Privacy-Preserving Verifiable Incentive Mechanisms for Crowd Sensing Applications

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Crowd sensing, as a new paradigm that leverages pervasive smartphones to efficiently collect and upload sensing data, recently has been intensively explored. Incentive mechanisms with the truthfulness are proposed to attract extensive users to participate so as to achieve good service quality, enabling numerous novel applications. Although these mechanisms are so promising, there still exist many security and privacy challenges in real-life environments, such as cost privacies, sensing preferences, and the payment behavior of the platform (the crowd sensing application organizer). In this paper, we present two privacy-preserving verifiable incentive mechanisms for crowd sensing applications with homogeneous services, heterogeneous services, and submodular services under the budget constraint, not only to explore how to protect the privacy of the users and platform, but also to ensure the verifiable correctness of payments between the platform and users for crowd sensing applications. Results show that our general privacy-preserving verifiable incentive mechanisms achieve the same results as the generic one without privacy preservation.

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1. INTRODUCTION

More recently, crowd sensing have emerged as an effective and efficient way to solve complex sensing issues [Ma et al. 2014]. For instance, Nericell [Mohan et al. 2008], SignalGruru [Koukoumidis et al. 2011], and VTrack [Thiagarajan et al. 2009] for providing omnipresent traffic information, Ear-Phone [Rana et al. 2010] and NoiseTube [Maisonneuve et al. 2009] for making noise maps. Although these crowd sensing applications have been developed, incentive mechanisms are necessary to achieve good service quality. Consequently, some researchers such as Singer et al, separately propose the auction mechanisms to incentivize extensive users to participate in crowd sensing applications so as to meet the previous service demands [Singer 2010, Singer and Mittal 2013] [Yang et al. 2012]. These novel mechanisms guarantee the truthful participation of users by determining near-optimal prices of assignments for crowd sensing applications with the budget constraint. More importantly, the mechanisms are incentive compatible, budget feasible, and have competitive ratio performance and performs well in practice, thereby ensuring these mechanisms applicable to crowd sensing applications.
Despite their merits, payments’ verifiability and privacy issues, two critical human factors in crowd sensing applications, have not been fully explored. A common hypothesis made in the above mechanisms is that the involved parties will follow the protocols honestly without the concern of their privacy. However, some users could behave selfishly to protect their cost privacy, sensing preferences’ privacy and identification privacy, thereby violating the hypothesis and making these well-designed mechanisms inefficient. On the other hand, the platform need to keep the set of current winners secrecy to maximize his utility when facing the adversarial users. Thus, it is imperative to provide some measures to eliminate the privacy-leakage concerns of users and platform so as to achieve good service quality.

In addition to the privacy issue, the payments’ verifiability issue is also a crucial human factor for the wide acceptance of the above crowd sensing applications. It is because that some controller of the platform (the crowd sensing organizer) may misbehave, e.g., provide false results or insert a fictitious bid and sensing preference just below the payment to the users so as to deceitfully decrease the payment to users [Parkes et al. 2008; Dong et al. 2011]. If the correctness of the payments from the platform is not well guaranteed, users will be reluctant to participate in crowd sensing applications. In practice, since a real-world platform is operated by an individual within a large corporation, or by a public servant within a government department, the possibility of incorrect operations from the platform exists in crowd sensing applications. For example, the World Bank recently estimated the volume of incorrect exchanging hands for public sector procurement alone to roughly US$200 billion per year, with the annual volume of the procurement projects tainted by incorrect operations close to US$1.5 trillion. Thus, how to deal with the payments’ verifiability is crucial for the success of crowd sensing applications.

Although both privacy and verifiability issues have been identified as two crucial human factors for the wide acceptance of crowd sensing applications, many recent research works [Huang et al. 2013; Jung et al. 2013a; Angel and Walfish 2013; Catane and Herzberg 2013] tend to separately study them in crowd sensing applications. The reason is that, if the privacy and verifiability issues are addressed at the same time in crowd sensing applications, the problem would become more challenging. For example, some privacy enhanced techniques [Ganti et al. 2008; Shi et al. 2010] enable a user to hide his identity and sensing profile (i.e., cost and sensing preferences like locations), but they could make some verifiable strategies, especially the non-truthfulness incentive strategies, hard to implement in the above truthful incentive mechanisms, since the platform needs to greedily select winners and compute the threshold payment based on the examination of a user’s sensing profile. However, the improvement of the verifiability needs to reveal more information, thereby reducing privacy of users and platform. Therefore, how to simultaneously address privacy and verifiability issues becomes particularly challenging in crowd sensing applications.

To tackle the above-mentioned challenges, in this paper, we present a first step towards a crowd sensing system in which users can verify the payments from the platform without revealing any additional information by using the order preserving encryption scheme (OPES) [Agrawal et al. 2004]. Our approach is to enable users to verify the payments with the help of an auction issuer (AI): The AI chooses winners and greedily computes the threshold payment based on encrypted user’s sensing profiles. Since these encrypted sensing profiles are order-preserving, the threshold payment is the same as the one produced by the platform, thereby solving the verifiability without reducing privacy of users and platform. Specifically speaking, we first introduce three incentive mechanisms for crowd sensing applications with homogeneous sensing jobs, heterogeneous sensing jobs and submodular sensing jobs (to be elaborated later). Then, we propose a general privacy preservation verifiable incentive mechanism.
for homogeneous sensing jobs and heterogeneous sensing jobs. Furthermore, we also propose a privacy preservation verifiable incentive mechanism for submodular sensing jobs. The two mechanisms are implemented by introducing the oblivious transfer (OT), the timed lapse cryptography services (TLC), and the bulletin board, satisfying the three desirable properties: the non-repudiation by users and the platform, secrecy, and verifiable correctness. Finally, analysis show that our privacy-preserving verifiable incentive mechanisms achieve the same results as the generic one without privacy preservation and verification.

The rest of the paper is organized as follows. In Section 2, we briefly discuss the related work and motivation. In Section 3, we present our relative models and our design goal. In Section 4, we introduce novel incentive mechanisms for crowd sensing applications with the budget constraint. Based on these mechanisms, in Section 5, we design two privacy-preserving verifiable incentive mechanisms satisfying the above three desirable properties, followed by the security analysis and performance evaluation in Section 6 and Section 7. Finally, we draw our conclusions in Section 8.

2. BACKGROUND AND RELATED WORK

Privacy-preserving mechanisms have been extensively explored in crowd sensing applications. Most of these research works are based on k-anonymity [Sweeney 2002], where a user's location is cloaked among k − 1 other users. For instance, the authors of [Kalnis et al. 2007] and [Gedik and Liu 2008] use the temporal and spatial cloaking techniques to preserve users' privacy. Their mechanisms blind the participant's location at a specific time in a cloaked area to achieve the privacy requirements. The authors of [Shilton et al. 2008], [Shin et al. 2011], [De Cristofaro and Soriente 2011] study the privacy protection in crowd sensing applications by applying a privacy regulation technique. Furthermore, the authors of [Shin et al. 2011] and [De Cristofaro and Soriente 2011] focus on how users submit the jobs to the platform without disclosing their identity. Different from the above anonymous collection mechanisms, the authors of [Huang et al. 2013] protect the privacy of users by applying the OT [Rabin 1981]. However, they do not consider the verifiability of user's inputs and outcomes.

Additionally, verifiability of the payment is also a vital factor an incentive mechanism design faced. The verifiability of payments have been extensively explored in traditional auction mechanisms. For instance, the authors of [Naor et al. 1999], [Juels and Szydlo 2003] apply the proxy OT to verify the payment of the platform by constructing a circuit. The authors of [Parkes et al. 2008] use a timed lapse cryptography service to keep users' bids secret from the platform before the auction closed, and prevent them from rigging their bids after bidding. However, they do not apply for crowd sensing applications, since they neglect the effect of a large of participants in crowd sensing applications. Recently, a timed commitment encryption method is adopted to enhance the level of the payment correctness from the platform for crowd sensing applications. For example, the authors of [Catane and Herzberg 2013], [Zhao et al. 2012], [Angel and Walishe 2013] apply the timed commitment to tackle the verifiable correctness issue in different aspects. However, these mechanisms are not applicable in real crowd sensing applications with the budget constraint.

In this paper, to solve the above challenges, we introduce the bulletin board, OT, and TLC to guarantee the privacy and verifiability for crowd sensing applications without sacrificing the platform's utility and truthfulness.

3. SYSTEM MODEL AND PROBLEM FORMULATION
In this section, we first expound our system model, auction model, adversarial model, and the bulletin board applied to our privacy-preserving verifiable incentive mechanisms. Then we present our goal for crowd sensing applications.

### 3.1. System Model

We consider the following system model for crowd sensing applications, illustrated in Fig. 1. The system consists of a crowd sensing platform that resides in the cloud, a requester, and many mobile device users that are connected to the platform by cellular networks (e.g., GSM/3G/4G) or WiFi connections. The requester posts a crowd sensing task with a budget \( B > 0 \) to the platform. There are \( m \) available assignments in each task. Receiving the task, the platform publicizes a crowd sensing campaign towards the area of interest (AoI), aiming at finding some users to maximize the number of assignments performed efficiently. Assuming that a set of users \( U = \{1, 2, \cdots, n\} \) in the AoI is interested in the campaign. In this paper, with respect to the model of sensing jobs completed by all users, we discuss the following three sensing job models proposed in [Singer 2010] for the crowd sensing campaign:

- **Homogeneous sensing job model:** Both each sensing job assignment and the limit of the number of assignments completed by each user are the same. Meanwhile, each user can complete only a single assignment.

- **Heterogeneous sensing job model:** Each sensing job assignment is the same, but the limit of the number of assignments completed by each user is different. It means that different users can complete different number of assignments.

- **Submodular sensing job model:** Each sensing job assignment is different, and each user \( i \) can do a subset \( \Gamma_i \) of assignments \( \Gamma \).

If the campaign is oriented to users with the homogeneous sensing job model and the heterogeneous sensing job model, receiving the campaign, each user \( i \) synchronously submits his sensing profile \( P_i = (b_i, l_i) \), where \( b_i \) is obtained based on a true cost \( c_i \) for performing a single assignment and \( l_i \) is a limit for the number of assignments he is willing to work on. This means that if he is a winner, at most \( l_i \) assignments can be allocated to him and the payment for each assignment must exceed \( b_i \). In this case, the sensing job model is the heterogeneous sensing job model, which indicates that different users can complete different number of assignments. When \( l_i = 1 \), the sensing job model is reduced to the homogeneous sensing job model, which indicates that each user can complete only a single assignment.

If the campaign is oriented to users with the submodular sensing job model, receiving the campaign, each user \( i \) synchronously submits his sensing profile \( P_i = (b_i, \Gamma_i) \), where \( b_i \) is obtained based on a true cost \( c_i \) for performing the sensing service with his assignments’ set \( \Gamma_i \), i.e., \( \Gamma_i \subseteq \Gamma = \{\tau_1, \tau_2, \cdots, \tau_m\} \). We assume that \( l_i \) or \( \Gamma_i \) is fixed. Furthermore, under the budget constraint \( B \), the platform, when presented with the sensing profiles of all users, must decide a subset of users to select, and how much payment to pay to each selected user. Our goal is to make incentive mechanisms to achieve non-repudiation by users and platform, secrecy, and verification without sacrificing the above standard economic goal such as utility maximization, truthfulness.

### 3.2. Auction Model

We model the above interactive process as a sealed-bid auction between the platform and users (see Fig. 2), in which there is a crowd sensing platform, a set of participatory users, and an AI. A set of assignments \( \Gamma \) publicized by the platform during the deadline \( T \) are auctioned towards \( n \) users in crowd sensing applications. Each user \( i \) submits his encrypted sensing profile \( P_i \), i.e., a pair of encrypted \( b_i \) and encrypted \( l_i \) or \( \Gamma_i \). The AI is semi-honest (passive or curious), and only checks the platform randomly. This will be further illustrated in Section 4.
3.3. Bulletin Board

The platform maintains a bulletin board. It can be a publicly known website maintained and updated by the platform. The platform applies the bulletin board to post all public information about the mechanism, including all abstractions (e.g., some auction details) as well as encrypted information about users’ profiles, the methods of the winner selection and payment determination that can be used to verify the payment correctness from the platform. All posted to the bulletin board will carry appropriate digital signatures so as to identify their originators. For the ease of exposition, we will refer to $\text{sign}_i(m)$ as the signature of the message $m$ from the user $i$ in the rest of this paper. All abstractions can be constructed by using standard cryptographic techniques. We calculate the communication overheads of our mechanisms as the number of auction details published on the bulletin board. It is worth noting that a robust bulletin board is needed for crowd sensing applications. Thus our mechanisms can just exploit standard broadcast techniques.

3.4. Adversarial Model

In the auction process with the budget constraint, the platform is supposed to know only the set of current winners, and their sensing profiles. Each user $i$ only learns whether he is the winner, and he is paid if he is a winner. He does not know anything about others’ profiles except for the very limited implicit information in the payment from the platform.

We assume that the platform and users are semi-honest adversaries in our mechanisms, and collusion of bidders and platform does not exist. That is, the platform is interested in inferring each user’s private information no matter he is a winner or not. Users try to infer others’ profiles to maximize their own utilities. Besides, the platform and users can also collude with each other. According to the above auction model, we give the analysis of the privacy in our framework below.
Definition 1. Given all the communication strings $C$ and its output of the auction $\text{Output}$ during the auction, an adversary’s advantage over the privacy information $\zeta_i$ of user $i$ is defined as $\text{Adv}_{\zeta_i} = P_{\zeta_i}^R[C, \text{Output}] - P_{\zeta_i}^R[\text{Output}]$, where $P_{\zeta_i}^R[\zeta_i]$ is the probability that a correct $\zeta_i$ is inferred. In this paper, $\zeta_i$ can be the bid or sensing services $\Gamma_i$ of user $i$.

Definition 2. A privacy-preserving scheme satisfies $k$-anonymity, if a user cannot be identified by the sensitive information with probability higher than $1/k$ [Sweeney 2002].

In this paper, our security goal is to achieve a scheme such that the advantage is of a negligible function of the security parameter or $k$-anonymity is guaranteed.

3.5. Problem Formulation

According to the above sensing job model, we need to consider two cases. One case is when sensing job model is the homogeneous sensing job model or the heterogeneous sensing job model. In the two models, the platform needs to design a mechanism $\mathcal{M} = (f, p)$, which consists of an allocation function $f : \mathcal{R}_+^n \rightarrow \mathcal{Z}_+^{[n]}$ and a payment function $p : \mathcal{R}_+^n \rightarrow \mathcal{R}_+^n$. The allocation function $f$ maps a set of $n$ bids to an allocation of assignments for a selected subset of users. In particular, in the homogeneous sensing job model, if user $i$ is selected, $f_i = 1$. The payment function $p$ returns a vector $(p_1, \cdots, p_n)$ of payments to the users. That is, each selected user $i \in S$ is allocated $f_i$ assignments at price $p_i$, per task. In the heterogeneous user model, the utility of user $i$ is $f_i(p_i - c_i)$ if it is selected, i.e., $i \in S$, 0 otherwise. The existing goal of the platform is to maximize the number of assignments under given budget $B$, i.e., $\max \sum_{i \in S} f_i$, subject to $\sum_{i \in S} f_i p_i \leq B$, $\forall i, f_i \leq 1$. In particular, when $l_i = 1$, the above results are also applicable to the homogeneous sensing job model.

The other case is when sensing job model is the submodular sensing job model. The platform needs to design a mechanism $\mathcal{M} = (f, p)$, which consists of an allocation function $f : \mathcal{R}_+^n \rightarrow 2^{[n]}$ and a payment function $p : \mathcal{R}_+^n \rightarrow \mathcal{R}_+^n$. The allocation function $f$ is a indicator function that returns 1 if user $i$ is allocated and 0 otherwise. The utility of user $i$ is $p_i - c_i$ if it is selected, i.e., $i \in S$, 0 otherwise. The payment function $p$ returns a vector $(p_1, \cdots, p_n)$ of payments to the users. The existing goal of the platform is to maximize the value from the selected users’ services under the budget constraint $B$, i.e., $\max V(S)$, subject to $\sum_{i \in S} p_i \leq B$, where $V(S)$ is monotone submodular.

However, the above maximal problem will bring many security and privacy issues including users’ sensing profiles. Since users are reluctant to disclose all these private information to others as well as the platform. On the other hand, both the winners and the platform should be able to verify the payment provided by our mechanisms. Thus, beyond the standard economic goals (e.g., truthfulness, individual rationality, utility maximization, etc.), our mechanisms also satisfy the following three desirable properties:

- **Non-repudiation by users and platform**: For each user, once it submits a encrypted profile, its encrypted profile is provably unalterable. For the platform, its exclusion of a properly submitted encrypted profile can be conclusively proven. Thus, it must action legally.
- **Secrecy**: These encrypted profiles are bidden to all users and the platform until their holders become winners of mechanisms. When they become winners, only the platform knows their decrypted profiles. When they become losers, their encrypted profiles are bidden to all other users and the platform. The current winners’ profiles of the platform are bidden to all users no matter whether these users are winners or not.
**Verifiable correctness:** Since the mechanism itself is truthful, we only need to guarantee that each user can verify the payment correctly provided from the platform by applying the computation method published on the bulletin board.

### 4. INCENTIVE MECHANISMS FOR CROWD SENSING APPLICATIONS

In this section, we introduce three incentive mechanisms for crowd sensing applications with homogeneous sensing jobs, heterogeneous sensing jobs, and submodular sensing jobs respectively. In essence, the incentive mechanisms for crowd sensing applications require the truthfulness, computationally effectiveness, budget feasibility and approximation. Singer et al. present these mechanisms meeting the four conditions well. For the ease of presentation, in the following section, we propose two privacy preservation verifiable incentive mechanisms based on the three mechanisms, but our mechanisms are easy to be extended to other truthful incentive mechanisms for real crowd sensing environments. Furthermore, their truthful mechanisms are illustrated as follows.

To better understand the following three incentive mechanisms, let us see the following familiar example. Given a budget constraint $B$ and subsets $\mathcal{U} = \{1, 2, \ldots, n\}$ of some ground set, where each user $i$ corresponds to a subset of the ground set and a associated cost $c_i$, find a users’ subset $S$ which maximizes $|\cup_{i \in S} \{i\}|$ under the budget constraint. This is a typical coverage problem, called submodular sensing job model here, in which each user’s value depends on the identity of the sensing data set it holds. When each user’s value only depends on the cardinality of the sensing data set, rather than the identity of the sensing data set it holds, it means that different users can complete different number of sensing data, thereby simplifying the submodular sensing job model to heterogeneous sensing job model. Furthermore, if each user only completes a single sensing data assignment, the heterogeneous sensing job model will become a homogeneous sensing job model. For the simplicity of presentation, we first introduce the incentive mechanism with homogeneous sensing job model.

#### 4.1. Incentive Mechanism with Homogeneous Sensing Jobs

For crowd sensing applications with homogeneous sensing jobs, consider the above-mentioned allocation rule $f$: Sort the $n$ bids reported by $n$ users so that $b_1 \leq b_2 \leq \cdots \leq b_n$, and find the largest $k$ so that $b_k \leq B/k$. That is, $k$ is the place where the curve of the increasing costs intersects the hyperbola $B/k$. The set allocated here is $\{1, 2, \ldots, k\}$. That is, winners’ set $S = \{1, 2, \ldots, k\}$. This is obviously a monotone allocation rule: a user can not be excluded when decreasing his bid. In [Singer 2010], the authors design the following incentive mechanism for crowd sensing applications with homogeneous sensing jobs and show the mechanism satisfies the above four conditions.

More formally, firstly, sorting the users’ bids: satisfying $b_1 \leq b_2 \leq \cdots \leq b_n$. Then find the largest integer $k$ such that $b_k \leq B/k$. Finally, determine the set of allocated users to be $S = \{1, 2, \ldots, k\}$, and provide same payment $p_i = \min\{B/k, b_{k+1}\}$.

#### 4.2. Incentive Mechanism with Heterogeneous Sensing Jobs

For crowd sensing applications with heterogeneous sensing jobs, the authors of [Singer and Mittal 2013] present the following mechanism for determining near-optimal prices of jobs for crowd sensing applications with heterogeneous sensing jobs. Their mechanism is illustrated as follows: Firstly, sort the users’ bids: satisfying $b_1 \leq b_2 \leq \cdots \leq b_n$. Then find the largest integer $k$ such that $b_k \leq B/\sum_{j \leq k} f_j$. Finally, determine the set of allocated users $S = \{1, 2, \ldots, k\}$, and provide the same payment $\min\{B/\sum_{j \leq k} f_j, b_{k+1}/l_{k+1}\}$ for completing a sensing job.

Obviously, the homogeneous user model is a special case of the heterogeneous user model, i.e., $l_i = 1$ for each user $i$. 

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4.3. Incentive Mechanism with Submodular Sensing Jobs

For crowd sensing applications with submodular sensing jobs, the authors of [Singer 2010; Tran-Thanh et al. 2012; Yang et al. 2012] apply the proportional share allocation rule proposed in [Singer 2010] to address the extensive user participation issue for crowd sensing applications, which consists of two phases: the winner selection phase and the payment determination phase. We first introduce definition of the submodular utility function.

**Definition 3 (SUBMODULAR FUNCTION).** Let \( \mathbb{N} \) be a finite set, a function \( U : 2^\Omega \to \mathbb{R} \) is submodular if \( U(S \cup \{i\}) - U(S) \geq U(T \cup \{i\}) - U(T), \forall S \subseteq T \subseteq \Omega \), where \( \mathbb{R} \) is the set of reals.

From the above Definition 3, we can know the utility function \( U \) is submodular and derive the following sorting according to increasing marginal contributions relative to their bids from users’ set to find the largest \( k \) satisfying \( b_k \leq U_k B / U(S \cup k) \).

\[
U_1 / b_1 \geq U_2 / b_2 \geq \cdots \geq U_{|\mathcal{U}|} / b_{|\mathcal{U}|},
\]

where \( U_k \) denotes \( U_{|\mathcal{U}| - 1} = U(S_{k-1} \cup \{k\}) - U(S_{k-1}) \), \( S_k = \{1, 2, \ldots, k\} \), and \( S_0 = \emptyset \).

To calculate the payment of each user, we sort the users in \( \mathcal{U} \setminus \{i\} \) similarly as follows:

\[
U_{i_1} (T_0) / b_{i_1} \geq U_{i_2} (T_1) / b_{i_2} \geq \cdots \geq U_{i_{n-1}} (T_{n-2}) / b_{i_{n-1}},
\]

The marginal value of user \( i \) at the position \( j \) is \( BU_{i(j)} (T_{j-1}) / U(T_j) \). Assume that \( k' \) to be the position of the last user \( i_j \in \mathcal{U} \setminus \{i\} \), such that \( b_{i_j} \leq U_{i(j)} (T_{j-1}) B / U(T) \). To guarantee the truthfulness, each winner should be given the payment of the critical value. This indicates that user \( i \) can not win the auction if it reports higher than this critical
value. More details are given in Algorithm 1, where 

\[ b_{i(j)} = U_{i(j)}(T_{j-1}) b_{i} / U_{i}(T_{j-1}) \]

and

\[ \eta_{i(j)} = U_{i(j)}(T_{j-1}) B / U(T_{j-1} \cup \{ i \}) . \]

However, although the above three mechanisms under the given budget constraint are so promising for crowd sensing applications, it also bring many verifiability and privacy issues including users’ sensing profiles and the payment correctness. In the following section, we will design two privacy-preserving verifiable incentive mechanisms for crowd sensing applications with homogeneous and heterogeneous sensing jobs, and submodular sensing jobs to address the above-mentioned challenges.

5. DESIGN DETAILS

During the above three auction mechanisms for crowd sensing applications with homogeneous, heterogeneous jobs and submodular jobs, we need to choose a set of winners and finish the payment of the winners according to the mechanism with the given budget constraint. In this section, we first introduce basic cryptographic schemes. Then we apply the schemes to design our privacy preservation verifiable auction mechanism for homogeneous, heterogeneous jobs and submodular jobs respectively.

5.1. Basic Cryptographic Schemes

In this section, we introduce the constructions of time-lapse cryptography service and blinded digital signature for achieving the goal of non-repudiation by users and platform, OT for making users’ sensing profile secret, and the computation of marginal utility and set union for making platform’ current winners’ set secret. Then, in the following details, we apply the bulletin board and the parameter \( \alpha \) to ensure verifiability of payments and the payment correctness.

5.1.1. Time-Lapse Cryptography Service. In our proposed mechanism we apply timed commitments on sensing profiles of all users until the auction closes. Cryptographic methods, as presented in [Boneh and Naor 2000] can be used to implement the timed-commitments. Considering the computation efficiency reasons, we choose a time lapse cryptography (TLC) service from [Rabin and Thorpe 2006], which makes it possible to use commitments with the classical hiding and binding properties. Besides, it prevents users from refusing to reveal committed sensing profiles and also preventing the platform from dropping received commitments, claiming not to have been able to reveal the committed sensing profiles. In our mechanisms, an auction issuer (AI), acting as the TLC service provider, publishes a public key of a non-malleable encryption scheme, and sends the corresponding private key only when the auction closes. Whenever timed commitments on sensing profiles are applied, it means that a user encrypts her sensing profile by applying the AI-generated public encryption key. Besides, receiving the corresponding private key, the platform can know the encrypted sensing profile.

5.1.2. Blinded Digital Signature. In our work, each user is a signer who is introduced only to keep the confidentiality of its the following transformed bid and sensing subset of assignments to the platform as well as other users. Considering the security, not all digital signature schemes can be used. To these goals, we apply the Nyberg-Rueppel signature scheme [Camenisch et al. 1995] (see Algorithm 2). Notably, we do not need the signer to verify the authenticity of them, and on the other hand the platform can obtain their transformed bids and sensing preference selections from all signers. For the ease of exposition, we will refer to \( \text{sign}_i(m) \) as the signature of the message \( m \) from the user \( i \) in the rest of this paper. Note that the signature scheme requires the message to be an integer, therefore, we need to apply \( \text{sign}(\lfloor 10^k m \rfloor) \) for the input \( m \) if \( m \) is not an integer like the bid, where \( k \) can be appropriately chosen to preserve
the rank from \{3, 4, \cdots\} and \( \psi(x) \) denotes the output of the signature scheme. At the same time, we remove the signature by using \( 10^{-k}\text{sign}^{-1}(c_m) \), where \( c_m \) is obtained by the signature \( c_m = \text{sign}_i(m) \). For ease of exposition, in the rest of the paper, we assume that the value of the signature is an integer. According to [Jung et al. 2013a], the deviation for the roundness of the signature is negligible. Thus, our assumption is reasonable.

**ALGORITHM 2:** Blinded Nyberg-Rueppel Signature.

1. Initialize a prime number \( p \), a prime factor \( q \) of \( p-1 \), and an element \( g \in \mathbb{Z}_p^\ast \) with order \( q \);
2. The signer selects \( \tilde{k} \in \mathbb{Z}_q \) and sends \( \tilde{r} = g^{\tilde{k}} \pmod{p} \) to signee;
3. The signee randomly chooses \( \alpha \in \mathbb{Z}_q, \beta \in \mathbb{Z}_q^\ast \), computes \( r = mg^\alpha \pmod{p} \) and \( \tilde{m} = r\beta^{-1} \pmod{q} \) until \( m \in \mathbb{Z}_q^\ast \). Then, he sends \( \tilde{m} \) to the signer;
4. The signer computes \( \tilde{s} = \tilde{m}x + \tilde{k} \pmod{q} \) and sends \( \tilde{s} \) to the signee;
5. The signee computes \( s = \tilde{s}\beta + \alpha \pmod{q} \), and the pair \((r, s)\) is the signature for \( m \);
6. Check whether \( m = g^{-x}s r \pmod{q} \) to verify the correctness.

5.1.3. OT for Privacy Preservation. OT is a paradigm of secret exchange between two parties, users and a platform. Each user can achieve one of \( n \) secrets from the user, without knowing any information about the rest of \( n \) secrets, while the platform has no idea which of the \( n \) secrets is accessed. Our work employs an efficient 1-out-of-\( z \) OT of integers [Tzeng 2004]. The detailed description is given in the Algorithm 3.

**ALGORITHM 3:** Oblivious Transfer (OT\(_1^z\)).

1. Initialization: System parameters: \((g, h, G_g)\); the AI’s input: \( m_1, m_2, \cdots, m_n \in G_g \); user \( i \)'s choice: \( a, 1 \leq a \leq n \);
2. User \( i \) sends \( y = g^a h^\alpha \);
3. The AI replies with \( c_i = (g^{k_i}, m_i(y/h)^{k_i}), k_i \in R \mathbb{Z}_q, 1 \leq i \leq n \);
4. By \( c_a = (a, b) \), user \( i \) computes \( m_a = b/a^\alpha \);

5.1.4. Marginal Utility Computation. Besides the above losers’ sensing preferences, the current winner set \( S \) produced by the platform, should be also kept secret to all users. In such problems, how to compute the marginal utility without knowing \( S \) is challenging. We address it by introducing multivariate polynomial evaluation protocol (MPEP) [Jung et al. 2013b] [Zhang et al. 2013], in which the multivariate polynomial are computed without disclosing any \( x_i \) input of various users as follows: \( f(\bar{x}) = \sum_{k=1}^{m} (c_k \prod_{i=1}^{n} x_i^{d_{i,k}}) \), where there is a group of open \( m \) powers for each user and \( m \) coefficients to any participant as well as the attackers. We compute the marginal utility by assuming that there are \( m \) sensing data points and \( n \) mobile users. Then we have \( m \)-dimensional vector \( C_S \) indicating whether \( m \) sensing data points are included in currently chosen sets \( S \), where \( c_{k,S} = 1 - \prod_{j=1}^{n} (1 - c_{j,k,S}) \). If \( k \)-th data point is in user \( j \)'s subset \( \Gamma_j \) of assignments and user \( j \) is in \( S \), \( c_{k,S} = 1 \), and 0 otherwise. Since each user knows whether it belongs to \( S \), each winning user’s marginal utility can be evaluated via one aggregator MPEP with the help of \( n \) users and only user \( i \) receives the result by applying the above MPEP equation. Finally, the user \( i \) can divide his bid \( b_i \),
to the result to compute the marginal-utility-per-bid value \( \omega_i \). The detailed expression is given as follows:

\[
\omega_i = \frac{1}{b_i} \left( \sum_{j=1}^{m} c_{j,S \cup \{i\}} - \sum_{j=1}^{m} c_{j,S} \right)
= \frac{1}{b_i} \left( \sum_{k=1}^{n} \left( 1 - \prod_{j=1}^{n} \left( 1 - c_{j,k,S \cup \{i\}} \right) \right) - \sum_{k=1}^{m} \left( 1 - \prod_{j=1}^{n} \left( 1 - c_{j,k,S} \right) \right) \right).
\]

5.1.5. Privacy Preservation Set Union Computation for Platform. Since the current winner set \( S \) is required to be kept secret to all users, for the platform, how to compute the set union without leakage the its privacy, i.e., the current winner set \( S \) is a challenging issue. In the paper, we address it by using Paillier cryptosystem \cite{Paillier1999} to the set union computation. About the set union computation, we refer interested readers to the paper \cite{Frikken2007}. The detailed description is illustrated in Algorithm 4. The Paillier cryptosystem as well as its homomorphic property is also shown below:

\[
E(m_1, r_1) \cdot E(m_2, r_2) = E(m_1 + m_2, r_1 + r_2)
E(m_1) \cdot g^{m_2} = E(m_1 + m_2, r_1)
E(m_1, r_1)^{m_2} = E(m_1 \cdot m_2, r_1 \cdot m_2)
\]

**Algorithm 4:** Privacy-preserving set union computation.

1: Initialize system parameter: two same-length prime numbers \( p,q \), public keys \( n = pq \), \( g \in \mathbb{Z}_{n^2}^* \), private key \( \lambda = (p-1)(q-1), \mu = \lambda^{-1} \mod n \);
2: The platform computes the polynomial \( f_A \) and sends the encrypted \( E_p(f_S) \) to the user \( u_i \);
3: Upon receiving \( E_p(f_S) \), the user \( u_i \) chooses a random value \( r \) (choose uniformly) and computes a tuple \( (E_p(f_S(r) + \tau * r), E_p(f_S(r) + r)) \) for each assignment value \( \tau \in S \). He randomly permutes all of the tuples and sends them to the platform;
4: For each tuple \( (E_p(x), E_p(y)) \), the platform decrypts \( x \) and \( y \). If both values are 0, then the platform continues to next tuple. Otherwise, the platform finds a good with the value \( x + y^{-1} \) and adds it to the output set; As such, the marginal utility of the user \( u_i \) can be obtained.

5.2. Design Privacy-Preserving Details for Homogeneous and Heterogeneous jobs

5.2.1. Initialization. The platform invites the AI to participate in the auction and sends the following information to him: the crowd sensing task identifier \( TID \) of the platform, the deadline \( T \), and the timed-lapse encryption key \( TPK \) to be used by all users in commitments. If the AI accepts them, he sets the probability of the auditions from users as \( \alpha \) so that \( \alpha \geq p_{\text{max}} / (F + p_{\text{max}}) \), where \( p_{\text{max}} \) and \( F \) are the maximal payment and fine paid from the platform respectively, and sends signed \( \alpha \) and signed auction details to the platform. If the platform accepts it, the platform posts them on the bulletin board. Finally, our mechanism also defines a set of possible bids as \( \beta = \{ \beta_1, \beta_2, \cdots, \beta_z \} \) and a set of possible limits of the number of assignments, \( \chi = \{ \chi_1, \chi_2, \cdots, \chi_v \} \), where \( \beta_1 < \beta_2 < \cdots < \beta_z \) and \( \chi_1 < \chi_2 < \cdots < \chi_v \) hold, and requires each user \( i \)'s bid \( b_i \in \beta \) and the limit of the number of assignments \( l_i \in \chi \). The AI maps each bid value \( \beta_i \) and limit value \( \chi_i \) to \( \gamma_i \) and \( \tau_i \) respectively, while preserving the rank, i.e., satisfying \( \gamma_1 < \gamma_2 < \cdots < \gamma_n \) and \( \tau_1 < \tau_2 < \cdots < \tau_n \). Similarly, users' bids and limits are transformed by using the OPES for preserving their ranks. To this end, we assume that the above AI can bootstrap the crowd sensing market application. All of the above data are posted on the bulletin board, accompanied by the platform’s signature sign_p.
ALGORITHM 5: PVI-H\// Privacy-preserving Verifiable incentive mechanism for Crowd sensing applications with homogeneous sensing jobs or Heterogeneous sensing jobs

**Input:** User set $\mathcal{U}$, the budget constraint $B$.

**Output:** $S$.

1. // Phase 1: Winner selection
   1. Initialize: Each user $i$ receives his encrypted sensing profile $(\tilde{b}_i, \tilde{r}_i)$ by using Algorithm 3 and submits their commitments to the platform; At time $T + 1$, the platform makes a decommitment and sorts users in $\mathcal{U}$ i.e., $\tilde{b}_1 < \tilde{b}_2 \cdots < \tilde{b}_n$; $S \leftarrow \emptyset$; $i = 1$;
   2. $b_i \leftarrow OPENS^{-1}(\tilde{b}_i)$;
   3. while $b_i \leq B/\sum_{j \in S} f_j$ do
   4. $f_i \leftarrow 1$;
   5. if jobs are heterogeneous then
   6. $f_i \leftarrow \min\{OPENS^{-1}(\tilde{b}_i), \tau_i\}$, where $\tau_i = [(B - b_i \sum_{j \in S} f_j)/b_i]$;
   7. end if
   8. $S \leftarrow S \cup i$;
   9. $i \leftarrow i + 1$;
   10. $b_i \leftarrow OPENS^{-1}(\tilde{b}_i)$;
   11. end while
   12. // Phase 2: Payment determination
   13. for each user $i \in S$ do
   14. $l_{i+1} \leftarrow OPENS^{-1}(l_{i+1})$;
   15. if $j \leq i - 1$ then
   16. Pay $p_j f_j$ to user $j$;
   17. end if
   18. if $j = i$ then
   19. $p_j \leftarrow \min\{B/\sum_{j \in S} f_j, b_{i+1}/l_{i+1}\}$; Pay $p_j f_j$ to user $j$;
   20. end if
   21. end for
   22. return $S$;

5.2.2. **Commitment.** Each user $i$ chooses a bid $b_i$ and a limit $l_i$ of the number of assignments to form his sensing profile, and then interacts with the AI. According to the Algorithm 3, each user $i$ receives $\tilde{b}_i = \gamma_x$ and his limit $\tilde{l}_i = \tau_x$, which are the rank-preserving-encrypted values of $\beta_x$ and $\chi_x$, respectively, thereby forming his encrypted sensing profile. Then each user $i$ encrypts the encrypted sensing profile as $e_i = E_{K_{ppub}}(\tilde{b}_i|\tilde{l}_i|\tilde{r}_i)$ by using the platform's Paillier encryption key $K_{ppub}$ and a randomly chosen values $r_i$. User $i$ then makes a commitment $c_i = E_{TPK}(e_i|s_i|TID)$, where $s_i$ is a randomly generated bit string for the proof of correctness and $TID$ is the auction identifier ID. Finally, the user signs this commitment, and sends a bidding request $BR = (sign_i(c_i|TID))$ to platform, if used, before time $T$ (see Fig. 5 step ①). The platform returns a signed receipt $R_i = sign_p(c_i|TID|T)$ (see Fig. 5 step ②). At time $T$, the platform posts all the received true commitments $c_1, c_2, \cdots, c_n$ on the bulletin board.

Note that hiding of the encrypted bids and of the random strings by applying the secondary encryption prevents anyone from learning any knowledge of the data prior to time $T$. In particular, neither the AI nor the platform has any meaningful information.

Furthermore, between time $T$ and $T + 1$, for any user who has a receipt for a bid which is not posted (see Fig. 5 step ③), he can appeal his non-inclusion, resorting to the AI.

5.2.3. **Decommitment.** At time $T + 1$, each party, including the platform and all users, can recover each encrypted sensing profile $e_i$ as well as each random string $r_i$ by employing the decryption key TSK posted by the AI. The platform recovers the pair for
computing the auction’s results and random values $r_1, \cdots, r_k$ for the verification of correctness by applying the platform decryption key. The platform then computes the set of winners and their corresponding payments from the platform according to the above auction mechanism with the given budget constraint. The platform posts the winner’s identity and the encrypted payment information so that any party can verify the correct results on the bulletin board.

(a) **Winners Selection:** In this stage, our goal of the winners’ selection is to find the biggest integer $k$ so that $b_k \leq B/\sum_{i=1}^{k} f_i$ holds, thereby obtaining the set of winners. Firstly, the platform first recovers the bids $\tilde{b}_i$ from the bulletin board and then sorts all users’ encrypted bids from all users and resorts to the AI to fetch the original value $b_1$ of $\tilde{b}_1$: $b_1 = OPENS^{-1}(\tilde{b}_1)$. If $b_i \leq B/\sum_{j<i} f_j$ holds, then users with the rank $1,2,\cdots, i$ are winners, thus, for the platform, privacy leakage does not exist. Otherwise, the largest number $k = i - 1$. When user $i$ is added to the set of winners, the platform then computes his assignments $\tilde{f}_i \leftarrow \min\{OPENS^{-1}(\tilde{b}_i), \tau\}$. The iteration is repeated until our goal is achieved. The set of winners $\{1,2,\cdots,k\}$ is found. Notable, when we determine the largest $k$, if $b_k \leq B/\sum_{j<k} f_j$ does not hold, the $k+1$-th user’s bids and assignments, i.e., its sensing profile, may be disclosed (see Fig. 5 step 4). Since in our crowd sensing applications, we assume that the number of users is much larger than the number $k$. As such, our scheme satisfies $k$-anonymity. So, neither the AI, nor the platform, can identify any user’s sensing profile with the probability higher than $1/k$.

The detailed description is given in the Algorithm 5.

(b) **Payment Decision:** In the payment determination phase, the platform pays $p_i f_j$ to user $j$ for $j \leq i$. Similarly, for each winner $i \in S$, the payment of per sensing job, i.e., $p_i$, is given in Algorithm 5. In particular, our payment scheme is applicable to homogeneous and heterogeneous sensing job models (see Fig. 5 step 5).

5.2.4. **Verification.** Since the above incentive mechanism guarantees the truthfulness for users, we only need to verify the payment correctness of the platform, that is, any of the users can verify the outcome of the auction on his own. The detailed descriptions are given as follows. Firstly, user $i$ requests AI to verify the payment outcome with the probability $\alpha$. After the AI receives the request, he asks for the random value $r_i$ of each user’s $c_i$. Then he derives each user $c_i$’s $\tilde{b}_i, \tilde{l}_i$ by decrypting $c_i$ on the bulletin board with $r_i$, thereby obtaining the payment according to the above auction details and the information from the bulletin board. He sends the encrypted payment $\tilde{f}_i p_i$ and his assignments $\tilde{f}_i$ to the user $i$ to verify the correctness of the outcomes from the platform, thereby obtaining the user’s feedback to determine whether to fine the platform (see Fig. 4). Analysis in the following section shows that the platform operates correctly and does not try to cheat.
5.3. Design Privacy-Preserving Details for Submodular Sensing Jobs

Different from the above mechanism, for the submodular sensing job model, we need overcome the challenge of protecting platform’s privacy, i.e., the privacy of the current winners’ set, by using the above-mentioned MPEP method and homomorphic encryption scheme. The detailed descriptions are described below.

5.3.1. Initialization. The platform invites the AI to participate in the auction and sends the following information to him: the crowd sensing task identifier $TID$ of the platform, the description of the mechanism, the deadline $T$, and the timed-lapse encryption key $TPK$ to be used by all users in commitments. If the AI accepts them, it sets the probability of the auditions from the users as $\alpha$ so that $\alpha \geq p_{\text{max}}/(F+p_{\text{max}})$, where $p_{\text{max}}$ and $F$ are the maximal payment and fine paid from the platform respectively, and sends signed $\alpha$ and signed auction details to the platform. If the platform accepts it, the platform posts them on the bulletin board. Our mechanism also defines a set of possible marginal utilities per bid as $\beta = \{\beta_1, \beta_2, \ldots, \beta_z\}$, where $\beta_1 < \beta_2 < \cdots < \beta_z$ holds, and requires that each user $i$’s marginal utility per bid $\omega_i \in \beta$. The AI maps each $\beta_i$ to $\gamma_i$, while preserving the rank, i.e., satisfying $\gamma_1 < \gamma_2 < \cdots < \gamma_n$. Similarly, each user’s marginal utility per bid is transformed by using the order preserving encryption scheme (OPES) [Agrawal et al. 2004] for preserving their ranks. To this end, we assume that the above AI can bootstrap the crowd sensing application. Then it constructs three dynamic lists for the verification of payments’ correctness initiated by each user. The first list $l^w_i$ for user $i$ is used to put his marginal utility per bid $\omega_i(S)$ for the winner determination phase. The second list $l^p_i$ is used to put his marginal utility per bid $\omega_i(T)$ for the payment determination phase. The last dynamic list $l^z_i$ is constructed for each winner. All of the above data are posted on the bulletin board, accompanied by the platform’s signature $\text{sign}_p$.

5.3.2. Commitment Round for Winner and Payment Determination. Each user $i$ initially chooses a bid $b_i$ and a subset $\Gamma_i$ of assignments according to his valuation he preferences. Each user $i$ initially computes his marginal utility $U_i(\emptyset)$, thereby obtaining his marginal utility per bid $\omega_i(\emptyset)$. Then he interacts with the AI by using the Algorithm\textbf{3} thereby receiving $\tilde{\omega}_{i,0}(\emptyset)$, where the subscript $0$ denotes the cardinality of the current winners’ set is equal to 0, and $\tilde{\omega}_{i,0}(\emptyset)$ is the rank-preserving-encrypted value of $\beta_z$. Then each user $i$ encrypts it as $e_i = E(\omega_{i,0}|r_i)$ by using the platform’s Paillier encryption key $K_{\text{pub}}$ and a randomly chosen value $r_i$. User $i$ then makes a commit $c_i = E_{TPK}([e_i, s_i, |TID|])$, where $s_i$ is a randomly generated bit string for the proof of correctness and $TID$ is the auction identifier $ID$. Finally, user $i$ signs this commitment $c_i$ and the encrypted value $e_i$. Then he adds $\text{sign}_i(c_i)$ to the list $l^w_i$ on the bulletin board and sends $\text{sign}_i(e_i)$ to platform. Receiving all users’ values $\text{sign}_i(e_i)$, the platform decrypts and sorts them, thereby obtaining the user $i$ with the maximal encrypted marginal utility per bid. Moreover, the platform enters the following winner determination phase.

![Fig. 4. Our verifiable phase for homogeneous and heterogeneous jobs.](image-url)
(a) **Winner Determination:** Firstly, the platform applies the homomorphic encryption scheme to compute the utility $U(S \cup \{i\})$ according to Algorithm 4, thereby obtaining $\omega_{p,0} = U(S \cup \{i\})/B$. By using the Algorithm 6, the platform interacts with the AI, and receives the encrypted $\omega_{p,0}$. The platform makes a commit $c_{p,0} = E_{TPK}(\omega_{p,0}|TID)$, where $TID$ is a randomly generated bit string for the proof of correctness and $TID$ is the auction identifier $ID$. Signing it, $\text{sign}_{p}(c_{p,0})$, the platform adds it to the list $l_{p}^{0}$ on the bulletin board. If $\omega_{i,0}(0) \geq \omega_{p,0}$, the platform will give user $i$ a notice that he is a winner. Then the user returns an acknowledgement and his encrypted $\Gamma_{i}$ and $\beta_{i}$ by using the platform’s public key. Receiving the acknowledgement, the platform adds user $i$ to the winners’ set $S$. Then it sorts all these encrypted marginal utilities per bid, i.e., $\omega_{i,1}$, by using the same method as the computation of $\omega_{i,0}$. These users also add their signed commitments to their corresponding lists $l_{p}^{i}$ on the bulletin board. When the platform receives all these $\omega_{i,1}$, it sorts them, thereby knowing which user has the maximal encrypted marginal utility per bid. The process is repeated until the $(k + 1)$-th user’s $\omega_{i,k+1}(0) < \omega_{p,k+1}$. Finally, we obtain the winners’ set that consists of $k$ users.

**Algorithm 6: Winner determination for sensing submodular jobs**

**Input:** User set $U$, the budget constraint $B$.

**Output:** ‘The winners’ set $S$.

1. $S \leftarrow \emptyset$; For every $j \in U$, the platform recovers $\omega_{j,0}(S)$ by using the decryption algorithm, and sorts all these values in a decreasing order, thereby obtaining the user $i$ with the maximal encrypted marginal utility per bid, i.e., $i \leftarrow \max_{j \in U} \omega_{j,0}(S)$;

2. The platform obtains $\omega_{p,0}(S)$ by using Algorithm 3 and 4 and adds a signed commitment to the list $l_{p}^{0}$ on the bulletin board;

3. while $\omega_{i,0}(0) \geq \omega_{p,0}$ do

4. The platform notices that user $i$ is a winner;

5. Receiving an acknowledgement, the platform adds user $i$ to the winner set $S$, i.e., $S \leftarrow S \cup \{i\}$;

6. Notify each user $j \in U \setminus S$ to compute his encrypted marginal utility per bid, i.e., $\omega_{j,1}$, by using the same method as the computation of $\omega_{i,1}$; Obtaining all these encrypted marginal utilities per bid, the platform finds the user $i$ so that $i \leftarrow \max_{j \in U \setminus S} \omega_{j,1}(S)$;

7. The platform obtains $\omega_{p,1}(S)$ by using Algorithm 3 and 4 and adds a signed commitment to the list $l_{p}^{1}$ on the bulletin board;

8. end while

9. return $S$;

(b) **Payment Determination:** At this stage, the encrypted values from the above OT algorithm cannot support the preserving rank under the multiplication opera-
tion. To address this challenge, we introduce the homomorphic encryption schemes, which enable multiplication operation of encrypted values without revealing privacy about the values themselves and the results of the computation (see equation (3)).

Firstly, at time $T$, for each winner $i \in S$, its payment computation from the platform is given in the following description. The platform initializes the user set $U'$ and set $T$ by using $U' \leftarrow U \setminus \{i\}$ and $T \leftarrow \emptyset$. Differentiating from the above winner set, we refer to $T$ as a referenced winner set. Each user $j \in U' \setminus T$ initially computes his marginal utility $U_j(\emptyset)$, thereby obtaining his encrypted marginal utility per bid $e_{j,0} = E_{AI}(\omega_{j,0}(\emptyset))$ by using the AI's homomorphic encryption public key. He makes a commit $c_{j,0}$ by using the above method. Finally, user $j$ signs this commit $c_{j,0}$ and the encrypted value $e_{j,0}$. Then he adds $sign_j(c_{j,0})$ to the list $l_{p,j}$ on these bulletin board (meaning that the list is used to put user $j$'s commitment for the computation of user $i$'s payment) and sends the $sign_j(e_{j,0})$ to the platform. Receiving the values of all users in $U'$, the platform sorts them, thereby obtaining the user $i_j$ with the maximal encrypted marginal utility per bid (i.e., $e_{i_j,0}$). Then the platform notices that user $i_j$ is a referenced winner and requests user $i$ for obtaining the $E_{AI}(U_{i_j}(j))$. After user $i_j$ receives the request, he computes the value $E_{AI}(U_{i_j}(j))$ by applying the above MPEP and AI's encryption public key. Signing it, he sends the signed $E_{AI}(U_{i_j}(j))$ to the platform. According to the homomorphic encryption, we have $E_{AI}(b_{ij}(j)) = E_{AI}(U_{i_j}(j) \cdot b_{ij} / U_{i_j}) = E_{AI}(U_{i_j} / \omega_{i_j}) = E_{AI}(U_{i_j})^{1 / e_{i_j,0}}$. Similarly, we can obtain $E_{AI}(\eta_{ij}(j)) = E_{AI}(U_{i_j}(j) \cdot B / U(T_j - \{i\})) = E_{AI}(U_{i_j}(j) / \omega_{p,j}) = E_{AI}(U_{i_j})^{1 / e_{p,j}}$, where $e_{p,j}$ means the encrypted marginal utility per bid when there are $j$ referenced winners. Since user $i$ is a true winner, the platform knows his bid and sensing preference $\Gamma_i$. Thus, the platform can compute the value $e_{p,j}$. Receiving the value $E_{AI}(U_{i_j}(j))$, the platform can obtain $E_{AI}(b_{ij}(j))$ and $E_{AI}(\eta_{ij}(j))$. Furthermore, the interim payment can be obtained by using the homomorphic encryption comparison operation. Subsequently, the platform adds user $i_j$ to the referenced winners' set. The process is repeated until the $(k' + 1)$-th user's $e_{i_{k'+1},k'+1}(T_{k'}) < e_{p,k'+1}(T)$. Finally, we obtain the payment of winner $i$. Other winners' payments are computed by adopting the same method as the winner $i$'s payment. The detailed description is given in Algorithm 7.

5.3.3. Decommitment Round for Verification. Since the mechanism itself is truthful, i.e., each user always submits his true cost, we only need to demonstrate that any user can verify the payment correctness of the platform on his own.

**Verification:** The verification process is similar to the above description (see Fig. 4). The only difference is that three dynamic lists in the bulletin board are used to recover associated values for the payment computation of each user. Generally speaking, some user initially sends the request of verification to the AI with the probability $\alpha$. Receiving the request, the AI runs the algorithm description on the bulletin board with the help of the values in the three lists until the payment is obtained. For more details of verification, we refer readers to Section 5.2.4 and Fig. 4.

5.3.4. Privacy-preserving Verifiable Incentive Mechanism for Sensing Submodular Jobs. In our truthful privacy-preserving verifiable incentive mechanism for sensing Submodular jobs, the platform determines a winner $i$'s payment illustrated in Algorithm 8. At the initial stage, there are some initial parameters specified by the platform. Then, the platform performs the winner selection algorithm and the payment determination algorithm. Once the platform finishes the payment, the user $i$ will request the AI to verify the platform's payment correctness with the probability $\alpha$. About the detailed descriptions of privacy preservation and verification are given in Algorithm 6. Algorithm 7 and Algorithm 8.
ALGORITHM 7: Payment determination for sensing submodular jobs

Input: User set $\mathcal{U}$, the budget constraint $B$, the set of winners $S$.
Output: $(\mathcal{U}, p)$.
1: for each user $i \in \mathcal{U}$ do
2: $\hat{p}_i \leftarrow E_{AI}(0)$;
3: end for
4: for all user $i \in S$ do
5: $\mathcal{U}' \leftarrow \mathcal{U}\{i\}$; the referenced winners’ set $T \leftarrow \emptyset$
6: repeat
7: Every $j \in \mathcal{U}'$ computes his encrypted marginal utility per bid $c_{j,T}$ by using $AI$’s homomorphic encryption public key for sending to the platform, and adds a signed commitment $\text{sign}_j(c_{j,T})$ to the list $l_{p,i}$ on these bulletin board; Receiving these encrypted values, the platform sorts them in a decreasing order, thereby obtaining the user $i_j$ with the maximal encrypted marginal utility per bid, i.e., $i_j \leftarrow \arg \max_{j \in \mathcal{U}' \setminus T} c_{j,T}(T)$;
8: Notice that user $i_j$ is a referenced winner and requests user $i$ for obtaining the $E_{AI}(U_i(j))$;
9: According to the description of Section 5.3.2, the platform computes $E_{AI}(b_{i_j})$ and $E_{AI}(\eta_{i_j})$ by applying equation (3); Obtain $\hat{p}_i \leftarrow \max\{\hat{p}_i, \min\{E_{AI}(b_{i_j}), E_{AI}(\eta_{i_j})\}\}$;
10: $T_{k+1} \leftarrow T_k; T \leftarrow T \cup \{i_j\}$
11: until $c_{i,k+1}(T_{k'}) < c_{p,k'+1}(T)$ or $T = \mathcal{U}'$
12: The platform requests the $AI$ for obtaining the payment, i.e., $p_i = D_{AI}(\hat{p}_i)$, where $D_{AI}$ denotes the decryption by using the $AI$’s private key;
13: end for
14: return $(\mathcal{U}, p)$;

ALGORITHM 8: PVI-S/ Privacy-preserving Verifiable auction mechanism for Crowd sensing application with sensing Submodular jobs

Input: User set $\mathcal{U}$, the budget constraint $B$.
Output: $(\mathcal{U}, p)$.
1: Initialize the auction information and encryption tools;
2: Choose the winners by applying the algorithm ;
3: Finish the payment for each winner;
4: The user requests the $AI$ to verify the payments with the probability $\alpha$;
5: return $(\mathcal{U}, p)$;

6. PRIVACY, VERIFIABILITY AND REVENUE ANALYSIS

6.1. Privacy of Users and Platform

Our mechanisms’ private information include users’ privacy and platform’s privacy, i.e., the sensing profile privacy of users and the current winners’ set privacy of the platform. Assume that there are two kinds of adversaries: adversarial users and adversarial platform or AI. The specific analysis is given as follows.

Lemma 1. The mechanisms PVI-H and PVI-S are privacy-preserving for users.

Proof. We only need to consider two cases in which the privacy of each user $i$ may be leaked as follows. The first case is for the adversarial platform or $AI$. In the two mechanisms, the platform performs the winners’ selection, and only can know the $(k+1)$-th user’s sensing profile $P_{k+1}$, but does not know which user it belongs to. In the stage of verification, similarly, the $AI$ also knows the $(k+1)$-th user’s sensing profile $P_{k+1}$, and does not know which user it belongs to. The $AI$ and platform only know the...
encrypted sensing profile, but have no way to decrypt any of them. No other party can get even more information than the platform or AI. On the one hand, user $i$ gets his sensing profile $P_{k+1}$ through a 1-out-of-$z$ OT from the AI, who is unaware of which sensing profile have been accessed by the user. User $i$ sends the encrypted sensing profile to the AI, who cannot decrypt the encrypted sensing profile without knowing the private key of asymmetric encryption scheme. Even if the AI may know the $(k+1)$-th user’s sensing profile later when the platform consults him, he still cannot infer his user owing to the random number. Thus, the AI cannot know the user of $(k+1)$-th user. Additionally, although the platform can obtain the $(k+1)$-th user’s sensing profile later, he can only reversely map the encrypted $(k+1)$-th user’s sensing profile to the original $(k+1)$-th user’s sensing profile with the help of the AI. However, the platform still cannot derive the user, to which $(k+1)$-th user’s sensing profile belongs out of at least $k$ members according to the Theorem 3.2 in [Singer 2010] due to a large number of users much larger than $k$ existing in the crowd sensing applications. Therefore, neither the AI, nor platform, can know any user’s sensing profile with the probability higher than $1/k$, thereby guaranteeing $k$-anonymity.

The second case is for an adversarial user. In the two mechanisms, an adversarial user $j$ does not learn side information during our mechanisms no matter he is a winner or not. All he learns from the two mechanisms are included in the valid auction’s Output, i.e., for an adversarial user $j$’s advantage $\text{adv}_P$, are all equal to 0 for all $i \neq j$.

Putting them together, the lemma holds. □

Besides, in the following lemma, we also analyze the privacy preservation performance of the platform.

**Lemma 2.** For the current winners’ set $S$ and referenced winners’ set $T$ of the platform (the privacy of the platform), an adversarial user $j$’s advantage, i.e., $\text{adv}_S$ and $\text{adv}_T$, are equal to 0. In other words, the mechanisms PVI-H and PVI-S are privacy-preserving.

**Proof.** For the current winners’ set $S$ and referenced winners’ set $T$, only platform and AI learn the two sets and each user learns nothing. Since the AI is semi-honest, and only check the platform randomly, adversarial users gain no useful information on the two sets from the communication strings. Thus, the priori probability is same as the posterior probability, i.e., $\text{Adv}_S = P_i[S|C, Output] - P_i[S|Output] = 0$ and $\text{Adv}_T = P_i[T|C, Output] - P_i[T|Output] = 0$. Thus, the mechanisms PVI-H and PVI-S are privacy-preserving for the platform. Thus, the lemma holds. □

Putting these lemmas together, we have the following theorem.

**Theorem 1.** The mechanisms PVI-H and PVI-S are privacy-preserving.

### 6.2. Verifiable Correctness of Payments

**Lemma 3.** The users in the mechanisms PVI-H and PVI-S is truthful.

**Proof.** For the mechanism PVI-H, we can easily extend the outcome of the homogenous jobs presented by Singer et al. [Singer 2010] the proof outcome to the homogenous jobs. For the mechanism PVI-S according to [Yang et al. 2012], since Algorithm PVI-S is designed based on the MSensing mechanism of [Yang et al. 2012], they have demonstrated the truthfulness of the mechanism, our mechanism PVI-S is also truthful for users in crowd sensing applications. Thus, the lemma holds. □

Generally speaking, the verifiability issue includes the Verifiability of users’ sensing profile and platform’s payment. From the above lemma we know that users’ bid is truthful. Besides, each user’s subset of assignments is fixed in our mechanisms.
Thus, each user's sensing profile is truthful. Therefore, we only need to guarantee the verifiable correctness of payments from the platform. Furthermore, we have the following lemma.

**Lemma 4.** The two proposed mechanisms, i.e., PVI-H and PVI-S, are correct for a rational platform.

**Proof.** Correctness of both PVI-H and PVI-S, follows from the assumption that the assumption that the platform is rational and the fine that he pays when checked cheating is high enough. If his expected utility when complying with both PVI-H and PVI-S is higher than his expected utility from his deviation he will abide by the algorithm, as such the proposed algorithms i.e. PVI-H and PVI-S, will be correct. We will show the probability $\alpha$ that the platform's incorrect payment will not be checked by the user with the help of the AI, set by the two algorithms i.e. PVI-H and PVI-S, ensures that the platform's expected utility is non-positive [Catane and Herzberg 2013].

\[ \alpha \geq \frac{p_{\text{max}}}{f + p_{\text{max}}} \Rightarrow (1 - \alpha)p_{\text{max}} - \alpha f \leq 0. \]

Considering the platform's expected utility, i.e., \((1 - \alpha)V_+ + \alpha V_-\), where \(V_+\) denotes the platform's utility when it gives incorrect payment but is not checked by the users, and \(V_-\) denotes the platform's utility when it gives incorrect payment but is checked by the users. Again, \(p_{\text{max}} \geq V_+\) and \( -f = V_-\), according to the outcome of the above derivation, further, we have \((1 - \alpha)V_+ + \alpha V_- \leq (1 - \alpha)p_{\text{max}} - \alpha f \leq 0\). Thus, if the platform does not comply with the algorithm PVI-H, its expected utility is non-positive. As such, for a rational platform, it is willing to abide by the rules of both PVI-H and PVI-S, and gives a correct payment for every user. Finally, the lemma holds.

Putting these lemmas together, we have the following theorem.

**Theorem 2.** The mechanisms PVI-H and PVI-S are verifiable correctness of payments.

6.3. Revenue of Platform

**Lemma 5.** The mechanisms in Section 4 are $O(1)$-competitive in maximizing the revenue of the platform.

**Proof.** To quantify the revenue of the platform running the mechanisms in Section 4, we compare their revenue with the optimal revenue: the revenue obtainable in the offline scenario where the platform has full knowledge about users' sensing profiles. A mechanism is $O(1)$-competitive if the ratio between the mechanism's revenue and the optimal revenue is a constant factor approximation. According to the Theorem 3.4 in [Singer 2010] and Theorem 4.5 in [Singer 2010], we know that the mechanisms in Section 4 are budget feasible constant-approximation mechanisms, and no budget feasible mechanism can do better than mechanisms of Section 4 in maximizing the homogeneous, heterogeneous sensing revenue and submodular sensing revenue of the platform. Thus, the lemma holds.

Furthermore, different from the mechanisms in Section 4, mechanisms PVI-H and PVI-S mainly apply the order preserving encryptions and the OT operations. However, these encryptions and operations in mechanisms PVI-H and PVI-S do not change the allocation and payment rules of the mechanisms in Section 4. Thus, mechanisms PVI-H and PVI-S keep the same revenue as the mechanisms in Section 4, thereby obtaining the following theorem.

**Theorem 3.** The mechanisms PVI-H and PVI-S achieve the same revenue as the generic one without privacy preservation.
7. PERFORMANCE EVALUATION

In this section, we analyze the communication and computation overhead to show our construction is both scalable and efficient, thereby applying to mobile devices for crowd sensing applications. Most of the complexities are linear to the number of users or the number of assignments, which allows huge number of users or the number of assignments. Meanwhile, the extra data transmission and the run time introduced by our mechanisms are almost negligible.

7.1. Simulation Setup

To better evaluate the computation overhead, we implemented the PVI mechanism in Ubuntu 12.04 using the GMP library based on C in a computer with Intel(R) Core(TM)i5-3470 CPU 3.20GHz. The order $p$ of the integer group $\mathbb{Z}_p$ is selected as a 1024-bit prime number, and users can get 128 bits of order-preserving encrypted value through oblivious transfer with the AI. Every operation is run 100 times to measure the average run time.

7.2. Performance Evaluation for The PVI-H Mechanism

7.2.1. Bulletin Board Storage Complexity. We require the bulletin board to store the auction details and dynamic lists used to store the parameters or values accessed by the platform and AI. In each list, there are only few elements. Therefore, the storage complexity is $\theta(n)$, where $n$ is the number of users.

7.2.2. Communication Overhead. The communication overhead based on the data transmission is illustrated in Table I where $b_{bit}$ is the bit length of the $p$ (i.e. the order of the integer group $\mathbb{Z}_p$).

Note that the computation of accumulated assignments in the winner determination phase is executed until the platform finds the largest $k$ so that $b_i \leq B/\sum_{j \leq i} t_j$ holds. Thus, the average communication rounds for the platform should be much less than $O(mn)$, which means that the real communication overhead will be much less than the worst case $O(mnb_{bit})$. Since the verification from the AI does not need the communication for the computation of accumulated assignments, it only requires information from the existing bulletin board. Thus their communication overhead is negligible. Fig. 6(a) shows that the overall communication overhead induced by Algorithm PVI-H. Obviously, the communication overhead is mainly from the OT.

| Table I. Communication Overhead of PVI-H |
|-----------------------------------------|
| **Winner Selection**                    |
| Send | Receive | $\omega_i$ computation | User sorting |
| Users | $O(n)$ | $O(n)$ | $O(n)$ | 0 |
| Platform | $O(mn)$ | $O(n)$ | 0 | $O(n^2)$ |
| AI | $O(n)$ | $O(n)$ | 0 | $O(n^2)$ |
| **Payment Determination**                |
| Each winner | $O(1)$ | $O(1)$ | $O(n)$ | 0 |
| Platform | $O(m^2)$ | $O(m)$ | 0 | $O(m^2)$ |
| AI | $O(n)$ | $O(n)$ | 0 | $O(n^2)$ |
| **Verification**                         |
| Each winner | $O(1)$ | $O(1)$ | 0 | 0 |
| Platform | $O(n)$ | $O(n)$ | 0 | $O(n^2)$ |
| AI | $O(n)$ | $O(n)$ | 0 | $O(n^2)$ |
7.2.3. Computation Overhead. In theory, the overhead of the computation is summarized in Table II.

In the PVI-H mechanism, the auction is composed of the winner selection phase and the payment determination phase. The winner selection phase mainly includes the OT, the sorting, users’ blind signature generation and the computation of accumulated assignments; the payment determination phase mainly includes the payment calculation of the platform. For each user’s verification, since data applied to verify the payment are stored in the bulletin board, the computation overhead of the verification is negligible when compared with the above parts. Thus, we do not account for it. Next, we analyze their run time in turn.

Table II. Computation Overhead of PVI-H

|                | Winner selection | Payment determination | Verification |
|----------------|------------------|------------------------|--------------|
| Users          | $O(1)$           | $O(1)$                 | $O(1)$       |
| Platform       | $O(nm^2)$        | $O(nm^3)$              | 0            |
| AI             | $O(1)$           | $O(1)$                 | $O(nm^3)$    |

(a) Blind Signature Generation: In the PVI-H mechanism, the signer’s run time for the user’s one is 19 ms and blindly generating one pair of the Nyberg-Rueppel signature is 11 $\mu$s (microseconds) on average.

(b) Calculation of Assignments and Payment:
Since a single calculation needs 0.4$\mu$s on average, and the overall computation overhead is very small, the run time of the calculation of accumulated assignments and payment for various number of assignments and payment is almost negligible.

7.3. Performance Evaluation for The PVI-S Mechanism

7.3.1. Bulletin Board Storage Complexity. We require the bulletin board to store the auction details and three dynamic lists of each user used to store the values accessed by the AI. In each list, there are only few elements. Therefore, the storage complexity is $\theta(n)$, where $n$ is the number of users.

7.3.2. Communication Overhead. The communication overhead in terms of transmitted bits is summarized in Table III. Note that the marginal-utility-per-bid computation in the winner selection and payment determination is executed until the platform and AI finish the winner selection and the payment determination. Because there are $m$ different assignments, and each winner should contribute at least one new assignment to be chosen, the number of winners in the payment determination phase is at most $m$. Thus, the average communication rounds for the platform should be much less than $O(m^2)$, which means the practical communication overhead will be much less than the worst case $O(m^2)$. Besides, the MPEP’s introduction for the marginal-utility-per-bid computation, makes the communication overhead of each user different with the PVI-H mechanism (see Table III).

7.3.3. Computation Overhead. In theory, the overhead of the computation is summarized in Table IV.

In general, the PVI-S mechanism consists of the winner selection phase, the payment determination phase, and the verification phase. The winner selection phase includes users’ blind signature, the sorting of the platform and the computation of marginal utility per bid. The payment determination phase includes the sorting of the platform and the computation of marginal utility per bid. In the verification phase, since data applied to verify the payment are stored in the bulletin board, the computation overhead of the verification is negligible when compared with the above parts. Thus, we do not account for it. Now, we analyze their run times respectively.
Table III. Communication Overhead of PVI-S

|                | Send                  | Receive                | $\omega_i$ computation | User sorting |
|----------------|-----------------------|------------------------|-------------------------|--------------|
| Users          | $O(n^2)$              | $O(n^2)$               | $O(n)$                  | 0            |
| Platform       | $O(n\cdot m)$         | $O(n)$                 | 0                       | $O(n^2)$     |
| AI             | $O(n)$                | $O(n)$                 | 0                       | $O(n^2)$     |

Payment Determination

|                | Each winner | Platform | AI |
|----------------|-------------|----------|----|
|                | $O(1)$      | $O(m^2)$ | $O(m)$ |
|                | $O(1)$      | $O(n)$   | $O(n^2)$ |
| Verification   | $O(1)$      | $O(n)$   | $O(n^2)$ |
|                | $O(1)$      | $O(n)$   | $O(n^2)$ |

Table IV. Computation Overhead of PVI-S

|                | Winner selection | Payment determination | Verification |
|----------------|------------------|------------------------|--------------|
| Users          | $O(1)$           | $O(m^2)$               | $O(1)$       |
| Platform       | $O(n\cdot m^2)$  | $O(n\cdot m^2)$        | $O(1)$       |
| AI             | $O(1)$           | $O(1)$                 | $O(n\cdot m^2)$ |

(a) Sorting, OT and Blind Signature: The PVI-S mechanism’s run time for one pair of the Nyberg-Rueppel signature including the AI, platform and users is 28 milliseconds on average. Further, we also evaluated the run time of the OT as well as the final sorting based on the encrypted values. We observed that the computation overhead of the signature is negligible when compared with the one of the OT and sorting. Users in the PVI-S have much less run time since they only generate the communication strings (ciphertexts) (see Fig. 6(b)).

(b) Computation of AI, Platform, Winners and Losers: We compared the computation overhead of the AI, the platform, winners and losers in Fig. 6(c) when the budget value is 2000. We observed that the computation overhead increases with the budget constraint and at last they were kept in a stable constant value respectively. It is because that at this moment the PVI-S mechanism reached saturation point.

(c) Effect of Budget Constraint on Computation Overhead: To assess the effect of different budget constraints on computation overhead of each winner $i$, we calculated the average computation overhead of each winner for different budget values respectively. We observed that the overall computation overhead increased with the number of winners at last reached a stable value (see Fig. 6(d)). The computation overhead of each user is very small, therefore the overhead induced by the PVI-S mechanism also can be applied to wireless mobile devices for crowd sensing applications.

8. CONCLUDING REMARKS

In this paper, we design two privacy-preserving verifiable incentive mechanisms for crowd sensing applications. We not only address the privacy preservation of users and the platform by applying the OPES and OT, but also provide a verification scheme for the payment correctness from the platform by using the signature technology and the bulletin board. We preserve the rank of the encrypted values by using the OPES scheme. Furthermore, we prevent bid repudiation by employing a TLC service. No party, including the platform, receives any information about bids before the mechanism closes, and no user is able to change or repudiate any sensing profile. Finally, we design and analyze the two mechanisms. Results from theory analysis and experiments indicate that our privacy-preserving verifiable incentive mechanisms achieve the same results as the generic one without privacy preservation and apply for mobile devices in crowd sensing applications. As such, they can apply generally or be extended to other truthful incentive mechanisms for real crowd sensing environments.
Fig. 6. (a) Communication overhead of PVI-H with different budgets; (b) Run time of the sorting, the OT and the blind Signature of PVI-S with the number of users when the value of the budget is 2000; (c) Run time of the AI, the platform, losers and winners of PVI-S with the number of users when the value of the budget is 2000; (d) Effect of budget constraint of PVI-S on computation overhead.

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