# Response Driven Efficient Task Load Assignment in Mobile Crowdsourcing

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***Abstract*—Mobile crowdsourcing paradigm is considered as one of the emerging techniques due to immense demand of location based services and various novel applications in recent years. The evolution of smart mobile users (SMUs), specifically due to high end mobile devices in terms of resources and capabilities has contributed towards the concept of collaborative task completion and a notion of crowdsourcing. Under general scenario of mobile crowdsourcing, an application based platform (task requester) tries to motivate a number of available participating users for completing a specific task by introducing certain incentive mechanism. However, the challenge remains in improving users' participation for a better result as not all users have similar attitude for a task due to resource constraints(energy profile), time, mobility, privacy issues and so on. Therefore, to address this situation, in this paper we propose users' response profile based incentive mechanism for improving participation that incorporates users' behavior and inconvenience metrics upon joining crowdsourcing. Secondly, we formulate utility based optimal task load allocation considering energy constraints of SMUs. Simulation results show response driven incentive mechanism supports platform owner to design an appropriate task load allocation scheme without overwhelming SMU's energy constraint and eventually loosing participation.**

***Index Terms*—Mobile Crowdsourcing, User Profiling, Incentive Mechanism, Utility Maximization**

## I. Introduction

Recent years have witnessed pervasive smartphones with high end capabilities, embedded with sensors [1] (such as gyroscope, camera, digital compass, microphones, accelerometer), which unprecedentedly enabled smartphone users to collect, share diverse information related with locations, mobility, images and sounds easily. This introduced a broader notion of realization - mobile crowdsourcing [2], an emerging problem resolving paradigm based upon number of smartphone users (SMUs) participation. Correspondingly such collective contribution of information significantly motivated in growth of various proximity based mobile crowd services [3]. Even the revenue from location based service market is expected to be as much as $43.3 billion worth by 2019 [4], and to support more and more sophisticated services following this drastic growth in location based services, more resourceful, complicated and comprehensive data are required. Some examples of such services include: road and traffic monitoring [5] [6] , pollution monitoring [7], urban monitoring [8], cross-space public information sharing [9], and indoor localization [10].

A critical observation to collect and transmit required data for the task requester is user's participation. However, there is a conflicting situation for users participation to crowdsourcing due to energy and computing capacity [11]. Such inevitable fact makes the user reluctant to participate which is one of the major challenge in crowdsourcing. Therefore, an appropriate motivation scheme i.e, incentive mechanism designs are required to ensure users' participation [12]. An incentive could be considered as financial rewards, societal approval, self-esteem [13].

In the literature, there has been introduced a number of incentive mechanisms [12], [14] to motivate users for participation which can potentially enhance the quality of received data due to strong commitments from users. Most of the proposed model focus on such incentive schemes based upon auction mechanisms where the participating users submit bids for a particular allocated task to the task requester, and the interaction between them turns out to be an individual utility maximization game [11], [12], [15]. However, the referred papers particularly remain silent about the inconvenience attributes of participating users' in terms of energy capacity, privacy concerns, participating time and so on, and their individual behavior for the tasks. This limits the scope of task load allocation problem i.e, the appropriate task load for each participating users without overwhelming their inconvenience measures. In [16] the authors proposed about a platform based campaign for optimizing mobile crowdsensing by performing users' profiling to maximize aggregated expected quality of users' contributions. Further, in literature ranking based crowdsourcing model [15], and even users' reputation factor were considered in [17], [18] that takes users' past behavior into account to design the incentive mechanism. These works has extended the notion of users behavior for a proper design incentive allocation. However, in our formulation we have included each users' behavior relevant to their inconvenience parameters as well to design the offered payment such that we improve platform's favorable condition. And for this, to capture individual users' behavior we analyze response driven historical datasets upon platform - users' interaction.

Motivated by different incentive allocation mechanism to

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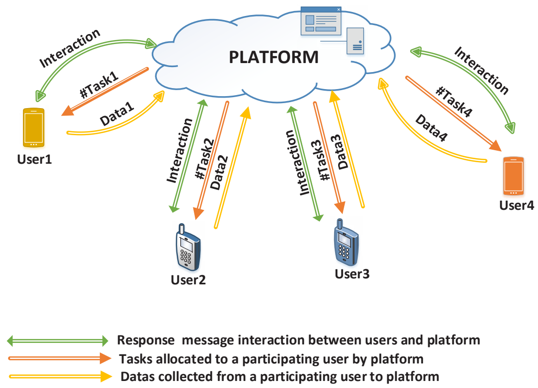


Fig. 1: Crowdsourcing system model with platform-user interaction based incentive mechanism and task allocation

improve users' participation for better quality of collected data, and their limitations about task load allocation as discussed before in this paper we deployed users' profile based incentive plan to ensure their participation. Furthermore, based upon the appropriate incentive requirement for maximizing number of participants we analyzed utility model for each user to identify proper task load plan ensuring their prolonged participation and its completion without overwhelming their energy restrictions.

The remainder of this paper is organized as follows. In the next section we present our system model, the interaction between users' and crowdsourcing platform. We formulate our problem in Section III, and illustrate our models for users' profiling. In Section IV we discuss simulation results of the proposed algorithm. Finally, we conclude this paper in Section V.

## II. System Model

We consider a set $\mathcal{U} = \{1,2, \ldots, N\}$, and number of users (SMUs) defined as $u \in \mathcal{U}$ who agree upon interaction to a platform (task requester) via an application. The set of users are defined according to their proximal location of a task description at a particular time instance. Also, the task requester has a number of task defined as a set $l \in \mathcal{L}$ and a budget constraint for that particular task $l$ as $C_l$. Each task $l$ comprises with a number of workload to complete it, and certainly a task owner tries to allocate it amongst the participating users in such a way that nobody leaves the platform once they agree upon the provided incentive based upon their response profile.

As shown in Fig.(1), at first individual user interact with the platform to generate a training dataset $D(t)$ for user profiling. For this we consider a feature set $x_{ul}$ $\{$ $x_p$ : offered incentive, $x_t$ : execution time$\}$ and the logistic response of participation for a task $l$ by user $u$ as defined by a binary variable $y_{ul}$ , where the output 1 represents the users' acceptance to participate,and 0 denotes rejection to contribute.

The response framework can be generated using the following formulation for individual [19] user:

$$Min.Incentives(p_u) = \beta_u * \text{execution time}(t) + \zeta_u \quad (1)$$

Where $\beta_u$ captures individual users' behavior towards participation and $\zeta_u$ quantifies platform's association cost. The assumptions made here can be argued valid because of individual user preferences for a particular task. In the later section, we will discuss more specifically about the impact of device's energy constraint including inconvenience metrics such as privacy concerns , and time of attention required for completing a particular task that may be used as a parameter to define users' bias and platform's association cost. In our case, we have defined $\zeta$ as strict positive bias value and $\beta \in [0, 1]$ , to model user training response samples. Secondly, following optimization model as discussed in the problem formulation, the platform can design an appropriate incentive scheme. And being based upon utility model for each participating user considering their individual energy constraints, the platform can assign task loads without disturbing their participation. Finally, participating users will complete the tasks by providing necessary data as requested by the platform

## III. Problem Formulation

In this section we formulate the user profiling , and response driven task load allocation problem with proper incentives.

### A. Problem Statement:

Main goal of this paper is to improve users' participation for a crowdsourcing task that eventually provides enhanced quality of data collected for a task requester. In order to keep users associated with the platform , a proper incentive plan and also an appropriate workload allocation needs to defined without overwhelming users' energy constraints.

- In order to design incentive plan for improving users' participation, a response driven dataset is generated. We implement logistic regression model for each individual user about their preferences upon a certain description of task using the aforementioned dataset.
- The model parameters are incorporated with platform's adverse impact and cumulative users' inconvenience metric in an optimization problem to evaluate proper incentive plan for motivating maximum number of users by improving favorable platform condition.
- Utility based model is formulated to design a proper workload assignment for individual user by the task requester once they join the platform. For this purpose, each users' energy profile is taken into consideration.

### B. Response Driven User Profiling:

The interaction between platform and users allow to generate datasets $D(t)$ defined by $\{(x_1^{(l)}, y_1^{(l)}), (x_2^{(l)}, y_2^{(l)}), \ldots, (x_N^{(l)}, y_N^{(l)})\}$ where $y_1^{(l)}$ denotes

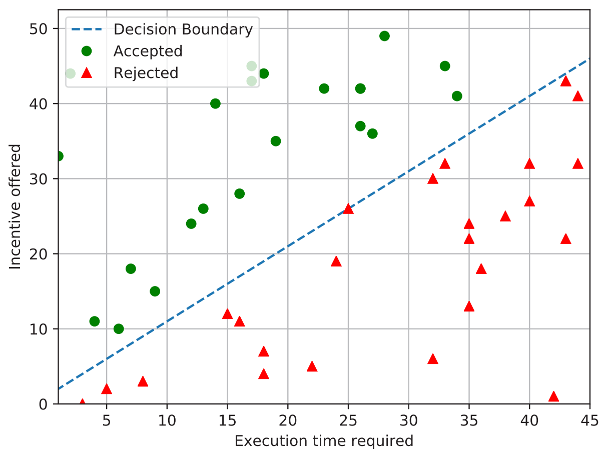


Fig. 2: Illustration of a single user training dataset model

user (1)'s response to a feature set offered by platform $x_1^l$ $\{\ x_p$ : offered incentive, $x_t$ : execution time$\}$ for $l$ set of tasks. As illustrated in Fig.(2), we generate users' response profile based upon Eq.(1). The problem is formulated as a classification problem where a user either accepts or rejects to participate in the crowdsourcing task offered by the task requester. For such case, likelihood function are defined as a good choice of classification function.

$$P(y_1, y_2, \ldots, y_N | x_1, x_2, \ldots, x_N) = \Pi_{n=1}^{N} P(y_n|x_n) = \sigma(\phi.x)$$

We apply maximum likelihood estimation (MLE) principle to quantify the optimal parameters (feature weights) $\phi_u$ that captures users' preference on feature sets for $k$ tasks , which can be interpreted as:

$$P(y_u|\phi_u) = \Pi_{l=1}^{k} P_u(A|x_{ul})^{y_{ul}}(1 - P_u(A|x_{ul}))^{1-y_{ul}}$$

where ,

$$P_u(A|x_{ul}) = \sigma(\phi_u.x_{ul})$$

We define our cost function as regularized log-likelihood function with parameter $\lambda$, and minimize it by applying gradient decent algorithm for obtaining proper weight values.

$$J(\phi_u) = -\ln P(y_u|\phi_n) + \frac{\lambda}{2}||\phi_u||^2 \tag{2}$$

The gradient of Eq.(2) is calculated as:

$$\nabla J(\phi_u) = \sum_{l=1}^{k}(P_u(A|x_{ul}) - y_{ul}) - y_{ul})x_{ul} + \lambda\phi_u \tag{3}$$

The optimal parameter values are obtained iteratively using the gradient method , and a learning rate $\alpha$ , which basically denotes the step size for updates in each round.

$$\phi_u^{t+1} = \phi_u^{(t)} - \alpha\nabla J(\phi_u) \tag{4}$$

### C. Optimization Problem:

Given a set of users $u \in \mathcal{U}$ that participate in this crowd-sourcing framework , the task requester's problem is to design a proper incentive plan $p_{ul}$ such that platform's favorable condition is maximized by improvement in users' participation for the offered tasks. The improvement in platform's condition signifies better quality of received data for the task requester. In our formulation , we have defined platform's adverse impact factor $(\psi < 1, \in [0, 1))$ , and $\hat{\beta}$ as normalized individual users' behavior towards participation $\sum_{u \in U} \beta_u / N$ as

$$\begin{aligned} &\max_{p_{ul}} \sum_{u\in U}\sum_{l\in L}(1-\psi\hat{\beta})\sigma([\phi_{ut}\ \phi_{up}]'[x_t\ p_{ul}]) \qquad (5)\\ &\text{subject to}\quad \forall u \in \mathcal{U}, \forall l \in \mathcal{L}\\ &C1: \qquad \sum_{l\in\mathcal{L}} p_{ul} = C_l\\ &C2: \qquad 0 \le p_{ul} \le p_{max} \end{aligned}$$

C1 is the budget constraint for the task requester for a particular task; the economic restriction. The platform also tries to ensure no individual is provided unfair incentive allocation that might results in budget exhaustion with low participation. C2 imposes this restriction to each user.

### D. Utility Model :

For each mobile user, consider energy profile defined as $E_u$ that will be responded to the platform at the time of interaction. To capture corresponding power consumption behavior based upon allocated task load for mobile devices, [20] provides two different approach: piece-wise linear function, and the quadratic function. We model considering the fact that it will be increasing with the increase in allocated task load. Therefore, from the above literature discussion , the utility model for users should be a concave function of allocation task load, i.e non- decreasing function when the task load is no more than a certain value. Then, the utility of a user $i$ is

$$u_i = \begin{cases} p_i - c_i, & \text{if } u \in \mathcal{U} \\ 0, & otherwise \end{cases}$$

which can be modeled as ,

$$U_{ul} = p_{ul}^{'} E_u \epsilon - \beta_u \epsilon^2 \tag{6}$$

where, $p_{ul}^{'}$ is offered incentive for task $l$ to user $u$, $\epsilon$ is task load allocated and $\beta$ is inconvenience parameter, previously discussed as an individual users' behavior towards participation in crowdsourcing. Fig.(3) reflects the basic utility model discussed in this section. Here, as user's utility not only depends on the number of task load allocation but also the offered incentive . The utility model also cannot guarantee users participation to the platform, and instead might overwhelm users with inappropriate task load allocation against their capacity.

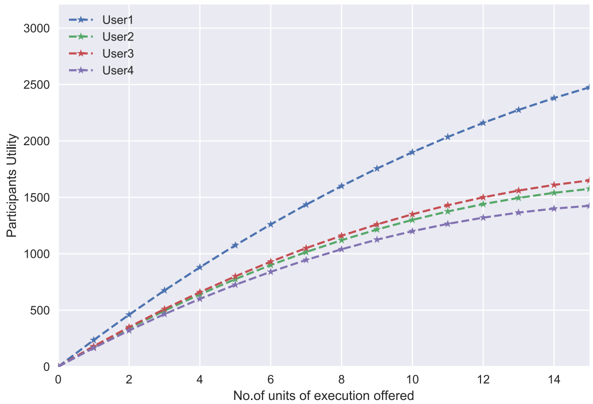


Fig. 3: User's utility response for number of task load allocation

## IV. Simulation Results

Simulation results are presented in this section to validate overwhelming task load allocation by task requester in the absence of proper user profiling as discussed. To incorporate user's participation that ensures their acceptance for performing the allocated task, a utility model based appropriate task load assignment is presented here as a result. Without loss of generality, we consider 10 participating users in the set $u \in \mathcal{U}$, task requester budget $C_l = 45$, and energy profile $E_u \in (\mu, \sigma^2)$.

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**Algorithm 1** Profile Based Task Load Allocation

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**Require**: $< U(T), D(T), L(T), C, E >$
**Initialize**: $T = 0$
**for** SMUs $u \in \mathcal{U}, D\{x_p, x_t\}$ **do**
    *Run training model to compute* $\phi_{up}, \phi_{ut}$
    *Observe user profile* $\leftarrow \phi_{up}, \phi_{ut}, E$
    **for** Each $u \in \mathcal{U}, l \in \mathcal{L}$ **do**
        *Run optimization problem*
        *Receive each users' incentive allocation* $p^*_{ul}$
    **end for**
    Evaluate utility profile of participating users
    Assign optimal task load based upon utility model
**end for**
$T \leftarrow T + \triangle T$
*Update user profile*

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As followed in Algorithm1, we implemented a single task scenario to analyze the incentive allocation problem as profile based, and average sharing mechanism. This way, firstly we evaluated parameter values on feature attributes for users based upon synthetic training dataset implementing gradient descent method. Secondly, using parametric values we computed $p^*_{ul}$ for each user to ensure participation for a particular task defined by task feature attributes (as discussed in the problem formulation ). Finally, we evaluated individual participating users' utility profile, and corresponding optimal task load allocation that ensures users' interaction with platform without overwhelming their energy constraints.

In Fig.(4) we can observe users utility upon number of task load allocation by task requester, based upon the incentive plan proposed while considering user's profile. Under reported energy constraints, the optimal task load for each user can be obtained setting the first order derivative of Eq.(6) as zero i.e, at $\frac{p'_{ul}E_u}{2\beta_u}$. We evaluated our proposal with sufficiently equal pay for participation based task load allocation in which task requester doesn't consider individual users' inconvenience parameters (energy constraints). That means it might overwhelm participating users with more number of task load that can exhaust their resources, and eventually motivate them to leave the crowdsourcing as suggested by utility model.

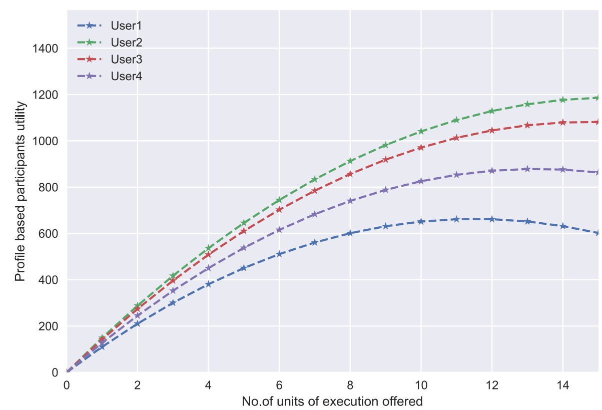


Fig. 4: Profile based user's utility response for number of task load allocation

Fig.(5) suggests this issues which could be rectified using our proposed response driven user profiling incorporated with utility model to enable task requester for a wise task allocation decision without loosing participants.

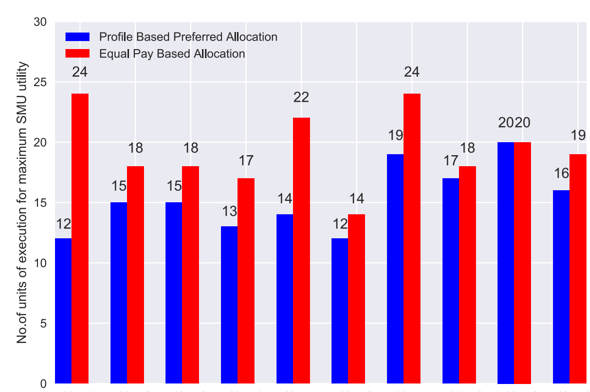


Fig. 5: Task load allocation for participating users

## V. Conclusion

In this paper, we formulated a profile based incentive mechanism for improving users' participation in mobile crowdsourcing with considerations to individual users' behaviors. We extended our investigation to define optimal task load allocation for the participating users being based upon incentive profile obtained by solving an optimization problem, and the utility model. Our approach, on one hand was to improve platform's favorable condition for better collected data by maximizing participation through proper incentive plan, while on the other eliminate overwhleming task load allocation to the participants so that they won't leave the platform because of energy constraints. Through simulation analysis we have shown that task requester allocates beyond preferred task load to the participating user which significantly affects their utility and force them to leave the crowdsourcing. However, here we haven't considered the interaction between profile based users' utility and task requester's utility, and our future work will be towards modeling such strategic incentive and task load assignment problem taking users' inconvenience metrics into account.

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