J. Parallel Distrib. Comput. 119 (2018) 50–63

Contents lists available at ScienceDirect

J. Parallel Distrib. Comput.

journal homepage: www.elsevier.com/locate/jpdc

Rethink data dissemination in opportunistic mobile networks with mutually exclusive requirement

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HIGHLIGHTS

- Consider the practical mutually exclusive data dissemination in opportunistic mobile networks.
- An optimal expectation algorithm with topology information is proposed.
- A probability-based algorithm based on k-hop forwarding paths is proposed.
- A distributed algorithm with one hop information is proposed.
- Experiments are based on two real human datasets.

ARTICLE INFO

Article history:
Received 2 June 2017
Received in revised form 7 January 2018
Accepted 28 March 2018
Available online 11 April 2018

Keywords:
Mobile data dissemination
Opportunistic mobile network
Delay tolerant network

ABSTRACT

With the increase of mobile devices, opportunistic mobile networks become a promising technique for disseminating data in a local area. However, existing works focus on the single data dissemination and fail to consider the practical applications where there are multiple data under different topics. Multiple data dissemination shows the potential applications in many scenarios, e.g., product coupon distribution. In this paper, we focus on budget-constrained multiple data dissemination services. A mobile user may be interested in data under different topics, but receiving data for any topic is enough due to user experiences and participation constraints. This is the mutually exclusive delivery requirement in many scenarios. In light of the different amounts of data and the different popularity levels of data in each topic, deciding which data should be forwarded to mobile users becomes an important problem. This paper aims to design an efficient data dissemination scheme that minimizes the maximum dissemination delay while incurring a small communication overhead for the aforementioned scenario. In this paper, we discuss three different scenarios according to different knowledge. We start with the data dissemination with network topology, and a corresponding optimal solution is proposed. Later, we consider the probability estimation with k-hop information, and lastly propose a distributed data forwarding algorithm, which considers the amount of data in different topics, the mobile users' interest, and their data forwarding abilities, respectively. The real trace-driven experiments show that the proposed scheme achieves a good performance.

1. Introduction

Recently, the widespread availability of personal mobile devices has generated new communication techniques, called proximity-based communication, in which mobile users walk around and communicate with each other via Bluetooth or Wi-Fi in their carried short-distance wireless communication devices. The Cisco 2014–2019 White Paper in [5] points out that as of 2014, the number of mobile-connected devices has exceeded the world's population, which has led to many contact opportunities. New technologies, such as Wi-Fi Aware in [2,23], extend Wi-Fi's capabilities with a real-time and energy-efficient discovery mechanism that provides an immediate on-ramp to rich here-and-now experiences. Furthermore, our world is bigger and more personalized than ever, with social media usage diversifying and expanding to include localized experiences based on proximity. As the result, proximity has become a critical element of today's mobile connected experiences, and the market for proximity-based applications is expected to grow significantly in 2017 and beyond. The above-mentioned reasons make the proximity-based communication scheme very attractive in academia and industry.

The topic-based publish/subscribe (pub/sub) system is widely used in many applications in [20] (e.g., RSS feeds, mobile advertisements, and online games). The publishers generate data

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https://doi.org/10.1016/j.jpdc.2018.03.012
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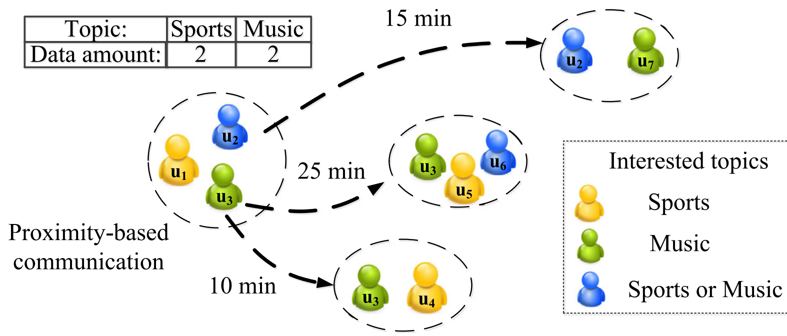


Fig. 1. A motivation example of our problem, where the mobile user u_1 has several data under different topics. Currently, mobile user u_1 can communicate with mobile users u_2 and u_3.

and label the data into some topics. The subscribers have diverse interests, and each subscriber creates a filter locally, which contains the topic it would like to receive. The subscriber will receive the data if and only if the topic of the data contains the topics in the filter. In this paper, we adopt the same concept in topic-based pub/sub systems to mobile users. With the wide availability of mobile devices, people want to apply the traditional pub/sub system into the opportunistic mobile network to conduct proximity-based communication. The advantage of the opportunistic mobile network is that the data dissemination has locality characters.

In the opportunistic mobile network, past research in [6,8,11] has lacked attention to data dissemination with a desired number of data. However, there are many budget-constrained data dissemination services that provide incentives to receivers, such as digital billboards in [14] and electric coupon systems in [10]. Though it is important to figure out how to minimize the data dissemination delay, an effective solution has not been found. Therefore, a good data dissemination scheme for opportunistic mobile networks should carefully select the right data to forward to the encountered mobile user. The real traces show that the number of subscribers frequently exhibits the well-known Zipf distribution in [12]. That is, some topics are subscribed to by many users, but other topics are only subscribed by a few users. In this case, a wrong forwarding decision will increase the overall delay significantly. In addition, we point out a practical issue in data dissemination, called the *mutually exclusive delivery requirement*, in this paper. That is, a mobile user may subscribe to *multiple* topics, but receiving data on *any matched topic* is enough.

An illustration of the proposed data dissemination problem is in Fig. 1, where the time above the arrows symbolizes the estimated delay. The mobile user u_1 has two data under the topics "sports" and "music", respectively. Currently, the mobile user u_1 can communicate with mobile users u_2 and u_3 through Bluetooth or WiFi. If the mobile user u_2 consumes the data in "music", the mobile user u_3 can forward the remaining data and finish in 25 min in expectation. However, if the mobile user u_2 consumes the data in "sports", the mobile users b can further relay data to the mobile user u_7, and the data dissemination can be finished in 15 min in expectation. If the data amount in "sports" and "music" is 1 and 3, the optimal solution will also change. In addition, estimating mobile users' forwarding abilities for different types of data is challenging, i.e., estimating the forwarding delay.

Motivated by the aforementioned problem in real applications, we propose the following delay minimization problem in this paper: the publishers/sources generate a certain number of data copies under different topics, e.g., the product coupons. Then, they would, ideally, disseminate them to the matching mobile users and the maximum delivery delay would be minimized. In this paper, we consider the real situation where some mobile users might be interested in multiple different data (coupons), but only one data can be received (applied) each time. This problem is further complicated by the heterogeneous data copy number and the popularity of each topic.

To solve the delay minimization problem, we first propose the optimal algorithm with the topology information by transforming it into a max-flow problem. In order to reduce the computation complexity, we propose a greedy data assignment algorithm. In the real opportunistic mobile network, mobile users might not know the accurate knowledge of the network. Solving the important issue of how to compress information while achieving a comparable result is a fundamental problem. Therefore, we further the probability-based solution based on nodes' inter-meeting distribution with partial knowledge. Finally, we propose an adaptive solution with local information which provides criterion for data selection for the mobile users with multiple interests. As for the relay selection, several efficient criteria are proposed to evaluate mobile users' forwarding abilities for data in different topics.

The contributions of this paper are four-fold:

- To our best knowledge, we are the first to consider the mutually exclusive delivery requirement during the data dissemination in the opportunistic mobile network.
- We provide an optimal solution with the network topology information, by formulating it into a max-flow problem. A greedy algorithm is also proposed and analyzed.
- We provide a probability-based solution with partial network information. The optimal probability-based algorithm is proposed and analyzed.
- We propose a distributed algorithm, which jointly captures the mobile users' interests, mobility patterns, and the data amount in each topic. It adaptively selects the best relays for each topic for a timely data delivery.

The remainder of the paper is organized as follows. The problem statement is introduced in Section 2. Then, the proposed optimal data dissemination algorithm with the network topology is provided in Section 3. We further present a probability-based algorithm based on inter-meeting distribution in Section 4. A local algorithm is proposed in Section 5. The performance evaluations are shown in Section 6. The related works are in Section 7. The acknowledgments and the conclusion are in Sections Acknowledgments and 8.

2. Problem statement

In this section, we first introduce the network model and problem clarification and formulation, followed by the applications and the challenges.

Table 1
Symbol summary.

Symbol	Meaning
D	Total number of data
m	Number of different data types
h	Number of different user types
d_i	Number of data under topic i
M_i	Mobile user type i, where $\|M_i\|$ is its cardinality
n_i	The number of mobile users under type i
N	Total number of mobile users
T	The delivery delay for N data
s_i	The number of data copy under topic i
p_i	The number of user assigned with data under topic i

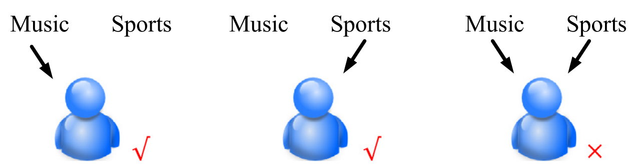


Fig. 2. An illustration of mutually exclusive data dissemination.

2.1. Model

In this paper, we consider an opportunistic mobile network, which is modeled as an undirected weighted graph $G = (V, E)$, where V is a set of mobile users (nodes), and $E \subseteq V^2$ is a set of links connecting the mobile users. The link weight is the contact probability of two neighbors. In the network, mobile users are typically equipped with short range interfaces (e.g., Bluetooth or Wi-Fi) to detect and communicate with each other. Note that we do not consider the contact duration and assume that it is always sufficient to exchange all data in one contact opportunity due to the recent advantage in wireless communication. Mobile users can serve as publishers, subscribers, or relays. The publishers/sources generate a pre-determined amount of data, N, and label each data into a special topic. The mobile users will consume their interested data and they can also act as relays to forward the data to other nodes, even for their uninterested data. In this paper, each mobile user will consume one and only one data that it is interested in. However, this constraint can be easily extended to any number of data. That is, if a mobile user wants to consume multiple data, this mobile user can be regarded as multiple dummy mobile users who are always together.

Let us assume that there exist a total number of m topics, the number of data in each topic is denoted by the set $\{d_1, d_2, \ldots, d_m\}$, $D = \sum_{i=1}^{m} d_i$. Due to the nodes' interest condition, regarding these m topics, the mobile users/subscribers can be divided into h types, denoted as $\{M_1, M_2, \ldots, M_h\}$, and the corresponding amount of mobile users in each type is denoted as $\{n_1, n_2, \ldots, n_h\}$, $D \leq \sum_{i=1}^{h} n_i$. Note that there is no specified destination as long as the data can be delivered to the matching mobile users. In addition, h might not be equal to m. This is because the mobile user might be interested in *multiple* topics as its interest. For example, $M_1 = \{1\}$ and $M_2 = \{1, 2\}$. This means that type M_1 nodes are interested in topic 1 and type M_2 nodes are interested in topics 1 and 2. Besides, we use $|M|$ to denote the number of topics that a type of nodes subscribe. In the above example, $|M_1| = 1$, and $|M_2| = 2$. Note that as long as a mobile user receives a matching data, it is a successful data delivery. For example, an M_2 node can receive a data under topic 1 or a data under topic 2, but not both. This is called *mutually exclusive delivery requirement* and an illustration is shown in Fig. 2, where this mobile user can receive a data under "music" or "sports". The mutually exclusive delivery requirement distinguishes our work with existing works. Without loss of generality, we assume that first $\{M_1, M_2, \ldots, M_m\}$ denotes the mobile users who are only interested in $\{d_1, d_2, \ldots, d_m\}$, respectively in the remainder of this paper.

2.2. Problem and applications

This paper addresses the following problem: given the interest of each mobile user, we consider how to design a data dissemination scheme so that N data in total can reach the matching mobile users with a small overhead, and the maximum dissemination delay can be minimized. It is an optimization from the view of information producer.

The proposed problem formulation can be applied to many budget-constrained data dissemination services. The following are two application scenarios. Some other potential applications in [14,28] include museum ticket distribution, traffic congestion notification, and mobile survey collections.

- *Mobile advertisement dissemination:* Fig. 3 shows the Facebook advertisement payment from their website. There is an advertisement dissemination budget and a deadline. For the Facebook advertisement, the advertisement will only deliver to users with certain profiles, and each successful delivery will have a fee. The mutually exclusive delivery requirement ensures that one user will not receive too many advertisements in a time period the user experience is not influenced.
- *Electric coupon advertisement:* a supermarket has a certain number of coupons in different types. These coupons cannot be further copied, otherwise, it will be over the budget. Customers might have interest in several types of coupons, but they can use only one coupon code in the supermarket per time. These coupons are distributed through the customers in this supermarket. These customers might also act as relays to further distribute these coupons, which furthers the supermarket's goal to distribute these coupons as quickly as possible.
- *Game organization:* An organizer would like to organize some games and each game has a capacity. The organizer disperses the information to their surroundings. If a person takes notice of it, and is interested in one or some of the games, they would choose one to join. Since all the games are organized at the same time, each person can only join one game. Therefore, it is important for the organizer to find a certain number of participants as soon as possible so that the games can begin.

2.3. Challenges and discussions

The main challenge lies in the unique mutually exclusive delivery requirement of the proposed problem. In real applications, the amount of data and their popularities in the m topics are different. Therefore, how to select the proper data for the mobile users with multiple interests is non-trivial.

Though we consider that each node can only get one data in our problem formulation, it can extend to a more flexible situation where a mobile user can get a pre-defined number of different data. For example, If a mobile user wants to get two data, it is the same as if there are two mobile users always moving together. Also, to overcome the situation that some mobile users leave the network and make sure that N mobile users will get the data in the end, we can distribute more than N initially, called the overbooking strategy in [6], which is widely used in airline ticket management, pricing, etc., to ensure a desired number of receivers. Note that once a mobile user consumes a data, it cannot change the assignment.

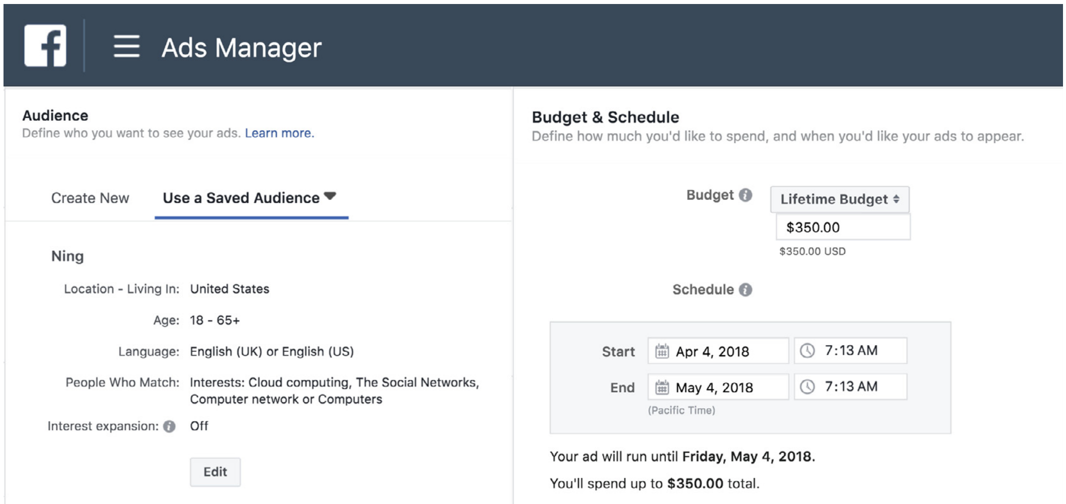


Fig. 3. An illustration of advertisement delivery in Facebook.

3. Data dissemination with network topology

In this section, we first propose a scheme to solve the data dissemination problem with the network topology information, in which the expected contact delay for a pair of neighbors is the reciprocal of their contact probability. All the pairwise expected contact delays are known in this section. This estimation has been used in early research in [16] and provides some road-maps for our solution. We transfer the problem into a matching problem and solve it by using max-flow methods in [1]. Then, we derive a greedy data dissemination algorithm, followed by the performance analysis in special situations.

3.1. Optimal assignment strategy

The data dissemination problem has two objectives: minimizing the maximum delay and distributing all the data. To solve them, we divide the original problem into two sub-problems. (1) Given the network information, what are the reachable nodes from the source within T? (2) Given the network topology and nodes' corresponding interests, is there a solution to distribute all the data? The idea is that we first figure out the reachable nodes within T. Then, we only need to check whether there is a solution by using the reachable nodes. If we cannot find a solution, we gradually increase T until we can finally find a solution within the minimum T.

The math formulation of the problem is as follows: the number of reachable mobile users from the source in type i mobile user is R_i^T within the time T. A data dissemination strategy is represented by using an $m \times h$ matrix, A, where the A_{ij}^T represents the number of mobile users M_i that receive data under topic j. For example, $A_{31} = 4$ means that four M_3 mobile users consume data under topic 1. Then, the problem can be written into the following:

$$\begin{aligned} &\min \quad T \\ &\text{s.t.} \sum_{i=1}^{h} A_{ij}^T = d_j, \forall j, \quad \sum_{j=1}^{m} A_{ij}^T \le R_i^T, \forall i, \quad A_{ij}^T \in \mathbb{Z} \end{aligned} \tag{1}$$

where the first constraint is delivery constraint. It indicates that for each data topic j, the sum of mobile users consume data topic j, i.e., $\sum_{i=1}^{h} A_{ij}^T$, equals the total number of data d_j, which means that all data are successfully delivered. The second constraint is feasibility constraint. It indicates that all reachable type i mobile users within T, i.e., $\sum_{j=1}^{m} A_{ij}^T$, should not exceed the reachable node at time T.

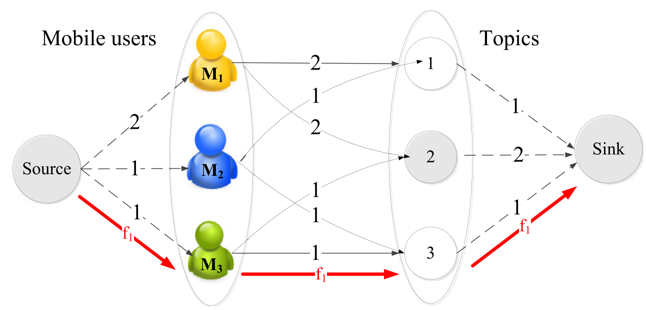
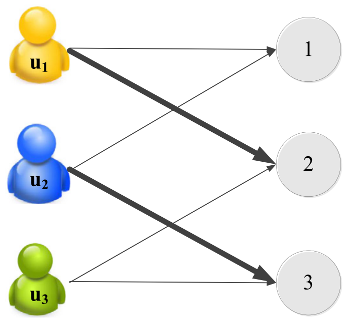


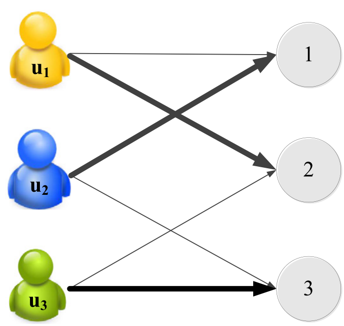
Fig. 4. An illustration of the max-flow problem formulation, where the nodes in the first column represent the different mobile users and the second column represents the different topics. If a type of mobile users are interested in a special topic, we draw a link between them. The weight of the link is the amount of that special type of mobile users. The weight from the source to the mobile users is also the amount of that special type of mobile users. The weight from the topics to the sink is the number of data in that topic.

As for the first sub-problem, we can get the expected shortest delay from the source to any particular node by using the shortest path algorithms in [7]. After that, if we order all the nodes according to their expected delivery delay from the source, we can easily find all the reachable nodes within T. Then, we find the first node, until whom the amount of nodes is the same as the amount of data. We set this time as the lower bound. We can also set an upper bound, which ensures there are enough nodes; e.g., the amount of mobile users with a single interest are larger than the corresponding amount of data in that topic. Then, we use the binary search algorithm to find the smallest T.

For the second sub-problem, it becomes how to maximize the amount of mobile users that receive the matching data, which can be formulated into the max-flow problem in [1]. The following is the problem transformation. First, the mobile users' subscriptions can be represented by using a bipartite graph. If we use a bipartite graph $G' = (V', E')$, where V' consists of two disjoint sets, the user sets and topic sets. If a type of mobile users is interested in a special topic, there is a link between them. The weight of a link is the amount of the mobile users. For example, in Fig. 4, there are three types of mobile users, M_1, M_2, and M_3, where the mobile users M_1 are interested in the topics 1 and 2, and n_1 is 2. To represent the available amount of data under each topic, we add a virtual sink. There is a link from every topic to the virtual sink and the weight in a link represents the amount of data in that



(a) One assignment.



(b) Optimal assignment.

Fig. 5. An illustration of the importance of order in the data assignment procedure, where the bold arrows indicate the data selection of mobile users.

topic. Then, the problem is transformed into a maximum matching problem from the mobile user sets to the topic sets. To find the maximum matching, we draw a virtual source in the figure. Then, every flow from the virtual source to the virtual sink represents a data assignment strategy. In Fig. 4, the flow f_1 indicates that we assign one M_3 mobile user with data in topic 3. By restricting the weight between the virtual source to the mobile users to the number of mobile users in that special type, we ensure that each mobile user can choose at most one data. If the maximum flow is the same as the amount of data, 4 in this example, there exists a solution. Otherwise, there is no solution.

3.2. Greedy data assignment strategy

The complexity of the well-known Ford–Fulkerson algorithm for solving the max-flow problem is $O(VE^2)$ in [27]. The complexity of the best known algorithm in the special case is $O(E \cdot f)$, where f is the maximum flow amount. Therefore, we propose a greedy algorithm to speed up the procedure. To simplify the description in the reminder of this paper, we define three concepts borrowed from machine scheduling problems in [19].

Definition 1 (*Supply level*)**.** The amount data of topic i, called d_i, is defined as the supply level of topic i.

Definition 2 (*Consumption level*)**.** The amount of mobile users who are interested in topic i, called c_i, is defined as the consumption level of topic i.

Definition 3 (*Feasibility level*)**.** The difference between the consumption level d_i and the supply level of the d_i, called l_i, is defined as the feasibility level of d_i.

In Fig. 5, there are three mobile users and three data. The supply level of the topics 1, 2, and 3 is one. The consumption level of the topics 1, 2, and 3 is two. The feasibility levels of the topics 1, 2, and 3 are one, respectively. The feasibility level represents the tolerance level for the bad assignment strategy. One idea is that we can use the greedy algorithm, which assigns data to mobile users with the most unfeasible topic first. However, this algorithm might not achieve a good performance, due to the importance of assignment order. For example in Fig. 5, the feasibility levels of the three topics are the same. If the mobile user u_1 is assigned to topic 2 and the mobile user u_2 is assigned to topic 3, the mobile user u_3 cannot be assigned. On the other hand, if the mobile user u_1 is assigned to topic 2 and mobile user u_2 is assigned to topic 1, the mobile user u_3 can be assigned to topic 3. In the former assignment strategy, after the mobile user u_1 is assigned, the mobile user u_2, which has two remaining selections, is assigned before the mobile user u_3, which only has one remaining selection. Based on this observation, we propose the second greedy algorithm, which considers the data assignment order. The mobile users with fewer remaining data selections have higher priorities. If the mobile users have the same amount of remaining selections, the mobile users that have the most unfeasible levels should be assigned first. If the remaining mobile users have the same number of selections and their feasibility levels are also the same, we begin to assign the mobile users whose amount are minimal.

Algorithm 1 Optimal Data Assignment with Topology

Input: The amount of data in each topic, $\{d_1, \ldots, d_m\}$, and the amount of mobile users in each type, $\{n_1, \ldots, n_h\}$ within T.

Output: The data assignment strategy, A_{ij}^T, $\forall i, j$.

1: Create a bipartite graph, $G' = (V', E')$, where V' consists of two disjoint sets, representing different data and mobile users.
2: Add the virtual source and sink to the bipartite graph, set the link weight between the mobile user node i and the sink node as n_i, and set the link weight between the source node and the data node j as d_j.
3: Set the link weight between the mobile user i the data node j as d_j.
4: Call the max-flow algorithm in the graph G', and $A_{ij} = |f_k|$, where $|f_k|$ is the flow volume from mobile user node i to data node j.

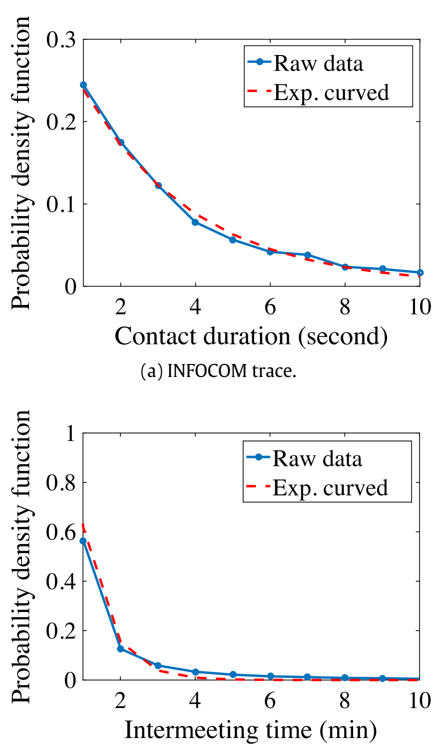
Theorem 1. *If each mobile user has at most two interests, the proposed greedy algorithm achieves an optimal data assignment.*

Proof. In Algorithm 2, the mobile users that have only one remaining interest will be assigned first, which can be regarded that we change the initial number of data in each topic. If the mobile users with one interest are not fully assigned, we can always use the mobile users with one interest to exchange the other mobile users in the optimal solution; the optimality will not change or there exists a contradiction. For the mobile users that have two interests, after they are assigned, there are two situations: (1) The mobile users with the minimum amount are fewer than the data in that topic. In this case, the feasibility level of that topic will not change. So, we will keep assigning mobile users with data in that topic until the topic is fully assigned or unable to be assigned. If data in a special topic cannot be fully assigned in the greedy algorithm, it is the optimal solution since we use up all the possible mobile users to assign data in this topic. (2) The mobile users with the minimal amount are equal to or larger than the data in that topic; this case is equal to the situation where the total number of topic reduces one. Then, we get another mobile user which has only one remaining interest. If the optimal solution is not the same as the greedy algorithm, we can always exchange the difference between these two algorithms. □

Algorithm 2 Greedy Data Assignment

Input: The amount of data in each topic, $\{d_1, \ldots, d_m\}$, and the amount of mobile users in each type, $\{n_1, \ldots, n_h\}$.
Output: The data assignment strategy, $A^T_{ij}, \forall i, j$.

```
while ∑ n_i > 0 do
  \\ find the set of mobile users with smallest cardinality.
  S = Θ, and c_min = ∞.
  for i from 1 to h do
    if n_i > 0 & |M_i| < c_min then
      θ = M_i,
    else if n_i > 0 & |M_i| == c_min then
      θ = θ ∪ M_i,
  \\ find the topic whose feasibility is the lowest.
  l_min = ∞, and j' = −1
  for j from 1 to m do
    if j ∈ θ & l_j < l_min then
      l_min = l_j and j' = j
  \\ find the mobile user type whose amount is the minimal.
  n_min = ∞, and i' = −1
  for i from 1 to h do
    if j' ∈ M_i & M_i ∈ θ & n_i < i' then
      n_min = n_i and i' = i
  A_{i'j'} = min{n_{i'}, d_{j'}}, and update n_{i'}, d_{j'} and M_{i'}.
```



(a) INFOCOM trace.

(b) SIGCOMM trace.

Fig. 6. Probability density function of inter-meeting times in the INFOCOM and SIGCOMM datasets.

4. Probability-based data dissemination

The unique challenge of the mobile opportunistic network is that contacts between users are opportunistic. Therefore, the real assignment should be feasible, since the path based assignment might not be the real case. Facing this challenge, we propose a probability-based approach which does not have specific forwarding path and thus can adjust the forwarding strategy based on the real situation.

4.1. Probability estimation

The recent research in [24] has found that inter-meeting time distribution follows exponential distribution in many datasets as shown in Fig. 6, which are the inter-meeting distribution results of people from two real datasets in [3,18] from international conferences.

Therefore, it is safe to approximate the average inter-meeting time distribution as an exponential distribution with a parameter λ in the network. That is, $f(t) = \lambda e^{-\lambda t}$. That is, the majority of inter-meeting times are very short and only a few inter-meeting times are large. Based on this observation, we try to analyze the data delivery opportunity, i.e., the opportunity that a data can be delivered within a time, as follows:

Let us denote percentage of nodes that can receive their topic i data within time t in the network, called reachable nodes, as $P(i, t)$. Then, the percentage of nodes that cannot receive their desired data at time t in the network, called unreachable nodes, is $1 - P(i, t)$. If β_i is the percentage of users who would like to consume one data in topic i,

$$\frac{\mathrm{d}(P(i, t))}{dt} = \beta_i \lambda P(i, t)(1 - P(i, t)), \tag{2}$$

which is the contact probability between reachable nodes and unreachable nodes for a particular time. Then, through solving the differential equation, we get the following result for a data within the time t.

$$P(i, t) = \frac{x_0 e^{\beta_i \lambda t}}{1 - x_0 + x_0 e^{\beta_i \lambda t}} = \frac{x_0}{(1 - x_0)e^{-\beta_i \lambda t} + x_0}, \tag{3}$$

where $x_0 = \frac{1}{N}$, which means that initially only source has the data. Here, we first consider the users that only have one interest and thus, β_i equals $\frac{n_i}{N}$. Then, for a type i user, the reachable type i user until t is $x_0 n_i/(((1 - x_0)e^{-\beta_i \lambda t} + x_0))$, according to Eq. (3). Note that $P(i, t)$ considers one-hop direct forwarding and multi-hop forwarding.

Considering the different supply levels for different data types, the maximum dissemination time should satisfy the following constraint

$$d_i = \frac{x_0 n_i}{(1 - x_0)e^{-\beta_i \lambda t} + x_0}. \tag{4}$$

Since Eq. (4) is an exponential function of t, it can be simplified into the following equation

$$t = -\frac{n_i}{\lambda N} \ln\left(\frac{\frac{n_i}{d_i} - 1}{N - 1}\right) = f(n_i, d_i). \tag{5}$$

Therefore, the maximum delivery delay can be estimated and calculated by n_i and d_i. From Eq. (5), we observe that when d_i is small, it takes a relatively short time to finish the data dissemination. The influence of n_i is a little bit complex. Another observation is that the λ has an influence on the delivery delay, the larger λ, the smaller expected delivery delay.

Theorem 2. *In an opportunistic mobile network, a schedule which makes* $\max\{\frac{d_1}{n_1}, \frac{d_2}{n_2}, \ldots, \frac{d_m}{n_m}\}$ *minimized, is the optimal assignment.*

Proof. The proof can be done by contradiction. If all the different types of mobile users are uniformly distributed in the network, the probability of encountering a mobile user with a special type becomes a constant probability. Then, once we give data selection criteria, the probability of encountering a mobile user who would

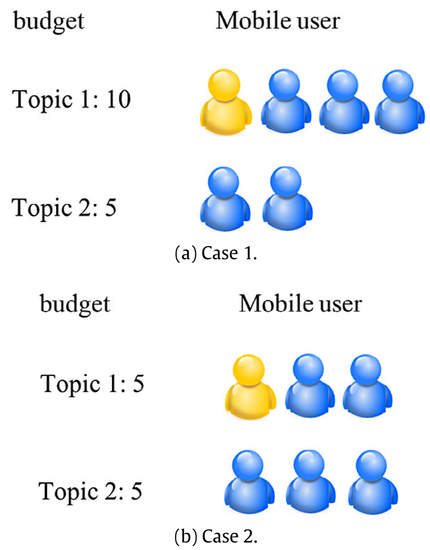


Fig. 7. An illustration of Theorem 2 in different cases.

like to consume a topic is a constant value. Therefore, $\frac{d_i}{n_i}$ is proportional to the delivery delay of d_i. Suppose $\frac{d_i}{n_i}$ is the maximum value produced by that optimal solution. If the optimal solution does not satisfy the above condition, some mobile users with multiple interests, δ, can be assigned to topic i from another topic, denoted as topic j. As a result, $n_i' = n_i + \delta$, $n_j' = n_j - \delta$, and $\frac{d_i}{n_i'} > \frac{d_j}{n_j'}$ is satisfied at the same time. Hence, this data selection method is better than the optimal solution, which is a contradiction. □

For mobile users with multiple interests, it can be used to minimize the maximum t_i, $\forall i$. This can be solved by using linear programming, since the problem is transferred into the following format.

$$\begin{aligned} \min \quad & t \\ \text{s.t.} \quad & f\Big(\big(\sum_{j \in M_i} n_i x_{ij} + n_j\big), d_j\Big) \le t, \qquad \forall i, j, \quad i \ne j \\ & \sum_{j \in M_i} x_{ij} = 1, \quad \forall i, j, \\ & 0 \le x_{ij} \le 1, \qquad \forall i, j \end{aligned} \tag{6}$$

where the first constraint means that all the data under each topic should be disseminated within t, specially, the left part of the first constraint is the expected delivery delay for each topic by using Eq. (5). The second constraint means that type M_i mobile users are assigned to a specific topic j, i.e., x_{ij} percentage of M_i mobile users are regarded as M_j mobile users to increase its supply level. An illustration of the optimal assignment is shown in Fig. 7, where the mobile users with multiple interests are assigned to two different users to balance the corresponding data copy delivery delay.

4.2. Probability optimal data forwarding

In Section 4.1, we discuss how to determine the minimal time so that we can finish the data dissemination and the optimal user assignment. After the probability user assignment, it is equivalent that the network has m different user types and each type of user has only one interest. In this sub-section, we will discuss how to do optimal relay data assignments from source nodes.

The basic idea of data forwarding is that data should be forward to the nodes which have more neighbors quickly so that these neighbors can further act as relays to increase the data dissemination speed. Based on this idea, we evaluate a node's forwarding ability using the following criterion.

Algorithm 3 Probability Data Forwarding

Input: The amount of data in each topic for relay node r, $\{d_1, \ldots, d_m\}$ for relay node, its neighbor set N_r, and the amount of mobile users in each type, $\{n_1, \ldots, n_h\}$.

Output: The data allocation strategy for each neighbor of node r.

Calculate the k-hop forwarding ability of node's neighbors within time T according to Eqs. (10) and (11).
Solve the Eq. (6) to get the optimal data assignment x_{ij}, $\forall i, j$.
for $i \in N_r$ **do**
  Node i consumes the data which minimizes maximum latency according to Eq. (5).
  for j from 1 to m **do**
    Assign node i number of $\lceil \frac{F_{ij}^k(T)}{\sum_{r' \in N_r} F_{r'j}^k(T)} \cdot d_j \rceil$ data in topic j.

Definition 4. A k-hop opportunistic path between two nodes (u_s, u_d) consists of a node set $V_p = \{u_s, u_1, u_2, \ldots, u_k, u_d\}$. The path weight is the probability that a data item is opportunistically forwarded from u_s to u_d within T.

An illustration of a k-hop opportunistic path is shown in Fig. 8, where the red arrow forms a 3-hop opportunistic forwarding path. Since the inter-contact time between two nodes, (u_k, u_{k+1}), follows an exponential distribution with $f(t) = \lambda_k e^{-\lambda_k t}$, we can calculate the path weight as follows:

$$p_{s,d}(T) = 1 - \int_T^{\infty} \int_0^{t_k} \int_0^{t_{k-1}} \cdots \int_0^{t_1} f(t_k - t_{k-1}) \, f(t_{k-1} - t_{k-2}) \cdots f(t_1) dt_1 \cdots dt_k. \tag{7}$$

According to the phase-type distribution in [15], the Probability Density Function (PDF) of the path weight with $\{\lambda_1, \lambda_2, \ldots, \lambda_k\}$ is

$$p_V = \sum_{i=1}^{k} C_i^{(k)} \lambda_k e^{-\lambda_k t} \tag{8}$$

where the coefficient $C_i^{(k)}$ is

$$C_i^{(k)} = \prod_{j=1, j \ne i}^{k} \frac{\lambda_j}{\lambda_j - \lambda_k}. \tag{9}$$

Therefore, Eq. (7) can be written as

$$p_{s,d}(T) = \int_0^T \sum_{i=1}^{k} C_i^{(k)} \lambda_k e^{-\lambda_k t} = \sum_{i=1}^{k} C_i^{(k)} (1 - e^{-\lambda_k T}). \tag{10}$$

Note that each mobile user maintains the opportunistic path with the largest forwarding probability for each other node as the path weight between them. Based on the path weight, we define the forwarding ability of each node as follows:

Definition 5. The k-hop forwarding ability of data topic j for a node i at time t

$$F_{ij}^k(t) = \sum_{i' \in N_i} p_{ii'} F_{i'j}^{k-1}(T - t) \tag{11}$$

where N_i is the mobile users within i's 1-hop neighbors, $p_{ii'}$ is contact probability between nodes i and i', and $F_{i'j}^{k-1}(T-t)$ is the $k-1$ hop probability that user i' can forward the type j data before deadline T.

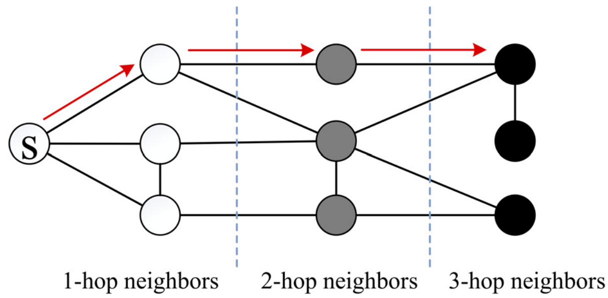


Fig. 8. An illustration of the multiple-hop opportunistic forwarding path.

Specially, $F_{ii}^0(t) = 1$ and $F_{ij}^1(t) = \lambda_1 e^{-\lambda_1 t}$. Based on each node's forwarding ability, the source node can distribute data according to its neighbor's forwarding abilities, i.e., the amount of data is split according to the reverse forwarding ability at that time.

Discussion. As for the selection of k, it would always be better if k is large, because the local network knowledge may not be optimal. However, to gather a larger number of k, it requires a high network overhead. There is a trade-off.

5. Distributed data dissemination

In this section, we propose the distributed data dissemination algorithm. Due to mobility or privacy issues, mobile users do not have accurate information about the network. The data dissemination becomes more challenging. To disseminate data in a distributed environment, a relay node has to make the following two decisions locally upon meeting with other mobile users: (1) If the encountered mobile user has not been assigned data, which data should the relay node forward? (2) If the encountered node has been assigned data, should the relay node forward data to it to accelerate the data dissemination?

5.1. Data selection for the mobile users with multiple interests

In this sub-section, we first propose the optimal strategy for the relay's data selection when there are two topics in total. Later, we extend it into a general scenario.

5.1.1. Two topics

When the relay walks into an area, there might exist several mobile users, waiting for data, within the relay's proximity. Therefore, the relay has to decide which data should be distributed to the encountered mobile users with multiple interests. Here, we propose an algorithm, which will balance the data distribution speed in different topics. When the relay meets a node with multiple interests, the node should choose the data whose consumption speed is low. Suppose that there are three types of mobile users. Among them, M_1 nodes are interested in topic 1, M_2 nodes are interests topic 2, and M_3 nodes are interested in topics 1 and 2. Their amounts are n_1, n_2, and n_3, respectively. The number of nodes having been assigned to topics 1 and 2 are n_1 and n_2. Before the M_3 mobile users are assigned, we propose the following criterion for them. If $\frac{d_1}{n_1} < \frac{d_2}{n_2}$, we will treat mobile users M_3 as mobile users M_1 until the condition is not longer held. If there are still some M_3 mobile users, the remaining mobile users M_3 are assigned data in these topics in proportion to the ratio of d_1 and d_2. Similarly, if $\frac{d_1}{n_1} > \frac{d_2}{n_2}$, we will treat mobile users M_3 as mobile users M_2 until the condition is no longer held. The remaining mobile users M_3 are assigned data in these two topics proportionally.

Algorithm 4 Data Selection in Two Topics

Input: The amount of data in topics 1 and 2, and the estimated mobile user's interest, respectively.

Output: The data allocation strategy for M_3 mobile users.

if $\frac{d_1}{n_1} < \frac{d_2}{n_2}$ **then**
  Treat $\min\{\lceil \frac{d_1}{d_2} n_2 - n_1 \rceil, n_3\}$ as M_1, $n_3 = \max\{n_3 - \lceil (\frac{d_1}{d_2} n_2 - n_1) \rceil, 0\}$.
else
  Treat $\min\{\lceil \frac{d_2}{d_1} n_1 - n_2 \rceil, n_3\}$ ad M_2, $n_3 = \max\{n_3 - \lceil (\frac{d_2}{d_1} n_1 - n_2) \rceil, 0\}$.
if $n_3 > 0$ **then**
  Treat $\lceil \frac{d_1}{d_1+d_2} n_3 \rceil$ and $n_3 - \lceil \frac{d_1}{d_1+d_2} n_3 \rceil$ M_3 users as M_1 and M_2.

Algorithm 5 Data Selection in Multiple Topics

Input: The amount of data in each topic for relay node, $\{d_1, \ldots, d_m\}$ for relay node, and the local utility and the global vectors of encounter node.

Output: The data forwarding strategy for this pair of nodes.

Calculate the overall utility of this pair of nodes according to Eq. (12), and denote them as $\{u'_1, u'_2, \ldots, u'_h\}$ and $\{u''_1, u''_2, \ldots, u''_h\}$.
Regard $\{u'_1 + u''_1, \ldots, u'_h + u''_h\}$ as $\{n_1, n_2, \ldots, n_h\}$ in Eq. (6), and calculate the result x_{ij}, $\forall i, j$.
Forward $\lceil \frac{\sum_{j \in M_i} u''_i x_{ij} + u''_j}{\sum_{j \in M_i} (u'_i + u''_i) x_{ij} + (u'_j + u''_j)} \cdot d_j \rceil$ to the encountered node, $\forall j$.

Theorem 3. *The proposed data selection algorithm for two topics is the optimal schedule in uniform distribution.*

Proof. If there exists a feasible schedule, the following two conditions must be satisfied: $n_1 \geq d_1$ and $n_2 \geq d_2$. If $\frac{d_1}{n_1} < \frac{d_2}{n_2}$, the algorithm will regard mobile users M_3 as mobile users M_1, until the above two ratios become the same. Then, $(n_1 + n_2 + n_3)\frac{d_1}{d_1+d_2} = n_1 \geq d_1$, and $(n_1 + n_2 + n_3)\frac{d_2}{d_1+d_2} = n_2 \geq d_2$, since $n_1 + n_2 + n_3 \geq d_1 + d_2$ in a feasible solution. If all the mobile users M_3 cannot make the two ratios the same, that is, all the M_3 mobile users are treated as M_1, i.e., $n_1 = n_1 + n_3$, $n_2 = n_2$. This case is true, when $\frac{d_1}{n_1+n_3} < \frac{d_2}{n_2}$. It can be written as $\frac{d_1}{d_2} n_2 < n_1 + n_3$. Besides, in a feasible solution, $n_1 + n_3 \geq d_1$ so that $n_1 + n_2 + n_3 \geq \frac{d_1}{d_2} n_2 + n_2 > d_1 + d_2$, as a result, $n_2 = n_2 > d_2$. In either case, our proposed algorithm is feasible. We can use the same way to prove it is true when we treat all the M_3 mobile users as M_2, in the case that $\frac{d_1}{n_1} > \frac{d_2}{n_2}$. In all the situations, if a feasible solution exists, the proposed algorithm will achieve it so that it is the optimal schedule. □

5.1.2. Multiple topics

If there are more than 2 topics, we can use the similar idea as the previous sub-section. Based on Theorem 2, we get the local optimal solution when different types of mobile users are uniformly distributed in the network. The mobile users which can be assigned with multiple types of data should be assigned with the data whose consumption level is the lowest.

5.2. Forwarding utility estimation

To answer the second question for the relay data distribution, we propose a distributed method to estimate each mobile user's ability to relay data in different topics, which jointly considers the mobility patterns and the mobile users' diverse interests in the local and global views by using two vectors.

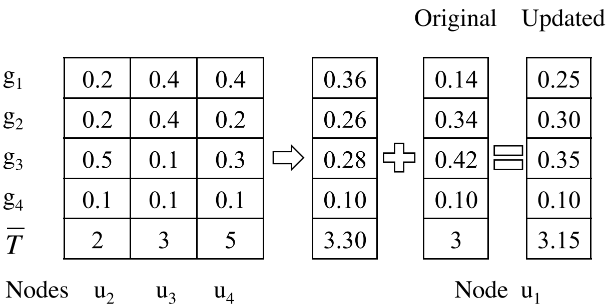


Fig. 9. An illustration of the global utility updating.

5.2.1. Local utility vector

The idea of the local utility vector is that each mobile user maintains a vector to record its encounter history summary with its neighbors for different types of mobile users. In the following, we use 2 topics as an illustration. In this case, we have 4 different mobile users, M_1, M_2, M_3, and M_4, which subscribe to topic 1, topic 2, topics 1 and 2, and none, respectively. A node's local utility vector is denoted as $\{l_1, l_2, l_3, l_4\}$. Each mobile node summarizes its neighbors' information. For example, if the current node has four neighbors, and the types of these four neighbors are M_1, M_2, M_1, and M_3, respectively, we can calculate its local utility as $\{0.5, 0.25, 0.25, 0\}$ to types M_1, M_2, M_3, and M_4 mobile users. We also record the average inter-meeting times of the current node, $\overline{T}_l$, which is important in estimating the delivery delay for the current node.

5.2.2. Global utility vector

The idea of the global utility vector summarizes a node's encountered history information, which represents its knowledge about its forwarding ability in the network. Specifically, each mobile user maintains a vector, $\{g_1, g_2, g_3, g_4\}$, which indicates the accumulated probability that a mobile user and its neighbors' forwarding abilities to each topic. The accumulated average inter-meeting delay, $\overline{T}_g$, is also recorded. Initially, each node keeps the vector, which indicates its own information. For example, a node belongs to M_2. Initially, its global vector is $\{0, 1, 0, 0\}$, and the $\overline{T}_g = \overline{T}_l$.

The global utility vector updates after every sliding window. The following is the updating procedure: each mobile user keeps exchanging the global utility vector while they encounter. The left part of Fig. 9 is a summary of the encounter history information of the mobile user u_1 in a sliding window. In this sliding window, the mobile user u_1 encountered three other nodes, u_2, u_3, and u_4. We accumulate the global utility of node u_1's neighbors by the sum operation. For example, for M_1 nodes, the accumulated global utility is $0.2 \times 2 + 0.4 \times 3 + 0.4 \times 5 = 3.6$. By using the same method, we get the accumulated global utility for type M_2, M_3, and M_4 mobile users as 2.6, 2.8 and 1, respectively. Then, we do normalization for the accumulated global utilities for different types of users, and it turns out to be $0.36, 0.26, 0.28$, and 0.1, respectively. The average inter-meeting time is $(2 + 3 + 5)/3 = 3.3$. By using the accumulated information in this sliding window, the mobile user u_1 updates its global vector. We accumulate the global utility of these two sliding windows by the sum operation. Then, we do normalization for the accumulated result, shown on the right side of Fig. 9. In the global utility updating, we consider the weight of the current sliding window to be the same as the past accumulated results. As the result, the current utility vector is assigned a heavier weight than the accumulated result.

The above-mentioned two vectors can be combined into the overall utility, called U, by using the parameter α.

$$U = \frac{\overline{T}_l\{l_1, l_2, \ldots, l_h\} + \alpha \overline{T}_g\{g_1, g_2, \ldots, g_h\}}{\sum_{i=1}^{h}(d_l l_i + \alpha \overline{T}_g g_i)}, \tag{12}$$

where α is a parameter vector to evaluate the importance of global utility in the data distribution procedure. It depends on the amount of data that the current relay can carry. If the data can be fully distributed within its one-hop neighbors, we will no longer assign a weight to the global utility. However, on the other hand, if there is a lot of data, we might put a high weight on the global utility. In the experiment, we assign the α proportionally to the amount of unassigned data in each topic.

5.3. An extension

In the aforementioned solution, there might be 2^m types of mobile users in an extreme case. To avoid the exponentially increasing number of mobile user types, which causes a relatively huge buffer consumption, we propose an efficient compressing scheme. Instead of recording the accurate type of each encountered mobile user, each node records the probability of the encountered mobile user subscribing to a particular topic. To deal with the mobile users with multiple interests, we propose two versions of estimation, positive estimation and negative estimation. In the positive estimation, if the current mobile user meets a mobile user with multiple interests, it is equivalent to the case that the current node meets with several mobile users, and each mobile user has one interest. In Fig. 10, u_2 is treated as two nodes. However, in the negative estimation, if a mobile user has multiple interests, the encountered node is still regarded as one node, so its contribution to each topic decreases. In negative estimation, mobile user u_2's contribution to topics 1, and 2 is $\frac{1}{2}$, since we only need to keep a vector size of m. This extension can significantly save the network overhead when the total topic number is large.

6. Experiments

In this section, we compare the proposed algorithms using extensive experiments based on a real dataset. We first introduce the experimental settings and their parameters. Then, we will discuss the performance evaluation results.

6.1. Trace introduction

The INFOCOM06 dataset [22] consists of two parts: contacts between the iMote devices carried by participants and social features of the participants, which are the statistics of participants' information from a questionnaire form. In the questionnaire, the participants indicated their interested topics. According to the questionnaire, there are 35 different topics in total. First, we discard some participants that do not have social features in their profiles. In this way, we reduce the number of participants to 61. There are 74,981 contacts between these participants over a period of 337,418 time slots in seconds.

The SIGCOMM09 dataset in [18] was collected during the SIGCOMM 2009 conference in Barcelona, Spain. Around 76 smartphones were distributed to a set of volunteers during the first two days of the conference. The participants were recruited on-site in conjunction with the conference registration. Each device was initialized with the social profile of the participant that included some basic information such as home city, country, and affiliation. We discard No. 73 participant, who does not have social features in his profile. The number of contacts is 285,879 in our experiments.

However, the scale of the INFOCOM06 and SIGCOM09 traces are relatively small, i.e., the average subscription number for a topic

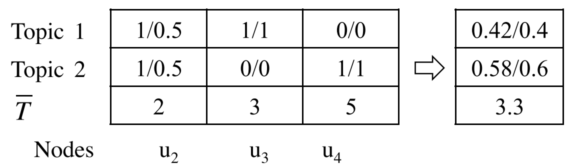


Fig. 10. An illustration of the positive/negative estimation of node u_1.

is 12, and the number of mobile users have two interests in the most popular topic is 14. To overcome this, we generate a synthetic dataset with 100 nodes with exponential contact distribution. In this synthetic dataset, we gradually change the amount of users who subscribe to a topic from 20 to 60 and the ratio of nodes that have multiple interests from 0 to 40. Therefore, the synthetic trace could provide some unrevealed insights into the data assignment.

6.2. Experimental setting

Some detailed experimental settings are as follows: we choose 2–6 topics with the topology information from the network. Without the topology information, we consider 2 topics in total. In each experiment round, we randomly selected several publishers, and each of them generates a certain amount of data. The total data is smaller than the amount of the corresponding subscribers to ensure all the data can be distributed. In the experiments, the source nodes and the destination nodes are randomly selected in each round and for each experiment.

6.3. Algorithm comparison

Our algorithm comparison consists of three parts, which address the three scenarios that we propose in this paper.

In the path-based approach, we compare the following four algorithms. The *random* algorithm randomly assigns data for the mobile users with multiple interest. The *Greedy* algorithm will select the topic which is most unfeasible *Greedy2* is the revised greedy algorithm version, which also considers the number of the nodes' remaining selections. The proposed *Flow-based* algorithm is explained in Section 3.1.

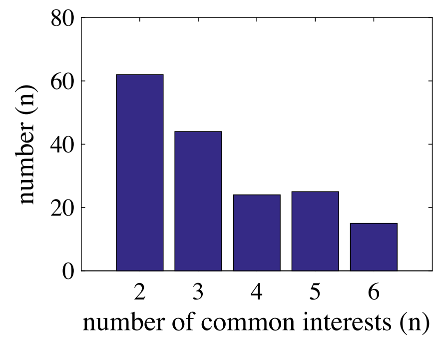
In the probability-based data dissemination, the proposed algorithm is called the *min–max speed* algorithm. In addition, an alternative solution is to minimize the max number of data in a topic, which is called the *min–max volume* algorithm. Another alternative solution is to randomly forward one data to the encounter node, called the *Random* algorithm.

As for the distributed data dissemination, the performance comparison is made by using different utility estimation schemes, there are four methods. If we just use the one-hop local information and global information to estimate the mobile users' ability, it is called the *Local* algorithm, and the *Global* algorithm, respectively. Two more efficient versions of the global estimation are called the *Positive* algorithm and the *Negative* algorithm, respectively.

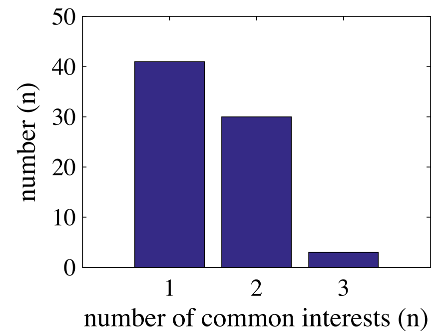
6.4. The performance results

6.4.1. Nodes with multiple common interests

We verify whether this is the case where there are many nodes with multiple common interests to demonstrate the necessity of mutually exclusive data dissemination. The results are shown in Fig. 11. The overall number of topics is 35 in the INFOCOM trace, which means that each node has at least 2 interests. In addition, Fig. 11(a) shows that it is very common that multiple nodes have multiple common interests; even when the number of common interests is 6, there are still 12 users. Fig. 11(b) shows the results from the SIGCOMM09 dataset. It also shows that multiple nodes have multiple common interests.

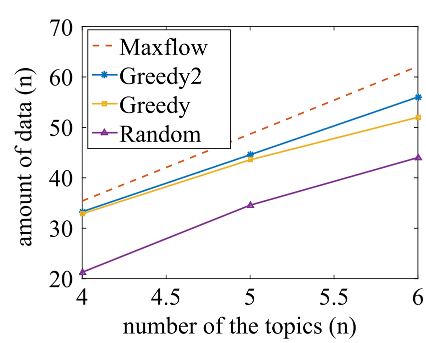


(a) INFOCOM06 dataset.

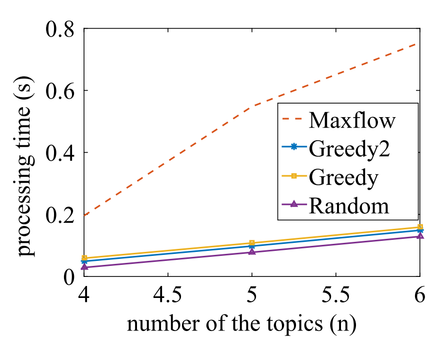


(b) SIGCOMM09 dataset.

Fig. 11. Users with multiple common interests.



(a) Amounts of assigned data.

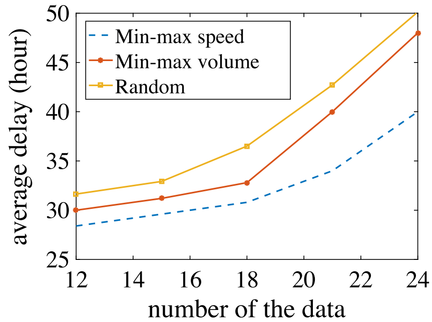


(b) Processing time.

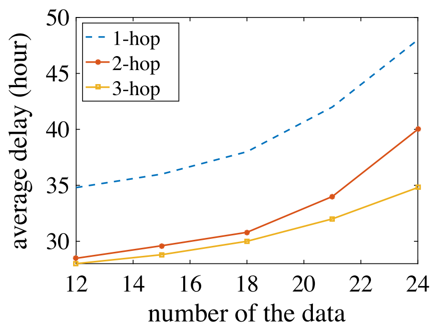
Fig. 12. Performance comparison with topology information.

6.4.2. Results with whole network information

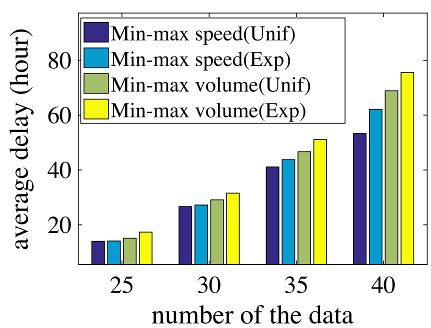
Fig. 12 shows the performance results of the proposed greedy algorithm, compared with the optimal flow-based solution in different numbers of topics. From the result, the proposed algorithm's



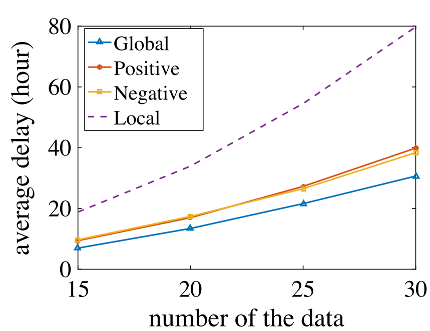
(a) Different assignment schemes.



(b) Different k.



(c) Different data distributions.



(d) Different local information.

Fig. 13. Performance comparison of our algorithms in the INFOCOM Dataset.

difference with the optimal solution increases. However, its performance is still close to the optimal solution. From the experiments, the greedy algorithm assigns more than 90% of nodes compared to the optimal solution when the topic number is 6. However, for the processing time, the greedy algorithm only uses about $\frac{1}{4}$ the time of the optimal algorithm. The Greedy2 and random algorithms achieve similar processing times but the performance is not good. Therefore, according to the difference scenario, we can use the flow-based optimal algorithm or greedy2 algorithm to trade-off the difference performance and delay.

6.4.3. Result with k-hop information

Figs. 13(a), 14(a), and 15(a) show the results of the proposed three different user assignment algorithms where number of data in each topic is randomly generated. The proposed min–max speed algorithm always achieves the best performances in the three datasets, followed by the min–max volume algorithm and the random algorithm. This demonstrates the importance of distributing topics smartly to users with multiple interests. Note that in the synthetic dataset as shown in Fig. 15(a), we observe that along with the increase of data, the min–max speed algorithm becomes better than the min–max volume algorithm and the random algorithm. One possible reason why this occurs is that when the amount of data is small, we can always find a sufficient amount of mobile users in our surroundings, which causes the assignment strategies to become unimportant. However, when the number of users increases, the min–max speed algorithm reduces by 20% delivery delay than min–max volume algorithm.

Figs. 13(b), 14(b), and 15(b) show the results of having different k values in the min–max speed algorithm. The results show that when k equals 2, the performance significantly improves. However, the marginal benefit is minimal when k increases to 3. Specifically, when k increases from 1 to 2, the maximum delay reduces by about 15%, 20% and 8% in the three datasets respectively. When k increases from 2 to 3, there is almost no benefit when the number of data is small. The reason is that most users can be reached within two-hops in the datasets. Therefore, it is not necessary to maintain 3-hop network information and the min–max speed algorithm always uses 2-hop information without specific explanations. Figs. 13(c), 14(c), and 15(c) show the influence of data amount distribution in different topics. In this setting, there are two different data amount distributions, i.e., exponential distribution and uniform distribution. The results show that a good mobile user assignment algorithm can increase the performance significantly, when the data amount distribution is exponentially distributed. The reason is that a small improper assignment will increase the maximum delivery delay.

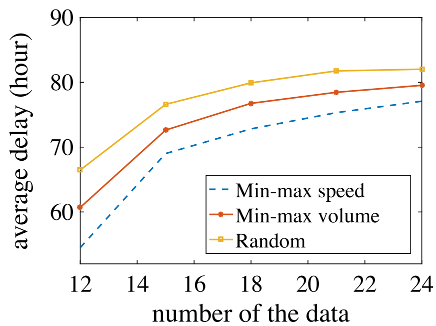
6.4.4. Result with local neighbor information

Figs. 13(d), 14(d), show the data dissemination with local neighbor information. The results show that the Global utility estimation method is much better than the local utility estimation, at the cost of more network overhead. The proposed Positive and Negative utility estimations reduce the network overhead and achieve a relatively good performance. In Fig. 15(d), we do not change the overall data amount for two topics, but adjust the percentage of data in each topic and the results show that the proposed algorithm has good performance in the different scenarios. Fig. 15(d) demonstrates that as the amount of mobile users with multiple interests increases, so do the advantages of the proposed algorithm, which demonstrates the effectiveness of the proposed min–max speed algorithm. When 40 users have multiple interests, the maximum delivery delay is reduced to a half.

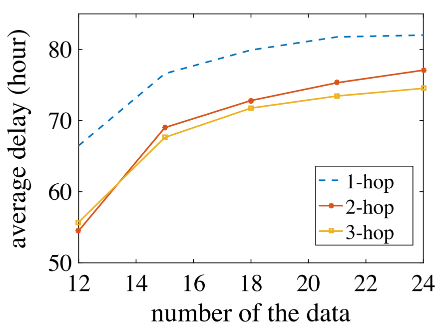
7. Related works

In this section, we capture some important issues arising from the design of the data dissemination scheme in the proximity-based communication in [4,8,11,13,17,25,26].

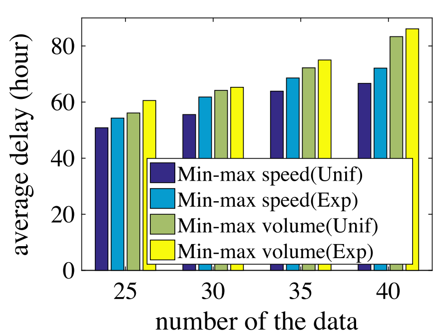
In the beginning, a lot of research was been done on the epidemic problem in [8,13,17,26]. The main concern in the epidemic problem is avoiding the outbreak of disease. In the epidemic problem, there are susceptible mobile users, infected mobile users, and recovered mobile users. In our problem, there are also three



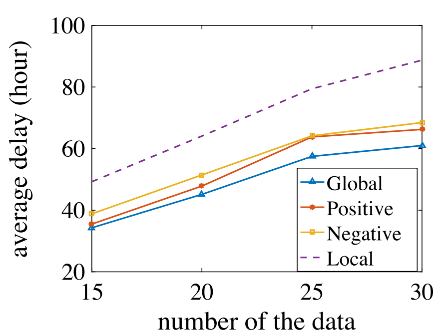
(a) Different assignment schemes.



(b) Different k.

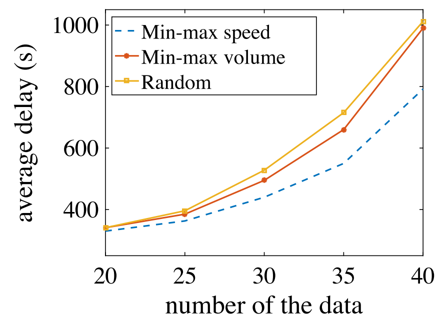


(c) Different data distributions.

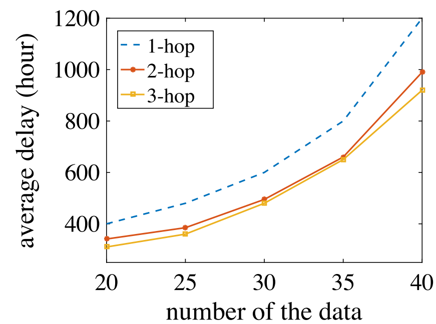


(d) Different local information.

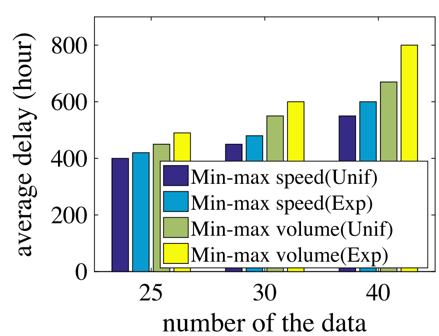
Fig. 14. Performance comparison of our algorithms in the SIGCOMM Dataset.



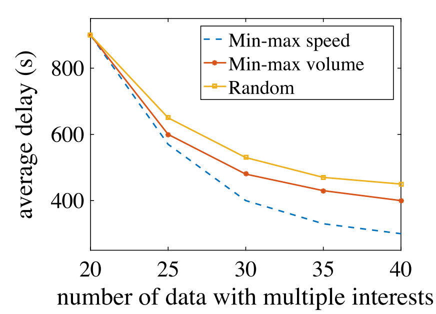
(a) Different assignment schemes.



(b) Different k.



(c) Different data distributions.



(d) Different local information.

Fig. 15. Performance comparison of our algorithms in the synthetic data Dataset.

types of mobile users: the mobile users that do not receive the data, the relay, and the mobile users which have received the data but do not act as relays. The difference between our problem and the epidemic problem is that infected mobile users can keep infecting the susceptible mobile users until they are recovered, i.e., unlimited copies. In addition, an infected user can infect any encountered mobile users in the epidemic problem. However, in our problem, the mobile user can forward data to others only if they carry some copies. In [11], the authors consider the broadcasting in delay tolerant networks, which is essentially the same as the epidemic problem, but its recovery rate is 0. The major difference with our problem is that in [11] all the infected mobile users have the same forwarding ability, while our problem considers that the relays have different forwarding abilities. This difference makes our problem more difficult than the epidemic problem.

In [8,9,24], the authors evaluate the forwarding ability of each node and forward data only to a node with a good forwarding ability. In addition, the problem in [9] is different than in this paper. In that paper, a certain amount of data should reach the corresponding destinations. It is an N to N mapping. However, in this paper, we do not specify the destination, thus any nodes that are interested in the data can be a destination. It is an N to many (more than N) mapping. As a result, it is harder to analyze a mobile user's forwarding ability. In [3], they propose to use social information to evaluate each node's forwarding ability. In [28], the authors focus on data dissemination to a desired number of receivers in a vehicular network. However, there is only one type of data and their problem is a simplified version of our problem. In [20], their problem only considers one type of data, making their work a simplified version of our problem. Furthermore, in [20], their analysis is under the assumption that all the nodes have an identical mobility pattern, which is not realistic. In [21,29], the authors applied the data dissemination problem into the vehicular networks and discussed some practical constraints, such as relay buffer size.

To the best of our knowledge, we are the first to consider the mobile users' mutually exclusive delivery requirement in mobile data dissemination, which distinguishes the proposed work from existing works. The practical budget based dissemination further increases the design difficulty.

8. Conclusion

The opportunistic mobile network can be applied to many scenarios by using proximity-based communication technology. In this paper, we design an efficient opportunistic mobile network to distribute a pre-determined number of data with a minimal delay. Our practical model considers the situation in which a mobile user might have multiple interests, and the mutually exclusive delivery requirement is proposed. Considering the different amounts of data in each topic and the different popularities of each topic, the above problem is non-trivial. We start with the data dissemination with topology information, which is transformed into a matching problem and is solved by the max-flow algorithm. We also propose a greedy data assignment algorithm, which achieves a good performance in theory and experiments. We further consider the data dissemination with partial k-hop contact knowledge and propose a probability-based forwarding algorithm. In addition, if we only have the local information, we propose a utility estimation scheme which jointly considers the amount of data, popularities in different topics, and mobile users' forwarding abilities, respectively. The experiments in the real trace show that our schemes achieve a good performance compared with existing schemes.

Acknowledgment

This research was supported in part by National Science Foundation grants CNS 1449860, CNS 1461932, CNS 1460971, CNS 1439672, CNS 1301774, and ECCS 1231461.

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