Social-Aware Data Dissemination via Device-to-Device Communications: Fusing Social and Mobile Networks with Incentive Constraints

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Abstract—Nowadays, pervasive mobile devices not only pose new challenges for existing wireless networks to accommodate the surging demands, but also offer new opportunities to support various services. For example, device-to-device (D2D) communications provide a promising paradigm for data dissemination with low resource cost and high energy efficiency. In this paper, we propose a three-phase approach for D2D data dissemination, which exploits social-awareness and opportunistic contacts with user mobility. The proposed approach includes one phase of seed selection and two subsequent phases of data forwarding. In Phase I, we build a social-physical graph model, which combines the social network and the mobile network with opportunistic transmissions. Then we partition the social-physical graph into communities using the Girvan-Newman algorithm based on edge-betweenness, and select seeds for the communities according to vertex-closeness. In Phase II, data forwarding only takes place among socially connected users. In Phase III, the base station intervenes to enable data forwarding among cooperative users. For Phase II and Phase III, we propose the new mechanisms for message selection and cooperation pairing, which take into account both altruistic and selfish behaviors of users. The theoretical analysis for the message selection mechanism proves its truthfulness and approximation ratio in the worst case. Extensive simulation results further demonstrate the effectiveness of the proposed three-phase approach with various synthetic and real tracing datasets.

Index Terms—Data dissemination, social-awareness, D2D communications, incentive constraints, truthfulness.

1 INTRODUCTION

The proliferation of mobile devices is enabling a variety of new services, which can take advantage of both long-range radio between the base station (BS) and mobile devices and short-range radio directly among mobile devices. In particular, the mobile-to-mobile, or device-to-device (D2D) communications, provide a promising paradigm to expedite data dissemination, which aims to deliver messages to a group of target users in a geographical region. Data dissemination has a broad range of applications, e.g., in disaster alert, event notification, and advertisement distribution.

One widely studied data dissemination approach is based on a two-phase procedure. A BS first delivers content objects to certain selective users, called initial sources or seeds. After that, the seeds propagate the objects to other users via D2D communications, and any user that receives the data further forwards the data to others resulting in an information epidemic. As seen, this two-phase procedure involves two key issues: 1) initial seed selection, and 2) subsequent data forwarding. Considering that portable wireless devices such as smart phones and tablets are carried by people, it is essential to address and exploit the social properties of human behaviors in cooperative data dissemination.

In the literature, there have been some existing studies on social-aware data dissemination. For the issue of seed selection, most work chooses seeds either based on users’ social ties in the social network [1] or according to the features and properties of users’ contact in the physical world [2,3]. In fact, as social relationships and mobility are both important characteristics of users, the seed selection should jointly exploit the social network and the physical network instead of merely focusing on one side. In addition, for the issue of data forwarding, most existing work either assumes that users are completely altruistic so that they are willing to transmit messages to anyone they encounter [2,3], or assumes that users are absolutely selfish so that they need to be incentivized to participate in the process of data dissemination [4,5]. In fact, a user tends to be double-faced such that he/she is selfish to strangers but altruistic to the people with social ties such as family members, friends, colleagues, etc. Therefore, users’ altruism and selfishness should be jointly exploited for effective data forwarding. Besides, during the process of data dissemination, users’ strategic behaviors should also be properly addressed, so that those selfish utility-maximizing users will truthfully report their preferences for the disseminated messages.

Based on these insights, in this paper, we propose a three-phase approach for social-aware data dissemination, which fuses the social network and mobile network for initial seed selection, and exploits users’ altruism and selfishness for subsequent data forwarding. Specifically, Phase I selects seeds based on a social-physical graph model, which characterizes users’ social relationships and transmission opportunities via D2D communications. We apply a graph partitioning approach to divide the social-physical graph into several tightly-knit communities, and then leverage a centrality measure to select central nodes in the generated communities as seeds. After that, it follows with Phase II and Phase III for data forwarding to accommodate users’ altruistic and selfish incentive constraints, respectively. In
Phase II, data forwarding only takes place among socially connected users and a truthful moneyless mechanism is proposed for message selection. In Phase III, the BS intervenes and activates data forwarding among cooperative users which are grouped by a stable matching mechanism. As such, data can be more effectively disseminated to users with fewer social connections or opportunistic contacts due to mobility.

The major contributions of this paper are three-fold:
- We propose a three-phase approach for social-aware data dissemination via D2D communications. The approach selects the initial seeds by fusing the social network and mobile network, and performs the subsequent data forwarding by accommodating users’ altruistic and selfish incentive constraints, respectively, while ensuring users’ truthfulness.
- We theoretically prove that the proposed mechanism for message selection in the phase of data forwarding among socially connected users is truthful and give a lower bound for the approximation ratio of the proposed mechanism with respect to the utility of the corresponding optimal algorithm.
- We conduct extensive simulations with both synthetic and real tracing datasets to evaluate the performance of our proposed approach. The simulation results show that the three-phase approach can effectively improve data dissemination efficiency, and our truthful mechanisms achieve high performance relatively close to that of the optimal algorithms.

The remainder of this paper is organized as follows. In Section 2, we review the existing work on data dissemination. Section 3 gives the system model for social-aware data dissemination via D2D communications. In Section 4, we introduce the proposed three-phase approach, and analyze its truthfulness property and approximation ratio. In Section 5, we evaluate the performance of our mechanisms using synthetic and real tracing datasets. Finally, Section 6 concludes this paper.

2 Related Work

In [2], the authors proposed a community-based source selection algorithm for mobile social networks (MSNs). Given the measured one-hop contact frequency between each pair of nodes, the BS can estimate their minimum traversal time via the best (shortest) path. Then, the nodes of highest contact frequencies with others are greedily selected sequentially as initial sources. Starting with an initial source $s$, breadth-first search is used to determine a community, which includes the set of users that can receive an object that originates from $s$ via multi-hop forwarding before the deadline. In [3], the community-based source selection algorithm is further integrated with a preference-aware opportunistic forwarding scheme, PrefCast [6]. In PrefCast, a forwarding scheduling algorithm is proposed to achieve a high global utility by exploiting an estimate on the potential contribution of forwarding objects for future contacts.

As another appealing approach, coalitional game theory has been considered in the literature to address content distribution due to inherent autonomous and decentralized features. In [7], a coalitional formation game is formulated to exchange content pieces among vehicles in vehicular ad hoc networks (VANETs). A coalitional graph game is considered in [1] for data dissemination for MSNs in a two-phase manner. A coalitional graph game takes into account the formed network graph, not just the grouping of coalitions. Initial seeds are selected according to a degree of popularity, which is essentially the degree centrality of nodes in social networks. These studies based on coalitional games mainly focus on characteristics such as convergence, stability, and efficiency.

In [1], D2D links are only established between socially connected users who fall within the D2D transmission range. This assumption is further extended in [8] to incorporate both social trust and social reciprocity in relay selection for cooperative D2D communications. From an incentive perspective, a user may seek assistance from its social ties or exchange relay service by joining a mutually beneficial group. Based on a coalitional game formulation, the authors proposed a network assisted relay selection mechanism, which assigns each node a best relay node with social trust or within a reciprocal relay cycle according to the reported preference lists of all nodes. Different from the aforementioned coalitional game theoretical approaches, [8] addresses the private information (preferences) held by each node, while similar information is assumed publicly known in [1,7]. Given such private information, an algorithmic solution needs to be translated into a mechanism to address the strategic behaviors of nodes. Truthfulness is one important desired property of mechanisms, which requires that selfish utility-maximizing agents truthfully report their real preferences. Though the mechanism proposed in [8] is shown to be truthful, individually rational, and computationally efficient, it addresses a relay selection scenario, which is simpler than data dissemination in a broader scope. In addition, a large reciprocal relay cycle is vulnerable in face of user mobility and opportunistic contacts, since any node leaving a coalitional group breaks the relay cycle and defeats further cooperation.

In addition, there are some studies that address the incentive issue of D2D-based data dissemination via an auction-based approach or a mechanism with monetary incentive. For instance, in [9], a randomized auction mechanism is proposed to offload data requests from the BS to helper devices which share their messages with nearby requesting devices. A key challenge for the auction mechanism is to determine the allocation of content requests and corresponding payments to helpers to guarantee truthfulness. However, the transfer of money may be a hassle in some environments due to the payment overhead or security concern. Hence, this work focuses on truthful moneyless incentive schemes for more lightweight implementation.

3 System Model

In this paper, we consider a data dissemination scenario depicted in Fig. 1, where a BS is requested to disseminate a sequence of $m$ messages, $M$, to a set of $n$ users, $N$, in an area. Assume that each user $i \in N$ has a heterogeneous preference toward a message $k \in M$, quantified by a normalized valuation (i.e., utility) $v_{ik}$ ($0 \leq v_{ik} \leq 1$). The BS first chooses a subset of users $D \subseteq N$ as seeds and directly
transmits the messages to them, and then the seeds and any receiving user further forward the data to others via D2D communications.

3.1 Social Graph Model

Considering the popularity of various social media, a social graph can be obtained from online social network platforms such as Facebook, Twitter, LinkedIn, Sina Weibo, and WeChat. Letting $N$ denote a set of users in the system, we use an unweighted and undirected social graph $G_0(N, E)$ to model the social ties among the users in $N$, where an edge $e = (i, j) \in E$ represents that nodes $i$ and $j$ are socially connected via social relationships, such as among family members, friends, colleagues, collaborators, etc. Social trust is a key social phenomenon among socially connected people, while altruistic behaviors are observed among people with social trust in many human activities [8,10]. That is, people are motivated to adopt a generous action that benefits their social contacts at their own costs. Therefore, a user is willing to expend its resources and share data with other users with social connections. Hence, an edge in the social graph $G_0$ captures the existence of social trust between the corresponding users that incentivizes them to disseminate data toward each other.

3.2 Physical Network Model

The physical network supporting data dissemination needs to be characterized by the transmission and contact processes among nodes. While the transmission feasibility in the mobile network depends on the D2D links between any two nodes, the contact process directly varies with user mobility. Considering a target data rate, we take the time to transmit a message at this rate as one time slot $\tau$. Then, we say that two nodes encounter each other, or are in contact, when their physical distance and D2D channel conditions can support the target data rate. For each pair of nodes $i$ and $j$, their contact process alternates between encounters and inter-contacts. Referring to previous studies on real contact traces [11], we assume that the inter-contact interval, up to a characteristic time in the order of half a day, follows a power-law tail, which can be modeled by a Weibull distribution or a Pareto distribution. The contact duration is modeled by a uniform distribution [12]. The probability that nodes $i$ and $j$ have at least one encounter within a time frame $T$ is termed as contact probability and denoted by $p_{ij}$.

4 Social-Aware Data Dissemination with Incentive Constraints

As data forwarding via D2D communications costs non-negligible bandwidth, energy, and computing resources, self-interested users should be incentivized to contribute to data spreading. Basically, there are two classes of incentives: monetary and moneyless. Monetary incentives involve transfer of money or virtual currency. That is, a forwarding node is rewarded money to compensate for its cost of resources in data forwarding. In contrast, moneyless incentives are often used in the environments where monetary compensation is difficult (e.g., due to security concern with online payment) or prohibited (e.g., for ethical or legal reasons).

As argued in [1,8], the existence of social trust between two socially connected users justifies their willingness to disseminate data to each other via D2D links when falling within the communication range. Thus, social trust can be regarded as one type of moneyless incentives, which is termed social incentive in the following. Moneyless incentives have been considered in cooperative communications, where a relay node helping a source-destination pair can be allocated higher transmit power or higher priority for channel access. There are also studies that group two [13] or more nodes [8] into a coalition, so that they can mutually benefit from relaying for each other and thereby remain in a stable structure. We refer to this form of moneyless incentives with exchange of resources (e.g., transmit power) or services (e.g., relaying) as cooperative incentive.

To accommodate the incentive constraint, we consider a three-phase approach as illustrated in Fig. 2. Similar to the existing two-phase approach, Phase I selects initial seeds such that the BS first dispatches the messages to the seeds. Differently, we take into account the social-physical graph given in Section 4.2. Further, we split the subsequent data forwarding into Phase II and Phase III among socially...
connected users and among cooperative users, respectively. The two phases of data forwarding properly address social incentive and cooperative incentive, respectively.

### 4.1 Phase I: Initial Seed Selection and Message Dispatching

The social and physical aspects have been jointly considered in previous works such as [8,14] for cooperative relaying and information diffusion, respectively. In this work, we specify the joint social-physical connection in our unique fashion and apply it to an opportunistic data dissemination scenario with the incentive constraint. To assimilate the social and physical aspects of the system, we couple the social graph \( G_0 \) and the physical network model to derive a weighted and undirected social-physical graph \( G \). Graph \( G \) inherits the node set and edge set from \( G_0 \) and further labels each edge \( e=(i,j) \in E \) by a length metric

\[
\text{length}(e) = \log \frac{1}{p_{ij}}.
\]

In social network analysis, betweenness and closeness are two classic centrality measures which can identify the most influential vertices or edges in a weighted or unweighted, undirected or directed graph. Betweenness of a vertex or an edge is the sum of the fraction of the shortest paths between each pair of vertices that pass through the vertex or edge in question. Here, we consider edge-betweenness defined by

\[
\text{betweenness}(e) = \sum_{s,d \in N, e \in E} \frac{\sigma_{sd}(e)}{\sigma_{sd}}
\]

where \( \sigma_{sd} \) is the number of shortest paths from node \( s \) to node \( d \), and \( \sigma_{sd}(e) \) is the number of those shortest paths that pass through edge \( e \). A high edge-betweenness implies that an edge behaves like a bridge connector between two sections of a graph, and its removal may impede communication between the nodes in the two sections [15]. Given the length metric in (1), the total length of a path from node \( s \) to node \( d \) is given by

\[
\text{length}(P) = \log \frac{1}{\prod_{e=(i,j) \in P} p_{ij}}
\]

which actually indicates the “transmissibility” [14] of information from node \( s \) to node \( d \), since the product term gives the probability that information spreading potentially happens over each link of the path.

Closeness of a vertex is defined by

\[
\text{closeness}(s) = \frac{1}{\sum_{s,d \in N, s \neq d} d_{sd}}
\]

where \( d_{sd} \) is the length of the shortest path(s) (i.e., the distance) from node \( s \) to node \( d \). This closeness definition actually measures the speed of spreading information sequentially from node \( s \) to all other nodes [16]. As the social-physical graph may not be fully connected, harmonic centrality [17] in the following is used instead:

\[
\text{closeness}(s) = \sum_{s,d \in N, s \neq d} \frac{1}{d_{sd}}.
\]

Based on the social-physical graph \( G \), we can perform social-aware community construction and corresponding seed selection for this phase. The basic idea is to first partition graph \( G \) into \( c \) densely connected subgraphs, i.e., communities, by iteratively removing edges that act like bridges linking different sections of the graph. Then for each generated community, the selected seed is the node which can spread data at the highest speed to other nodes in this community. Specifically, we use the Girvan-Newman algorithm [18] based on the edge-betweenness defined in (2) to partition the social-physical graph into \( c \) communities, as illustrated in Fig. 3. The key idea of the Girvan-Newman algorithm is to remove the edge of the highest betweenness (break a tie randomly), recalculate the betweenness of remaining edges, and repeat until there are \( c \) connected components that are “reasonably” large (e.g., of a size not less than 3) corresponding to \( c \) communities. Thereby, the nodes within each community are more strongly connected than those in the rest of the communities. After the graph partitioning, we further evaluate the vertex-closeness of each node according to the definition in (5). Here, the calculation of closeness depends on the local community structure instead of the original social-physical graph. For each community, the node of the highest closeness is then selected as a seed. Note that the number of seeds can be limited by adjusting the minimum size of communities. Since more seeds improve the dissemination speed but also cost more resources of the BS, we need to achieve a good balance between the dissemination speed and resource cost of the BS.

### 4.2 Phase II: Data Forwarding Among Socially Connected Users

Due to the dynamic and autonomous nature in D2D data forwarding, a decentralized solution is more feasible in practice. Hence, Phase II focuses on data forwarding from the perspectives of individual nodes. Any node that receives some messages automatically becomes an ego node and when active spreads out its available messages to its socially connected nodes (for simplicity, generally referred to as “friends” in the following) within the D2D communication range. At the beginning of Phase II, the initial seeds

![Fig. 3: Partitions of social-physical graph for community formation and seed selection. Here, three nodes (1, 6, and 13) are selected for three reasonably large communities. Nodes (11, 12, 16, and 17) are not connected to any seed and have to leverage cooperative means to receive messages in dissemination.](image-url)
selected in Phase I first become ego nodes and ready for further dissemination. After that, any node that receives some messages also turns into an ego node and disseminates messages toward its friend nodes. To improve energy efficiency, we assume that each ego node is only periodically activated for dissemination according to a certain schedule. In view of user mobility and availability, a user’s friends may not be always active or stay in the close proximity. Some friend nodes may move away while others may come up. Therefore, at the beginning of an active period, an ego node first performs peer discovery, e.g., by broadcasting a probing signal, to identify its friends within the D2D communication range. Then, the ego node sends a catalog of available messages in possession to the friend nodes that echo its probing. Each receiving friend node returns a list of message IDs it is missing. Suppose that the ego node is subject to an energy constraint and only able to send at most $g$ messages in one dissemination period. The ego node then needs to decide the messages it will forward to its friends.

Fig. 4 illustrates a concrete example, where an ego node has 6 messages $\{m_1, m_2, ..., m_6\}$ available and 4 active friend nodes $\{u_1, u_2, u_3, u_4\}$ within its D2D transmission range. Here, $u_1$ is missing messages $\{m_1, m_3, m_4\}$ and quantifies its valuation toward these messages as 0.9, 0.3, and 0.16, respectively. The other nodes $\{u_2, u_3, u_4\}$ have different preferences on the messages. This situation can also be abstracted as a bipartite graph in Fig. 5. Here, an edge between a friend node $u_i$ and a potential message $m_k$ indicates that node $u_i$ is interested in message $m_k$ and has a valuation $v_{u_i,m_k}$ toward this message according to its preference. Then, the ego node needs to choose at most $g$ messages on the right side to maximize the total valuation of the edges incident on the selected messages.

This message selection problem involves two key issues. First, the ego node intends to maximize the total utility of its friends with its restricted energy. We refer to this as an efficiency requirement. This looks similar to a maximum weight bipartite matching (MWBM) problem formulated in [3,6], between a set of objects and a sequence of broadcast time slots to determine an optimal forwarding schedule. Nonetheless, we consider a many-to-one matching rather than a one-to-one matching in MWBM. This is because a multicast message will potentially benefit multiple nodes which are expecting it. Moreover, the number of selected messages for matching is upper-bounded to accommodate the energy constraint.

Second, we want to address the strategic behavior of the receiving nodes. As illustrated in Fig. 4, each friend node on the left has its private preference toward the available messages on the right, which is only known to the friend node itself and needs to be solicited by the ego node. To maximize the receiving nodes’ total utility with the selected messages, it is crucial to ensure that each friend node submits a truthful report consistent with its private information.

Since the ego node is socially connected to all receiving nodes, the social trust in between can justifiy the altruism of the ego node toward the receiving nodes. According to the strong triadic closure property [19] of social networks, if node $A$ is connected to nodes $B$ and $C$ with strong ties, it is likely that nodes $B$ and $C$ are also connected for reasons such as opportunity, trusting, and incentive. Nonetheless, the ego node may have weak ties and violate the triadic closure property, which implies there is lack of social trust among the receiving nodes.

Without social trust among each other, a receiving node can lie about its private preference toward the available messages to maximize its own payoff. Since the ego node integrates the preferences of all receiving nodes and selects certain messages to maximize the overall utility, a receiving node may lie to the ego node its preference toward the messages such that its most preferred messages are selected. Such untruthful strategic behavior is detrimental because the untruthful declaration leads to a nonoptimal and even unpredictable solution. Therefore, we require a truthful mechanism which incentivizes the receiving nodes to report their true preferences. A truthful mechanism ensures that a receiving node maximizes its payoff by revealing its true preferences, regardless of other receiving nodes’ reports. Then, there is no incentive for the receiving node to submit
an untruthful report.

A natural idea to ensure truthfulness is to hold a combinatorial auction for each receiving node to submit bids for their interested messages based on their valuations. Then, a pricing scheme that determines the monetary payments of winning nodes can be carefully designed to ensure truthfulness. However, the overhead of enforcing and collecting payments prompts favor toward mechanisms without money. On the other hand, without the payment leverage, it becomes more challenging to guarantee truthfulness. The Gibbard-Satterthwaite Theorem proves that the truthful mechanisms for three or more alternatives must be dictatorial such that an outcome is selected by aligning with the preference of a single agent [20].

To get around the impossibility result, many studies focus on restricted preference domains that may present in highly structured environments, such as the assignment problem. In [21], it shows that a non-trivial result exists for MWBM with a restricted valuation model, where all possible values \( v_{ik}'s \) are assumed known a priori or verifiable, but the edges in the bipartite graph are private. This turns the private information held by each node on the left into \( \delta_{ik} = \{0, 1\} \) for each present edge. It is proved that an optimal solution to MWBM is inherently untruthful, whereas a greedy algorithm of approximation ratio 2 is shown to be truthful. In view of the observations in [21], for the message selection problem in Fig. 5, we assume that the private information of a receiving node \( u_i \) on the left is whether there exists an edge toward any message \( m_k \), i.e., whether it requests message \( m_k \). Applying the method in [21], we obtain the following result.

**Theorem 1.** An optimal solution to the message selection problem with \( n \geq 2 \) is not truthful; and no deterministic truthful mechanism can achieve an approximation ratio better than \( \frac{1+\sqrt{5}}{2} \).

**Proof.** Consider the example in Fig. 6 with two users \( u_1 \) and \( u_2 \) which request one or two messages \( m_x \) and \( m_y \). The ego node which holds the two messages needs to select only one message to send to \( u_1 \) and \( u_2 \). Fig. 6(a) shows the truthful preferences of users \( u_1 \) and \( u_2 \) toward messages \( m_x \) and \( m_y \). That is, \( u_1 \) only needs message \( m_x \) and has a valuation \( (1 - \epsilon) \) toward \( m_x \), where \( 0 < \epsilon < 1 \); \( u_2 \) asks for both messages \( m_x \) and \( m_y \), and has valuations \( \epsilon \) and \( \theta \) toward these messages, respectively. Here, \( \frac{1}{2} < \theta < 1, \theta > \epsilon, \) and \( \theta > 1 - \epsilon \).

Let us focus on the strategic actions of \( u_2 \). If \( u_2 \) truthfully reports its choices of messages, as shown in Fig. 6(a), an optimal solution (denoted by \( \text{OPT} \)) should select message \( m_x \) for multicast, which achieves the maximum total utility \( U_{\text{OPT}} = (1 - \epsilon) + \epsilon = 1 \). This is because choosing message \( m_y \) leads to a total utility \( \theta \) and \( \theta < 1 \). Correspondingly, the utility of \( u_2 \) in the optimal solution is \( \epsilon \).

On the other hand, if \( u_2 \) lies about its choice by hiding its demand for \( m_x \) as shown in Fig. 6(b). Then, an optimal solution switches to select message \( m_y \), since choosing \( m_x \) and \( m_y \) result in total utility \( (1 - \epsilon) + \theta \), respectively, and \( \theta > 1 - \epsilon \) according to the setup. As a result, the utility of \( u_2 \) becomes \( \theta \) in this case. Comparing the utility of \( u_2 \) in Case (a) and Case (b), since \( \theta > \epsilon \), we see that \( u_2 \) successfully increases its utility by lying. This demonstrates that an optimal solution is not guaranteed to be truthful. This is quite different from truthful mechanisms with money transfer, which rely on optimality of the selected outcome in many cases.

Next, we assume by contradiction that a truthful mechanism \( \text{ALG} \) achieves an approximation ratio \( \rho < \kappa \), where \( 1 < \kappa < \frac{1 + \sqrt{5}}{2} \approx 1.618 \). Consider the example in Fig. 6 but with an additional condition that \( \theta < \frac{1}{\kappa} \).

- **Case (a).** Obviously, the optimal solution is \( m_x \), since \( (1 - \epsilon) + \epsilon > \theta \), which results in a total utility \( U_{\text{OPT}} = 1 \). By the contradiction assumption that \( \rho < \kappa \), we have
  \[
  U_{\text{ALG}} \geq \frac{U_{\text{OPT}}}{\rho} > \frac{U_{\text{OPT}}}{\kappa} = \frac{1}{\kappa}.
  \]

Since the only alternative solution has a total utility \( \theta < \frac{1}{\kappa} \), \( \text{ALG} \) cannot choose \( m_y \) but \( m_x \). Thus, both \( \text{OPT} \) and \( \text{ALG} \) select \( m_x \) with truthful reports in Case (a).

- **Case (b).** As discussed above, \( u_2 \) attempts to hide its edge to \( m_x \) and force \( m_y \) to be selected to improve its utility from \( \epsilon \) to \( \theta \) given \( \theta > \epsilon \). In this case, \( \text{OPT} \) will select \( m_y \) for a total utility \( U_{\text{OPT}} = \theta \) since \( \theta > 1 - \epsilon \). However, \( \text{ALG} \) cannot select \( m_y \) but \( m_x \) to ensure truthfulness, which results in a total utility \( U_{\text{ALG}} = 1 - \epsilon \). Thus, the approximation ratio is given by
  \[
  \rho = \frac{U_{\text{OPT}}}{U_{\text{ALG}}} = \frac{\theta}{1 - \epsilon} < \frac{\theta}{1 - \theta} < \frac{1/\kappa}{(1 - (1/\kappa))} = \frac{1}{\kappa - 1}.
  \]

Since \( 1 < \kappa < \frac{1 + \sqrt{5}}{2} \), we have \( \frac{1}{\kappa - 1} > \kappa \), which is easily seen by solving the quadratic equation with equality in the preceding inequality. Therefore, if we can find valid values for \( \theta, \epsilon, \) and \( \kappa \) such that \( \rho = \frac{\theta}{1 - \epsilon} = \kappa \), it gives contradiction to the assumption \( \rho < \kappa \) and concludes the proof.

In fact, it is not hard to find feasible values to validate this condition, since it simply requires

\[
\theta = \kappa(1 - \epsilon) > \epsilon \quad \Rightarrow \quad \frac{\epsilon}{1 - \epsilon} < \kappa < \frac{1 + \sqrt{5}}{2} \approx 1.618
\]

\[
\epsilon < \frac{1 + \sqrt{5}}{3 + \sqrt{5}} \approx 0.618.
\]

One example can be obtained as \( \theta = 0.6, \epsilon = 0.58, \) and \( \kappa = \frac{\theta}{1 - \epsilon} \approx 1.429 \).

\( \square \)

Though we have showed that a deterministic truthful mechanism must have an approximation ratio no less than \( \frac{1 + \sqrt{5}}{2} \) (this includes the optimal solutions), we are not clear whether this bound is tight. Hence, we propose a greedy
Algorithm 1 A truthful approximate mechanism for message selection.

Input: $N, M, L = \{(u_i, m_k) : \delta_{ik} = 1, u_i \in N, m_k \in M\}$, $\{v_{ik} : u_i \in N, m_k \in M\}, g$
Output: $S \subseteq M = \{m_k : x_k = 1, 1 \leq k \leq m\}, x_k \in \{0, 1\}$
1: $x_k = 0, \forall 1 \leq k \leq m$ // Initialize message selection
2: $S \leftarrow \emptyset$
3: $m' \leftarrow$ number of messages with positive total values
4: if $m \leq g$ then
   // Select all messages for which an interest exists
5:   $x_k = 1$, if $\sum_{i=1}^{n} \delta_{ik} v_{ik} > 0, \forall 1 \leq k \leq m$
6:   return $S$
7: end if
8: $\ell \leftarrow 0$ // Track number of selected messages
9: Sort pairs $(i, k)$ in a non-increasing order of $v_{ik}$, breaking ties consistently and arbitrarily
10: for all $e = (i, k) \in L$ in the above order do
11:   if $\ell = \min\{g, m'\}$ then
12:      break // No more message is available or allowed
13: end if
14: if $x_k = 0$ then
15:   $x_k \leftarrow 1$ // Add the newly incident message
16: $S \leftarrow S \cup \{m_k\}$
17: $\ell \leftarrow \ell + 1$
18: end if
19: end for
20: return $S$

Theorem 2. The mechanism based on Algo. 1 is truthful and $n$-approximate.

Proof. To prove truthfulness, we consider an arbitrary friend node $u_i$, which reports an edge set $L_i$. It is easily seen that $L_i \subseteq L$, where $L_i$ denotes $u_i$’s true edges. This is because an edge $e = (i, k) \notin L_i$ indicates that $u_i$ does not need message $m_k$ and receiving such a message if it is selected eventually costs unnecessary energy without any real gain. Therefore, $u_i$ has no incentive to report nonexistent edges.

On the other hand, suppose that $u_i$ intends to improve its utility by hiding some edges in $L_i$. Since there is no competition when an ego node has sufficient capacity to multicast all interested messages, we focus on the case when the number of selected messages is $g' = \min\{g, m'\}$. Let $S = \{m_{\alpha_1}, \ldots, m_{\alpha_g}\}$ denote the selected messages with $u_i$’s truthful report which are sorted in a non-increasing order of the maximum values incident on these messages. Notice that this is also the order that these messages are selected by Algo. 1. Similarly, we denote the selected messages with $u_i$’s untruthful report by $\hat{S} = \{m_{\hat{\alpha}_1}, \ldots, m_{\hat{\alpha}_{g'}}\}$.

Filtering out the unique messages in $S$ and $\hat{S}$, we can pair these two subsets of messages one by one in the order defined above. Fig. 7 shows a simple example to facilitate understanding. In this example, $S = \{m_1, m_2, m_5, m_3\}$ and $\hat{S} = \{m_1, m_5, m_3, m_6\}$. The unique messages $m_2$ and $m_6$ are paired. This can be interpreted as the misreporting of $u_i$ leading to a switch of selection from $m_2$ to $m_6$.

Here, we notice one important observation which is key to the proof of truthfulness. That is, $u_i$ is only able to change a selection from $m_\alpha$ to $m_\beta$ if $v_\alpha$ is the maximum value among all edges incident on $m_\alpha$. If $u_i$ hides such an edge, it can only affect the selection of those messages whose maximum values are less than $v_\alpha$. Because Algo. 1 selects messages in a non-increasing order of $v_{ik}$’s, a hidden edge that causes the change from $m_\alpha$ to $m_\beta$ must satisfy $v_\alpha > v_\beta$. The net gain of this change $(v_\beta - v_\alpha)$ must be negative. The same reasoning can be applied to each pair of unique messages. Therefore, no positive gain motivates $u_i$ to hide edges.

Next, we use a charging argument to prove the approximation ratio in the worst case. Let $S_{\textsc{alg}}$ and $S_{\textsc{opt}}$ denote the set of messages selected by Algo. 1 and an optimal solution, respectively. Consider each message $m_k \in S_{\textsc{opt}}$. If $m_k \in S_{\textsc{alg}}$ as well, we charge $U_k = \sum_{i=1}^{n} v_{ik}\delta_{ik}$ to $m_k$. If $m_k \notin S_{\textsc{alg}}$, it must be because there exists an available message $m'_k$ whose maximum incident value is greater than that of $m_k$. Defining $v_{k,\text{max}} = \max_{1 \leq i \leq n} v_{ik}\delta_{ik}$ and $\delta_{k',\text{max}} = \max_{1 \leq i \leq n} \delta_{ik}\delta_{ik'}/$, we have $v_{k',\text{max}} > v_{k,\text{max}}$. Since at most $n$ edges from $n$ friend nodes are incident on $m'_k$, it can be seen that

\[
U_k = \sum_{i=1}^{n} v_{ik}\delta_{ik} \leq n \cdot v_{k,\text{max}} \leq n \cdot \delta_{k',\text{max}}.
\]

Hence, if $m_k \in S_{\textsc{opt}}$ but $m'_k \notin S_{\textsc{alg}}$, we charge $\frac{1}{n}U_k$ to $m'_k$. According to the above charging scheme, the weight charged to each message in $S_{\textsc{alg}}$ is no more than the total utility of the message. Therefore, the total utility of $S_{\textsc{alg}}$ is lower-bounded by the total charged weight, which is at least $\frac{1}{n}$ of the total utility of $S_{\textsc{opt}}$, i.e., $U_{\textsc{alg}} \geq \frac{1}{n}U_{\textsc{opt}}$.

This approximation ratio may not look appealing at first...
sight. Note that this is the approximation ratio in the worst case which may only occasionally happen in practice. Fig. 8 illustrates the variation of average approximation ratio \( \overline{\rho} \) with the maximum number of allowed broadcast messages \( g \). In the numerical experiments, we set the valuations of \( n \) nodes toward \( m \) messages as uniformly distributed within \([0, 1]\), and set the choices of each node among the \( m \) messages as a uniform number within \([0, m]\). Here, \( n = 8 \), \( m = 10 \), and \( g \) is varied from 1 to 10. For each setting of \( g \), we generate 1000 random cases and run Algo. 1 and the optimal algorithm for each case. The approximation ratio for each case is given by \( \frac{U_{2LC}}{U_{OPT}} \). The average approximation ratio \( \overline{\rho} \) is obtained by averaging over the resulting approximation ratios of 1000 random cases. As seen, when \( g \geq 3 \), \( \overline{\rho} \) is usually bounded by 1.2.

4.3 Phase III: Data Forwarding Among Cooperative Users

In Phase II, data forwarding periodically takes place among socially connected nodes according to each node’s individual dissemination schedule. This one-hop incentive-compliant data dissemination is resilient to network dynamics arising from node mobility and availability, since such a decentralized approach only relies on each node’s local information, which can be easily acquired and updated. Nevertheless, the data dissemination result through Phase II itself may be insufficient. It is possible that even after time \( W (W < T) \), some node has not received any dissemination message as it has not had a chance to encounter its friends. In addition, as seen in Fig. 3, there exist some “orphan” nodes that are not connected to any seed because they are isolated or belong to small communities. If data forwarding only happened when social trust exists, these orphan nodes could not receive any message from the seeds and their connected nodes.

On the other hand, multi-hop scheduling for the data forwarding is potentially more efficient, but it is more difficult to construct a multi-hop path in which every intermediate node is a friend of the receiving node to satisfy the social incentive constraint. Besides, a multi-hop path induces higher uncertainty and recovering cost in case that the dissemination through any intermediate node fails. To balance between resilience and efficiency, we include Phase III to expand the coverage of data dissemination beyond one hop but still within a manageable scope. In particular, we enable cooperation that mutually benefits both orphan nodes and socially connected nodes.

Consider the scenario illustrated in Fig. 9. Here, \( u_\alpha \) and \( u_\beta \) are two socially connected nodes, while \( u_\gamma \) is an orphan node. Suppose \( u_\alpha \) wants to disseminate the messages in its possession to its friend \( u_\beta \) but cannot meet \( u_\beta \) due to their mobility patterns. If \( u_\gamma \) has a high chance to encounter both \( u_\alpha \) and \( u_\beta, u_\alpha \) may like to disseminate its messages to this stranger node. If \( u_\gamma \) finally meets \( u_\beta \) and forwards its carried messages to \( u_\beta, u_\alpha \) can be granted access to these messages as a reward. To implement this cooperation idea, it is important to ensure that \( u_\gamma \) only can receive the reward when successfully performing the carry-and-forward task. A simple solution is that \( u_\alpha \) encrypts the messages using a randomly generated session key \( y_{s, \gamma} \), and attaches the session key encrypted by the public key of \( u_\beta \). Only when \( u_\beta \) receives the messages from \( u_\gamma \), will \( u_\beta \) pass the decrypted session key to \( u_\gamma \) to unlock the messages.

The cooperative forwarding is in line with the principle of social reciprocity discussed in [8]. A major difference is that we limit the size of reciprocal coalitions to be more robust to opportunistic contacts. The two socially connected nodes actually correspond to an edge in the social-physical graph \( G \). If we consider the two friend nodes as one entity, the grouping of reciprocal coalitions becomes a bipartite matching problem. As shown in Fig. 10, the left side is the set of orphan nodes \( N' \subset N \). The right side is the set of directional edges, denoted by \( E' \). For each edge \((u_s, u_d) \in E\), two entities, \((u_s, u_d)\) and \((u_d, u_s)\), are included in \( E' \) for both directions.

As \( u_s \) and \( u_d \) may hold a different set of messages, denoted by \( M_s \) and \( M_d \), respectively, an orphan node \( u_r \) thus achieves a different utility with a forwarding task from \( u_s \) to \( u_d \) or from \( u_d \) to \( u_s \). Given a set of messages available at \( u_r \), we say that \( u_r \) falls within the acceptable set of \((u_s, u_d)\) and vice versa, if \( M_s \cap M_r \cap M_d \neq \emptyset \), i.e., \( u_s \) contains at least one message that is commonly interested to \( u_r \) and \( u_d \). Specifically, \( u_r \) ‘s expected valuation toward

![Fig. 8: Average approximation ratio with \( n = 8 \) and \( m = 10 \).](image)

![Fig. 9: Data forwarding among an orphan node \( u_\gamma \) and two socially connected nodes \((u_\alpha, u_\beta)\).](image)
Fig. 10: A cooperation pairing example modeled as a stable matching problem with a bipartite graph.

\[(u_s, u_d)\] is defined by

\[
\mathcal{V}_{u_i}((u_s, u_d)) = p_{sr} \cdot p_{rd} \sum_{m_k \in \mathcal{M}_r \cap \mathcal{M}_d} v_{rk}. \quad (10)
\]

As seen, \(u_i\)'s valuation depends on its contact probabilities with \(u_s\) and \(u_d\), and its utility from the messages that are available at \(u_s\) and demanded by both \(u_r\) and \(u_d\). Similarly, the preference of \((u_s, u_d)\) over \(u_i\) can be measured by

\[
\mathcal{V}_{(u_s, u_d)}|u_r = p_{sr} \cdot p_{rd} \sum_{m_k \in \mathcal{M}_r \cap \mathcal{M}_d} v_{dk}. \quad (11)
\]

Based on the definition in (10), each orphan node \(u_i\) has a strict preference order with respect to the directional edges in its acceptable set, denoted by \(E'_r\). That is, \(\forall e_{\alpha} = (s_{\alpha}, d_{\alpha}), e_{\beta} = (s_{\beta}, d_{\beta}) \in E'_r, e_{\alpha} \succ u_i, e_{\beta}\) if and only if \(\mathcal{V}_{u_i}((s_{\alpha}, d_{\alpha})) > \mathcal{V}_{u_i}((s_{\beta}, d_{\beta}))\). Similarly, according to (11), each edge in \(E'\) has a strict preference order toward the orphan nodes in its acceptable set.

Given the set of orphan nodes \(N_o^r\) and the set of directional edges \(E'\) representing socially connected pairs, we want to properly match \(N_o^r\) and \(E'\) as illustrated in Fig. 10, such that both sides are satisfied with the matching. This can be formulated as the stable matching problem (a.k.a. the stable marriage problem) [22]. A matching is said to be (two-sided) stable if and only if there is no blocking pair which would both prefer each other to their present assignments (i.e., a matched partner or an unassigned state). In our context, suppose \(u_{r_1}\) is matched to \(e_1\) and \(e_2\) is matched to \(u_{r_2}\). Then \(u_{r_1}\) and \(e_2\) which are not matched become a blocking pair if and only if \(e_2 \succ u_{r_1}, e_1 \succ u_{r_1} \succ e_2 \succ u_{r_2}\).

Gale and Shapley proved in [22] that a stable matching always exists and propose the deferred acceptance algorithm (DAA) to find a stable matching which is optimal to the proposing side. The stable matching problem originally focuses on an equal number of agents on both sides and a complete preference list for each agent. Here, we actually consider a variant with unequal sets and partial preference lists. The agents excluded from a preference list are often called blacklisted or unacceptable. Based on the conclusion that all stable matchings engage exactly the same sets of left and right agents, DAA is extended in [23] to address unequal sets. Note that the extended version needs to be slightly modified to accommodate partial preference lists. If there are fewer nodes on the left (\(n_l\)) than the right (\(n_r\)) and the left side proposes, the algorithm cannot terminate when all right agents have been proposed to. Due to the existence of unacceptable choices, the algorithm can only stop when each proposing agent is either assigned a partner or has exhausted all candidates in its acceptable set.

Last, we need to address the incentive constraint before applying DAA to determine a stable matching. In Fig. 10, clearly, there is no social trust between the two sides or among the orphan nodes on the left, though some entities on the right possibly involve friend nodes. Because the preference order of each entity is private information, it is preferable to use a stable matching mechanism in which each entity on both sides is incentivized to report its preference truthfully. The stability and truthfulness requirements for both sides are stronger than the single-sided requirements for message selection in Fig. 5 where the ego node is unselfish toward its friend nodes on the left. However, it was shown in [24] that no stable matching mechanism is truthful for both sides. Since DAA produces a stable matching optimal to the proposing side, when the proposed side behaves honestly, the proposing side has no incentive to misreport their preferences.

Further, it is found in [25] that in an unbalanced (i.e., \(n_l \neq n_r\)) random matching market with complete preference lists, even a slight imbalance can cause the core (i.e., the set of stable matchings) to collapse. In a typical realization, almost all agents have a unique stable partner, and each agent has almost the same average rank of assigned partners under all stable matchings. Particularly, for any \(\epsilon > 0\), when the imbalance is sufficiently large, it is an \(\epsilon\)-Bayes-Nash equilibrium for all agents to report truthfully. Moreover, we show in Fig. 11 that, even with \(n_l = n_r\), the restricted preference lists also induce imbalance and leave little manipulation scope for the proposed side. Here, we control the size of incomplete preference lists using a ratio of the number of unacceptable choices of each agent to the size of a complete list. The double Y-axes show the size of the set of stable matchings and the average fraction of agents with more than one unique stable partner. As seen, when 30% of the preference lists are unacceptable choices, the fraction of multi-partner agents in stable matchings quickly drops below 0.1, and the number of stable matchings is less than 2 on average. This implies that the restricted preferences also collapse the core similar to imbalance when the unacceptable ratio is sufficiently large, thus allowing little room for agents to gain from untruthful reports.

After Phase II when it comes to cooperative pairing in Phase III, it is likely that the number of orphan nodes in \(N_o^r\) is much fewer than that of directional edges in \(E'\). Even if there are an equal number of nodes on both sides of the bipartite graph in Fig. 10, each user often holds a different subset of the messages and thus a partial preference list. Complementing the conclusion in [25] with our observation in Fig. 11, we are confident that it is reasonable to apply the extended DAA to the cooperative pairing problem while accommodating the incentive constraint.

As given in Algo. 2, we first transform the edges in the social-physical graph into a set of directional edges, \(E'\), and identify a set of cooperative candidate nodes, including the orphan nodes and the nodes which have social connections but have received no more than \(\theta\) (e.g., 0.8) of the messages in dissemination, i.e., \(N_o^r\). After that, we derive the
valuations of each agent toward its acceptable candidates in the opposite side. The valuations can be translated to the agent’s preference ordering. Then, letting the candidate nodes propose, we apply DAA to produce a stable matching between \( N' \) and \( E' \). Note that the termination condition is slightly modified to accommodate unequal sets and restricted preferences.

5 SIMULATION RESULTS

5.1 Synthetic Datasets

To evaluate the performance of our proposed mechanisms, we first conduct computer simulations over synthetic datasets, in which the number of users \( n \) is set to 30 and the number of messages \( m \) is set to 10. For comparison purpose, users’ preference for a message, \( v_{ik} \), is set to be uniformly distributed in the range of \([0, 1]\). For generating the social graph of the users, we randomly select 2 users as orphans and then use a classic social network model, the caveman model [26], to generate the social relationships for the remaining 28 users. The caveman model starts with \( c' \) isolated complete graphs, also known as caves, in which every vertex is adjacent to every other vertex. Then in a rewiring stage, every edge of a cave in the original network is randomly rewired by pointing to a node in another cave with probability \( p \). The rewiring procedure intends to establish random inter-connections between individual nodes of different caves. It has been proved in [26] that social networks based on this model are very close to real ones. Here, we set the number of caves to 7, the size of each cave to 4, and the rewiring probability to 0.2.

For generating the user contact process in the physical network, we assume that users’ contact duration follows a uniform distribution [12] and average encounter duration is in the range of \([3, 6]\). Users’ intercontact duration is assumed to follow a heavy-tailed Weibull distribution [11] and average intercontact duration is in the range of \([5, 25]\). In order to better simulate the real scenarios, we randomly select some users in each social connected component and make these users encounter other users in the same component infrequently. Users’ average periodic activation duration is set to 5 and inter-activation duration is set to 10.

Algorithm 2 The deferred acceptance algorithm for cooperation pairing.

Input: \( G, M, D \)

Output: \( \{y_{ij} : u_i \in N', e_j \in E'\} \), where \( y_{ij} \in \{0, 1\} \)

1: \( E' = \{e' = (s, d), (d, s) : e = (s, d) \in E\} \)

2: \( N' \leftarrow \) nodes in \( N \) with completion ratio no more than \( \delta \)

3: // Initialize set of cooperative candidate nodes

4: for all \( u_i \in D \) do

5: // Find nodes reachable from seeds in \( D \)

6: \( N' \leftarrow N' \cup \) unvisited vertices in \( N \) (orphan nodes)

7: \( A_i \leftarrow \emptyset, \forall u_i \in N', B_j \leftarrow \emptyset, \forall e_j \in E' \)

8: // Sets of acceptable candidates of \( u_i \) and \( e_j \)

9: for all \( e_j = (u_s, u_d) \in E' \) do

10: if \( M_s \cap M_i \cap M_d \neq \emptyset \) then

11: \( A_i \leftarrow A_i \cup \{e_j\}, B_j \leftarrow B_j \cup \{u_i\} \)

12: \( v_{ij}^{(A)} = p_{si} \cdot p_{id} \sum_{m_k \in M_i, m_k \cap M_d \neq 0} v_{ik} \)

// \( u_i \)'s valuation toward \( e_j \)

13: \( v_{ij}^{(B)} = p_{ji} \cdot p_{id} \sum_{m_k \in M_i} \sum_{B_k \in M_d} v_{dk} \)

// \( e_j \)'s valuation toward \( u_i \)

14: end if

15: end for

16: end for

17: \( \text{stop} \leftarrow \text{false} \)

// Terminate when a stable matching between \( N' \) and \( E' \) via extended DAA

18: while \( \text{stop} = \text{false} \) do

19: // Let each node in \( N' \) propose to its acceptable choices in \( E' \)

20: for all \( u_i \in N' \) do

21: \( u_i \) proposes its most favorable choice, \( e_{j^*} = \arg \max_{e_j} v_{ij}^{(B)} \)

22: \( e_{j^*} \) accepts \( u_i \) if \( u_i \in B_{j^*} \) and \( v_{ij^*}^{(B)} > v_{ij^*}^{(B)} \), and rejects \( u_i \) otherwise, where \( u_i \)'s present assignment, assuming \( v_{ij^*}^{(B)} = 0 \) if \( u_i \) is \( \emptyset \)

23: end for

24: if each \( u_i \in N' \) is either assigned some \( e_j \in E' \) or rejected by all candidates in \( A_i \) then

25: \( \text{stop} \leftarrow \text{true} \)

26: end if

27: end while

5.2 Average Utility / Completion Ratio vs. Time

In this subsection, we compare our truthful mechanisms with the corresponding optimal algorithms with the synthetic datasets. For Phase II, we consider the optimal algorithm, in which an ego node selects at most \( g \) messages with the highest total utility for multicast in one dissemination period. For Phase III, we use the Hungarian algorithm [27] to obtain the optimal solution to the MWBM problem. In the simulation, the number of seeds is set to 4 and \( g \) is set to 3. It is assumed that each message can finish transmission within one time slot. For the truthful mechanisms, the BS intervenes and performs matching when the increase of average completion ratio in two adjacent observation periods
shows that the total utility of Phase II is relatively close to that of initial sources, such that the seeds in different communities is to select nodes belonging to disjoint communities as data dissemination. The key idea of this reference scheme consider a related work [2], which proposes a novel corresponding optimal solution. In this subsection, we fur-

In Section 5.2, we have compared our approach with the effectiveness improve users’ total utility. Although Theorem 2 the entire process, combining Phase II and Phase III can effectively improve users’ total utility. Although Theorem 2 shows that the total utility of $S_{\text{ALG}}$ in Phase II is at least $\frac{1}{4}$ of that of $S_{\text{OPT}}$, this is the theoretical result for the worst case. Actually, the worst case might not occur frequently in practice. As seen in Fig. 12, the total utility of $S_{\text{ALG}}$ in Phase II is relatively close to that of $S_{\text{OPT}}$. Moreover, with the execution of Phase III, the total utility of our truthful mechanisms is fairly close to that of the corresponding optimal algorithms.

Fig. 13 presents users’ average completion ratio over time. Similar to Fig. 12, Fig. 13 shows that our mechanisms achieve a high completion ratio with Phase II and Phase III together, and the optimal algorithms are slightly better than our mechanisms.

5.3 Latency Performance

In Section 5.2, we have compared our approach with the corresponding optimal solution. In this subsection, we further consider a related work [2], which proposes a novel and inspiring community-based scheme for opportunistic data dissemination. The key idea of this reference scheme is to select nodes belonging to disjoint communities as initial sources, such that the seeds in different communities can propagate the data object in parallel to reduce the dissemination latency. This scheme first ranks the nodes in an ascending order of the summation of its contact frequency to others. According to the ranking, each node is sequentially considered as a seed to construct a community that covers the nodes reachable from the seed through multi-hop forwarding within a deadline. This procedure continues until every node is covered by a community. Different from [2], our approach first constructs communities and then selects seeds. For community construction, we form a social-physical graph and use the Girvan-Newman algorithm to partition the graph into communities based on edge-betweenness. After that, we select the node of the highest vertex-closeness in each community as a seed. In addition, we consider multiple dissemination messages, which induces the message selection problem.

Fig. 14 compares the performance of our approach, the scheme proposed in [2], and the optimal solution. As the scheme in [2] involves randomness in forwarding, we run the scheme for 100 times to obtain an average for each case. In [2], it is assumed that any user who already receives the data object can help distribute it to other users through opportunistic transmission. That is, it does not take into account user incentive. Hence, we consider two variants of this reference scheme with or without social incentive. With social incentive, a user is only willing to disseminate data to its socially connected users rather than anyone. Accordingly, we adapt the ranking of sources and community construction by counting only users with social connections. As such, the scheme is protected from performance degradation to accommodate social incentive.

Here, the simulation settings are similar to those in Section 5.2, except that Phase III starts at 260, and the number of seeds is set to 8 when social incentive is satisfied. The dissemination deadline is set at 400. When social incentive is neglected in the reference scheme, one seed is sufficient to cover every user. As shown in Fig. 14(a), when the incentive constraint is relaxed in the reference scheme, it starts with one seed and spreads data very fast since a user distributes the object to any encountered user. The dissemination latency is around 100 time slots when the completion ratio reaches 100%. In contrast, the dissemination process is slowed down to meet the incentive constraint. As seen, it takes about 110 time slots for our truthful mechanism and the optimal approach to achieve a completion ratio of 60%, while it takes 180 time slots in the reference scheme with the incentive constraint. In addition, the incentive constraint bounds the completion ratio of this reference variant by 82.3% when the dissemination scope is limited by social connections. On the other hand, when our proposed approach further includes cooperative forwarding in Phase III, we can expand the data spreading
coverage. As seen in Fig. 14(a), it takes 320 time slots in total for our approach to attain a completion ratio of 97.3%. Though the incentive constraint causes extra overhead, our approach can successfully address the challenge and achieve satisfactory performance.

5.4 Effect of Number of Seeds

In this subsection, we examine the effect of the number of seeds on our mechanisms. The simulation is also carried out with the previous synthetic datasets and the cases with 1 to 5 seeds are tested respectively. The condition for the BS to intervene and perform matching is also that the increase of average completion ratio of two adjacent observation periods is not larger than 0.01.

Fig. 15 shows the results of average completion ratio with different numbers of seeds. As seen in Fig. 15, with the increase of the number of seeds, average completion ratio increases more rapidly and substantially with time during Phase II and then reaches a higher value at the end of Phase III. It is worth mentioning that when the number of seeds reaches a threshold (e.g., 4 in this experiment), the influence of seed number on data dissemination becomes less evident. Specifically, when the number of seeds increases from 4 to 5, the increase of average completion ratio is not so fast or significant as that in the previous situations.

5.5 Performance in Erdos-Renyi Networks

In this subsection, we evaluate our truthful mechanisms and the corresponding optimal algorithms using different social network topologies. Here, the social networks are simulated by the Erdos-Renyi graph model [28], which generates a random graph with $n$ nodes where the social tie between each pair of nodes exists with a preset probability $P_L$. We set $n$ to 100 and $P_L$ ranges from 0.1 to 0.9. In order to generate a social network with multiple clusters and orphans, we preset three groups of nodes of size 32 and let the remaining 4 nodes to be orphans. Then for each group of nodes, social relationships are generated within the group according to $P_L$. For each value of $P_L$, we run our truthful mechanisms and the optimal algorithms for 100 times respectively and record the corresponding time that 20 users have received all messages. The number of seeds is set to 5, while the number of messages is 10. Users’ intercontact duration is still heavy-tailed Weibull but with an average within $[20, 40]$. Other parameters are the same as in Section 5.1.

Fig. 16 shows the average time that 20 users have received all messages with the increase of $P_L$. As seen, for a different social link density of the social graph, our mechanisms take an average time fairly close to that of the optimal algorithms, and the average time both decreases gradually with $P_L$. This is because with the increase of $P_L$, a user will have more friends in its social group so that in Phase II, the user can transmit data to more potential receivers which will contribute to data dissemination. In addition, as there are more socially connected pairs, more users can benefit from the cooperative forwarding in Phase III. Further, it is noticed that when $P_L \geq 0.8$, some users receive all messages even before cooperative pairing starts, which introduces a larger gap between truthful and optimal solutions.

5.6 Performance with Real Tracing Datasets

In this subsection, we test our mechanisms with the real tracing datasets, Infocom06 [29] and Sigcomm09 [30].
The trace Infocom06 records Bluetooth contacts between iMotes distributed to 78 users who attended the conference IEEE INFOCOM 2006 for several days. The trace Sigcomm09 records the encounter information among 76 participants who carried HTC S620 smartphones with the pre-installed application, MobiClique, for a few days in the conference ACM SIGCOMM 2009. Because of the limitations of these real tracing datasets, we perform some preprocessing to these datasets before using them in the simulations. As for the trace Infocom06, no explicit social relationships are given. Here, we infer users’ social relationships based on their total contact duration. Two users are considered to be friends if their total contact duration is not less than 18000s. For the trace Sigcomm09, contact duration is not given for each contact between a pair of users. Here, we set the duration of each contact to 10s.

In addition, it is noticed that users in the two real tracing datasets have various movement and contact patterns, and they join and leave the conference sites with different schedules. If we continued to periodically activate each user’s data dissemination task for energy-saving purpose, users would have very few opportunities to disseminate data. Therefore, we choose to suspend periodic activation for the real tracing datasets; that is, users are active all the time in Phase II. In the simulation, we set the number of seeds to 5, the number of messages to 10, and $g$ to 5 for the two datasets, respectively.

Fig. 17 shows the number of users who have received all the data. This is because the social relationships in the two trace scenarios are more dense; that is, each user generally has more friends in this trace. As a consequence, users will have more potential target receivers in Phase II and there will be more pairs of socially connected users in Phase III, so that more users can benefit in these phases.

6 Conclusion and Future Work

In this paper, we propose a three-phase approach for social-aware data dissemination via D2D communications. Our approach includes Phase I for initial seed selection and message dispatching to seeds, and Phase II and Phase III for data forwarding among socially connected users and among cooperative users, respectively. Phase I exploits users’ social relationships in the social network and physical contacts with mobility in the physical network to improve data dissemination efficiency. The two phases of data forwarding properly address social incentive and cooperative incentive. Both altruistic and selfish behaviors of users are taken into account. The proposed mechanisms for message selection and cooperation pairing accommodate the incentive constraints of users without resorting to monetary rewards. Thus, the mechanisms are free of the hassle of payment transfer. The theoretical analysis for the message selection mechanism proves its truthfulness and approximation ratio in the worst case. Extensive simulation results further demonstrate the effectiveness of the three-phase approach with various synthetic and real tracing datasets. The performance of our proposed mechanisms is fairly close to that of the optimal algorithms in many cases.

In the future, this work can be extended by further taking into account devices’ energy levels in the dissemination process. It is known that the energy consumption of mobile devices may be widely disturbed by many factors, such as device standby mode and users’ daily activities like making phone calls and browsing the Internet. Depending on limited observations on a user’s behaviors, it is challenging to obtain reasonably accurate estimation on the device’s actual capabilities for data dissemination. This would be an interesting and promising direction for future work.