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A Dynamic Community Creation Mechanism in Opportunistic Mobile Social Networks

Daqing Zhang
Department of RST
Institut TELECOM SudParis
Evry, France 91000
Email: daqing.zhang@it-sudparis.eu

Zhu Wang, Bin Guo, Xingshe Zhou
School of Computer Science
Northwestern Polytechnical University
Xi'an, P. R. China 710072
Email: wangzhu@mail.nwpu.edu.cn
{guobin, zhouxs}@nwpu.edu.cn

Vaskar Raychoudhury
Department of RST
Institut TELECOM SudParis
Evry, France 91000
Email: vaskar@gmail.com

***Abstract*—Web-based social networking services enable like-minded people to collaborate and socialize with each other. With rich sensing and communication capabilities, mobile phones provide new possibilities for enhancing face-to-face social interaction among people who are both socially and physically close to each other. Research challenges arise as how to exploit the characteristics of people's mobility patterns and form a social community with a specific goal in the mobile environment. In this paper, we present SOCKER - a dynamic community creation mechanism based on social-aware broker selection strategies. SOCKER gradually forms a mobile social community by dynamically selecting a broker during each opportunistic encounter, and the selected broker disseminates community creation requests to the encountered users for match-making. Based on real human mobility traces, extensive evaluations are conducted showing that SOCKER achieves high community completion ratio as well as high user social satisfaction, while incurring a small overhead.**

***Keywords*-mobile social community; opportunistic networks; community creation;**

I. Introduction

The recent boom of Web-based social networking services (e.g., Facebook and LinkedIn) has been significantly improving human social connectivity by enabling effective online social interactions. While all these services lead to a social interaction shift from physical communities to virtual communities, we are not much better in the traditional face-to-face interactions. Currently even people who live or work in the same places miss opportunities to leverage inter-personal affinities (e.g., shared interests) for social interactions due to the lack of awareness.

The increasing pervasiveness of sensor-rich mobile phones, which are constantly carried by users, provides new possibilities of enhancing face-to-face social interactions among people. In general, people follow certain mobility patterns in daily life. These mobility patterns can be used to facilitate the dynamic formation of user group. As long as each of us carries a WiFi or Bluetooth enabled mobile phone and each group encounter forms a mobile ad-hoc network, the interactions among us can be viewed as Opportunistic Mobile Social Networks (OSNs). To facilitate face-to-face social interactions in OSNs, it is necessary to dynamically group users with similar characteristics, such as preferences, interests and goals. In this paper, we define such dynamically formed user groups in OSNs as Mobile Social Community (MSC).

The mobile social community creation problem has been studied from different aspects based on various criteria, such as, physical location and co-location, social relationship, and social activity [1], [2], [3], [4]. In this paper we focus on the creation of mobile social community in OSNs. Previous research work on OSNs exploit face-to-face social interactions to detect existing social community structures and facilitate the information dissemination in OSNs [5], [6]. Our work, instead, aims to enhance face-to-face social interactions through convenient formation of mobile social community in OSNs. This is a challenging problem because of the following issues:

First, while the Web-based social networking service is able to group like-minded people to collaborate and socialize with each other, it leads to a social interaction shift from physical communities to virtual communities. Hence, we need mobile social community to enhance face-to-face social interactions. Furthermore, as a user-centric service, the proposed mechanism should be easy to use as well as non-invasive.

Second, when organizing a specific social activity the expected number of participants is fixed. A community creation mechanism which may lead to overwhelming response would either lower the initiator's social experience or disappoint some of the interesters.

Third, when organizing social activities the initiators have different social goals. For social activities such as travels and football games, the initiator may want to make some new friends; for social activities like parties and picnics, the initiator may want to invite well acquainted friends. To provide high user social experience, various community creation strategies should be adopted to support different social goals.

We present SOCKER, a dynamic community creation mechanism which aims to facilitate social interaction in opportunistic mobile social networks, by leveraging adaptively selected social-aware brokers. Various community creation metrics and strategies have been investigated to meet the requirements of organizing different social activities, by means of dynamically creating communities in a way that achieves high community completion ratio as well as high user social satisfaction.

In summary, the main contributions of this paper include: (1)

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We transform the mobile social community creation problem into a single-copy based information dissemination and matchmaking problem in OSNs. (2) We come out with various community creation and evaluation metrics to address different social activity needs. (3) We propose an efficient dynamic community creation mechanism which can gradually form mobile social community and achieve high community completion ratio as well as high user social satisfaction.

The rest of this paper is structured as follows: in Section 2, we present the related work. In Section 3, we describe the community creation metrics used. In Section 4, we develop the broker selection strategies and the dynamic community creation algorithm. In Section 5, we present the simulation setup, evaluation metrics, benchmark and the experimental results. We conclude our work in Section 6.

II. Related Work

A. Community Creation in Mobile Social Networks

The first research area related to the work presented in this paper is community creation (group formation). Even though group formation is a well-studied research topic in Web-based social network, to the best of our knowledge quite little work has been done from the mobile social network perspective.

Urbiflock [1] supports dynamic user group creation based on user profiles and physical proximity. Users can semantically specify restrictions to create groups using smart phones. MobilisGroups [2] is a location based group creation service, and each created group is tied to a specific location. Urbiflock and MobilisGroups can be referred as geographic-based community creation systems.

Cluestr [3] leverages contacts from personal social networks to form groups. It aims to facilitate efficient initiation of group interaction from mobile terminals. Based on the fact that each user belongs to several social communities, Cluestr employs existing social networks to recommend contacts. ADESSO [4] supports opportunistic social networking based on a set of self-organizing brokers. A user who wants to participate in social activities specifies her/his preferences in a "user task" and publishes it to the elected brokers. Brokers collect user tasks and perform task matching once they encounter each other, and based on matching results users who share the same activity tasks will be notified. We classify Cluestr and ADESSO as social-based community creation systems.

Our work belongs to the social-based community creation category. However, it differs from the above approaches in the following aspects. Firstly, while Flocks and MobilisGroups aim to cluster users that are physically close to a specific location or a specific person (community initiator), and Cluestr can only recommend candidate members that are already in the initiator's personal contact list. SOCKER aims to leverage the opportunistic encounter characteristics of OSNs to create communities. Secondly, when initiating a community creation task the initiator may have different expectations about the candidate members. ADESSO doesn't address this issue, while in this paper we propose different strategies to meet diverse user requirements. Finally, while ADESSO is only designed to facilitate social activities among users who actively specify and publish community creation requests, the broker-to-user matching mode enables SOCKER to motivate inactive users to participate in more social activities, as long as they maintain activity profiles on their own smart phones.

B. Broker/Relay Selection in Opportunistic Networks

The research on relay selection strategies in opportunistic networks originates from epidemic routing [7], and mainly includes two different research approaches: non-socially aware routing and socially aware routing.

For non-socially aware routing, PROPHET [8] calculates the delivery predictability at each node by using encounter history, [9] employs some nodes with desirable mobility patterns as message ferries, [10] analyze the performance of mobility-assisted schemes theoretically, and [11] provides an unified approach on mobility-based metrics. Other work make contributions on improving data forwarding performance by either estimating the delivery likelihood [12] or calculating the cost-effectiveness before a new broker is selected [13].

Social-based data dissemination schemes in opportunistic networks have been studied based on various social network concepts including centrality and communities. SimBet routing [5] uses egocentric similarity and betweenness centrality metrics to calculate SimBet utility and select nodes with higher SimBet utility as brokers. In [14], one broker is selected for each detected social community to facilitate inter-community data exchange. BUBBLE [6] proposes a hybrid routing algorithm which selects high centrality nodes and community members of destination as relays.

Most of the existing research manage the data dissemination scheme from a multi-copy approach, which would lead to the asynchrony problem among different brokers for a size-fixed community creation task and can not been directly used in this paper. We have to adopt a single-copy approach to cope with the size-fixed community creation problem. Specifically, by considering the existing broker selection metrics and the specific requirement (e.g., size-fixed community, different social expectation), this paper adopts two broker selection metrics which are user popularity and inter-user closeness by employing users' mobility patterns.

III. Community Creation Metrics

In OSNs, community can be created based on similar characteristics of individuals, including physical and social characteristics. In some cases, communities can be created in advance; while in other cases, communities are dynamic and can only be created gradually. The specific strategy for the creation of MSC depends on initiators' social goals. As a basis, this section will present the two community creation metrics used in this paper.

A. User Popularity

We employ user popularity to describe a user's capability of meeting other people. Specifically, each user's device continuously logs the devices it encounters and uses these encounter

records to predict how many users she/he is likely to meet in a forthcoming period ΔT. We define this predicted value as user popularity $Pop_{\Delta T}(u_i)$. Intuitively, a user with high popularity is likely to meet more other users and thereby accelerate the community creation process. In this paper we adopt weekly-popularity, which measures the amount of users one expects to meet in the next week.

The weekly-popularity value is acquired based on historical encounter records, and various calculation methods can be adopted. A basic method is to calculate the average of historical popularity values, which can be regarded as assigning the same weights. Considering that the human mobility pattern varies from time to time, a reasonable assumption is that:

Assumption 1: the recent historical popularity values should be able to reflect the future popularity more exactly and thus should be given higher weights than earlier values.

If this assumption holds, a better method is to introduce a forgetting factor to the historical popularity values and only the recent encounter records (within a window size of S) should be considered. Hereby, weighted weekly popularity (*WWP*) can be formally defined as:

$$WWP(u_i) = \sum_{s=1}^{S/7} w(s) HWP(u_i, s). \tag{1}$$

In Formula 1, *HWP* stands for the *historical weekly popularity*, and $w(s)$ is a weight vector for *HWP*. Obviously, the average weekly-popularity (*AWP*) can be regarded as a particular case of *WWP*, where the *HWP* has been assigned with the same weights.

B. Inter-User Closeness

According to the findings in [15], users who are socially close to each other are also likely to encounter each other more frequently; thereby an assumption is:

Assumption 2: a broker socially close to the initiator is more likely to encounter users that are familiar to the initiator and effectively facilitate inter-community social interaction.

Based on this assumption, we adopt inter-user closeness as the second metric which describes the relationship strength between two users. Similar to user popularity, inter-user closeness is also calculated based on historical encounter records. Specifically, considering that spending a couple of hours in close proximity on a Saturday night is quite different from spending a couple of hours on a Wednesday afternoon [15], encounter time should be an important factor to describe inter-user closeness, where the chance of non-working time encounters among friends should be much higher than non-friends. Consequently, we divided encounter records into two parts according to the encounter time: working time encounters and non-working time encounters. In particular, only encounters that occur during non-working time (including 8 p.m. to 8 a.m. of weekdays and the whole day of weekends) are used to calculate inter-user closeness.

We define encounters that occur during non-working time as valid encounters. Then, for each day within the window size of encounter records, the inter-user closeness value γ between two users increases to (γ+1) if these two users have at least one valid encounter during this day. Inter-user closeness between u_i and u_j can be defined as:

$$\gamma(u_i, u_j) = \sum_{s=1}^{S} \theta_t, \text{ where}$$
$$\theta_t = \begin{cases} 1 & \text{if } \exists\, e \in E(u_i, t), e \text{ is a valid encounter} \\ 0 & \text{otherwise} \end{cases}. \tag{2}$$

In Formula 3, $\gamma(u_i, u_j)$ represents the inter-user closeness value between user u_i and u_j.

IV. Dynamic Creation of Mobile Social Community

The strategies used for the creation of a mobile social community depends on the type of the community. In this section, we present a dynamic community creation mechanism by leveraging adaptively selected socially-aware brokers, which can effectively facilitate *social-activity-based* creation of mobile social communities.

A. Broker Selection Strategies

As we have mentioned when organizing a social activity the initiator may have different social expectations about the members. For some activities, the initiator may want to make some new friends, and this kind of activity is defined as *open-activity*; for other activities, the initiator may hope participants to be familiar ones, and this kind of activity is defined as *close-activity*. Thereby, different broker selection strategies should be adopted to satisfy activity initiators' social expectations.

1) Broker Selection for Open-Activity: To facilitate open-activity driven community creation, we leverage user popularity when constructing the broker selection strategy. As a first step, we put forward the following broker selection rule:

Rule 1: For a open-activity driven community creation task t_n, once its current broker u_i joins a new mobile ad-hoc network Net, a new broker will be selected if and only if there is an user u_j who has the highest popularity in Net and $Pop(u_j)$ is higher than $Pop(u_i)$ as well. This rule can be formally defined as:

$$\begin{gathered} B(t_n) = u_j \leftarrow B(t_n) = u_i, \\ \text{iff } Pop(u_j) > Pop(u_i), \text{ where } u_j \in Net \\ \& \ Pop(u_j) = \max\{Pop(u_x), \forall u_x \in Net\}. \end{gathered} \tag{3}$$

In Formula (3), $B(t_n)$ denotes task t_n's broker, and $Pop(u_i)$ denotes user u_i's popularity.

2) Broker Selection for Close-Activity: When organizing a close-activity, the initiator usually hopes that the participants are socially close to him. Thus, based on Assumption 2, we introduce the following broker selection rule for the close-activity.

Rule 2: For a close-activity driven community creation task t_n initiated by user u_x, once its current broker u_i join a new mobile ad-hoc network Net, a new broker will be selected if and only if: (1) there is an user u_j who has the highest popularity in Net and $Pop(u_j)$ is higher than $Pop(u_i)$ as

Algorithm 1: ***SOCKER*** - Dynamic Community Creation

Input: User u_x initiates a community creation task t_n and specifies the Required Community Size (*RCS*) and the Creation Expiry Time (*CET*).
Output: Matched User List (*MUL*).

1 Current Community Size (*CCS*) = 0; *MUL* = NULL;
2 a broker selection strategy is selected based on t_n's type;
3 u_x publishes task t_n and become the first broker $B(t_n)$;
4 **repeat**
5 **for** *each mobile ad-hoc network* Net *that* $B(t_n)$ *joins* **do**
6 each u_i in Net calculates its *WWP*;
7 $B(t_n)$ estimates whether there is a better broker;
8 **if** u_j *is the best broker candidate* **then**
9 $B(t_n)$ = u_j; *%broker switch*
10 **end**
11 **for** *each user* u_i *in* Net **do**
12 **if** u_i*'s profile matches task* t_n **then**
13 *MUL*.add(u_i); *CCS* = *CCS* + 1;
14 **if** CCS $\geq$ RCS **then**
15 break;
16 **end**
17 **end**
18 **end**
19 **end**
20 **until** *CCS* $>$ *RCS* & *CurrentTime* $>$ *CET*;

well; and (2) the inter-user closeness $\gamma(u_j, u_x)$ is higher than a given threshold Γ. Rule 2 can be defined as:

$$\begin{gathered} B(t_n) = u_i \leftarrow B(t_n) = u_j, \\ \text{iff } Pop(u_j) > Pop(u_i) \ \& \ \gamma(u_j, u_x) > \Gamma, \\ \text{where } u_j \in Net \\ \& \ Pop(u_j) = \max\{Pop(u_x), \forall u_x \in Net\}. \end{gathered} \tag{4}$$

B. Dynamic Community Creation

Based on the above proposed community creation metrics and strategies, we present SOCKER - a dynamic community creation algorithm as shown in Algorithm 1.

Algorithm 1 presents the procedure for the dynamic creation of social activity driven communities. Once join a new mobile ad-hoc network, the current broker initiate a broker selection process and a new broker will be selected if broker switch condition is satisfied (step 6-10). In case a broker switch event happens (step 9), the former broker will stop acting as broker and pass all the data to the new broker, including task specification, *CCS*, *MUL* et al. This avoids the asynchrony problem among multi brokers and guarantees the consistency of the OSNs. The broker pushes tasks to every member in the mobile ad-hoc network where task matching is performed (step 12). It is worth notice that such a mechanism ensures the protection of individual's privacy. A community creation task is successfully accomplished if and only if the target number of members are found before *CET* (step 20).

V. Evaluation

This section presents the performance evaluation of the SOCKER mechanism. We begin with the description of the simulation setup and the evaluation metrics. We then list the experiments conducted and analyze the results obtained.

A. Simulation Setup

1) Mobility Traces: The MIT traces contain co-location information from 106 subjects (staff and students) at the MIT campus over the 2004-2005 academic year. These subjects were equipped with Bluetooth-enabled Nokia 6600 phones, and their co-location information was collected via frequent (every 5 minute) Bluetooth device discoveries. To make the dataset more manageable, we extracted 12 weeks of co-location data, corresponding to the duration between Sept. 13th and Dec. 7th 2004. Specifically, the first 8 weeks were used as training dataset and the last 4 weeks were used as testing dataset; during the selected period, there are 84 active users.

2) Social Network: We employed the inter-user closeness metric defined in section IV to construct the social network in this paper. The constructed 84×84 matrix contains 1976 non-zero values. Particularly, the social network based on this matrix is a weighted network, where the weights depend on the intensity of co-location between each pair of users. This implicit social network extraction allowed us to tie real social behavior with the actual user movement.

3) Social Activity Simulation: While real world human mobility traces are available, social activity related information does not exist in the MIT dataset. To evaluate the proposed mobile social community creation strategies, we assume that: (1) there are only 10 different social activity types; (2) each user u_i has p_i different activity preferences, where p_i is a random integer ($0 \leq p_i \leq 10$); (3) for every user u_i, we randomly select p_i social activity preferences from the 10 types; (4) each user has 5 preferences on average; (5) in each simulation experiment, we randomly generate 100 social activity, where both the initiators of these activity and the time to publish these activity are randomly selected.

B. Evaluation Metrics

We employed the following three metrics:

1) Community Completion Ratio: The first metric we used is community completion ratio (*CCR*) which is defined as the percentage of successfully created mobile social communities. It measures whether SOCKER is able to effectively support social activity based community creation. However, while community completion ratio is a valuable metric for the open-activity based community creation, it is not sufficient for the close-activity based community creation, as for such close-activity we concern more about user social satisfaction.

2) User Social Satisfaction: We introduce the user social satisfaction metric (*USS*) to quantify how well the system performed in creating close-activity driven communities, based on the extracted social network. The optimal result for a user u_i who initiated task tn should be that all the members of the created community are socially close to the task initiator.

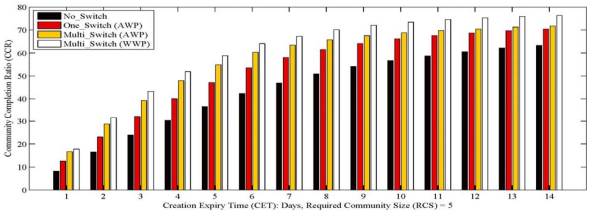


Fig. 1. *CCR* performance of different user-popularity driven approaches.

The sum of inter-user closeness between user u_i and each community member u_j is defined as u_i's social satisfaction provided by the system which can be formally described as:

$$USS(u_i, t_n) = \sum_{j=1}^{RCS} (\gamma(u_i, u_j)), u_j \in MUL(t_n). \quad (5)$$

In Formula (5), $USS(u_i, t_n)$ stands for user u_i's social satisfaction on task t_n, and $MUL(t_n)$ is the matched user list of task t_n.

3) Overhead: Overhead in SOCKER includes both the broker-to-broker activity transfer cost (*ATC*) and the broker-to-user activity matching cost (*AMC*). For the evaluation of both *ATC* and *AMC*, only the overhead entailed by brokers will be considered. The data exchange between non-broker users (e.g., the exchange of user popularity) will not be taken into account as it is the same for different broker selection strategies and community creation algorithms.

C. Benchmark

We compare the performance of SOCKER scheme with the following approaches:

No-Switch, in which the activity initiator acts as broker itself, and broker switch is not allowed.

One-Switch, in which each activity task can have at most one broker, in other words, each activity task can only be transferred once at most.

Multi-Switch, in which each task can be transferred for multiple times, until the completion of community creation or the expiration of creation time. Different from the SOCKER scheme, this approach selects brokers only based on average user popularity. Neither weighted popularity nor inter-user closeness is considered.

D. Experimental Results

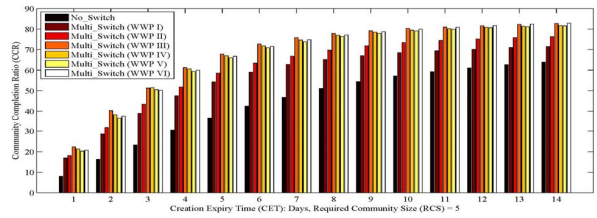
In this section, we evaluate the performance of the proposed SOCKER scheme based on the above mentioned simulation setup, evaluation metrics and benchmark.

The simulation settings vary from the basic setting, where *RCS* is set as 3, 5 and 7 (number of members) respectively while *CET* is assigned as 1, 2, 3, ..., and 14 (days). The experiment results are shown in Figure 1.

1) Does broker based community creation approaches improve the CCR: According to Figure 1, it is obvious that broker based community creation approaches provide much higher *CCR* than no-broker approach, and multi-switch approaches perform better than the one-switch approach.

TABLE I
WEIGHT VECTORS

	1	2	3	4	5	6	7	8
I	1/8	1/8	1/8	1/8	1/8	1/8	1/8	1/8
II	0.02	0.05	0.08	0.11	0.14	0.17	0.20	0.23
III	0.00	0.00	0.00	0.00	0.10	0.20	0.30	0.40
IV	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.50
V	0.00	0.00	0.00	0.00	0.00	0.00	0.30	0.70
VI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00



(a) *CCR* performance of different weight vectors.

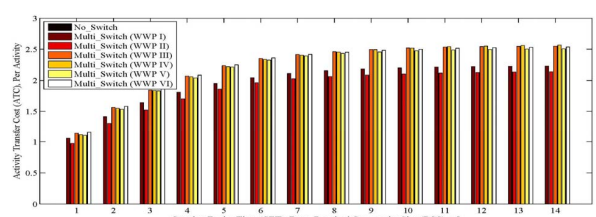
Fig. 2. Performance of different weight vectors.

The above results indicate that the broker based approach is efficient for the creation of mobile social communities. This is because different people have different user popularity. On the one hand, a user with high popularity is capable of encountering more people, hereby accelerating the community creation process. On the other hand, an activity initiator who has low popularity may not be able to complete the community creation task on her/his own. Therefore, the introducing of brokers can increase the *CCR* within the given *CET*.

2) Does Assumption 1 hold: To evaluate this, we introduce 6 different weight vectors, as shown in Table I.

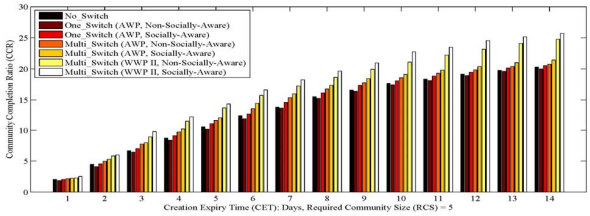
According to the experimental results shown in Figure 2, different weight vectors produce different performance. In general, the *WWP* approach (*WWP* II, III, IV, V, and VI) produces higher *CCR* than the *AWP* approach (*WWP* I, which is the same as *AWP*). Specifically, *WWP* III provides the highest *CCR* and *WWP* VI performs a little bit poor. According to Figure 2(b) both *WWP* III and VI introduce similar *ATC* as the others. Furthermore, these approaches also introduce similar *AMC*, we didn't present the result due to space limitation. fig:two:a

The above results can be explained as follows. First, while both *WWP* II and III adopt a gradually increasing approach, they use different encounter records window size, which are



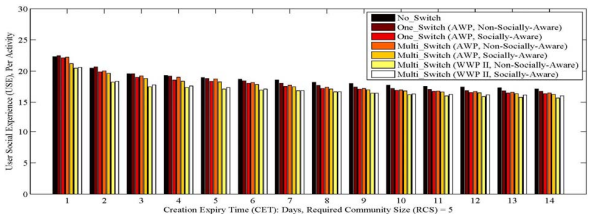
(b) *ATC* performance of different weight vectors.

Fig. 2. Performance of different weight vectors.



(a) *CCR* of non-socially-aware and socially-aware approaches.

Fig. 3. Performance of non-socially-aware and socially-aware approaches.



(b) *USS* of non-socially-aware and socially-aware approaches.

Fig. 3. Performance of non-socially-aware and socially-aware approaches.

8 weeks and 4 weeks respectively. This indicates that the latest month's historical data is enough to select the most efficient brokers. Second, the fact that *WWP* VI provides a good performance suggests that the latest week's encounter records are most influential.

Therefore, Assumption 1 holds due to the fact that the *WWP* approach is much more cost-effective than the *AWP* approach.

3) Does Assumption 2 hold: According to the definition of close-activity, initiators of such activities want the matched members to be socially close. We adopted both the non-socially-aware approach and the socially-aware approach to create close-activity driven communities, where the socially-aware approach takes both user-popularity and inter-user closeness into consideration to select brokers. As shown in Figure 3(a), the socially-aware community creation approach produces much higher *CCR* than the non-socially-aware approach. Meanwhile, the socially-aware approach is also much more cost-effective as the non-socially-aware approach introduces a lot of meaningless *ATC* and *AMC*, we didn't present the results due to space limitation. In addition, Figure 3(b) revealed the *USS* performance of different community creation approaches. Given the same *CET* value, the socially-aware approaches can produce similar *USS* as the corresponding non-socially-aware approaches. Meanwhile, it is understandable that the *USS* values decline gradually as the *CET* increases.

Thereby, Assumption 2 holds due to that the socially-aware approach can produce better performance. *It should be pointed out that while all the above observations are obtained based on experiments where RCS is set as 5, these observations also hold for other RCS values.* Due to space limitation, we didn't present the results by changing RCS values.

VI. Conclusion

While Web-based social networking services enable virtual interactions between socially related people, the widespread adoption of mobile devices will foster physical interactions between people who are not only socially but also physically close to each other. In order to facilitate face-to-face social interactions in opportunistic mobile social networks, we presented SOCKER, a dynamic community creation mechanism which is able to gradually form mobile social communities based on opportunistic encounters. SOCKER provides several community creation metrics and strategies to achieve the goal of organizing different social activities, by means of dynamically creating communities in a way that produces high *CCR* as well as high *USS*. The preliminary evaluation confirmed that SOCKER can effectively support the creation of mobile social community.

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