Stable Task Assignment with Range Partition under Differential Privacy

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Abstract. With the development of cloud computing, spatial crowdsourcing (SC) has become a significant concern in data processing, including food delivery and online car-hailing. However, privacy leakage presents a challenge for requesters who need to share their task information with the server. Differential privacy (DP) is a robust privacy protection paradigm that allows the release of useful information while safeguarding requesters' privacy. However, task assignment under DP often results in ineffective utility. In this paper, we propose a stable task assignment scheme that enables requesters to apply for workers and achieve effective stable matching while preserving the privacy of the requests (tasks). Specifically, we introduce an approach called ECM that achieves stable matching while protecting the preference of requesters. We demonstrate the efficiency and effectiveness of our ECM on synthetic and real datasets.

1 Introduction

With the increasing popularity of cloud computing, spatial crowdsourcing has emerged as a computing paradigm for solving spatial tasks that involve human participation. To access content services, individuals are required to provide certain personal information to the server. This enables the server to efficiently execute task computing based on the provided information.

However, the location information of users may be sensitive and can compromise their privacy. To address this issue, differential privacy [4] can be used to protect individual data while still ensuring accurate statistical results for the entire data set.

Most schemes [13,14] disturb task positions under different privacy levels and then send the noisy data to the server. The server has to match tasks and workers using the disturbed data, which increases the error in the matching result. In

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this paper, we propose a new model where tasks compete for workers based on their knowledge of workers' information. In this model, the location of tasks is not made public to others. The tasks compete for workers while using differential privacy counters.

In this paper, we study the problem of spatial crowdsourcing, specifically the Private Stable Task Assignment Problem (PSTAP). In this context, tasks can be assigned to workers based on their proximity without revealing the tasks' locations. We assume that the workers' information is publicly available, the server is honest but curious, and the tasks are rational. To address this problem, we propose a private stable matching scheme called Enhanced Concentric Mechanism (ECM). This scheme divides the plane into multiple areas centered around each worker and transforms distances into preferences. It leverages the binary mechanism [2] and extends the Private Gale-Shapley Mechanism [15] to achieve a stable matching between tasks and workers. ECM ensures the privacy of workers' preferences under joint differential privacy. The contributions of this paper are as follows:

(1) We formally define the Private Stable Task Assignment Problem (PSTAP) in Section 3.
(2) We propose the Enhanced Concentric Mechanism (ECM) in Section 4 to solve PSTAP.
(3) We evaluate the efficiency and effectiveness of ECM on synthetic and real datasets in Section 5.

2 Related Work

We introduce the related work on stable allocation and private data stream publication under differential privacy.

Stable Allocation. Stable allocation can be seen as a variation of the stable marriage matching problem, which can be solved using the Gale-Shapley algorithm [6]. However, the Gale-Shapley algorithm can only handle matching scenarios where both sides have strict preference tables. And it does not consider the privacy of individual agents.

Golle [7] proposes Matching Authorities to perform private matching, which provides privacy and correctness as long as the majority of Matching Authorities are honest. Keller and Scholl [9] and Doerner et al. [3] use RAM-based secure computation to implement stable matching. However, all of the above methods are time-consuming during the matching progress. Hsu et al. [8] have declared that private matching and allocation problems cannot be solved under differential privacy. They relax the privacy constraint as joint differential privacy (JDP) and design a private billboard to achieve JDP.

Private Data Stream Publication under Differential Privacy. Differential privacy [4] is an efficient approach to protect location privacy. To et.al [12] first decompose the spatial using Private Spatiotemporal Decomposition (PSD) [10] and then perform task assignment with obscure task location geocasted to those near regions with workers with high probability.

Dwork et al. [5] focus on private data stream publication and propose a binary tree technique for finite streams. Chan et al. [2] formalize the differentially private continual counter and design it to achieve ϵ-differential privacy with $\emptyset(\frac{1}{\epsilon} \cdot (\log t)^{1.5} \cdot \log \frac{1}{\delta})$ error with probability $1 - \delta$. Zhang et al. [15] propose the Joint Differentially Private Gale-Shapley Mechanism for Location Privacy Protection. They use the differentially private continual counter to protect preferences. However, it does not consider the distance between different entities.

3 Problem Definition

We define a spatial task as t_i and its location as loc_i. We also define a spatial worker as w_j and its location and capacity as loc_j and c_j respectively. The notations are summarized in Table 1. We assume that workers are honest and public. The server is honest-but-curious, which means it will execute required algorithms correctly but may attempt to obtain information from data and requests. The tasks are rational, as they seek to maximize their benefits.

Definition 1 ((α, β)-stable matching). *Given a set P with size $|P|$ and a set Q with total capacity $|Q.c|$ satisfying $|P| \leq |Q.c|$. A matching $M = (P_m, Q_m)$ is a (α, β)-stable matching, if there exists a stable matching M' such that with probability $(1 - \beta)$,*

$$\sum_{i \in M.P_m \cup M'.P_m, (i,j) \in M, (i,j') \in M'} |rank(i,j) - rank(i,j')| \leq \alpha$$

where $rank(i,j)$ is the rank of j in i's preference list.

Definition 2. *(Private Stable Task Assignment Problem, PSTAP) Given a set of spatial tasks $T = \{t_1, t_2, ..., t_m\}$, and a set of spatial workers $W = \{w_1, w_2, ..., w_n\}$, the Private Stable Task Assignment Problem aims to find a (α, β)-stable matching [11] M that ensures the tasks' location privacy while satisfies the following conditions:*

$$\begin{aligned} \min \quad & \sum_{t_i \in T} \sum_{w_j \in W} x_{i,j} \cdot d_{i,j} \\ s.t. \quad & x_{i,j} \in \{0, 1\} \\ & \sum_{t_i \in T} x_{i,j} \leq c_j, \qquad \forall j = 1, 2, ..., n \\ & \sum_{w_i \in W} x_{i,j} \leq 1, \qquad \forall i = 1, 2, ..., m \end{aligned} \tag{1}$$

4 Enhanced Concentric Mechanism

4.1 The Overview of ECM

The main idea of ECM is using the Private Gale-Shapley algorithm [15] to obtain a stable matching between spatial tasks and spatial workers. This is done

Table 1. Notations

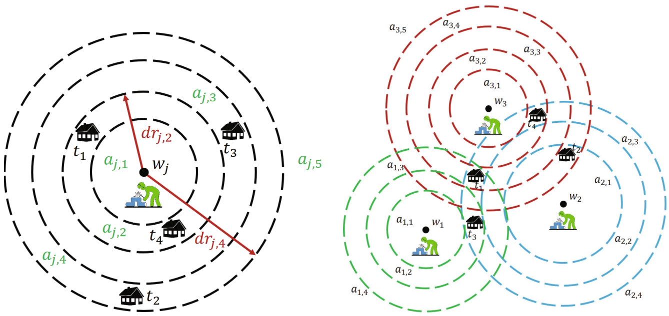
Notations	Description
t_i	the i-th task
w_j	the j-th worker
T	the task set
W	the worker set
$d_{i,j}$	the real distance from t_i to w_j
$B(j,k)$	the count-element in B recording the applying count to the k-th serving area of w_j
$PR_{i,W}$	the distance set from t_i to all workers
AP_i	the area set of t_i in all workers' serving range
$RP_i^{(k)}$	the random area set of t_i in all workers' serving range at k-th round
b_i	the count vector held by t_i
c_j	the capacity of w_j
μ_i	the index of worker proposed by t_i in the current round
$a_{j,k}$	the k-th serving area of w_j
$o_i(j)$	the distance rank of w_j in t_i's preference list
$o_i^{-1}(k)$	the index of the worker who is in the k-th position in t_i's preference list
$r_j(i)$	the area rank of t_i in the serving range of w_j
$Sum(C_i)$	the noise sum of counters not ranking behind t_i's current applying area

under a differential private streaming counter [2] structure, with preference lists constructed based on distance. ECM can be divided into the following 4 steps.

Task Preference Construction. At first, Each task t_i calculates the distance $d_{i,j}$ between itself and each worker w_j. Then t_i sorts these distances in ascending order to construct the preference rank list $PR_{i,W} = \{d_{i,o_i^{-1}(1)}, ..., d_{i,o_i^{-1}(n)}\}$. All of the $PR_{i,W}$ (for $i \in [m]$) together form the tasks' preference list $PR_{T,W}$.

Worker Preference Construction. Each worker w_j first selects a series of distance values $PD_{j,A} = \{dr_{j,1}, dr_{j,2}, ..., dr_{j,U_j}\}$ in ascending order. w_j then publishes $PD_{j,A}$ to S. Centered at loc_j, $PD_{j,A}$ divides the plane into $U_j + 1$ serving range areas $PR_{j,A} = \{a_{j,1}, a_{j,2}, ..., a_{j,U_j+1}\}$. The collection of all $PR_{j,A}$ (for $j \in [n]$) forms the workers' preference list $PR_{W,A}$. An example of w_j with $U = 4$ is illustrated in Figure 1(a).

Area Positioning. After obtaining the ranges of each worker, t_i looks up the range $a_{j,k}$ for w_j that satisfies $dr_{j,k-1} < d_{i,j} \leq dr_{j,k}$ (recorded as $r_j(i) = k$). t_i keeps track of all workers' area positions in a list $AP_i = \{a_{j,r_j(i)}\}$ for each $j \in [n]$. We provide an instance in Figure 1(b). t_1 falls within the serving range of w_1, w_2, and w_3. It is in $a_{1,3}$ for w_1, $a_{2,2}$ for w_2, and $a_{3,3}$ for w_3. Therefore, the area positions for t_1 are $AP_1 = \{a_{1,3}, a_{2,2}, a_{3,3}\}$.



(a) The preference area of w_j (b) The preference area of w_1, w_2, and w_3

Fig. 1. Area division by workers.

Matching Construction. In this step, all tasks help the server S perform task assignment using the private Gale-Shapley algorithm. They hold a billboard [2,8] to record the application process of the tasks. Each task will iteratively apply to a worker in its worker rank list when the task is available. Once the application process is complete, S assigns the tasks to workers according to the billboard.

Next, we present the construction of our Enhanced Concentric Mechanism (ECM) algorithm which is shown in Algorithm 1.

Algorithm 1: ECM

Input: Tasks: t_i's location loc_i for each $i \in [m]$, Workers: w_j's locations loc_j, range preferences $PR_{j,A}$ and capacity c_j
Output: Matching results

```
S initializes the billboard B by setting B(j, s) = BM(ε/2mn, mn²) for each
  j ∈ [n] and s ∈ [U_j];
Each task t_i gets its rank of workers PR_{i,W};
Set R_T as the tasks with candidate workers in PR_{T,W};
while R_T is not empty do
    for t_i ∈ R_T do
        Initializes current applying worker w_a as the next element in PR_{i,W};
        Set b_i(a) = B(a, r_a(i));
        Set b_i(j) = B(j, random(AP_j))) for w_j ∈ PR_{i,W} \ w_a;
        Update b_i by executing Private Gale-Shapley algorithm [15];
        t_i sends b_i to S;
        S updates B by b_i;
Each t_i sends its μ(i) to S;
S gets the matching M by μ(i) for i ∈ [m];
return B;
```

We provide an example in Figure 1(b) and Figure 2. Suppose there are 4 tasks: t_1, t_2, t_3, and 3 workers: w_1, w_2, w_3. At the beginning, w_1, w_2, and w_3 publish their serving distances, locations and capacities (The first table in Figure 2). The serving distances of the workers divide the plane into multiple areas (as shown in the second table in Figure 2) which form the preference list of all workers. After that, all tasks construct their preference tables for workers. S holds a billboard B. In B, each element is a counter and initialized as 0.

Server S

Worker ID	Location	Serving distance rank	Capacity
w_1	$loc(w_1)$	10m, 20m, 30m	1
w_2	$loc(w_2)$	20m, 30m, 40m	1
w_3	$loc(w_3)$	10m, 20m, 30m, 40m	2

$PR_{W,A}$	Area 1	Area 2	Area 3	Area 4	Area 5
w_1	$a_{1,1}$	$a_{1,2}$	$a_{1,3}$	$a_{1,4}$	---
w_2	$a_{2,1}$	$a_{2,2}$	$a_{2,3}$	$a_{2,4}$	---
w_3	$a_{3,1}$	$a_{3,2}$	$a_{3,3}$	$a_{3,4}$	$a_{3,5}$

t_1	w_1	w_3	w_2
$PR_{1,W}$	$d_{1,1}$	$d_{1,3}$	$d_{1,2}$
AP_1	$a_{1,3}$	$a_{3,3}$	$a_{2,3}$
$RP_1^{(1)}$	$a_{1,2}$	$a_{3,1}$	$a_{2,2}$
$RP_1^{(2)}$	$a_{1,1}$	$a_{3,2}$	$a_{2,3}$
$RP_1^{(3)}$	$a_{1,3}$	$a_{3,1}$	$a_{2,1}$

t_2	w_2	w_3	w_1
$PR_{2,W}$	$d_{2,2}$	$d_{2,3}$	$d_{2,1}$
AP_2	$a_{2,1}$	$a_{3,4}$	$a_{1,4}$
$RP_2^{(1)}$	$a_{2,2}$	$a_{3,2}$	$a_{1,1}$
$RP_2^{(2)}$	$a_{2,3}$	$a_{3,1}$	$a_{1,2}$

t_3	w_1	w_2	w_3
$PR_{3,W}$	$d_{3,1}$	$d_{3,2}$	$d_{3,3}$
AP_3	$a_{1,2}$	$a_{2,3}$	$a_{3,5}$
$RP_3^{(1)}$	$a_{1,3}$	$a_{2,2}$	$a_{3,2}$
$RP_3^{(2)}$	$a_{1,1}$	$a_{2,1}$	$a_{3,4}$

t_4	w_3	w_2	w_1
$PR_{4,W}$	$d_{4,3}$	$d_{4,2}$	$d_{4,1}$
AP_4	$a_{3,2}$	$a_{2,3}$	$a_{1,4}$
$RP_4^{(1)}$	$a_{3,5}$	$a_{2,1}$	$a_{1,2}$
$RP_4^{(2)}$	$a_{3,4}$	$a_{2,2}$	$a_{1,1}$

B (Round 1)	Area 1	Area 2	Area 3	Area 4	Area 5
w_1	0	0.7	0.8	0	---
w_2	0.6	0	0	0	---
w_3	0	0.9	0	0	0

B (Round 2)	Area 1	Area 2	Area 3	Area 4	Area 5
w_1	0	0.7	0.8	0	---
w_2	0.6	0	0	0	---
w_3	0	0.9	1.1	0	0

Round 1

t_1	L_1	$a_{1,3}$	$a_{3,1}$	$a_{2,2}$
	b_1	$b_1(1)$	$b_1(3)$	$b_1(2)$
		0.8	0	0
	μ_1	1		

t_2	L_2	$a_{2,1}$	$a_{3,2}$	$a_{1,1}$
	b_2	$b_2(2)$	$b_2(3)$	$b_2(1)$
		0.6	0	0
	μ_2	2		

t_3	L_3	$a_{1,2}$	$a_{2,2}$	$a_{3,2}$
	b_3	$b_3(1)$	$b_3(2)$	$b_3(3)$
		0.7	0	0
	μ_3	1		

t_4	L_4	$a_{3,2}$	$a_{2,1}$	$a_{1,2}$
	b_4	$b_4(3)$	$b_4(2)$	$b_4(1)$
		0.9	0.6	0.7
	μ_4	3		

Round 2

t_1	L_1	$a_{1,1}$	$a_{3,3}$	$a_{2,3}$
	b_1	$b_1(1)$	$b_1(3)$	$b_1(2)$
		0	1.1	0
	μ_1	3		

t_2	L_2	$a_{2,2}$	$a_{3,2}$	$a_{1,1}$
	b_2	$b_2(2)$	$b_2(3)$	$b_2(1)$
		0	0.9	0
	μ_2	2		

t_3	L_3	$a_{1,3}$	$a_{2,2}$	$a_{3,2}$
	b_3	$b_3(1)$	$b_3(2)$	$b_3(3)$
		0.8	0	0.9
	μ_3	1		

t_4	L_4	$a_{3,5}$	$a_{2,1}$	$a_{1,2}$
	b_4	$b_4(3)$	$b_4(2)$	$b_4(1)$
		0	0.6	0.7
	μ_4	3		

... ...

Fig. 2. Task assignment under ECM.

In the first round, t_1, t_2, and t_3 first set their counter vectors b_1, b_2, and b_3 as the billboard values in the related areas. For example, t_1 want to apply to w_1, it sets b_1 as $B(1,3)$. t_1 randomly chooses areas for w_3 and w_2 (suppose they are $a_{3,1}$ and $a_{2,2}$), and set $b_1(3)$ as $B(3,1)$, $b_1(2)$ as $B(2,2)$. Then, t_1 feeds private 1 (e.g., 0.8) to $b_1(1)$, which means it sets $B(1,3) = 0.8$, and feeds private 0 to $b_1(3)$ and $b_1(2)$ (i.e., $B(3,1) = 0$,$B(2,2) = 0$). After that, it calculates the sum $C_1 = B(1,1) + B(1,2) + B(1,3) = 0.8$. t_1 checks if $C_1 \leq c_1$ ($c_1 = 1$). Since this condition is satisfied, t_1 sets its assignment worker index μ_1 as 1. In the same way, t_2, t_3, and t_4 set μ_2, μ_3, and μ_4 as 2, 1, and 3 respectively. In the second round, t_1 calculates the sum $C_1' = B(1,1) + B(1,2) + B(1,3) = 1.5 > c_1$. It then applies to the next worker w_3. t_1 feeds private 1 (e.g., 1.2) to $b_1(3)$, which means it sets $B(3,3) = 1.2$, and feeds private 0 to $b_1(1)$ and $b_1(2)$ (i.e., $B(1,1) = 0$, $B(2,3) = 0$). After that, it calculates the sum $C_1 = B(3,1) + B(3,2) + B(3,3) = 2 \leq c_3$ ($c_3 = 2$). Thus, t_1 sets μ_1 as 3. t_2, t_3, and t_4 calculate their sums $C_2 \leq c_2$, $C_3 \leq c_1$, and $C_4 \leq c_3$ respectively. Therefore, they feed private 0 to all elements in b_2, b_3, and b_4. In the third round, there are no assignment changes, and thus the applying process terminates.

4.2 Performance Analysis

Time cost. In our ECM, each task applies to at most n workers, and there are m tasks. Therefore, there will be an application time complexity of $O(mn)$. For each application, a task feeds n data, resulting in a computation complexity of $O(mn^2)$.

Accuracy. Let $Z_A = \max_{j\in[n]} U_j + 1$ represent the maximum area size among all workers. Let $G(a_{j,k}) = \sum_{i\in[m], AP_i \ni a_{j,k}} \mathbf{1}$ denote the task size in area $a_{j,k}$. Let $G_T = \max_{j\in[n], a_{j,k}\in PR_{j,A}} G(a_{j,k})$ denote the maximal task size among all areas. Let $F_T = \max_{j\in[n], a_{j,k}\in PR_{j,A}} \left(\frac{n-1}{U_j} \cdot (m - G(a_{j,k})) + G(a_{j,k})\right)$ be the maximal average applying times among all areas. We present Theorem 1 below.

Theorem 1. *ECM satisfies* (α, β)*-useful and* (α, β)*-stable matching where* $\alpha = \frac{4\sqrt{2}\cdot Z_A \cdot mn}{\epsilon} \cdot \ln\left(\frac{2}{1 - \sqrt[Z_A]{1-\beta}}\right) \cdot \left(\sqrt{\log\left(G_T \cdot n\right)}\right)^5$. *Furthermore, ECM satisfies* (α_A, β)*-useful where* $\exp(\alpha_A) = \frac{4\sqrt{2}\cdot Z_A \cdot mn}{\epsilon} \cdot \ln\left(\frac{2}{1 - \sqrt[Z_A]{1-\beta}}\right) \cdot (\sqrt{\log F_T})^5$ *with* $\alpha_A \leq \alpha$.

Privacy. Next, we provide the privacy and security guarantees of our ECM.

Theorem 2. *ECM is* ϵ*-joint differentially private.*

5 Experiment

5.1 Data Sets

Real Data Set. We conducted our experiments on Didi Chuxing [1] in Chengdu, China (referred to as *chengdu*). We utilized the node file *chengdu.node*, which contains the coordinates of 214,440 vertices in Chengdu's road network. We randomly divide these vertices into two parts to represent tasks and workers.

Synthetic Data Sets. We generate a synthetic data sets: uniform data nodes (denoted as *uniform*). *uniform* consists of 100,000 points extracted from a 2-dimensional uniform distribution. We randomly divide these points into two data sets to represent tasks and workers.

5.2 Experimental Setup

We randomly extract points from data sets to create data scales of different sizes. Let S_T and S_W represent the sets of tasks and workers, respectively. We define the value $p_t = \frac{|S_T|}{|S_W|}$ as the *task ratio*. We costruct the Basic Concentric Mechanism (BCM) by replace choosing randomly area as choosing real area (Set the step in Line 7 and 8 as $b_i(j) = B(j, r_j(i))$ for all $w_j \in PR_{i,W}$). We construct a non-private scheme of BCM by using non-private counters in the billboard. We refer to this scheme as Non-private Basic Concentric Mechanism (NP-BCM). For the worker preferences in the Joint Differentially Private Gale-Sharley Mechanism [15], we use random preferences and denote it as Joint Differnetially Private Gale-Shapley with Random Worker Preferences (JDP-GS-RWP). We then compare BCM and ECM with NP-BCM and JDP-GS-RWP.

We examine the impact of various factors such as data scale, task ratio (p_t), worker capacity (c), ring radius (the distance between neighboring serving circles), serving circle number, and total privacy budget (ϵ) on the Average Running Time ($Time_{AVG}$), Average Receiving Distance (RD_{AVG}), and Average Task Rank Value (TRV_{AVG}). The parameter settings are presented in Table 2.

Table 2. Settings for different factors

Parameters	Value range	Default value
data scale ($\|D\|$)	$200, 400, 600, 800, 1000$	200
task ratio (p_t)	$4, 5, 6, 7, 8$	6
worker capacity (c)	$1, 2, 3, 4, 5$	4
ring radius	$600, 700, 800, 900, 1000$	1000
serving circle number	$60, 80, 100, 120, 140$	100
total privacy budget (ϵ)	$100, 200, 300, 400, 500$	300

5.3 Experiment Results

1) Average Time Cost: Figure 3(a) and Figure 3(b) display the average time cost for data scales ranging from 200 to 1000. We observe that the running time increases quadratically with the data scale. Figure 3(c) and Figure 3(d) illustrate the average time cost for task ratios ranging from 4 to 8. We observe that as the task ratio increases, the running time decreases. This is because with more tasks, the smaller workers can complete the tasks more quickly. Additionally, the running time of the non-private mechanism is significantly smaller than that of the private mechanisms.

2) Average Receiving Distance: Figure 4 illustrates the impact of various factors on average distance. We observe that the receiving distance decreases as the task ratio increases. This is because workers can receive more tasks with a lower

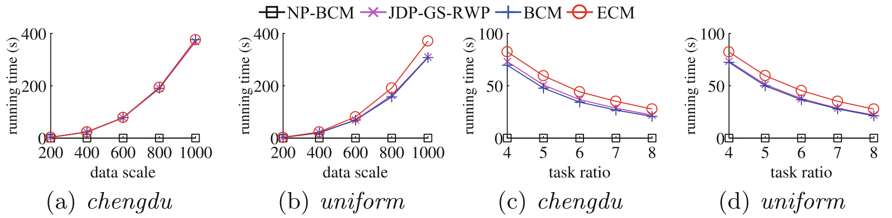


Fig. 3. The impact of data scale and task ratio on the time cost.

distance. Additionally, the receiving distance increases as the worker capacity increases. This is because a larger worker capacity slows down the competition in smaller ranges and reduces the overall distance. Furthermore, BCM and ECM consistently outperform the JDP-GS-RWP in these parameters for both the *chengdu* and *uniform* data sets.

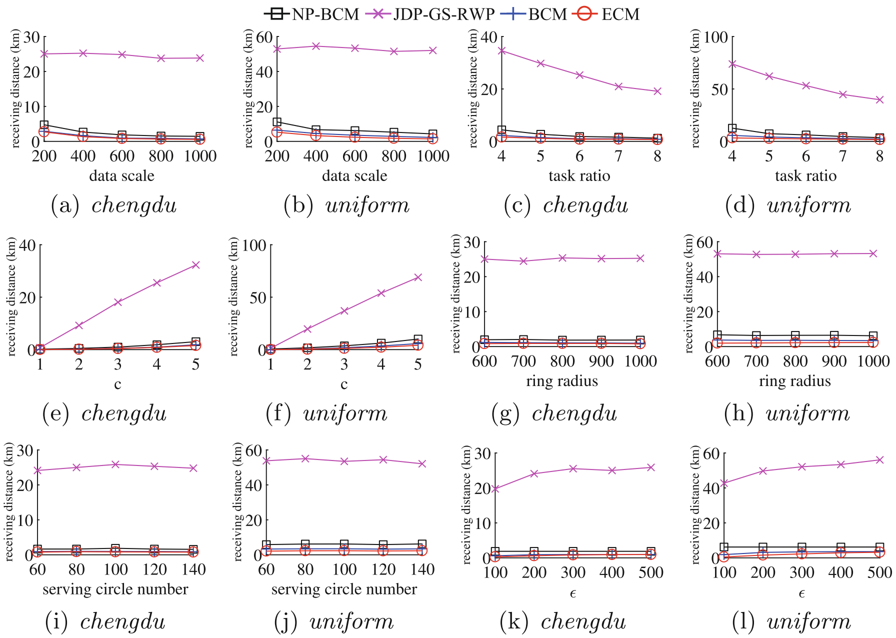


Fig. 4. The impact on average receiving distance.

3) Average Task Rank Value: Figure 5 shows the average task rank value for different ring radius and circle numbers. We can observe that both BCM and ECM consistently outperform JDP-GS-RWP in the *chengdu* and *uniform* data sets. From Figure 5(a) and Figure 5(b), we can see that there is a slight impact on the average task rank value as the ring radius varies. The average task rank value generally increases and then decreases as the ring radius increases in BCM, ECM, and NP-BCM. Similarly, from Figure 5(c) and Figure 5(d), we can see that the serving circle number also has a slight influence on the task rank value. The average task rank value generally increases and then decreases as the serving circle number increases in BCM, ECM, and NP-BCM.

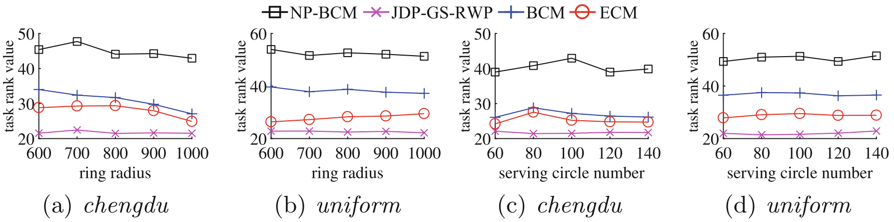


Fig. 5. The impact of data scale and task ratio on the average task rank value.

6 Conclusion

In this paper, we investigate the problem of stable allocation with location protection. To safeguard the location information of tasks, we transform it into preference information and present the ECM. Our experiments demonstrate that ECM exhibit improved efficiency and accuracy compared to the state-of-the-art work (Joint Differentially Private Gale-Shapley Mechanisms) with random preferences for workers and do not significantly decrease compared to the non-privacy scheme.

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