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Behavior Dynamics of Multiple Crowdsourcers in Mobile Crowdsourcing Markets

Jia Peng, Yanmin Zhu, Wei Shu, and Min-You Wu

Abstract

Mobile crowdsourcing has shown great potential to address problems with large scale by outsourcing tasks to pervasive smartphone users. Smartphone users will join a crowdsourcer if they can receive satisfying rewards. In a mobile crowdsourcing market, smartphone users have free choice of crowdsourcers, and multiple crowdsourcers will interact with the rest of the market to share the limited smartphone contributions (i.e., sensed data). To better fit the gap between the demands of crowdsourcers and the capabilities of smartphone users, the underlying rationale of crowdsourcers' behavior needs to be well understood. However, little attention has been given to this issue. In this article, we analyze and predict the behavior (i.e., adjust the price paid) of crowdsourcers. We use a dynamic non-cooperative game to formulate the interaction among crowdsourcers and extend it to a repeated game since crowdsourcers may cooperate with each other to get the optimal profit considering the long-term profit when the game is played multiple times.

Introduction

Crowdsourcing is a very real and important business term coined by Jeff Howe in 2006 [1]. The basic idea is to harness the collective intelligence of the public to perform tasks (e.g., obtaining services, ideas). Crowdsourcing can address problems beyond the scale that was possible with traditional methods. Recently, powerful mobile devices (e.g., smartphones), which are pervasive in our daily life, have significantly enhanced the development of crowdsourcing, and mobile crowdsourcing has emerged as the next generation of crowdsourcing [2, 3]. Mobile devices are a new kind of tool to perform tasks. With powerful capabilities to perform data computation and communication, mobile devices make the tasks easier to perform. In particular, they can sense the environment with various sensors and be used to collect other kinds of data, such as video/image data (with cameras) and location information (with GPS).

Realizing the great potential of mobile crowdsourcing, both industry and academics have drawn extensive attention to it. Numerous applications and systems have been developed, such as Gigwalk [4] for workforce management, Jigsaw [5] for indoor plan reconstruction, and Ear-Phone [6] for urban noise mapping. When mobile crowdsourcing becomes the mainstream, there will be more applications and systems in the mobile crowdsourcing market. With limited resources, such as time and CPU, mobile device holders (e.g., smartphone users) will decide which applications or systems to join and make contributions to the corresponding applications or systems. We name the applications or systems as crowdsourcers here.

In this article, we analyze the behavior dynamics of the participants in a mobile crowdsourcing market, which consists of multiple mobile crowdsourcers and a crowd of smartphone users. One crowdsourcer targets a certain type of task (e.g., collect data for air quality, traffic status, or noise level). A crowdsourcer recruits smartphone users to provide sensing services and offers a reward for participation. While participating in a mobile crowdsourcing task, smartphone users consume their own resources such as battery and computing power. A user would not be interested in participating in mobile crowdsourcing unless they receive a satisfying reward as compensation for its resource consumption. Thus, it is natural for smartphone users to choose the crowdsourcers they serve in the free market.

Each crowdsourcer in the market has to offer a competitive reward (i.e., price) to attract sufficient participation. Without the contributions of a large number of smartphone users, a crowdsourcer is not able to collect enough data to accomplish its functionality. A crowdsourcer is not capable of offering a very high reward to smartphone users, as the cost of the crowdsourcer goes up significantly along with the increasing number of smartphone users. The prices of the crowdsourcers jointly influence the willingness of smartphone users to contribute to each crowdsourcer. Thus, the issue of competition arises: crowdsourcers compete for limited smartphone contributions.

How will crowdsourcers adjust their prices? How will they interact with the rest of the market? Will the market be in a stable state? In this article, we address these issues to explore the underlying rationale in the mobile crowdsourcing market. With this understanding, relevant authorities can better regulate the mobile crowdsourcing market to better fit the gap between the needs of crowdsourcers and the capabilities of smartphone contributors. The problem addressed in this article falls into the category of smart data pricing [7–9].

Few research efforts have been made in mobile crowdsourcing when considering the competition of crowdsourcers. Most studies assume a single crowdsourcer [10–12]. Different from existing work, the key challenge when considering the competition of multiple crowdsourcers is that a smartphone user might withhold their participation from a crowdsourcer when it can gain a larger utility from other crowdsourcers. The smart-

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phone user can freely transfer among crowdsourcers. Thus, the prices of the crowdsourcers will be affected by each other, making the market more complex.

We apply a dynamic non-cooperative game [13] to model the mobile crowdsourcing market. The crowdsourcers are selfish and rational players. They adjust their prices for their own maximum profit. The price competition will be in a stable state, converging to a Nash equilibrium [14]. We observe that crowdsourcers may cooperate with each other to obtain the optimal profit, considering the long-term profit when the game is played multiple times. Then we extend the game to a repeated game [14] and analyze the condition to maintain collusion among crowdsourcers.

The remainder of this article is organized as follows. We first introduce the mobile crowdsourcing market, and then present the game analysis of crowdsourcers. Finally, we show some simulation results and conclude the article.

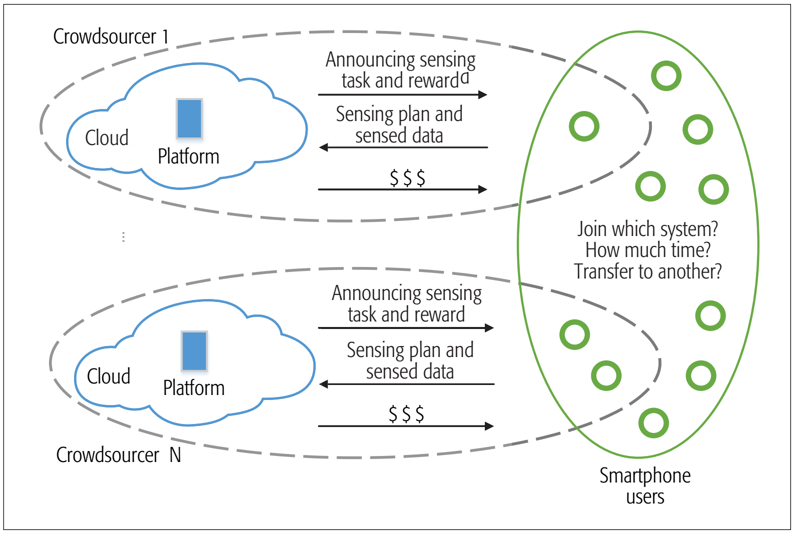

FIGURE 1. A mobile crowdsourcing market with multiple crowdsourcers.

A Mobile Crowdsourcing Market

We consider a mobile crowdsourcing market that consists of multiple crowdsourcers and a population of smarphone uers. We denote $\mathcal{N} = \{1, 2, 3, ..., N\}$ as the set of crowdsourcers. An example is shown in Fig. 1. Crowdsourcers compete for the limited sensing service provided by smartphones in the market.

When crowdsourcers announce their tasks and prices per unit time, smartphone users will decide whether to participate in the tasks and how many time units they will contribute to each crowdsourcer. Smartphone users make sensing plans based on the utility gained, with the goal to maximize overall utility. In response to the choice of smartphone users, crowdsourcers will adjust their prices, aiming at the highest individual profit. The crowdsourcers are rational and selfish. The market will be in a stable state when there are no crowdsourcers changing their prices.

One round of price adjustment can be viewed as one iteration. Crowdsourcers make price adaptations at the beginning of one iteration. In this article we measure the price and cost of a sensing task by time units. At iteration t, crowdsourcer i pays $p_i[t]$ per unit time of sensing service to smartphone users. The cost of doing the sensing task for crowdsourcer i is $k_i[t]$ per unit time of sensing service. After the price announcement, smartphone users decide to contribute $b_i[t]$ time units to crowdsourcer i. $b_i[t] = 0$ means that smartphone users will not join crowdsourcer i at iteration t. $\mathbf{p}[t] = \{p_1[t], ..., p_i[t], ..., p_N[t]\}$ stands for the price profile of all crowdsourcers.

In this article we focus on the analysis and prediction of the behavior of crowdsourcers. We view the population of smartphone users as a continuum of service providers of the same type, which can also be called a representative service provider. We will discuss the behaviors of smartphone users in a future work.

Game Analysis of Crowdsourcers

We apply game theory to analyze the behavior of competitive crowdsourcers. Game theory provides a formal analytical framework to study the interactions among rational agents. It can predict the behavior of decision makers. A game is made up of three components: a set of players, a set of actions, and a preference relation on the actions. Typically, we use a payoff function to evaluate the preferences for different actions. A player will prefer an action with a higher payoff to an action with a lower payoff. The actions also can be called strategies.

Game Formulation

In the crowdsourcer competition game, the players are the crowdsourcers. The strategy set of crowdsourcer i ($\forall i \in \mathcal{N}$) is the prices it announces (denoted by $p_i[t]$). The payoff of crowdsourcer i is its profit function. The profit function $p_i[t]$ of crowdsourcer i is the earnings on sensing data minus the price paid to smartphone users. The earnings on sensing data is $cb_i[t]$, where c ($c > 1$) reflects the value of sensing data. The price paid to smartphone users is $b_i[t]p_i[t]$. The parameter $b_i[t]$ will be revealed when smartphone users make sensing plans and upload the sensing data to crowdsourcers.

The dynamic game will be stable until there is no crowdsourcer who can increase their profit by adjusting their price unilaterally. That is the stable state of the market such that no crowdsourcer has an incentive to change their price. There is an important concept in game theory: the Nash equilibrium. A set of strategies are said to be in Nash equilibrium if no player can improve their utility by changing their strategy unilaterally. The existence and uniqueness of a Nash equilibrium demonstrates that the price adaption will converge to one fixed point. If there are multiple Nash equilibriums, it remains uncertain which Nash equilibrium all crowdsourcers will converge to. We will show that the crowdsourcer competition game has a unique Nash equilibrium.

A Nash equilibrium is a profile of best response strategies [14] if it exists. If a player has a unique best response strategy if it exists, the Nash equilibrium of the game is unique if it exists. The best response strategy is a strategy with which a player can obtain the maximum payoff given others' strategies. In the crowdsourcer competition game, the profit of a crowdsourcer is a continuous and concave function of other crowdsourcers' prices. The crowdsourcer has a unique best response

We observe that Nash equilibrium can not obtain the maximum overall profit when crowdsourcers cooperate with each other. That is the inefficiency of Nash equilibrium. However, the cooperation is unstable because some players have incentive to deviate from the optimal price, especially when the game is played only once. If the game is repeated, the players may decide to cooperate considering the long-term profit.

strategy. We can obtain this result by replacing smartphone users' responses $b_i[t]$ into the profit function of crowdsourcer i.

Smartphone Users' Responses

Now we introduce smartphone users' responses into the strategy profile of crowdsourcers. The sensing plan $\mathbf{b}[t] = \{b_1[t], ..., b_i[t], ..., b_N[t]\}$ of smartphone users has a significant effect on crowdsourcers' profit. At iteration t, when crowdsourcers announce their prices $p_i[t]$ ($\forall i \in \mathcal{N}$), smartphone users will make a sensing plan $\mathbf{b}[t]$ to maximize overall utility, that is, how to set the value of $b_i[t]$ to maximize utility function $U(\mathbf{b}[t])$. In this article, we propose a solution considering that smartphone users can switch among crowdsourcers. Note that the saturation of smartphone users' satisfaction on utility can be achieved. Otherwise, there will be no crowdsourcers entering the crowdsourcing market if the winners are smartphone users only. Here we show the steps to obtain $\mathbf{b}[t]$. First, differentiate $U(\mathbf{b}[t])$ with respect to $b_i[t]$ and set it to 0. Second, solve the set of equations in the first step and obtain $b_i[t]$, which is presented by a function of $\mathbf{p}[t]$.

The utility function of smartphone users $U(\mathbf{b}[t])$ is demonstrated as follows. Typically, the utility function of smartphone users is defined as the sum of reward from every crowdsourcer minus the sum of the cost to contribute sensing data to every crowdsourcer. The reward of crowdsourcer i is $b_i[t]p_i[t]$. The cost to contribute sensing data to crowdsourcer i is $b_i[t]k_i[t]$. In addition, the willingness of smartphone users to switch among different crowdsourcers will affect the utility of smartphone users. We adopt the service changing parameter v ($v \in [0.0,1.0]$) to characterize this feature. When $v = 0.0$, smartphone users are not willing to change the crowdsourcers they serve, while for $v = 1.0$, smartphone users transfer among the crowdsourcers frequently. The idea is inspired by the linear model in the theory of oligopoly [15]. Thus, the utility function of smartphone users $U(\mathbf{b}[t])$ has two more subtrahends. One is the result of v multiplied by the sum of $b_i[t]b_j[t]$, where $i \neq j$, $i, j \in \mathcal{N}$. The other is half the sum of the squares of $b_i[t]$, $i \in \mathcal{N}$.

Iterative Algorithm for Crowdsourcers

The mobile crowdsourcing market will be in a stable state (i.e., Nash equilibrium) when no crowdsourcer can increase its profit by changing prices unilaterally. We propose two distributed algorithms for crowdsourcers to gradually reach the Nash equilibrium.

In a market with complete information, a crowdsourcer can observe other crowdsourcers' strategies in previous iterations. Given the strategies adopted by other crowdsourcers at iteration t, crowdsourcer i adjusts its price at iteration $t + 1$ (i.e., $p_i[t + 1]$) according to the best response strategy.

In a market with incomplete information, a crowdsourcer cannot observe other crowdsourcers' strategies in previous iterations since the information remains unrevealed. It can only use the local information and the amount of contributed data (i.e., $b_i[t]$) from smartphone users to adjust its strategy. A crowdsourcer will adjust its strategy in the direction that maximizes its profit with an adjusting speed $0 < \alpha < 1$. For a given $p_i[t]$, the derivative of $P_i[t]$ with respect to $p_i[t]$ represents the direction of greatest increase. A crowdsourcer is capable of observing the marginal smartphone users' response (i.e., $b_i[t]$) for a small variation in price. Then it can estimate the marginal profit.

Repeated Game for Crowdsourcers

We observe that the Nash equilibrium can not obtain the maximum overall profit when crowdsourcers cooperate with each other. That is the inefficiency of the Nash equilibrium. However, the cooperation is unstable because some players have incentive to deviate from the optimal price, especially when the game is played only once. If the game is repeated, the players may decide to cooperate considering the long-term profit. In this section, we present a repeated game [14] to formulate the behavior of crowdsourcers to analyze the condition to maintain collusion among crowdsourcers. The optimal price of crowdsourcer i can be obtained as follows: first, differentiate the sum of all crowdsourcers' profit with respect to $p_i[t]$ and set to 0. Second, solve for $p_i[t]$ in the equation.

Repeated Game Formulation

In a repeated crowdsourcer competition game, the crowdsourcer competition game is played multiple times. We view one time as a stage. A stage starts at the time all crowdsourcers make action decisions, and ends at the time the steady state is reached. The crowdsourcers adjust their strategies based on the knowledge learned from history (e.g., the profit in previous stage).

The action set consists of three actions: maintaining collusion (i.e., optimal price), deviating from collusion, and punishment ((i.e., best response price)). The collusion action is efficient only when all the crowdsourcers agree to do so. If a crowdsourcer deviates from the collusion, all of the other crowdsourcers will use the punishment action permanently. In this case, all crowdsourcers choose the Nash equilibrium strategy from which no one wants to deviate. Then, the cooperation is broken and the optimal overall profit will not be achieved. The non-cooperative situation will be changed when crowdsourcers consider the long-term profit in a repeated game. The long-term profit includes the profit that will be gained in the future stages. The profits in the future stages are usually weighted less than that in the current stage. We use a discount factor γ_i ($0 \leq \gamma_i \leq 1$) to characterize this fact. For example, if the current profit is P_i, the profit in the next stage is worth of γP_i.

Condition for Collusion Maintenance

We analyze the condition that the collusion will be maintained. A crowdsourcer will not deviate from collusion if he is able to obtain a higher long-term profit from cooperation. If a crowdsourcer deviates from the optimal price, he wants to increase profits by increasing the price to attract

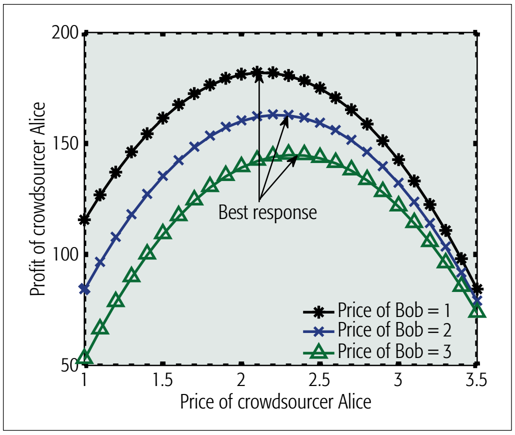

FIGURE 2. Best response of crowdsourcer Alice.

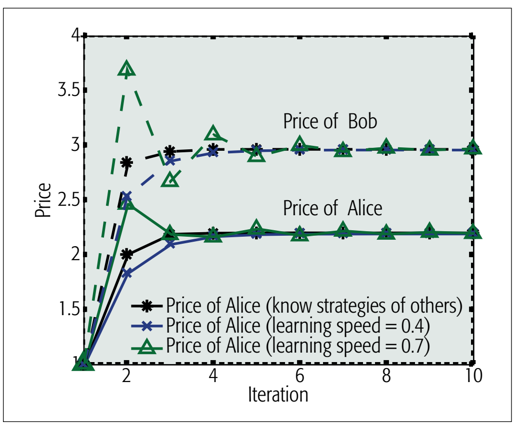

FIGURE 3. Convergence to the Nash equilibrium.

more contributions of sensing data. However, the other crowdsourcers will punish him permanently by increasing their prices to the Nash equilibrium, whose price is higher than the deviating price. Thus, the deviating crowdsourcer will gain deviated profit in the first stage, and the profit at the Nash equilibrium during the rest of the stages.

Setting the long-term profit when deviating lower than that when all crowdsourcers cooperate, we can obtain the lower bound of γ_i. For the values of γ_i higher than the lower bound, the crowdsourcers will cooperate with each other. They adopt the optimal price to gain the highest profit in each stage, and consequently, the highest long-term profit.

We give an example to explain the repeated game model. Assume that there are two crowdsourcers named Alice and Bob. At the first stage, they choose to maintain collusion. At the second stage, crowdsourcer Alice increases the price to increase profits and crowdsourcer Bob keeps the optimal price. At the third stage, crowdsourcer Bob will punish crowdsourcer Alice and increase the price to the Nash equilibrium. Now the best choice of crowdsourcer Alice is to set a price at the Nash equilibrium. The cooperation is broken and no one can benefit. At the later stages, the situation remains the same as in the third stage.

Simulation Results

In this section, we present a series of experiments simulating a mobile crowdsourcing market with two crowdsourcers. We name the two crowdsourcers Alice and Bob. We conduct our numerical simulations using Matlab R2013a on Windows 8. The default settings are as follows. The system parameter is c = 4. The cost of joining crowdsourcer Alice and Bob are $k_1[t]$ = 0.1 dollar and $k_2[t]$ = 0.5 dollar, respectively. The service changing parameter v lies between 0.2 to 0.8. These parameters are set to make the reward of a smartphone user rational in practice. Note that some of these parameters will be varied according to the evaluation scenarios.

We show the best response of a crowdsourcer first. Figure 2 depicts the profit of crowdsourcer Alice as a function of price. When the price increases, the profit increases since more system return is generated due to more smartphone users' participation. However, the profit decreases since the higher price results in a higher cost paid to smartphone users after a certain point. The price that results in the highest profit is the *best response*. We also observe that a higher price offered by crowdsourcer Bob results in a larger value of the best response (i.e., price) of crowdsourcer Alice. This is because when the price offered by crowdsourcer Bob increases, the sensing data that crowdsourcer Alice attracts decreases. As a result, crowdsourcer Alice has to offer a higher price to attract more smartphone users' participation and gains a relatively higher profit.

Then we study the impact of service changing parameter v on best response prices. The best response functions for both crowdsourcers are shown in Fig. 4 under a different parameter v. When smartphone users change the crowdsourcers they serve with high frequency (i.e., v is high), the best response results in a larger price. This is because each crowdsourcer must offer a higher price to increase smartphone users' participation when the degree of competition among the crowdsourcers becomes higher.

Now we present the dynamic behavior of crowdsourcers. Figure 3 shows the process of price adaptation by crowdsourcers. The crowd-

The collusion action is efficient only when all the crowdsourcers agree to do so. If a crowdsourcer deviates from the collusion, all of the other crowdsourcers will use the punishment action permanently. In this case, all crowdsourcers choose the Nash equilibrium strategy from which no one wants to deviate. Then, the cooperation is break and the optimal overall profit will not be achieved.

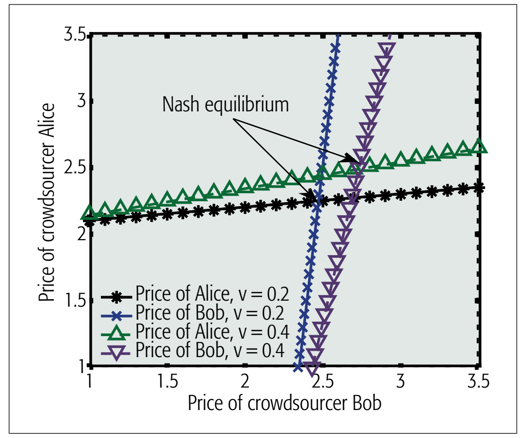

FIGURE 4. Intersection point of best responses.

The higher best response price means that a crowdsourcer will pay more money to smartphone users. This is the price of competition. Note that Nash equilibrium cannot get the maximum overall profit when crowdsourcers maintain collusion. The deviating price is higher than the optimal price and lower than the best response price.

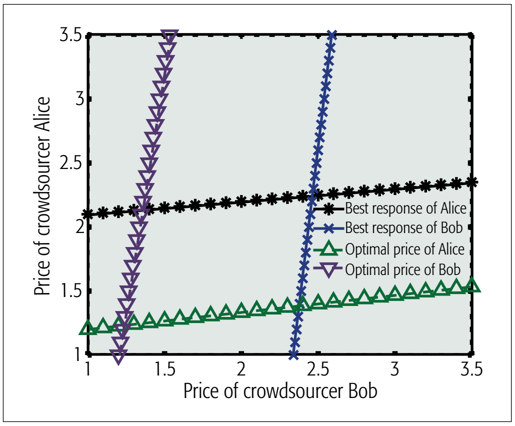

FIGURE 5. Optimal price vs best response price.

sourcing market will be in a stable state when every crowdsourcer achieves the maximum profit they can obtain in the competition and all smartphones are content with the revenues from selling sensing services. A crowdsourcer adjusts its strategy in the direction that maximizes its profit with the speed α. A higher value of adjusting speed α means that it takes the crowdsourcer fewer iterations to reach the stable state.

Now we show that crowdsourcers actually benefit from cooperation. A crowdsourcer chooses to maintain collusion by setting an optimal price, which is lower than the best response price, as shown in Fig. 5. The higher best response price means that a crowdsourcer will pay more money to smartphone users. This is the price of competition. Note that the Nash equilibrium cannot obtain the maximum overall profit when crowdsourcers maintain collusion. The deviating price is higher than the optimal price and lower than the best response price.

Conclusion

In this article, we present analysis and prediction of the behavior of multiple crowdsourcers in a mobile crowdsourcing market. The crowdsourcers adjust their prices paid to smartphone users for sensed data. First, we use a dynamic game to formulate the behavior of crowdsourcers. The Nash equilibrium can be achieved. All crowdsourcers cannot increase individual profit by ultimately changing their prices and the smartphone users obtain the highest overall profit. Then, we extend the dynamic game to a repeated one. The crowdsourcers may cooperate with each other to obtain the optimal overall profit, considering the long-term profit. However, the crowdsourcers have incentive to deviate from the optimal price. We study the condition that the collusion will be maintained. Simulation results show that the mobile crowdsourcing market will be in a stable state. Our model can be used in many practical scenarios, such as urban noise mapping, traffic mapping, and air quality mapping.

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