Postprint: An Online Incentive Mechanism Optimization Algorithm for Mobile Crowdsourcing Systems

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Abstract

In big data environments, research on mobile crowdsourcing models has emerged as a focal point. To improve the effectiveness and reliability of mobile crowdsourcing systems, we design a comprehensive optimization algorithm for online incentive mechanisms. Addressing the asynchronous behavior of user arrival and task participation, we propose an improved multi-stage reverse auction algorithm that adaptively determines the "density threshold" through online learning, dynamically selects the optimal user set, and updates user reputation after each transaction to guide subsequent task allocation. Simulation results demonstrate that the optimization algorithm satisfies computational efficiency, individual rationality, and truthfulness, and can achieve better performance under certain budget and time constraints.

Full Text

Optimization Algorithm of Online Incentive Mechanism for Mobile Crowdsourcing System

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Abstract: In big data environments, research on mobile crowdsourcing models has become a focal point. To enhance the effectiveness and reliability of mobile crowdsourcing systems, this paper designs a comprehensive optimization algorithm for online incentive mechanisms. Addressing the asynchronous behavior of users arriving at and participating in tasks, we propose an improved multi-stage reverse auction algorithm that adaptively determines the "density threshold" through online learning, dynamically selects optimal user sets, and updates user reputation after each transaction to guide subsequent task allocation. Simulation results demonstrate that the proposed optimization algorithm satisfies computational efficiency, ensures positive returns for both parties, and maintains truthfulness, while achieving superior performance under budget and time constraints.

Key words: mobile crowdsourcing; data awareness; optimization algorithm; intelligent optimization

0 Introduction

Crowdsourcing [1] is a distributed problem-solving model enabled by the Internet. In recent years, with the proliferation of mobile devices and rapid development of wireless communication technologies, the concept of mobile crowdsourcing [1] has emerged. Users can leverage the rich sensors built into smart devices and their powerful storage and computing capabilities to participate in crowdsourcing tasks anytime and anywhere. Task requesters and users can also communicate directly through wireless network technologies such as Wi-Fi, Bluetooth, or D2D, reducing the intervention of base stations and crowdsourcing platforms and enabling better resource sharing and task collaboration. Unlike traditional Web-based crowdsourcing models, mobile crowdsourcing systems exhibit stronger real-time capabilities and mobility, making existing offline algorithms unsuitable for addressing related problems.

Since participating in crowdsourcing tasks inevitably consumes mobile device resources and power, and even poses threats such as location privacy leakage, the design of incentive mechanisms is particularly important. Existing research on user recruitment and incentives mostly relies on offline synchronous scenarios, selecting optimal user sets through Stackelberg game [2] or greedy search algorithms [3]. However, these approaches require all participants to submit bids simultaneously or share information publicly, which is unsuitable for realistic scenarios where users arrive and depart asynchronously. In the past two years, asynchronous online auction algorithms with fixed thresholds were first proposed. Subsequently, Zhang et al. [4] proposed a two-stage auction algorithm that rejects and uses information from users who submitted bids in the first stage as a reference, but this is unfair to early-arriving users. Wang et al. [5] proposed an online incentive mechanism combining reputation updates and privacy protection, but it measures crowdsourcing tasks entirely by sensing time, limiting application scenarios. Zhao et al. [6] introduced the idea of a multi-stage auction algorithm but did not fully consider breach-of-contract situations for both parties. Building upon previous research, this paper proposes a complete online incentive mechanism for more realistic asynchronous mobile scenarios, including an improved multi-stage reverse auction algorithm and a reputation update algorithm. Both theoretical and simulation results prove that this incentive mechanism optimization algorithm satisfies computational efficiency, positive returns for both parties, and truthfulness, while achieving better performance under certain time and budget constraints.

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1 System Model

Assume the candidate user set is $\{1, 2, \ldots, n\} = C$. The task requester publishes task information (including deadline T and budget B) at a certain time and place. Arriving users submit bids (including expected reward b_i and contribution value v_i) based on personal interest. The cost for user i to complete this task is c_i, and the current reputation value is r_i. Upon receiving each user' s bid information, the task requester must immediately decide whether to accept the user. If accepted, the reward p_i is paid and the transaction occurs. After the transaction, the user' s reputation value is updated based on task completion quality. Therefore, the utility function for each participating user i is:

$$u_i = \begin{cases} p_i - c_i & \text{if } i \in S \\ 0 & \text{else} \end{cases}$$

where S represents the selected user set. Define the task requester' s actual benefit as:

$$U(S) = \sum_{i \in S} v_i - \sum_{i \in S} p_i$$

2.1 Improved Multi-Stage Reverse Auction Algorithm

For the aforementioned system model, this paper first proposes an improved multi-stage reverse auction algorithm. The task process is divided into multiple stages based on deadline T, dynamically increasing samples and updating the "density threshold" for each stage in real-time through online learning [7] to guide decision-making for the next stage. Since threshold calculation incorporates actual user conditions, it can adaptively adjust to optimal values, improving upon the uncertainty and irrationality of manual settings. Meanwhile, initializing a smaller threshold acceptable to the task requester guides first-stage decision-making, giving first-stage users opportunities to win auctions and encouraging early arrival, thus resolving the fairness issues of two-stage auction algorithms.

The improved multi-stage online reverse auction algorithm is as follows:

Input: budget B, deadline T
Initialize: $t = 1, S = \emptyset, \rho = \varepsilon$

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while $t \leq T$ do
    if there is a user $i$ arriving at time step $t$ with bid $b_i$ and value $v_i$ then
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        if $U(S \cup \{i\}) - U(S) \geq \rho' \leq \frac{b_i}{B-P(S)} \leq u_i$ then
            $p_i \leftarrow b_i$
            $S \leftarrow S \cup \{i\}$
            $U(S) \leftarrow U(S) + u_i$
            $P(S) \leftarrow P(S) + p_i$
        end if
    end if
    $t \leftarrow t + 1$
end while
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2.2 True Online Reputation Update Algorithm

The transaction behavior between task requesters and users is divided into two scenarios: paying rewards first or completing tasks first. Considering individual selfishness, both parties tend to minimize their own costs to obtain higher benefits, thus leading to "breach of contract" behavior [8]. This paper uses scenario one as an example to set up reward-penalty incentives for the user side, with scenario two being similar for the task requester.

Assume r_i^k is the current reputation value of user i, and r_i^{k+1} is the reputation value after completing task φ_k. Define $r_{\max}$ as the maximum reputation value for system users, and $\{\theta_0, \theta_1, ..., \theta_m\}$ as the set of reputation thresholds required by each task, where θ_0 is the system minimum reputation threshold and $\theta_1, \theta_2, ..., \theta_m \geq \theta_0$. Let n be the number of system task participants. The monotonic submodular function reflects the diminishing marginal benefit trend in economics and is applicable to many realistic scenarios.

Each user i provides actual marginal benefit to the task requester as:

$$u_i = \log\left(1 + \lambda \frac{v_i}{V(S)}\right) - \log\left(1 + \lambda \frac{p_i}{P(S)}\right)$$

where θ_k corresponds to the reputation threshold of task φ_k. Define $q \in \{good, bad\}$ representing whether the user chooses a trustworthy/untrustworthy strategy in this task. Then the reputation update algorithm for user i after completing task k is as follows:

$$r_i^{k+1} = \begin{cases} \min(r_{\max}, r_i^k + q) & \text{if } q = good \\ \max(0, r_i^k - q) & \text{if } q = bad \text{ and } r_i^k > \theta_k \\ \theta_0 & \text{if } q = bad \text{ and } r_i^k = \theta_k \\ r_i^k & \text{if } q = bad \text{ and } r_i^k < \theta_k \\ \theta_0 - 1 & \text{if } q = bad \text{ and } r_i^k = \theta_0 \\ \max(0, r_i^k - q) & \text{if } q = bad \text{ and } r_i^k < \theta_0 \end{cases}$$

Equation (3) is used to measure the user's actual individual contribution. Based on this, the goal of this paper is to design a reasonable online incentive mechanism that maximizes system benefit under budget and time constraints, i.e.:

$$\begin{aligned} \text{Maximize} \quad & U(S) \\ \text{subject to} \quad & P(S) \leq B \text{ and } t \leq T \end{aligned}$$

3 Simulation Results and Analysis

A MATLAB program was developed with task deadline $T = 8$ min, budget $B = 500$, user arrival times following a Poisson distribution with rate $\lambda = 0.6$ [8], user bids and contribution values randomly distributed in the range 1-10, number of system task participants $n = 12$, and initial density threshold $\rho = 12$. This was compared with a conventional online auction algorithm with fixed density threshold $\rho = 12$. Each experiment was run independently 50 times and averaged. The simulation results are shown in Figure 1 [Figure 1: see original paper].

3.1 Improved Multi-Stage Reverse Auction Algorithm Simulation Results and Analysis

From Figure 1, it can be seen that the multi-stage auction algorithm proposed in this paper outperforms traditional online auction algorithms in both benefit and time. In fact, if the traditional algorithm selects an appropriate threshold, it can achieve performance close to our algorithm, but manual threshold selection is extremely difficult—this represents one of our algorithm' s advantages. Figure 1(b) shows program runtime representing transaction time, indicating that the multi-stage auction algorithm can achieve higher benefits with fewer transactions, optimizing task efficiency and energy consumption from a global perspective. However, in real-world scenarios, rejecting users and waiting for new arrivals also consumes time, which is the cost paid by this algorithm. Considering densely populated scenarios with sufficient participating users, this time consumption can be negligible.

Simulations were conducted by individually varying deadline T, task budget B, and user arrival rate λ to compare algorithm performance, with results shown in Figure 2 [Figure 2: see original paper]. From Figure 2, it can be seen that larger budgets, longer deadlines, and higher user arrival rates lead to greater actual benefits for the task requester, as these conditions correspond to recruiting more high-quality users to participate in tasks. This aligns with real-world scenarios and further proves the algorithm' s rationality.

3.2 Online Reputation Update Algorithm Simulation Results and Analysis

This paper first analyzes the behavioral evolution trend of trustworthy users in mobile crowdsourcing systems using evolutionary game theory [9]. The game payoff matrix for both parties is: if the task requester selects trustworthy users, both parties gain $u_i - p_i$; if untrustworthy users are selected, both parties gain $p_i - c_i$, where $c_i > p_i > 0$; rejecting users yields zero benefit for both parties. Based on the game payoff matrix analysis of Nash equilibrium [10], the initial proportion of trustworthy users in the system was set from 0.3 to 0.9 with step size 0.1, with average user reward and cost being 5 and 2 respectively. The evolution trend of trustworthy user behavior is shown in Figure 3 [Figure 3: see original paper].

From Figure 3, it can be observed that when the initial proportion of trustworthy users is less than 0.6, users tend to choose untrustworthy strategies, making reward-penalty incentives necessary. Simulations were conducted on the proposed reputation update algorithm with initial trustworthy user count of 100 and system minimum reputation thresholds of $\theta_0 = 6, 7, 8, 9$, with task requirement threshold $\theta_k = 9$. Compared with conventional reputation update algorithms using a single threshold, results are shown in Figure 4 [Figure 4: see original paper].

From Figure 4, it can be seen that the new reputation update algorithm offers greater tolerance for users, enabling the number of trustworthy users to stabilize at a higher proportion and better maintain system operation. In contrast, conventional algorithms expel users from the system after a single untrustworthy behavior, which can excessively punish potentially trustworthy users.

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4 Conclusion

This paper proposes a complete online incentive mechanism optimization algorithm for emerging mobile crowdsourcing scenarios, including an improved multi-stage reverse auction algorithm and a reputation update algorithm. Theoretically, it can be proven that this mechanism satisfies computational efficiency, positive returns for both parties, and truthfulness. Simulation results further demonstrate that the proposed incentive mechanism can achieve better performance under certain budget and time constraints.

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Note: Figure translations are in progress. See original paper for figures.