Selecting Most Informative Contributors with Unknown Costs for Budgeted Crowdsensing

***Abstract*—Mobile crowdsensing has become a novel and promising paradigm in collecting environmental data. A critical problem in improving the QoS of crowdsensing is to decide which users to select to perform sensing tasks, in order to obtain the most informative data, while maintaining the total sensing costs below a given budget. The key challenges lie in (i) finding an effective measure of the informativeness of users' data, (ii) learning users' sensing costs (*e.g.*, time and battery consumption) which are unknown a priori, and (iii) designing efficient user selection algorithms that achieve low-regret guarantees. In this paper, we build Gaussian Processes (GPs) to model spatial locations, and provide a mutual information-based criteria to characterize users' informativeness. To tackle the second and third challenges, we model the problem as a budgeted multi-armed bandit (MAB) problem based on stochastic assumptions, and design algorithms for both static and dynamic scenarios respectively with theoretically proven low-regret guarantees. Our theoretical analysis and evaluation results both demonstrate that our algorithms can efficiently select most informative users under stringent constraints.**

I. Introduction

The rapid proliferation of smartphones is evolving the way we collect information of environmental phenomena. Most of the smartphones and wearable devices are embedded with various types of sensors, *e.g.*, GPS, accelerometer, gyroscope, proximity sensor, and thermometer, which can be utilized to monitor users' surrounding environment and infer human activities. Mobile crowdsensing [1], as a new sensing paradigm raised in recent years, employs smartphone users to collect and share their local information. It has been applied in a broad range of applications, including localization [2], [3], environmental monitoring [4], transportation [5], [6], and indoor floorplan construction [7].

In monitoring environmental phenomena (*e.g.*, air quality, noise, or temperature), one of the important QoS problems that have not been carefully addressed in crowdsensing is how to reduce the redundancy of the collected information. Specifically, we intend to select the users whose data are most informative about the monitored environment. This is motivated by two insights from spatial statistics [8]. First, the environmental conditions of two nearby locations tend to be similar [9]. If the sensing data of some specific locations have already been collected, it is of less necessity to collect nearby information. Second, in many cases, environmental conditions have certain spatial correlations [10], which allow us to model existing observations and make predictions for unobserved locations. Thus, it is of great significance to select users who are most informative about unobserved locations, especially under the circumstances where the crowdsensing platform has only limited budget to pay the users.

In mobile crowdsensing, performing a sensing task requires users to devote not only their time and intelligence, but also the hardware resources (*e.g.*, battery, computation resource, and storage space) of their smartphones. To motivate users' participation, the platform needs to pay a certain amount of reward to those selected users. Given a limited budget, a natural idea is to make use of the budget feasible mechanisms [11], [12]. However, directly applying these approaches to crowdsensing scenarios incurs at least three practical limitations.

First, letting users determine their own deserved payments has critical drawbacks. Existing works on crowdsensing (*e.g.*, [12]–[14]) are usually based on a reverse-auction model, where each user is assumed to be aware of her sensing cost and submits her cost as a reverse price, or bid, for performing a requested task. However, this assumption may not be practical in reality, since users' contributions in a crowdsensing task are not purely financial, but involve hardware consumptions (*e.g.*, battery, CPU, and storage) and their data qualities. Quantifying the consumption of users' hardware resources requires complicated technical skills, and hence is infeasible for most users. Furthermore, the payment that each user deserves should be related to her data quality [15]. Intuitively, users with high data qualities deserve higher payments, and vice versa. Thus, instead of passively listening to users' bids, we prefer a more "aggressive" crowdsensing platform that actively quantifies users' contributions and determines their deserved payments in a proper manner.

Second, even though the state-of-the-art techniques (*e.g.*, energy accounting [16] and data mining [17]) can be applied to quantify users' hardware consumptions and data qualities, such information is unknown to the platform in advance. In other words, the platform can access to a user's sensing cost and data quality of a specific task only after the user has finished the task and submitted her sensing data. Thus, an online learning and decision-making process [18] is required to estimate users' expected costs from their historical records. One approach is to divide the task into multiple rounds, *s.t.*, the platform can learn users' costs after each round, and decide which users to select in the next round, based on users' expected costs. However, the multi-rounded scenarios really complicate the budgeted optimization of the total informativeness, even with the full knowledge of users' costs.

Last but not least, the unavailability of prior knowledge on users' sensing costs further brings another challenge in user selection. Suppose we have already found some cheap and informative users, we need to decide whether to keep selecting these users to maintain good performance, or to select other users in hope of finding even cheaper and more informative ones. This is an instance of the *exploration* and *exploitation* dilemma in reinforcement learning [19], where an agent needs to decide whether to explore new information about the effectiveness of an action, or to exploit the action that is already known to be effective.

In this paper, we address the problem of selecting the most informative users, while the platform has no prior knowledge of users' sensing costs and the total payments are limited by a fixed budget. We model the spatial environment using the Gaussian Processes (GPs), and adopt the mutual information criteria to quantify the informativeness of users. We show that our characterization of the informativeness is a nonnegative monotone submodular function. Next, we consider an unrealistic but instructive scenario where the platform has full knowledge of users' costs. To tackle the NP-hardness of the budgeted maximization of submodular functions, we propose an efficient multi-rounded algorithm that achieves $(1-1/e)/2$ approximation ratio. Then, we consider a realistic scenario where the prior knowledge of users' costs is not available. We examine the major contributing factors of users' sensing costs, and propose two efficient Budgeted Informativeness Maximization algorithms, namely BIM-ST and BIM-DY, to actively learn users' costs and decide which users to select. BIM-ST considers a static scenario where users' locations are fixed during the entire task, while BIM-DY assumes that users may move during the intervals between two consecutive rounds. Our theoretical analysis shows that both algorithms achieve zero regret in an asymptotic case. We also evaluate our proposed algorithms in various settings. Our evaluation results demonstrate good performance of our algorithms.

Our main contributions are listed as follows:

- First, we investigate the problem of selecting most informative users in crowdsensing with budget constraint and no prior knowledge of users' sensing costs, and provide a mutual information-based criteria to quantify users' informativeness based on a Gaussian Process model.
- Second, we propose an efficient multi-rounded informativeness maximization algorithm with full knowledge of users' sensing costs, and achieve $(1-1/e)/2$ approximation ratio of the optimum.
- Third, without the prior knowledge of users' costs, we propose two stochastic MAB algorithms, which tackle different user movements and balance the exploration and exploitation tradeoff.
- Finally, we implement and evaluate our proposed algorithms in various settings. Our evaluation results show that our proposed algorithms can efficiently select most informative users under the budget constraint.

The rest of this paper is organized as follows. We first present an overview of our proposed approaches in Section II. Then, we address the budgeted informativeness maximization with and without prior knowledge in Section III and Section IV, respectively. In Section V, we evaluate our algorithms and present the evaluation results. The related works are presented in Section VI. Finally, we conclude this paper in Section VII.

II. System Overview

In this section, we first formalize our problem, present the characterizations of users' informativeness and sensing costs, and finally introduce the multi-armed bandit problems.

A. Problem Statement

A typical crowdsensing architecture consists of three major components: service requesters, mobile device users, and a crowdsensing platform. After receiving location-based sensing requests from the service requesters, the platform releases specific sensing tasks to the mobile device users (we will refer as users for simplicity). Without loss of generality, we focus on one task only, *e.g.*, noise monitoring at a specified park. We assume that the task consists of T consecutive rounds and each round has a fixed duration D. The specified sensing area is represented by a set of finite discrete locations $\mathcal{L} = \{l_1, l_2, \dots, l_m\}$, *e.g.*, a grid discretization of $\mathbb{R}^2$.

Users interact with the platform through a pre-installed mobile application. They can check the released tasks and register to their interested tasks on their smartphones. Suppose there is a set $\mathcal{N} = \{1, 2, \dots, n\}$ of users interested in the task. For simplicity, we consider a fixed set of users through entire T rounds of the sensing task. The settings, where users can join and leave during the task, do not fundamentally complicate our problem. At the beginning of each round $t \in \{1, 2 \dots, T\}$, the platform selects a subset of users $\mathcal{S}_t \subseteq \mathcal{N}$ to sense in this round, based on users' informativeness and expected costs, and the platform's remaining budget. After round t, each selected user $i \in \mathcal{S}_t$ submits her sensing data and receives her payment $p_{i,t}$ of this round. Users' real-time locations are measured by the GPS modules of their smartphone and reported to the platform via WiFi or celluar network. During each round t, each selected user $i \in \mathcal{S}_t$ is required to stay at a same location, denoted by $l_{i,t}$. But they are allowed to move during the intervals between two consecutive rounds (as in BIM-DY).

The main objective of the crowdsensing campaign is to maximize the total informativeness within a given budget B. We let $F(\mathcal{S})$ denote how informative a set $\mathcal{S} \subseteq \mathcal{N}$ of users is. Our problem is formalized as follows:

$$\max_{\mathcal{S}_t \subseteq \mathcal{N}} \sum_{t=1}^{T} F(\mathcal{S}_t), \text{subject to} \sum_{t=1}^{T} \sum_{i \in \mathcal{S}_t} p_{i,t} \leq B. \quad (1)$$

B. Quantifying Informativeness

In deciding which users to select to maximize the informativeness, one approach is to assume that each users has a fixed sensing radius and to treat this problem as a coverage maximization problem [20]. However, this approach does not suit environmental crowdsensing, because the spatial environmental correlations between different locations are usually complicated and cannot be simply characterized by a regular disk, as also pointed out by [21], [22].

In this paper, we adopt the mutual information criteria [23] to model users' informativeness. We associate a random variable X_{l_s} with each location $l_s \in \mathcal{L}$. For a subset $\mathcal{S} \subseteq \mathcal{N}$, let $\mathcal{L}_\mathcal{S} \subseteq \mathcal{L}$ denote the set of locations of users $\mathcal{S}$, then $X_{\mathcal{L}_\mathcal{S}}$ is the set of random variables associated with the locations $\mathcal{L}_\mathcal{S}$. To simplify notation, we write l_s instead of X_{l_s} and $L_\mathcal{S}$ instead of $X_{\mathcal{L}_\mathcal{S}}$. Before we present the formal definition of mutual information, we first briefly review the concept of entropy.

Definition 1 (Entropy [23]). *The (differential) entropy $H(X)$ of a random variable X is defined by*

$$H(X) = -\int_{\mathcal{X}} p(x) \log p(x)\, dx. \quad (2)$$

Entropy is a measure of uncertainty of a random variable, and could be an intuitive criteria to characterize the informativeness. However, it has been pointed out [24] that the entropy-based selection schemes tend to select sensing points located along the boundary of the space and thus may lose information. To address this limitation, mutual information-based methods have been adopted in various scenarios (*e.g.*, sensor placement [21], [22] and feature selection [25]).

Definition 2 (Mutual Information [23]). *The mutual information $I(X;Y)$ between two random variables X and Y are defined as*

$$I(X;Y) = \int_{\mathcal{Y}} \int_{\mathcal{X}} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} dx\, dy. \quad (3)$$

Intuitively, mutual information measures the information that X and Y share, *i.e.*, how much knowing one of these variables reduces uncertainty about the other. For example, if X and Y are independent, then knowing X does not give any information about Y and vice versa, and thus their mutual information is zero. In monitoring spatial environment, suppose we have already deployed users $\mathcal{S} \subseteq \mathcal{N}$ to perform the sensing task, then $I(\mathcal{L}_\mathcal{S}; \mathcal{L}\backslash\mathcal{L}_\mathcal{S})$ represents how much knowledge observing $\mathcal{L}_\mathcal{S}$ gives about the unobserved locations $\mathcal{L}\backslash\mathcal{L}_\mathcal{S}$. According to Equation (2) and (3), we have

$$I(X;Y) = H(X) + H(Y) - H(X,Y), \quad (4)$$

where $H(X,Y) = -E[\log p(X,Y)]$ is the the joint entropy of X and Y. We define the informativeness function as:

$$F(\mathcal{S}) = I(\mathcal{L}_\mathcal{S}; \mathcal{L}\backslash\mathcal{L}_\mathcal{S}), \quad (5)$$

so that maximizing the informativeness of selected users is equivalent to finding the subset $\mathcal{S}$ of users such that the mutual information between $\mathcal{L}_\mathcal{S}$ and $\mathcal{L}\backslash\mathcal{L}_\mathcal{S}$ is maximized.

C. Multivariate Gaussian Distribution and Gaussian Process

In environmental crowdsensing, it is often desirable not only to predict the values of environmental conditions, but also to estimate their probabilistic distributions, *s.t.*, the platform can respond to location-based queries with both the estimated values and their confidence levels. A simple but efficient approach is to assume that the monitored phenomena follow a joint multivariate Gaussian distribution [10]. Mathematically, the joint distribution of a set $X_\mathcal{L} = \{X_{l_1}, X_{l_2}, \ldots, X_{l_m}\}$ of random variables with m discrete locations is

$$P(X_\mathcal{L} = x_\mathcal{L}) = \frac{1}{(2\pi)^{m/2}|\Sigma|^{1/2}} e^{-\frac{1}{2}(x_\mathcal{L}-\mu)^T \Sigma^{-1}(x_\mathcal{L}-\mu)}, \quad (6)$$

where μ is the mean vector, Σ is the covariance matrix, and $|\Sigma|$ the determinant of Σ. We note that the conditional distribution of a joint Gaussian distribution is still Gaussian. If in some round t, we have observed the noise of locations $\mathcal{L}_t \subseteq \mathcal{L}$, then for some unobserved location $l_s \in \mathcal{L}\backslash\mathcal{L}_t$, its conditional mean $\mu_{l_s|\mathcal{L}_t}$ and conditional variance $\sigma^2_{l_s|\mathcal{L}_t}$ are given by:

$$\mu_{l_s|\mathcal{L}_t} = \mu_{l_s} + \Sigma_{l_s\mathcal{L}_t}\Sigma^{-1}_{\mathcal{L}_t\mathcal{L}_t}(x_{\mathcal{L}_t} - \mu_{\mathcal{L}_t}), \quad (7)$$

$$\sigma^2_{l_s|\mathcal{L}_t} = \sigma^2_{l_s} - \Sigma_{l_s\mathcal{L}_t}\Sigma^{-1}_{\mathcal{L}_t\mathcal{L}_t}\Sigma_{\mathcal{L}_t l_s}. \quad (8)$$

The $\Sigma_{l_s\mathcal{L}_t}$ is a vector of the covariance of l_s with all the variables in $\mathcal{L}_t$, and $\Sigma_{\mathcal{L}_t\mathcal{L}_t}$ is the covariance matrix where the entry (u,v) is the covariance of u and v.

In some cases, we are not only interested in specified locations, but also those unspecified locations. Gaussian process can be utilized to generalize multivariate Gaussian distribution to scenarios with infinite number of random variables. In our noise monitoring example, we can have infinite number of location indexes, *e.g.*, $\mathcal{L} \subseteq \mathbb{R}^2$, and each location l_s is associated with a random variable X_s. The Gaussian process is specified by a mean function $M(\cdot)$ and a symmetric positive definite kernel function $K(\cdot,\cdot)$. For each random variable X_u, $M(u)$ represents its mean, and for any two random variables X_u and X_v, their covariance is represented by $K(u,v)$.

Given a set $X_{\mathcal{L}_\mathcal{S}}$ of k random variables, if they follow a multivariate normal distribution with mean vector $\mu_\mathcal{S}$ and covariance matrix $\Sigma_{\mathcal{S}\mathcal{S}}$, then their (differential) entropy can be calculated by [23]:

$$H(X_{\mathcal{L}_\mathcal{S}}) = \frac{1}{2}\log((2\pi e)^k |\Sigma_{\mathcal{S}\mathcal{S}}|) \quad (9)$$

Based Equation (4) and (9), we are now able to estimate the mutual information between locations of selected users and unobserved locations.

D. Quantifying Costs

In practice, users' sensing costs are influenced by many factors, including but not limited to time devotions, energy consumption, storage space, and their sensing behaviors.

Time devotion is one of the major contributing components of users' sensing costs, since selected users are required to spend some time performing a specific sensing task. It can be easily measured by the crowdsensing application.

Battery consumption is critical in mobile devices due to their limited battery capacity. Although it may be infeasible for most smartphone users to measure their energy consumption, it is possible for the platform to collect the resource usage information and to adopt the state-of-the-art energy accounting policies (*e.g.*, [16], [35]) to calculate users' energy consumption after each round. The pre-installed application can readily obtain these information from each smartphone's system resource monitor. After each round, the application

TABLE I
COMPARISON WITH EXISTING WORKS

	DOG [26]	Budgeted ϵ-first [27], [28]	KUBE [29]	DTA [30]	UCB-BV [31]	CUCB [32]	BP-UCB [33]	Biswas *et al.* [34]	This work
#Pulls per round	Fixed	Fixed	Fixed	Fixed	Fixed	Unfixed	Fixed	Fixed	Unfixed
Objective function[1]	Sub.	Addt.	Addt.	Addt.	Addt.	Mono.	Sym.	Addt.	Sub.
Budget constraint	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Costs of pulling[2]	\	Known	Known	Known	Unknown	\	Unknown	Unknown	Unknown

[1] Abbreviations "Sub.", "Addt.", "Mono.", and "Sym." stand for submodular, additive, monotone, and symmetric respectively.
[2] Works that do not consider pulling costs are marked with "\".

collects the usage of different hardware resources (*e.g.*, CPU, memory) during this round, and submits these information, as well as users' sensing data, to the platform. The measurement of storage space can be done in a similar way.

Another factor that influences users sensing costs is their sensing behaviors, *i.e.*, if users have took the correct sensing approaches. Although users' sensing behaviors are not transparent to the platform, their consequences—data qualities, do reflect how much effort the users have put in the task. For example, putting the smartphone in the pocket involves less trouble than holding it in the hands, but results in low quality data in noise monitoring [9]. Higher data qualities usually indicate that the users have took serious in the sensing task and behaved carefully during the sensing. Thus, users contributed higher quality data should deserve higher payoffs. Some quality estimation techniques (*e.g.*, [15]) can be adopted to measure each user's data quality.

After each round t, the platform actively collects information related to users' costs from their smartphone systems, and calculates each user i's cost $c_{i,t}$ using a pre-defined method. After quantifying users' costs, the platform can determine each user's payment $p_{i,t}$, which is proportional to her cost $c_{i,t}$. The exact calculation formulas depend on specific crowdsensing scenarios, and are left for the platform to decide.

We note that users' costs and payments are calculated after each round t. However, the user selection process must be done at the beginning of each round, and we have no knowledge of $c_{i,t}$ then. Therefore, we need to design an online learning and decision-making algorithm. Multi-armed bandit problems provide us insights to solve this problem.

E. A Multi-Armed Bandit Problem

The void of prior knowledge of users' costs brings us the exploration and exploitation dilemma, originally proposed by Robbins [18] as a multi-armed bandit (MAB) problem. In a classical stochastic MAB framework [19], there is a slot machine with multiple non-identical arms, and pulling each arm generates a random reward according to some unknown distribution with unknown mean. A gambler must decide which arms to pull in sequence, with the objective of minimizing *regret*, *i.e.*, the difference between the optimal payoff with expert knowledge and the actual payoff. A pulling strategy is called no-regret if its average regret tends to zero as the number of pulls approaches infinity.

In our problem, we model the set of smartphone users as n non-identical arms. Selecting user i in round t incurs a cost $c_{i,t}$, which follows some unknown distribution with unknown mean c_i. At the beginning of each round t, the gambler (crowdsensing platform in our case) decides which users $\mathcal{S}_t \subseteq \mathcal{N}$ to perform the sensing task. After round t, the platform obtains each selected user i's real cost $c_{i,t}$ in round t and updates i's expected cost.

A plenty of MAB algorithms have been proposed based on different approaches (see a survey in [36]). However, our problem has key differences from the existing works. First, most of the existing MAB works assume that the gambler can pull one or fixed number of arm(s) at a time, while in our cases, the number of selected users in each round is uncertain. Though some work considers a combinatorial MAB approach (*e.g.*, [32]), it never takes the budget constraint into consideration. Second, the optimization functions of most previous works are either additive [27]–[31], [34] or symmetric (the function output only depends on the cardinality of the input set) [33], [37], [38], but in our cases, the mutual information-based criteria is a submodular function, which is more challenging. Third, in contrast to many previous works on budgeted MAB (*e.g.*, [27]–[29]), where they consider maximizing unknown profits (with additive optimization function) with known costs, we have no prior knowledge of users' costs. Although [31], [33], [34] consider variable costs, their problem models are quite different from ours (see Table I for comparisons).

In Table I, we compare this paper with existing works on budgeted MAB and MAB-based crowdsourcing/crowdsensing.

III. BUDGETED INFORMATIVENESS MAXIMIZATION WITH FULL KNOWLEDGE

In this section, we address the budgeted informativeness maximization problem with full knowledge of users' sensing costs. Although the full knowledge assumption is unrealistic, the algorithms proposed in this section are the building blocks of our subsequent designs without this assumption.

A. Single-Rounded Budgeted Informativeness Maximization

We first present the definition of submodular functions, which have a natural diminishing return property, *i.e.*, the marginal gain when adding a single element to a input set decreases as the size of the input set increases.

Definition 3 (Submodular). *The function $F : 2^{\mathcal{N}} \to \mathbb{R}$ is submodular if $\forall \mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{N}, \forall i \in \mathcal{N} \backslash \mathcal{B}$,*

$$F(\mathcal{A} \cup \{i\}) - F(\mathcal{A}) \geq F(\mathcal{B} \cup \{i\}) - F(\mathcal{B}). \qquad (10)$$

Algorithm 1: Single-Rounded Budgeted Informativeness Maximization with Full Knowledge

Input: The total budget B and users' costs $\{c_i\}$
Output: Selected user $\mathcal{S}$

Calculate each user's payment p_i based on c_i;
$i^* \leftarrow \underset{i \in \mathcal{N}, p_i \leq B}{\operatorname{argmax}} F(\{i\})$;
$\mathcal{S}' \leftarrow \{i^*\}$, $\mathcal{S}'' \leftarrow \emptyset$, $\mathcal{N}' \leftarrow \mathcal{N}$, $B' \leftarrow B$;
while $\mathcal{N}' \neq \emptyset$ **do**
  $i^* \leftarrow \underset{i \in \mathcal{N}'}{\operatorname{argmax}} \frac{F(\mathcal{S}'' \cup \{i\}) - F(\mathcal{S}'')}{p_i}$;
  if $B' \geq p_{i^*}$ **then**
    $\mathcal{S}'' \leftarrow \mathcal{S}'' \cup \{i^*\}$;
    $B' \leftarrow B' - p_{i^*}$;
  $\mathcal{N}' \leftarrow \mathcal{N}' \backslash \{i^*\}$;
return $\underset{\mathcal{S} \in \{\mathcal{S}', \mathcal{S}''\}}{\operatorname{argmax}} F(\mathcal{S})$;

Although mutual information is not submodular in general [39], our informativeness characterization $F(\mathcal{L}_\mathcal{S}) = I(\mathcal{L}_\mathcal{S}; \mathcal{L} \backslash \mathcal{L}_\mathcal{S})$ is a non-negative submodular function. The function F, with a careful discretization over the monitored environmental area, is non-decreasing over $\mathcal{L}_\mathcal{N}$ [21].

Lemma 1. *The function $F(\mathcal{S}) = I(\mathcal{L}_\mathcal{S}; \mathcal{L} \backslash \mathcal{L}_\mathcal{S})$ is non-negative and submodular.*

Proof. According to the definition of mutual information, F is clearly non-negative. Next, we prove that F is submodular. $\forall \mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{L}$ and $\forall s \in \mathcal{L} \backslash \mathcal{B}$ (recall that s is short for X_s and A is short for $X_\mathcal{A}$), we have:

$$\begin{aligned} & F(\mathcal{A} \cup \{s\}) - F(\mathcal{A}) \\ = & I(\mathcal{A} \cup \{s\}; \mathcal{L} \backslash (\mathcal{A} \cup \{s\})) - I(\mathcal{A}; \mathcal{L} \backslash \mathcal{A}) \\ = & H(\mathcal{A} \cup \{s\}) - H(\mathcal{A}) + [H(\mathcal{L} \backslash (\mathcal{A} \cup \{s\})) - H(\mathcal{L} \backslash \mathcal{A})] \\ = & H(\{s\} | \mathcal{A}) - H(\{s\} | \mathcal{L} \backslash (\mathcal{A} \cup \{s\})) \end{aligned}$$

According to the "Information never hurts" principle [23], we have $H(\{s\}|A) \geq H(\{s\}|B)$ and $H(\{s\}|\mathcal{L} \backslash (\mathcal{B} \cup \{s\})) \geq H(\{s\}|\mathcal{L} \backslash (\mathcal{A} \cup \{s\}))$, then

$$F(\mathcal{A} \cup \{s\}) - F(\mathcal{A}) \geq F(\mathcal{B} \cup \{s\}) - F(\mathcal{B}),$$

thus the function F is a non-negative submodular function. □

When the crowdsensing task has only a single round, all we need to do is to select a subset of users that maximize the informativeness function F under the budget constraint, *i.e.*,

$$\underset{\mathcal{S} \subseteq \mathcal{N}}{\operatorname{argmax}} F(\mathcal{S}), \text{ subject to } \sum_{i \in \mathcal{S}} p_i \leq B. \qquad (11)$$

This problem is NP-hard even with the full knowledge of users' costs [40]. A simple greedy algorithm that greedily selects the next user that maximizes the marginal informativeness gain/cost ratio before the budget drains out has unbounded approximation ratio. But with a slight modification [40], it can achieve $(1 - 1/e)/2$ approximation to the optimal selection[3]. The algorithm is presented in Algorithm 1.

Algorithm 2: Multi-Rounded Budgeted Informativeness Maximization with Full Knowledge

Input: The total budget B, the total round T, and users' costs $\{c_i\}$
Output: User selections $\{\phi_i\}, \forall i \in \mathcal{N}$

Calculate each user's payment p_i based on c_i;
$\langle i^*, \phi^*_{i^*} \rangle \leftarrow \underset{i \in \mathcal{N}, \phi_i \in \Phi, |\phi_i| p_i \leq B}{\operatorname{argmax}} G(\{\phi_i\})$;
$\mathcal{V}' \leftarrow \{\phi^*_{i^*}\}, \mathcal{V}'' \leftarrow \emptyset$, $\mathcal{N}' \leftarrow \mathcal{N}$, $B' \leftarrow B$;
while $\mathcal{N}' \neq \emptyset$ **do**
  foreach $i \in \mathcal{N}'$ **do**
    if $B' \geq p_i$ **then**
      $\phi^*_i \leftarrow \underset{\phi_i \in \Phi, |\phi_i| p_i \leq B'}{\operatorname{argmax}} G(\mathcal{V}'' \cup \{\phi_i\}) - G(\mathcal{V}'')$;
    else $\mathcal{N}' \leftarrow \mathcal{N}' \backslash \{i\}$;
  if $\mathcal{N}' \neq \emptyset$ **then**
    $i^* \leftarrow \underset{i \in \mathcal{N}'}{\operatorname{argmax}} \frac{G(\mathcal{V}'' \cup \{\phi^*_i\}) - G(\mathcal{V}'')}{|\phi^*_i| p_i}$;
    $\mathcal{V}'' \leftarrow \mathcal{V}'' \cup \{\phi^*_{i^*}\}$;
    $\mathcal{N}' \leftarrow \mathcal{N}' \backslash \{i^*\}$;
    $B' \leftarrow B' - |\phi^*_{i^*}| p_i$;
return $\underset{\mathcal{V} \in \{\mathcal{V}', \mathcal{V}''\}}{\operatorname{argmax}} G(\mathcal{V})$;

B. Multi-Rounded Budgeted Informativeness Maximization

In our cases, the multi-rounded user selection, formalized in Equation (1), is more challenging, since the total budget over the entire T rounds is limited. A careful design is required on how to allocate the total budget among the T rounds.

A simple equally shared scheme can be arbitrarily bad. For example, consider a two-rounded crowdsensing with only two users, denoted by n_1 and n_2. The costs of n_1 and n_2 are 2 and 1 per round respectively. Suppose these two users have fixed locations, and their informativeness is characterized as follows: $F(\{n_1\}) = o \gg 1$ and $F(\{n_2\}) = 1$. If the total budget is 2, then one optimal solution is to choose n_1 for the first round and neither for the second round. The optimal result is o. However, if we divide the budget equally into these two rounds, then the user selection ends up with n_2 in both rounds, with the total output being 2. The approximation ratio is $o/2$, which is unbounded and can be arbitrarily bad.

To tackle the NP-hardness of the multi-rounded budgeted informativeness maximization, we extend the single-rounded approximation algorithm to support multi-rounded user selection with $(1 - 1/e)/2$ approximation guarantee, when users' locations are fixed during the entire T rounds.

The algorithm is presented in Algorithm 2. Instead of trying to allocate the total budget among the T rounds, we consider

[3]Although the approximation ratio can be improved to $1 - 1/e$ using a partial enumeration method [40], the improved algorithm is more complicated and infeasible to extend to multi-rounded scenarios, especially when the prior knowledge of users' costs are unavailable.

a global coordination of user selections. For each user $i \in \mathcal{N}$, we define ϕ_i to be a T-ary vector of user i's selection instance, where $\phi_{i,t} \in \{0,1\}$ denotes if user i has been selected in round t ("1" denotes selected and "0" otherwise). Let Φ denote the set of all possible permutations of the T-ary vector. We define $|\phi_i|$ to be how many times user i has been selected among T rounds, *i.e.*, $|\phi_i| = \sum_{i=1}^{T} \phi_{i,t}$. The set $\{\phi_1, \phi_2, \ldots, \phi_n\}$ is denoted by $\mathcal{V}$. The extended informativeness function $G : 2^{\mathcal{V}} \rightarrow \mathbb{R}$ is defined as follows:

$$G(\mathcal{V}) = \sum_{i=1}^{T} F(\mathcal{S}_t), \tag{12}$$

where $\mathcal{S}_t = \{i | \phi_{i,t} = 1, i \in \mathcal{N}, \phi_i \in \mathcal{V}\}$. We can see that G is a nondecreasing submodular function, since the addition of several monotone submodular functions is still monotone submodular. Now, our problem can be treated as selecting a set $\mathcal{V}'$ of users' selection instances that maximizes the submodular function G under the budget constraint B.

Our algorithm follows the similar design rationale of the single-rounded approximation algorithm. For each user i, we first calculate her best affordable selection instance $\phi_i^* \in \Phi$ that maximizes the marginal informativeness gain under current user selection $\mathcal{V}''$ (Line 7), *i.e.*, $G(\mathcal{V}'' \cup \{\phi_i\}) - G(\mathcal{V}'')$. Then, we greedily select the best user i^* that maximizes the marginal informativeness gain of her best instance over the instance's cost (Line 10). We note that for each user i, her current best selection instance ϕ^* (Line 7) can be calculated efficiently by sequentially activating $\phi_{i,t} = 1$ for some round t that maximizes the the marginal informativeness gain before the budget drains out. Afterwards, the performance of this greedy policy $G(\mathcal{V}'')$ is then compared with the best performance that selecting only one user can achieve, *i.e.*, $G(\mathcal{V}')$, and the better user selection is returned.

Theorem 1. *The proposed multi-rounded budgeted informativeness maximization algorithm can achieve an approximation ratio of $\frac{1-1/e}{2}$, with polynomial time complexity.*

Proof. The proof is similar to the proof of the single-rounded algorithm [40]. We omit the proof due to space limitation. $\square$

IV. Budgeted Informativeness Maximization without Prior Knowledge

In this section, we address the budgeted informative user selection problem without prior knowledge of users' sensing costs. Two MAB algorithms are proposed, namely BIM-ST and BIM-DY. BIM-ST assumes that users' locations are fixed during the entire task, while BIM-DY allows users to move during the intervals between two consecutive rounds.

A. BIM-ST

Under the cases where the knowledge of users' costs are unknown in advance, we need to learn users costs. We propose a simple but effective method to balance the exploration and the exploitation. The intuitive idea of our algorithm is that we allocate a portion of the total budget $B' = \epsilon B, \epsilon \in (0,1)$ to learn users' costs, and the remaining budget will be used to choose the best users.

Algorithm 3: BIM-ST

Input: The total budget B, payment upper bound p_{max}, a constant ϵ
Output: Selected user $\{\mathcal{S}_1, \ldots, \mathcal{S}_T\}$

```
1  B' ← εB, B'' ← (1 − ε)B, T' ← 0;
   // Exploration Phase
2  while B' ≥ n·p_max and T' < T do
3      T' ← T' + 1;
4      S_{T'} ← N;
5      Collect users data and calculate c_{i,T'}, ∀i ∈ N ;
6      Calculate each user's payment p_{i,T'}, ∀i ∈ N;
7      B' ← B' − Σ_{i∈S_{T'}} p_{i,T'};
   // Exploitation Phase
8  ĉ_i ← Σ_{t=1}^{T'} c_{i,t}/T', ∀i ∈ N;
9  B'' ← B'' + B';
10 V ← Alg_2(B'', T − T', {ĉ_i});
11 Calculate S_t, ∀t ≥ T' + 1 based on V;
12 return {S_1, ..., S_T};
```

Our algorithm is shown in Algorithm 3. It consists of an exploration phase and an exploitation phase. In the exploration phase, we select all the users in each round, so as to collect information about users' sensing costs. After each round t, the platform quantifies each user i's sensing cost $c_{i,t}$, and calculate each user's payment $p_{i,t}$ according to her cost. Suppose the maximum payment the platform is willing to pay each user per round is p_{max}, which is high enough to cover any user's sensing cost in a single round. The p_{max} is only used to estimate if the remaining budget of B' can afford another exploration round (Line 2). After the exploration phase, we calculate the estimate of each user i's sensing cost $\{\hat{c}_i\}$ (Line 8), and recycle the remaining budget of the exploration phase (Line 9). In the exploitation phase, we treat $\hat{c}_i$ as each user i's true sensing cost, and apply Algorithm 2 to determine the user selections of the following rounds.

To analyze the performance of BIM-ST, we need to calculate the *regret* of BIM-ST, which is the difference between its obtained informativeness and the optimum. However, the optimal informativeness cannot be feasibly achieved, due to the NP-hardness of the submodular maximization problem. To address this infeasibility in regret analysis, we adopt the concept of *α-approximation regret*.

Definition 4 (α-approximation regret [32], [41])**.** *The α-approximation regret of a sequence of user selection $\{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_T\}$ is*

$$R_\alpha = \alpha \cdot \sum_{t=1}^{T} F(\mathcal{S}_t^*) - \sum_{t=1}^{T} F(\mathcal{S}_t), \tag{13}$$

where $\{\mathcal{S}_1^*, \mathcal{S}_2^*, \ldots, \mathcal{S}_T^*\}$ is the optimal user selection sequence. The average α-approximation regret is R_α/T.

The intuitive meaning of α-approximation regret is that our regret metric does not compare against the informativeness of the optimal user selection sequence, but against the informativeness of an α-approximation oracle. Based on the above definition, we can analyze the $(1-1/e)/2$-approximation regret of BIM-ST, *i.e.*, to compare the performance of BIM-ST against Algorithm 2.

Theorem 2. *The $(1-1/e)/2$-approximation regret of BIM-ST is $(T-\lfloor\frac{B}{np_{max}}\rfloor)F(\mathcal{N})$.*

Proof. (Sketch) Let $\mathrm{Alg}_2(B,T,\{c_i\})$ denote the total informativeness obtained by the Algorithm 2, where there are T rounds with budget B and the full knowledge of users' costs $\{c_i\}$ are known a prior. Suppose the exploration phase has T' rounds. The total informativeness obtained by BIM-ST without prior knowledge of users' sensing costs is

$$T'F(\mathcal{N})+\mathrm{Alg}_2(B-\sum_{t=1}^{T'}\sum_{i\in\mathcal{N}}p_{i,t},T-T',\{\hat{c}_i\}),$$

where $\{\hat{c}_i\}$ is the set of estimated users' costs, and the first and the second terms are the informativeness achieved by the exploration phase and the exploitation phase respectively.

According to Hoeffding's inequality, $\forall i\in\mathcal{N}$, and for any positive δ_i, we have

$$P(|c_i-\hat{c}_i|\geq\delta_i)\leq e^{-2T'\delta_i^2}.$$

Let $\delta_i=\sqrt{\frac{-\ln\beta}{2T'}}$, then it is easy to prove, that with probability $(1-\beta)^n$, $|c_i-\hat{c}_i|\leq\delta_i$ holds for each $i\in\mathcal{N}$. By choosing an appropriate p_{max}, we can assume that $p_{max}\geq\hat{c}_i,\forall i\in\mathcal{N}$ with probability $(1-\beta)^n$.

Let $B''=B-\sum_{i=1}^{T'}\sum_{i\in\mathcal{N}}p_{i,t}$. We can see that in the exploitation phase, selecting users using Algorithm 2 achieves no worse result than simply selecting all the users in each round until the budget drains out, *i.e.*,

$$\mathrm{Alg}_2(B'',T-T',\{\hat{c}_i\})\geq\lfloor\frac{B''}{np_{max}}\rfloor F(\mathcal{N}).$$

Thus, we have

$$T'F(\mathcal{N})+\mathrm{Alg}_2(B'',T-T',\{\hat{c}_i\})\geq\lfloor\frac{B}{np_{max}}\rfloor F(\mathcal{N}).$$

Since the optimal informativeness achieved with full knowledge is no more than $2\mathrm{Alg}_2(B,T,\{c_i\})/(1-1/e)\leq TF(\mathcal{N})$, the upper bound of the regret is $(T-\lfloor\frac{B}{np_{max}}\rfloor)F(\mathcal{N})$. The regret approaches zero as the total budget B increases. □

B. BIM-DY

In some cases, the interval between two consecutive rounds could be large, *s.t.*, users' locations may vary greatly, which further change users' informativeness. In such cases, we can only estimate users' informativeness at the beginning of each round, and thus a global user selection over the future rounds is unlikely.

To solve this problem, we first divide the budget of the exploitation phase equally over these rounds. In each round of the exploitation phase, we collect users' current locations, estimate their informativeness, and apply the single-rounded budgeted submodular maximization algorithm to select users. To improve the overall performance, a small modification is adopted, *i.e.*, the remaining budget of some round in the exploitation phase will be equally distributed to the following rounds. The algorithm is presented in Algorithm 4.

Algorithm 4: BIM-DY

Input: The total budget B, payment upper bound p_{max}, a constant ϵ
Output: Selected user $\mathcal{S}_t$ in each round t

$B'\leftarrow\epsilon B$, $B''\leftarrow(1-\epsilon)B$, $T'\leftarrow 0$;
`// Exploration Phase`
while $B'\geq np_{max}$ *and* $T'<T$ **do**
  $T'\leftarrow T'+1$;
  $\mathcal{S}_{T'}\leftarrow\mathcal{N}$;
  Collect users data and calculate $c_{i,T'},\forall i\in\mathcal{N}$;
  Calculate each user's payment $p_{i,T'},\forall i\in\mathcal{N}$;
  $B'\leftarrow B'-\sum_{i\in\mathcal{S}_t}p_{i,T'}$;
`// Exploitation Phase`
$\hat{c}_i\leftarrow\sum_{t=1}^{T'}c_{i,t}/T',\forall i\in\mathcal{N}$;
$B''\leftarrow B'+B''$;
for $t=T'+1$ *to* T **do**
  $\mathcal{S}_t\leftarrow\mathrm{Alg}_1(B''/(T-t+1),\{\hat{c}_i\})$;
  Calculate each users' payment $p_{i,t},\forall i\in\mathcal{S}_t$;
  $B''\leftarrow B''-\sum_{i\in\mathcal{S}_t}p_{i,t}$;
return $\{\mathcal{S}_1,\dots,\mathcal{S}_T\}$;

We analyze the performance of BIM-DY by comparing it to a full-knowledged benchmark, which directly runs the exploitation phase of BIM-DY without exploration phase.

Theorem 3. *The $(1-1/e)/2$-approximation regret of BIM-DY is $(T-\lfloor\frac{B}{np_{max}}\rfloor)F(\mathcal{N})$.*

Proof. (Sketch) Let $\mathrm{Alg}_1(B,\{c_i\})$ denote the informativeness obtained by the Algorithm 1 given budget B with full knowledge of users' costs $\{c_i\}$. Suppose the exploration phase of BIM-DY has T' rounds. The informativeness obtained by BIM-DY without prior knowledge of users' costs is at least

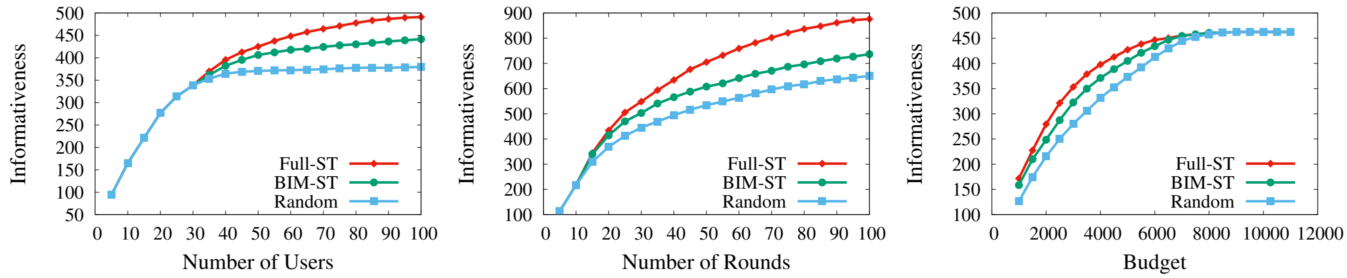
$$T'F(\mathcal{N})+(T-T')\mathrm{Alg}_1(\frac{B-\sum_{t=1}^{T'}\sum_{i\in\mathcal{N}}p_{i,t}}{T-T'},\{\hat{c}_i\}),$$

where the first and the second terms are the informativeness obtained by the exploration phase and the exploitation phase respectively.

Let $B''=(B-\sum_{i=1}^{T'}\sum_{i\in\mathcal{N}}p_{i,t})/(T-T')$, we have

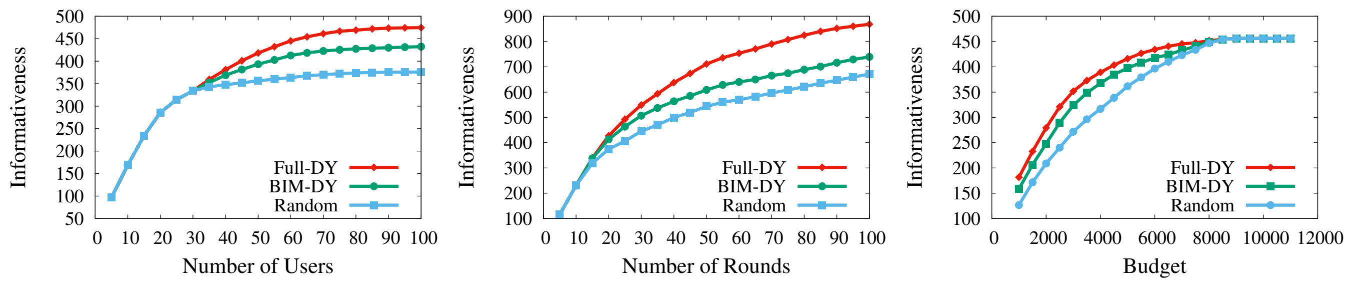
$$T'F(\mathcal{N})+(T-T')\mathrm{Alg}_1(B'',\{\hat{c}_i\})\geq\lfloor\frac{B}{np_{max}}\rfloor F(\mathcal{N}).$$

We can see that the total informativeness achieved by the benchmark algorithm is no more than $TF(\mathcal{N})$, thus the upper bound of the regret is $(T-\lfloor\frac{B}{np_{max}}\rfloor)F(\mathcal{N})$. The regret tends to zero as the total budget B approaches infinity. □



(a) Fixed Budget with Varying Users (b) Fixed Budget with Varying Rounds (c) Varying Budget with Fixed Users and Rounds

Fig. 1. BIM-ST in the First Three Settings



(a) Fixed Budget with Varying Users (b) Fixed Budget with Varying Rounds (c) Varying Budget with Fixed Users and Rounds

Fig. 2. BIM-DY in the First Three Settings

V. Evaluation

In this section, we evaluate the performance of our proposed algorithms by comparing them with two benchmarks. One of the benchmarks is the full-knowledged greedy algorithm. Specifically, BIM-ST is compared to the Algorithm 2, and BIM-DY is compared to the Algorithm 4 with no exploration phase. For simplicity, we refer to these two full-knowledged algorithms as “Full-ST” and “Full-DY” respectively. The other benchmark is a random scheme that randomly selects users until the budget drains out. We first describe the simulation setup, and then present our evaluation results.

A. Simulation Setup

We consider a squared sensing area of $1km \times 1km$. The area is discretized into 400 locations, and each location is a $50m{*}50m$ grid. The mean of each user i's cost c_i is uniformly generated in (5,10), and i's cost in each round t follows a Gaussian distribution with mean c_i and variance 0.2, *i.e.*, $c_{i,t} \sim N(c_i, 0.2)$. In BIM-ST, users' locations are randomly generated and fixed during the entire task, while in BIM-DY, we regenerate users' locations randomly at the beginning of each round. The Gaussian process is characterized by a classic Gaussian Kernel:

$$K(u,v) = \exp(-\frac{\parallel u,v \parallel^2}{h^2}), \tag{14}$$

where $\parallel u,v \parallel^2$ is the squared Euclidean distance of u and v, and h is a constant parameter. We set h=1000 in simulation.

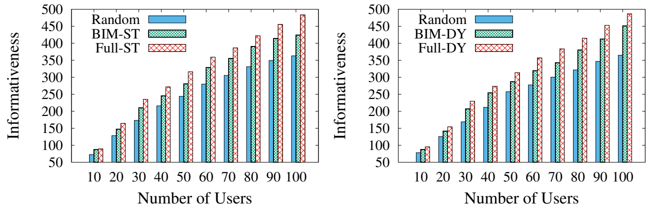
Five different settings are used to evaluate our algorithms. In the first setting, we vary the number of users n from 5 to 500 with the increment of 5. The number of rounds and the total budget are fixed at 20 and 5000 respectively. In the second setting, we fix the number of users at 50 and the budget at 500, while the number of rounds varies from 5 to 100 with the increment of 5. The third setting varies the total budget from 1000 to 11000 with the increment of 1000, while fixing the number of users and the number of rounds at 50 and 20 respectively. In the forth and fifth setting, we consider scenarios where the total budget varies with the increase of the number of users or the number of rounds. In the forth setting, the number of users changes from 5 to 100 and the budget is set to $50n$. In the fifth setting, the number of rounds changes from 5 to 100 and the budget is set to $200T$. The default number of users and rounds are 50 and 20 respectively. The constant ϵ is set to 0.5 in all the five settings. We summarize our settings in Table II.

TABLE II
Evaluation Settings

Setting	#Rounds (T)	#Users (n)	Budget (B)
1	20	5-100	5000
2	5-100	50	5000
3	20	50	1000-11000
4	20	5-100	$50n$
5	5-100	50	$200T$

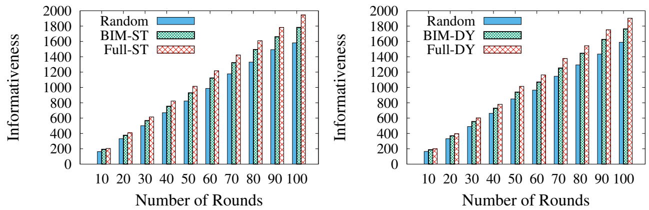
B. Evaluation Results

The evaluation results of BIM-ST and BIM-DY in the first setting are presented in Fig. 1(a) and Fig. 2(a) respectively. We can see that the total informativeness increases as the number of users gets larger, and finally tends to reach a stable state, when the budget has been fully used. It can also be observed that when the number of users is small, *e.g.*, less than 30, all the three algorithms achieve the same informativeness. This is because the total budget can afford all the users to perform



(a) BIM-ST (b) BIM-DY

Fig. 3. The Forth Setting



(a) BIM-ST (b) BIM-DY

Fig. 4. The Fifth Setting

the sensing task in each round. When the number of users gets larger, the performance differences of these algorithms start to reveal, *i.e.*, full-knowledged algorithms beat BIM, and BIM beats the random scheme.

Fig. 1(b) and Fig. 2(b) show the evaluation results in the second setting. We observe that all the three algorithms achieve the same informativeness when the number of round is small (*e.g.*, less than 15), since the budget can afford all the users in each round. As the number of rounds gets larger, full-knowledged algorithms achieve the best performance, since they are exploration-free and thus can utilize the total budget in the most efficient way. Different to the curves in the first setting, the total achieved informativeness keeps increasing and does not tend to saturate. This is because that with more rounds, the submodularity of the informativeness always allows us to reschedule some selected users to the new rounds without decreasing the total informativeness.

The third setting is used to measure the influence of the total budget in user selections. It varies the total budget with fixed n and fixed T. The results are presented in Fig. 1(c) and Fig. 2(c). We observe that the obtained informativeness first grows as the budget increases. That is because that more budget results in more selected users and thus more obtained sensing information. As the budget keeps increasing, the saturation will be reached when all the users are selected in every round.

Fig. 3 shows the performance of BIM-ST and BIM-DY in the forth setting. We can see that the achieved informativeness increases as the number of users grows. This is because that more budget allows more users to be selected. We also observe that the growth of informativeness tends to get slow as the number of users increases, *e.g.*, 50 users can achieve over 300 informativeness by Full-ST, while 100 users only achieve less than 500. This is due to the submodularity of the informativeness function. Besides, both BIM-ST and BIM-DY achieve superior performance to the random selection scheme, and close performance to the full-knowledged algorithms.

Fig. 4 presents the evaluation results in the fifth setting. We can see that the achieved informativeness is nearly proportional to the number of rounds. This is supported by an intuitive observation that under the varying budget $200T$, if we keep selecting the best users in the upcoming rounds, the achieved informativeness is linear to the round number. It can be seen that our MAB algorithms achieve close informativeness to the full-knowledged algorithms.

VI. Related Work

The crowdsensing approach has been applied in many practical applications. Azizyan *et al.* [2] proposed a mobile phone-based logical localization system based on ambient fingerprinting. Rai *et al.* [3] designed a indoor localization technique that utilizes the sensors in mobile devices to track the indoor environment. Dutta *et al.* [4] studied the problem of monitoring air quality with handheld mobile devices. Zhou *et al.* [5] presented a bus arrival time prediction system based on mobile crowdsensing. ParkSense [6] is a smartphone-based sensing system that automatically finds on-street parking space. Jigsaw [7] leverages crowdsensing data from mobile device users to construct the indoor floorplan. A good survey of crowdsensing is provided in [1]

Mobile crowdsensing has also been intensively studied from the theoretical perspective. Yang *et al.* [14] studied a platform-centric model and a user-centric model in crowdsensing, and provided incentive mechanisms for them respectively. Zhao *et al.* [12] studied the budgeted online crowdsensing, and proposed two online budget feasible mechanisms. Huang *et al.* [9] studied the design of reputation systems in long-term crowdsensing, and proposed unsupervised learning techniques to characterize users' qualities and reputations. Jin *et al.* [42] incorporated a quality of information metric into the design of incentive mechanisms for mobile crowdsensing systems, and proposed two truthful combinatorial mechanisms. Peng *et al.* [15] considered the quality-based pricing in crowdsensing, and presented an EM algorithm to quantify users' data qualities. However, to the best of our knowledge, none of the previous work in crowdsensing has addressed the problem of selecting most informative users, nor considered users' unknown costs.

The Gaussian process and mutual information-based model have been widely studied in sensor networks. In [10], the authors built a statistics model for sensor querying, based on the spatial and temporal correlations of environmental phenomena. Guestrin *et al.* [21] studied the most informative sensor placement problem, and adopted the mutual information-based sensor selection scheme. Krause *et al.* [22] further studied the problem of maximizing mutual information of sensors while minimizing the communication costs. However, the crowdsensing scenarios have clear differences from sensor networks, not only because users' costs are influenced by many factors and unknown a prior, but also due to the fact that autonomy of users makes us can only select users based on their current locations, instead of directly deploying users to sense some specific locations.

Multi-armed bandit problem was originally described by Robbins [18], after which a good number of researchers have studied different approaches (*e.g.*, [19], [36], [43]) to solve this problem. In applying MAB model to real scenarios, Babioff *et al.* [37] studied the truthfulness of MAB mechanisms in pay-per-click auctions, and provided several design principles. Devanur and Kakade [38] analyzed the achievable regret in designing a truthful MAB mechanism for pay-per-click auctions. Chen *et al.* [32] studied a general framework for combinatorial multi-armed bandit problem. Budgeted MAB problems were preliminarily studied by [27]–[29], where they considered to optimize an additive objective function with known costs. Different from the previous works, in this paper, the optimization function is submodualr, the number of selected users each round is uncertain, and users' sensing costs are unknown a priori.

VII. Conclusion

In this paper, we have considered the budgeted informativeness maximization problem in crowdsensing. We have proposed a mutual information-based criteria to quantify the informativeness. When users' sensing costs are known in advance, we have provided a multi-rounded approximation algorithm that achieves $(1-1/e)/2$ approximation ratio. Without prior knowledge of users' costs, two MAB algorithms, namely BIM-ST and BIM-DY, have been proposed to tackle the static and dynamic scenarios respectively. Our evaluation results have shown that our proposed algorithms achieve desirable performance in terms of the total obtained informativeness.

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