"Friend is Treasure": Exploring and Exploiting Mobile Social Contacts for Efficient Task Offloading

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***Abstract*—In this paper, we investigate the task offloading issue in mobile social networks. Although the "d-choice" paradigm in "ball and bin" theory had shown the power of random choice in load balancing with a random walk model, its performance could be fairly poor where real-trace data sets are concerned. According to our preliminary evaluation results with "MobiClique," the "d-choice" scheme could not achieve well-balanced allocations in a real-trace data set. Nevertheless, it would bring fundamental challenges to task reassignment in the following aspects: First of all, some of the friendships are relatively stable, which would lead to a more imbalanced task assignment, even if the "d-choice" scheme is applied for balancing. Second, some users would meet quite infrequently, which could inevitably lead to intolerable time delay and unfair task allocations. In tackling these difficulties, we revisit the real data sets for exploring the contact property among users. We find that the frequently met users could be leveraged for efficient task execution due to higher task priority. To this end, we propose the "iTop-K" algorithm, leveraging the basic concept, i.e., "your friends are more powerful than you," which encourages mobile users to assign tasks among intimate friends instead of pure random assignment. With careful selections of "Top-K" friends, we achieve balanced load and guaranteed performance at the same time. Experimental studies verify our scheme and show the effectiveness with three typical data trace sets, including "MobiClique." In this typical networking scenario, ours outperforms the conventional random choice scheme up to 15$\times$ and the social relationship assignment without priority method up to 9$\times$. Moreover, the "Top-K" scheme could be adaptive, even when no intimate friends are available. By scaling the "K" factor to larger values, our scheme outperforms random assignment and could be inspiringly close to the optimal solution. In summary, ours could effectively explore the social relationship and leverage it for efficient task assignment, which would further encourage more mobile users to work together under the rule of social contacts.**

***Index Terms*—Mobile social network, task allocation, traffic balancing.**

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I. Introduction

NOWADAYS, the smartphone is the main tool to access any kind of information from fixed or mobile ad hoc terminals. When mobile services are provided to the masses [6], the self-organized computing, communication, and storage services are main concerns for most mobile users. Specifically, organizing distributed participants' sensing data and services in an ad hoc way will need distributed coordination in sensing and computing, together with relatively low communication overhead. In particular, participatory sensing solutions enable more users to share their sensing data in a noninvasive manner [7]–[9], which encourages collaboration among massive number of mobile participants [10]. Specifically, in a data-intensive mobile computing environment, more concrete collaborations are desperately needed. Mobile users with heavy tasks need to offload their tasks to the contacted friends for efficient execution. Users could offload their tasks to the contacted friends with higher energy and computing efficiency.

Previous studies have failed to achieve perfect load balancing for two reasons. First, for centralized task reassignment systems, the tasks are sent to the remote cloud instead of nearby users, which would inevitably cost too much bandwidth, and could not leverage the resources in cloud effectively [5], [7], [11]. Second, even for pure distributed networks, the balanced task offloading is still hard to achieve [7], [12] because of the transitory intercontact and highly dynamic queuing length [10], [13], [14].

In this paper, we revisit the load balancing scheme according to "ball and bin" theory [1], which has been proposed as a simple but effective approach for traffic balancing in distributed networks [11], [12]. Leveraging the real-trace data "MobiClique" [2], we make some basic trace-driven simulations. We find that such scheme is not applicable, particularly when real mobility traces are applied because for real-trace data, the social relationship dominates users' contact duration. For users with a close relationship or similar interests, the contact duration could be extremely large. Due to the nonuniformly distributed contact duration, random assignment leads to imbalanced user load distribution. Moreover, for some users without such intimate relationship, task assignment in "ball and bin theory" will inevitably lead to low efficiency. In summary, the root reason is, conventional "ball and bin" scheme failed to explore and exploit the inherent social relationships among mobile users effectively.

We propose a new concept for balanced task offloading algorithm design, i.e., "Your friends are more powerful than you." Considering the social relationship among users, we propose an "iTop-K" approach in building a robust and efficient task offloading scheme.

Such design is based on two fundamental observations in our preliminary experimental study.

1) Social contacts are relatively stable and could be used for task assignment [15], [16]. To this end, there are closer "social relationships" [17] among users with shorter contact interval, which will lead to higher task execution priority as well as efficiency [5], [18].
2) The statistical results in social contacts can also be used for further optimization. For example, users are willing to assign their tasks to those with higher social-contact frequency.

Leveraging these two basic but important findings, we propose a lightweight and distributed algorithm to enable task offloading according to social relationships. The contribution of this paper is threefold.

- First, we explore the social contacts and exploit the "Top-K" users with contacting frequency to improve the task offloading efficiency. In that, social contacts are used for the "Top-K" mobile users, which are further leveraged for task execution priorities.
- Second, we validate "iTop-K" with real traces, where the proposed algorithm could outperform "d-choice" scheme [1], [19] significantly. To the best of our knowledge, this paper is the first to achieve balanced task assignment in pure distributed mobile networks, particularly when real-trace data sets are considered for evaluation.
- Third, considering the case that there is no intimate friends in contact window, we use a scalable "K" scheme, where the "K" value could be adaptively adjusted in selecting friends. The "K" value means the number of candidate users[1] for task allocation. We find that, under the scalable "K" scheme, "iTop-K" significantly outperforms the basic scheme when "$K = 2$" and shows improved balancing property, even when "$K = 16$."

[1] Here, the candidate users denote the users in communication range with each other and could successfully accomplish task offloading in contact windows.

The remainder of this paper is organized as follows. We review the state of the art in Section II and make a further understanding on social contacts with real-trace data in Section III. Further, we present the problem formation in Section IV. After that, algorithm design is introduced in Section V. To validate our proposed scheme, extensive evaluations have been done and illustrated thoroughly in Section VI. Finally, we conclude this paper in Section VII.

II. Related Work

A. Random Walk

This paper relates to the efficient data transfer schemes over disruption-tolerant networks or opportunistic networks [10], which highly correlate with the random walk model. The random walk concept was proposed by Pearson [20]. Note that, in a mobile social network, the social relationship dominates the trajectories of the mobile users. Fortunately, random walks can be incorporated into the mobile social network for exploring the character and opportunities in data transmissions. For instance, Newman [21] proposed the random-walk betweenness centrality. This interesting metric reasonably defines how often a node in a graph is visited by a random walker between all possible mobile users. Similar to the betweenness evaluation, Noh and Rieger [22] introduce the random-walk closeness centrality metric, which measures how fast a node can effectively get a message from other mobile nodes, in the random deployed system, such as the distributed mobile social networks.

The intermittent contacts are useful for data sharing, which have been well explored and studied in variety of network settings, from military warfare [23] to disaster recovery [24]. These proposals believe that the fixed infrastructure is unavailable, costly, or even highly unreliable. With numerous cheap and distributed working nodes, more complex tasks could be accomplished successfully with proper and distributed cooperation.

B. Task Allocation

Many working crowdsourcing systems are making efforts to realize this vision, in terms of designing actual platforms, providing cooperative task execution among users with similar interests and demands. In smart city sensing applications, crowdsourcing paradigms leverage the pervasive human behaviors, e.g., walking, driving, and shopping, to provide a large-scale urban sensing network with wider coverage in time and space domains. Even further, the social relationship, e.g., the crowd gathering and migration are also important for some specific applications, e.g., flu influence detection, air quality, and traffic monitoring. The booming of smartphones speeds up the crowdsourcing-based applications for urban sensing. Recently, crowdsourcing-based sensing applications are exploited to monitor the urban environment [28]–[31]. More specifically, Mun *et al.* [32] employed the customized and portable sensors on each participant to monitor the air quality of the city. More effort has been made for environmental monitoring with pervasive computing [30], [31], [33], [34]. For example, the constructions of noise map for the smart city are discussed in [35]. Leveraging the microphones of the participants, these works focus on implementation of the monitoring system. However, they failed to consider the task allocation efficiency because unreliability and inaccuracy of the observations are inevitable in participatory sensing networks. To this end, more efforts are needed for efficient and cooperative task execution. One of the most fundamental requirement is to balance tasks among users, since overloaded tasks would lead to intolerable processing delay and single point of failure.

For traffic balancing schemes, few solutions have been proposed or formally addressed in dealing with the aforementioned challenges, particularly in mobile networks for data delivery [36]. Key *et al.* [12] proposed an efficient load balancing scheme for multipath routing networks. They creatively leverage the "ball and bin" theory, where traffic is assigned to paths with "d" choices. Here, "d" is the number of network paths. Recently, inspired by this idea, an efficient task offloading scheme has been proposed for mobile social networks [11], where tasks are assigned to the least loaded mobile users among "d" choices, where "d" is the number of candidate mobile users.

The main focus of this paper is load balancing in distributed crowdsourcing system. Different from previous crowdsourcing applications, we use a pure distributed computation and communication model, where users do not need to transmit any messages for centralized computation. Moreover, our major concern is how to apply the proposed task allocation scheme with real-trace data, where social relationships could be effectively explored and exploited.

III. Revisiting the "d-Choice" Scheme With Real-Trace Data Set

First, we evaluate the impact of the real-trace data on a task offloading scheme. As it has been verified in previous studies, simple allocation schemes based on "ball and bin" theory [11], [12] could effectively balance the network load without global information. We revisit this problem with real-trace data [2] and find that the conventional "ball and bin" scheme could not provide balanced allocations, particularly when real data traces are applied. After that, we make two basic observations on real-trace data. First, the contact frequency is extremely high for some specific user pairs. Second, the social contact frequency is not uniformly distributed. These observations motivate us to explore the social relationship and leverage it for efficient task offloading.

A. Impact of the Social Relationship in Real-Trace Data

The basic content of "ball and bin" theory could be stated as follows. Given n nodes are to be thrown into n bins, where each ball is chosen to each bin uniformly and independently. The focus is the maximum loaded bin, i.e., the largest number of balls in all the bins, which is approximately $\log n/\log\log n$. If the balls are thrown sequentially, and each ball is placed in the least loaded bins of $d \geq 2$, the maximum load is $(\log\log n/\log d) + \Theta(1)$ with high probability. We call this method "d-choice paradigm."

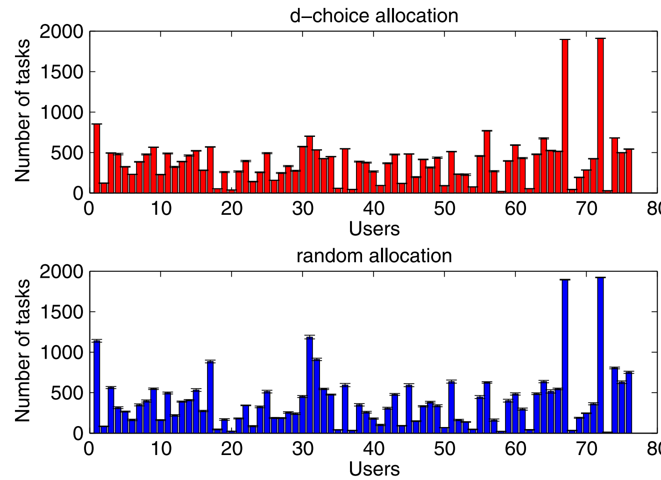


Fig. 1. Allocating tasks with d-choice paradigm.

In "d-choice" paradigm, each user randomly selects "d" users among the contacted neighbors and assigns tasks to the least loaded one. In light of the real-trace data [2], we make statistical analysis on the contact times of mobile users. The task load in each user could be available by basic communication model. When the users are in contact range, there is a probing/answering process among the contacted neighbors. To this end, the task load on each user could be shared among the contacted neighbors. Moreover, according to the basic scheme of "d-choice," only two neighbors need to be probed, and the traffic load could be relatively small. This property is favorable for bandwidth-constrained crowdsourcing network. As shown in Fig. 1, the "d-choice" scheme could not balance the tasks among users effectively. Comparing with random assignment, it gets similar performance when task load is concerned. Specifically, it significantly differs from previous results evaluated under the random walk model [11].

B. Basic Observations

As shown in Fig. 2(a), there are some extremely high contact ratio (over 1500 times during data collection period) between some specific user pairs. In mobile social networks, two persons with a high social relationship would frequently meet each other. These extremely high contact frequencies are indeed existing but not representative. As shown in Fig. 2(b) and (c), we remove them by the following rules. First, the mitigated values should be at least 10 times higher than the average value. Second, the percentile of the mitigated values should be less than 1% of all the contacts. According to Fig. 2(c), the distribution is clearly nonuniform such that we could not assign each user with equal tasks. In fact, it is a "weighted bin" problem in "ball and bin" theory [1].

For mobile social networks, the contacts are dominated by the social relationship instead of the stochastic features in the random walk model. Taking mobile users equally will lose the valuable opportunity for improving task allocation efficiency, which is the root reason leading to poor load balancing performance of the "d-choice" paradigm.

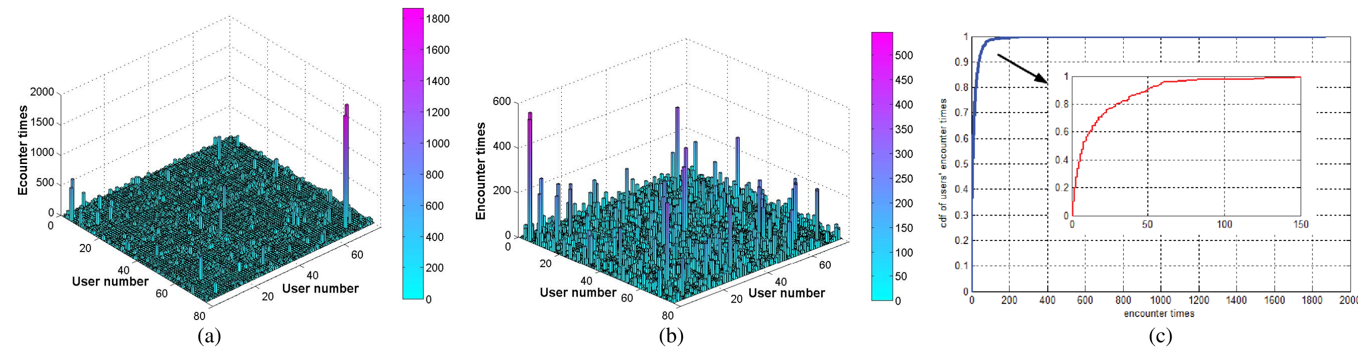


Fig. 2. Encounter frequency of users. (a) Encounter frequency of users. (b) Encounter frequency of users after mitigating extremely high values. (c) CDF of users' encounter frequency.

Inspired by these observations, we need to exploit the social relationship to enhance the task offloading schemes, where mobile users are classified according to social contact frequencies. Further more, task execution time is tightly coupled with the social relationships.

IV. System Model and Problem Formation

A. System Model

We consider a mobile social network where n mobile users are included in a user set, denoted by $U = \{u_1, u_2, \ldots, u_n\}$. Here, we assume the application scenario needs cooperation to work out the given tasks in the system. The applications [25]–[27] could be user-centric [37], providing cooperative task completion among interested users.

Each user $u_i \in U$ owns a task set $\mathrm{T}_i = \{t_i^1, \ldots, t_i^m\}$. For each task of user i, when it is reallocated to another user j, it will be processed at user j without being further forwarded to other users. We do not consider multi-hop forwarding schemes in this paper. The reason is that task offloading is a relatively vital issue for each user. The users would like to believe their friends in direct contacts.[2] Moreover, different from delay-tolerant network routing, there is no destination for task forwarding. Thus, multiple forwarding will inevitably affect the task execution time seriously. We put it to future work, where routing with social relationship technology is incorporated for enhanced load balancing. The tasks in user i have not given priority here, and we do not consider the "dequeueing" and "enqueueing" technologies for task priority. Because in a social task offloading network, there would be very few urgent tasks for reassignment. The tasks with extremely high priority should be processed on local devices.

For user i, the tasks getting from other users are listed in queue $Q_i = \{\tilde{t}_i^1, \tilde{t}_i^2, \ldots, \tilde{t}_i^m\}$, and the queuing length is $\|Q_i\|$. Note that, the tasks assigned to user i are different from the previous task definition because these tasks are from different users. Thus, we denote these tasks with $\tilde{t}_i^j$, which means the jth tasks assigned to user i.

[2]Here, contacts means the two users are in communication range and could exchange data successfully. Direct contacts are denoted to differ based on the case that needs forwarding.

B. Problem Formation

The investigated problem could be formulated by minimizing the gap between the average value and the maximum queueing length achievable with high probability. The gap evaluation has two advantages. First, it is simple. Instead of computing the gap between the average value and all the queues, the maximum queueing length is investigated, which saves a large amount of communication overhead in a distributed mobile network. Without loss of generality, such evaluation is also reasonable. Second, it is an important metric in evaluating between the worst and average cases. For example, we need to know the task finishing time in average and worst cases. Moreover, in the batched task offloading case, the task finishing time depends on the latest one, which corresponds to the longest queueing length. Thus, such evaluation is given by

$$\min\left(\max_{i\in U}\|Q_i\| - E_{i\in U}[Q_i]\right).$$

Two technical challenges need to be formally addressed before applying social relationship into task offloading algorithms. First, when considering the social relationship, the selection of mobile users becomes unstable and inefficient. Increasing the number of candidate users will not help much because the number of contacted users is subjected to mobility patterns, which might not be large particularly during specific "contact window." Second, there are "exceptional effects" in our model, i.e., some extremely high and low meeting frequencies among users will affect the overall performance significantly. Once the tasks are assigned to an infrequently contacted user, the task completion time would be extremely long, particularly when acknowledgment is required. Thus, the design requirement needs efficient and stable mobile user selection schemes, where balanced task assignment could be achieved, without being seriously affected by intermittently connected mobile users. We show this property with simulation and statistical results in Sections V and VI.

TABLE I
ILLUSTRATION FOR SOCIAL RELATIONSHIP RANKING LIST

User	Top-K(K=3) contact user	Priority
1	5 (545), 10 (231), 69 (119)	1, 2, 3
2	75 (23), 63 (16), 66 (12)	1, 2, 3
3	32 (146), 33 (126), 4 (58)	1, 2, 3
4	3 (58), 32 (53), 29 (47)	1, 2, 3

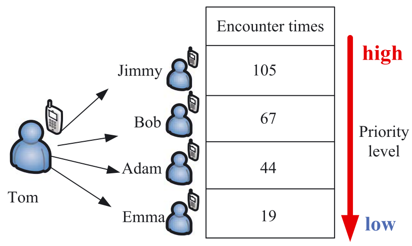


Fig. 3. Considering task priority with social contacts.

V. "iTop-K": Social-Relationship-Based Task Offloading Algorithm

In tackling the aforementioned challenges, we propose a social-relationship-based task offloading algorithm. We leverage the concept of "Top-K," where the first K users in the friend list are selected for task allocation. The "Top-K" friends bear more regular contact pattern than others, which will lead to more stable task allocations. The only negative effect of "Top-K" scheme is that when there are no users in the contact window, the "Top-K" scheme will lead to unbalanced allocation or longer delay. In this paper, we use an adaptive scheme, where the number of "K" is adaptive and scalable. Thus, we call our scheme "iTop-K," which means a customized and adaptive method. The "iTop-K" algorithm slightly modifies the original "d-choice" scheme, where the random "d" candidates are replaced by the selected "friends" in "Top-K" discipline.

A. Finding the "Top-K" Social Contacts

We leverage the trace data from MobiClique application at ACM Sigcomm conference 2009 [2]. The trace data recorded traces of Bluetooth encounters, opportunistic messaging, and social profiles of 76 users. We pick up the records of user i $(1 \leq i \leq 76)$ and sort them in descending order such as in Table I. As a result, we get the "Top-K" friend list for each user i.

We build a relationship table according to the encountering frequency similar to Fig. 3. Note that, for user Jimmy, who has the highest priority level, the number of contacts between Jimmy and Tom is 105 during the data collection period. To decrease the task execution time, we need to assign the tasks to close friends or familiar people.

In a mobile social network, the mobility dominates the task allocation opportunity. Different from conventional task allocation, the availability of each mobile user is considered in a mobile network as the availability differs from one another. Pure balancing among users would lead to unfairness among users. The reason for this claim is when the availability of different users differs, e.g., some mobile users are frequently contacted, whereas others are not. If we still allocate tasks to each user equally, the task allocation might be not efficient.

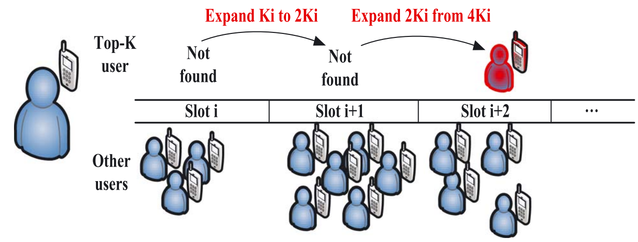


Fig. 4. Waiting for "Top-K" users with scalability.

First, the tasks assigned to inactive mobile users would lead to larger task execution time. In contrast, the active mobile users could be more efficient in task allocation. For efficient offloading consideration, the active mobile users could bear more tasks and make the network more efficient. Specifically, since the availability among users differs, we should not simply apply the load balancing scheme to the mobile crowdsourcing network directly.

Thus, in our scheme, we pursuit another form of balancing, i.e., users are allocating tasks according to the availability of mobile users, which is subjected to the mobility patterns. Moreover, there should be a balanced allocation among users with unequal availability. Thus, allocating more tasks to frequently contacted user could effectively improve the network efficiency because tasks assigned to these users could be effectively executed, and the task execution results could be returned to the task sender in a relatively short time. In contrast, for the infrequently contacted users, when more tasks are assigned, the time delay could be very long. Thus, the balancing scheme should be tailored for mobility features. Moreover, in the social domain, the mobility patterns could be leveraged for task execution. Because in social network discipline, intimate users would have a close relationship and would like to execute the tasks with higher priority. This feature has been widely explored and exploited in many studies [24], [38]. We make further exploration on our trace data for spatial and temporal correlation features. Such features could further support the close relationship between frequently contacted users. Thus, in our scheme, we fully consider the mobile and social features in the load balancing scheme, where tasks are allocated according to the mobility patterns and social relationships.

B. Waiting for K Friends With Scalability

We consider the task execution time when "Top-K" friends are identified. As shown in Fig. 4, if there is no user in the "Top-K" list in one contact window, assigning tasks to "non-Top-K" users will not ensure the high contact frequency. Moreover, the task execution priority will not be guaranteed, which will be discussed in Section V-C. As shown in Fig. 4, at the given slot, e.g., slot i, if in the next slot $i+1$, there is no user in the "Top-K" list. Thus, the selection scope K_i would be scaled to $2K_i$.

Further, if in the next slot $i+2$, there is still no "Top-K" friends, the selection scope K_{i+2} would be $2K_{i+1} = 4K_i$. Once there are users in the scalable "Top-K" list, the selection scope returns to $K_{\min}$, and in our scheme, we set it to 2 since it is the minimum value required for "d-choice" scheme.

The scaling law of selection scope K is given by the following equations:

$$K_{i+1} = \begin{cases} 2K_i, & \text{if there is no Top-K friend in slot } i \\ 2, & \text{if there is at least one Top-K friend in slot } i. \end{cases}$$

C. Considering Task Priority With Social Contacts

In social networks, friends often contact with each other frequently. According to previous studies, people meeting each other often would indicate higher social relationships among them [17]. In these relationships, the task execution priority will be higher than others.

Previous studies have considered fully on the social relationship and the psychology factors. As the task execution priority is affected by the psychology reasons, the task execution time would follow the exponential feature, where users in different ranks may differ significantly in execution time [18]. In this paper, the task execution time formula is empirical. We set the task execution time for user ranked in the ith place to

$$T^i = T_\alpha \times 2^i$$

where T_α is the original task execution time, e.g., without priority. K is the selection scope for "Top-K" selection. Note that, for the scalable case, the factor K also scales.

Considering various psychology impacts and social relationships, the task execution time can be given by

$$T^i = T_\alpha \times g^i$$

where $g > 1$ is the base factor.

The algorithm description is shown in Algorithm 1. The procedure FindTop-K(n, K) is called to get the "Top-K" list of each user, and the procedure Top-KAllocate(n) allocates tasks to users according to the "Top-K" list. The function Rank(S) could get the actual rank of user S. Moreover, Top-KContain(i) could check if user i has "Top-K" friends in contacted ranges, where $K_{\max}$ is the maximum number of scalable K.

Algorithm 1 iTop-K algorithm for task offloading in mobile social network

```
Input:
    trace data of Sigcomm2009 [2]
    users number, n
Output:
    queue length: w_1, w_2, ..., w_n
Initialize {w_1, w_2, ..., w_n} = 0, count = 0
Load trace data of SIGCOMM 2009
Procedure FindTop-K(n,K)
    Sort the encountering frequency list for each user
    Record in file
End Procedure
Procedure Top-KAllocate(n)
    For each slot do
        search for encounters between users
        For each user i do
            If Top-KContain(i)==true then
                S ← Top-K user first met in this slot
                Flag=Rank(S)
            Else Expand K value
            End
            w_s = w_s + 1/g^(K_max − Flag)
        Endfor
    Endfor
End Procedure
return w_1, w_2, ..., w_n
```

D. Discussions

The duration of a contact window could be formally defined in the following way: $T_w = t_e - t_s$, where the t_s denotes the starting time that the mobile users could transmit data over a contact session, and t_e denotes the time that the contact session ends. Before the contact session, the neighbor discovery and handshake process for data transmission have been initiated. In our scheme, we assume that the task information, i.e., the task execution, is delay tolerant. Thus, the major concern is the task load. We do not evaluate the finishing time for tasks. The execution results for tasks need not to be fed back to the task sender within contact windows. In our model, we only consider the balancing property among mobile users. The application is for cooperative task execution, which is typical in most of the previous studies on the crowdsourcing network. The main purposes for this cooperation are to save energy and make good use of computation resources with fair task allocations.

The contact duration is also an important factor to our scheme, particularly when the task offloading overheads are concerned. In our system model, we assume that the duration of contacts is sufficient for task sharing for two reasons. First, the mobile users would use short-range high-bandwidth transmissions, such as Wi-Fi and Bluetooth, where short transmission duration is required. Second, the contact duration, particularly for the trace data set, are sufficiently large for simple data sharing. According to our statistical results, most of the contact duration is larger than several tens of seconds. Moreover, in most of the studies [24], [38], very short contact duration with unstable connections is generally not considered contacts.

In this scenario, we also assume that the intercontact interval is much greater than task execution time. In the delay-tolerant network, the intercontact interval could be several seconds to several minutes long. Considering the bandwidth-constrained mobile device-to-device scenario, the tasks could be generally simple with little traffic, which means a relatively short time to return the results. We make further simulation study and show the aforementioned effects. As shown in the following figures, mobile users with shorter intercontact interval are selected as friends or Top-K users, where the tasks are executed more efficiently. Even for the case where the task execution time is longer than intercontact time since the users with a close relationship have higher priority for task execution, the task could also be processed in a shorter time. We compare the

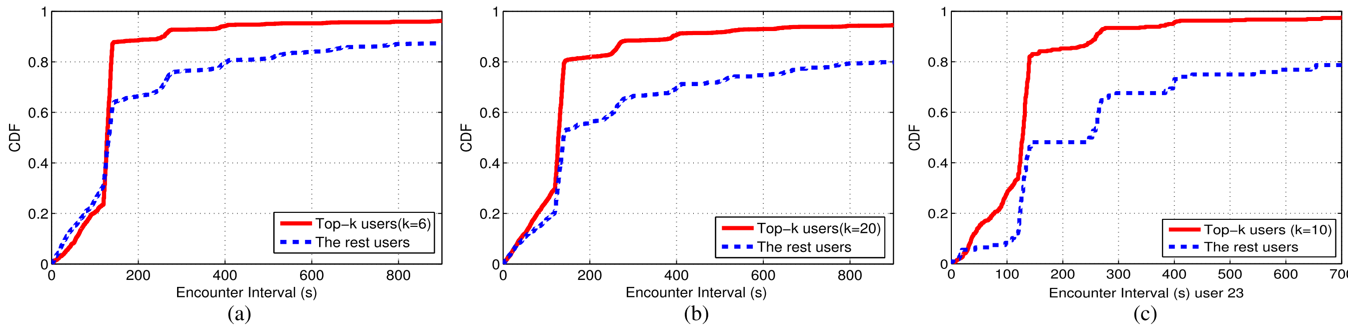


Fig. 5. Evaluations for Top-K users intercontact interval. (a) Encounter records of user 59 ($K = 6$). (b) Encounter records of user 59 ($K = 20$). (c) Encounter records of user 23 ($K = 10$).

encounter interval of Top-K users and the rest of the users. As shown in Fig. 5, we find that, for highly contacted users, the intercontact interval could be smaller than others, which have been depicted in the previously shown evaluation results. Without loss of generality, in Fig. 5(a), user No. 59 is selected for illustration. Users 23 and 40 are further evaluated, and comparisons are made among the "Top-K" users and the rest of the common users, which are shown in Fig. 5(b) and (c). Thus, when tasks are assigned to Top-K users, the execution results could be returned to the task sender when next time contact happens.

VI. Experimental Study With Real-Trace Data Sets

A. Finding "Top-K" Users

In this paper, we use three experimental data sets for evaluations, including *Sigcomm-2009* [2], *Infocom05* [4], and *Stanford-2010* [3].

- *Sigcomm-2009* [2] recorded encounters between 76 people participating at Sigcomm'09;
- *Infocom-2005* [4] collected the same data between 41 people at Infocom'05 at the Grand Hyatt Miami in March 2005;
- *Stanford-2010* [3] logged face-to-face contacts among 789 participants at a U.S. high school between 7:00 A.M. to 4:00 P.M.

The simulator is implemented in MATLAB platform and executed on a Lenovo X201 laptop with an Intel i5CPU (2.53 GHz) and 4-GB memory. This simulator has been tested and verified in our previous studies [11], [19].

B. Impact of Top-K Without Priority

Sigcomm-2009 [2]: We first evaluate the performance of the scalable "K" with real traces from MobiClique. To execute task allocation in every time slot, we divide the original time data into a series of time slots. As the earliest timestamp is 30 s, and the latest is 320 684 s; the slot interval is set into 200 s according to previous analysis about contact intervals and distributions. It is a typical value for most of the mobile contacts and is sufficient for data transfer if necessary. In each time slot, each user will share only one task. Thus, users allocate their tasks in each time slot, respectively.

First, to show the effectiveness of task execution priority, we make an experimental study on the scheme "Top-K" without priority. As shown in Fig. 6(a)–(c), the "K-value" is set into 2, 6, and 20, respectively. Note that $K = 2$ is a basic setting, and $K = 6$ is a typical value when mobile traces are applied. Moreover, note that the case $K = 20$ indicates a very large selection scope for candidate users.

Infocom-2005 [4]: We then evaluate the performance of the scalable "K" with real traces from "Haggle." Considering that the earliest timestamp is 20–733 s and the latest is 274–883 s, the slot interval is set into 200 s, which is appropriate according to previous analysis about contact intervals and distributions. Fig. 6(d)–(f) depicts the task load, particularly when tasks are executed without priority. Even when the K value increases, there are still a large number of imbalanced task loads among users.

Stanford-2010 [3]: The third trace comes from [3]. Fig. 6(g)–(i) shows the performance of the same scheme on "Top-K" without priority. Although the Stanford trace has shown significantly good social relationship property, the task execution without priority still leads to poor performance. As shown in these subfigures, the task allocations have not shown effective load balancing among users. To this end, we can conclude that increasing selection scope K only will not improve the balancing performance, particularly when social relationships are dominating the user contacts.

C. Impact of Top-K With Priority

Sigcomm-2009 [2]: We show the effectiveness of task execution priority in *Sigcomm-2009* data set. The task priority is set according to the method proposed in Section V-C. Fig. 7(a) shows that the tasks are well balanced among users, even when K is set to 2. Notably, when the K-value increases, the performance improves accordingly. The "scalable K" scheme ($K_{\min} = 2$) performs better compared with the static case when "$K = 2$" and performs even better than the case when "$K = 16$."

Infocom-2005 [4]: As shown in Fig. 7(b), we evaluate the scheme "Top-K" with priority in data set "*Infocom-2005*."

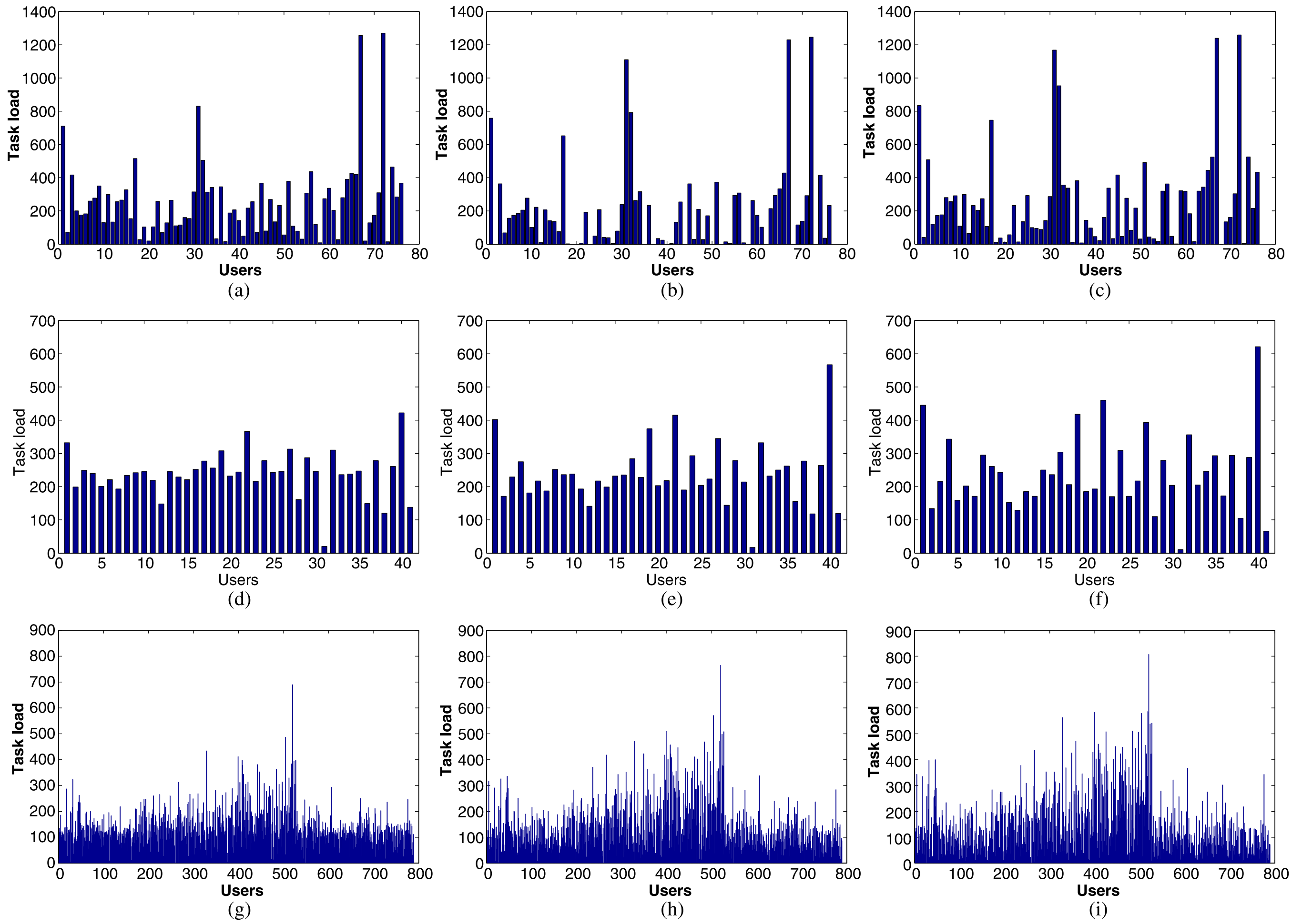


Fig. 6. Impact of K-value when tasks are executed without priority. (a) Sigcomm $K = 2$. (b) Sigcomm $K = 6$. (c) Sigcomm $K = 20$. (d) Infocom $K = 2$. (e) Infocom $K = 6$. (f) Infocom $K = 20$. (g) Stanford $K = 2$. (h) Stanford $K = 6$. (i) Stanford $K = 20$.

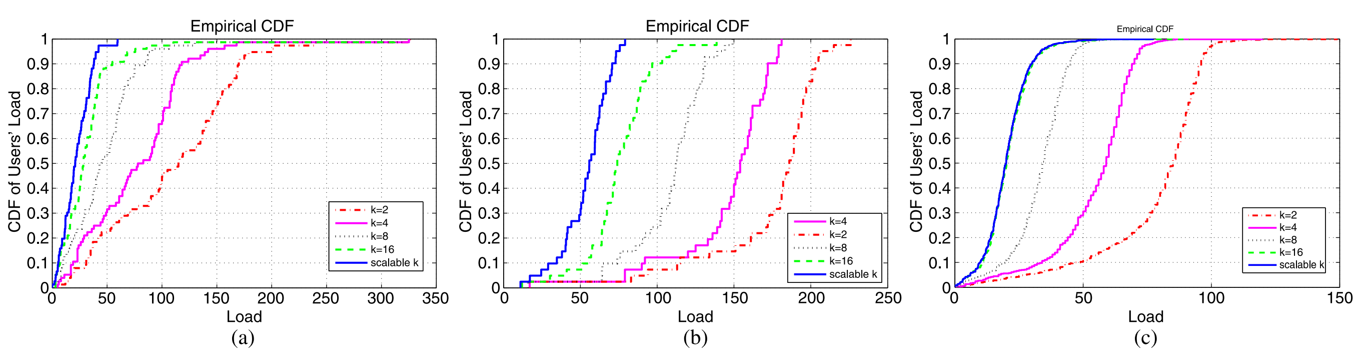


Fig. 7. Top-K scheme with task priority. (a) Data from Sigcomm'09. (b) Data from Infocom'05. (c) Data from Stanford'10.

The figure validates that the effective load balancing could be achieved when task priority is applied. Since *Infocom-2005* trace data has not shown strong social contact relationship, the value of K should be set larger to achieve balanced performance. We can see that when K is greater than 8, particularly when $K = 16$, the tasks can be well balanced, achieving similar performance as shown in Fig. 7(a).

Stanford-2010 [3]: As shown in Fig. 7(c), note that the "scalable K" curve is almost in the same shape with the "$K = 16$" line. The reason is that the number of users in this trace is far greater than the previous two data sets, where "marginal effects" are more significant. Selecting "Top-K" friends becomes more easy and convincible, which shows more potential when the algorithm is applied to the realistic social networks.

Remarks: The priority-based execution effectively improves the task balancing performance. First, the social relationship, which is dominated by mobile contacts, could be fully leveraged for more than task assignment and even further for execution. Second, the favorable feature is that the "Top-K" users could be effectively used for efficient task offloading,

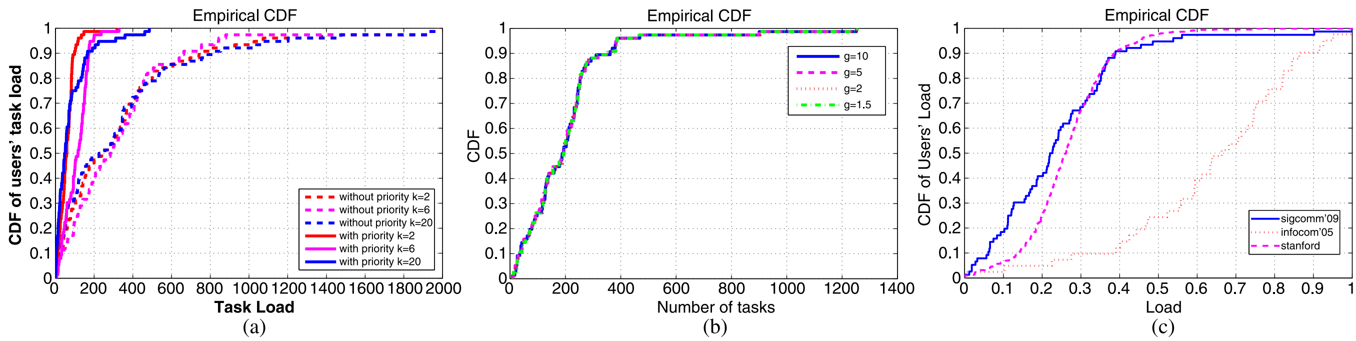


Fig. 8. Evaluations for different factors affecting the task balancing performance. (a) CDF of tasks for schemes with and without priority. (b) Top-K scheme with task priority when the base value changes. (d) Efficiency compared among three data sets.

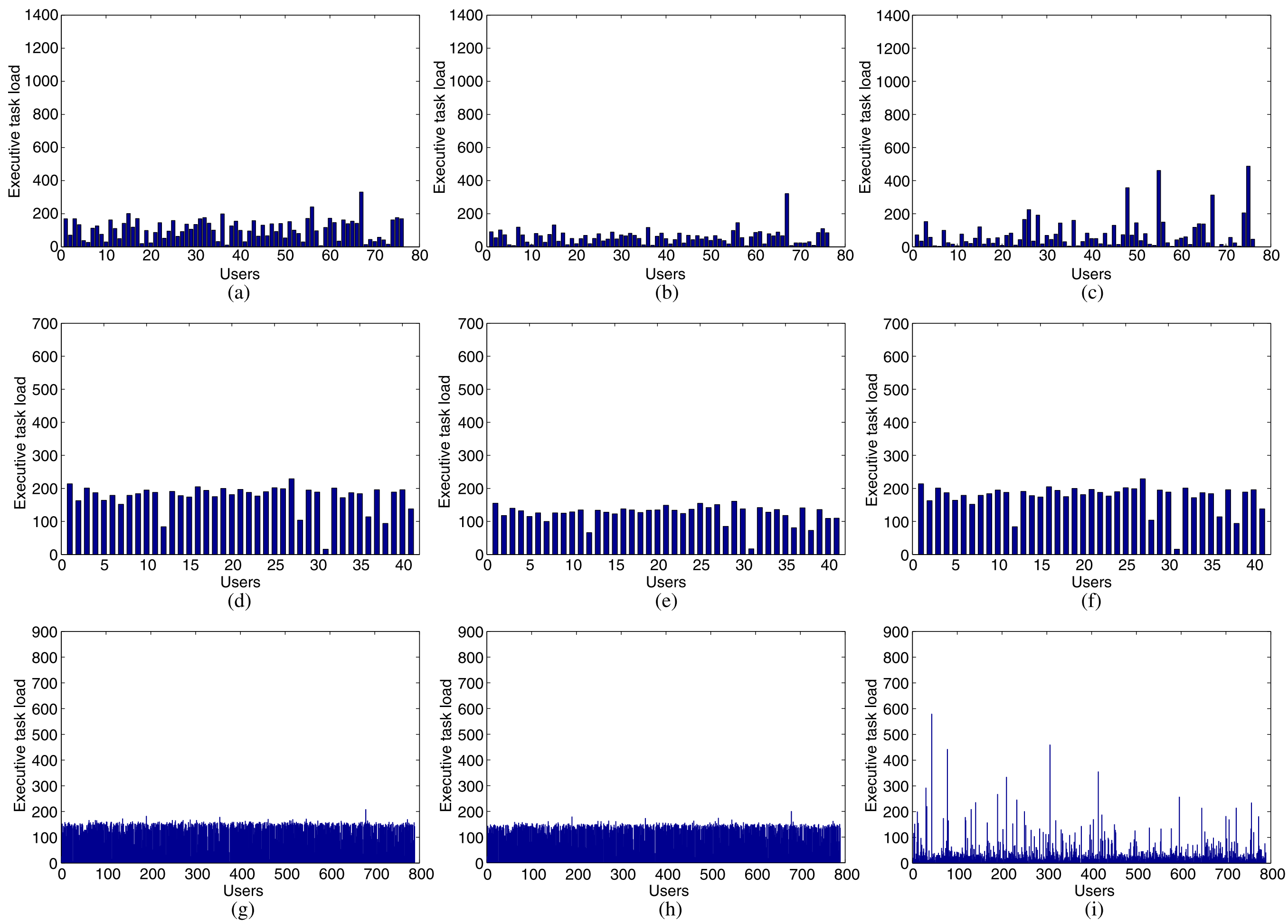


Fig. 9. Impact of K value when tasks are executed with priority. (a) Sigcomm $K = 2$. (b) Sigcomm $K = 6$. (c) Sigcomm $K = 20$. (d) Infocom $K = 2$. (e) Infocom $K = 6$. (f) Infocom $K = 20$. (g) Stanford $K = 2$. (h) Stanford $K = 6$. (i) Stanford $K = 20$.

where users could reach the relatively frequent user without much effort. As shown in Fig. 8(a), the priority-based schemes outperforms those methods without priority significantly.

D. Scaling the Task Execution Factor

We also consider the case when the base value g is set to other values for psychology and social relationship reasons. That is, we need to scale this factor to see the impact of task execution. Fig. 8(b) shows that when the base value g changes, the task assignments provide similar performance, and we conclude that this factor does not impact the performance significantly when task balancing is concerned.

E. Efficiency Comparison Among Different Data Sets

To compare the execution time of algorithm "iTop-K" with three data sets, we normalize the task weight into the range

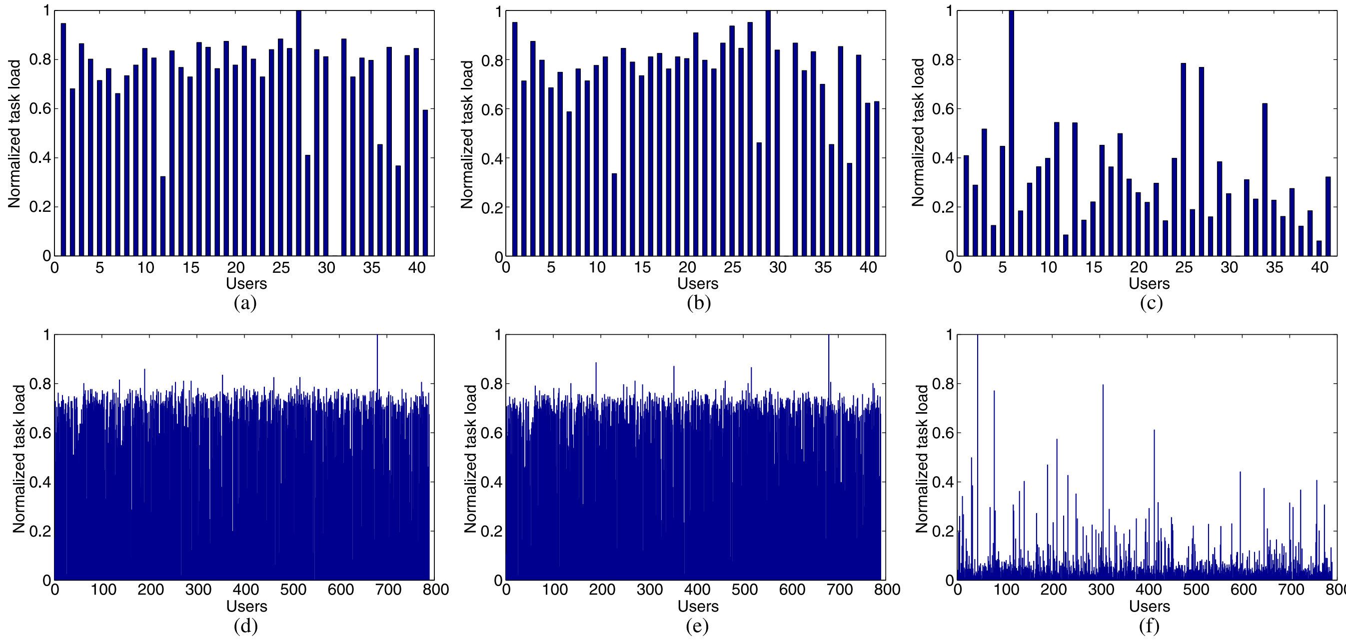


Fig. 10. Normalized task load performance of scheme with priority (Infocom and Stanford). (a) Infocom $-$ $K = 2$. (b) Infocom $-$ $K = 6$. (c) Infocom $-$ $K = 20$. (d) Stanford $-$ $K = 2$. (e) Stanford $-$ $K = 6$. (f) Stanford $-$ $K = 20$.

[0, 1]. As shown in Fig. 8(c), under trace data set *Infocom-2005*, "iTop-K" performs relatively poor compared with the other two data sets. The reason is that records in "Infocom-2005" are a little bit sparse as far as the encountering frequencies are concerned. The relatively infrequent contacts would possibly lead to weak "Top-K" friend list. In contrast, "iTop-K" performs well when *Stanford-2010* is applied. When more participants could be involved, particularly for the real social environment, "iTop-K" would achieve better performance.

In summary, compared with the most loaded users, our proposed scheme outperforms the conventional random choice up to 15$\times$ and the social relationship assignment without priority method up to 9$\times$.

We show our results with the bar chart and CDF form, making comparisons for schemes with priority and without priority. As shown in Fig. 6, the scheme without priority performs poorly with imbalanced task load assignment,whereas for the priority-based scheme, as shown in Fig. 9, the balancing performance significantly improves, compared with the scheme without priority. However, for trace Infocom and Stanford, the results are in Fig. 10. In general, the scheme with priority works better than the scheme without priority. However, when $K = 20$, the scheme with priority has not shown much superiority, where the friend list is so long that the lower ranking users have little difference in task execution time.

VII. Conclusion

We have proposed a social-relationship-based algorithm for efficient task offloading, with trace data collected from real deployed mobile social networks [2]–[4]. We have found that the social relationship could be explored and exploited for balanced task offloading among mobile users. Task priority associates with the social relationships and plays an important role for task execution time. Further, waiting for forthcoming friends is applicable and effective for mobile users. In future work, we are going to further explore the social relationship and find more convincible models for task execution among social friends. Moreover, more effective methods for Top-K friends are called for, particularly when the task execution time differs significantly among friends and strangers. Finally, we plan to apply our methods to realistic applications such as processing pictures to translate words within a crowd of people.

References

[1] M. Mitzenmacher, A. W. Richa, and R. Sitaraman, "The power of two random choices: A survey of techniques and results," in *Handbook of Randomized Computing*, Boston, MA, USA: Kluwer, 2000, pp. 255–312.

[2] A.-K. Pietilainen, E. Oliver, J. LeBrun, G. Varghese, and C. Diot, "Mobiclique: Middleware for mobile social networking," in *Proc. 2nd ACM SIGCOMM Workshop Online Soc. Netw.*, 2009, pp. 49–54.

[3] M. Salathé *et al.*, "A high-resolution human contact network for infectious disease transmission," *Proc. Nat. Academy Sci.*, vol. 107, no. 51, pp. 22 020–22 025, 2010.

[4] "Haggle project." [Online]. Available: www.cambridge.intel-research.net/haggle/

[5] B. Han and A. Srinivasan, "Your friends have more friends than you do: Identifying influential mobile users through random walks," in *Proc. 13th ACM Int. Symp. Mobile Ad Hoc Netw. Comput.*, 2012, pp. 5–14.

[6] Z. Fu, X. Sun, Q. Liu, L. Zhou, and J. Shu, "Achieving efficient cloud search services: Multi-keyword ranked search over encrypted cloud data supporting parallel computing," *IEICE Trans. Commun.*, vol. E98-B, no. 1, pp. 190–200, 2015.

[7] K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow, "Sociablesense: Exploring the trade-offs of adaptive sampling and computation offloading for social sensing," in *Proc. MobiCom*, 2011, pp. 73–84.

[8] K. K. Rachuri, M. Musolesi, and C. Mascolo, "Energy-accuracy trade-offs in querying sensor data for continuous sensing mobile systems," in *Proc. Mobile Context-Awareness Workshop*, 2010, pp. 1–4.

[9] D. Wang, L. Kaplan, and C. C. Aggarwal, "On quantifying the accuracy of maximum likelihood estimation of participant reliability in social sensing," in *Proc. Int. Workshop DMSN*, 2011, pp. 1–6.

[10] C. Shi, V. Lakafosis, M. H. Ammar, and E. W. Zegura, "Serendipity: Enabling remote computing among intermittently connected mobile devices," *Proc. MobiHoc*, 2012, pp. 145–154.

[11] Q. Li and P. Yang, "Store: Simple task offloading and reassignment for mobile social network," in *Proc. IEEE Chinacom*, 2013, pp. 581–586.

[12] P. Key, L. Massouli, and D. Towsley, "Multipath routing, congestion control and load balancing," in *Proc. IEEE ICASSP*, 2007, pp. 1–4.

[13] L. Rudolph, M. Slivkin-Allalouf, and E. Upfal, "A simple load balancing scheme for task allocation in parallel machines," in *Proc. 3rd. Annu. ACM Symp. Parallel Algorithms Archit.*, 1991, pp. 237–245.

[14] V. Stemann, "Parallel balanced allocations," *Proc. 8th ACM Symp. Parallel Algorithms Archit.*, 1996, pp. 261–269.

[15] J. Fan *et al.*, "Geo-community-based broadcasting for data dissemination in mobile social networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 4, pp. 734–743, Apr. 2013.

[16] J. Fan, J. Chen, Y. Du, P. Wang, and Y. Sun, "Delque: A socially-aware delegation query scheme in delay tolerant networks," *IEEE Trans. Veh. Technol.*, vol. 60, no. 5, pp. 2181–2193, Jun. 2011.

[17] T. Hossmann, T. Spyropoulos, and F. Legendre, "Putting contacts into context: Mobility modeling beyond inter-contact times," in *Proc. ACM MobiHoc*, 2011, pp. 1–11.

[18] B. Schwartz, "Queries, priorities, and social process," *Socila Psychol.*, vol. 41, no. 1, pp. 3–12, 1978.

[19] Q. Li, P. Yang, and Y. Tao, "Your friends are more powerful than you: Efficient task offloading in mobile social networks," in *Proc. IEEE ICC*, 2014, pp. 5–14.

[20] K. Pearson, "The problem of the random walk," *Nature*, vol. 72, p. 294, 1905.

[21] M. E. Newman, "A measure of betweenness centrality based on random walks," *Social Netw.*, vol. 27, no. 1, pp. 39–54, Jan. 2005.

[22] J. D. Noh and H. Rieger, "Random walks on complex networks," *Phys. Rev. Lett.*, vol. 92, 2004, Art. ID. 118701.

[23] P. Marshall, "Darpa progress towards affordable, dense, and content focused tactical edge networks," in *Proc. IEEE Milcom*, 2008, pp. 1–7.

[24] K. Fall, G. Iannaccone, and J. Kannan, "A disruption-tolerant architecture for secure and efficient disaster response communications," in *Proc. IEEE ISCRAM*, 2010, pp. 1–5.

[25] "Casting words." [Online]. Available: http://castingwords.com

[26] "Crowd flower." [Online]. Available: http://crowdower.com

[27] "Crowd spring." [Online]. Available: http://www.crowdspring.com

[28] R. Rana, C. Chou, S. Kanhere, N. Bulusu, and W. Hu, "Ear-phone: An end-to-end participatory urban noise mapping system," in *Proc. Int. Conf. IPSN*, 2010, pp. 105–116.

[29] M. Faulkner *et al.*, "The next big one: Detecting earthquakes and other rare events from community-based sensors," in *Proc. IEEE IPSN*, 2011, pp. 13–24.

[30] W. Willett, P. Aoki, N. Kumar, S. Subramanian, and A. Woodruff, "Common sense community: Scaffolding mobile sensing and analysis for novice users," *Pervasive Comput.*, vol. 6030, pp. 301–318, 2010.

[31] P. Volgyesi, A. Ndas, X. Koutsoukos, and Ldeczi, "Air quality monitoring with sensormap," in *Proc. IPSN IEEE Comput. Soc.*, 2008, pp. 529–530.

[32] M. Mun *et al.*, "Peir, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proc. 7th Int. Conf. Mobile Syst., Appl., Services*, 2009, pp. 55–68.

[33] P. Guo, J. Wang, B. Li, and S. Lee, "A variable threshold-value authentication architecture for wireless mesh networks," *J. Internet Technol.*, vol. 15, no. 6, pp. 929–936, 2014.

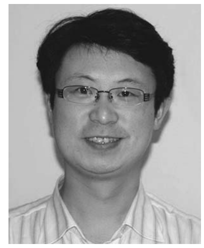
[34] J. Shen, H. Tan, J. Wang, J. Wang, and S. Lee, "A novel routing protocol providing good transmission reliability in underwater sensor networks," *J. Internet Technol.*, vol. 16, no. 1, pp. 171–178, 2015.

[35] N. Maisonneuve, M. Stevens, and B. Ochab, "Participatory noise pollution monitoring using mobile phones," *Inf. Polity*, vol. 15, no. 1, pp. 51–71, Apr. 2010.

[36] S. Xie and Y. Wang, "Construction of tree network with limited delivery latency in homogeneous wireless sensor networks," *Wireless Pers. Commun.*, vol. 78, no. 1, pp. 231–246, Sep. 2014.

[37] D. Yang, G. Xue, X. Fang, and J. Tang, "Crowdsourcing to smartphones: Incentive mechanism design for mobile phone sensing," in *Proc. MobiCom*, 2012, pp. 173–184.

[38] D. Zheng, W. Ge, and J. Zhang, "Distributed opportunistic scheduling for ad hoc networks with random access: An optimal stopping approach," *IEEE Trans. Inf. Theor.*, vol. 55, no. 1, pp. 205–222, Jan. 2009.



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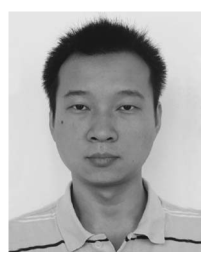

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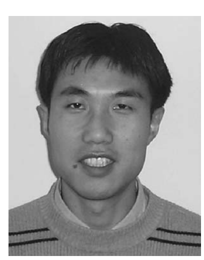

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