Mobile Data Sharing with Multiple User Collaboration in Mobile Crowdsensing (Short Paper)

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Abstract. With the development of the Internet and smart phone, mobile data sharing have been attracted many researcher's attentions. In this paper, we investigate the mobile data sharing problem in mobile crowdsensing. There are a large number of users, each user can be a mobile data acquisition, or can be a mobile data sharing, the problem is how to optimal choose users to collaborative sharing their idle mobile data to others. We consider two data sharing models, One-to-Many and Many-to-Many data sharing model when users share their mobile data. For One-to-Many model, we propose an OTM algorithm based on the greedy algorithm to share each one's data. For Many-to-Many model, we translate the problem into the stable marriage problem (SMP), and we propose a MTM algorithm based on the SMP algorithm to solve this problem. Experimental results show that our methods are superior to the other approaches.

Keywords: Crowdsensing · Mobile data sharing · Multiple users collaboration · Stable marriage problem

1 Introduction

In recent years, with the popularization and development of mobile technology, everyone has one or more mobile terminals, such as mobile phone, tablet, laptop

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and so on. Each users have their data plan per month to use mobile terminals surf on the Internet. However, the mobile data usage of each user per month is uncertain. Some users may use little per month, but others may be completely inadequate. Therefore, some users could use redundant mobile data to share with others who need data. The mobile data sharing users sell their data to the mobile data requesters, and obtain some reward. In the other hand, the mobile data requesters could take less money to buy mobile data.

In the data sharing systems, users who need data are data request users (DR users for short), and users who share data are data sharing users (DS users for short). In crowded places, such as a train, airport, shopping center, etc, the mobile DS users has a coverage area, and the mobile DR users can obtain shared data only within the coverage area of any DS users. If there are lots of DS users, the data sharing coverage will expand to a larger area. Similarly, If there are lots of DR users, the DS user can share his data easily, and do not limit the fixed position, as long as the DR users is nearby. Therefore, to some extent, it is win-win to mobile data sharing users and requesters. As shown in Fig. 1, there are four mobile DS users, DS1, DS2, DS3 and DS4, and three DR users, DR1, DR2 and DR3. There are two data sharing models. One data sharing model is One-to-Many model, that is, a DS user can find multiple DR users simultaneously, and choose one DR users to share the mobile data, such as DR1, DR2, DR3, DS2 group. The other data sharing model is Many-to-Many model. In this model, any DR users can find multiple DS users simultaneously, and any DS users will cover multiple DR users, such as DS2, DS3, DR2, DR3 group. Moreover, the group DR1 can obtain DS1,DS2 shared signals at the initial location 1. When DR1 moves to location 2, he can not get a shared signal, and when DR1 moved to location 3, he get the shared signals from DS4.

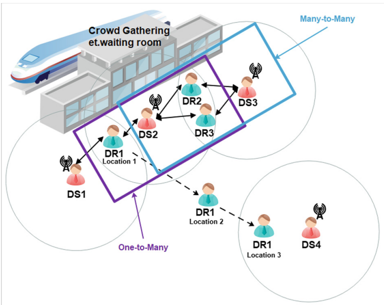

Fig. 1. Mobile data sharing example.

Nowadays, there are some researches focus on the mobile data sharing and trading. Yu et al. [1] investigated the data trading and introduced a trading platform that matches the market supply and demand. Jiang et al. [2] proposed a quality-aware data sharing market, where the users sell data to data requesters. Ma et al. [3] proposed how to develop a shared WiFi operation strategy to motivate users to participate. However, they did not propose how to matching optimal users among two groups. In this paper, different models are divided according to different user groups, and solved how to match the two kinds of users in the same range. The main difference between this paper and previous research is that two algorithms are proposed to match two kinds of data sharing model. Overall, the contributions of this paper are summarized as follows:

– We considering two data sharing models, One-to-Many and Many-to-Many data sharing model when users share their mobile data. Then, we formulate this two kind of data sharing models.
– We propose an OTM algorithm to solve the One-to-Many data sharing problem based on the greedy algorithm, which greedy choose the optimal users to sharing the mobile data. Then, we translate the Many-to-Many data sharing problem into a stable marriage problem (SMP), and we propose a MTM algorithm base on the SMP algorithm.
– We conduct extensive simulations over different environments to evaluate the performances of the proposed algorithm. Simulation results show the proposed algorithms is superior to the traditional algorithms.

2 Related Work

In the sharing economy, such as sharing bicycles [4], it has adopted a shared model. Ma et al. [5] proposed a framework of independent service sharing coordination, which sharing of spectrum and radio access networks (RANs). Ferrari et al. [6] described a unifying optimization framework to share backhaul network resources across different operators and wireless platforms.

Mobile crowdsensing (MCS) is a new paradigm of sensing by taking advantage of the rich embedded sensors of mobile user devices [7]. Zhu et al. [8] provided a (reverse)VCG Auction at each time slot the user is trusted to disclose the address of the information, where SP is the auctioneer (buyer), and the user is the bidder (seller).

Wang et al. [9] proposed a VM allocation mechanism based on stable matching. He et al. [10] proved that the allocation problem is NP-hard between tasks and users in crowdsensing, and devised an efficient local ratio based algorithm (LRBA) to solve. Gu et al. [11] studied matching theory for wireless networks and analyzed three classic matching problems. Different from the previous study, we studied One-to-Many case and Many-to-Many case in the sharing model.

3 System Model and Problem Formulation

3.1 System Model

In the system, we set three types of role: mobile data sharing users (DS for short), mobile data requester (DR for short), Services Platform (SP for short). DS users share their mobile data to DR users, and DR users get the mobile data which DS users share, and the SP is used to guarantee the fairness of the transaction. When the DR users is covered by the DS users, and the required data and the data download tolerance time of the DR users are satisfied, the optimal DS user is selected, and DS users share data for DR users, and DR users pay DS users rewards. SP is used to ensure the reliability of the transaction, at the same time, record the relevant transaction information, and constrain DR users and DS users according to certain rules.

We consider two sharing model, One-to-Many (OTM for short) sharing models and Many-to-Many (MTM for short) sharing models. For OTM model, there is only one DS user (or DR user) and multiple DR users (or DS users), the DS user (or DR user) choose an optimal DR user (DS user). For MTM model, there are multiple DS user and multiple DR users, the system should choose an optimal match between DR user and DS user.

3.2 One-to-Many Sharing Problem

We consider One-to-Many sharing problem firstly. No loss of generality, we consider that there is only one DS user and multiple DR users. Let $\mathbb{R} = \{R_1, R_2, ..., R_n\}$ as the set of DR users, and n is the number of DR users. We denote f_i as the required data size of DR users R_i, and denote t_i as the data download tolerance time when DR users R_i downloads the required data. As different sharing data users have different hardware and different configurations, they could offer different network speeds to DR users. We set V as the available sharing network speed of DS users, and set F as the sharing data size of DS user. Then, the sharing network speed should be more than the data download network speed of the DR users. Let x_i represents whether the DS user choose the DR users R_i to share his data. We define variance $\{Q(x) = |F - f_i * x_i|, 1 \leq i \leq n\}$ as the matching degree, which indicates the matching result of DS user and DR user R_i. The matching degree $Q(x)$ is the closeness degree to which sharing data and acquiring data. The smaller the $Q(x)$, the better matching stability and the smaller the sharing data gap of DS users and DR users. Conversely, the larger the $Q(x)$, the worse matching stability.

In order to achieve data sharing, our One-to-Many sharing problem is that: When DR users within the coverage of one DS user, and DS user meets the DR user R_i data download tolerance time t_i, how to choose the optimal DR users, making DS users and DR users matching degree are minimal? Therefore, our One-to-Many sharing problem is to minimize the total matching degree, that is:

$$\min Q(x) = \sum_{i=1}^{n} |F - f_i * x_i| \tag{1}$$

subject to:

$$V \geq x_i * f_i / t_i \tag{2}$$

$$x_i \in \{0, 1\}, 1 \leq i \leq n \tag{3}$$

Constraint (2) denotes that the sharing network speed should be more than the data download network speed of the DR users. Constraint (3) guarantees that x_i only choose 0 or 1.

3.3 Many-to-Many Sharing Problem

For Many-to-Many sharing problem. There are multiple DS users and multiple DR users. For DR users, the notations is the same as the One-to-Many sharing problem. For DS users, we denote $\mathbb{S} = \{S_1, S_2, ..., S_m\}$ as the set of DS users, and m is the number of DS users. As different sharing data users have different hardware and different configurations, they could offer different network speeds to DR users. We set V_i as the available sharing network speed of DS users S_i, and set F_i the sharing data size of DS users S_i. We use a failure rate r to indicate the failure rate of the matching result, the smaller the r, which indicates that few users have not been matched to. Relatively, the smaller the r, indicating that the more successful matches are. We use $\mathbb{R}'$ as the successful matching set, and $|\mathbb{R}| - |\mathbb{R}'|$ is the number of failure matching set. Then, the failure rate is $r = \frac{|\mathbb{R}|-|\mathbb{R}'|}{|\mathbb{R}|}$. In this problem, we also want the failed matching set is a little less. We set y_j represents whether the DS user S_j sharing his data to the DR users. Therefore, our Many-to-Many sharing problem is that: When DR users within the coverage of DS users, and DS user S_j meets the DR user R_i data download tolerance time t_i, how to choose the optimal DS users and DR users to match, making the failure rate and matching degree are minimal? Therefore, our Many-to-Many sharing problem is:

$$\min Q(x) = \frac{|\mathbb{R}| - |\mathbb{R}'|}{|\mathbb{R}|} * \sum_{i=1}^{n} \sum_{j=1}^{m} |F_i * y_j - f_i * x_i| \tag{4}$$

subject to:

$$v_j y_j \geq x_i * f_i / t_i \tag{5}$$

$$x_i, y_j \in \{0, 1\}, 1 \leq i \leq n, 1 \leq j \leq n \tag{6}$$

Constraint (5) denotes that the sharing network speed of DS user y_j should be more than the data download network speed of the DR users x_i. Constraint (6) guarantees that x_i and y_j only choose 0 or 1.

4 Our Solution

In this section, we first give the define of data matching ratio and its calculation formula. Then, we propose One-to-Many Greedy Algorithm and Many-to-Many Match Algorithm to solve the above problems. In order to better solve the above problems, we define some notations. First, We define a cost rate C of DR users to measure the matching results. Cost rate C represents the ratio of unmet data requirements to total data requirements for DR user in a successful match. If data requirements is met for DR user, we set the cost rate C as 0. That is:

$$C_i = \begin{cases} (f_i - F_i)/f_i, f_i > F_i \\ 0, f_i \leq F_i \end{cases} \tag{7}$$

Then, we define data matching ratio φ, it also gains rate of DS users. It determines the order of DS users to select DR users. φ_i is the proportion of DR user R_i data size f_i and DS user S_i data size F_i. If $f_i \geq F_i$, the ratio φ_i is 1. That is:

$$\varphi_i = \begin{cases} 1, f_i \geq F_i \\ f_i/F_i, f_i < F_i \end{cases} \tag{8}$$

4.1 One-to-Many Solution

We propose Algorithm 1 based on Greedy Algorithm. In Algorithm 1, we greedy find the maximum data matching ratio and find the optimal DR user to acquire data in each step.

Algorithm 1. One-to-Many Greedy Algorithm (OTM)

Input :
$\mathbb{R}$: DR user set, S: a DS user.
Output :
$SelectedDR$: Selected DR user.

begin
$SelectedDR \leftarrow \varnothing$, $SecondSelectedDR \leftarrow \varnothing$, TAG $\leftarrow$ 0, isNotFirstSelected $\leftarrow$ true, $Max(\varphi) \leftarrow 0$;
sort ($\mathbb{R}$) by the merging algorithm according to f;
while $TAG \leq |\mathbb{R}|$ **do**
  $Tem(\varphi) \leftarrow$ the data matching ratio (DS user , the TAG'th DR user);
  if $Tem(\varphi) > Max(\varphi)$ **then**
    $Max(\varphi) \leftarrow Tem(\varphi)$;
    if isNotFirstSelected **then**
      isNotFirstSelected $\leftarrow$ false;
    else
      $SecondSelectedDR \leftarrow SelectedDR$;
    end if
    $SelectedDR \leftarrow$ the TAG'th DR user;
  end if
  if $Max(\varphi) \geq 1$ **then**
    break;
  end if
  TAG $\leftarrow$ TAG+1;
end while
if $|F$ - $f_{SecondSelectedDR}| \leq |F$ - $f_{SelectedDR}|$ **then**
  SelectedDR $\leftarrow$ SecondSelectedDR;
end if
return SelectedDR;
end;

In the algorithm, we sort the DR users according to f. When the data download tolerance t of DR user was met by the DS user, we calculate the matching ratio φ. When the matching ratio φ is 1 or greater, and stop. Suppose r_1 and r_2 are optimal and suboptimal elements of $\mathbb{R}$ set, we could derive to two matched pairs (S, r_1) and (S, r_2). and choose the pair to match that the least sharing data gap between DS users and DR users pair.

4.2 Many-to-Many Solution

In the problem, we can abstract the DR user as the male, the DS user as the female, each DS user sort to the DR users according to the data matching ratio. In turn, each DR user will have a preferred order to DS users based on similar principle. We assume that the number of DR users equals the number of DS users, that is classic SMP problem. When the number of DS users and

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Algorithm 2. Many-to-Many Match Algorithm (MTM)

Input :
$\mathbb{R}$: DR user set, $\mathbb{S}$: DS user set.
Output :
$\mathbb{R}'$: the successful matching set.
begin
sort($\mathbb{R}$) and sort($\mathbb{S}$) by merging algorithm according to f and F;
Initialize all $m \in \mathbb{R}$ and $w \in \mathbb{S}$ to be free;
while some DS users w is free and $\exists$ DR user m is free **do**
  w:= first DS user on $\mathbb{S}$ list;
  Calculate a preference ranking set SR for w ;
  if $|SR| \geq 1$ **then**
    suppose r_1 and r_2 of SR set can be matched to w, two pairs (DS, r_1) and (DS, r_2) can be matched;
  end if
  if the optimal matching user of r_1 is not w **then**
    suppose optimal user is s_1 and sub optimal user is s_2, two pairs (r_1, s_1) and (r_1, s_2) can be matched;
  end if
  Choose the pair as successfully matched that |F - f| is least among the pairs, w as a successful matching DS user, m as a successful matching DR user;
  if some DR user p is matched to w **then**
    assign p to be free;
  end if
  assign m and w to be matched to each other;
  for each successor m of $\mathbb{R}$ list and w of $\mathbb{S}$ list **do**
    delete the pair(m,w);
    join the pair (m,w) to set $\mathbb{R}'$;
  end for
end while
return $\mathbb{R}'$;
end;

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the number of DR users are not equal, this problem becomes an SMI (stable Marriage with incomplete list) problem [12]. When the number of DS users and the number of DR users are not equal, if there are no matching users in each round, waiting for the next round to match.

We propose the Algorithm 2 to match the DS users and DR users based on SMP algorithm. In this algorithm, the optimal matching users is selected iteratively. Firstly, DR users are sorted according to the required data size, and DS users are sorted according to the shared data size. Secondly, we calculate a preference ranking set SR of each DS user according to matching ratio 8. If the size of SR greater than or equal to 2, we could further infer the matching result. Suppose r_1 and r_2 are optimal and suboptiaml elements of SR set, S_1 is the first elements of DS users. We could derive to two matched pairs (S_1, r_1) and (S_1, r_2). In the same way, we could get another two pairs (R_1, s_1) and (R_1, s_2), where s_1 and s_2 are optimal and suboptiaml elements of preference ranking set of DR user R_1. Finally, we choose the least sharing data gap between DS users and DR users pair. Repeat the above steps until the matching is finished.

5 Performance Evaluation

Here, we evaluate the performance of the proposed algorithm and conducted a simulation experiment in One-to-Many case and Many-to-Many case respectively by setting different numbers of users. In the experiment, the cost rate C and matching degree $Q(x)$ between DS user and DR user are compared and analyzed. We compare several algorithms as follows.

Common Matching Algorithms(COM): In this algorithm, a DS user is selected from $\mathbb{R}$, and matched with a DR user when the data download tolerance t of DR user was met by the DS user. **Stable Matching Problem(SMP):** In this algorithm, according to the classical SMP algorithm [12], each DS user find a preference ranking set SR to DR users according to matching ratio φ, and each DS user selects the first DR user that no matched from its preference SR set to match. **Random Matching Algorithms(RM):** In this algorithm, a DS user of $\mathbb{S}$ is matched to a DR user that selected randomly from $\mathbb{R}$ when the data download tolerance t of DR user was met by the DS user.

According to Eqs. (7) and (8), we calculate the gains rate of DR users through by $(1-C)$, so, the sum of gians rate of DS users and DR users can be expressed by $B = (\varphi_i + (1-C))$. We mainly compare the sum of gains rate B and the matching degree $Q(x)$.

5.1 One-to-Many Simulation

In the One-to-Many experiment, we simulated a DS user and 5 to 15 DR users respectively. We calculate the sharing data gap of DS user and DR user, then, compare the value of $Q(x)$. After each case is simulated 100 times, then solve the average value. The sum of gains rate result of users are shown as Fig. 2, the matching degree result are shown as Fig. 3.

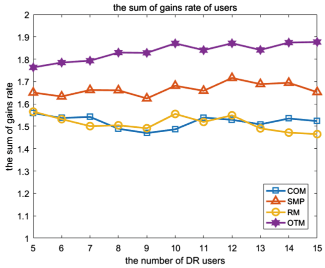

Fig. 2. The sum of gains rate of users.

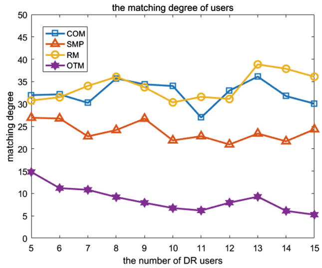

Fig. 3. The matching degree of users.

In the One-to-Many case, we know that the sum of the algorithm gains is the highest in Fig. 2. From Fig. 3, we can see that the matching degree $Q(x)$ of our algorithm is the smallest and the matching result is the most stable.

5.2 Many-to-Many Simulation

In the Many-to-Many experiment, we simulated 50 DS users and 10 to 100 DR users respectively. The sum of gains rate result of users are shown as Fig. 4, the matching degree result of users are shown as Fig. 5.

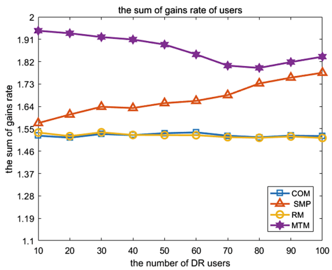

Fig. 4. The sum of gains rate of users.

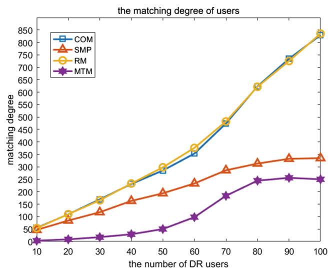

Fig. 5. The matching degree of users.

In the Many-to-Many case, the number of DS users greater than the number of DR users or less, we know that the sum of the MTM algorithm gains is the highest and the matching degree $Q(x)$ is the lowest. We can see that our algorithm has the optimal overall gains and the most stable matching result.

We can know that the sum of our algorithm gains is the highest and the matching degree $Q(x)$ is the lowest. By improving social welfare, the user's income is increased or the user's cost is reduced. The matching degree $Q(x)$ is lowest, the matching result is the most stable, and the benefits of DS users and the costs of DR users are balanced. So, our proposed algorithms is superior to the other approaches.

6 Conclusions

In this paper, we investigate mobile data sharing problem based on multi users Collaborative and crowdsening. To solve the problem, we introduced two mobile data sharing models, One-to-Many model and Many-to-Many model. Basic these two models, we proposed two algorithms to solve the mobile data sharing problem. Extensive simulations show that the performance of our proposed algorithms is superior to the other approaches.

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