Incentive Mechanism for Mobile Crowdsourcing Using an Optimized Tournament Model

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***Abstract*— With the wide adoption of smart mobile devices, there is a rapid development of location-based services. One key feature of supporting a pleasant/excellent service is the access to adequate and comprehensive data, which can be obtained by mobile crowdsourcing. The main challenge in crowdsourcing is how the service provider (principal) incentivizes a large group of mobile users to participate. In this paper, we investigate the problem of designing a crowdsourcing tournament to maximize the principal's utility in crowdsourcing and provide continuous incentives for users by rewarding them based on the rank achieved. First, we model the user's utility of reward from achieving one of the winning ranks in the tournament. Then, the utility maximization problem of the principal is formulated, under the constraint that the user maximizes its own utility by choosing the optimal effort in the crowdsourcing tournament. Finally, we present numerical results to show the parameters' impact on the tournament design and compare the system performance under the different proposed incentive mechanisms. We show that by using the tournament, the principal successfully maximizes the utilities, and users obtain the continuous incentives to participate in the crowdsourcing activity.**

***Index Terms*— Mobile crowdsourcing, incentive mechanism, contract theory, moral hazard, tournament.**

I. Introduction

OWING to the wide adoption of embedded sensors in smartphones and the fast development of big data technologies, various locations based services have been introduced to bring convenience in every aspect of our daily lives [1]. There are mobile applications available that can detect WiFi hotpots and upload related information to cloud within a certain distance of the userâŁ™s current location. Smartphone users help to collect the WiFi hotpot information which includes the location, router name, etc. for the service provider which is denoted as principal hereafter [2]. The location based service market led to a profit of $12.2 billion in 2014, and is expected to reach $43.3 billion in revenue by 2019 [3]. With the drastic growth in the location based service market, more complicated and comprehensive data are required to support more sophisticated services [4].

One possible solution for such a data crunch is crowdsourcing, in which a large group of users (with sensors embedded smartphones) regularly collect and transmit data required from the principal [5]. The users' participation and cooperation are essential in crowdsourcing [1]. While a conflict is that when participating in such crowdsourcing, users consume their resources such as battery and computing capacity [6]. Such a conflict leads to an inevitable fact that, many users may be reluctant to participate, which is a major impediment to the development of mobile crowdsourcing [7]. Therefore, appropriate incentive mechanism designs are needed to ensure users' participation. In the literature, it has already been noticed that there is an urgent need to alleviate the conflict by introducing incentive mechanism for users [8], [9]. A clear motivation can potentially lead to higher commitment of users and better quality of received data [10]. There are many types of incentives such as monetary rewards, social approval, self-esteem [11].

Meanwhile, [10], [12], and [13] found that there are possibilities of "free-riding" and "false-reporting" in crowdsourcing if an inefficient incentive mechanism has been applied. "Free-riding" happens when rewards are paid before the task starts, since users usually have the incentive to take the reward while dislike placing efforts [1]. On the other hand, if the rewards are paid after the task is complete, the problem of "false-reporting" arises since the principal has the incentive to lower the reward for the users by lying about the outcome of the task [1]. Methodologies such as game theory and auction theory have been applied to forbid those dishonest behaviors [14]. Additionally, [10], [13], [15], and [16], take user's reputation into consideration, which relies on the user's past behavior, to design the incentive mechanism. On the other hand, inspired by the effort based reward from the labor market, several works have been proposed to address this problem by providing users with the reward that is consistent with their performance. Examples are the works in [17]–[19], as well as one of our previous works [20].

The previously mentioned works capture the fundamental aspect of providing necessary and efficient incentives for users to participate in crowdsourcing. Yet, they mainly assume that

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the principal employs only one user and rewards it on the basis of the absolute performance. However, when rewarding users based on the absolute performance, the principal still has a strong incentive to cheat by claiming that users had poor performances and deserved low rewards, so that the principal can pay less, as the "false-reporting" problem [21]. Apparently, this will result in a decrease of all users' utilities. Another example is that when there is a positive mean measurement error at users' performances, every user's performance will result in an abnormal increase at the principal's observation [22]. Thus, users are rewarded more than they should be, while the principal encounters a loss of utility since more rewards have to be paid. Green and Stokey [23] name this case that affects both sides as *common shock*, which usually appears in economic study to denote macro-economic conditions such as economic boost or depression [24], [25]. *Common shock* can be either positive or negative to user's performance and reward. If both users and principal are aware of this *common shock*, we can regard the trading between them as trading with *full information*. However, in the general case, this *common shock* is unobservable to either or both sides [26].

It has been proven in [23] and [27] that contract based on the absolute performance can be easily affected, while the tournament design can filter out this *common shock* problem and dominate the mechanism based on the absolute performance. One salient advantage of rank-order tournament over absolute performance rewards is that the ordinal ranking is easy to measure and hard to manipulate [28]. In a tournament, the principal has to offer the fixed amount of rewards no matter who wins [29]. The other advantages of tournaments include lower monitoring costs for the principal since only the rank-order of participating users needs to be monitored [30], and non-monetary utilities for the users derived from a high rank such as self-esteem [31], and [32] benefits received from the content they have collected.

In this paper, we will propose a multi-user design that rewards users' performance in crowdsourcing by a tournament reward structure. We will incentivize users to participate in crowdsourcing by providing them with fixed prizes based on their performance rank orders. A brief illustration of crowdsourcing tournament rewarding mechanism is shown in Fig. 1. The principal first designs the optimal tournament prizes which increase with the ranks. After obtaining the data from the users, the principal will sort users' performances in an ascending list. Then, each user will receive a reward in consistent with their ranks in the tournament. Here, user 1 achieves the highest performance and will be rewarded the highest amount reward 4, while user 2 performs worst with the smallest amount of reward 1.

The main contributions of this paper are as follows. First we consider a tournament-based incentive mechanism that rewards users by their rank orders, which can overcome the *common shock* problem in mobile crowdsourcing. To the best of our knowledge, this formulation in mobile crowdsourcing is rarely tackled by other works. Second, we introduce the tournament model together with the contract model under full information, which rewards users based on their absolute performance. The contract model serves as the ideal comparison

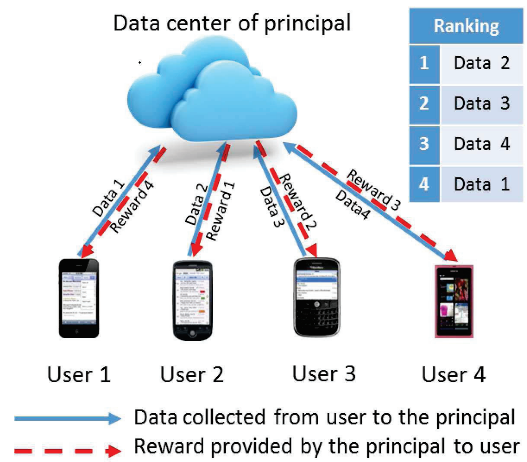


Fig. 1. Crowdsourcing incentive mechanism by tournament.

case, and is also used to derive the solution of the tournament. Third, we give further analysis about how the key features in a tournament design: the optimal effort exerted by users, the number of winners, and the inter-rank spread are affected by three parameters: the number of participating users, the variance of measurement error, and the risk tolerance degree of users. Furthermore, in the simulation part, we present numerical results to show the impact of the parameters settings on the tournament design. Last, we introduce another well-known tournament mechanism for comparison purposes and demonstrate the effectiveness of tournament mechanisms in terms of improving the principal's utility. The proposed mechanisms allow the principal to successfully maximize the utilities and the users to obtain continuous incentives of participating in the mobile crowdsourcing.

The remainder of this paper is organized as follows. First, we will introduce the contract and tournament model in Section II. Then, the design of the tournament is described in Section III, in which we also give the analysis of the optimal contract with full information. The detailed analysis of key features in the tournament is given in Section IV. The performance evaluation is conducted in Section V. Finally, conclusions are drawn in Section VI.

II. System Model

In this section, we will first propose the incentive mechanism by the tournament design. As we have mentioned in the introduction part, the tournament can filter out the impact from *common shock*, which can easily affect the incentive mechanism by the absolute performance. Thus, the contract which rewards users based on their absolute performance under *full information* will be a perfect comparison for the tournament design. In the later part of this section, we will also provide the incentive mechanism by the contract design when the *common shock* is observable.

We refer to the model in [33] and consider a mobile crowdsourcing network in which one risk neutral principal employs a fixed group of identical risk averse users, $i = 1, \ldots, n$, to collect data. The output data quality is a general link to the incentive mechanism. The principal rewards users based on their relative performances which can be referred to the quality of the received data (e.g., quantity, correctness, and importance).

A. Common Shock Problem

When users help collect data for the principal, the user exerts an effort a. Note that the user's effort a is a hidden information, since the principal can only observe the performance level q of the users, i.e., the quality of the received data. Therefore, the performance of user i, q_i, depends stochastically on the user's effort level, a_i. In particular,

$$q_i = z_i + \varepsilon, \tag{1}$$

where ε is a random variable representing the *common shock* that affects all of the users and z_i is a random variable whose distribution depends on a_i. Due to the *common shock*, such as the measurement error at the principal, the quality of received data q_i cannot reflect the user's actual performance or effort exactly. Therefore, the performance of the user is a noisy signal of its effort.

Let G denote the distribution function for the *common shock* (μ, σ'^2), where σ'^2 is the variance. Obviously, ε has zero mean when no *common shock* presents:

$$\int \varepsilon dG(\mu, \sigma'^2) = 0. \tag{2}$$

Otherwise, there exists a *common shock* which can be either positive or negative. It has been proved by [23] that, no matter what value this integration has, the rewards in the tournament will not be affected.

In our model, we assume the contract model is under *full information*. By this assumption, we can normalize the distribution to $\mu = 0$ regardless of its assessment of μ. Thus, every user believes that its performance and that of every other user have the same mean if they take the same effort.

B. Tournament Model

In a n-user tournament, the users' performances are sorted in an ascending order, and the fixed prizes $(W_1, W_2, \ldots, W_n)$ are rewarded. We use the numbering conventional in the study of order statistics: "first place" is the lowest performance. So, W_1 is the prize received by the user with the lowest performance, and W_n is rewarded to the user with the highest rank.

1) Rank Order Statistic: Let $F(z_i; a_i)$ denote the cumulative distribution function (CDF) for z_i, given a_i. $F(z_i; a_i)$ has a continuous probability distribution function (PDF) $f(z_i; a_i)$ which is positive everywhere and continuously differentiable in a_i. Since the users are identical ex-ante, F does not depend on i. The value of z_i is not known to the user until its choice of a_i is made. We assume that z_i and (μ, σ^2) independent, since the term z_i is independently and identically distributed for every common value of a_i and q_i.

Assume that the principal observes only the performance levels of the users, $q = (q_1, q_2, \ldots, q_n)$, but cannot directly observe the users' effort levels. Under the tournament, user i's prize depends only on the rank order of q_i in q, instead of the performance level q_i. According to user's performance given by (1), we can easily obtain $z_i \geq z_j$ from $q_i \geq q_j$. That is, the rank order of the performances depends only on z_i and not on ε. Therefore, the realization of (μ, σ^2) does not affect the game played by the users, and the equilibrium effort level will be independent of σ^2. Hence, we can analyze the game in terms of just z_i. In a n-user tournament, user i wins prize W_j if and only if z_i, is the jth-order statistic of $(z_1, \ldots, z_n)$. The density function $\phi_{jn}(z; a)$ for the jth-order statistic in a sample of size n drawn from the distribution $F(z; a)$ is [23]

$$\phi_{jn}(z; a) = \frac{(n-1)!}{(n-j)!(j-1)!} f(z; a) F^{j-1}(z; a)[1 - F(z; a)]^{n-j}. \tag{3}$$

This density function denotes that the user i's performance outperforms $j - 1$ number of users, and falls behind $n - j$ number of users.

Given that the other users exert the optimal effort, we can have the probability that the user is in the jth place among all n users at the measured performance level $q = z + \varepsilon$ as

$$\begin{aligned} P(\text{rank} = j) &= \int \phi_{jn}(z; a) dz, \\ &= \int \frac{(n-1)!}{(n-j)!(j-1)!} f(z; a) F^{j-1}(z; a) \\ &\quad \times [1 - F(z; a)]^{n-j} dz. \end{aligned} \tag{4}$$

2) Utility of the Users: The realized performance of each user then is a stochastic function of its effort and the value of the *common shock*. Here, we consider the user's reward from the principal's prize in terms of utility, as well as the cost of exerting effort. The preferences of each user i over the prize, W_i, and the exerted effort, a_i, are represented by the utility function

$$U_t(W_i, a_i) = u(W_i) - \gamma(a_i), \quad W_i \geq 0, \ a_i \geq 0, \tag{5}$$

for $i = 1, \ldots, n$, where u is a strictly increasing and concave function of W_i, and γ is strictly increasing and convex with a_i. The user's utility is the prize minus the exerting effort.

For convenience, the principal can also consider the user's reward function in terms of utility $w = (w_1, w_2, \ldots, w_n)$ by defining $w_i = u(W_i)$, $\forall i$. We have the user's expected utility is the expected value of rewards minus the cost,

$$U_t(w, a) = \sum_{j=1}^{n} w_j P(\text{rank} = j) - \gamma(a). \tag{6}$$

Given the density function $\phi_{jn}(z; a)$, the probability can be obtained by an integration of the density function $\phi_{jn}(z; a)$. Thus, the user's utility function can be rewritten as

$$U_t(w, a) = \sum_{j=1}^{n} w_j \int \phi_{jn}(z; a) dz - \gamma(a). \tag{7}$$

In the symmetric equilibrium all users spend the same amount of effort $\bar{a}$ and expect an equal probability $1/n$ of reaching any of the n ranks. Given the effort choice of $\bar{a}$, we can derive the users' expected utility from (7) as

$$U_t(w, \bar{a}) = \frac{1}{n}\sum_{j=1}^{n} w_j - \gamma(\bar{a}). \tag{8}$$

3) Utility of the Principal: The principal's problem is to design a prize structure for n users. We assume that the principal is constrained to offer a fixed minimum level of expected utility to each user, so that we can judge the relative performance of tournaments by examining the expected utility of the principal. The risk neutral principal's utility is the summation of all the users' performances minus the total prizes to the users:

$$V_t(W, a) = E\left[\sum_{i=1}^{n}(q_i - W_i)\right]. \tag{9}$$

Given that the performance q follows a conditional distribution $f(q-\varepsilon, a)$ and under a *common shock*, the principal's expected utility can be written as:

$$V_t(w, a) = \int\int q f(q-\varepsilon, a) dG(\mu, \sigma^2) dq - \sum_{j=1}^{n} W_j, \tag{10}$$

$$= \int z f(z, a) dz - \sum_{j=1}^{n} W_j, \tag{11}$$

where (10) is resulting from our previous conclusion that z is independent from the common shock (μ, σ^2), and thus we can simply replace q with z.

C. Contract Model

In the contract model, the principal rewards users based on the absolute performance. We define the reward function $R(q)$ as a linear and increasing function of q. Thus, the utility user obtained from the reward is $u(R(q))$, and denoted as $v(q)$ here after for simplicity. As u is a strictly increasing and concave function, so is v. The contract that the principal offered to a given user is (v, A), where A is the effort in the contract to distinguish it from a in the tournament. As we have mentioned previously, in this *full information* case, we simply assume G is given by $\mu = 0$ with probability 1, i.e., the principal knows ε.

1) Utility of the User: Thus, for $i = 1, \ldots, n$, the user i's utility under contract is represented by

$$U_c(v_i, a_i) = v(q_i) - \gamma(a_i), \quad q_i \geq 0, \ a_i \geq 0. \tag{12}$$

The utility of a user is also the prize minus the cost. As we can see, $v(q_i)$ is a piecewise continuous utility which is related to the quantity of q_i instead of its rank. As noted above, $F(z; a)$ denotes the conditional distribution function for z given a, and $f(z; a)$ is the continuous density function of $F(z; a)$. As $\varepsilon = 0$ with probability 1, we can rewrite the user's expected utility function as

$$U_c(v, a) = \int v(z) f(z; a) dz - \gamma(a), \tag{13}$$

which is positive everywhere and continuously differentiable in a.

TABLE I
SYSTEM MODEL PARAMETERS

Parameter	**Value**
Effort	a
Performance	q
Common Shock	$\varepsilon \sim (\mu, \sigma^2)$
Effort related variable	z
$F(z; a)$	CDF of z
$f(z; a)$	PDF of z
Ranking density function	ϕ
Ranking probability	$P(\text{rank} = j)$
User utility by tournament	U_t
Principal utility by tournament	V_t
User utility by contract	U_c
Principal utility by contract	V_c
Reward in tournament	W
Cost function	γ
Reward in contract	R
Utility of tournament reward	w
Utility of contract reward	v

2) Utility of the Principal: Followed by user's expected utility function in contract, the principal's expected utility can be written as

$$V_c(v, a) = E\left[\sum_{i=1}^{n}(q_i - R(q_i))\right]. \tag{14}$$

Similarly, the expected utility of the principal from the contract (v, a) is

$$V_c(v, a) = \int \{z - R(z)\} f(z; a) dz. \tag{15}$$

The notations of all parameters are summarized in Table I.

III. PROBLEM FORMULATION

In this section, we are going to formulate the principal's utility maximization problem in both tournament and contract models. Afterwards, we will solve the tournament design by deriving from the optimal contract with full information.

A. Optimization Problem of Tournament

Given the number of users n that participate in this crowdsourcing, the principal's problem is to design $(w, \bar{a})$ to maximize (10) subject to the two constraints that $\bar{a}$ is an optimal decision rule for the user given w and that the expected utility of the user is at least $\bar{u}$, i.e.,

$$\max_{(w,\bar{a})} \int z f(z; a) dz - \sum_{j=1}^{n} W_j,$$

$$s.t.$$

$$(a) \quad \bar{a} = \arg\max_{a} \sum_{j=1}^{n} w_j \int \phi_{jn}(z; a) dz - \gamma(a),$$

$$(b) \quad \frac{1}{n}\sum_{j=1}^{n} w_j - \gamma(\bar{a}) \geq \bar{u}. \tag{16}$$

(a) is the incentive compatible (IC) constraint; it represents that given any reward structure, the problem facing each user is to choose a level of effort that maximizes own utility. **(b)** is the individual rationality (IR) constraint; it provides the necessary incentive for users to participate. We must have the utility no less than the reservation utility when a user is not taking any effort ($a = 0$). Here, we define $S_t(n)$ as the set of feasible n-user tournaments that satisfy the IC and IR constraints. The set of feasible tournaments is always nonempty, since it always contains the "no incentive" tournament, $[(\bar{u}, \bar{u}, \ldots, \bar{u}), 0] \in S_t(n)$, for all n.

From the problem formulation, we see that the optimal tournament depends on the number of users n, and the distribution function F, but not on the distribution function G. In other words, the tournament approach is robust against the lack of information or the lack of agreement about G.

B. Optimal Contract Under Full Information

Similar to the problem formulation in the tournament model, in the contract model with *full information*, the principal's problem is to design (υ, A) to maximize (15) subject to the two constraints that A is an optimal decision rule for the user given υ and that the expected utility of the user is at least $\bar{u}$. With the user and principal's utility functions in the contract model, we can formulate the contract which rewards users by their absolute performance as

$$\begin{aligned} &\max_{(\upsilon, A)} \int \{z - R(z)\} f(z; a) dz, \\ &s.t. \\ &\quad (a) \quad A = \arg\max_{a} \int \upsilon(z) f(z; a) dz - \gamma(a), \\ &\quad (b) \quad \int \upsilon(z) f(z; A) dz - \gamma(A) \geq \bar{u}. \end{aligned} \tag{17}$$

As in the tournament, **(a)** is the IC constraint and **(b)** is the IR constraint. The principal's problem is to choose (υ, A) to maximize its expected utility subject to the two constraints that A is the optimal decision rule for the user given prize υ, and that the expected utility of the user is at least $\bar{u}$. Here, we define $S_c(G)$ as the set of feasible contracts that satisfy the IC and IR constraints.

C. Tournament Design

To obtain the tournament design, we can utilize the design of the optimal contract with full information. Next, we will show that with a feasible contract (υ, A) be given under optimal condition, we can approximate it by constructing a sequence of contracts $\{(\upsilon_k, A_k)\}_{k=1}^{\infty}$, where υ_k is a step function with k steps, A_k is a constant function, and $\upsilon_k \to \upsilon$ in measure.

Given the definition of utility function, cost function, CDF $F(z; a)$, and PDF $f(z; a)$, the first thing we need to do is to approximate the continuous utility function $\upsilon(z)$ by a step function. Let $I_{k1}, \ldots, I_{kk}$ be the intervals corresponding to quantized values of the cumulative distribution $F(z; A)$:

$$I_{kj} = \{z | (j-1)/k < F(z; A) \leq j/k\}, \quad j = 1, \ldots, k, \quad k = 1, 2, 3, \ldots \tag{18}$$

Then, define $\bar{\upsilon}_{k1}, \ldots, \bar{\upsilon}_{kk}$ as the expected utility of the user under (υ, A) on each of these intervals:

$$\overline{\upsilon}_{kj} = \int_{I_{kj}} \upsilon(z) f(z; A) dz, \quad j = 1, \ldots, k; \quad k = 1, 2, 3, \ldots. \tag{19}$$

Thus, with $\overline{\upsilon}_{kj}$, we can define the step function $\hat{\upsilon}_k(z)$ by

$$\hat{\upsilon}_k(z) = \bar{\upsilon}_{kj}, \quad z \in I_{kj}. \tag{20}$$

If $k \to \infty$, we will have $\hat{\upsilon}_k(z) = \upsilon(z)$ in measure. Thus, we can replace $\upsilon(z)$ with $\hat{\upsilon}_k(z)$ in (17), and solve the optimization problem by the following steps.

First, taking the values of $\hat{\upsilon}_k(z)$ into the integral, the optimal effort A_k is obtained by

$$A_k = \arg\max_{a} \int \hat{\upsilon}_k(z) f(z; a) dz - \gamma(a), \quad \forall k. \tag{21}$$

The detailed steps to obtain A_k are presented in Appendix B. Second, taking A_k into the condition density function $f(z; a)$, and calculate the error e_k encountered with the given contract (υ, A). Here we must notice that, the user's utility must be equal to the reservation utility $\bar{u}$ in the optimal contract and tournament. Thus, we have the error term e_k as

$$e_k = \bar{u} + \gamma(A_k) - \int \hat{\upsilon}_k(z) f(z; A_k) dz, \quad \forall k, \tag{22}$$

where $\bar{u}$ is the user's reservation utility under (υ, A). Then, correct the value of the step function $\upsilon_k(z)$ by adding up the error term,

$$\upsilon_k(z) = \hat{\upsilon}_k(z) + e_k, \quad \forall z, k. \tag{23}$$

By now, we have the step function approximated optimal contract with full information $\{(\upsilon_k, A_k)\}_{k=1}^{\infty}$. Next, we can construct a sequence of tournaments $(w_{ni}, \bar{a}_n)$ that approximate the contract $(\upsilon, A) \in S_c(G)$ obtained from the previous steps, where w_{ni} is a step function with n steps, $\bar{a}_n$ is a constant function.

The first thing we need to do is to approximate the continuous utility function $\upsilon(z)$ by a step function. We notice that, the probability that a user achieves a specific rank is equal to the probability that the user's performance level falls into a corresponding interval of the CDF. Thus, given a specific rank, we can find the effort value q_{ni} by the inverse CDF of $F(q_{ni}; A) = i/(n+1)$ [23]. Then, we can have the expected reward utility $\hat{w}_{ni}$ with performance q_{ni}, by

$$\hat{w}_{ni} = \frac{1}{n} \upsilon(q_{ni}), \quad i = 1, \ldots, n. \tag{24}$$

Thus, we can replace the w_j in (16) with this approximation $\hat{w}_{ni}$. The optimal effort under tournament can be solved by

$$\bar{a}_n = \arg\max_{a} \sum_{i=1}^{n} \hat{w}_{ni} \int \phi_{in}(z; A) dz - \gamma(A). \tag{25}$$

Again, we calculate the error term $\bar{e}_n$ in this tournament design, and have

$$\bar{e}_n = \bar{u} + \gamma(\bar{a}_n) - \frac{1}{n} \sum_{i=1}^{n} \hat{w}_{ni}. \tag{26}$$

Finally, the utility in tournament is obtained by adding up the approximated $\hat{w}_{ni}$ and error $\bar{e}_n$:

$$w_{ni} = \hat{w}_{ni} + \bar{e}_n, \quad i = 1, \ldots, n. \tag{27}$$

By now, we have the tournament $(w_{ni}, \bar{a}_n)$ that is close to the optimal contract with full information. To summarize, we employ the probability of a user in achieving a certain rank in backward induction algorithm and derive the optimal effort. Then, by making use of the optimal effort derived from the optimal contract, we successfully use step functions to derive the tournament design through approximation. In [23], it is proved that each of these step-function contracts can be approximated arbitrarily close by a tournament with a sufficiently large number of users. Hence, the principal's expected utility is approximately unchanged. Moreover, the tournament's efficiency is unaffected by changes in G (the distribution of ε and the user's information about ε), so that the same tournament's utility remains arbitrarily close to the full information utility for any G as well as if the users can observe ε directly.

IV. Tournament Design Parameters and Properties

In this section, we will give further analysis to the structure of an optimal tournament. First, we will provide the specific form of the conditional distribution, utility and cost functions we have defined in the system model to simplify our mathematical analysis. Then, we will show that the three parameters, i.e., the number of participating users, the variance of measurement errors, and the risk tolerance degree of users, can affect the three key features in a tournament, i.e., the optimal effort exerted by users, the number of winners, and the inter-rank spread.

A. Model Setup

We assume that the conditional distribution $f(z; a)$ follows the logistic distribution. The logistic distribution is a symmetric and bell shaped distribution, like the frequently used normal distribution. The PDF of a logistical distribution is

$$f(z; a) = \frac{\exp(-\frac{z-a}{\beta})}{\beta[1 + \exp(-\frac{z-a}{\beta})]^2}, \tag{28}$$

and the CDF is

$$F(z; a) = \frac{1}{1 + \exp(-\frac{z-a}{\beta})}, \tag{29}$$

where β is the coefficient related to the variance σ^2 of logistic distribution, which is $\pi^2\beta^2/3$. As β is positively correlated with the variance σ^2, we will use β to represent the variance σ^2 in the sequel.

In the system model, we have defined the evaluation function u as a concave function. Thus, here, we set up the evaluation function u in a form of power function as

$$u(W) = \frac{W^\rho}{\rho}, \tag{30}$$

where ρ is the power coefficient and $0 < \rho < 1$. Here we further define the user's risk tolerance degree as

$$\tau = -\frac{u''}{u'} = \frac{W}{1-\rho}, \tag{31}$$

and the user's risk averse degree as

$$\eta = -\frac{u'}{u''} = \frac{1-\rho}{W}. \tag{32}$$

We see that, as ρ and τ are positively correlated with each other, we use ρ to denote risk tolerance hereafter. Under the same amount of reward, the larger the risk tolerance degree τ/ρ, the smaller the risk averse degree η, the less conservative and sensitive is user towards risk, and vice versa. When ρ approaches 1, the user is risk neutral.

In the system model, we have assumed that the reward function R is a linear function of performance q. For simplicity, here we define the reward function as $R(q) = q$. Thus, the utility function in the contract model becomes

$$v(q) = u[R(q)] = u(q) = \frac{q^\rho}{\rho}. \tag{33}$$

Furthermore, we have defined the cost function in the system model as a convex function. Thus, we set up the cost function γ in a quadratic form as

$$\gamma(a) = \frac{1}{2}a^2. \tag{34}$$

We assume that the reservation utility, when the user does not participate in the crowdsourcing, is $\bar{u} = 0$.

B. Analysis

In this section, we will give an analysis of three key features that determine the rewards structure of a tournament, which includes the optimal effort, number of winners, and inter-rank spread.

1) Optimal Effort: In the optimization problem (16), each user must choose a level of effort that maximizes own utility. We can solve the optimal effort by taking the first derivative of the IC constraint, which is given by

$$\sum_{j=1}^{n} w_j \frac{\partial P(\text{rank} = j)}{\partial a} - \gamma'(a) = 0. \tag{35}$$

For easier notation, we define the partial derivative of the probability for the jth-order with respect to effort a as $\psi(j)$. With the PDF and CDF of logistic distribution, we can simplify the partial derivative to

$$\psi(j) = \frac{2j - n - 1}{\beta[n(n+1)]}. \tag{36}$$

The detail of the derivation can be found in Appendix A.

Take the partial derivative $\psi(j)$ with the definition of the cost function given in (34) into (35), we can derive the optimal effort exerted by user as

$$a = \sum_{j=1}^{n} w_j \frac{2j - n - 1}{\beta[n(n+1)]}. \tag{37}$$

The optimal effort can be affected by the number of participating users n, and is decreasing with the variance of the conditional distribution β. In addition, from the definition of the utility function $w_j = u(W_j)$, we see that the optimal effort increases with the risk tolerance ρ.

2) Maximum Number of Winners: According to (35), where w_j and $\gamma'(a)$ are all positive, so we must have $\psi(j) > 0$ in order to have a positive prize. For the negative elements in ψ, we can set up them as 0, since it is meaningless to have a negative prize. From the inequality $\psi(j) > 0$ we see that in order to receive a prize, users must achieve a rank $j > (n-1)/2$. As a result, the maximum number of prize recipients will not be more than half of the participating users. The prize recipients should be the users whose rank is higher than $(n+1)/2$. While the users whose rank is lower than $(n+1)/2$, will only receive a zero reward.

The maximum number of winners increases with the number of participating users n. Similar to the optimal effort a, the maximum number of winners is also impacted by the variance of the conditional distribution β, and the risk tolerance degree ρ.

3) Inter-Rank Spread: The inter-rank spread is defined as the difference of rewards between the jth and $j+1$th winners:

$$d_j = W_{j+1} - W_j, \tag{38}$$

where $j = m+1, \ldots, n$. m is defined as the smallest integer that is larger than or equal to $(n+1)/2$.

Considering two ranks j and k, there is a condition that must be satisfied so that all reward prizes are guaranteed to be positive [34]:

$$u'(W_j)(2j-n-1) = u'(W_k)(2k-n-1). \tag{39}$$

To analyze the spread between two ranks, we can set $k = j+1$. Then, we have the following equality that must be met for two adjacent ranks,

$$\frac{u'(W_{j+1})}{u'(W_j)} = \frac{2j-n-1}{2j-n+1}. \tag{40}$$

According to the prize utility function u which is defined in (30), we can further derive

$$\left[\frac{W_{j+1}}{W_j}\right]^{\rho-1} = \frac{2j-n-1}{2j-n+1}, \tag{41}$$

$$\frac{W_{j+1}}{W_j} = \left[\frac{2j-n+1}{2j-n-1}\right]^{\frac{1}{1-\rho}}. \tag{42}$$

Since $0 < \rho < 1$ and $\frac{2j-n+1}{2j-n-1} > 1$, the ratio between W_{j+1} and W_j is larger than 1 and grows exponentially as j increases, and thus the inter-rank spread d_j, as well. In other words, the higher the rank, the larger inter-rank spread between the adjacent prizes. We also see that, the factors that impact the inter-rank spread also include the number of participating users n, the variance of effort and performance correlations β, and the risk tolerance degree of users ρ.

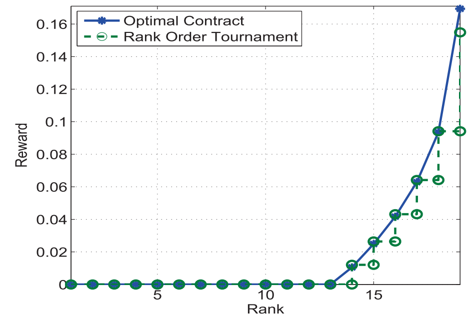


Fig. 2. Approximation of optimal contract by tournament.

V. Simulation Results and Analysis

In this section, we will give numerical simulations to illustrate our results. First, we will show the tournament and contract obtained by the step function. Then, we will show the three parameters' impact on the features in a tournament. Finally, we will analyze the system performance by varying different parameters, and conduct a comparison with other incentive mechanisms.

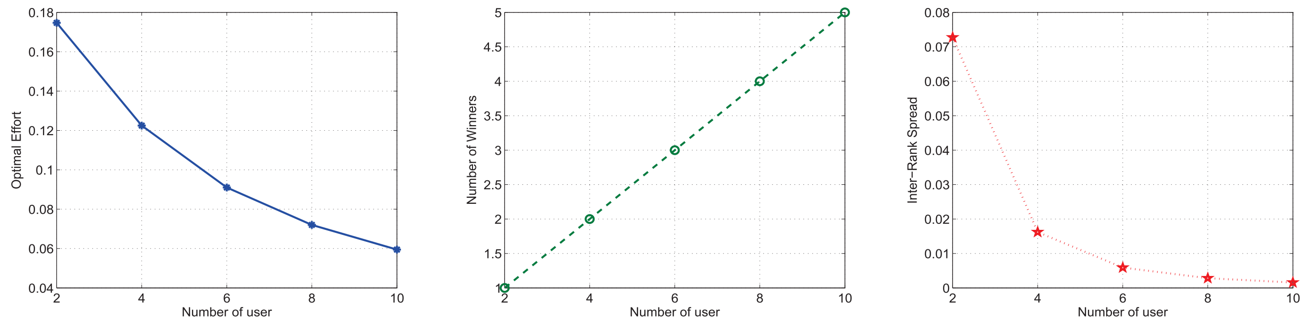
A. Prizes Structure

In Fig. 2, we show the optimal contract and tournament with 19 users participating in crowdsourcing following the steps in Section III, with x axis representing the rank of the users in an ascending order. As we can see, the prize obtained by the tournament is close to the prize from the optimal contract with full information. If we increase the number of users to infinity, the tournament can approximate the optimal contract arbitrarily close. In addition, we see that, only users with rank larger or equal to 14 received a positive reward, which is consistent with our conclusion previously that no more than half of the users should be rewarded. Another observation from Fig. 2 is that, the higher the user rank, the larger the spread, that is $W_j - W_{j-1} < W_{j+1} - W_j$. This result is consistent with our conclusion in the previous section, and is due to the power function form of the evaluation function u. If we change the evaluation function u to a log function, the spread will be the same for all ranks. While if the evaluation function u follows the exponential form, the spread will become smaller for higher ranks.

B. Parameters Effect on Tournament Design

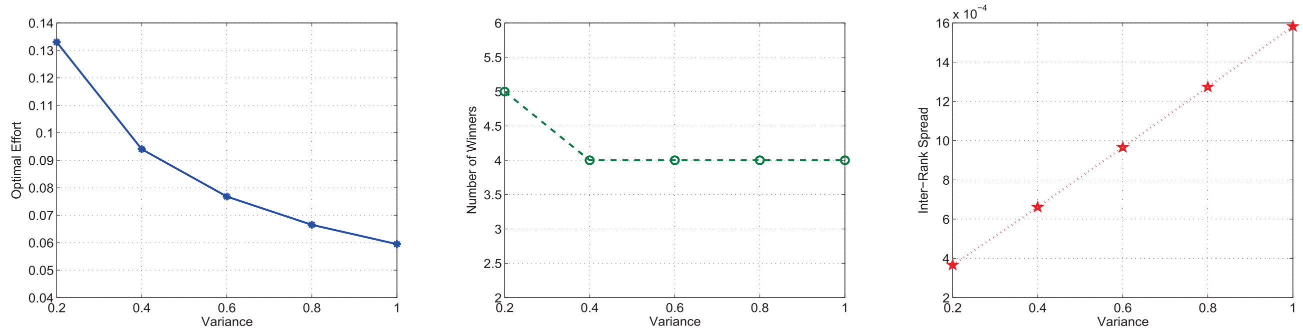
In the previous sections, we have shown that the number of participating users, the variance of effort and performance correlations, and the risk tolerance degree of users are the factors that impact the tournament design. This part, we will show how the optimal effort, the number of winners, and the inter-rank spread in a tournament vary when the three parameters change.

1) Number of Users: In Fig. 3, we increase the number of participating users from 2 to 10, and observe that the optimal effort decreases in Fig. 3a, the number of winners increases in Fig. 3b, and the inter-rank spread decreases in Fig. 3c. These results are consistent with the analysis in Section IV-B. The reason for this phenomenon can be explained since the



(a) Optimal effort. (b) Number of winners. (c) Inter-rank spread.

Fig. 3. The impact of the number of users on tournament design.



(a) Optimal effort. (b) Number of winners. (c) Inter-rank spread.

Fig. 4. The impact of the variance on tournament design.

probability of winning the contest decreases with the number of participating users, and thus, the users will lower their effort. However, this is not preferred by the principal. So, to provide more incentives and attract users exerting effort, the principal must increase the number of winners. But in order to compensate for the cost of rewarding more users, the principal decreases the inter-rank spread between rewards.

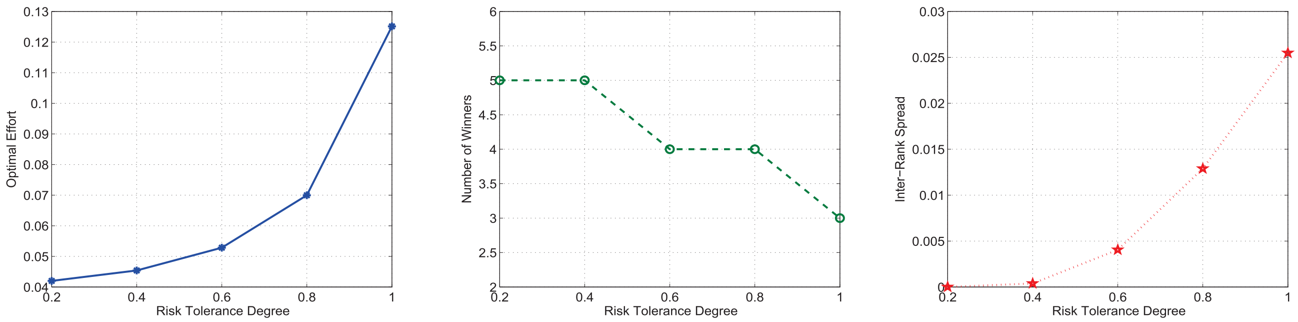
2) Variance: In Fig. 4, we fix the number of participating users as 10, and increase the variance β of measurement error from 0.2 to 1. A larger variance β indicates a weaker relation between effort levels and the observed performance, and the expected rank achieved. In the simulation results, we see that the optimal effort decreases in Fig. 4a, as well as the number of winners in Fig. 4b, but the inter-rank spread is increasing in Fig. 4c. Since we only consider 10 users in this simulation, we cannot see a steep decrease in Fig. 4b. It is intuitive that users do not want to waste their efforts if the strength of the performance-effort relation is weak. But the decrease of the number of winners and increase of inter-rank spread is counter intuitive. The reason is that, with the increase of variance, the utility that users obtain will increase, which will be proved by the simulation results in the next subsection. As the users have higher participation incentives, the principal can attract enough users without offering too many rewards. In order to achieve higher utility, the principal should thus decrease the number of winners when the variance is high.

3) Risk Tolerance Degree: In Fig. 5, we fix the number of participating users and the variance of measurement error, but increase the risk tolerance degree from 0.2 to 1. From the definition of risk tolerance degree we see that when ρ increases, users become less conservative to risk and evaluate prizes more, thus more willing to participate in crowdsourcing. Thus, we see that the optimal effort increases in Fig. 5a. Also due to the same reason, the principal can attract enough users without offering too many rewards. Thus, we see a decrease of the number of winners in Fig. 5b. However, the principal is able to induce more help by using larger prizes for top ranks and larger inter-rank spread. So the inter-rank spread is increasing in Fig. 5c.

C. Comparison

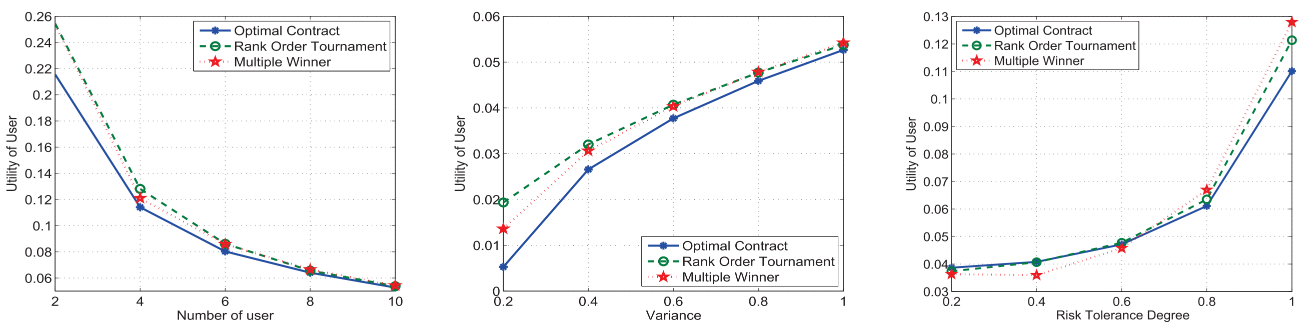
In this part, we are going to analyze user and principal's utilities by varying the three factors impacting the design of the contest including the number of users for whom the contest is conducted, the degree of performance uncertainty in the environment (i.e., the strength of the relation between effort and performance realized), and the user's risk tolerance degree towards the crowdsourcing activity. Furthermore, we are going to do comparisons between different tournament designs.

In the tournament we have proposed, there are many winners and the amount of reward is based on the relative rank achieved, with larger amounts rewarded to higher ranks. We refer to this tournament design as the Rank-Order Tournament (ROT). We will compare the results from the ROT with that from the optimal contract with full information, and another special case of ROT: the Multiple-Winners (MW). In the MW tournament, several top winners share the reward equally, i.e., the inter-rank spread $d_j = 0$.



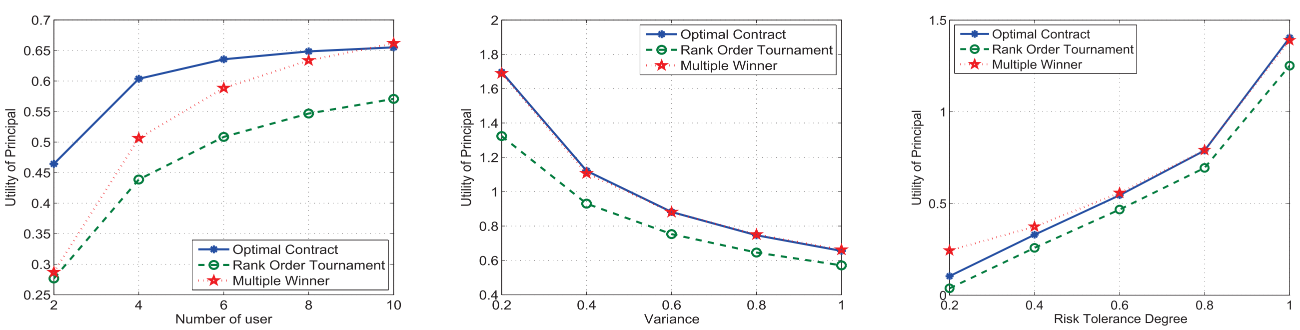
(a) Optimal effort. (b) Number of winners. (c) Inter-rank spread.

Fig. 5. The impact of the risk tolerance degree on tournament design.



(a) Number of users. (b) Variance. (c) Risk tolerance degree.

Fig. 6. The utility per user as parameters vary.



(a) Number of users. (b) Variance. (c) Risk tolerance degree.

Fig. 7. The utility of the principal as parameters vary.

1) Utility of Users: In Fig. 6 we show the utility per user when varying different parameters. First, we see that the user's utility decreases with the number of users in Fig. 6a. The reason is that when the number of users n increases, the marginal change in the probability of achieving any rank decreases. Consequently, as the pool of users increases, the user will be less likely to induce higher effort levels and less incentive to participate. Thus, we see the user's utility decreases with the increase of n. Second, we see from Fig. 6b that the user's utility is increasing as the variance increases. In Section V-B.2 we have mentioned that increasing of variance leads to a lower optimal effort, which occurs regardless of the tournament design. Thus, as the expected utility of the tournament keeps the same as rewards remain unchanged, the users encounter lower cost and receive higher utility. Third, we see from Fig. 6c that the user's utility increases with the risk tolerance degree τ. As we have explained in Section V-B.3, when τ increases, users become less conservative and will exert more effort. Thus, the user's utility will result in an increase.

2) Utility of Principal: In Fig. 7 we show the three factors' impacts on the utility of the principal. First, we see that the principal's utility increases with the number of users in Fig. 7a. It is an intuitive result that with more users participating in the crowdsourcing, more data are collected, which brings a higher utility for the principal. This also proves the importance of a larger number of users' participation in crowdsourcing. Second, from Fig. 7b we see that the principal's utility is decreasing as the variance increases. As we have mentioned previously, users are reducing their effort in this scenario, and less data is obtained from the user. But as the rewards offered by the principal remain unchanged, the principal's utility will certainly decrease. Last, from Fig. 7c we see that the principal's utility also increases with the user's risk tolerance degree τ. This scenario is similar to the previous case, with more data obtained from the user, the principal's utility will certainly increase.

3) Comparisons: Overall, we see that the optimal contract serves as the upper bound of the principal's utility, and the lower bound of the user's utility for the other two tournament mechanisms in most of the cases. This is intuitive since the optimal contract solves the optimal contract based on the absolute performance. While in tournament, we only have a limited number of users in the simulation. Thus, tournaments lose accuracy during the approximation. The optimal contract provides the principal with a maximum utility while extracting as much utility from the users as possible.

From Fig. 6 and Fig. 7, we also see that the MW outperforms ROT in many cases. In addition, MW outperforms both the optimal contract and ROT when users are risk neutral in Fig. 6c and Fig. 7c. The reasons for both results can be inspired from the conclusions drawn in [34]. First, when the number of participating users is small, MW is a better mechanism for the principal rather than ROT. As we only consider no more than 10 participating users due to the computation capacity of the computer. With such a small group of users in our simulation, we see MW outperforms ROT in all simulation results. In real cases, with the larger number of users, the ROT will be a better mechanism for the principal than the MW. Second, when users are risk neutral, it is optimal to give the entire reward to the highest rank user rather than offering contract with positive spread in ROT and optimal contract. In this special case of MW, the utility that the principal obtained is higher than that from the ROT and optimal contract.

VI. Conclusions

In this paper, we have investigated the problem of providing incentives for users to participate in mobile crowdsourcing by applying the rank order tournament as the incentive mechanism. We have solved the rank order tournament by approximating the absolute performance based optimal contract with full information using step functions. We have also analyzed and proven how the tournament is affected by different parameters. Finally, through numerical simulations, we have compared the user's and principal's utilities under the optimal contract and different tournament mechanisms. We have shown that by using the tournament, the principal successfully maximizes the utilities regardless of *common shock*. The principal's utility benefits from a large number of users and higher risk tolerance of users, but deteriorates with weaker relationship between exerted and observed effort levels.

Appendix A

To obtain the simplified form of $\psi(j)$ which is the first derivative of the probability of ranking j, we can make use of convenient form of the logistic distribution by the following procedures. First, we take the first derivative of the probability of ranking j with respect to effort result z, and rewrite $\psi(j)$ as

$$
\begin{aligned}
\psi(j) &= \frac{\partial P(\text{rank}=j)}{\partial a} \\
&= \int \frac{(n-1)!}{(n-j)!(j-1)!} \\
&\quad \times \{(n-j)[1-F(z;a)]^{n-j}(-f(z;a))F^{j-1}(z;a)f(z;a) \\
&\quad + [1-F(z;a)]^{n-j}(j-1)F^{j-2}(z;a)f^2(z;a)\}dz, \\
&= \int \frac{(n-1)!}{(n-j)!(j-1)!} \\
&\quad \times [1-F(z;a)]^{n-j-1}F^{j-2}(z;a)f^2(z;a) \\
&\quad \times [(j-1)-(n-1)F(z;a)]dz, \\
&= \frac{(n-1)!}{(n-j)!(j-1)!} \\
&\quad \times \{(j-1)\int [1-F(z;a)]^{n-j-1}F^{j-2}(z;a)f^2(z;a)dz \\
&\quad - (n-1)\int [1-F(z;a)]^{n-j-1}F^{j-1}(z;a)f^2(z;a)dz\}.
\end{aligned} \tag{43}
$$

Taking the specific form of the logistic distribution into $\psi(j)$, we have

$$
\begin{aligned}
\psi(j) &= \frac{\partial P(\text{rank}=j)}{\partial a} \\
&= \frac{(n-1)!}{(n-j)!(j-1)!} \\
&\quad \{(j-1)\int \frac{\exp(-\frac{x}{\beta})^{n-j-1+2}}{[1+\exp(-\frac{x}{\beta})]^{n-j-1+j-2+4}}dz \\
&\quad - (n-1)\int \frac{\exp(-\frac{x}{\beta})^{n-j-1+2}}{[1+\exp(-\frac{x}{\beta})]^{n-j-1+j-1+4}}dz\}, \\
&= \frac{(n-1)!}{(n-j)!(j-1)!}\{(j-1)\int \frac{\exp(-\frac{x}{\beta})^{n-j+1}}{[1+\exp(-\frac{x}{\beta})]^{(n-1)+2}}dz \\
&\quad - (n-1)\int \frac{\exp(-\frac{x}{\beta})^{n-j+1}}{[1+\exp(-\frac{x}{\beta})]^{n+2}}dz\},
\end{aligned} \tag{44}
$$

For the logistic distribution, there is a property that

$$
\int \frac{\exp(-\frac{x}{\beta})^k}{[1+\exp(-\frac{x}{\beta})]^{n+2}}dx = \frac{(k-1)!(n-k+1)!}{(n+1)!}\beta, \tag{45}
$$

when $k \geq 2$. With this property, we can simplify a integration to a fraction. Thus, we are able to simplify $\psi(j)$ as follows:

$$\begin{aligned}\psi(j) &= \frac{\partial P(\text{rank} = j)}{\partial a} \\ &= \frac{(n-1)!}{(n-j)!(j-1)!} \\ &\quad \{\frac{(j-1)}{\beta}\frac{(n-j+1-1)![n-1-(n-j+1)+1]!}{(n-1+1)!}\beta \\ &\quad - \frac{(n-1)}{\beta}\frac{(n-j+1-1)![n-(n-j+1)+1]!}{(n+1)!}\beta\}, \\ &= \frac{(n-1)!}{(n-j)!(j-1)!}\{\frac{(j-1)}{\beta}\frac{(n-j)!(j-1)!}{n!}\beta \\ &\quad -\frac{(n-1)}{\beta}\frac{(n-j)!j!}{(n+1)!}\beta\}, \\ &= \frac{2j-n-1}{\beta[n(n+1)]}. \end{aligned} \tag{46}$$

Now, we obtain the simplified form of the partial derivative $\psi(j)$.

Appendix B

To obtain the value of A_k, we can follow the following steps. First, we rewrite the user's utility maximization function here:

$$A_k = \arg\max \int \hat{v}_k(z) f(z; a) dz - \gamma(a), \quad \forall k. \tag{47}$$

To find the optimal A_k, we can take the fist derivative regarding a in (47), and have

$$\begin{aligned}&\frac{d[\int \hat{v}_k(z) f(z; a) dz - \gamma(a)]}{da} \\ &\quad = \sum_{k=1}^{n} \hat{v}_k(z) \frac{d\int_{I_{kj}}(z; a)dz}{da} - \gamma'(a). \end{aligned} \tag{48}$$

As $\hat{v}_k$ is a step function, and is a constant value since we have obtained from the previous equations. Thus, we can take $\hat{v}_k$ out of the integral.

Next, with the PDF and CDF of the logistic distribution, we now have

$$\int f(z; a)dz = F(z; a) = \frac{1}{1+\exp(-\frac{z-a}{\beta})}. \tag{49}$$

Thus,

$$\frac{d\int f(z; a)dz}{da} = \frac{dF(z; a)}{da} = \frac{-\frac{1}{\beta}\exp(-\frac{z-a}{\beta})}{[1+\exp(-\frac{z-a}{\beta})]^2}. \tag{50}$$

Thus, we can integrate the function with the summation of each interval of the step function as

$$\begin{aligned}&\frac{d[\int \hat{v}_k(z) f(z; a) dz - \gamma(a)]}{da}, \\ &= \sum_{k=1}^{n} \hat{v}_k(z) \frac{d[\int_{I_{kj}} f(z; a)dz]}{da} - \gamma'(a), \\ &= \sum_{k=1}^{n} \hat{v}_k(z) [\frac{dF(z_{k+1}; a)}{da} - \frac{dF(z_k; a)}{da}] - \gamma'(a). \end{aligned} \tag{51}$$

By setting this partial derivative equal to 0, we can obtain the optimal effort A_k in the contract.

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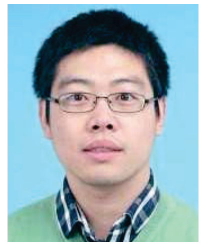

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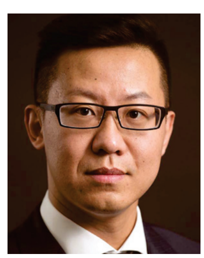

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