

Mutually Exclusive Data Dissemination in the Mobile Publish/Subscribe System

Ning Wang and Jie Wu

Department of Computer and Information Sciences, Temple University, USA

Email: {ning.wang, jiewu}@temple.edu

Abstract—The topic-based mobile publish/subscribe (pub/sub) system has shown the potential applications in many scenarios, e.g., product coupon distribution. In this paper, we focus on the budget-constrained data dissemination services with a pre-determined total amount of copy. A mobile user may subscribe data under different topics, but receiving a copy in any topic is enough. 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 in the aforementioned scenario, which minimizes the maximum dissemination delay, and incurs small communication overhead at the same time. We start with the offline message dissemination problem, and the corresponding optimal solution is proposed. Later, we consider the online situation, and propose a distributed data forwarding algorithm, which considers both the amount of data in different topics, mobile users' subscription, and their data forwarding abilities, respectively. The real trace driven experiments show that the proposed scheme achieves a good performance.

Index Terms—Mobile data dissemination, publish/subscribe, delay tolerant network.

I. 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 [1] 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 [2, 3], 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 2015 and beyond.

The topic-based publish/subscribe (pub/sub) system is widely used in many applications [4] (e.g., RSS feeds, mobile advertisements, and online games). The publishers generate data, and label the data into some topics. The subscribers have diverse interests, and each subscriber creates a filter

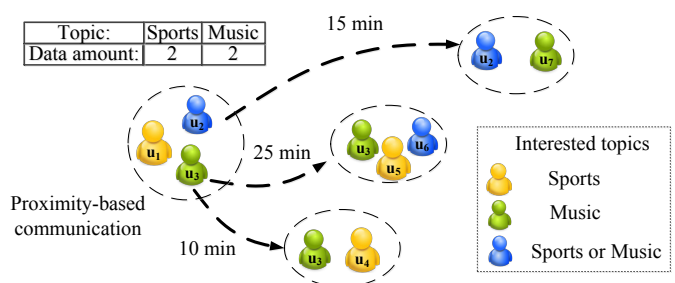


Fig. 1. A motivation example of our problem, where the mobile user u_1 has several data under different topics. Currently, mobile user u_1 can communicate with mobile users u_2 and u_3 .

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 the mobile pub/sub system using the proximity-based communication techniques, the past researches [5, 6, 11] have lacked attention on the data dissemination with a desired number of data. However, there are many budget-constrained data dissemination services that provide incentives to receivers, i.e., credit, such as Digital Billboards [7] and Electric Coupon System [8]. Practically, one problem with these systems is that a mobile user may subscribe *multiple* topics, but receive a data in *any matched topic* is enough to satisfy the mutually exclusive delivery requirement. 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 in mobile pub/sub systems 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 [9]. That is, some topics are subscribed 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.

An illustration of the proposed problem is in Fig. 1, where the time above the arrows symbolizes the estimated delay. The mobile user u_1 has two data under 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 topic "music", the mobile user u_3 can forward the remaining data, and finish in 25 min with expectation. However, if the mobile user u_2 consumes the data in topic "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 with expectation. If the data amount in topic "sports" and "music" is 1 and 3, the optimal solution will also change. Besides, it is challenging to estimate mobile users' forwarding abilities for different types of data.

Motivated by the aforementioned problem in real applications, we propose the following delay minimization problem in this paper: the publishers generate a certain number of data under different topics, e.g., the product coupons. Then, they would, ideally, disseminate them to the matching mobile users, while simultaneously minimizing the maximum delivery delay. Note that in the real situation, some mobile users might be interested in multiple coupons, but one coupon can be applied each time. This problem is further complicated by the differences in the data amount and the popularity of each topic.

To solve the delay minimization problem, we first propose the optimal algorithm in the offline scenario, 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 mobile pub/sub system, 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 in the online situation is a fundamental problem. Therefore, we further propose an adaptive solution, which provides a criterion for the 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 threefold:

- To our best knowledge, we are the first to consider the mutually exclusive delivery requirement during the data dissemination in the mobile pub/sub system.
- We provide the optimal solution in an offline situation, by formulating it into a max-flow problem. A greedy algorithm is also proposed and analyzed.
- We propose a distributed online 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 timely data delivery.

The remainder of the paper is organized as follows. The problem statement is introduced in Section II. Then, the proposed offline data dissemination algorithm is provided in Section III. We further present an online algorithm in Section IV. The performance evaluation are shown in Section V. The related works are in Section VI. The acknowledgment and the conclusion are in Sections VII and VIII.

II. PROBLEM STATEMENT

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

A. Model and Problem

In this paper, we consider a 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 among 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. Mobile users can serve as publishers, subscribers, or relays. The publishers generate a pre-determined amount of data, N , and label each data into a special topic. The mobile users can act as relays to forward the data to other nodes. During the communication with the publishers or the relays, the subscribers will consume one data that they subscribe.

Let us assume that there exist a total number of m topics, the number of data in each topic is denoted by the set $\{t_1, t_2, \dots, t_m\}$, $N = \sum_{i=1}^m t_i$. Due to the nodes' subscription condition, regarding these m topics, the mobile users can be further divided into h types, denoted as $\{M_1, M_2, \dots, M_h\}$, and the corresponding amount of mobile users in each type is denoted as $\{n_1, n_2, \dots, n_h\}$, $N \leq \sum_{i=1}^h n_i$. Note that there is no specified destination, as long as the data can be delivered to the matching mobile users. Besides, h might not be equal to m . This is because the mobile user might subscribe *multiple* topics as its interest. For example, $M_1 = \{1\}$. $M_2 = \{1, 2\}$. It means type M_1 nodes subscribe topic 1 and type M_2 nodes subscribe 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. This *mutually exclusive delivery requirement* distinguishes our work.

This paper addresses the following problems: 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 small overhead, and the maximum dissemination delay is minimized.

B. Applications

The proposed problem formulation can be applied into many budget-constrained data dissemination services. The following are two application scenarios. Some of other potential applications [7, 10], such as museum ticket distribution, traffic congestion notification, and mobile survey collections.

- *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 as a certain number of participants as soon as possible so that the games can begin.

C. Challenges and Discussions

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

Though we consider 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 multiple different data. For example, topics 1 and 2. It is the same as if there are two mobile users moving together. One wants to get data in topic 1, and the other one wants to get data in topic 2. Also, to overcome the situation that some mobile users leave the network, and make sure that N mobile users will get the data at the end, we can distribute more than N initially, this is called the overbooking strategy [11], which is widely used in the 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.

III. OFFLINE DATA DISSEMINATION

In this section, we first propose a scheme to solve the data dissemination problem in the offline situation, in which the expected contact delay for a pair of neighbors is the reciprocal of their contact probability. This estimation have been used in many early researches [12] and provides some road-maps for our solution. We transfer the problem into a matching problem, and solve it by using the max-flow methods [13]. Then, we derive a greedy data dissemination algorithm, followed by the performance analysis in special situations.

A. 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 offline problem is as follows: the number of reachable mobile users from source in each type is x_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 to receive data under t_j . Then, the problem can be written into the following:

$$\begin{aligned} & \text{minimize} && T \\ & \text{s.t.} && \sum_{i=1}^h A_{ij}^T = t_j, \forall j, \quad \sum_{j=1}^m A_{ij}^T \leq x_i^T, \forall i, \quad A_{ij}^T \in \mathbb{Z} \end{aligned} \quad (1)$$

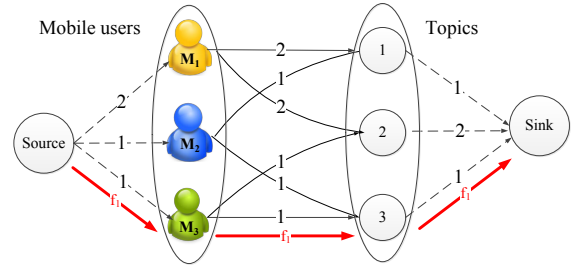


Fig. 2. An illustration of max-flow problem formulation, where the nodes in the first column represent the different mobile users and the second column represent the different topics. If a type of mobile users are interested in a special topic, we draw a link between them. The weight of the link is the 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.

where the first constraint indicates that all the data must be delivered. The second constraint indicates that it is a feasible solution within T .

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 [14]. 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 [15] 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 [13]. The following is the problem transformation. First, the mobile users' subscriptions can be represented by using the 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 the Fig. 2, 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 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. 2, 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

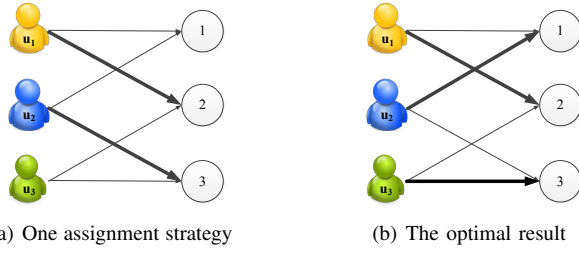


Fig. 3. An illustration of the importance of order in the data assignment procedure, where the bold arrows indicate the data selection of mobile users.

choose at most one data. If the maximum flow is the same with the amount of data, 4 in this example, there exists a solution. Otherwise, there is no solution.

B. Greedy Data Assignment Strategy

The complexity of the well-known Ford-Fulkerson algorithm to solve the max-flow problem is the $O(VE^2)$ [16]. 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 following of this paper, we define three concepts here.

Definition 1. Supply level: The remaining amount of data of the t_i is defined as the supply level of t_i .

Definition 2. Consumption level: The remaining amount of mobile users which subscribe t_i is defined as the consumption level of t_i .

Definition 3. Feasibility level: The difference between the consumption level t_i and supply level of the t_i is defined as the feasibility level of t_i .

In Fig. 3, there are three mobile users and three data. The supply level of the topics 1, 2, and 3, are one. The consumption level of the topics 1, 2, and 3, are two. The feasibility level 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 good performance, due to the importance of assignment order. For example in Fig. 3, the feasibility level of 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 first than 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

Algorithm 1 Optimal Data Assignment

Input: The amount of data in each topic, $\{t_1, \dots, t_m\}$, and the amount of mobile users in each type, $\{n_1, \dots, n_h\}$.

Output: The data assignment strategy for each node.

- 1: Create a bipartite graph, $G' = (V', E')$, where V' consists of two disjoint sets.
 - 2: Add the link weight according to the mobile user amount.
 - 3: Add the virtual source and sink to the bipartite graph.
 - 4: Call the max-flow algorithm in the graph.
-

Algorithm 2 Greedy Data Assignment

Input: The amount of data in each topic, $\{t_1, \dots, t_m\}$, and the amount of mobile users in each type, $\{n_1, \dots, n_h\}$.

Output: The data assignment strategy for each node.

- 1: **while** We can still assign topic to mobile users **do**
 - 2: find $\min\{|M_1|, \dots, |M_h|\}$ from the remaining topics.
 - 3: **if** It returns only one type of nodes **then**
 - 4: Assign topic whose feasibility is the lowest to that type of mobile users.
 - 5: **else**
 - 6: Find the topic whose feasibility is the lowest.
 - 7: Assign topic to the type of the mobile users whose amount is minimal.
-

the same amount of selection, the mobile users which have the most unfeasible level should be assigned first. If the remaining mobile users have the same number of selections and their feasibility level is also the same, we begin to assign the mobile users whose amount are minimal.

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

Proof. In our algorithm, the mobile users which 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 have two interests, after they are assigned, there exist two situations: (1) The mobile users with minimum amount are fewer than the data in that topic, 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 that the total number of topic reduces one. Then, we get another mobile users which has only one remaining interest. If the optimal solution is not the same as the greedy algorithm, we can always exchange the difference

Algorithm 3 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.

- 1: **if** $\frac{t_1}{c_1} < \frac{t_2}{c_2}$ **then**
 - 2: Treat the mobile users, M_3 as the mobile users M_1 .
 - 3: **if** $\frac{t_1}{c_1} > \frac{t_2}{c_2}$ **then**
 - 4: Treat the mobile users M_3 as the mobile users, M_2 .
 - 5: The remaining M_3 node is proportionally assigned to these two topics based on the ratio of t_1 and t_2 .
-

between these two algorithms. If the results are not the same, there is a contradiction. \square

IV. ONLINE DATA DISSEMINATION

In this section, we propose the online data dissemination algorithm, in which the data assignment decision is made when mobile users can communicate with each other through proximity-based communication. Due to the mobility or the privacy issues, mobile users do not have the 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 relay node forward data to it to accelerate the data dissemination?

A. Data Selection for the Mobile Users with Multiple Interests

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

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 in which the 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, 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 c_1 and c_2 . Before the M_3 mobile users are assigned, the $c_1 = n_1$ and $c_2 = n_2$. Then, we propose the following criterion for mobile users M_3 . If $\frac{t_1}{c_1} < \frac{t_2}{c_2}$, 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 the these topics in proportion to the ratio of t_1 and t_2 . Similarly, if $\frac{t_1}{c_1} > \frac{t_2}{c_2}$, 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.

Theorem 2. *The proposed data selection algorithm for two topics is the optimal schedule.*

Proof. If there exists a feasible schedule, which means the following two conditions must be satisfied: $c_1 \geq t_1$ and $c_2 \geq t_2$. If $\frac{t_1}{c_1} < \frac{t_2}{c_2}$, the algorithm will regard mobile users M_3 as mobile users M_1 , until the above two ratios become the same. Then, $(n_1 + n_2 + n_3) \frac{t_1}{t_1 + t_2} = c_1 \geq t_1$, and $(n_1 + n_2 + n_3) \frac{t_2}{t_1 + t_2} = c_2 \geq t_2$, since $n_1 + n_2 + n_3 \geq t_1 + t_2$ in a feasible solution. If all the mobile users M_3 cannot make the two ratios become the same, that is, all the M_3 mobile users are treated as M_1 , i.e., $c_1 = n_1 + n_3$, and $c_2 = n_2$. This case is true, when $\frac{t_1}{n_1 + n_3} < \frac{t_2}{n_2}$. It can be written as $\frac{t_1}{t_2} n_2 < n_1 + n_3$. Besides, in a feasible solution, $n_1 + n_3 \geq t_1$ so that $n_1 + n_2 + n_3 \geq \frac{t_1}{t_2} n_2 + n_2 > t_1 + t_2$, as the result, $n_2 = c_2 > t_2$. 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 $\frac{t_1}{c_1} > \frac{t_2}{c_2}$. In all the situation, if there exists a feasible solution, the proposed algorithm will achieve it, so that it is the optimal schedule. \square

Theorem 3. *If different types of mobile users are uniformly distributed in the network, a schedule which makes $\max\{\frac{t_1}{c_1}, \frac{t_2}{c_2}, \dots, \frac{t_m}{c_m}\}$ 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 a data selection criteria, the probability of encountering a mobile user which would like to consume a topic is a constant value. Therefore, $\frac{t_i}{c_i}$ is proportional to the delivery delay of t_i . Suppose $\frac{t_i}{c_i}$ 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_c , can be assigned to topic i from another topic, denoted as topic j . As a result, $c'_i = c_i + \delta_i$, $c'_j = c_j - \delta_c$, and $\frac{t_i}{c'_i} > \frac{t_j}{c'_j}$ is satisfied at the same time. Hence, this data selection method is better than the optimal solution, which is a contradiction. \square

2) *Multiple topics:* If the topics type are more than 2, we can use the similar idea as the above sub-section. Based on the theorem 3, we get the 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.

B. 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 pattern and the mobile users' diverse interests in the local and global view by using two vectors.

	Original			Updated		
g_1	0.2	0.4	0.4	0.36	0.14	0.25
g_2	0.2	0.4	0.2	0.26	0.34	0.30
g_3	0.5	0.1	0.3	0.28	0.42	0.35
g_4	0.1	0.1	0.1	0.10	0.10	0.10
\bar{T}	2	3	5	3.30	3	3.15
Nodes	u_2	u_3	u_4	Node u_1		

Fig. 4. An illustration of the global utility updating.

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, topic 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 neighbor 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 type M_1, M_2, M_3 , and M_4 mobile users. We also record the average inter-meeting times of the current node, \bar{T}_l , which is important to estimate the delivery delay for the current node.

2) *Global utility vector*: The idea of 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, \bar{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 $\bar{T}_g = \bar{T}_l$.

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. 4 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 type 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

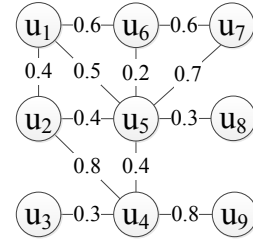


Fig. 5. An illustration of the reducing the influence of the overlapping.

the accumulated result, shown in the right side of the Fig. 4. In the global utility updating, we consider the weight of the current sliding window to be the same as the past accumulated result. As the result, the utility vector in the recent time is assigned a heavier weight in the accumulated result.

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

$$U = \frac{\bar{T}_l \{l_1, l_2, \dots, l_h\} + \alpha \bar{T}_g \{g_1, g_2, \dots, g_h\}}{\sum_{i=1}^h (T_i l_i + \alpha \bar{T}_g g_i)}, \quad (2)$$

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 carried. If the data can be fully distributed within 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.

3) *Overlapping elimination*: In the data distribution, multiple relays might forward data to one mobile user with good forwarding ability, which is called overlapping in this paper. As the result, the data are not distributed evenly in the network, therefore causes a relatively large delay based on Theorem 3. This is due to the fact that the relay's forwarding ability is over estimated. To eliminate the influence of overlapping, we propose to use the two-hop topology information of the mobile user. The reason is that the information within two hops converges quickly. If the current relay is aware of the existence of other relays within two-hops, the current mobile user will forward less data to the encountered node, due to the possibly overlapping.

For example, in Fig. 5, when mobile users u_2 and u_5 encounter, mobile user u_2 knows that mobile user u_1 might also forward some data to mobile user u_5 , so that mobile user u_2 might consider forwarding fewer data to mobile user u_5 . Suppose a mobile user which has q neighbors acting as relays; its overall utility is treated as $\frac{1}{q}$. In Fig. 5, the mobile users u_6, u_5 , and u_4 's overall utilities are treated as 1, $\frac{1}{2}$ and $\frac{1}{2}$, respectively, based on the viewpoint of mobile user u_1 . This local algorithm is not optimal, due to the limited knowledge about the network topology. In Fig. 5, mobile users u_1 and u_3 might not be aware of the existence of each other, since they are three-hop neighbors. In the optimal situation, they will distribute their data equally to the three unassigned neighbors,

u_4, u_5, u_6 . However, mobile users u_1 and u_3 will forward more data to mobiles u_6 and u_4 , with limited two-hop estimation.

In summary, when relay encounters another node, it re-think its overall ability by considering the possible overlapping problem based on its two-hop information. The amount of data each mobile user gets is proportional distributed.

C. An Extension

In the aforementioned solution, there might be 2^m types of the mobile users in the 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, the positive estimation and the 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. 6, the mobile 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, 2 are $\frac{1}{2}$. Since we only need to keep a vector size of m . This solution is good when the total topic number is large.

V. EXPERIMENTS

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

A. Experimental Setting

In the experiment, we use the INFOCOM06 [17] trace, which is collected by the small devices (iMotes) for four days during the INFOCOM 2006 conference. There exist 98 nodes; among them the 20 nodes are stable access points, and the 78 nodes are students. Once two nodes come into proximity, the iMotes will generate a record. In addition, each participant was asked to fill out a questionnaire with a number of questions about themselves. In the questionnaire, the participants indicated their interested topics. According to the questionnaire, there are 35 different topics in total.

However, the scale of the INFOCOM06 trace is small, i.e., average subscription number for a topic is 12, and the number of mobile users have two interests in the most popular topic is 14. To overcome it, we generate a synthetic dataset with 100 nodes with identical contact distribution. In this synthetic dataset, we gradually change the amount of users which subscribe to a topic, from 20 to 60, and the ratio of nodes which have multiple interests from 0 to 40. Therefore, the synthetic trace could provide some unrevealed insights in the data assignment.

Topic 1	1/0.5	1/1	0/0	⇒	0.42/0.4
Topic 2	1/0.5	0/0	1/1		0.58/0.6
\bar{T}	2	3	5		3.3
Nodes	u_2	u_3	u_4		

Fig. 6. An illustration of the positive/negative estimation of node u_1 .

Some detailed experimental settings are as follows: we choose the 2-6 topics in the offline scenario. In the online scenario, 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.

B. Algorithm Comparison

Our comparison consists of two parts. In the offline situation, we compare the proposed *Maxflow* algorithm and the proposed *Greedy2*, greedy algorithm version two. Furthermore, two more algorithms are proposed: the *Greedy* algorithm is the same as the proposed algorithm, except that the number of the nodes' remaining selection is not considered in the priority setting, the *random* algorithm, which randomly assigns data for the mobile users with multiple interest. As for the online scenario, the performance comparison is made up of two parts: (1) the delay regarding the different the data selection strategies for the mobile users with multiple interests. (2) the delay regarding the different utility estimation schemes. For the data selection strategy, we call the proposed strategy the *min-max speed* algorithm. 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. For the utility estimation scheme, 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. The two more efficient versions of global estimation are called the *positive* algorithm and the *negative* algorithm, respectively. We can further adapt the local and global estimation by considering the remaining amount of data in each topic. This method is called the *proposed* algorithm. We also compare the performance of algorithms, which consider the influence of overlapping or not. These two algorithms are called the *without overlap* algorithm and the *overlap* algorithm, the utility estimation method of these two algorithms are the proposed algorithm.

C. The Performance Results

1) *Offline results*: Fig. 7 shows the performance results of the proposed greedy algorithm, compared with the optimal solution in different numbers of topics. From the result, the proposed algorithm's difference with the optimal solution increases. However, its performance is still close to the optimal

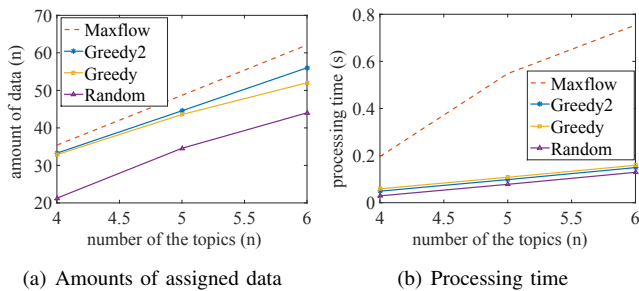


Fig. 7. Offline performance comparison

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 the similar processing time but the performance is not good.

2) *Data assignment strategies*: The results are shown in Figs. 8. In the synthetic dataset, we focus on the comparison of the different data assignment strategies. From Fig. 8(a), we observe that along with data amount increasing, the the min-max speed algorithm's 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. In Fig. 8(b), we do not change the overall data amount for two topics, but adjust the percentage of data in each topic, the results show that the proposed algorithm has good performance in the different scenarios. Fig. 8(c) demonstrates that as the amount of mobile users with multiple interests increases, so do the advantages of the proposed algorithm.

3) *Utility estimation strategies*: We compare the different utility estimation strategies, and the results are shown in Fig. 9. In Fig. 9(a), the results indicate that considering only the local estimation and global estimation will lead to poor performance in some cases. Due to its careful consideration of local and global estimates, the proposed algorithm always achieves low delay. Furthermore, we compare the four types of the utility estimation. The global algorithm achieves the best performance. However, it causes more storage consumption. In Fig.9(c), we also compare the influence of overlapping. When the amount of data is small, we do not need to worry about the overlap too much. The two utility estimation achieve nearly the same results. Along with the increasing amount of data, the proposed algorithm, which considers the overlap, performs better than the algorithm without considering the overlap.

VI. RELATED WORKS

In this section, we capture some important issues arising from the design of the data dissemination scheme in the proximity-based communication.

At the beginning, a lot of works have been done on the epidemic problem [5, 18–20]. The main concern in the

epidemic problem is how to avoid 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 types of mobile users: the mobile users without receiving 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. However, in our problem, the mobile user can forward data to others only if they carry some copies. In [6], the authors consider the broadcasting in delay tolerant network, which is essentially the same as the epidemic problem, but its recovery rate is 0. The major difference with our problem is that in [6] 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 epidemic problem.

In [21], the authors consider the data multi-casting, which means that a certain amount of data should reach the corresponding destinations. It is a N to N mapping. However, in this paper, we do not specify the destination, any nodes which are interested in the data can be a destination. It is a N to many (more than N) mapping. As a result, it is harder to analyze a mobile user's forwarding ability. In [10], the authors focus on data dissemination to a desired number of receivers in a vehicular network. However, there is only one type of data, so that their problem is a simplified version of our problem. In [4], their problem only considers one type of data making their work a simplified version of our problem. Furthermore, in [4], their analysis is under the assumption that all the nodes have an identical mobility pattern, which is not realistic.

To the best of our knowledge, we are the first to consider to distribute a desired number of data, considering the mobile users' mutually exclusive delivery requirement.

VII. ACKNOWLEDGMENT

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

VIII. CONCLUSION

The mobile pub/sub system can be applied to many scenarios by using the proximity-based communication technology. In this paper, we design an efficient mobile pub/sub system to distribute a pre-determined number of data in 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 amount of data in each topic and the different popularities of each topic, the above problem is non-trivial. We start with the offline data dissemination, 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 online situation, and propose a distributed

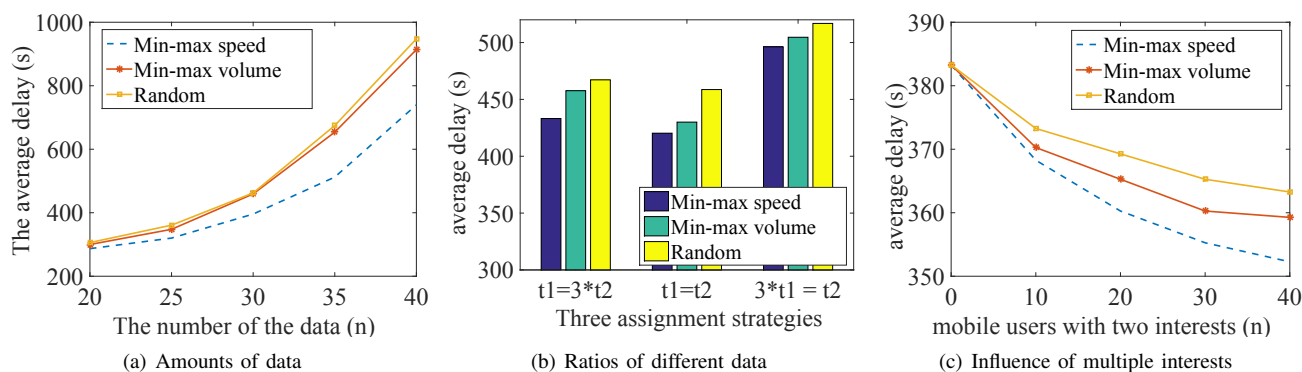


Fig. 8. Performance comparison in the synthetic dataset about data assignment strategies.

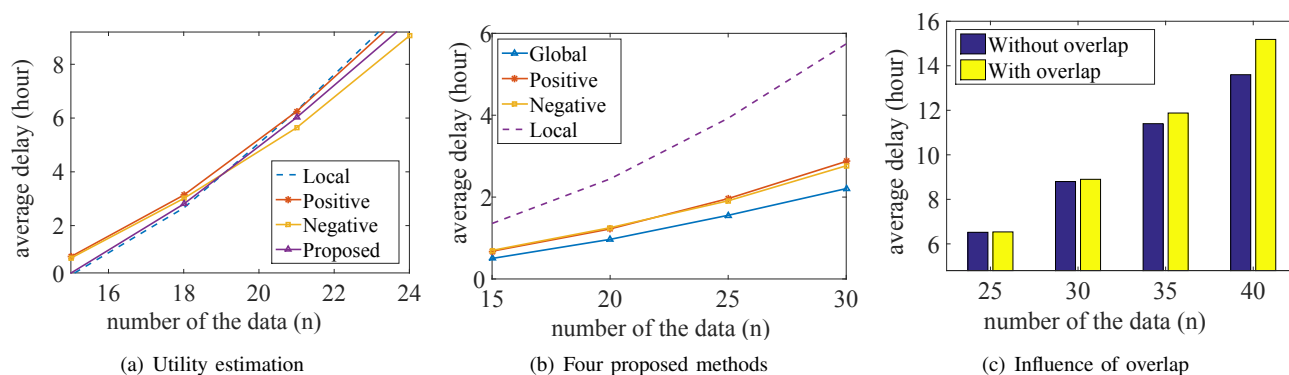


Fig. 9. Performance comparison in the INFOCOM06 dataset about utility estimation strategies.

algorithm, 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 scheme achieves a good performance.

REFERENCES

- [1] C. V. N. I. Cisco, "Global mobile data traffic forecast update, 2013–2018," *white paper*, 2014.
- [2] <http://www.wi-fi.org/>.html.
- [3] M. Seufert, G. Darzanos, I. Papafili, R. Łapacz, V. Burger, and T. Hoßfeld, "Socially-aware traffic management," in *Socioinformatics-The Social Impact of Interactions between Humans and IT*. Springer, 2014, pp. 25–43.
- [4] W. Rao, K. Zhao, Y. Zhang, P. Hui, and S. Tarkoma, "Towards maximizing timely content delivery in delay tolerant networks," *IEEE Transactions on Mobile Computing*, vol. 14, no. 4, pp. 755–769, 2015.
- [5] W. Gao, Q. Li, B. Zhao, and G. Cao, "Multicasting in delay tolerant networks: a social network perspective," in *Proceedings of the ACM MobiHoc*, 2009.
- [6] K. C.-J. Lin, C.-W. Chen, and C.-F. Chou, "Preference-aware content dissemination in opportunistic mobile social networks," in *Proceedings of the IEEE INFOCOM*, 2012.
- [7] A. Nandan, S. Das, B. Zhou, G. Pau, and M. Gerla, "Adtorrent: digital billboards for vehicular networks," in *Proceedings of the IEEE/ACM V2VCOM*, 2005.
- [8] J. Kangasharju and A. Heinemann, "Incentives for electronic coupon systems," in *Proceedings of the ACM DIWANS*, 2006.
- [9] H. Liu, V. Ramasubramanian, and E. G. Sirer, "Client behavior and feed characteristics of rss, a publish-subscribe system for web micronews," in *Proceedings of the ACM SIGCOMM conference on Internet Measurement*, 2005.
- [10] T. Yan, W. Zhang, and G. Wang, "Dove: Data dissemination to a desired number of receivers in vanet," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 4, pp. 1903–1916, 2014.
- [11] D. De Niz, L. Wrage, A. Rowe, and R. R. Rajkumar, "Utility-based resource overbooking for cyber-physical systems," *ACM Transactions on Embedded Computing Systems*, vol. 13, no. 5s, p. 162, 2014.
- [12] J. Ott, D. Kutscher, and C. Dwertmann, "Integrating dtn and manet routing," in *Proceedings of the ACM SIGCOMM*, 2006.
- [13] R. K. Ahuja, "Network flows," Ph.D. dissertation, 1993.
- [14] N. Deo and C.-Y. Pang, "Shortest-path algorithms: Taxonomy and annotation," *Networks*, vol. 14, no. 2, pp. 275–323, 1984.
- [15] https://en.wikipedia.org/wiki/Binary_search_algorithm, 2015.
- [16] D. B. West *et al.*, *Introduction to graph theory*. Prentice hall Upper Saddle River, 2001, vol. 2.
- [17] J. Scott, R. Gass, J. Crowcroft, P. Hui, C. Diot, and A. Chaintreau, "CRAWDAD data set cambridge/haggle (v. 2006-01-31)," Jan. 2006.
- [18] R. Pastor-Satorras and A. Vespignani, "Epidemic spreading in scale-free networks," *Physical Review Letters*, vol. 86, no. 14, p. 3200, 2001.
- [19] D. López-Pintado, "Diffusion in complex social networks," *Games and Economic Behavior*, vol. 62, no. 2, pp. 573–590, 2008.
- [20] N. Wang and J. Wu, "Opportunistic wifi offloading in a vehicular environment: Waiting or downloading now?"
- [21] W. Gao, Q. Li, B. Zhao, and G. Cao, "Social-aware multicast in disruption-tolerant networks," *IEEE Transactions on Network-*