Hybrid SN: Interlinking Opportunistic and Online Communities to Augment Information Dissemination

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***Abstract*—In modern life, people are involved in multiple online and offline social communities. Previous works on content sharing and information dissemination are single-community oriented. The complementary features as well as the joint-effect of distinct forms of social communities, however, has not been well explored. In this paper, we present hybrid social networking (HSN), which highlights the interweaving and cooperation of heterogeneous communities. In particular, we present and demonstrate how HSN augments information dissemination in human daily life. The infrastructure, community creation and cross-community information dissemination algorithms, and a use case of HSN are presented. A real mobility trace of 104 users is employed to validate the performance of HSN, in comparison with single-community dependent methods.**

Keywords- Hybrid social networking, opportunistic community, ad hoc networks, information dissemination, social features

I. INTRODUCTION

People now connect and interact in heterogeneous social communities within cyber-physical spaces. Two forms of social communities have gained particular popularity in recent years. The first type is *online communities* in the virtual world, where people are connected by sharing content, opinions, and experiences in Web-based social network services (e.g., Facebook, Twitter). The second type is *opportunistic communities* in the physical world [1-5], which exploits opportunistic contacting and ad hoc connection between pairs of devices (e.g., mobile phones, vehicles) to disseminate information (e.g., local traffic information, public profile). It mimics the way people seek information via social networking through direct, face-to-face contacts.

The two forms of communities have distinct features. First, *they have distinct formation manners and exist in separate spaces*. Online communities enable people to foster interaction with their friends irrespective of physical distance in the virtual space, while opportunistic communities pertain to traditional way of interaction to people within physical proximity. Second, *they differ from each other on infrastructure support and work environments*. Online communities rely on services in the network infrastructure, and can be accessed to people in the environments with Internet connection (e.g., at home, in the office, hot spots with wireless access points). Opportunistic communities are developed based on mobile ad hoc networks (infrastructure-less), where co-located users can build connections leveraging short-range radio techniques (e.g., Bluetooth). They have advantages on connecting and providing collaboration services to traveling users, who have difficulty in connecting the network infrastructure [1, 2, 5]. Although there are many differences, the two forms of communities also share some commons. For example, they all facilitate information dissemination and social collaboration among users. Further, people are involved in both forms of communities, and they often switch their roles among them (or co-present in one more communities) in their daily life.

In the past few years, significant research efforts have been made on facilitating information sharing in both online and opportunistic communities. However, they follow separate research lines, and the interlinking of the two forms of communities has little been explored (see Section 2). In this paper, the *hybrid social networking* (HSN) infrastructure is proposed. It is inspired by the multi-community involvement and cross-community traversing nature of modern people. For example, at one moment, Bob is staying at a place with Internet connection and he can communicate with his online friends (in the *online community*); later, he may travel by train with merely ad hoc connection with nearby passengers (forming an *opportunistic community*). Here we use HSN to indicate the smooth switch and collaboration between online and opportunistic communities. By aggregating the complementary features of both networks, HSN can enhance the efficiency and population coverage of information dissemination in comparison with single network environments. We illustrate the concept of HSN through the following "*opportunistic trading*" use case.

Bob has a "Harry Potter" book, and he wants to sell it by using OBuy. OBuy is a HSN service that supports sell/buy request dissemination & matchmaking across heterogeneous communities. Bob's request is firstly published and shared in the ***online community*** *(a social network site). If no online-match exist, it is disseminated in opportunistic networks by exploiting the opportunistic contact of OBuy users. To augment the dissemination process in opportunistic networks, several friends of Bob from the* ***online community*** *are chosen as "brokers" (to carry and forward Bob's request). When Bob and the selected brokers move in the physical world, the request is replicated to physically adjacent people (forming* ***opportunistic communities****) and matched. Once a match is detected, the potential "buyer" is informed and the transaction can then be conducted.*

The above use case demonstrates the floating of information over heterogeneous communities. In the following sections, we will firstly present the related work on HSN. The conceptual model of HSN and its enhancement to information dissemination will be described in Section 3, followed by the elaboration of HSN's main building blocks, including community creation, online broker selection, and cross-community information dissemination protocols. Section 5 reports the experiments to validate the profits of HSN, which is based on real human mobility traces collected from sensor-equipped mobile phones. We conclude our paper in the last section.

II. RELATED WORK

The work presented in this paper brings together research on social connection and information sharing/dissemination in communities, spanning two major directions: *online communities* and *opportunistic communities*.

Online communities exist in many forms in the virtual world, such as those based on friendship (e.g., Facebook), profile similarity or common interests (e.g., LinkedIn, Twitter, YouTube), location-dependence (e.g., FourSquare), and so on. Individually each form indicates a certain type of connection or similarity between people [6]. In other words, people in online communities are linked based on their existing social relationships or feature similarity. When people connect in online communities, they can share information with their social links. For example, LinkedIn allows users to share their profile and work experience with their directed links. The mobile social network application CenseMe [7] exploits smart phones to automatically infer people's presence (e.g., walking on the street) and then shares this presence with their friends. However, since the linkage relations in online communities are mostly static, the "audience" covered for the information shared is usually limited.

Opportunistic communities are formed spontaneously (in an ad hoc manner) in the physical world, following the way humans come into contact. Unlike online communities, people in opportunistic communities are connected based on chiefly physical proximity. The members of an opportunistic community can share content with each other, but consumers of a content may not be involved at the same time in the same community (opportunistic communities are not formed based on common interests). Benefiting from its human-centric nature, information from an opportunistic community can be opportunistically disseminated (to potential interested users) when its carriers move (from one opportunistic community to another) [1]. However, this usually comes at the price of additional delay in information delivery. Therefore, many studies have been conducted to achieve efficient information dissemination in opportunistic networking environments. A trivial solution is epidemic-like flooding, where all users contacted become the so-called "brokers" to carry and forward the shared information [8, 9], but this would clearly saturate both network resources (in terms of available bandwidth) and device resources (e.g., in terms of energy, storage, and so on). A better solution is to replicate the information to only "selected" nodes that have more chances to contact and influence others. To this end, researchers start to explore *mobility patterns* [4,10,11] as key pieces of context information to predict nodes' activeness and estimate their "social popularity" to serve as brokers.

As reviewed above, research on online and opportunistic communities follow two separate research lines. The interlinking of the two forms of communities has yet little been explored. There have been studies about social network analysis across heterogeneous networks. For example, Tang *et al.* [12] developed a framework for classifying the type of social relationships by learning across different networks (e.g., email network, mobile communication network). Researchers from CMU study the relationship between the users' mobility patterns and structural properties of the online social network, to identify the implicit social link between physical interaction and online connection [13]. However, to the best of our knowledge, the combination of the complementary features of distinct social networks to augment information dissemination remains unstudied.

Rather than viewing online communities and physical communities as competing entities, we think of them as complementary. In view of the cross-space presence and multi-community involvement nature of modern people, HSN is designed in a way that links virtual and physical social networks to enhance both. By combining the merits of both networks, HSN can (1) enlarge the population covered to a shared message in comparison with online social networks, and (2) decrease the latency of information dissemination comparing with purely opportunistic networks. Particularly, we demonstrate how HSN augments information dissemination through the opportunistic trading use case.

III. AN OVERVIEW OF HSN

This section provides necessary background information required to present the main contribution of this paper by presenting HSN-enhanced information dissemination and giving the architecture of HSN.

A. HSN-Enhanced Information Dissemination

Information dissemination in HSN can be formulated as follows. Users are by default involved in a global, online community C_{on}. When people moves, opportunistic contacts (co-located users) can form a series of opportunistic communities $\{C_{opp}(1 \sim n)\}$. Any user involved in a community is its member, and a user (e.g., u_i) often switches his/her membership while he/she moves (e.g., $u_i \in C_{opp}(i) \rightarrow u_i \in C_{opp}(j)$).

The information shared have two major types: *content* and *request*. Content dissemination refers to replicate the content from one node to another. Request dissemination has an additional requirement on request matchmaking (e.g., to match the buy/sell request in the opportunistic trading use case). In the following, we focus on presenting request dissemination. Requests from community members are shared within a community, which forms the request pool of this community, formulated as: $C(i).req$. For a given request r_i, we do not assume any particular destination of it; rather, the request is disseminated over and across the communities with a matched request of shared interests are the potential destinations of the message. In HSN, we say that request r_1 matches r_2 when the degree of similarity is above a predefined threshold δ; i.e., $sim(r_1, r_2) > \delta$ (r_1 and r_2 belong to the same $C(i).req$). Note that each request must have a time-to-live (TTL) [4, 10], before which the publisher of this request expects to receive at least one matched user. The request expires if no matched result is obtained during this period. For example, the sell request in the opportunistic trading use case can be set to one week.

In opportunistic network studies, to facilitate information dissemination, brokers are often used to carry and forward information, such as *epidemic*-brokers [8, 9] or *popular*-brokers (to select the nodes who are more likely to meet the largest number of people) [4, 14]. One basic assumption is used here, which considers that all users are willing to act as brokers (the so-called "selflessness brokers"). However, traditional broker-based protocols have several limitations. (*i*) The selflessness assumption does not always hold. According to social theories, most people are selfish [15, 16]. Since brokers have to contribute computational resources during the data carrying and forwarding process, a node may not be willing to forward packets for others. Therefore, previous algorithms may not work well since some packets are forwarded to nodes unwilling to relay, and will be dropped (the "data drop" issue). (*ii*) In existing popularity-based broker selection protocols [4, 14], brokers are chosen based on direct contact of popular nodes (whose popularity is higher than a predefined threshold). However, due to the dynamic feature of human mobility, popular nodes may not be chosen if the publisher does not meet them. Besides, it also suffers from high delay on broker selection. (*iii*) Existing opportunistic information dissemination protocols suffer from problems on task notification and termination. Due to dynamic network topology, when a matched user is found, how to notify the result to the publisher becomes a big challenge. Also, this result should also be informed to other brokers to terminate their dissemination task. The encounter-history based routing mechanism has been used to address this issue [10]. However, it suffers from the delivery failure problem due to the dynamic network topology. Moreover, the performance of routing-based approaches largely decrease when more brokers are recruited (and should be notified). The interlinking of online and opportunistic communities in HSN brings new opportunities to address the above three issues.

(1) *Social willingness based broker filtering*. To address the selfishness issue, existing studies have focused on using reputation-based approaches [17, 18]. We, instead, want to capture user selfishness in a more realistic manner, mainly from the social perspective. It has been observed that a selfish user is usually willing to help others with whom he/she has social ties (e.g., friends, coworkers, roommates), because he/she gets help from them in the past or will probably get help from them in the future [19]. We call it the *social willingness* phenomena. The broker selection protocol of HSN is founded on this phenomena, where a request from a publisher can be copied to a selected number of his/her acquaintances to release the data drop issue.

(2) *Popularity-based online broker selection*. Different from existing protocols, the online broker selection approach we proposed allows users to choose brokers *online* from his social connections (i.e., from the ones who are willing to contribute), while not requiring direct contacts with other users in the physical world. Users advertise their predicted popularity in the online community, and a publisher can choose the ones with highest-popularity among them. Online broker selection also decreases the time cost on task allocation: the selected nodes can be allocated the dissemination task with no delay if they are online, while offline brokers can be informed and obtain the allocated task once they are within an environment with Internet connection (hotspots, wired network, etc.)

(3) *Online task notification and termination*. With the integration of online and offline communities, the publisher can be notified about the matched node through online channels. The brokers can also be informed to terminate the dissemination task through online communication.

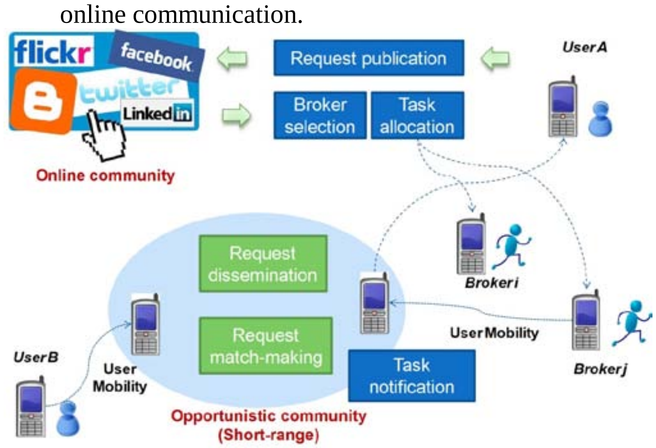

Figure 1. The HSN Infrastructure.

B. The HSN Infrastructure

We illustrate the infrastructure of HSN in Fig.1. There are two kinds of components: *online components (blue colored)* and *opportunistic components (green colored)*. Online components are used for the linkage between mobile nodes and the centralized online community server; opportunistic components are running on the mobile phone and for opportunistic communication with other mobile nodes in the proximity.

- *Online components*. *Request publication* component allows users to post their new requests (buying things, making friends) to the server. Upon receiving a request, the *broker selection* component will choose *k* brokers from the online community. The *task allocation* component allocates the request to the *k* selected brokers. The brokers will carry and opportunistically disseminate the request to the nodes they contact. The *task notification* component notifies the matched request to its publisher. The request is terminated by its publisher after a successful transaction.

- *Opportunistic components*. With the *request duplication* component, the publisher and selected brokers copy the handling requests to the mobile nodes within the range of short-range radio. The *request matching component* matches the requests a node carries with new coming requests.

IV. DETAILED DESIGN OF HSN

In this section, we present the main building blocks of HSN as well as the implementation of the HSN-based OBuy service.

A. Community Creation and Willingness based Broker Filtering

To address individual selfish based on social willingness, we have to extract the social relationship among users. There are many approaches that can be applied by HSN, such as extracting social connections from existing online social networks (e.g., Facebook), predicting social ties among users to create new online communities, and so on. In this paper, we focus on supporting user collaboration and information dissemination in urban environments (as demonstrated in the opportunistic trading use case), which raises a requirement to create city-dependent community. Note that we do not use friend lists that can be obtained from existing online communities, where "friends" may live far from each other (in different cities). Instead, we have proposed a contact-pattern-based community creation approach, which can derive social relations among users (as output) from historical user mobility traces (as input) to build an online community. The approach is described in detail below.

In [20], *contact time* (e.g., in the evening, at weekends) is used as an important predictor to identify interpersonal relation, where the ratio of encounters during non-working time is much higher for friends than non-friends. HSN has a broader definition about social relations, where we assume that people are willing to act as brokers for others with certain social ties, not merely friends. In other words, we do not distinct *family*, *friend*, or *colleague* relation, counting them whole as the "*familiar*" relation. We choose to characterize the familiar relation by means of two other important contact features: *contact duration* and *contact frequency*.

- *Contact duration*. The duration of a contact is the total time that a tagged couple of mobile nodes are within reach of each other. Friends, family members, and colleagues usually have long contact durations. Compared to encounters that last for a certain time period, short encounters (e.g., two persons crossing each other in the street) are less important for the calculation of familiar relation. We introduce a threshold δ for contact duration, and only those encounter records that last longer than the threshold are used to estimate inter-user closeness.
- *Contact frequency*. It is easy to understand that people who are familiar with each other usually have higher meeting frequencies. We use it as another predictor to identify the familiar relation.

The familiar relation is estimated leveraging historical encounter records. With the support of well-equipped mobile devices, long-term user meeting events can be tracked and recorded. However, the fact is that human often alters his social behaviors and thus causes the change of social ties (e.g., starting a new job). Therefore, when calculating the familiar relation, we should give the historical encounter records a valid period *VP*. Encounter records expire *VP* are meaningless for the measurement of familiar relation. We use φ to represent the sum of valid encounters of two users (u_i and u_j) within the *VP* of encounter records, formulated in (1):

$$\varphi(u_i, u_j) = N_{VP}(u_j) \quad (1)$$

Where: $N_{VP}(u_j)$ is the number of valid meeting times with u_j within *VP* period.

The familiar relation between u_i and u_j can be represented as:

$$BeFamiliar(u_i, u_j) = \varphi(u_i, u_j) > f \quad (2)$$

Where: *f* is the contact frequency parameter.

With this, when choosing brokers for a request based on social willingness, we can filter the ones who do not have the familiar relation with the publisher to enhance reliable information dissemination.

B. Popularity-based Online Broker Selection

We employ user popularity to measure a user's capability of acting as a broker. Each user's device continuously logs the devices it encounters and such encounter records are used to predict how many users this user is likely to meet in a forthcoming period ΔT .

We define this predicted value as $Pop_{\Delta T}(u_i)$. For example, $Pop_{7d}(u_i)$=25 means that user u_i is expected to meet 25 different users in the next 7 days. We call $Pop_{7d}(u_i)$ as *weekly-popularity* of u_i (simplified as *WP*(u_i)), which measures the number of users that u_i expects to meet in the next week. Similar to the familiar relation, the weekly-popularity is also measured based on historical encounter records. We calculate the average value of u_i's historical weekly-popularity values as *WP*(u_i). All users advertise their predicted popularity in the online community, and a publisher can choose the ones with highest-popularity among them. To advance information dissemination, people often need to choose multiple brokers while not a single one

[10]. The following popularity-based broker selection algorithm chooses k brokers with the highest popularity from the "familiar" list of a user.

Algorithm-1: Popularity-based online broker selection

Input: a user u_b, specify the number of brokers K needed
FamiliarList FL=null
BrokerList BL=null
For each user u_i, $u_i \neq u_b$
  IF **BeFamiliar (u_i, u_b)**
    Add u_i to FL
  End
End
If *length (FL)<=K*
  BL=FL
  Output *BL*
Else
  For each f_i in FL
    Compute ***WP (f_i)***
  End
  WPList = **Sort** *(WP(f_i),* ***descend)***
  Select top K records (*WP(f_j)*) from WPList
  For each record *WP(f_j)*
    Add f_j in BL
  End
  Output *BL*
End

As mentioned in Section 3.1, the selected brokers can be informed and obtain the allocated task from the online community once they are within an environment with Internet connection.

C. *Request Notification and Termination*

Besides broker selection, there are two other problems to be addressed by HSN. They are: how to notify the request publisher of the matched request; how to terminate brokers' work when the task is completed.

(1) Matched result notification. If the matched node is found by the request publisher, the publisher can be directly informed. If it is found by a broker, the publisher should be notified by the broker. Two possible ways are available in HSN: (i) the broker can inform the information to the publisher through the online community (once he/she has Internet connection); (ii) an alternative notification method is asking the broker to communicate with the publisher by phone call or SMS once a matched node is found (more efficient than the prior method).

(2) Task termination. The publisher resets the request state to "*completed*" if his/her request is matched. The updated information can be obtained by brokers when their mobile phone is online.

D. *Use Case Implementation*

Having described the main building blocks of HSN, this subsection we present how the opportunistic trading service OBuy is implemented based on it.

There are two types of requests: *sell request* and *buy request*. To reduce network cost on data flooding, in OBuy, only sell requests will be disseminated, the buyer (while not the seller) is notified when his/her request is matched. The buyer can select brokers and replicate his/her request to them. To lower traffic and communication cost, the brokers only carry and match the assigned requests but do not forward them to others. Based on the aforementioned broker selection and task management strategies, here we give the whole opportunistic trading algorithm. In the current stage, the algorithm is based on pre-collected human mobility traces.

Algorithm-2: OBuy – an opportunistic trading service

Input: a buyer u_b, a seller u_s($u_b \neq u_s$), the request expiry time (TTL)
u_s publishes a seller request R_s at time t_s,
u_b publishes a buyer request R_b at time t_b (for simplicity, in the simulation, we set t_b=t_s-*1*)
Match Flag mFlag=0; //to indicate if a match happens
If //If u_s and u_b have the familiar relation in the online community, the algorithm terminates
  BeFamiliar (u_s , u_b)
  Complete Time $T_c = t_b$
  mFlag = 1;
  Output: T_c and seller ID
Else
  k familiars of u_b will be selected as the broker using a broker selection algorithm
  For each broker b_i
    //Compute the time t_i that b_i receives R_b
    If b_i is within an environment with Internet connection (in the simulation, we assume a user has Internet connection ***at home*** or ***in the office***)
      $t_i = t_b$;
    Else
      Calculate the latest time t_i that b_i enters an environment with Internet connection
    End
  End
  //Buyer and selected brokers carry and match incoming requests
  For each R_b carrier c_i (including u_b and all selected brokers b_i)
    Calculate Encounter List EL (c_i , t_i , t_b + TTL), in the order of encounter time ET (Note that t_i (u_b)= t_b)
    For each e_i in EL
      If $e_i = u_s$
        Matching time $T_m = ET\ (c_i, e_i)$
        mFlag=1
        break
      End
    End
    If mFlag!=1
      T_m= *-1*
    End
  End
  IF mFlag=0
    Output: The match **fails**
  Else
    Compute the shortest T_m (among all R_b carriers) as T_c
    Output: T_c and seller ID
  End
End
Notification and Transaction
Task Termination

Algorithm-2 presents the procedure for opportunistic trading. The major components of HSN infrastructure are used here, including *request publication*, *broker selection*, *task allocation*, *request dissemination and match-making*, and *task notification*. An example to showcase the above algorithm is illustrated in Fig. 2. *S1* publishes a sell request of "*Piano*" at time *T0*. *B1* publishes a buy request of "*Piano*" at *T1*. Two of *B1*'s social ties (*Br-m* and *Br-n*) are selected as brokers, and the tasks are allocated to them via online community at time *T2* and *T3*. When *S1* moves, people within the *n*-hop of him form an opportunistic community. Requests are shared and matched within the opportunistic community. At time *T5*, *S1* and *Br-n* meets in a coffee shop, and the buyer/seller requests are matched. *B1* is then informed of the matched result, either through online communication or phone calls. The task is terminated after the transaction is completed.

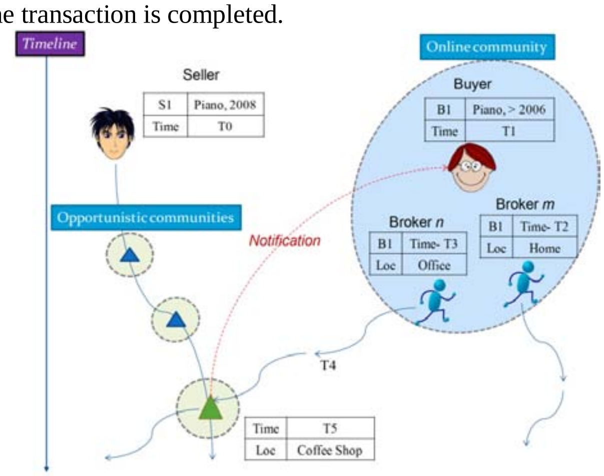

Figure 2. Opportunistic Trading: An Example.

V. Evaluation

This section presents the evaluation of HSN. It starts with a description of the simulation setup and evaluation metrics. Since OBuy is a typical HSN service, we have conducted experiments based on it to validate the performance of HSN.

A. Simulation Setup

(1)Mobility Traces. Simulations based on real mobility traces are much more dependable for testing than simulations based on generic random mobility models [4, 14, 21]. We also employ the trace-driven approach in the testing.

The evaluation is based on the MIT Reality Mining (RM) trace (http://reality.media.mit.edu/). In terms of human movement, the RM traces contain collocation information from 104 subjects (staff and students) at the MIT campus over the course of the 2004-2005 academic year; co-location information was collected via frequent (every 5 minute) Bluetooth device discoveries. Each logged contact includes the two contact parties, the start-time, and the duration. To make the dataset more manageable, we have extracted twelve-weeks of collocation data, corresponding to Sep. 14th to Dec. 7th, 2004. Specifically, the first eight weeks were used as historical training dataset (i.e., *VP* in formula (1)), while the last four weeks used as testing dataset. Over the 104 subject records, 22 are removed because they only contain few encounter records. Thereby, there are finally 82 subject records used in the evaluation.

(2) Online Community Creation. While social network can be extracted based on call logs and text messages exchanged between users from the RM dataset, there are only 236 non-zero values for the whole 82×82 matrix (we only exploited 82 valid users), which implies that each user only has around three friends on the average. The result does not meet the facts in the real world. Therefore, we employed the social tie measurement metric defined in Section 4.1 to build the online community. In the simulation, we set δ to 10 minutes, f to 3. It means that if A meets B for 3 times in the latest eight weeks, and each meeting duration is above 10 minutes (above two Bluetooth scans), we consider B and A are familiar. The result is that the constructed 82×82 matrix contains 2002 non-zero values. One important feature of a social network is the average number of social ties per node. Each node has 25 social ties on average.

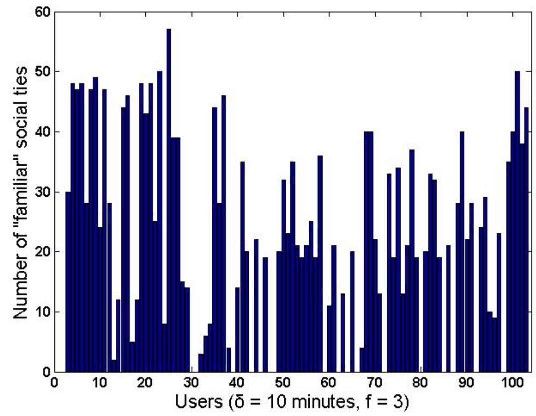

Figure 3. Number of "Familiar" Social Ties to RM Dataset Users.

B. Experiment Metrics and Benchmarks

We use the following two metrics to evaluate HSN, based on the OBuy service.

- *Effectiveness*. The objective is to test the effectiveness of HSN using the *success rate* metric. The success rate examines the percentage of successfully completed trading (both buyer and seller exist in an experiment) times among the total of *N* experiments. *Matching latency* is used as another parameter, which measures the time needed for a random buyer or its brokers to meet one of the nodes with a matched request.
- *Usefulness*. The objective is to validate if HSN performs better on information dissemination than purely online/opportunistic social networking methods. In online SN, information are shared among people with certain social ties, which limits the range of covered nodes. It is thus easy to understand that HSN has merits on broadening the "audience" of shared information than online SN. In this paper, we mainly compare the performance of HSN and opportunistic SN.

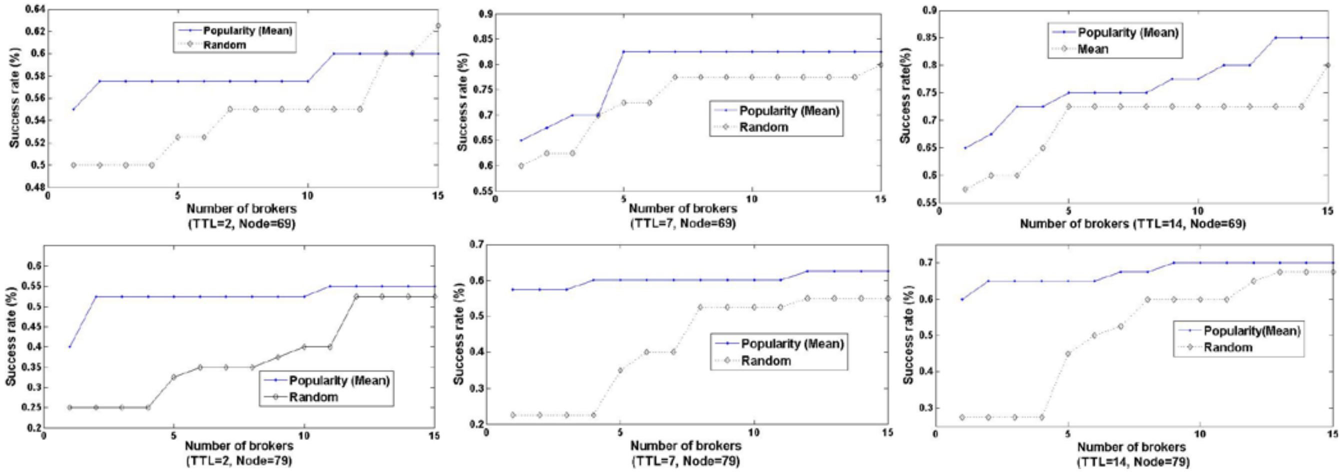

Figure 4. The Effect of Popularity.

We compare the performance of HSN with the following approaches:

- *Random broker selection (Random in short).* To evaluate the effect of popularity-based broker selection method, we employ the *Random* broker selection method. Similar to HSN, *Random* selects brokers from the online community. The major difference is that, in *Random*, brokers are selected randomly from the familiar list, not concerning their popularity.
- *Offline method.* To compare hybrid SN with opportunistic SN, we employ the *Offline* method, which is often used in previous work on opportunistic information dissemination [4, 14]. Similar to HSN, brokers are chosen based on their popularity (i.e., to evaluate if it is above a predefined threshold). The major difference to HSN is that it only uses opportunistic contact of people for broker selection.

C. Experiment Design and Results

(1) Does HSN work effectively?

The objective of this experiment is to measure how broker popularity affects the performance of HSN. The popularity-based method (*Popularity* in short) presented in Section 4.2 and the benchmark method *Random* is used in the evaluation. The experiment process is described as follows:

(a) Input specification: giving one buyer and a TTL; generating a random seller.

(b) Repeat Popularity and Random 50 times, compute the average success rate.

Two buyers (69 and 79) with different number of "familiar" social ties are employed in the experiment. To investigate whether the functionality is affected by the user tolerable matching latency, three *TTLs* (2, 7, and 14) are used, corresponding to *emergent*, *weekly*, and *long-lived trading need*. The results are illustrated in Fig. 4.

It is obvious that in general, popularity-based method performs better than the random method, independent of the popularity of the node, the number of brokers *k*, and *TTL*. In addition, we have the additional findings as presented below.

As we imagine, the success rate grows with the increase of the number of brokers (i.e., *k*). However, the performance grows slowly after *k* is increased to a certain value. It can also be seen from Fig. 4 that the social-interaction pattern of the buyer affects the results. When a small *k* (e.g., $k = 1$) is applied, the performance gap of the two methods is much bigger for buyer with few friends (e.g., 79) than those with many (e.g., 69). This is because that an individual (saying *A*) with more friends implies that he/she is more socially-active. When *A* posts a buyer request, he can be viewed as a high-effective information disseminator; the application of a high-popularity broker, however, cannot improve much the system performance.

With the growing of *TTL*, the success rate also increases. For *Popularity*, it increases from 60% to 85% when *TTL* is extended from 2 to 7 ($k = 15$). This implies that emergent needs has low success rate, because short dissemination period decreases the opportunity to cover more nodes. By contrast, long-lived needs can be better served.

(2) The effect of social selfishness

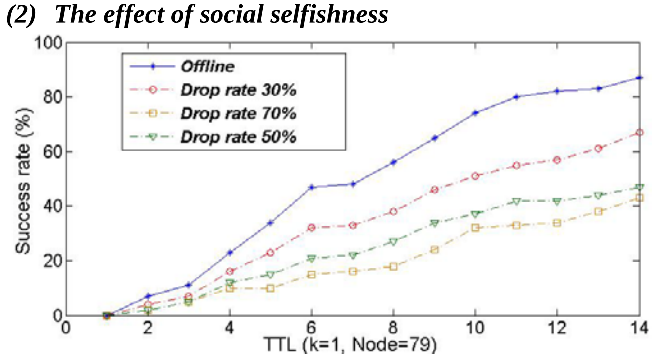

Figure 5. The Effect of Social Selfishness.

To validate the effect of social selfishness on information dissemination, we have introduced the data drop rate in the traditional *Offline* method. The data drop rate indicates the rate of task non-acceptance in terms of brokers' willingness. To make it simple, only one broker is used, who has to find one matched node (from three candidates in the community). The results are shown in Fig. 5. It can be seen that with the increase of the drop rate, the success rate (100 experiment times) also decreases. This reveals that data drop rate has a negative effect on opportunistic information dissemination, thus our social-willingness based method is promising.

(3) The effect of hybrid social networking

The objective is to validate the usefulness of HSN. The *Offline* method, as a benchmark, is used here.

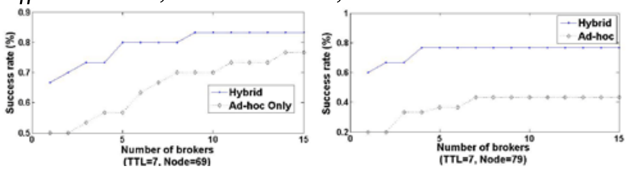

Figure 6. HSN vs. Offline (Success Rate).

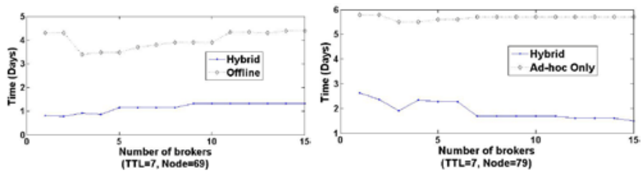

Figure 7. HSN vs. Offline (Match Latency).

As shown in Fig. 6, great performance improvement (in terms of success rate) is obtained when using HSN. For example, the improvement is about 15% for node 69 and almost 40% for node 79. On the other hand, the matching latency is largely reduced (see Fig. 7), decreasing about 60% for node 69 and more than 70% for node 79. It is because that the integration of an online community shortens the broker selection process, and increases the opportunity to select brokers with high popularity (in *Offline*, brokers with high popularity may not be encountered and chosen). The performance improvement to node 79 is higher than node 69, because node 79 is less popular than node 69, and the leverage of HSN can have a better effect.

VI. Conclusion

In this paper we have presented the hybrid social networking (HSN) infrastructure. By interlinking online and opportunistic communities, the HSN has been proved to be useful for improving information dissemination efficiency. We present the main building blocks of HSN, including the contact-pattern based online community creation approach, the popularity-based online broker selection, and the implementation of the HSN-based service – opportunistic trading. The performance of HSN has been evaluated using a real mobility trace. The experimental results indicate that, comparing with single-community oriented methods, HSN can significantly improve the success rate while decrease the matching latency on information dissemination. As part of our ongoing work, we are conducting experiments using different mobility traces and social networks. We also intend to study a general model for cross-community information dissemination. Ultimately, we believe that hybrid social networking systems that can intelligently exploit heterogeneous user communities will bring many new research opportunities and novel user experiences.

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