Incentive Mechanisms for Smartphone Collaboration in Data Acquisition and Distributed Computing

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***Abstract*—This paper analyzes and compares different incentive mechanisms for a client to motivate the collaboration of smartphone users on both *data acquisition* and *distributed computing* applications.**

Data acquisition from a large number of users is essential to build a rich database and support emerging location-based services. We propose a reward-based collaboration mechanism, where the client announces a total reward to be shared among collaborators, and the collaboration is successful if there are enough users willing to collaborate. We show that if the client knows the users' collaboration costs, then he can choose to involve only users with the lowest costs by offering a small total reward. However, if the client does not know users' private cost information, then he needs to offer a larger total reward to attract enough collaborators. Users will benefit from knowing their costs before the data acquisition.

Distributed computing aims to solve computational intensive problems in a distributed and inexpensive fashion. We study how the client can design an optimal contract by specifying different task-reward combinations for different user types. Under complete information, we show that the client will involve a user type as long as the client's preference for that type outweighs the correspoinding cost. All collaborators achieve a zero payoff in this case. But if the client does not know users' private cost information, he will conservatively target at a smaller group of efficient users with small costs. He has to give most benefits to the collaborators, and a collaborator's payoff increases in his computing efficiency.

I. Introduction

Smartphones are becoming the mainstream in mobile phones. According to a survey by ComScore in 2010, over 45.5 million people owned smartphones out of 234 million total mobile phone subscribers in the United States [1]. In March 2010, Berg Insight reported that global smartphone shipments increased 74% from 2009 to 2010 [2].

Given millions of smartphones sold annually, some recent phone applications start to utilize the power of smartphone users' collaborations [3], [4]. In such an application, there is a *client* (e.g., Apple or Google in the following examples) who wants to implement some application or service based on user collaborations. We can roughly categorize these applications in two types as follows.

In the first type of *data acquisition* application, a client wants to acquire enough data from smartphone users to build up a database. According to [4], Apple's iPhone and Google's Android smartphones regularly transmit their owners' location data (including GPS coordinates) back to Apple and Google, respectively. For example, an Android phone collects its location data every few seconds and transmits the data to Google at least several times an hour. The phone also transmits back the name, location, and signal strength of any nearby Wi-Fi networks. After collecting enough location data from users, Google can successfully build a massive database capable of providing location-based services. One service can be live map of auto traffics, where the dynamics of users' location data on a highway indicate whether there is a traffic jam. Another service can be constructing a large-scale public Wi-Fi map. According to [5], the global location-based service market is growing strongly, and its revenue is expected to increase from US$2.8 billions to US$10.3 billions between 2010 and 2015. In order to perform the above data acquisition, a lot of efforts need to be spent to get users' consent and protect users' privacy (e.g., [6]–[9]). When a user collaborates in this kind of applications, he will incur a cost such as loss of privacy.

In the second type of *distributed computing* application, a client wants to solve complex engineering or commercial problems inexpensively using distributed computation power. Smartphones now have powerful and power-efficient processors (e.g., Dual-core A5 chip of Apple iPhone 4S), outstanding battery life, abundant memory, and open operating systems (e.g., Google Android) [10] that make them suitable for complex processing tasks. Since millions of smartphones remain unused most of the time, a client might want to solicit smartphone collaborations in distributed computing (e.g., [11], [12]). In this case, a user's collaboration cost may be due to loss of energy and reduction of physical storage.

In this paper, we will design incentive mechanism for smartphone collaborations in both data acquisition and distributed computing applications. Then we can compare the similarity and difference in mechanism design for both applications. For each type of applications, we will consider different information scenarios, depending on what the client and users

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know. In particular, the client may or may not know each smartphone user's characteristics such as collaboration costs and collaboration efficiencies.

The two types of applications have different requirements and lead to different models. In data acquisition applications, we consider a threshold-based revenue model, where a client can earn a fixed positive revenue only if he can involve enough (larger than a threshold) smartphone users as collaborators, such that he can build a large enough database to support the application. Since data acquisition only requires simple periodic data reporting, we can assume that users are homogeneous in contribution and efficiency. In distributed computing applications, however, we consider a model where the client's revenue increases in users' efforts. Also, users are heterogeneous in computing efficiencies and should be treated differently. For example, the most efficient users should be highly rewarded to encourage them to undertake large tasks.

Our key results and contributions are as follows:

- *New reward-based collaboration mechanism for data acquisition:* In Section II, we model the interactions between the client and users as a Stackelberg game. The client first announces the total reward to be shared among collaborators and the minimum number of collaborators needed. Each user needs to take other users' decisions into account in estimating the shared reward and the chance of collaboration success.
- *Performance of reward-based mechanism:* Under complete information, the client will only involve users with the lowest costs by offering a small total reward. The client can achieve a similarly good performance under symmetrically incomplete information, when both the client and users do not know users' cost information. But if users know their costs while the client does not (asymmetrically incomplete information), the client needs to offer a large total reward to attract enough collaborators. Overall, users benefit from holding private information.
- *New contract-based collaboration mechanism for distributed computing:* In Section III, we use contract theory to study how a client efficiently decides different task-reward combinations for heterogeneous users.
- *Performance of contract-based mechanism:* Under complete information, the client involves a user type as long as the client's preference of the type is larger than the user cost. All collaborators get a zero payoff. But if users have private information and can hold from the client, the client will conservatively target at a smaller group of efficient users with small costs. He has to give most benefits to the collaborators and a collaborator's payoff increases in the computing efficiency.

A. Related Work

Our first collaboration model on data acquisition is closely related to the literature on location-based services (LBS) [13]. In LBS, a customer needs to report his current location to the database server in order to receive his desired service. Prior work are focusing on how to manage data and how customers can safely communicate with the database server (e.g., [8], [9], [14]), especially when the massive database has already been built up. Other work considered the technical issues of data collection from users [14]. Our paper focuses on the client's problem of incentive mechanism design for attracting enough users (may or may not be LBS customers later) to provide location data, so that the client can build a LBS later on.

Our second collaboration model is relevant to mobile grid computing, which integrates mobile wireless devices into grid computing (e.g., [12], [15]–[17]). The main focus of mobile grid computing literature is on the technical issues of resource management or load balancing (e.g., [16], [17]). Only few results have considered (mobile) users' incentives issues in joining in collaboration [12], [18]–[20]. Kwok *et al.* in [19] evaluate the impact of selfish behaviors of individual users in a Grid. Subrata *et al.* in [20] present a Nash bargaining solution for load balancing among multiple clients. Ghosh *et al.* in [12] and Sim in [18] use a two-player alternating bargaining model to study collaboration between clients and users. The novelty of our model is that a client interacts with all users simultaneously to distribute computing work, and users are heterogeneous in their computing efficiencies and costs. We propose a new contract-based mechanism that maximizes the client's profit.[1]

It should also be noted that our model follows a principal-agent structure in different information scenarios, and is quite different from the P2P structure. Note that in a P2P network, each peer interacts with other peers to obtain local storage and uploading services [22], and the incentive mechanisms in P2P network cannot apply to our principal-agent model.

II. Collaboration on Data Acquisition

A. System Model of Data Acquisition

In this application, the client is interested in building up a database by collecting information from enough smartphone users. We consider a set $\mathcal{N} = \{1, \cdots, N\}$ of smartphones, and the total number N is publicly known.[2] User $i \in \mathcal{N}$ has a collaboration cost $C_i > 0$.[3] We assume that the collaboration costs are independent and identically distributed, with a mean μ and a cumulative probability distribution function $F(\cdot)$.

We consider a *threshold revenue model* for the client. If the client attracts at least n_0 users as collaborators, he will successfully build the database and receive a revenue of V. Otherwise, the client does not receive any revenue.

The client interacts with the users through a two-stage process. In Stage I, the client announces (R, n_0), where R is the total reward to all users and n_0 is the threshold number of required collaborators. In Stage II, each user chooses to be a collaborator or not.

[1]The design of contract-based mechanism here is similar to that in our previous work [21] in methodology, but that work focuses on a different problem on cooperative spectrum sharing and the derived mechanisms are significantly different.

[2]We assume that all N users are active. The client (e.g., Apple) can learn the number of active users (e.g., iPhones) by checking users' usage history, or regularly send control messages to each user for status confirmation.

[3]A user's collaboration cost is determined by his privacy loss. The cost can be property loss due to disclosure of bank account information in data reporting to the client or frequent annoyance from unwanted advertising.

Assume that there are n users willing to serve as collaborators in Stage II. A collaborator i's payoff is

$$\left[\frac{R}{n} - C_i\right] \mathbf{1}_{\{n \geq n_0\}}. \quad (1)$$

where $\mathbf{1}_{\{A\}}$ is the indicator function (equals 1 when event A is true). That is, if the collaboration is successful, user i pays his collaboration cost C_i, and gets the reward R/n (equally spitted among n collaborators). In this case, n users will only collaborate if the client notifies them that $n \geq n_0$ and the collaboration will be successful. This means that no users will pay collaboration cost if the collaboration is not successful. Here, we assume that the client will truthfully inform the collaborators about the value of n.[4]

In this model, the client obtains a profit of

$$(V - R)\mathbf{1}_{\{n \geq n_0\}}.$$

The *collaboration game* is a two-stage Stackelberg game [24]. The way to analyze Stackelberg game is backward induction. We will first analyze Stage II, where the users play a game among themselves based on the value of the reward R and the threshold n_0.[5] Users reach a *Nash equilibrium* (NE) in this stage, if no user can improve his payoff by changing his strategy (collaborate or not) unilaterally. The equilibrium in Stage II leads to a collaboration success probability $P(n \geq n_0; R)$. As we will see, there may be multiple Nash equilibria in Stage II. Then we study Stage I, where the client chooses the value of R to maximize his expected profit $(V - R)P(n \geq n_0; R)$. These two-step analysis enables us to obtain an equilibrium of the whole collaboration game.

Next we will analyze the Stackelberg game, and study how the client's and the users' information about the collaboration costs will affect the outcome. **Most of the proofs are quite lengthy and are given in our online technical report [23].**

B. Collaboration under Complete Information

We first consider the complete information scenario, where the client and all users know the cost C_i of every user $i \in \mathcal{N}$.[6] This is possible when the client and users have extensive prior collaboration experiences. The equilibrium of the collaboration game is as follows.

Theorem 1 (Collaboration under Complete Information): Let C_0 be the n_0-th smallest collaboration cost among all N users. The collaboration game admits the following unique *pure* strategy equilibrium.

- If $V < n_0 C_0$, then the client does not initiate the collaboration in Stage I (i.e., setting $R^* = 0$). No user will become collaborator in Stage II.
- If $V \geq n_0 C_0$, the client offers a reward $R^* = n_0 C_0$ in Stage I. In Stage II, every user i with $C_i \leq C_0$ collaborates and obtains a nonnegative payoff $C_0 - C_i$, and the remaining $N - n_0$ users decline to collaborate and get a zero payoff. The profit of the client is $V - n_0 C_0$.

[4]Here we focus on the incentive issue of users rather than the one of the client. In [23], we further consider the client's incentive issue and propose a solution for it.

[5]We consider that each user will join the collaboration as long as his payoff is nonnegative.

[6]We assume that no two users have the exactly same cost, as there are infinite possible values for the cost.

Under complete information, we can show that users will not benefit from using a mixed-strategy.

C. Collaboration under Symmetrically Incomplete Information

Now we consider the symmetrically incomplete information scenario, where both the client and the users only know the cumulative probability distribution function $F(\cdot)$ of the collaboration costs.[7] A user i even does not know the value of his own cost C_i.[8] In this case, we can view all users as homogeneous.

1) Analysis of Stage II: It turns out that there are multiple equilibria of the collaboration game in Stage II as follows.

Theorem 2: (Stage II under Symmetrically Incomplete Information): Stage II admits the following Nash equilibria:

- *(No Collaboration):* If $R < n_0\mu$, no user will collaborate at any equilibrium in Stage II.
- *(Pure strategy NE):* If $n_0\mu \leq R < N\mu$, $n^* = \lfloor \frac{R}{\mu} \rfloor$ users choose to collaborate and the remaining users decline. If $R \geq N\mu$, all N users will collaborate.
- *(Mixed strategy NE):* If $n_0\mu < R < N\mu$, every user collaborates with a probability p^*, which is the unique solution to

$$\mathbb{E}_m\left(\left[\frac{R}{m+1} - \mu\right] \mathbf{1}_{\{m+1 \geq n_0\}}\right) = 0, \quad (2)$$

where the expectation $\mathbb{E}$ is taken over the random variable m which follows a binomial distribution $B(N-1, p)$.

We note that the pure and mixed strategy equilibria in Theorem 2 share a common parameter range, $n_0\mu < R < N\mu$.

In the pure strategy NE, a subset of n^* users is picked up among $\binom{N}{n^*}$ possible subsets. Thus there exist multiple pure NEs in this case.[9]

Next we show how the mixed strategy NE p^* is derived. As all users have the same statistical information, we will focus on the symmetric mixed Nash equilibrium. Assume that all users collaborate with a probability p. If user i collaborates, his expected payoff is

$$u(R, p) := \mathbb{E}_m\left(\left[\frac{R}{m+1} - \mu\right] \mathbf{1}_{\{m+1 \geq n_0\}}\right),$$

where m is the number of users (other than i) who collaborate and the expectation is taken over m. Note that m follows a binomial distribution $B(N-1, p)$, and is independent of user i's decision.

Given all the other $N - 1$ users collaborate with the equilibrium probability p^*, user i's payoffs by choosing to collaborate or not are the same. Thus p^* should satisfy

$$u(R, p^*) = 0,$$

[7]The client can estimate $F(\cdot)$ by learning from his collaboration history or making a customer survey. A user can estimate $F(\cdot)$ by checking his or other users' collaboration experiences. There are many public sources (e.g., the client's or some third party's market or customer surveys) that help a user's cost estimation [5], [14].

[8]It is sometimes difficult for a user to know his precise loss of privacy before an actual security threat happens to him. Users may face many possible security threats by losing sensitive information, e.g., direct property loss or advertising harassment.

[9]In our online technical report [23], we provide further discussions on how to select among multiple pure NEs.

and is a function of R. Thus we can rewrite p^* as $p^*(R)$. One can show that there exists a mixed strategy Nash equilibrium $p^*(R) \in (0, 1)$ as long as $n_0\mu < R < N\mu$. Note that $R \leq n_0\mu$ leads to $p^*(R) = 0$, which is not a mixed strategy. Also, $R \geq N\mu$ leads to $p^*(R) = 1$, which is not a mixed strategy either.

2) Analysis of Stage I: First we consider the case where users use the mixed strategy in Theorem 2 and collaborate with probability $p^*(R)$. The client's expected profit is then

$$f(R) := \mathbb{E}_n \left([V - R] \mathbf{1}_{\{n \geq n_0\}} \right),$$

where the expectation is taken over n which follows a binomial distribution $(N, p^*(R))$. One can show that $f(R)$ has a unique maximum $f(R^*)$, which is positive when $V > n_0\mu$. However, under $n_0\mu < R < N\mu$ there is always a chance that there are less than n_0 users choosing to collaborate under the mixed strategy. Thus the client may want to avoid this. Theorem 2 shows that by choosing $R = n_0\mu$, the client can guarantee n_0 collaborators with a pure strategy Nash equilibrium in Stage II. This leads to the following result.

Theorem 3: (Stage I under Symmetrically Incomplete Information:) The collaboration game admits the following unique equilibrium.

- If $V < n_0\mu$, the client will not initiate the collaboration and choose $R^* = 0$.
- If $V \geq n_0\mu$, the client will announce a reward $R^* = n_0\mu$. A set of n_0 users will collaborate in Stage II. The collaborators achieve a zero expected payoff, and the client achieves a profit $V - n_0\mu$.

D. Collaboration under Asymmetrically Incomplete Information

In this subsection, we study the case where each user i knows his own exact cost C_i, but not other users' costs. The client only knows $F(\cdot)$.

1) Analysis of Stage II: We have the following result for Stage II.

Theorem 4: (Stage II under Asymmetrically Incomplete Information): A user i will collaborate if and only if $C_i \leq \gamma^*(R)$. The common equilibrium decision threshold $\gamma^*(R)$ is the unique solution of $\Phi(\gamma) = 0$, where

$$\Phi(\gamma) := \mathbb{E}_m \left(\left[\frac{R}{m+1} - \gamma \right] \mathbf{1}_{\{m+1 \geq n_0\}} \right), \tag{3}$$

and the expectation is taken over m which follows a binomial distribution $B(N-1, F(\gamma))$. The equilibrium $\gamma^*(R)$ satisfies $\frac{R}{N} < \gamma^*(R) < \frac{R}{n_0}$.

We can also show that a user will not be better off by changing from the current pure strategy to any mixed strategy. To see why Stage II has the NE in Theorem 4, we consider that all users other than i collaborate if and only if their costs are less than some $\gamma > 0$. If user i collaborates, his payoff is

$$\left[\frac{R}{m+1} - C_i \right] \mathbf{1}_{\{m+1 \geq n_0\}},$$

where m follows a binomial distribution $B(N-1, F(\gamma))$ and represents the number of users (other than i) who collaborate. (Recall that cdf $F(\gamma) = P(C_i \leq \gamma)$.) Accordingly, the expected payoff of user i if he collaborates is

$$\mathbb{E}_m \left(\left[\frac{R}{m+1} - C_i \right] \mathbf{1}_{\{m+1 \geq n_0\}} \right), \tag{4}$$

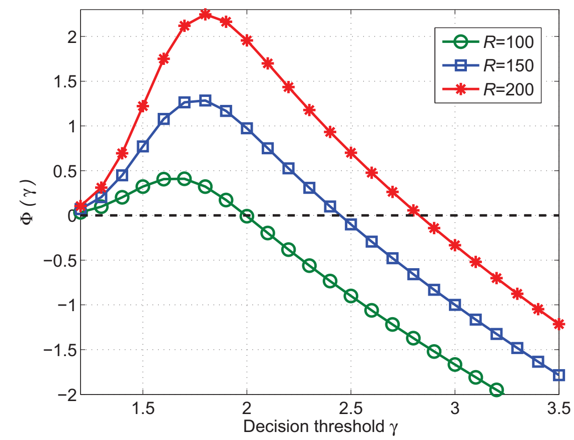

Fig. 1. $\Phi(\gamma)$ as a function of γ and R. Other parameters are $n_0 = 40$ and $N = 100$. We consider a uniform cost distribution with $F(\gamma) = \min(\gamma/4, 1)$.

and zero otherwise. At the Nash equilibrium, (4) should equal to 0 when $C_i = \gamma$. That is, having the common collaboration threshold γ is a Nash equilibrium if and only if $\Phi(\gamma) = 0$. We denote the solution to (3) as $\gamma^*(R)$, which is proved to be unique in [23].

Figure 1 shows $\Phi(\gamma)$ as a function of both γ and R. The solution $\gamma^*(R)$ to $\Phi(\gamma) = 0$ is always unique and satisfies $\frac{R}{N} < \gamma^*(R) < \frac{R}{n_0}$.[10] When $R = 100$, for example, we have $\gamma^*(R) = 2$, which is larger than $R/N = 1$ and is smaller than $R/n_0 = 2.5$. It is also interesting to notice that all users share the same decision threshold $\gamma^*(R)$ although they have different costs.

Theorem 5: The equilibrium decision threshold $\gamma^*(R)$ increases in R, and decreases in N and n_0.

Intuitively, as N or n_0 increases, more users will participate in the collaboration and thus the shared reward per collaborator decreases. As a result, the decision threshold decreases, and each user is less likely to collaborate.

2) Analysis of Stage I: We are now ready to consider Stage I. Given users' equilibrium strategies based on threshold $\gamma^*(R)$ in Stage II in Theorem 4, the client chooses reward R to maximize his expected profit, i.e.,

$$\max_R f(R) = \mathbb{E}_n \left([V - R] \mathbf{1}_{\{n \geq n_0\}} \right), \tag{5}$$

where the expectation is taken over n which follows a binomial distribution $B(N, F(\gamma^*(R)))$. A smaller reward R leads to a larger value of $V - R$, but decreases the collaboration success probability $P(n \geq n_0; R)$.

Let us denote the client's equilibrium choice of reward in Stage I as R^*, which is derived by solving Problem (5).

Theorem 6: The equilibrium expected profit $f(R^*)$ of the client increases in V and N, and decreases in n_0.

As the client's revenue V increases, he benefits more from the collaboration. As the threshold n_0 increases, however, each user is less likely to collaborate. Thus the client has to give a larger total reward to attract enough collaborators. This decreases his equilibrium expected profit.

[10] It should be noted that $\gamma^*(R)$ should always be positive, otherwise no users will collaborate and there exists no decision threshold then.

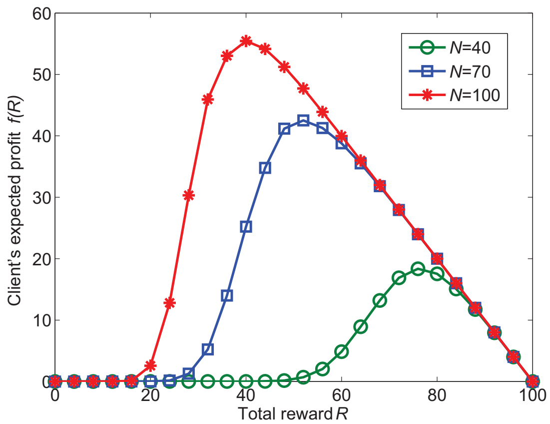

Fig. 2. Client's expected profit $f(R)$ as a function of R and N. Other parameters are $n_0 = 30$ and $V = 100$. Also, we consider a uniform cost distribution with $F(\gamma) = \min(\gamma/3, 1)$.

Figure 2 shows that the client's expected profit $f(R)$ as a function of R and N. We can see that both $f(R)$ and the equilibrium $f(R^*) = \max_R f(R)$ are increasing in N. Intuitively, as N increases, more users have small collaboration costs (as the cdf function $F(\cdot)$ does not change), and more users will collaborate under the same total reward. Thus the client can lower the equilibrium reward R^* and obtain a larger profit.

By comparing the performances of the client and users under complete information, symmetrically incomplete information, and asymmetrically incomplete information, we have the following result.

Theorem 7: At the equilibrium of the collaboration game, the client obtains the smallest expected profit under *asymmetrically* incomplete information, whereas the users obtain the smallest (zero) expected payoffs under *symmetrically* incomplete information.

Theorem 7 shows that the users benefit from knowing their own costs, while the client incurs profit loss when the users know their costs and can hide the information from the client.

Recall that the client obtains an expected profit $V - n_0\mu$ under symmetrically incomplete information, and obtains a profit $V - n_0 C_0$ under complete information. The relation between these two values depends on N, n_0, and $F(\cdot)$. Take the uniform distribution $F(\cdot)$ as an example. If n_0 is much smaller than $N/2$, the expected value of C_0 will be smaller than μ and the client is better off under complete information.

III. Collaborations on Distributed Computing

A. System Model on Distributed Computation

In this type of applications, the client solicits the collaboration of users to perform distributed computing. Different from requiring fixed and periodic data reporting as in data acquisition applications, the client here can assign different amounts of work to different user types. Smartphones are generally different in terms of CPU performance, memory and storage, battery life, and connectivity [15]. Even with the same smartphones, two users may have different phone usage behaviors and different sensitivities (e.g., to power consumption).

We consider a total of N users belonging to a set $\mathcal{I} = \{1, \cdots, I\}$ of I types. Each type $i \in \mathcal{I}$ has $N_i \geq 1$ users, with $\sum_{i\in\mathcal{I}} N_i = N$. A type-$i$ user can perform at most $\bar{t}_i$ units of work, and faces a cost K_i per unit of work he performs. The upper bound $\bar{t}_i$ reflects the limited battery capacity, time constraint, or other physical constraints. It should be noted that here users know their unit costs before the collaboration, since (i) many factors of these costs (e.g., power consumption) are explicitly reflected by smartphones' technical specifications, and (ii) users explicitly know their own sensitivities (e.g., to power consumption) in costs.[11]

The payoff of a type-i user who accomplishes t units of work and receives a reward r from the client is

$$u_i(r, t) = r - K_i t, \text{ for } 0 \leq t \leq \bar{t}_i. \quad (6)$$

Note that the user can always choose not to collaborate with the client and thus receive zero payoff with $t = r = 0$. Without loss of generality, we order user types in the descending order of the unit cost, i.e., $K_1 > K_2 > ... > K_I$, i.e., a higher type of user has a smaller cost.

By asking each type-i user to accomplish the amount t_i of work and rewarding him with r_i, the client's profit is

$$\pi(\{(r_i, t_i)\}_{i\in\mathcal{I}}) = \sum_{i\in\mathcal{I}} (\theta_i \log(1 + N_i t_i) - N_i r_i). \quad (7)$$

The term $\theta_i \log(1 + N_i t_i)$ is increasing in users' efforts and well characterizes the client's diminishing return (or utility) from the total work $N_i t_i$ finished by type-i (as in [25], [26]).[12] The parameter $\theta_i > 0$ characterizes the client's preference for work performed by type-i users, and does not depend on K_i. In particular, θ_i's may or may not be decreasing in i. The term $N_i r_i$ in (7) is the total reward that the client offers to type-i users. The summation operation in (7) is motivated by the fact that many complex engineering or commercial problems can be separated into multiple subproblems and solved in a distributed manner [12].

By examining (6) and (7), we can see that the client and users have conflicting objectives. The client wants users to accomplish a larger task, which increases the client's utility as well as users' collaboration costs. Users want to obtain a larger reward, which decreases the client's profit. Next we study how client and users interact through a contract.

B. Contractual Interactions between Client and Users

Contract theory studies how an economic decision-maker constructs contractual arrangements, especially in the presence of asymmetric (private) information [27]. In our case, the user types are private information.

The client proposes a contract that specifies the relationship between a user's amount of task t and reward r. Specifically, a *contract* is a set $\mathcal{C} = \{(t_1, r_1), \ldots, (t_M, r_M)\}$ of $M \geq 1$ (amount of task, reward)-pairs that are called *contract items*.

[11] Recall that in data acquisition, users' costs mainly come from implicit insecurity and they may not know their collaboration costs.

[12] The assumed logarithmic utility term helps us derive closed-form solutions and engineering insights. Using other concave terms are not likely to change the main conclusions.

The client proposes $\mathcal{C}$. Each user selects a contract item (t_m, r_m) and performs the amount of work t_m for the reward r_m. According to [27], it is optimal for the client to design a contract item for each type, i.e., $M = I$. Note that a user can always choose not to work for the client, which implies an implicit contract item $(r, t) = (0, 0)$ (often not counted in the total number of contract items). Once a user accepts some contract item, he needs to accomplish the task and the client needs to reward him according to that item.

Each type of users selects the contract item that maximizes his payoff in (6). The client wants to optimize the contract items and maximize his profit in (7). We will again focus on a two-stage Stackelberg game, where the client proposes the contract first and users choose the contract items afterwards.

Next, we study how the client determines the contract that maximizes his profit, depending on what information he has about the users' types. As explained in the beginning of Section III-A, we assume that a user knows his unit cost. This means that we only need to consider two information scenarios, complete information and asymmetrically incomplete information, depending on what the client knows. **Most of proofs are lengthy and are given in our online technical report [23] due to page limit.**

C. Contract Design under Complete Information

In this subsection, we study the case where the client knows the type of each user. This makes it possible for the client to monitor and make sure that each type of users accepts only the contract item designed for that type. The client needs to ensure that each user has a non-negative payoff so that the user will accept the contract. In other words, the contract should satisfy the following individual rationality constraints.

Definition 1 (IR: Individual Rationality): A contract satisfies the individual rationality constraints if each type-i user receives a non-negative payoff by accepting the contract item for type-i, i.e.,

$$r_i - K_i t_i \geq 0, \ \forall i \in \mathcal{I}. \tag{8}$$

Under complete information, the optimal contract $\mathcal{C} = \{(r_i^*, t_i^*)\}_{i\in\mathcal{I}}$ solves the following problem:

$$\begin{aligned} \max_{\{(r_i,t_i)\}_{i\in\mathcal{I}}} \ & \pi(\{(r_i, t_i)\}_{i\in\mathcal{I}}) \\ & = \sum_{i\in\mathcal{I}} (\theta_i \log(1 + N_i t_i) - N_i r_i), \\ \text{subject to: } & \text{IR constraints (8) and } 0 \leq t_i \leq \bar{t}_i, \forall i \in \mathcal{I}. \end{aligned} \tag{9}$$

It is easy to check that the IR constraints are tight at the optimal solution to Problem (9), and the client will leave a zero payoff to each type-i user with $r_i^* = K_i t_i^*$. Also, due to the independence of each type in Problem (9), we can decompose Problem (9) into I subproblems. For each type $i \in \mathcal{I}$, the client needs to solve the following subproblem

$$\begin{aligned} \max_{t_i} \ & \pi_i(t_i) = \theta_i \log(1 + N_i t_i) - N_i K_i t_i, \\ \text{subject to: } & 0 \leq t_i \leq \bar{t}_i. \end{aligned} \tag{10}$$

By solving all I subproblems, we have the following result.

Theorem 8 (Optimal Contract under Complete Information): At the equilibrium, the client will hire the type-i users if $\theta_i > K_i$. The total involved user type set is

$$\mathcal{I}_C = \{i \in \mathcal{I} : \theta_i > K_i\}. \tag{11}$$

The subscript C in $\mathcal{I}_C$ refers to the complete information assumption. For a user with type $i \in \mathcal{I}_C$, the equilibrium contract item is

$$\begin{aligned} (r_i^*, t_i^*) &= (K_i t_i^*, t_i^*) \\ &= \left(\min\left(\frac{\theta_i - K_i}{N_i}, K_i\bar{t}_i\right), \min\left(\frac{\theta_i - K_i}{K_i N_i}, \bar{t}_i\right)\right). \end{aligned} \tag{12}$$

For a user with type $i \notin \mathcal{I}_C$, the equilibrium contract item is $(r_i^*, t_i^*) = (0, 0)$. All users (no matter joining collaboration or not) receive a zero payoff. The client's equilibrium profit is

$$\begin{aligned} \pi^* = & \sum_{i\in\mathcal{I}_C} \\ & \min\left(\theta_i \log\left(\frac{\theta_i}{K_i}\right) - \theta_i + K_i, \theta_i \log(1 + N_i\bar{t}_i) - N_i K_i \bar{t}_i\right). \end{aligned} \tag{13}$$

Proof. By observing Problem (10), the client will only hire type-i users when his marginal utility is larger than marginal cost (i.e., reward to users) at $t_i = 0$. That is,

$$\frac{d\pi_i(t_i)}{dt_i}|_{t_i=0} = \left(\frac{N_i\theta_i}{1 + N_i t_i} - N_i K_i\right)|_{t_i=0} = N_i(\theta_i - K_i) > 0,$$

Thus the client will hire type-i users only when $\theta_i > K_i$. Since $\pi_i(t_i)$ is concave in $0 \leq t_i \leq \bar{t}_i$, we can directly examine the first-order condition of $\pi_i(t_i)$ over t_i for each type. Then we can derive the equilibrium contract item for type-i in (12).

By substituting all contract items into the objective function in Problem (9), we can further derive the client's equilibrium profit in (13). ■

Intuitively, the client needs to compensate a collaborator's cost, thus he will hire type-i users only when his preference characteristic θ_i is larger than the unit cost of that type K_i. Users will receive a zero payoff since their private information about unit costs are known to the client.

By looking into all parameters in the equilibrium contract in (12) and payoff π^* in (13), we have the following observation.

Observation 1: For $i \in \mathcal{I}_C$, the equilibrium task t_i^* to a type-i user increases in θ_i, and decreases in N_i and K_i. Also, the client's equilibrium profit π^* increases in θ_i, N_i, and $\bar{t}_i$, and decreases in K_i.

By looking into (12), we also have the following result.

Observation 2: The client may or may not offer a larger task or reward to a higher type-i collaborator, depending on the number of collaborators N_i and the client's preference characteristic θ_i for that type.

Notice that a higher type-i collaborator has less unit cost where the client needs to compensate, but the client may not give him a larger task or reward. This can happen when there are too many collaborators of that type, or the client evaluates this type with a small value of θ_i.

D. Client's Contract Design under Asymmetrically Incomplete Information

In this subsection, we study the case where the client only has asymmetrically incomplete information about each user's type. A user's actual type is only known to himself, and the client and the other users only have a rough estimation on this. We consider that others believe a user belonging to type-i with a probability q_i. Everyone knows the total number of users N.[13]

1) Feasibility of contract under asymmetrically incomplete information: According to [27], the client's contract should first be feasible in this scenario. A feasible contract must satisfy both individual rationality (IR) constraints (Definition 1 in Section III-C) and incentive compatibility constraints defined as follows.

Definition 2 (IC: Incentive Compatibility): A contract satisfies the incentive compatibility constraints if each type-i user prefers to choose the contract item for his own type, i.e.,

$$r_i - K_i t_i \geq r_j - K_i t_j, \ \ \forall i, j \in \mathcal{I}. \tag{14}$$

Under asymmetrically incomplete information, the client does not know the number of users N_i of type-i. Let us denote the users' numbers of all types as $\{n_i\}_{i\in\mathcal{I}}$, which are random variables following certain distributions and satisfying $\sum_{i\in\mathcal{I}} n_i = N$. Note that the realizations of $\{n_i\}_{i\in\mathcal{I}}$ depend on N and probabilities $\{q_i\}_{i\in\mathcal{I}}$ of all types that a user may belong to. The client's profit for a particular realization of $\{n_i\}_{i\in\mathcal{I}}$ is

$$\pi(\{(r_i,t_i)\}_{i\in\mathcal{I}}, \{n_i\}_{i\in\mathcal{I}}) = \sum_{i\in\mathcal{I}} (\theta_i \log(1+n_i t_i) - n_i r_i). \tag{15}$$

Thus the client's expected profit is

$$\begin{aligned}&\mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[\pi(\{(r_i,t_i)\}_{i\in\mathcal{I}}, \{n_i\}_{i\in\mathcal{I}})]\\ &= \sum_{n_1=0}^{N} \sum_{n_2=0}^{N-n_1} \cdots \sum_{n_{I-1}=0}^{N-\sum_{j=1}^{I-2} n_j} \frac{N! q_1^{n_1} \ldots q_{I-1}^{n_{I-1}} q_I^{N-\sum_{j=1}^{I-1} n_j}}{n_1! \ldots n_{I-1}! (N-\sum_{j=1}^{I-1} n_j)!}\\ &\quad \times \pi(\{(r_i,t_i)\}_{i\in\mathcal{I}}, \{n_i\}_{i\in\mathcal{I}}).\end{aligned} \tag{16}$$

The client's profit optimization problem as

$$\begin{aligned}\max_{\{(r_i,t_i)\}_{i\in\mathcal{I}}} \ & \mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[\pi(\{(r_i,t_i)\}_{i\in\mathcal{I}}, \{n_i\}_{i\in\mathcal{I}})]\\ \text{subject to: } & \text{IR constraints in (8)},\\ & \text{IC constraints in (14)},\\ & 0 \leq t_i \leq \bar{t}_i, \forall i \in \mathcal{I}.\end{aligned} \tag{17}$$

The total number of IR and IC constraints is I^2. Next, we show that it is possible to represent these I^2 constraints with a set of much fewer equivalent constraints.

Proposition 1: (Sufficient and Necessary Conditions for feasibility): For a contract $\mathcal{C} = \{(r_i,t_i), \forall i \in \mathcal{I}\}$ with user costs $K_1 > \ldots > K_I$, it is feasible if and only if all the following conditions are satisfied:

1) $\texttt{Condition}(+)$: $r_1 - K_1 t_1 \geq 0$;
2) $\texttt{Condition}(\uparrow)$: $0 \leq r_1 \leq \ldots \leq r_I$ and $0 \leq t_1 \leq \ldots \leq t_K$;
3) $\texttt{Condition}(\leq)$: For any $i = 2, \ldots, I$,

$$r_{i-1} + K_i(t_i - t_{i-1}) \leq r_i \leq r_{i-1} + K_{i-1}(t_i - t_{i-1}). \tag{18}$$

Intuitively, $\texttt{Condition}(+)$ ensures that all types of users can get a nonnegative payoff by accepting the contract item (r_1, t_1), as it implies $r_1 - K_j t_1 \geq 0$ for all $j \geq 2$. Thus this can replace the IR constraints in (8). $\texttt{Condition}(\uparrow)$ and $\texttt{Condition}(\leq)$ are related to IC constraints in (14). $\texttt{Condition}(\uparrow)$ shows that a user with a higher type should be assigned a larger task, because his unit cost is lower (and more efficient) and the client needs to compensate this user less per unit work. Also, a larger reward should be given to this user for the larger task undertaken by him, otherwise this user will choose another contract item in order to work less. $\texttt{Condition}(\leq)$ shows the relation between any two neighboring contract items.

[13] Users can know N by checking some third party's market survey, or the news on recent penetration or shipment of smartphones.

Based on Proposition 1, we can simplify the client's problem in (17) as

$$\begin{aligned}\max_{\{(r_i,t_i)\}_{i\in\mathcal{I}}} \ & \mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[\pi(\{(r_i,t_i)\}_{i\in\mathcal{I}}, \{n_i\}_{i\in\mathcal{I}})]\\ \text{subject to, } & \texttt{Condition}(+), \texttt{Condition}(\uparrow), \texttt{Condition}(\leq),\\ & 0 \leq t_i \leq \bar{t}_i, \forall i \in \mathcal{I},\end{aligned} \tag{19}$$

where the previous I^2 IR and IC constraints have been reduced to $I+2$ constraints.

2) Analysis by sequential optimization: Now we want to solve the client's optimal contract. However, (19) is not easy to solve as it has coupled variables and many constraints. The way we solve is a sequential optimization approach: we first derive the optimal rewards $\{r_i^*(\{t_i\}_{i\in\mathcal{I}})\}_{i\in\mathcal{I}}$ given any feasible tasks $\{t_i\}_{i\in\mathcal{I}}$, then further derive the optimal tasks $\{t_i^*\}_{i\in\mathcal{I}}$ for the optimal contract.

Proposition 2: Let $\mathcal{C} = \{(r_i,t_i)\}_{i\in\mathcal{I}}$ be a feasible contract with any feasible tasks $0 \leq t_1 \leq \ldots \leq t_I$. The unique optimal rewards $\{r_i^*(\{t_i\}_{i\in\mathcal{I}})\}_{i\in\mathcal{I}}$ satisfy

$$r_1^*(\{t_i\}_{i\in\mathcal{I}}) = K_1 t_1, \tag{20}$$

$$\begin{aligned}r_i^*(\{t_i\}_{i\in\mathcal{I}}) &= r_{i-1}^* + K_i(t_i - t_{i-1})\\ &= K_1 t_1 + \sum_{j=2}^{i} K_j(t_j - t_{j-1}), \forall i = 2, \ldots, I.\end{aligned} \tag{21}$$

Proof (Sketch): First, we can prove (20) by showing that $\texttt{Condition}(+)$ binds at the optimality. This guarantees the IR constraints of the contract. Second, we can prove (21) by showing that the left-hand side inequality in $\texttt{Condition}(\leq)$ binds at the optimality. This guarantees the IC constraints of the contract. ■

Based on Proposition 2, we can greatly simplify the client's optimization Problem in (19) as

$$\begin{aligned}\max_{\{t_i\}_{i\in\mathcal{I}}} \ & \mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[\pi(\{(r_i^*(\{t_i\}_{i\in\mathcal{I}}), t_i)\}, \{n_i\}_{i\in\mathcal{I}})]\\ \text{subject to, } & 0 \leq t_1 \leq \ldots \leq t_I,\\ & t_i \leq \bar{t}_i, \forall i \in \mathcal{I}.\end{aligned} \tag{22}$$

Problem (22) can be solved by various methods in nonlinear programming [28]. In the following, to avoid a loss of optimality, we use exhaustive search to solve Problem (22). This helps us explicitly compare the client's performances in different information scenarios.

Without solving Problem (22), we can already derive some interesting results as follows.

Theorem 9: The total involved user type set under asymmetrically incomplete information is

$$\begin{aligned}\mathcal{I}_A = \{&i \in \mathcal{I} :\\ &\mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[n_i(\theta_i - K_i) - (K_i - K_{i+1}) \sum_{\forall j>i, j\in\mathcal{I}} n_j > 0]\}.\end{aligned} \tag{23}$$

The subscript A in $\mathcal{I}_A$ refers to the asymmetrically incomplete information assumption.[14] Compared with the collaborator set $\mathcal{I}_C$ under complete information case, here the client involves less collaborators, i.e., $|\mathcal{I}_A| \leq |\mathcal{I}_C|$. Moreover, the client assigns a larger task and gives a larger reward to a higher type of collaborator, which may not be the case under complete information (see Observation 2). Only the lowest type of collaborator(s) in set $\mathcal{I}_A$ obtains a zero payoff, and higher types of collaborators in set $\mathcal{I}_A$ obtain positive payoffs that are increasing in their types.

Proof: All involved users in set $\mathcal{I}_A$ will receive positive rewards and tasks. According to `Condition`($\uparrow$), the rewards and tasks are non-decreasing in the types. Let us denote the lowest type of involved users in set $\mathcal{I}_A$ as type-$\hat{j}$. If $\hat{j} = 1$, then relation (20) shows that a type-1 collaborator receives a zero payoff. If $\hat{j} > 1$, then any lower type $k < \hat{j}$ is not in set $\mathcal{I}_A$, and receives zero task and zero reward. By using relation (21), we can further derive that $r^*_{\hat{j}} = K_{\hat{j}} t^*_{\hat{j}}$, which means the lowest type collaborator still obtains a zero payoff.

According to (21), the type-i collaborator's equilibrium payoff is $r_i^* - K_i t_i^* = r_{i-1}^* - K_i t_{i-1}^*$, which is strictly larger than type-$(i-1)$ collaborator's payoff $r_{i-1}^* - K_{i-1} t_{i-1}^*$ as $K_i < K_{i-1}$. Thus a higher type collaborators receive a larger positive payoff.

Next we show which types of users are involved as collaborators. The first derivative of the client's expected profit in (16) over t_i is

$$\frac{\partial \mathbb{E}_{\{n_i\}_{i\in\mathcal{I}}}[\pi(\{(r_i^*(\{t_i\}_{i\in\mathcal{I}}), t_i)\}, \{n_i\}_{i\in\mathcal{I}})]}{\partial t_i} = \sum_{n_1=0}^{N} \sum_{n_2=0}^{N-n_1} \cdots \sum_{n_{I-1}=0}^{N-\sum_{j=1}^{I-2} n_j} \frac{N! q_1^{n_1} \ldots q_{I-1}^{n_{I-1}} q_I^{N-\sum_{j=1}^{I-1} n_j}}{n_1! \ldots n_{I-1}! (N - \sum_{j=1}^{I-1} n_j)!} \left(\frac{n_i \theta_i}{1 + n_i t_i} - n_i K_i - (K_i - K_{i+1}) \sum_{\forall j > i, \forall j \in \mathcal{I}} n_j \right), \forall i \in \mathcal{I}, \tag{24}$$

where t_i only appears in the last bracket. The client will involve type-i users only when the last bracket of (24) is positive at $t_i = 0$. This leads to the collaborator set in (23). By comparing $\mathcal{I}_C$ in (11) and $\mathcal{I}_A$ in (23), we conclude that $|\mathcal{I}_A| \leq |\mathcal{I}_C|$. ■

Intuitively, as the client does not know each user's type, he needs to provide incentives (in terms of positive payoffs) to the users to attract them revealing their own types truthfully. If he involves a low type user, he needs to give increasingly higher payoffs to all higher types. Thus he should target at users with high enough types. We have $|\mathcal{I}_A|$ smaller than $|\mathcal{I}_C|$, which means that some low types belong to set $\mathcal{I}_C$ may not be included in set $\mathcal{I}_A$. By comparing (23) and (11) for the highest type-I, we know that that this type is involved in both information scenarios.

Recall that under complete information, Observation 2 shows that the client may not give a larger task and reward to a higher type-i collaborator. This can happen when θ_i is small or the number of users of that type is large. Under asymmetrically

[14] Note that the client will design $(r^*, t^*) = (0, 0)$ for the types not in set $\mathcal{I}_A$. Thus the users of these types are not involved as collaborators.

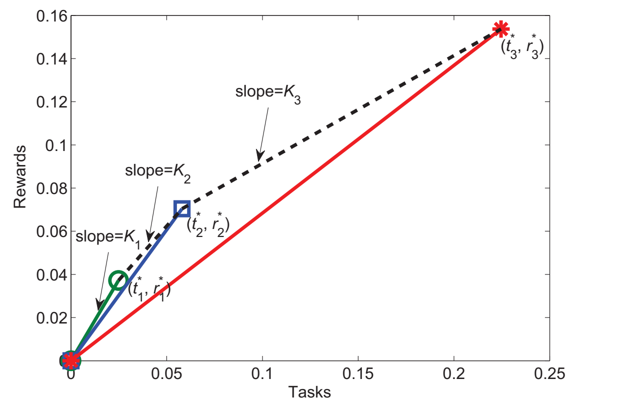

Fig. 3. The client's optimal contract items for three types (I=3). Other parameters are $N = 120$, $K_1 = 1.5$, $K_2 = 1$, $K_3 = 0.5$, $\theta_i = 5$, and $q_i = 1/3$ for any $i \in \mathcal{I}$.

incomplete information, however, the IC constraints require the reward and task to be nondecreasing in the collaborator types, independent of θ_i and the number of users in each type (which is a random variable). Otherwise, some collaborators will have incentives to choose contract items not designed for their own types, and thus violate IC constraints. This is not optimal for the client based on the Revelation Principle [27].

Figure 3 shows the client's optimal contract $\{(r_i^*, t_i^*)\}_{i=1}^3$ for three collaborator types. A higher type-i user obtains a larger task t_i^*, a larger reward r_i^*, and a larger payoff (not shown in this figure). The slope of the dashed line between two points (r_i^*, t_i^*) and (r_{i+1}^*, t_{i+1}^*) equals to cost K_{i+1} (as shown in Proposition 2). In the contract, the ratio between the reward and task (i.e., r_i^*/t_i^*) for type-i decreases with the type. Thus a lower type $j < i$ collaborator will not choose the higher contract item (r_i^*, t_i^*), since it is too costly and not be efficient for him to undertake the task. A user will not choose a lower type contract item either, otherwise his payoff (though still positive) will decrease with a smaller reward.

Observation 3: The client's optimal task allocation t_i^* to a type-i collaborator increases in the client's preference characteristic θ_i and decreases in the collaborator's cost K_i. The client's equilibrium expected profit increases in θ_i for all $i \in \mathcal{I}_A$.

Next, we compare the client's profits under complete and asymmetrically incomplete information.

Observation 4: Compared with complete information, the client obtains a smaller equilibrium expected profit under asymmetrically incomplete information. The gap between his realized profit under two information scenarios is minimized when the realization (users' numbers in different types) is the closest to the expected value.

Figure 4 shows the ratio of the client's realized payoffs under asymmetrically incomplete and complete information, which is a function of users' realizations $\{n_i\}_{i=1}^3$ in all three types. This ratio is always no larger than 1, as the client obtains the maximum profit under complete information. This profit ratio reaches its maximum 92% when users' type realization matches the expected value, i.e., $n_i = N q_i = 40$ for $i = 1, 2$ (and thus $n_3 = N - n_1 - n_2 = 40$ as well). This is consistent

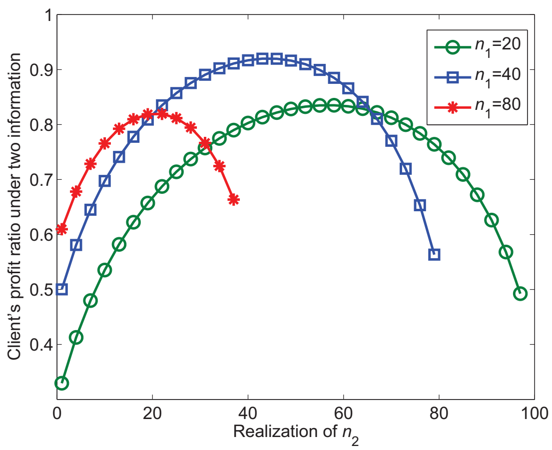

Fig. 4. The ratio of the client's realized payoffs under asymmetrically incomplete and complete information as a function of users' realized numbers $\{n_i\}_{i=1}^3$ in three types (I=3). Here we only show n_1 and n_2, and n_3 can be computed as $N - n_1 - n_2$. Other parameters are $N = 120$, $K_1 = 1.1$, $K_2 = 1$, $K_3 = 0.9$, $\theta_i = 5$, $q_i = 1/3$ for any $i \in \mathcal{I}$.

with the fact that the client maximize its expected profit under asymmetrically incomplete information.

IV. Conclusion

This paper analyzes and compares different mechanisms that a client can use to motivate the collaboration of smartphone users on both *data acquisition* and *distributed computing*. Our proposed incentive mechanisms cover several possible information scenarios that the client may face in reality.

For data acquisition applications, we propose a reward-based collaboration scheme for the client to attract enough users by giving out the minimum reward. We show that when the client knows the users' collaboration costs, he only involves users with the lowest costs to build up the database. However, if users can hold their private information from the client, the client needs to offer a larger reward to get enough collaborators.

For distributed computing applications, we use contract theory to study how a client decides different task-reward combinations for many different types of users. Under complete information, the client involves a type of users as long as his preference of that type outweighs that the user's unit cost. All collaborators receive a zero payoff in this case. Under asymmetrically incomplete information, however, the client has to offer a larger reward to a higher user type. Most collaborators then receive a positive payoff, and a collaborator's payoff increases in his type.

There are several possible ways to extend the results in this paper. For the data acquisition applications, for example, we can consider a flexible revenue model instead of a threshold one. For example, Google can still benefit if a few users take pictures of some critical events. It is also interesting to study the repeated collaborations between the client and users.

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