Identifying the Most Valuable Workers in Fog-Assisted Spatial Crowdsourcing

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Abstract—In this paper, we study worker selection in spatial crowdsourcing, which is the recruitment of human workers in a specific location to collect geographical data. To achieve better performance, spatial crowdsourcing task relies on both worker's effort and skill. Therefore, to maximize the long-term platform utility, we exploit Fog platform as a service to identify valuable workers through learning their performance information. Worker's historical performance data are recorded at local Fog server, based on which valuable workers are identified and selected to perform the tasks. During worker selection, we aim at balancing the exploration and exploitation, and propose an online algorithm that promotes workers who are not fully explored. With budget constraint, the proposed algorithm is able to maximize the long-term platform utility. Theoretical analysis indicates that the proposed learning algorithm achieves asymptotically diminishing regret. Finally, extensive simulations on real-world dataset are conducted, which demonstrate the advantage of our algorithm over other methods.

Index Terms—Fog computing, spatial crowdsourcing, worker selection, online learning, budget constraint.

I. INTRODUCTION

Crowdsourcing exploits the collective intelligence of human crowd, provides an effective paradigm for large-scale data acquisition and distributed computing [1], [2]. Traditionally, crowdsourcing applications are performed over the Internet. Workers are requested to complete online tasks on platforms like Amazon MTurk and Quora. Recently, due to the popularity of smartphones with various built-in sensors, *Spatial Crowdsourcing* emerges as a typical Internet-of-Things (IoT) application that solicits human workers to complete certain tasks in a specific location [3], [4]. To perform a spatial task, human workers are requested to conduct location-related activities, such as taking a photo of a local place[1], or making comments on a local restaurant. Spatial tasks favor workers in

a certain location mainly because workers from other places do not have the required knowledge and experiences.

Fog computing is an ideal carrier for accommodating spatial crowdsourcing applications. By extending cloud resources to the proximity of things, Fog computing can provision localized services in a fine-grained and context-aware manner [5], [6]. Meanwhile, by processing requests locally, it also contributes to higher responsiveness and lower traffic burden in core networks. In addition, worker's privacy can be better protected as the dissemination of both requests and responses are restricted to a limited scale [7]. As a result, Fog computing could provide platform as a service to spatial crowdsourcing applications, which can efficiently accommodate functions like task receipt, worker evaluation and selection, result recomposition and recording, etc.

The primary issue in spatial crowdsourcing is worker selection. General crowdsourcing tasks require worker's effort in the form of time or physical exertion. A widely adopted approach for worker selection is modeling the interactions between workers and the crowdsourcing platform as a game or auction [8]-[12]. Both workers and the platform are strategic and attempt to maximize their own utilities. This approach works well on ordinary crowdsensing tasks, where worker's utility is determined directly by the received payment and its cost of effort exertion. Nevertheless, this approach may not be applicable to spatial tasks due to the following reasons.

1) Spatial tasks not only require workers to exert efforts but also require certain skills. For example, when workers are asked to review a local restaurant or shoot a picture of a local site, besides workers' efforts, their skills of commenting and photography also matter. Therefore, effort and skill should be jointly considered when evaluating candidate workers.

2) Worker's effort and skill information do not come for free. Previous efforts were to ensure that workers reveal their effort information truthfully [9], [10], [11]. In spatial crowdsourcing, however, even if workers are telling the truth, the valuation on their skills might be too subjective to be accurate. As a result, worker's performance is hard to predict as the value of skill is ambiguous.

3) The platform utility is featured by diminishing return, i.e., a worker's performance is more valuable when fewer workers have been selected. Practical evidence of this feature includes comments on a restaurant by different workers share certain similarities, and contents of photo on a subject from different workers may be overlapped. Hence, the platform utility is no longer a linear combi-

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[1] https://www.microsoft.com/en-us/research/project/spatial-crowdsourcing/

nation of individual worker's performance.

In this paper, we resort to Fog intelligence to address those issues. Instead of focusing on the interactive game or auction among workers and the platform, we propose to record workers' historical performance information on Fog server, and directly let Fog platform select workers. Specifically, while assessing a candidate worker, both its empirical performance and frequency of being selected are taken into consideration. The set of workers who are predicted to maximize the platform utility are selected. For each task, the worker selection is a bandit-type decision, i.e., only selected workers will reveal their performance information [28]. Therefore, there is a trade-off between *exploitation* and *exploration*, which corresponds to exploiting workers with better empirical performance and exploring workers who perform not so well but are less selected. The latter workers may be underestimated due to the randomness. To balance the exploitation and exploration, a perturbation is added to each worker's empirical performance, which helps to promote workers who are not fully explored.

Generally, each task is requested with a budget constraint. With this constraint, the platform needs to identify the most valuable workers for each task so as to maximize the long-term utility. Considering the diminishing return property of worker's contribution, the platform utility is modelled as a submodular function. The worker selection problem is thus formulated as a combinatorial optimization of submodular function with cardinality constraint, which is NP-hard. To effectively solve this problem, an online learning algorithm is proposed, which dynamically adapts the rate of exploration and exploitation. The contributions of this paper are summarized as follows:

1) We propose to carry out spatial crowdsourcing by adopting the paradigm of Fog platform as a service, which is applicable to general Fog services.

2) We consider budget constrained worker selection for spatial crowdsourcing applications, where worker's effort and skill are uncertain. We propose a learning algorithm that identifies and selects the most valuable workers for each task so as to maximize the long-term platform utility.

3) We prove that the proposed learning algorithm achieves asymptotically diminishing per-task regret. Extensive simulations on real dataset from Yelp are conducted to illuminate the superiority of the Fog-assisted solution.

The remainder of this paper is organized as follows. Related work is reviewed in Section II. System model and problem formulation are presented in Section III. Section IV starts with a static greedy algorithm, followed by the proposed online learning algorithm UCBG. Section V gives the detailed theoretical regret analysis of the UCBG algorithm. Section VI demonstrates simulation results and performance validation of the proposed algorithm on real-world dataset. The paper is concluded in Section VII.

II. RELATED WORK

A. Fog-enabled Services

Fog provides storage, compute and networking resources in the proximity of things, making contents, processing and management functions readily available to end users [5], [6].

Consequently, Fog enables service provisioning with minimized latency, and meanwhile, contributes to reduced traffic volume in core networks as considerable user requests can be processed locally. Fog computing has brought forward lots of promising solutions for IoT applications. Ni *et al.* designed a Fog-based two-step task allocation mechanism for precise task allocation and secure data de-duplication in spatial crowdsourcing [13]. Yang *et al.* designed a software-defined network based framework to facilitate the Fog-Cloud interoperation [14]. Hou *et al.* also investigated collectively carrying out Fog resources from individual vehicles [15].

B. Worker Selection of Crowdsourcing

Existing works on worker selection focus on identifying honest and high-contribution workers to achieve both fairness and high platform utility. Zhang *et al.* investigated reputation-based worker selection [8]. Worker's reputation value will be decreased if it exerts low effort. Workers whose reputation value lower than certain threshold are isolated from further participation. Zhang *et al.* proposed to enhance physical layer security through crowdsourcing, where partner selection and incentive mechanism are jointly considered in a game [16]. Yang *et al.* investigated the game and auction in platform-centric and user-centric crowdsourcing, respectively [10]. Workers are encouraged to reveal their effort information truthfully so that the platform can make informed decisions in the game. Besides, Kazemi *et al.* also focused on truthful worker selection with location awareness [17], [18]. In case workers lack of related expertise, Shah *et al.* proposed to encourage workers to answer only the questions that they are sure of and skip the rest [20]. For spatial tasks, however, worker's performance is not deterministic due to the uncertainty of worker's skill and effort level.

In this paper, by harnessing local Fog intelligence, our algorithm aims to learn and predict worker performance information, and further maximize the long-term platform utility by selecting the most valuable workers. In particular, workers are no longer required to reveal their effort information to the platform. Instead, workers who are predicted to have the potential to maximize the platform utility are directly selected. Additionally, the algorithm is resilient to malicious behaviors, i.e., untruthful workers have limited influence on the long-term platform utility.

III. SYSTEM MODEL AND PROBLEM FORMULATION

New paradigms have been proposed to extend Cloud resources to the proximity of mobile users, such as *edge cloud* on the edge of Internet [21] and *cloudlet* on local servers [22]. In this paper, Fog computing is adopted and Fog servers are deployed on legacy base stations or RRH and BBU of Cloud radio access network [14], [23]. With lightweight storage and compute resources, Fog server can accommodate services like video streaming and face identification [24] with reduced latency. In this paper, we adopt platform as a service to carry out spatial crowdsourcing applications from Fog servers. As shown in Fig. 1, the platform locates on the Fog server and accepts crowdsourced spatial tasks that target
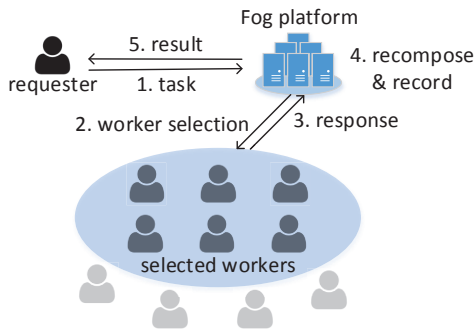
Fig. 1. Fog-based Spatial Crowdsourcing model.

on Fog's coverage area. Let $\mathcal{T} = \{t_1, t_2, \ldots, t_n\}$ denote the sequentially received spatial task requests. A set of workers $\mathcal{W} = \{w_1, w_2, \ldots, w_K\}$ of size K are willing to participate in the crowdsourced tasks for monetary rewards. The platform constantly receives spatial task requests. The platform needs to select a set of workers to perform each task. We assume all tasks come with the same budget[2] b.

A. Worker Model

Different workers may have different levels of willingness to participate in spatial tasks. Moreover, individual worker's perception of different tasks also varies. For a given spatial task, let ε_k be the associated effort level of worker w_k. Unlike the binary assumption in [8], where worker's effort level is either high or low, we consider worker's effort level to be continuous and normalized in $[0, 1]$. Let ζ_k be the skill level on the assigned task of work w_k and the universal production function $p(\pi_k | (\varepsilon_k, \zeta_k))$ be the probability of obtaining performance π_k when worker's effort and skill profile is (ε_k, ζ_k). Without loss of generality, we rescale the performance so that π_k is in $[0, 1]$ for all workers. Though function $p(\cdot)$ may appear different under diverse worker and task settings, a golden standard is that with higher effort and skill levels, one can always expect a better performance. To make our work more applicable, we only make the following First-Order Stochastic Dominance (FOSD) assumption on the production function $p(\cdot)$: for two effort levels $\varepsilon \geq \varepsilon'$, ε has FOSD over ε', where FOSD is defined below [25].

Definition 1. *(First-Order Stochastic Dominance). Let* $F(\pi | (\varepsilon, \zeta)) = \int_{\pi' \geq \pi} p(\pi' | (\varepsilon, \zeta)) d\pi'$ *be the probability of obtaining an performance at least as good as π when a worker's effort and skill profile is (ε, ζ). Then, for any two effort levels ε and ε', we say ε has FOSD over ε' if for any π, $F(\pi | (\varepsilon, \zeta)) \geq F(\pi | (\varepsilon', \zeta))$ always holds.*

For any production function that satisfies FOSD assumption of effort, we have the following Lemma.

Lemma 1. *A worker will have better expected performance when it exerts higher effort level.*

Proof. Let $\varepsilon \geq \varepsilon'$ and $F'(\pi | (\varepsilon, \zeta))$ be the cumulative distribution function of $p(\pi | (\varepsilon, \zeta))$. The FOSD assumption indicates that $F'(\pi | (\varepsilon, \zeta)) = 1 - F(\pi | (\varepsilon, \zeta)) \leq 1 - F(\pi | (\varepsilon', \zeta)) = F'(\pi | (\varepsilon', \zeta))$. The expected performance of exerting effort level ε is $\Pi_\varepsilon = \int_0^1 \pi p(\pi | (\varepsilon, \zeta)) d\pi = [\pi F'(\pi | (\varepsilon, \zeta))]_0^1 - \int_0^1 F'(\pi | (\varepsilon, \zeta)) d\pi = \pi - \int_0^1 F'(\pi | (\varepsilon, \zeta)) d\pi$. Then we have $\Pi_\varepsilon - \Pi_{\varepsilon'} = \int_0^1 \left(F'(\pi | (\varepsilon', \zeta)) - F'(\pi | (\varepsilon, \zeta)) \right) d\pi \geq 0$, which completes the proof. $\square$

Similarly, the production function also satisfies FOSD assumption in terms of skill: for two skill levels $\zeta \geq \zeta'$, ζ has FOSD over ζ'. When workers exert the same level of effort, the expected performance of worker with better skill is larger than that of the worker with lower skill level. We assume that both workers and the platform are aware of the FOSD conditions on effort and skill. In this way, the platform needs to identify and select workers with both higher effort and skill levels to maximize its utility. Note that, regardless of its performance, each selected worker will receive one unit payment for each task.

B. Platform Utility

In spatial crowdsourcing applications, responses from different workers will share certain similarities [18], [19]. For example, in crowdsourced sensing tasks, neighbouring workers may have overlapped sensing area; and in crowdsourced restaurant review tasks, workers may provide same information on the cuisine. Hence, when recomposing results from different workers, the platform utility is submodular, which can be characterized by diminishing return: a worker's marginal value to the platform is higher if few workers have been selected, and lower if more workers have been selected. Let $v(\cdot): 2^{\mathcal{W}} \to \mathbb{R}^+$ denote the set function measuring the utility of worker sets in $\mathcal{W}$. For subsets $\mathcal{S} \subseteq \mathcal{W}$ and $\mathcal{A} \subseteq \mathcal{W} \setminus \mathcal{S}$, define

$$\Psi_v(\mathcal{A} | \mathcal{S}) \triangleq v(\mathcal{A} \cup \mathcal{S}) - v(\mathcal{S}) \qquad (1)$$

as a set function that measures the marginal value of worker set $\mathcal{A}$ to a given set $\mathcal{S}$.

Moreover, different workers will provide different responses, so two workers' collective utility is larger than that of any one of them, i.e., $v(\{w_1, w_2\}) > \max\{v(\{w_1\}), v(\{w_2\})\}$. In this way, the platform utility function is monotone. Formally, the submodularity and monotonicity of the utility function are defined below [26].

Definition 2. *(Submodularity and Monotonicity). A set function $v : 2^{\mathcal{W}} \to \mathbb{R}$ is submodular if for $\mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{W}$ and $w_k \in \mathcal{W} \setminus \mathcal{B}$, $\Psi_v(w_k | \mathcal{A})$[3] $\geq \Psi_v(w_k | \mathcal{B})$ is always true. Equivalently, $v(\cdot)$ is submodular if for $\mathcal{A} \subseteq \mathcal{W}$ and $w_1, w_2 \in \mathcal{W} \setminus \mathcal{A}$, $\Psi_v(w_1 | \mathcal{A}) + \Psi_v(w_2 | \mathcal{A}) \geq \Psi_v(\{w_1, w_2\} | \mathcal{A})$.*

A submodular function v is monotone if for any $\mathcal{A} \subseteq \mathcal{B} \subseteq \mathcal{W}$, $v(\mathcal{A}) \leq v(\mathcal{B})$ holds.

For each task t_i, the platform needs to select a subset $\mathcal{S}_i \subseteq \mathcal{W}$ of workers to complete the task. Let $v_i(\mathcal{S})$ be the utility

of worker set $\mathcal{S}$ to task t_i, the objective of the platform is to select a subset $\mathcal{S}_i$ such that:

$$\mathcal{S}_i = \arg\max_{|\mathcal{S}| \leq b} v_i(\mathcal{S}). \tag{2}$$

C. Problem Formulation

It is a thorny issue for the platform to choose the optimal worker set that maximizes the submodular function in Eq. (2) due to the following two reasons. Firstly, worker's effort and skill information are uncertain in advance. In this way, it is impossible for the platform to directly measure the utility of any subset of $\mathcal{W}$. Secondly, even if worker's effort and skill information is known to the platform, maximizing a submodular set function with cardinality constraint is NP-hard [26]. Greedy algorithm has been proposed to maximize the submodular function, which achieves no less than $(1 - 1/e)$ of the maximum utility $\max_{|\mathcal{S}| \leq b} v_i(\mathcal{S})$.

Note that directly selecting a set of workers that achieve the optimum is intractable, one feasible alternative is to let the Fog-based platform learn to make decisions. In this work, we attempt to design learning algorithm for the worker selection problem. Without any information on worker's effort and skill distribution, our goal is to sequentially select workers $\mathcal{S}_i$ for coming task t_i, and finally maximize the cumulative utility $\sum_{i=1}^{n} v_i(\mathcal{S}_i)$ of tasks in $\mathcal{T}$. This is a bandit-type learning process, since we can only observe the performance information of the selected workers. A common measure of such learning algorithm is comparing its average n-task utility against the utility of hindsight optimal solution [27]. The gap between them is called *regret* and is defined as:

$$\tilde{R}(n) = \max_{|\mathcal{S}| \leq b} \mathbb{E}\left[\sum_{i=1}^{n} v_i(\mathcal{S})\right] - \mathbb{E}\left[\sum_{i=1}^{n} v_i(\mathcal{S}_i)\right]. \tag{3}$$

Note that this definition indicates that the hindsight optimum has knowledge on worker's performance information and the sequence of production functions $\{v_1, v_2, \ldots, v_n\}$, but it must choose the same set of workers for all the n tasks. Since optimal solution of maximizing submodular function is unavailable in polynomial time, our goal is instead to minimize the regret:

$$R(n) = \left(1 - \frac{1}{e}\right) \cdot \max_{|\mathcal{S}| \leq b} \mathbb{E}\left[\sum_{i=1}^{n} v_i(\mathcal{S})\right] - \mathbb{E}\left[\sum_{i=1}^{n} v_i(\mathcal{S}_i)\right]. \tag{4}$$

Related learning algorithms have been proposed for single worker selection [28], [29] or combinatorial selection with linear utility function [31]. Those algorithms achieve asymptotically diminishing regret. In this paper, we develop online learning algorithm to select workers for spatial crowdsourcing tasks, which features combinatorial selection with submodular utility function.

IV. ONLINE LEARNING ALGORITHM FOR WORKER SELECTION

The uncertainty of both worker's effort level ε_k and skill level ζ_k brings uncertainty to the platform utility. Instead of

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Algorithm 1 Static Greedy Algorithm

Input: worker set $\mathcal{W}$ with empirical mean performance $\{\pi_k\}_{k=1}^{K}$, utility function $v : 2^{\mathcal{W}} \to \mathbb{R}^+$, budget b.

Output: selected worker set $\mathcal{S}$.

1: $\mathcal{S}_0 \leftarrow \emptyset$, $t \leftarrow 0$
2: **while** $t < b$ **do**
3:     $t = t + 1$
4:     based on performance information $\{\pi_k\}_{k=1}^{K}$, select $w_t = \arg\max_{w_k \in \mathcal{W} \setminus \mathcal{S}_{t-1}} \Psi_v(w_k | \mathcal{S}_{t-1})$
5:     $\mathcal{S}_t = \mathcal{S}_{t-1} \cup \{w_t\}$
6: **end while**

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coping with such uncertainties, we focus on worker's performance π_k rather than the effort and skill. Assume worker's performance is characterized by the FOSD assumption given by Lemma 1. To maximize the platform utility, we develop learning algorithm that identifies workers with higher performance and, further, selects the most valuable combination of workers for each spatial task.

A. Static Greedy Approach

Before solving the online worker selection problem, we first consider the offline scenario. Imagine that at a certain time epoch, each worker has completed at least one task. The platform keeps recording each worker's historical performance information and calculates the empirical mean performance π_k. With this information, the platform greedily adds worker with the highest marginal value into the selected set. Due to the monotonicity of utility function, the budget constraint b is always effective, i.e., there always exists a non-selected worker that can be added to the b selected workers to improve the platform utility. The greedy algorithm is generalized in Algorithm 1. Before analyzing the performance of Algorithm 1, the following general Theorem is given.

Theorem 1. *Define a perturbed performance $\hat{\pi}_l = \pi_k + \epsilon_k$ for worker w_k with perturbation $\epsilon_k \geq 0$. Let $\mathcal{S} = \{w_t\}_{t=1}^{b}$ be the sequentially selected workers according to Algorithm 1 based on perturbed information $\{\hat{\pi}_l\}_{k=1}^{K}$, and let $\mathcal{P}$ be the hindsight optimal worker set, we have*

$$\mathbb{E}[v(\mathcal{S})] \geq \left(1 - \frac{1}{e}\right) \cdot \mathbb{E}[v(\mathcal{P})] - \sum_{w_k \in \mathcal{S}} \epsilon_k. \tag{5}$$

Proof. Denote $\mathcal{S}_t = \{w_j\}_{j=1}^{t}$ the first selected t workers and $\Psi_t = \mathbb{E}[\Psi_v(w_t | \mathcal{S}_{t-1})]$ the expected marginal value of the t-th selected worker. The monotonicity and submodularity of $v(\cdot)$ indicate that

$$\mathbb{E}[v(\mathcal{P})] \leq \mathbb{E}[v(\mathcal{P} \cup \mathcal{S}_t)]$$

$$\leq \mathbb{E}\left[v(\mathcal{S}_t) + \sum_{w_k \in \mathcal{P} \setminus \mathcal{S}_t} \Psi_v(w_k | \mathcal{S}_t)\right]. \tag{6}$$

Define $\hat{v}(\cdot)$ the utility function based on the perturbed performance $\hat{\pi}_l$ and $\hat{\Psi}_t = \mathbb{E}[\Psi_{\hat{v}}(w_t | \mathcal{S}_{t-1})]$ the perturbed marginal value, we have $\hat{v}(w_k) \leq v(w_k) + \epsilon_k$. As worker w_{t+1} is selected among others in the $(t + 1)$-th loop, the perturbed

marginal value of w_{t+1} satisfies $\Psi_{\hat{v}}(w_{t+1}|\mathcal{S}_t) \geq \Psi_{\hat{v}}(w_k|\mathcal{S}_t)$ for any $w_k \in \mathcal{P} \setminus \mathcal{S}_t$. With $|\mathcal{P} \setminus \mathcal{S}_t| \leq b$, the inequality goes as

$$\mathbb{E}[\upsilon(\mathcal{P})] \leq \mathbb{E}[\upsilon(\mathcal{S}_t)] + b\hat{\Psi}_{t+1}. \tag{7}$$

By applying the submodularity of $\upsilon(\cdot)$, we have $\hat{\Psi}_{t+1} \leq \Psi_{t+1} + \epsilon_{t+1}$, and the above inequality can be rewritten as

$$\mathbb{E}[\upsilon(\mathcal{P})] \leq \Psi_1 + \cdots + \Psi_t + b\Psi_{t+1} + b\epsilon_{t+1}. \tag{8}$$

Let $\Psi_0 = 0$, a series of inequalities can be generated for $0 \leq t \leq b-1$. We multiply the t-th inequality by $(1-1/b)^{b-1-t}$ and sum them up, the resulting coefficient of $\mathbb{E}[\upsilon(\mathcal{P})]$ is $\sum_{t=0}^{b-1}(1-1/b)^{b-1-t} = \sum_{t=0}^{b-1}(1-1/b)^t = b(1-(1-1/b)^b)$, while the coefficient of Ψ_t is $b(1-1/b)^{b-t} + \sum_{i=t}^{k-1}(1-1/b)^{b-1-i} = b$. Therefore, we have

$$(1 - (1-1/b)^b) \cdot \mathbb{E}[\upsilon(\mathcal{P})] \leq \sum_{t=1}^{b} \Psi_t + \sum_{w_k \in \mathcal{S}} \epsilon_k. \tag{9}$$

As $(1 - 1/b) \leq e^{-1/b}$ always holds, the conclusion immediately follows. $\square$

The following Lemma on the performance of Algorithm 1 directly follows Theorem 1 by letting $\epsilon_k = 0$ for all workers.

Lemma 2. *For spatial crowdsourcing platform with K workers and task budget b, worker selection according to static greedy Algorithm 1 achieves $(1 - 1/e)$ of the optimum.*

It can be seen from Theorem 1 that, in the static scenario where the platform makes one-time decision, pure exploitation outperforms any perturbed (exploration) strategy. In pursuing higher long-term utility, however, exploration weighs the same as exploitation.

B. UCB-based Online Learning Approach

Based on static greedy worker selection, we present the online approach for worker selection. The underlying methodology for online learning is to optimize the rate of exploration and exploitation. In the long term, the platform may face the dilemma of selecting workers with better performance or exploring the ones who perform not so well but are less selected. As the latter ones may appear to have bad performance due to the randomness. With the increase of assigned tasks, the platform gains more empirical information on worker's performance, which helps to make better decisions on worker selection. Specifically, we repeat the static greedy algorithm with *regret-free* bandit approach, allowing the platform to achieve asymptotically vanishing per-task regret.

The online learning strategy is inspired by the celebrated upper confidence bound (UCB) algorithm [28]. The platform evaluates workers according to the UCB of their expected performance, and gradually picks the worker with highest marginal value. Let $\tilde{\pi}_{i,k}$ be the empirical mean value of worker w_k's performance after the assignment of task t_i, and $f_i(k)$ be the frequency of worker w_k being selected after i tasks have been assigned. The online algorithm consists of three steps. For each task, the platform first computes the UCB of the

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Algorithm 2 UCBG: online maximization of Fog platform utility.

Input: worker set $\mathcal{W}$, utility function $\upsilon : 2^{\mathcal{W}} \to \mathbb{R}^+$, budget b.

Output: worker set $\mathcal{S}_i$ for each task t_i.

1: Initialization: Choose each worker once for the first $i_0 = K/b$ tasks, obtaining the initial empirical performance $\{\tilde{\pi}_l\}_{k=1}^K$. $\forall w_k \in \mathcal{W}, f_{i_0}(k) \leftarrow 1$.
2: **for** $i = i_0 + 1, \ldots, n$ **do**
3:     $\forall w_k \in \mathcal{W}, \bar{\pi}_{i,k} \leftarrow \min\{\tilde{\pi}_{i-1,k} + c_{i-1,f_{i-1}(k)}, 1\}$
4:     $t \leftarrow 0, \mathfrak{S}_0 \leftarrow \emptyset$
5:     **while** $t < b$ **do**
6:         $t \leftarrow t + 1$
7:         select $w_t = \arg\max_{w_k \in \mathcal{W} \setminus \mathfrak{S}_{t-1}} \Psi_{\bar{\upsilon}_i}(w_k|\mathfrak{S}_{t-1})$
8:         $\mathfrak{S}_t \leftarrow \mathfrak{S}_{t-1} \cup \{w_t\}$
9:     **end while**
10:     **for** $w_k \in \mathfrak{S}_b$ **do**
11:         $f_i(k) \leftarrow f_{i-1}(k) + 1$
12:         observe $\pi_{i,k}$ and update $\tilde{\pi}_{i,k} \leftarrow \frac{f_{i-1}(k)\tilde{\pi}_{i-1,k} + \pi_{i,k}}{f_i(k)}$
13:     **end for**
14:     **for** $w_k \notin \mathfrak{S}_b$ **do**
15:         $f_i(k) \leftarrow f_{i-1}(k)$ and $\tilde{\pi}_{i,k} \leftarrow \tilde{\pi}_{i-1,k}$
16:     **end for**
17:     $\mathcal{S}_i \leftarrow \mathfrak{S}_b, i \leftarrow i + 1$
18: **end for**

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expected performance of each worker, then greedily selects a set of workers that maximize the platform utility based on their UCB performance, and finally updates the empirical information of each worker. Noticing that $\pi_k \in [0, 1]$, the UCB $\bar{\pi}_{i,k}$ of worker w_k at the i-th assignment is given as

$$\bar{\pi}_{i,k} = \min\{\tilde{\pi}_{i-1,k} + c_{i-1,f_{i-1}(k)}, 1\}, \tag{10}$$

where

$$c_{i,f_i(k)} = \mu\sqrt{\frac{\log i}{f_i(k)}} \tag{11}$$

is the upper confidence around the empirical mean value $\tilde{\pi}_{i,k}$. With this setting, the mean performance π_k lies in the confidence interval $[\tilde{\pi}_{i,k} - c_{i,f_i(k)}, \tilde{\pi}_{i,k} + c_{i,f_i(k)}]$ with high probability, which can be concluded from the Chernoff-Hoeffding inequality as follows.

Lemma 3. *(Chernoff-Hoeffding Inequality). Let $X_1, X_2, \ldots, X_n$ be random variables taking values in $[0, 1]$ and $\mathbb{E}[X_t|X_1, X_2, \ldots, X_{t-1}] = \xi$. Suppose that $S_n = X_1 + X_2 + \cdots + X_n$, then for $\forall a \geq 0$, we have*

$$\mathbb{P}\{S_n \geq n\xi + a\} \leq e^{-2a^2/n}, \ \mathbb{P}\{S_n \leq n\xi - a\} \leq e^{-2a^2/n}.$$

The above Lemma indicates that the violation probability $\mathbb{P}(|\pi_k - \tilde{\pi}_{i,k}| \geq c_{i,f_i(k)}) \leq 2e^{-2\mu^2 \log i} = 2i^{-2\mu^2}$. With $\mu \geq 1$, the probability of π_k outside of the confidence interval tends to infinitesimal rapidly. The upper confidence $c_{i,f_i(k)}$ offers good balance between exploration and exploitation. The selected frequency $f_i(k)$ plays an important role. Workers who are less selected have larger upper confidence values, and hence have higher chances to be selected. Workers who have

been frequently selected will have smaller upper confidence values, indicating that their performance information is well explored. In case all workers are well explored, they will have comparable upper confidence. Consequently, workers with higher empirical performance will be selected, which corresponds to pure exploitation. The underlying rationale is the law of large numbers, which offers a criteria to determine how well a worker is explored. Hence, valuable workers can be identified and selected by the Fog platform. The UCB-based greedy (UCBG) learning approach for worker selection is sketched in Algorithm 2.

V. THEORETICAL REGRET ANALYSIS

This Section starts with a Theorem on the performance of the proposed UCBG algorithm, followed by the theoretical proof of the cumulative regret of UCBG algorithm.

Theorem 2. *For spatial crowdsourcing platform with K workers, if the budget of each task is b, the UCBG algorithm for worker selection achieves asymptotically diminishing per-task regret, i.e., $R(n)/n \to 0$ as $n \to \infty$.*

Proof. Let $\mathcal{S}^* = \arg\max_{|\mathcal{S}| \leq b} \mathbb{E}[\sum_{i=1}^n v_i(\mathcal{S})]$ be the hindsight optimal solution of worker selection, and $\mathcal{P}$ be the greedy optimal set in polynomial time. From Lemma 2,

$$\mathbb{E}\left[\sum_{i=1}^n v_i(\mathcal{P})\right] \geq (1 - \frac{1}{e}) \cdot \mathbb{E}\left[\sum_{i=1}^n v_i(\mathcal{S}^*)\right]. \quad (12)$$

Let $\mathcal{S}_i$ be the chosen set for task t_i and $R_i = \mathbb{E}[v_i(\mathcal{P})] - \mathbb{E}[v_i(\mathcal{S}_i)]$ the corresponding expected regret. Then, the cumulative regret $R(n)$, as given by Eq. (4), of Algorithm 2 satisfies

$$R(n) \leq \mathbb{E}\left[\sum_{i=1}^n v_i(\mathcal{P})\right] - \mathbb{E}\left[\sum_{i=1}^n v_i(\mathcal{S}_i)\right] = \sum_{i=1}^n R_i. \quad (13)$$

With $\pi_k \in [0, 1]$ and $|\mathcal{P}| = |\mathcal{S}_i| = b$, we have $\forall i : R_i \leq b$. Let $\mathcal{X}_i = \{\exists w_k \in \mathcal{W} : |\pi_k - \tilde{\pi}_{i-1,k}| \geq c_{i-1,f_{i-1}(k)}\}$ be the event that there exists at least one worker whose expected performance lies outside the confidence interval around $\tilde{\pi}_{i-1,k}$ when assigning task t_i. Let $\bar{\mathcal{X}}_i$ be the complementary event of $\mathcal{X}_i$, i.e., all workers' expected performance fall into the confidence interval around $\tilde{\pi}_{i-1,k}$. We use divide and conquer policy to bound $R(n)$ by rewriting it as

$$R(n) \leq \sum_{i=1}^{i_0} R_i + \sum_{i=i_0+1}^n \mathbb{1}_{\{\mathcal{X}_i\}} R_i + \sum_{i=i_0+1}^n \mathbb{1}_{\{\bar{\mathcal{X}}_i\}} R_i, \quad (14)$$

where the first part specifies the regret in initialization phase and the rest on online selection phase. $\mathbb{1}_{\{\mathcal{X}_i\}}$ is an indicator variable which equals to 1 if event $\mathcal{X}_i$ happens and equals to 0 otherwise. The three components of $R(n)$ are bounded sequentially.

Since each worker is selected at most once during the initialization phase, we have

$$\sum_{i=1}^{i_0} R_i \leq i_0 b \leq K. \quad (15)$$

For the second component, the violation probability of event $\mathcal{X}_i$ is bounded by Lemma 3. As a result, the frequency of event $\mathcal{X}_i$ happens can be bounded as

$$\sum_{i=i_0+1}^n \mathbb{1}_{\{\mathcal{X}_i\}} \leq \sum_{w_k \in \mathcal{W}} \sum_{i=1}^n \sum_{f=1}^i \mathbb{P}(|\pi_k - \tilde{\pi}_{i,k}| \geq c_{i,f})$$
$$\leq 2 \sum_{w_k \in \mathcal{W}} \sum_{i=1}^n \sum_{f=1}^i i^{-2\mu^2}$$
$$\leq 2K \sum_{i=1}^\infty i^{-2\mu^2+1}. \quad (16)$$

When $\mu^2 \geq 3/2$, $\sum_{i=1}^\infty i^{-2\mu^2+1} \leq \sum_{i=1}^\infty i^{-2} = \pi^2/6$. Since for $\forall i : R_i \leq b$, the second component of $R(n)$ can be trivially bounded as $\sum_{i=i_0+1}^n \mathbb{1}_{\{\mathcal{X}_i\}} R_i \leq \pi^2 K b/3$.

Finally, we bound the third component of $R(n)$. When event $\bar{\mathcal{X}}_i$ happens, each worker's expected performance falls into the confidence interval around its empirical value, or equivalently, $\forall w_k \in \mathcal{W} : \pi_k - c_{i-1,f_{i-1}(k)} \leq \tilde{\pi}_{i-1,k} \leq \pi_k + c_{i-1,f_{i-1}(k)}$. With $\pi_k \in [0, 1]$ and $\bar{\pi}_{i,k} = \min\{\tilde{\pi}_{i-1,k} + c_{i-1,f_{i-1}(k)}, 1\}$, the following inequality holds:

$$\pi_k \leq \bar{\pi}_{i,k} \leq \pi_k + 2c_{i-1,f_{i-1}(k)}. \quad (17)$$

For notational simplicity, define the intersection $\mathcal{I}_i = \mathcal{S}_i \cap \mathcal{P}$, the set difference $\mathcal{S}_i^d = \mathcal{S}_i \setminus \mathcal{P}$ and $\mathcal{P}_i^d = \mathcal{P} \setminus \mathcal{S}_i$. The regret regarding task t_i is rewritten as

$$R_i = \mathbb{E}[v_i(\mathcal{I}_i) + \Psi_{v_i}(\mathcal{P}_i^d|\mathcal{I}_i)] - \mathbb{E}[v_i(\mathcal{I}_i) + \Psi_{v_i}(\mathcal{S}_i^d|\mathcal{I}_i)]$$
$$= \mathbb{E}[\Psi_{v_i}(\mathcal{P}_i^d|\mathcal{I}_i)] - \mathbb{E}[\Psi_{v_i}(\mathcal{S}_i^d|\mathcal{I}_i)]. \quad (18)$$

Also, denote $\bar{v}(\cdot)$ the UCB utility based on UCB of worker's empirical performance. Note that workers in set $\mathcal{S}_i$ are selected for task t_i, so their UCB utility should be no less than that of the hindsight optimum, that is $\bar{v}_i(\mathcal{S}_i) \geq \bar{v}_i(\mathcal{P})$, or alternatively,

$$\Psi_{\bar{v}_i}(\mathcal{S}_i^d|\mathcal{I}_i) \geq \Psi_{\bar{v}_i}(\mathcal{P}_i^d|\mathcal{I}_i), \quad (19)$$

which implies that the marginal value of set $\mathcal{S}_i^d$ to set $\mathcal{I}_i$ is higher than that of $\mathcal{P}_i^d$. The submodularity of the utility function and Eq. (17) ensures the following bounds on the UCB utility of each worker

$$\mathbb{E}[v_i(w_k)] \leq \bar{v}_i(w_k) \leq \mathbb{E}[v_i(w_k)] + 2c_{i-1,f_{i-1}(k)}. \quad (20)$$

Collectively, the marginal UCB utility of set $\mathcal{S}_i^d$ to $\mathcal{I}_i$ can be derived from the above inequality as

$$\Psi_{\bar{v}_i}(\mathcal{S}_i^d|\mathcal{I}_i) \leq \mathbb{E}[\Psi_{v_i}(\mathcal{S}_i^d|\mathcal{I}_i)] + 2 \sum_{w_k \in \mathcal{S}_i^d} c_{i-1,f_{i-1}(k)}. \quad (21)$$

Meanwhile,

$$\Psi_{\bar{v}_i}(\mathcal{P}_i^d|\mathcal{I}_i) \geq \mathbb{E}[\Psi_{v_i}(\mathcal{P}_i^d|\mathcal{I}_i)], \quad (22)$$

by combining Eq. (18), (19), (21) and (22), when event $\bar{\mathcal{X}}_i$ happens, it holds

$$R_i \leq 2 \sum_{w_k \in \mathcal{S}_i^d} c_{i-1,f_{i-1}(k)}, \quad (23)$$

which means that the regret corresponding to task t_i is determined by the upper confidence of workers who are selected but not in the hindsight optimum. To further bound Eq. (23), by Eq. (11), we need to bound the selection frequency $f_{i-1}(k)$ of workers in $\mathcal{S}_i^d$.

The UCBG algorithm promotes workers that are not fully explored, especially the ones with selection frequency $f_{i-1}(k) \leq \mu^2 \log i$, as their upper confidence is larger than 1. However, Eq. (23) indicates that selecting many workers who are not fully explored will lead to high regret. Define the less selected set of workers in $\mathcal{S}_i^d$ as

$$\mathcal{Q}_i \triangleq \left\{ w_k \in \mathcal{S}_i^d : f_{i-1}(k) \leq \alpha \log n \right\}, \qquad (24)$$

based on which we define the following events:

$$\mathcal{Y}_i^1 = \left\{ |\mathcal{Q}_i| \geq \gamma \right\}; \qquad (25)$$
$$\mathcal{Y}_i^2 = \left\{ |\mathcal{Q}_i| < \gamma, \left[\exists w_k \in \mathcal{S}_i^d : f_{i-1}(k) \leq \beta \log n \right] \right\}, (26)$$

where α and β are positive constants. Let $R_{\min} = \min_i R_i$, the cumulative regret when $\bar{\mathcal{X}}_i$ happens can be bounded immediately with the following Lemma.

Lemma 4. *When event $\bar{\mathcal{X}}_i$ happens, let $0 < \gamma \leq b$, $\alpha = 16\mu^2 b^2 / R_{\min}^2$ and $\beta = 16\mu^2 \gamma^2 / R_{\min}^2$, then either event $\mathcal{Y}_i^1$ or $\mathcal{Y}_i^2$ happens. Moreover, the frequency of event $\mathcal{Y}_i^1$ and $\mathcal{Y}_i^2$ happens are bounded by $\sum_i \mathbb{1}_{\{\mathcal{Y}_i^1\}} \leq \frac{K}{\gamma} \alpha \log n$ and $\sum_i \mathbb{1}_{\{\mathcal{Y}_i^2\}} \leq K\beta \log n$, respectively.*

Please refer to Appendix A for detailed proof. Based on this Lemma and letting $R_{\max} = \max_i R_i$, we are able to bound the cumulative regret when $\bar{\mathcal{X}}_i$ happens as

$$
\sum_{i=i_0+1}^{n} \mathbb{1}_{\{\bar{\mathcal{X}}_i\}} R_i \leq R_{\max} \sum_{i=i_0+1}^{n} \left(\mathbb{1}_{\{\mathcal{Y}_i^1\}} + \mathbb{1}_{\{\mathcal{Y}_i^2\}} \right)
$$
$$
\leq 16\mu^2 K \left(\frac{b^2}{\gamma} + \gamma^2 \right) \frac{R_{\max}}{R_{\min}^2} \log n. \quad (27)
$$

By letting $\gamma = b^{\frac{2}{3}}$, and substituting Eq. (15), (16) and (27) into Eq. (14), the cumulative regret is bounded as:

$$R(n) \leq 32\mu^2 K b^{\frac{4}{3}} \frac{R_{\max}}{R_{\min}^2} \log n + \frac{\pi^2}{3} K b + K, \qquad (28)$$

which concludes the proof as $R(n)/n \to 0$ when $n \to \infty$. $\square$

Remark 1. *The Fog-based UCBG algorithm is computationally efficient as the selection decision for task t_i can be made in $poly(K, i)$ time.*

For each assignment, the most computationally intensive task is b times sorting of K workers' marginal utilities, which has a typical computational complexity of $O(Kb \log K)$. Complexity of the value assignments could be neglected. Hence, the UCBG algorithm requires limited resources on the Fog server.

Remark 2. *The Fog-based UCBG algorithm is resilient to untruthful workers.*

Myopic workers always have the incentive to contribute nothing after taking the payment. According to the UCBG algorithm, the empirical performance of such workers will

TABLE I
STATISTICS OF YELP DATASET (PITTSBURGH)

Number of businesses	3,625
Number of users	30,797
Number of reviews	104,396
Time span	2005.04 $\sim$ 2016.07
Average reviews per business	28.77
Average reviews per user	3.39
Average reviews per day	25.35

experience a plunge, hence, they will not be selected and their influence on long-term platform utility is effectively suppressed.

Remark 3. *The Fog-based UCBG algorithm can be applied to heterogeneous budget constraints and general utility functions.*

Relying on the compute and storage resources on Fog servers, worker's performance information on spatial tasks is available for revisitation. The essential objective of UCBG is to learn and predict worker's performance on future spatial task. With reliable information on worker's performance, selecting a budget-feasible set of workers to maximize general utility function is achievable. As proved by extensive simulations in Section VI, the proposed UCBG algorithm outperforms others on practical dataset even with dynamic worker set and varying utility function.

VI. PERFORMANCE EVALUATION

The online platform Yelp publishes crowdsourced reviews on local businesses. As being investigated in [18], it provides abundant data traces for emulating spatial crowdsourcing applications. In this section, we conduct experiment on the latest Yelp dataset[4] to evaluate the UCBG algorithm. This dataset contains detailed information on local businesses, such as business ID, location, open hours, parking, etc. Meanwhile, user information like ID, date joining Yelp and review comments is also provided. To collect relevant data for our experiment, user ID and business ID are first extracted from each review comment. Further, full information of those users and businesses is obtained. After comparing datasets of different cities, reviews related to businesses in the city of Pittsburgh are extracted for further analysis. The final Pittsburgh dataset contains information of 3,625 businesses, 30,797 users and 104,396 reviews. Statistics of the Pittsburgh dataset are summarized in Table I.

A. Evaluation Methodology

In our experiment, Yelp users are viewed as workers and reviewing local businesses are regarded as spatial tasks. Note that reviews on Yelp are voluntarily contributed by Yelp users, which is different from our scheme where only selected workers will perform the spatial tasks. However, this dataset provides essential real-world traces on worker information, task instances and worker performance, which are adequate

[4]Round 8 Yelp Dataset Challenge, accessed November, 2016. https://www.yelp.com/dataset_challenge
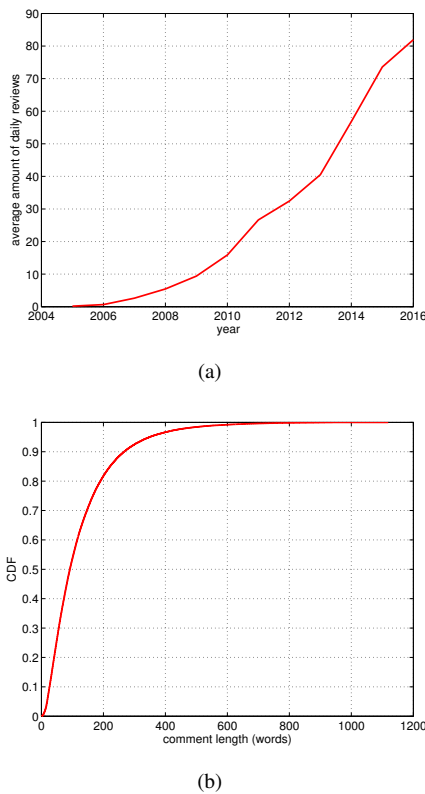
(a)

(b)

Fig. 2. Review statistics of the Pittsburgh dataset. (a) Annual average amount of daily reviews. (b) Cumulative distribution of review comment length.

to emulate spatial crowdsourcing applications [18]. In the experiment, Yelp is considered as a crowdsourcing platform that selects workers to complete reviewing tasks. We divide time span of the dataset into daily instances, and every day a set of workers are selected to review business.

1) Task Budget: Note that the dataset is divided into daily instances, and the amount of reviews is different everyday. Meanwhile, new workers join Yelp continuously, and hence the potential worker set also expands everyday. As a result, to carry out experiment on a more practical and comparable basis, we evaluate the UCBG algorithm with varying budget constraints. Specifically, the daily budget is the same as the amount of daily reviews on that particular date in the dataset. Fig. 2(a) shows the annual average amount of daily reviews across the time span, which also gives trend of varying budget in our experiment.

2) Worker Performance: We evaluate worker's performance of each review task according to the review text length. Statistics of text lengths of all reviews are given in Fig. 2(b). It can be seen that, the text lengths of nearly 80% reviews are less than 200 words. The distribution of each worker's review text length is also analyzed, by which we obtain each worker's performance range bounded by the minimal and maximal review text length respectively. In our experiment, once selected, a worker will submit a review with text length uniformly distributed in her or his performance range. Before each task assignment, each worker chooses a business to review.
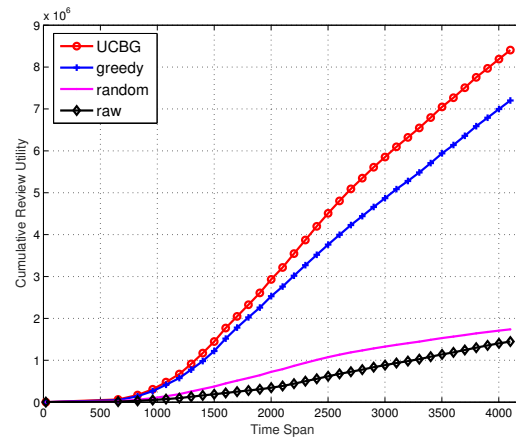

Fig. 3. Comparison of cumulative utility of the crowdsourcing platform.

3) Platform Utility: When soliciting reviews on local businesses, the Fog platform may expect more businesses covered under the budget constraint. Equivalently, the platform should try to avoid popular businesses being reviewed excessively while others are left unattended. Therefore, individual worker's marginal value to the platform is maximized only if each of them reviews a distinct business. In case a business is reviewed more than once, the value of subsequent reviews will be discounted. That is because people's descriptions on the same object share certain similarities. For example, customers may have common feelings on the environment of a restaurant. Nevertheless, the additional reviews are not useless as they improve level of evidence of the description. Let $\Re_{ij}$ denote the j-th review on the i-th business, the platform utility is given by

$$U = \sum_i \sum_j \frac{1}{j} \upsilon(\Re_{ij}), \qquad (29)$$

where $\upsilon(\Re_{ij})$ is the text length of review $\Re_{ij}$. As subsequent comments may be partially similar to the existing ones, the marginal value of review $\Re_{ij}$ is depreciated to $\frac{1}{j}\upsilon(\Re_{ij})$. According to Definition 2, the platform utility function is submodular and monotone. In the experiment, the Fog platform selects a group of workers to gradually improve its utility on a daily basis.

B. Simulation Results

We evaluate the proposed UCBG algorithm by comparing it with greedy and random algorithms. The statistics of the original Pittsburgh dataset are also demonstrated as benchmark under the name of raw. The greedy algorithm dynamically selects workers according to Algorithm 1, where worker's marginal value is evaluated according to its empirical performance. Workers with higher marginal value are gradually selected, which corresponds to full exploitation. The random algorithm randomly chooses available workers to complete the review tasks.

We firstly evaluate the accumulative platform utility across the time span under different worker selection schemes. As shown in Fig. 3, the UCBG algorithm always outperforms other

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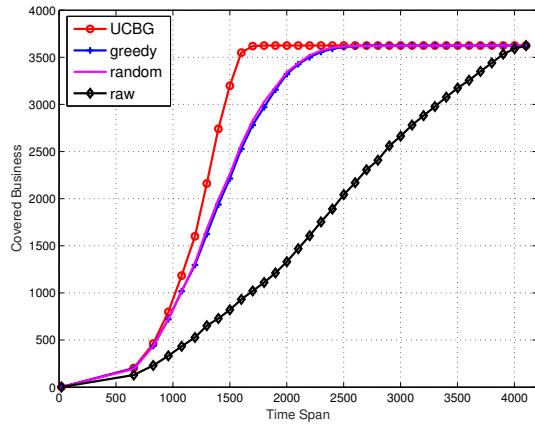
9

Fig. 4. Comparison of business covering speed.
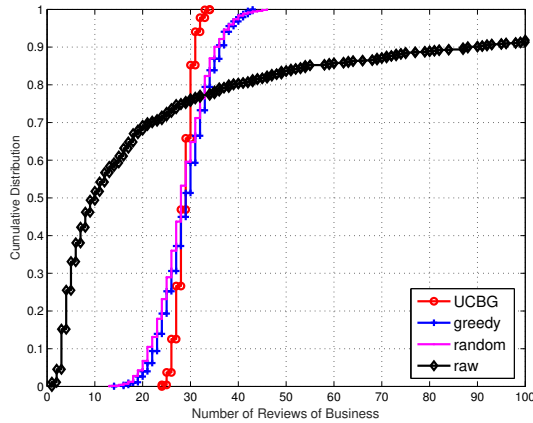
Fig. 5. Comparison of cumulative distribution of individual business's review count in the final state.

Fig. 6. Comparison of cumulative distribution of individual business utility in the final state.

schemes. This is because it not only exploits workers with better empirical performance, but also offers chances to the ones that are not fully explored. Fig. 4 shows the number of covered businesses of each algorithm along the time span. It can be seen that the UCBG algorithm quickly covers all the businesses, requiring only 65% of the time needed by the greedy algorithm.

The skewness of the final-state utility is also analyzed. Fig. 5 shows the cumulative distribution of the amount of reviews of individual business. It can be seen that final-state utility of the UCBG algorithm is the most evenly distributed. Unlike greedy and random algorithms, which lead to review amount varying from 15 to 40, the UCBG algorithm gives almost all businesses around 30 reviews. Meanwhile, as Fig. 6 shows, UCBG is also dominant in terms of individual business utility. The average utility of each business of the UCBG algorithm has an obvious advantage over others. As a result, each business is more thoroughly reviewed.

C. Remarks

Since prospective workers might choose different businesses at each assignment, the utility function is varying constantly.
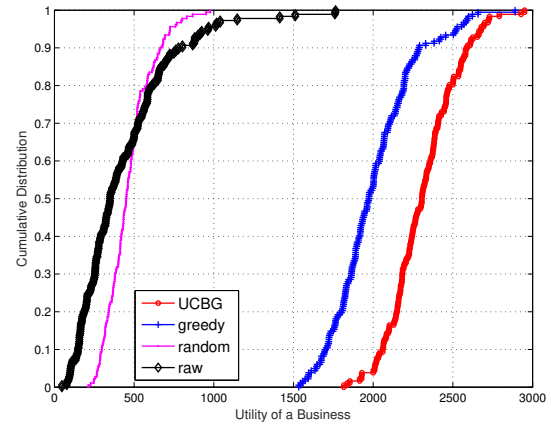
Meanwhile, the available worker set and daily review budget are also fluctuating, which verifies that UCBG algorithm has good performance even with heterogeneous utility function, varying worker set and task budget. The bottomline is that UCBG algorithm focuses on balancing the exploitation and exploration. Regardless of the number of workers and the budget, UCBG algorithm assigns higher upper confidence to the ones that are not fully explored, avoiding local sub-optimal exploitation and thus achieving higher utility.

VII. CONCLUSION

In this paper, we have proposed a Fog-based solution to address worker selection problem in spatial crowdsourcing. The proposed UCBG algorithm can exploit location-aware Fog intelligence to learn worker's historical data, and predict worker's performance on each spatial task, and further select the most valuable combination of workers to perform the task. The proposed solution does not rely on the information of worker's utility information, which is intricate in spatial crowdsourcing applications. By balancing the exploration and exploitation of the learning process, UCBG algorithm can help to improve the long-term utility of the platform. Theoretical analysis indicates that UCBG algorithm achieves asymptotically diminishing per-task regret. Extensive simulations on real-world dataset from Yelp demonstrate the advantage of the proposed algorithm. For our future work, we will investigate task allocation with the aid of Fog intelligence.

APPENDIX A
PROOF OF LEMMA 4

The lemma is proved in two steps.

1) When $\bar{\mathcal{X}}_i$ happens, either $\mathcal{Y}_i^1$ or $\mathcal{Y}_i^2$ happens: This part is proved based on the idea of Lemma 2 in [30]. Define another event $\bar{\mathcal{Y}}_i$ as follows:

$$\bar{\mathcal{Y}}_i = \left\{ |\mathcal{Q}_i| < \gamma, \left[\forall w_k \in \mathcal{S}_i^d : f_{i-1}(k) > \beta \log n \right] \right\}. \quad (30)$$

We can see that events $\mathcal{Y}_i^1$, $\mathcal{Y}_i^2$ and $\bar{\mathcal{Y}}_i$ are exhaustive and mutually exclusive. Therefore, if event $\bar{\mathcal{Y}}_i$ does not happen,

then either $\mathcal{Y}_i^1$ or $\mathcal{Y}_i^2$ happens. Now we prove that when $\bar{\mathcal{X}}_i$ happens, $\bar{\mathcal{Y}}_i$ will never happen due to the following contradiction

$$
\begin{aligned}
R_i &\leq 2\sum_{w_k \in \mathcal{S}_i^d} c_{n,f_{i-1}(k)} \\
&= 2\sum_{w_k \in \mathcal{S}_i^d \setminus \mathcal{Q}_i} c_{n,f_{i-1}(k)} + 2\sum_{w_k \in \mathcal{Q}_i} c_{n,f_{i-1}(k)} \\
&< 2\mu b \sqrt{\frac{\log n}{\alpha \log n}} + 2\mu\gamma\sqrt{\frac{\log n}{\beta \log n}} \qquad (31) \\
&= R_{\min}. \qquad\qquad\qquad\qquad\qquad\qquad\qquad (32)
\end{aligned}
$$

Inequality (31) holds because 1) $|\mathcal{S}_i^d \setminus \mathcal{Q}_i| \leq b$ and all workers in $\mathcal{S}_i^d \setminus \mathcal{Q}_i$ have been selected more than $\alpha \log n$ times and 2) when $\bar{\mathcal{Y}}_i$ happens, $|\mathcal{Q}_i| < \gamma$ and all workers in $\mathcal{S}_i^d$ have been selected more than $\beta \log n$ times. With the above contradiction, when $\bar{\mathcal{X}}_i$ happens, either $\mathcal{Y}_i^1$ or $\mathcal{Y}_i^2$ happens.

2) Bounding the frequency of $\mathcal{Y}_i^1$ and $\mathcal{Y}_i^2$ happens: $\mathcal{Y}_i^1$ indicates that at least γ workers in $\mathcal{S}_i^d$ are selected less than $\alpha \log n$ times. If we let $\mathcal{Y}_i^1$ happen $\frac{K}{\gamma}\alpha \log n$ times, all the workers that may appear in $\mathcal{Q}_i$ have been selected at least $\alpha \log n$ times. If event $\mathcal{Y}_i^1$ happen again, at least one worker in $\mathcal{Q}_i$ has been selected more than $\alpha \log n$ times, so we can easily conclude that $\sum_i \mathbb{1}_{\{\mathcal{Y}_i^1\}} \leq \frac{K}{\gamma}\alpha \log n$.

Similarly, $\mathcal{Y}_i^2$ happens only when at least one worker in $\mathcal{S}_i^d$ has been selected less than $\beta \log n$ times. If we let $\mathcal{Y}_i^2$ happen $K\beta \log n$ times, all workers in next difference set $\mathcal{S}_{i+1}^d$ were selected more than $\beta \log n$ times. So we have $\sum_i \mathbb{1}_{\{\mathcal{Y}_i^2\}} \leq K\beta \log n$.

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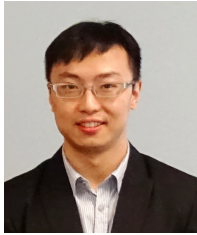
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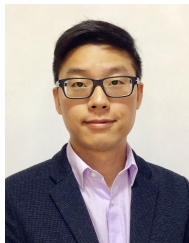
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