Small Profits and Quick Returns: A Practical Social Welfare Maximizing Incentive Mechanism for Deadline-Sensitive Tasks in Crowdsourcing

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Abstract

As the driving force of crowdsourcing is the interaction among participants, various incentive mechanisms have been proposed to attract sufficient participants. However, the existing works assume that all the providers always meet the deadline and the task value accordingly remains constant. To bridge the gap of such impractical assumption, we model the heterogeneous punctuality behavior of providers and the task value depreciation of requesters. Based on those models, we propose an Expected Social Welfare Maximizing (ESWM) mechanism that aims to maximize the expected social welfare in polynomial time. Simulation results show that our heuristic-based mechanism achieves higher expected social welfare and platform utility via attracting more participants.

Introduction

The existing incentive mechanisms for crowdsourcing assume that all the providers always meet the deadline of requested tasks. In practice, however, we cannot guarantee such perfect punctuality. Therefore, the existing mechanisms, despite their well-defined system models, do not fully reflect the realistic behavior of providers.

Besides, without guaranteeing the perfect punctuality, there can be task value depreciation if tasks are completed after the deadline. Typically, a requester can achieve a full task valuation if its requested task is completed within the deadline. Otherwise, the later task is completed, the less valuation it achieves (Yeo and Buyya 2005). In addition, the rate of depreciation can be different among participants. Therefore, due to such potential task value depreciation, the existing works may not accurately estimate task valuation in crowdsourcing system.

In addition, such task value depreciation can affect the payment policy in incentive mechanisms. In the existing works, providers are rewarded with a fixed payment policy. However, when tasks are deadline-sensitive, the valuation of tasks depreciates after the deadline or even become valueless, which will inflict loss of utility to requesters. Despite such loss, they are not accounted for their loss. As a result, the satisfaction level of requesters will degrade.

Therefore, we model the providers' punctuality behavior and the task value depreciation to build an incentive mechanism under more practical and realistic assumptions. Based on our new system model, we propose an expected social welfare maximizing (ESWM) mechanism that aims to maximize the expected social welfare in polynomial time.

Related Works

Yang et al. (Yang et al. 2012) presented two models of incentive mechanisms: platform-centric model and user-centric model to motivate mobile users' participation. By rewarding participants proportionally to their contribution, D. Peng et al. (Peng, Wu, and Chen 2015) proposed a quality based incentive mechanism for crowdsensing. To maintain sufficient participants and promote dropped users to participate again, Lee and Hoh (Lee and Hoh 2010) propose a mechanism, called RADP-VPC, to provider long-term incentives to participants.

Expected Social Welfare Maximizing Problem

The objective of the platform is to find the optimal requester-provider matches L that maximize the expected social welfare as formulated below

$$L^* = \underset{L}{\operatorname{argmax}} \sum_{r_j \in R} \sum_{w_i \in W} (\mathbf{E}_i(v_j(t)) - c_i) l_{ji}, \tag{1}$$

subject to

$$\sum_{r_j \in R} x_j \leq K, \tag{11.a}$$

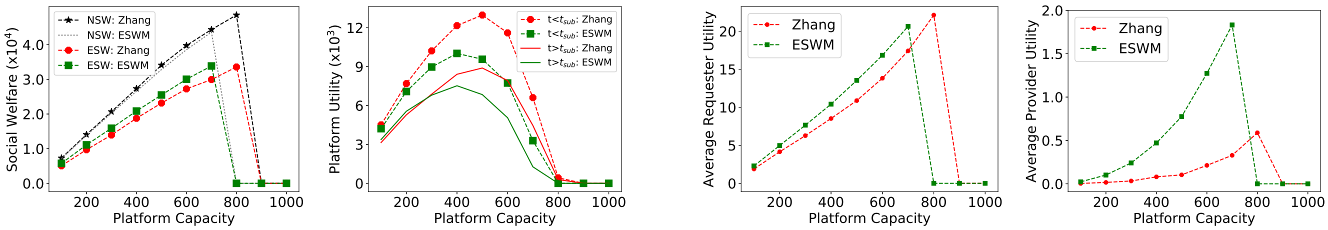
$$\sum_{r_j \in R} x_j = \sum_{r_j \in R} \sum_{w_i \in W} l_{ji} = \sum_{w_i \in W} y_i, \tag{11.b}$$

$$x_j \in \{0, 1\}, \quad \forall r_j \in R, \tag{11.c}$$

$$y_i \in \{0, 1\}, \quad \forall w_i \in W, \tag{11.d}$$

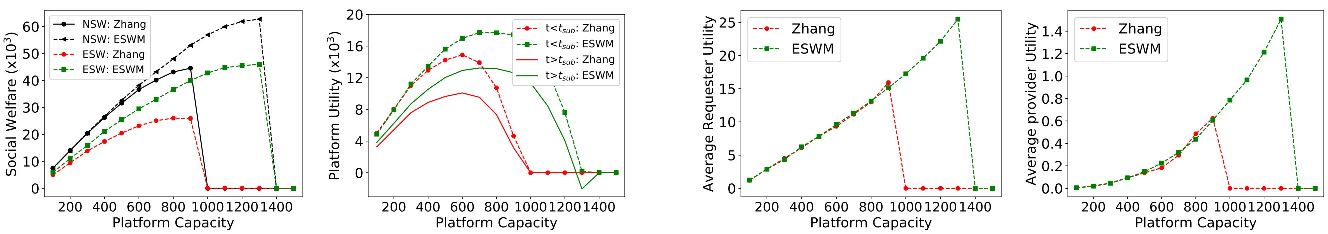
$$l_{ji} \in \{0, 1\}, \quad \forall l_{ji} \in L. \tag{11.e}$$

where r_j (R) and w_i (W) denote a requester (a set of requesters) and a provider (a set of providers), respectively. r_j wants to complete a task with certain deadline, of which valuation is v_j . w_i wants to work on a requested task and get rewarded for the task to compensate the incurred cost, c_i. $\mathbf{E}_i(v_j(t))$ is the expected task valuation of a task from r_j when completed by w_i. l_{ji} indicates that r_j and w_i are matched together. x_j and y_i indicate whether r_j and w_i are selected or not. Constraint (11.a) specifies that the platform has a limited capacity to handle K task requests and constraint (11.b) specifies that each selected requester will be matched to only one provider. To obtain the optimal solution



(a) Social Welfare (b) Platform Utility (c) Average Requester Utility (d) Average Provider Utility

Figure 1: Benchmark VS ESWM



(a) Social Welfare (b) Platform Utility (c) Average Requester Utility (d) Average Provider Utility

Figure 2: Benchmark VS ESWM with reselection

in (1), we need to solve a binary integer programming problem, which is NP-complete. Thus, to overcome such impracticality, we propose an expected social welfare maximizing mechanism (ESWM) that is based on a greedy algorithm to heuristically obtain the locally optimal solution.

Performance Evaluation

As performance metrics, we consider the naïve social welfare (NSW) to simply sum the task valuation and the expected social welfare (ESW), the platform utility, and the average utility of requesters and providers. We compare the performance metrics of our mechanism to those of the benchmark (Zhang et al. 2015) whose winner selection process is based on the greedy algorithm, but only considering the platform utility.

In reality, as all the participants are rationally selfish, they are likely to select the mechanism that provides higher utility to them. Thus, when both the benchmark and our mechanism exist in a crowdsourcing system, the number of participants that each mechanism attracts can vary depending on the average utility each mechanism provides. To reflect such difference of attractiveness between two mechanisms to participants, we set the participation probability of a participant proportional to the square root of the average utility of participants in Figure 1 where both mechanisms are given the same number of requesters and providers, based on (Akerlof 1982). According to the probabilities, each participant decides which mechanism it will participate in. We call such decision making process *reselection*. Figure 2a and Figure 2b show that the ESWM mechanism achieves higher social welfare and platform utility than the benchmark. Such outperformance can be achieved as the ESWM mechanism can attract more participants, which increase the chance of getting better providers. Figure 2c and Figure 2d show that the ESWM mechanism and the benchmark achieve almost the same average utility as long as both can handle task requests. This is because the increased number of requesters and providers participating in the ESWM mechanism ironically decreases the average utility of participants. Based on our observation from Figure 2c and Figure 2d, we can anticipate that there will not be a significant increase in the number of reselection again as the benchmark and the ESWM mechanism reached the balance point of the average utility of participants. In addition, the ESWM mechanism can support more task requests.

Conclusion

In this work, we proposed an Expected Social Welfare Maximizing (ESWM) mechanism that is based on a greedy algorithm to heuristically obtain the locally optimum in polynomial time. Simulation results show that the ESWM mechanism achieves higher expected social welfare and platform utility than those of the benchmark mechanism via attracting more participants.

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