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Extended Abstract†

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ABSTRACT

In recent years, crowdsourcing has been widely used in every profession and trade. In this paper, we focus on the workers' acceptance rate of assigned tasks in crowdsourcing problems. Previous papers only considered the relationship between the acceptance rate of tasks and the travel distance of workers, but this is one-sided. We further improve the task acceptance rate model and optimize the task acceptance rate with two current task allocation strategies based on the differential location privacy framework under crowdsourcing problems. Moreover, we analyze the overhead of crowdsourcing platforms based on different task allocation strategies and make an experimental comparison from the perspective of time overhead and bandwidth overhead. Finally, we consider the trade-off between privacy and bandwidth overhead and give the trade-off expression between the two and the corresponding optimal privacy budget.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability;

KEYWORDS

ACM proceedings, LaTeX, text tagging

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‡Dr. Trovato insisted his name be first.
§The secretary disavows any knowledge of this author's actions.
¶This author is the one who did all the really hard work.

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1 INTRODUCTION

In recent years, location privacy has become an increasingly concerned issue, and differential privacy has proved to be the best way to resist background knowledge attacks. In the location privacy-preserving model based on differential privacy, there are two main implementation methods. One is based on the obfuscation on the number: constructing a spatial grid structure and adding noise to the number of workers in the grid; Another way is based on differential geo-obfuscation mechanisms: obfuscating the real location of the worker and uploading it.

We mainly consider the differential geo-obfuscation in this paper. Miguel E. Andrés et al. proposed a location difference privacy framework based on Laplace obfuscation. In recent years, some scholars have put forward a mixed-integer non-linear programming model and demonstrated that this model could play a useful role in optimizing the travel distance and improving the coverage of the target location.

Based on location privacy-preserving, we consider an essential performance evaluation index in crowdsourcing problems, which is the task acceptance rate. When the tasks are assigned to workers on a crowdsourcing platform, it is uncertain whether workers will accept the tasks. Rejection may occur with long travel distance or low reward, which is what crowdsourcing platform is trying to avoid when optimizing the allocation strategies. Therefore, we choose the worker's acceptance rate as the performance index. At the same time, we optimize and compare the task allocation strategies with mainstream privacy-preserving methods based on the location differential privacy model.

Moreover, not only performance but also overhead need to be considered in crowdsourcing problems. At the crowdsourcing server, bandwidth overhead and time overhead need to be considered. Since the crowdsourcing server needs to return all tasks within the area of retrieval (AOR) to the worker, the bandwidth overhead can be represented as area S_{AOR}. On the other hand, the time overhead depends on the different optimization methods. Comparing with the Laplace method, the method based on Benders Decomposition that allows the obfuscation function and task allocation strategy to iterate with each other requires more calculation overhead and correspondingly more time overhead. We will analyze the bandwidth overhead and time overhead respectively. The main work of this paper is as follows:

1) Based on the framework of differential geo-obfuscation privacy-preserving, we introduce an improved model of the task acceptance rate in crowdsourcing problems. We also consider the task acceptance rate as the optimization goal from the perspective of task allocation.

2) We optimize the task acceptance rate and get the optimal solution using the two current task allocation strategies under the framework of differential geo-obfuscation privacy-preserving. Considering the overhead of crowdsourcing server, we analyze and compare two task allocation strategies from the perspective of bandwidth overhead and runtime overhead respectively.

3) By constructing a comprehensive evaluation model, we consider the trade-off between privacy and bandwidth overhead and solve the optimal privacy budget choice.

2 BACKGROUND

2.1 Spatial Crowdsourcing

Crowdsourcing is aimed at ordinary users that have not explicitly been assigned, and they can all accept and complete published tasks on the platform. Spatial Crowdsourcing is a kind of crowdsourcing based on spatial geographic location. Its task is to assign a set of spatial tasks to workers so that workers can perform corresponding tasks at a specific workplace. As an online platform, spatial crowdsourcing currently has two main modes, one is the server assigned tasks (SAT), and the other is worker selected tasks (WST). For SAT mode, online workers on the platform need to send their location coordinates to the crowdsourcing server, which then assigns appropriate tasks to nearby workers. For WST mode, it requires requesters to publish online tasks on crowdsourcing platforms so that registered workers can independently select their nearby tasks based on the travel distance, and then the results are fed back to the platform, and communications with task requesters are established to complete the corresponding tasks. Up to now, SAT mode is still the current mainstream mode due to the consideration of assignment success rate (ASR).

2.2 Differential Privacy

Definition 2.1. Differential privacy is defined on adjacent datasets which differ by only one record. For two adjacent datasets D_1 and D_2, Q is a randomized algorithm performing a query operation on the database. Let $Range(Q)$ denote the set of all possible outputs of the algorithm Q. We say that Q satisfies the ε-differential-privacy mechanism if and only if the following inequality holds, $\forall S \in Range(Q)$:

$$P_r[Q(D_1) = S] \leq e^{\varepsilon} \cdot P_r[Q(D_2) = S]$$

Andrés et al. (2013) gave a basic framework of location privacy-preserving based on differential privacy mechanism and extended the concept of one-dimensional differential privacy to the two-dimensional plane. The key insight is that for any point $L_0 \in \mathbb{R}^2$ in the plane, an obfuscated point $L^* \in \mathbb{R}^2$ is generated near L_0 through a specific noise function. From the perspective of privacy-preserving of the user's location, the user uploads the obfuscated location L^* instead of the real location L_0.

Definition 2.2. The mechanism M that takes a location as input satisfies ε-geo-indistinguishability if the following inequality holds $\forall S \in Range(M)$:

$$\frac{P(S|L_1)}{P(S|L_2)} \leq e^{\varepsilon d(L_1, L_2)}$$

L_1 and L_2 are two locations. $d(L_1, L_2)$ denotes the distance between the two locations. ε denotes the privacy budget.

The smaller ε is, the closer the distributions of the two conditional probabilities are, which means that it is difficult for attackers to distinguish L_1 from L_2 based on the output S, hence the privacy is secured.

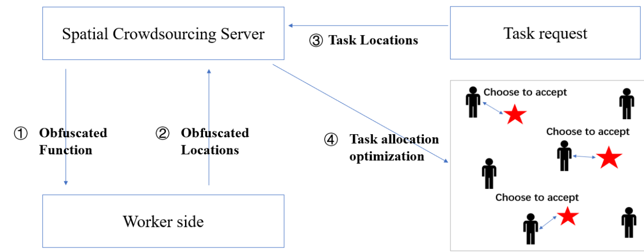

Figure 1: System Model

2.3 System Model

The Figure 1 indicates the procedures of the geo-obfuscation in crowdsourcing model:

The detailed procedures are as follow: First, the crowdsourcing server generates the location obfuscation function based on the differential privacy framework and sends it to workers. After obfuscating the real location locally, the worker uploads the obfuscated location to the server. Meanwhile, the task requester uploads the location of the task to the server. The crowdsourcing server then optimizes the task allocation according to specific evaluation standards. Finally, the workers choose to accept or reject the tasks assigned to them.

Many of the current crowdsourcing platforms collect workers' location information directly, which can lead to the disclosure of workers' location privacy. However, by uploading the obfuscated location, the privacy of the location can be adequately protected. The differential obfuscation mechanisms will be analyzed in Section 3.2.

Speaking of optimizing task allocation, Leye Wang (WWW' 17) optimized the planar crowdsourcing task allocation by minimizing the travel distance. However, in reality, workers accept the tasks assigned to them with a certain probability. If specific tasks assigned by the server are frequently rejected by workers, the overall performance of the platform will be significantly affected.

3 FRAMEWORK

3.1 Optimization Goals

There are mainly two optimization goals in this paper. One is to improve the performance of the crowdsourcing platform by optimizing the average task acceptance rate (*AR*) through adjusting the obfuscation function P and the task allocation strategy X; The second is to consider the trade-off between the privacy and the system overhead to select the optimal privacy budget ε.

We express two models as follow:

$$\hat{P}, \hat{X} = \arg\max_{P,X}\{\frac{1}{N_t}\sum_{N_t} AR(Rew, WTD)\}$$

$$\hat{\varepsilon} = \arg\min_{\varepsilon}\{T(\varepsilon, \frac{\sum_{N_w} S_{AOR}}{N_w})\}$$

In the former model, *AR* can be expressed as a function of the reward (*Rew*) and the travel distance of the worker (WTD). N_t denotes the number of tasks. $\hat{P}$ and $\hat{X}$ are the optimal obfuscation function and task allocation strategy we seek. In the latter model, we use the actual search area S_{AOR} to represent the overhead. T is the trade-off expression which we aim to minimize. N_w denotes the number of workers. $\hat{\varepsilon}$ is the optimal privacy budget we seek.

3.2 Acceptance Rate

When the crowdsourcing server assigns tasks to workers, workers need to further select appropriate tasks to complete. We use the acceptance rate (*AR*) to indicate the probability that workers will accept the task. A vital optimization goal in crowdsourcing is how to allocate tasks to workers reasonably to improve the overall task acceptance rate.

So far, most scholars in the crowdsourcing field used the univariate model to model *AR*. They believed that *AR* is only related to the travel distance needed of workers, and expressed *AR* as a function of travel distance. (Hien To, Differentially Private Location Protection for worker datasets in spatial crowdsourcing, IEEE Transactions on Mobile Computing16'). Two basic models are shown in Figure 2. Intuitively, this is one-sided. Therefore, we will introduce an improved bivariate model in Section 4.1.

The current privacy-preserving framework is based on the location differential privacy model. The location obfuscation function mentioned in Section 2.3 also satisfies the definition of location differential privacy. Currently, there are two differential obfuscation mechanisms, one is based on the Laplace mechanism, and the other is based on Benders Decomposition mechanism (Leye Wang, WWW'17). In the Laplace mechanism, the obfuscation function is known, whereas obfuscation function in the BD mechanism is unknown. Hence, we need to optimize the obfuscation function and task allocation strategy respectively.

3.2.1 Planar Laplace Mechanism. The most common mechanism in the field of location privacy-preserving uses planar Laplace distribution in the two-dimensional plane. Under planar Laplace obfuscation, the probability density of obfuscated point L^* in the plane decreases exponentially as the distance from the real location L_0 increases.

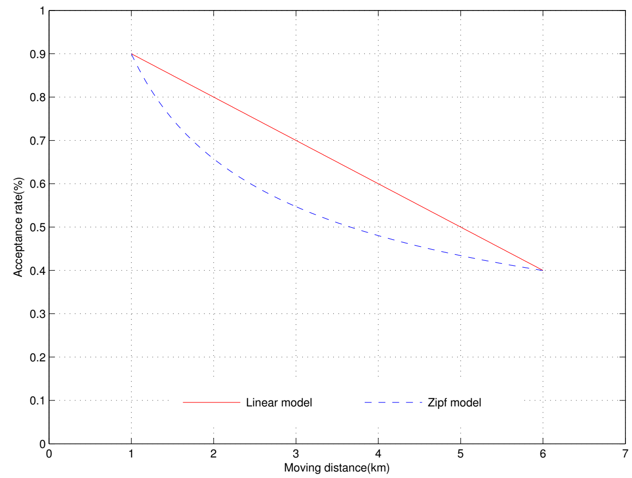

Figure 2: Univariate Model of AR

Given a privacy budget ε and the real location $L_0 \in \mathbb{R}^2$, an obfuscated point L^* can be obtained by adding noise on L_0. The probability density function of L^* centered at L_0 is:

$$P_\varepsilon(L_0)(L^*) = \frac{\varepsilon^2}{2\pi}e^{-\varepsilon d(L_0, L^*)}$$

$\frac{\varepsilon^2}{2\pi}$ is the normalization factor, and we call this function the planar Laplace function centered at L_0. It is obvious that the further away L^* is from the center point L_0, the smaller the value of probability density is and decreasing exponentially.

3.2.2 Benders Decomposition. This method was first used to solve the linear programming problems. In this method, the location obfuscation function is discretized. In recent years, some scholars have proposed that the BD algorithm can be used to optimize the differential privacy problems. Unlike the Laplace mechanism described above, the location obfuscation function in this method is unknown, which means that two unknowns need to be solved for one optimization objective.

The basic idea of BD method is to use the definition of differential privacy to set up linear programming equations, and decompose the optimization problem into an obfuscation function problem (P-subproblem) and a task allocation problem (X-subproblem). The solution of each subproblem is substituted as a known parameter of the other subproblem so that each subproblem is transformed into a conventional linear programming problem that can be solved easily. Thus, the obfuscation mechanism and the task allocation strategy can iterate over each other to find the optimal solution.

(Leye Wang WWW' 17) Wang used this method to optimize the travel distance of workers in crowdsourcing problems and decomposed the mixed-integer non-linear programming problem into two linear programming subproblems. Finally, Wang proved that this method could effectively reduce the overall travel distance of workers on the premise of satisfying the definition of differential privacy.

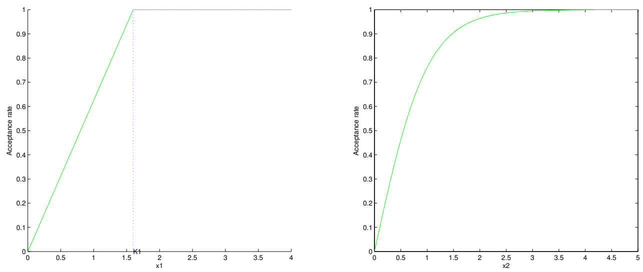

Figure 3: Linear and Hyperbolic Tangent Model

3.3 Overhead

In spatial crowdsourcing model, crowdsourcing workers often need to query nearby tasks. Because of the difference in the differential obfuscation mechanism, the search area that the crowdsourcing server needs is different, which means that the search overhead is different. In addition to search overhead, we also need to consider the time overhead. In the task assignment process, the time complexity based on different obfuscation mechanisms is also different.

On the other hand, crowdsourcing service based on LBS requires high real-time performance. As the scale of the problem, i.e., the number of workers and tasks, increases, the time spent on solving optimization problems will also increase accordingly. Therefore, it is necessary to analyze the overhead problem in the crowdsourcing model.We will analyze the overhead in Section 5.

4 ANALYSIS ON TASK ACCEPTANCE RATE

4.1 Improvement of the Task Acceptance Rate Model

In the analysis of task acceptance rate in crowdsourcing problems, previous papers only considered task acceptance rate as negatively correlated (linearly or exponentially) to travel distance. However, by considering the actual situation, whether workers accept tasks or not is affected by not only travel distance but also other factors. Therefore, we introduce the Reward factor for the tasks. In general, a higher reward for tasks is conducive to improving the probability which workers accept and complete tasks. We consider the linear model and hyperbolic tangent model shown in Figure 3 respectively.

4.1.1 Linear Model. We firstly consider modeling the task acceptance rate with a linear model. Let $x_1 = Rew/WTD$, where the Rew denotes the reward of the task, WTD denotes the travel distance of the worker. Within a certain range, AR (acceptance rate) can be expressed as a linear function with respect to x_1. Considering the actual situation, when the reward is high enough, or the distance is close enough, the worker will hardly reject the task. k_1 is defined as the threshold, so when x_1 exceeds k_1, AR is set to 1.

$$AR = \begin{cases} \frac{x_1}{k_1} & x_1 < k_1 \\ 1 & x_1 \geq k_1 \end{cases}$$

4.1.2 Hyperbolic Tangent Model. In addition to the above linear model, the hyperbolic tangent function is also considered to model the task acceptance rate.

$$AR = \tanh(k_2 \cdot \frac{Rew}{WTD})$$

Where the tanh is a hyperbolic tangent function and k_2 is the ratio parameter. Let $x_2 = k_2 \cdot \frac{Rew}{WTD}$. The hyperbolic tangent function expression is as follows:

$$AR = \tanh(x_2) = \frac{e^{x_2} - e^{-x_2}}{e^{x_2} + e^{-x_2}}$$

4.2 Optimization of Task Acceptance Rate

We aim to maximize overall AR while satisfying the differential privacy constraints. Considering that the current task allocation strategies of differential privacy mainly includes Laplace mechanism and Benders Decomposition linear programming mechanism, we will use these two mechanisms to optimize AR.

Unlike Laplace mechanism, the mechanism based on solving linear programming equation with BD algorithm is to transform the location obfuscation function into discrete form $P(L^*|L)$, and the distribution is uncertain in advance, which needs to be iteratively optimized with the task allocation problem (X-subproblem). On the other hand, the obfuscation function of the Laplace mechanism satisfies the planar two-dimensional Laplace distribution, so we only need to adjust the task allocation strategy to optimize AR. These are the essential difference between the two ways.

1) Laplace Mechanism

If location $L^* \in \mathbb{R}^2$ is obtained by adding noise on real location $L_0 \in \mathbb{R}^2$, the probability density of L^* is negatively exponentially distributed. We aim to maximize the acceptance rate and solve the optimal task allocation strategy. Therefore, we set up linear programming equations is as follows:

$$\max \tanh k \cdot \frac{Rew}{WTD}$$

$$s.t. \quad P(L^*|L) \propto e^{-\varepsilon d(L^*,L)}$$

$$WTD = \frac{\sum_L \pi(L) P(l^*|L) d(L, L_t)}{\sum_L \pi(L) P(L^*|L)} \chi(L^*, L_t)$$

$P(L^*|L)$ indicates the probability of obfuscation from location L to L^*. $d(L, L_t)$ is the distance between location L and Lt. π represents the overall location distribution of workers in the location set, ($\sum_L \pi(L) = 1$). $\chi(L^*, L_t)$ gives the number of task assignments between workers which located at L^* and tasks which located at L_t.

2) Based on BD algorithm, we set up a linear programming model, and solve optimization goal with differential inequalities and related constraints.

$$\max \tanh k \cdot \frac{Rew}{WTD}$$

$$s.t. \quad WTD = \frac{\sum_L \pi(L) P(l^*|L) d(L, L_t)}{\sum_L \pi(L) P(L^*|L)} \chi(L^*, L_t)$$

$$P(L^*|L_1) \leq e^{\varepsilon d(L_1, L_2)} P(L^*|L_2)$$

$$\sum_{L^*} \chi(L^*, L_t) = N_t(L_t)$$

$$\sum_{L^*} P(L^*|L) = 1$$

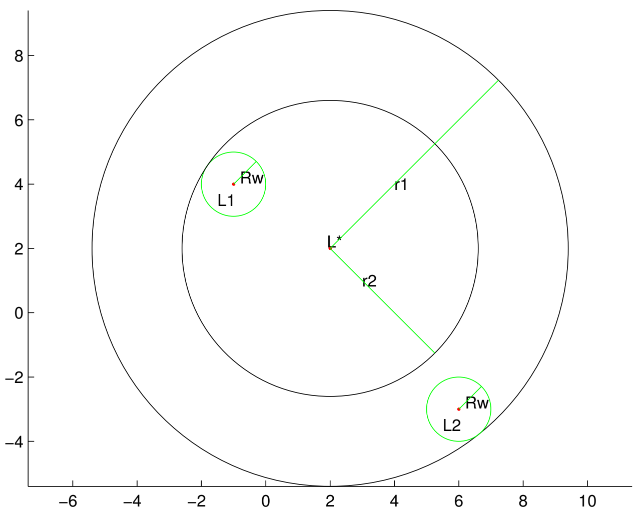

Figure 4: Area of Retrieval

Unlike the Laplace mechanism, $P(L^*|L)$ here does not follow a specific distribution. It is obtained by solving the linear programming equation iteratively with the task allocation problem (X-subproblem), which satisfies the definition of differential privacy. In the above two equalities, $N_t(L_t)$ represents the total number of tasks located at L_t. The total probability that the user's real location L is obfuscated to other locations is always 1.

5 OVERHEAD ANALYSIS

5.1 Bandwidth Overhead

Since workers often need to query nearby tasks, we use R_w to indicate the scope of the worker's query, which centered at the actual location of the worker. The circle with radius R_w is the area of interest to the worker, denoted as R_{AOI}.

The crowdsourcing server obtains the obfuscation location uploaded by the worker instead of the actual location. In order to accurately return all tasks within the range R_w of the worker, the crowdsourcing server needs to search with a larger radius near the obfuscation location so that this larger circle with radius R_{AOR} can cover the smaller circle with radius R_{AOI} which is the real range needed to be covered. The larger the search area is, the larger the bandwidth overhead is. (Andrés, Geo-Indistinguishability, CCS'13)

Based on different task allocation strategies, the required search area is also different, so it is necessary to compare the search overhead. Thus, we can simplify the problem by finding actual search area S_{AOR}. Next, the above two task allocation strategies will be analyzed separately.

S_{AOR} can be expressed as a weighted average of multiple areas of search circles. The radius of each search circle is represented by r_i, $r_i = d(L^*, L_i) + R_w$. R_w indicates that workers only accept tasks within the range of R_w. [Figure 4]

$$S(L_k^*) = \frac{\pi \sum_i P(L_k^*, L_i)(d(L_k^*, L_i) + R_w)^2}{n^2}$$

$$\bar{S} = \frac{\sum_k S(L_k^*)}{N_w}$$

$P(L_k^*, L_i)$ represents the possibility that location L_i is obfuscated to location L_k^*. $S(L_k^*)$ represents the weighted average of the actual search area. N_w indicates the number of workers, i.e., number of obfuscated locations uploaded to crowdsourcing server. $\bar{S}$ is the average of $S(L_i^*)$.

With the mechanism using the Benders Decomposition algorithm, $P(L_k^*, L_i)$ is obtained by solving linear programming problems P and X iteratively. Then we can calculate the corresponding bandwidth overhead from S_{AOR}.

5.2 Runtime Overhead

Considering that the locations of workers and crowdsourcing server both need to be continuously updated under practical situations, and the LBS also require real-time performance. Hence it is necessary for us to consider the time overhead.

Since the obfuscation function of the Laplace mechanism is fixed, we only need to adjust the task allocation strategy to optimize the objective function. However, the mechanism based on BD algorithm need to iteratively solve two linear programming problems, i.e., the obfuscation function problem (P-subproblem) and the task allocation problem (X-subproblem), until it converges to the optimization point. As the number of tasks (N_t) and the number of workers (N_w) increase, the scale of the problem also increases rapidly. As a result, a large number of equalities and inequalities need to be calculated during iteration, which will cause a significant increase of the time overhead.

In the later experiment part, we will observe and compare the time overhead of two mechanisms.

6 TRADE-OFF BETWEEN PRIVACY AND OVERHEAD

6.1 Problem Analysis

In the differential privacy mechanism, the smaller the privacy budget is, the better the privacy-preserving effect will be. However, since the search area needs to be increased at this time, the search overhead will need to be increased accordingly.

We aim to consider the trade-off between privacy and search overhead comprehensively. First, we use the search area to represent the search overhead. Then, our optimization goal which based on the privacy budget and search area is to reduce the overhead as much as possible while ensuring privacy. Finally, we work out the optimal searching scheme and ε by minimizing the optimization goal.

6.2 Trade-off Expression

We can construct the expression of he average search area $\bar{S}$ as a negative correlation function of ε. Then, we introduce the trade-off expression T as follows:

$$\hat{\varepsilon} = \arg\min_{\varepsilon} T(\varepsilon, \bar{S}) = \arg\min_{\varepsilon}\{\beta \cdot \varepsilon + \ln(\bar{S})\}$$

Where β is the hyperparameter which can be adjusted according to experience. In this case $\hat{\varepsilon}$ is the optimal point of ε which not only preserves privacy, but also avoids large overhead.

Table 1: Default Value of Key Parameters

Notation	Default	Description
N_t	30	Number of tasks
N_w	60	Number of workers
ε	ln(4)	Privacy budget
n	4	Scale parameter

Table 2: Experiment Platform

Hardware & Software	Configuration
Processor	Intel(R)Core(TM)i7-7500U CPU@2.70GHz 2.90GHz
Memory	4GB
Operating System	Windows 10
Operating Environment	MATLAB R2012b

7 EXPERIMENT

Wang(Leye Wang, WWW'17) used the CVX of MATLAB together with the MOSEK in the experiment, as commercial software performs better than open source software. In order to compare two mechanisms, we choose linear programming functions which embedded in MATLAB directly.

7.1 Optimization Results of Task Acceptance Rate

In this experiment, we not only compared the Laplace mechanism with the mechanism based on BD algorithm but also considered the no-privacy version, i.e., the locations of workers are uploaded directly to crowdsourcing server without obfuscation. The no-privacy version can be considered as the upper bound of the acceptance rate *AR*. In the experiment, we observed how acceptance rate varied with N_t, N_w, ε, and n. In addition, randomly generated dataset, i.e., the simulated dataset, and the real location dataset, i.e., D4D dataset, are tested and compared respectively. By default, the key parameters are shown in Table 1:

7.1.1 Cases with the Linear Model. The Figure 5 shows how acceptance rate varies with N_t, N_w, ε, and n respectively, using simulated dataset. The threshold k_1 of the linear model is set to be 1.6.

In addition, we also used the Data for Development (D4D) dataset. This dataset recorded the real locations of the users in communication. The results are shown in Figure 6:

By comparing the graphs given by two different datasets, we can conclude that the simulated dataset and the D4D dataset provide approximately the same results. The increase of N_t and ε can moderately increase the task acceptance rate. The increase of n will reduce the optimization effect of task acceptance rate. Finally, N_w has almost no influence on the result. In this experiment, we assume that N_t is smaller than N_w, which means that the increase of N_t has a greater impact on the optimization of task allocation compared with N_w. On the other hand, the increase of privacy budget ε improves the task acceptance rate, which can be seen as sacrificing privacy for performance.

7.1.2 Cases with Hyperbolic Tangent Model. We set the ratio parameter k_2 in the hyperbolic tangent model to be 0.7 in the following experiments. Similar to the linear model, we use simulated dataset first, and Figure 7 indicates how task acceptance rate varies with N_t, N_w, ε, and n.

Then, Figure 8 gives the results of D4D dataset.

It can be seen that no matter in the linear model or the hyperbolic tangent model, the mechanism based on the BD algorithm outweighs the Laplace mechanism on optimizing the task acceptance rate. Furthermore, increasing N_t and ε appropriately will improve the task acceptance rate.

7.2 Overhead Comparison

7.2.1 Search Overhead. In this section, we take the optimization result given by simulated dataset under hyperbolic tangent model as an example and use the search area S_{AOR} to represents the bandwidth overhead. Then, in Figure 9 we compare the mechanism based on the BD algorithm and the Laplace mechanism and plot the search area against N_t, N_w, ε, and n respectively.

ε and n have a significant impact on the search overhead. Reducing privacy and scale parameters can efficiently decrease search overhead. On the other hand, N_t and N_w have little impact.

7.2.2 Runtime Performance. Online crowdsourcing has requirements for real-time performance, so it is necessary to consider the runtime overhead. The core idea of BD differential obfuscation mechanism is to decompose the general problem into two subproblems. The optimal solution is obtained by iterating over obfuscation function P and task allocation problem X multiple times, which causes more time overhead.

The environment of the experiment is shown in Table 2.

First, considering BD obfuscation mechanism, let $N_w = 60$. When N_t varies from 10 to 50, the running time is approximately in the range of 35 to 45 seconds.

Next, the number of grids n directly determines the number of locations in the location set. Thus, the value of n has a significant impact on the time overhead, which is about 3 seconds when $n = 2$ and about 7 minutes when $n = 5$. The time overhead increases dramatically with the increase of n.

Finally, for the Laplace mechanism, let $N_w = 60$. When N_t varies from 10 to 50, the running time is all within 1 second. The increase of n has no significant effect on the running time.

7.3 Curve Fitting and Trade-off

We consider the trade-off between privacy and search overhead according to the trend of search overhead obtained using simulated dataset and the hyperbolic tangent model. First, we construct the expression of $\bar{S}$ with respect to ε that has the best fit to the data, and then the optimal privacy budget is selected according to the result of the optimized trade-off expression.

7.3.1 Results based on Benders Decomposition. Based on the BD mechanism, let $N_t = 30$, $N_w = 60$, we fit the curve to the data points in Figure 10.

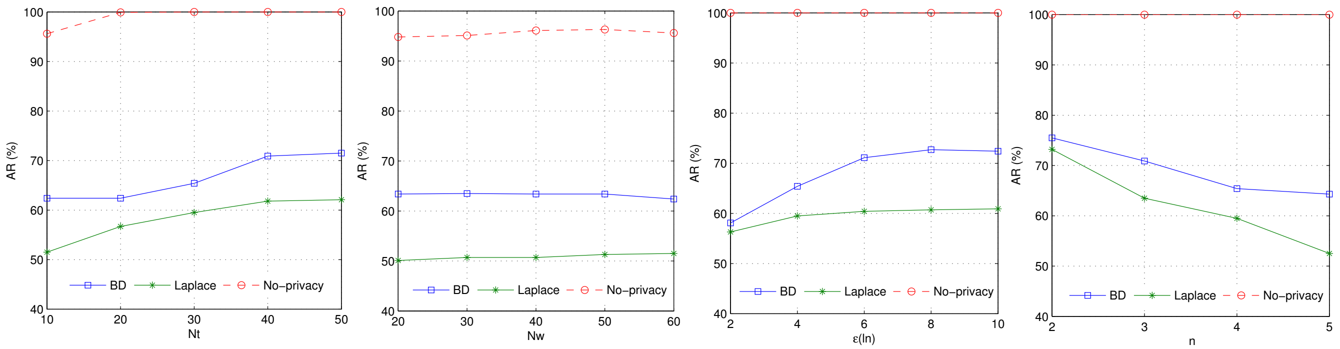

Figure 5: Linear Model & Simulated Dataset

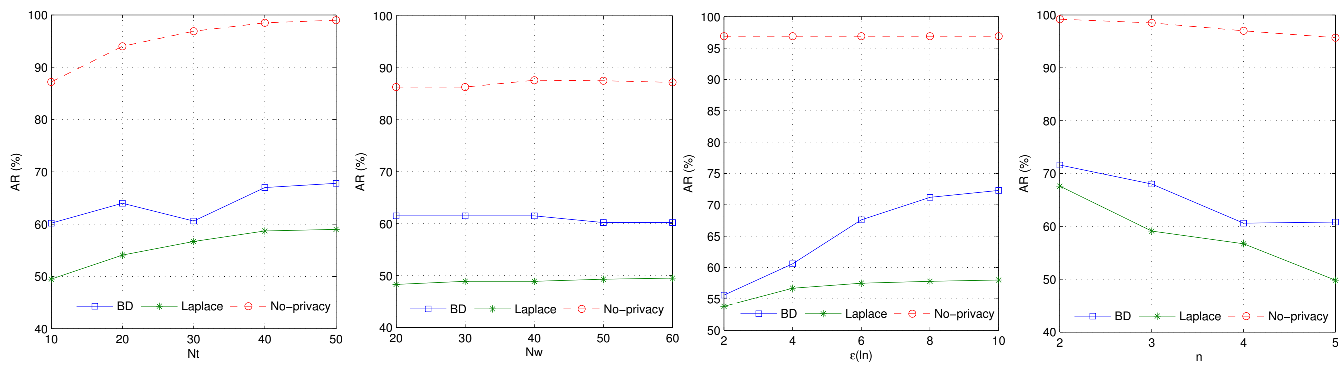

Figure 6: Linear Model & D4D Dataset

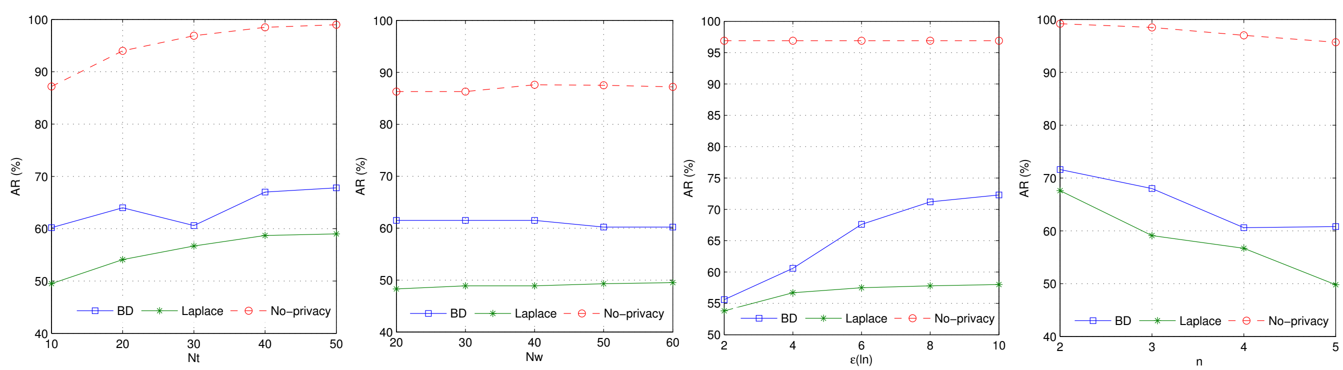

Figure 7: Hyperbolic Tangent Model & Simulated Dataset

The approximate expression of $\bar{S}$ is $\bar{S} = \frac{p_1}{\varepsilon + q_1}$, where $p_1 = 43.7$, $q_1 = 1.0$. Then we substitute $\bar{S}$ into the trade-off expression:

$$T(\varepsilon, \bar{S}) = \beta \cdot \varepsilon + \ln(\bar{S}) \quad \beta \in (0, 1)$$

When $\beta = 0.6$, we plot T against ε in Figure 11.

The minimum point of the graph corresponds to the optimal ε we seek. At this point, we can think that not only the privacy of the user's location is preserved, but also the excessive search overhead is avoided.

7.3.2 Results based on Laplace Mechanism. Similarly, based on the Laplace mechanism, let $N_t = 30$, $N_w = 60$, we fit the curve to the data points in Figure 11.

The approximate expression of $\bar{S}$ is $\bar{S}(\varepsilon) = \frac{p_1 \cdot \varepsilon + p_2}{\varepsilon + q_1}$, where $p_1 = 24.4$, $p_2 = 2.9$, $q_1 = -0.02$. Then we substitute $\bar{S}$ into the trade-off expression:

$$T(\varepsilon, \bar{S}) = \beta \cdot \varepsilon + \ln(\bar{S}) \quad \beta \in (0, 1)$$

When $\beta = 0.6$, we plot T against ε in in Figure 11.

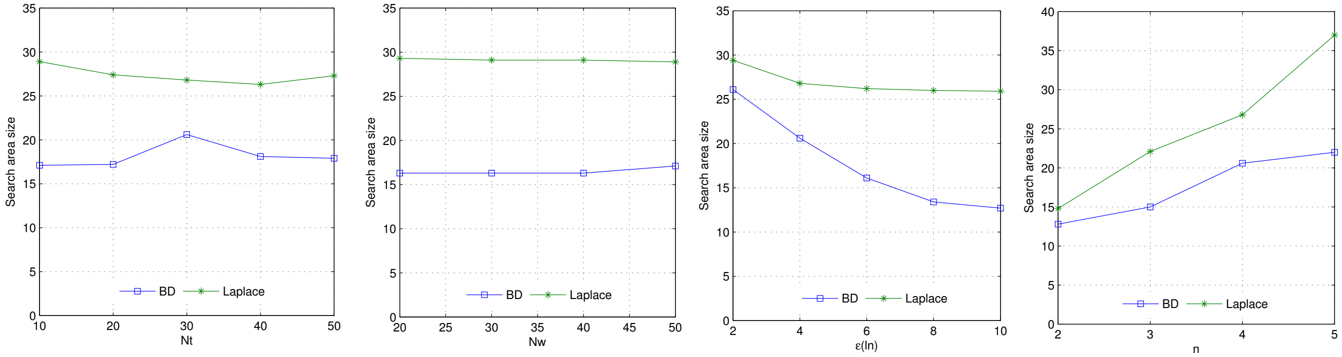

Figure 8: Hyperbolic Tangent Model & D4D Dataset

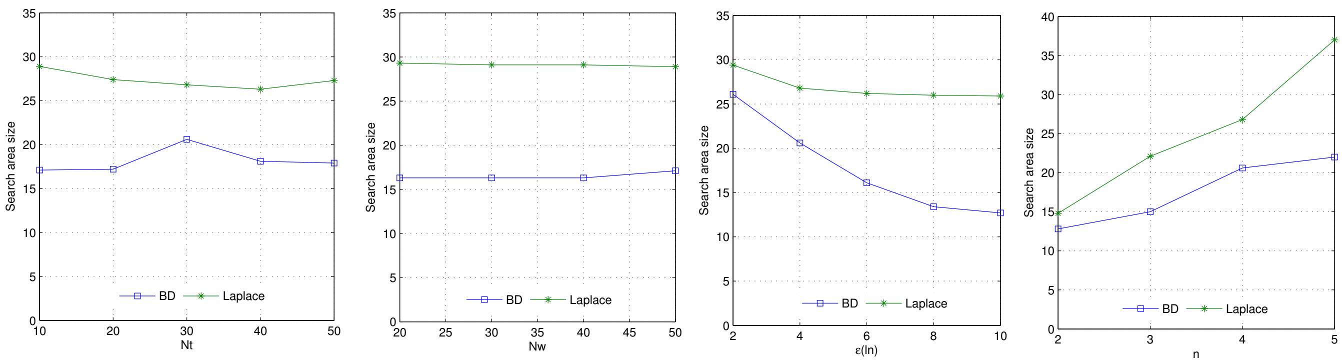

Figure 9: Search Overhead

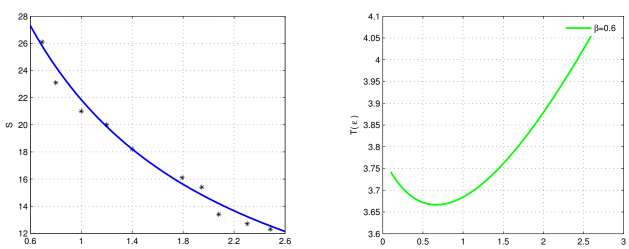

Figure 10: BD Curve Fitting & Trade-off

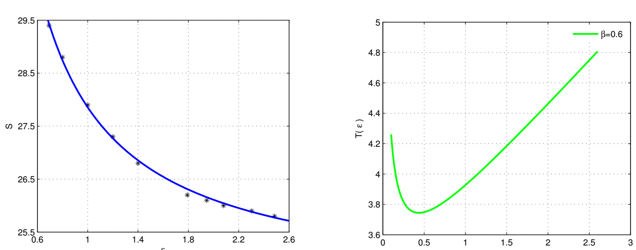

Figure 11: Laplace Curve Fitting & Trade-off

The BD mechanism and the Laplace mechanism provide similar results. The minimum point of the graph is the optimal privacy budget that comprehensively weighted privacy and overhead.

8 CONCLUSION

In this paper, we improved the model of task acceptance rate under crowdsourcing scenario. We constructed the linear model and the hyperbolic tangent model, and optimized and compared the task acceptance rate with two current task allocation strategies, i.e., the Laplace mechanism and the mechanism based on solving linear programming with Benders Decomposition algorithm. Generally, the obfuscation function and task allocation strategy based on the BD mechanism can achieve higher task acceptance rate, but it requires more time overhead than the Laplace mechanism and increases significantly with the increase in the size of the problem. In addition, we compared and analyzed the search overhead of two mechanisms. By considering the trade-off between privacy and search overhead, we gave the best privacy budget choice.