally, the rationality and effectiveness of this approach are verified based on a data analysis of a real SNS network site.

Keywords: Mobile social networking services; friend recommendation; context-awareness.

1. Introduction

Social networking service[1] is an online service, platform, or site that focuses on building and reflecting of social networks or social relations among people, e.g., who share interests and/or activities. A social network service essentially consists of a representation of each user (often a profile), his/her social links, and a variety of additional services. In a broader sense, social network service usually means an individual-centered service whereas online community services are group-centered. Social networking sites allow users to share ideas, activities, events, and interests within their individual networks. The emergence of SNS promotes a new development wave in the Internet field. Social networking sites and services, such as Facebook, MySpace, Twitter, QQ, Kaixin, have become primary communication media for a new generation social era. With the large-scale deployment of 3G /WLAN and popularity of smart phones, network bandwidth and mobile phone performance are no longer the bottleneck restricting the development of mobile SNS. Therefore, these traditional SNS sites rapidly penetrate to the mobile network users by providing terminal application software oriented to the smart phones. In this way, users can freely access to SNS sites anytime and anywhere. The amount of mobile SNS users is even more than that of traditional internet SNS users. However, the traditional SNS sites only provide a mobile access way for mobile users and the providing services did not fully consider the rich user context information (such as location, preferences). So the potential values integrating mobile computing with social computing have not been fully mined. In the recent years, some professional location-based mobile SNS sites are emerging and users can know the locations of their friends or the surrounding points of interest (such as restaurants, bars, etc.) in real time. These new mobile SNS applications have created some new business models. For example, users can "check in" the point of interest and the business company will give some gifts like cents-off coupons to the regular customers, such as Foursquare[2]. Currently, mobile SNS play the very important roles and its commercial value and market prospect are very optimistic[3 4].

The friend recommendation is one important feature of social networking services. SNS maps the real relationship network to information space. A large-scale complex network is formed by the connection relationship between the friends. In 1998, Watts and Strogatz proposed that a complex network has the small-world effect[5]. In 1999, Barabasi and Albert pointed out that many real networks are scale-free networks[6]. In fact, real social networks not only have the small-world and scale-free features, also show the obvious community structures[7 8]. For the social network, the users belonging to the same community have a closer relationship. The discovery of community structure in social network will contribute to a more profound understanding and awareness of the inherent relationship. And the reasonable division of the community has important application value, such as the friend recommendation or precise marketing based on the specific policy community discovery. Compared with the traditional SNS, mobile SNS greatly enhance the user's authentic and regional characteristics[9]. Some more interesting applications can be developed[11 12 13]. In real life, sometimes certain mobile SNS users gather together at a specific time and specific location, such as conference, meeting or other activities. How to dynamically build up a temporary community for these gathering people to facilitate smooth exchanges and expand the social relations has important practical significance and research value. However, compared with traditional SNS oriented to Web users, the community discovery of mobile SNS is facing tow new challenges: (1) **The dynamics of user groups**: the existing community discovering methods are mainly oriented to static social relation network information. Initially, users need to manually establish the connection relationship between friends. And then system will recommend new friends to users according to the number of common friends. In this way, users can expand their social network constantly. Several algorithms have been proposed to address the community discovery problem of complex networks10. In recent years, the related study work in this field has turned to hierarchical clustering method. However, these existing community discovery algorithms mainly aimed at static social relationship network. Mobile SNS are more concerned about the dynamic change of user groups, such as user location changes over time.

Therefore, the traditional community discovery algorithms oriented to the static social network can not be directly used to address the dynamic discovery of mobile SNS community with the time and location sensitive environment. (2) **The sparsity of user relationship network**: In real life, the social relationship networks of mobile SNS site are often incomplete, and only a part of the real social circles. It means that the users who have the friend relationships in real life may not establish the connection relations in the SNS sites. Thus, for the temporarily gathering mobile SNS users, if we still directly use the existing friend relationships in SNS sites to conduct the community division or friend recommendation, the results will be a very sparse relationship network in many cases. The size of each community is likely to be very small, but the number of community might be too many, and even a lot of isolated nodes will arise. Many uses having the hidden social connections can not be recommended as friends. The goal of expand the social relationships by dynamically building community could not be achieved. Therefore, how to mine the hidden social relationships (such as alumni, fellow-villager, senior and junior fellow apprentice) among the temporarily gathering mobile SNS users and then add these hidden social connections to the existing sparse relationship network to form a relatively dense relationship network is a meaningful research topic. Based on this dense network, users can find more interested friends and then expand their social circles. This will greatly improve the user's experiences.

To address the above new challenges of mobile SNS, this paper presented a user dynamic recommendation method for mobile community by integrating community discovery with context-awareness and ontology modeling technologies. This approach firstly mines the hidden social relationships among mobile SNS users by employing semantic reasoning. This step can facilitate the formation of relatively dense social network. And then based on this dense social network, the community division algorithm can be conducted to cluster the users. Experiments show that this approach can effectively solve dynamic community discovery problem under the dynamic user groups and sparse relationship network conditions. The community division modularity is more visible and the accuracy of the dynamic community recommendation is effectively improved.

The rest of this paper is organized as follows: Section 2 mainly proposes a dynamic recommendation method for mobile SNS community based on the user context information. In section 3, the experiment environment and results are introduced. At last, conclusions are drawn in section 4.

2. The Context-awareness Friend Dynamic Recommendation Approach

In generally, the context is any environment character information that can be used to indentify an instance, such as the person, the location as well as other objects interacted with users. Comparing with the traditional SNS, the mobile SNS combines mobile computing with social computing seamlessly and the context information around users is increasing significantly, for example, the capacity of mobile terminal, the user location (obtained via the GPS in the mobile phone or mobile networks), the presence information of user (e.g. online, offline, meeting and so on), the calendar on the mobile phone, the user preferences, the social relation of users and comments received from friends, so the mobile SNS can provide intelligent services whenever and wherever users want by mining and using these context information above. The paper mainly sets the user location, the social network and the personal information as the basis of dynamic recommendation in the mobile community.

2.1. *Location-based selection of user cluster in the mobile SNS community*

To build a mobile community dynamically, the first thing is to select some related users lived in the limited area as the basis of community division or recommendation. The existing SNS system consists of the client-side software in the mobile phone and the server-side software. There are two ways getting the user locations in the mobile SNS system. For the smart phone using GPS location, the client-side software running on the mobile phone uses the GPS to get the location automatically or manually. For the smart phone without GPS location, the mobile SNS system can keep track of user locations by using the mobile communication network. Once a user makes a request for creating a mobile community, the system will get the current location of the user first. Then the system will scan other users who are at the same place with the user mentioned before in order to create the user basis of mobile SNS community shown in Figure 1. The system can mine the latent social relation via analyzing personal attributes among these users, and then construct the interesting social network which is easy for information sharing and communication for people clustered dynamically.

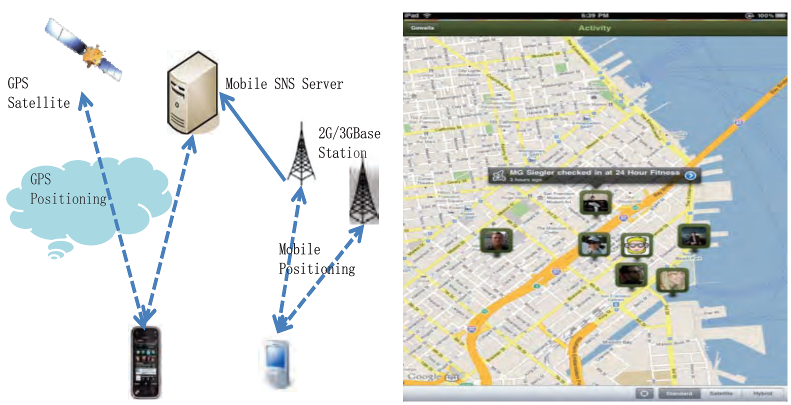

Fig. 1. The location-based selection of community user cluster.

2.2. *Latent social relation mining based on user's context*

There is still lack of direct friend relations among many friends in our real life because the existing SNS networks are not good enough, so the crowd gathered temporarily based on the location always constructs a very sparse relation network. If we divide the community directly based on the existing topology of friend relations, then the scale of the divided communities will be small, even there will be many isolated nodes. If so, the aim that recommending friends for users and extending the social relation network won't be reached, therefore, the mobile SNS system needs to mine latent social relations among the crowd automatically. Meanwhile, the user context information is the important resource for social relation mining. For example, the user information within the existing social network includes many kinds of personal information, such as school, hometown, workplace and so on. The relations about classmate, countryman and coworker are created using the previous personal information. Adding these latent social relations to the social network, which is essential for dividing mobile community reasonably, will create a denser topology of the relation network. Next, we mine the latent social relation by considering user's personal information. To make the description of social relation network clearer, we give some terms' definitions.

Definition 1 Real Relation: The relation that has been built for the user and his or her friends in the mobile SNS community is called the real relation.

Definition 2 Real Connection Graph: If we use V_0 and E_0 to express the set of community user nodes and the set of real relations respectively, then the existing social relation network among users can be described by the graph $G_0(V_0, E_0)$, which is called the real connection graph and shown in Figure 2.

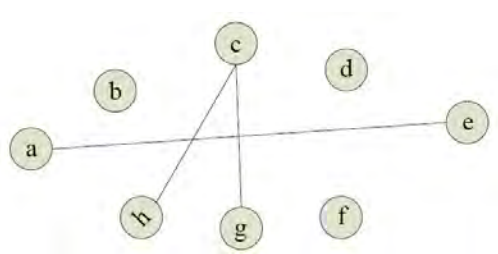

Fig. 2. The real connection graph.

Definition 3 Virtual Relation: The temporary relation built by mining one or some particular characters among users is called the virtual relation when the real relation that hasn't been built.

Definition 4 Virtual Connection Graph: If we use V_0 and E_0' to represent the set of community user nodes and the set of virtual relations respectively, then the latent social network among users can be described by the graph $G_0'(V_0, E_0')$,which is called the virtual connection graph.

Definition 5 Attributes of Virtual Relation: Any virtual relation between two users has a particular meaning in the virtual connection graph. The attributes, which can be used to build the virtual connection between two users, are called the attributes of this virtual relation. For example, the dotted lines represent countryman relations in Figure 3.

Definition 6 Attribute Relation Graph: The set of community user nodes is shown as V_0. The set of virtual relation with respect to one particular attribute of virtual relation x is shown as E'_x. The relation graph among community users built by using x is shown as $G'_x(V_0, E'_x)$, which is called the attribute relation graph.

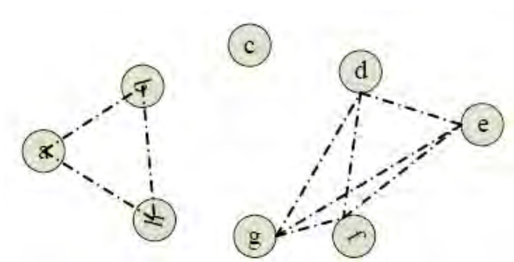

Fig. 3. The countryman relation graph.

Definition 7 Full relation graph: Supposing we define n different attributes of virtual relations, then the full relation graph $G_F = \bigcup_{i=1}^{n} G'_i \cup G_0$ shown in Figure 4.

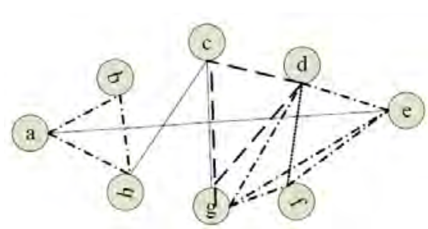

Fig. 4. The full relation graph.

From above we can find that the full relation graph not only contains the existing relations among community users, but also has the latent social relations added newly, so the full relation graph solves the problem of sparsity of relations among mobile community users well and then build the basis of community division and recommendation.

To mine the latent social relation among users, we need to analyze and compare the attributes among users. The current description of personal information

Table 1. OWL ontology Inference rules

Transitive-Property	(?P rdf: type owl: TransitiveProperty)∧(?A?P?B)(?B?P?C) ⇒(?A?P?C)
SubClassOf	(?a rdf: SubClassOf ?b) ∧(?b rdfs: SubClassOf ?c) ⇒(?a rdfs: SubClassOf ?c)
SubPropertyOf	(?a rdf: SubPropertyOf ?b) ∧(?b rdfs: SubPropertyOf ?c) ⇒(?a SubPropertyOf ?c)
equivalentProperty	(?a rdf: equivalentProperty ?b) ∧(?x?a?y)⇒(?x?b?y)
sameIndividualAs	(?X owl: sameIndividualAs ?Y) ∧(?V ?P ?X)⇒(?V ?P ?Y)

in the social network, however, is just a structured expression and only supports the grammar analysis. The information is lack of formatted expression and cannot support automatic semantic inference and analysis14. For example,"BUPT" and "Beijing University and Posts and Telecommunications" are actually the same university, from which the alumni relation can be inferred. The other example is that the countryman relation can be inferred from the fact that "Rongcheng City" and "Rushan City" belong to "Weihai City". But the computer cannot understand the latent semantic information automatically based on the existing modeling method for structured user information, therefore the grammar-based expression way of structured information is very difficult to mine the latent social relations among users inferred automatically by the computers. Meanwhile, the ontology is a specification of a representational vocabulary for a shared domain of discourse 15 and is the description of objective existences such as concepts and relations. And the ontology can get the formatted expression of concepts hidden in the analyzer's mind or the developer's program and reduce the misunderstanding caused by complex concepts and logical relations in the problem domain, therefore, to support the automatic inference and precise matching of user context in the SNS network and avoid the singularity of context, the paper proposes the method that use ontology to describe the personal information and this method can mine the social relation on the semantic level. Table 1 lists parts of rules of ontology inference. If we model the user context information (e.g. personal attribution, location and interpersonal relationship) in the mobile SNS network by using ontology, we can use inference rules based on ontology and user-defined rules to do the semantic inference. For example, the equivalence relation between individuals (sameIndividualAs) can be automatically used to infer the fact that "BUPT" and "Beijing University of Posts and Telecommunications" are the same university. The transitive inference rules of attribute can be used to get the fact that "Rongcheng City" and "Rushan City" are belong to "Weihai City", from which we can get the countryman relation.

To mine the latent virtual relation among users, the paper format the user's attributes in the community by using ontology. The FOAF (Friend Of A Friend)16,17 is an ontology that is used to describe users in the social network exclusively. The glossary of FOAF provides the basic expression for community users, such as name, email and so on. The Person Class in the FOAF is used to describe the information of all users but the information is not enough because the FOAF cannot describe some important personal information such as hometown, school and so on and this personal information is the essential context for mining the latent social relation among users, so the paper extents some attributes in the Person Class of FOAF shown in Figure 5, such as hometownls (the range of it is the Place Class), ofUniversity (the range of it is the University), ofschool (the range of it is the School Class), ofHighSchool (the range of it is the HIghSchool Class). Note that the University Class and the HighSchool Class are the sub-class of the School Class.

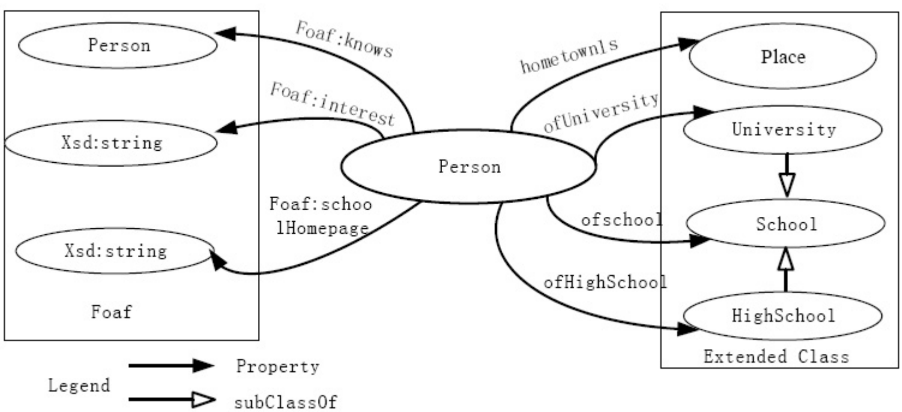

Fig. 5. The extension of social network ontology based on FOAF.

After the extension of social network ontology like above, the system can mine the latent social relation, for example, the latent countryman relation can be mined from the Person Class and the Place Class in the ontology. The hometown attribute of the user is hometownls($person, $place); the subordination attribute of different administrative level region is ContainedIn ($place1,$place2) and this attribute has transitivity; the attribute of countryman relation between persons is IsTownee ($person1,$place2) and this attribute has symmetry and transitivity. If a and b are the instances of the Person Class, and $x, x1, y, y1$ and z are the instances of the Place Class, and hometownls(a, x), ContainedIn$(x, x1)$, ContainedIn$(x1, z)$, hometownls(b, y),ContainedIn$(y, y1)$, ContainedIn$(y1, z)$, then we can get the result that hometownls(a, z), hometownls(b, z) and further get the fact that IsTownee(a, b), which means that a and b are countryman relation. The inference process is shown in Table 2.

Table 2. Inference of latent social relation of users

Input	Inference rules based on ontology itself	(?P1 ContainedIn ?P2) ∧(?P2 ContainedIn ?P3) ⇒(?P1 ContainedIn ?P3)
	User-defined Inference rules	(?A hometownls ?P1)∧(?P1 ContainedIn ?P3) ⇒ (?A hometownls ?P3) (?A hometownls ?P) ∧ (?B hometownls ?P) ⇒(?A IsTownee ?B) ∧ (?B IsTownee ?A)
	Explicit context	<Place rdf:ID=“Rongcheng City”> <ContainedIn rdf: resource =“♯Weihai City” / > < /Place> <Place rdf:ID=“Weihai City”> < ContainedIn rdf: resource =“♯Shandong Province”/ > < /Place> <Place rdf:ID=“Longkou City”> < ContainedIn rdf: resource =“♯Yantai City”/ > < /Place> <Place rdf:ID=“Yantai City”> < ContainedIn rdf: resource =“♯Shandong Province”/ > < /Place> <Place rdf:ID=“Zhang San”> < hometownls rdf: resource =“♯Rongcheng City”/ > < /Person> <Place rdf:ID=“Li Si”> < hometownls rdf: resource =“♯Longkou City”/ > < /Person>
Output	Implicit context	<Person rdf:ID=“Zhang San”> < hometownls rdf: resource =“♯ShanDong Province”> < IsTownee rdf: resource=“♯Li Si”> < /Person> <Person rdf:ID=“Li Si”> < hometownls rdf: resource =“♯ShanDong Province”> < IsTownee rdf: resource=“♯Zhang San”> < /Person>

2.3. *The division and evaluation approach of mobile community based on fully connected graph*

The G_F describes the topology of the social network and the vertex of the graph corresponds to persons in the social network, such as the registered members of the online community-Renren[19]. If the two persons in the SNS are friends, then there is the real relation between the two corresponding vertex. If there is an attribute of a defined virtual relation between two users, then the virtual relation will exist between two corresponding vertex. For the community discovery of a simple graph, we just group most nearest vertex that have same or similar attributes to create many clusters. The GN algorithm[7] given by Girvan and Newman in 2002 is widely used, which proposed that the edge betweenness of connection between clusters should be more than the one within a cluster. The edge betweenness of connection is the number of shortest paths between pairs of nodes that run along the connection. GN algorithm is to calculate the edge betweenness repeatedly, recognize and remove the connection between clusters, and create a hierarchical dendrogram by the way from top to the bottom. The main shortcoming of GN algorithm is slow computation because the computing cost of the betweenness is too large, which is $(O(mn))$, and the time complexity of GN algorithm is high, which is $(O(m^2n))$. But the scale of dynamic mobile community users is not large, so the paper adapts the GN algorithm.

To verify the result of community division more accurately, the paper introduces the term "prediction strength", which is first proposed by Tibshiranietal18 and is used to measure the credibility of cluster models generated from training set in the test set. Firstly, the whole data are divided in to two parts: training set and test set, which are represented by X_{tr} and X_{te}. Then the training set is divided into k clusters and the process of clustering is represented by $C(X_{tr}, k)$. In the test set, all samples are divided into k clusters $A_{k1}, A_{k2}, \cdots, A_{kk}$ using the same clustering algorithm. The n_{kj} represents the number of samples in the A_{kj}. One of k clusters is A_{kj}, and i and i' are the number of any two samples, and the range is from 1 to n_{kj}. When the test set is predicted based on the result of clustering the training set, the two samples i and i' are grouped into either the same cluster or the different ones. We can measure any two samples of A_{kj}. $D[C(X_{tr}, k), X_{te}]$ is a matrix, the element at the i-th row and i'-colume has two alternative values-0 or 1. The value is equal to 1 means that the two test samples i and i' are grouped into the same cluster while the value is equal to 0 means that the two test samples are grouped into different clusters. We can get the matrix like this one referring to every A_{kj}. The expression is as follows

$$\mathrm{ps}(k) = \min_{1\leq j\leq k} \frac{1}{n_{kj}(n_{kj}-1)} \sum_{i\neq i'\in A_{kj}} I(D[C(X_{tr}, k), X_{te}]_{ii'} = 1) \tag{1}$$

where ps is the abbreviation of the prediction strength and k is the argument of the prediction strength. According to the expression above, we can find that the prediction strength is actually the minimum of a serial of numbers and each number is the proportion of samples predicted correctly in clusters in the corresponding test set. The interval of the prediction strength is $[0, 1]$.

The paper makes the result of community discovery in the graph G_F containing all relations (friend, countryman, high school classmate and alumni) as the baseline. And we compare four cases of community discovery with the baseline: friend relation only, friend relation added with countryman relation, friend relation added with high school classmate relation and friend relation added with alumni relation. Meanwhile, we loose the assumption that the number of clusters is k for comparison and we change the minimum value to the mean value for the prediction strength. The updated expression of prediction strength is:

$$\mathrm{ps}_{rt} = \mathrm{mean}_j \frac{1}{n_j(n_j-1)} \sum_{i \neq i' \in A_j} I(D[C(X_{tr}, k), X_{te}]_{ii'} = 1),$$
$$r = 1,2,3,4;\ j = 1, \cdot, k_t,\ t = 1, \cdots, 30 \tag{2}$$

where, the r values of networks for friend relation only, friend relation added with countryman relation, friend relation added with high school classmate relation and friend relation added with alumni relation are equal to 1,2,3 and 4 respectively (the r value of the network containing all kind of relations is equal to 0); R_n is the data at the t-th test of the r-th network; k_t is the number of communities generated at the t-th test for the network containing all kinds of relations; A_j is the community element of the J-th community in the network containing all kinds of relations; n_j is the number of elements in A_j ; the matrix CD shows the comparison between the result of community discovery for the R_{rt} data and the discovery result of the t-th test for the network R_{0t} containing all kinds of relations.

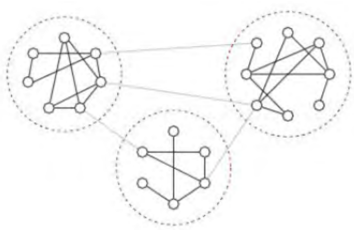

Fig. 6. The graphical model of a social network.

3. Experiment Analysis and Evaluation

3.1. *The experimental data set*

To get more accurate experiment result, we selected the real data of 1286 users from Renren.com. These user nodes and friend relations among users set up a small complex network, which consists of 1286 nodes and 21612 edges and shown in Figure 7.

3.2. *Experiment result and analysis*

In practice, the users in the particular area are located by the GPS. But in our experiment we get the user data randomly selected to simulate the real situation. We set 30 groups of data selected from the raw community data set randomly as the analyzing object. Each of 30 groups has 60 users and the relations among these users. The division of the community is conduced by the software R. The experimental

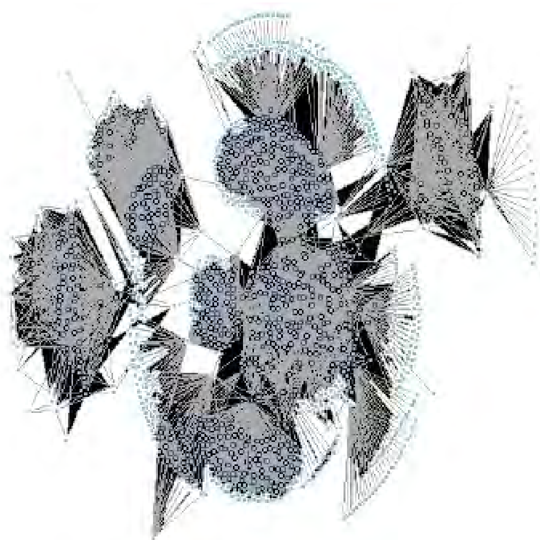

Fig. 7. The friend relation network selected from Renren.com.

environment includes 2.6GHz CPU, 2G memory, 160G hard disk and Windows XP. The basic user set composed of 60 nodes selected from the large network of relation with 1000 nodes is used to simulate the location-based temporary users. We run the comparison of effect of community discovery on the basic user set mentioned before and repeat the comparison 30 times to verify the statistical features of related statistics.

3.2.1. *The comparison of community division before and after mining the latent virtual relations*

The experiment demonstrates that the problem of sparsity in the community user relation network is solved well after mining the latent social relation among users by automatic inference based on ontology. The left side of Figure 8 shows a network topology about the existing friend relation and the right side is a fully connected graph after adding the latent social relation.

To compare the situation of community division after and before mining the latent virtual relations, the paper runs the community division of real connection graph and full relation graph separately. Through comparing the result of community partition of the real connection graph (the left side of Figure 9 and Figure 10) and the full relation graph (the right side of Figure 9 and Figure 10), we find that the relations are sparse and the number of communities is large in the real connection graph. It is very hard to find the latent social relation among users by using friend relations. Meanwhile, the relations are dense and the community relation is

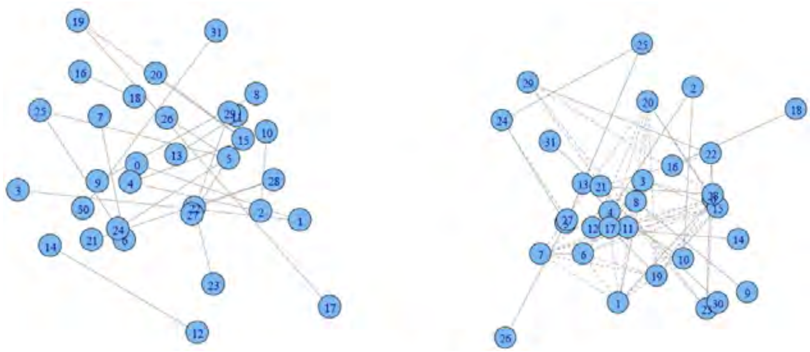

Fig. 8. The real connection graph and full relation graph of random network.

intensive, so we can find more friends via the friends of friends or other personal attributes.

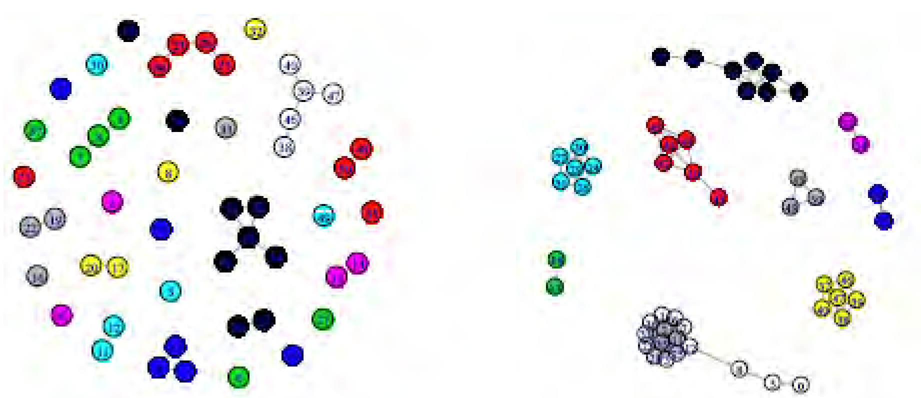

Fig. 9. The chart of result for community division.

3.2.2. *The statistical analysis of multi-times experiment results*

To make the comparison fair, all experiment use the same algorithm for community discovery. And we use the algorithm [6] based on the edge betweenness proposed by Girvan & Newman to make the experiment result stable. From Figure 11 we find that all relation networks are sparse in the experiment and the average edge betweenness of network containing friend relations only is 50 and the betweenness of network containing all kinds of relations is 150. After observing carefully, the change of the situation, the friend relation→the relation of high school classmate→the

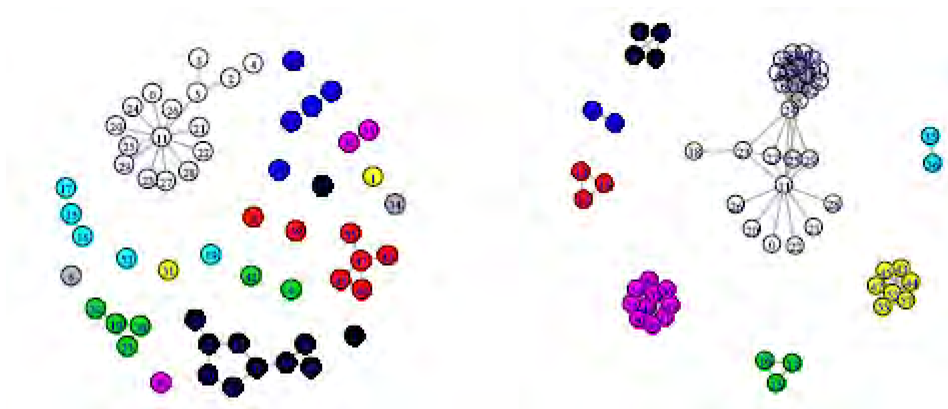

Fig. 10. The chart of result for community division.

countryman relation→the alumni relation→all kind of relations, shows that the number of relations is increasing, which tell us that the social network is gradually expanding. The increased number of relations in the network added with high school classmates is almost same as the number in the network added with countryman relation, both of which are significantly more than the network with the friend relation only. The effect of increasing in the network with the alumni relation is most significant. Of course, the number of relations in the network with all kinds of relations is most.

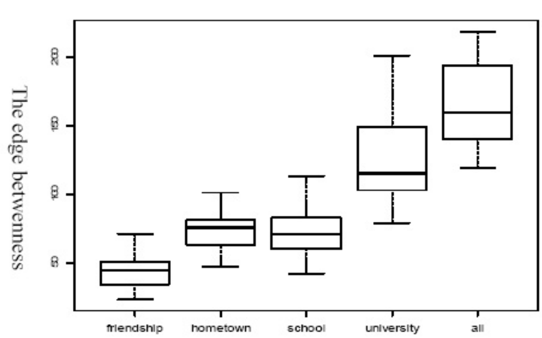

Fig. 11. The comparison of edge betweenness for different relation graphs.

Using the community discovery algorithm based on the edge betweenness for the relation networks above, we find that the number of communities is decreasing with the increase of relations. Figure 12 shows that the number of communities in the network with all kinds of relations is fewest, the average of which is 7. Next the average number of communities in the network with the countryman relation or the alumni relation is 17. The average number of communities in the network with the high school classmate relation also decreases significantly, which is 19. And the number of communities in the network with friend relation only is 25.

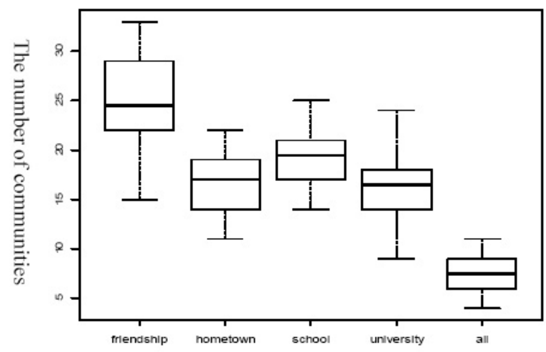

Fig. 12. Comparison for the number of community division of defferent relation graphs.

In generally, whether the samples can be divided is usually used to verify the performance of the clustering results. The difference in the traditional clustering analysis is measured by the distance, which means that the further the distance between clusters is, the more easily these clusters can be separated, so there are many clustering algorithm by defining different kinds of distances. But whether the samples can be separated is evaluated by the prediction performance for new samples by using the current clustering result in the prediction strength algorithm. This method holds the opinion that a reasonable clustering result is also suitable to the new samples, so the result obtained from the prediction for the new samples by using the existing data should have high degree of agreement with the result by clustering the new samples themselves. The prediction strength is the measurement for the degree of agreement. With the idea of the prediction strength and setting the result of community discovery for the network with all kinds of relations (friend, countryman, high school classmate and alumni) as the baseline, the paper evaluate four cases of community discovery, the community with friend relation only, the community with friend relation and countryman relation, the community with friend relation and high school classmate relation and the community with friend relation and alumni. Furthermore, the paper compares the impact degree of different relations for the effect of community discovery. The method proposed by this paper reaches the aim of discovering communities effectively by filtering the useless relations. The paper sets the network containing all kinds of relations as the baseline and calculates the effect of community discovery in other networks added with one kind of relation. The paper adopts the prediction strength as measurement that is the better the performance is, the more close to 1 the prediction strength is. After observing, we find that the effect of community discovery in the network with friend relation only is worst, the prediction strength of which is less than the 20% of the one in the network with all kinds of relations. The effect of community discovery in the network with the high school classmate relation is similar with the effect in the network with the alumni relation. The results show that the mining of hometown relationship is a very efficient approach for community division.

4. Conclusions and future work

Over the recent years the analysis of mobile community network is a hot research topic. Mining data with ontology and context knowledge is an effective method for improving the accuracy of data mining. This paper first combined the context-awareness with the ontology modeling and dynamic recommendation of mobile community and then proposed the context-awareness dynamic recommendation approach for mobile community. Next, the paper analyzed the result of community division. The approach not only solved the problem of community division in the sparse network, but also has high practical value. The experiment demonstrated that the user context-awareness recommendation approach for mobile community is reliable and accurate.

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