An Incentive Mechanism Design for Socially-Aware Crowdsensing Services with Incomplete Information

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***Abstract*—Traditional crowdsensing platforms rely on sensory information collected from a group of independent users or sensors. Recently, socially-aware crowdsensing services have been introduced as the integration of social networks and crowdsensing platforms. For example, in health-related crowdsensing applications, a user benefits from information regarding food, exercise, medicine and medical treatment collected and shared by his/her socially-connected friends and family members. In this article, we first introduce basic concepts of socially-aware crowdsensing services and highlight the importance of "social network effects" in the services. Typically adopted in social networks, network effects are used to quantify an influence of an action or preference of one user to the other users with social ties. With this focus, we then discuss important aspects of the socially-aware crowdsensing services with network effects and some technical challenges. We find that game theory is a suitable analytical tool to investigate such crowdsensing services, for which important related work is surveyed. To address existing research gaps, we propose a game model for an incentive mechanism design with incomplete information about social network effects in socially-aware crowdsensing. The proposed model is shown to improve the benefits of the crowdsensing service provider as well as those of the users.**

***Index Terms*—Crowdsensing, social network effect, Bayesian game, incentive mechanism, incomplete information**

I. Introduction

In recent years, crowdsensing is being transformed from sensor/machine-driven systems to socially-aware services; these services further involve humans and make them the essential part of the data collection and sharing functions of the crowdsensing services. Many socially-aware crowdsensing services, e.g., healthcare, travel, leisure, and entertainment, are introduced and gain popularity quickly and tremendously. For example, in health and wellness domains, applications like Foodstand, DietSensor, LiveStrong, and MyFitnessPal allow users to use smartphones or wearable devices to collect and share information about their food, exercise, and medication. It is evident that the users can benefit from such integrated social networks and crowdsensing services.

In a socially-aware crowdsensing system, social ties among users appear to be an important factor, because the information can benefit not only the users, but also the service provider. For example, a study suggests that Fitbit can increase the users' engagement in physical activities thanks to a high sense of relatedness [1]. Likewise, the accuracy of food recommendation for a certain user can be improved at different degrees by utilizing nutrition information shared by the user's family members (with stronger social ties) and friends (with weaker social ties) taking similar types of food [2]. The social ties or influence that one user has on the other users in socially-aware crowdsensing are regarded as "social network effects". The network effects are useful for the service provider not only to enhance the quality of the services, but also to increase the provider's profit and to explore new business opportunities. The network effects can be used also to optimize an incentive provided to users in collecting and sharing their information. Users who provide reliable information and/or who have diverse and strong social ties can be rewarded a higher incentive from the provider to promote their participation in the crowdsensing services. As such, incentive mechanism designs for socially-aware crowdsensing are of great importance and require a thorough investigation.

This article focuses on socially-aware crowdsensing and its incentive mechanism design. We first present an overview of socially-aware crowdsensing and social network effects. We also highlight some open research challenges. We then briefly introduce several game-theoretic approaches to incentive mechanisms for crowdsensing and outline some open issues. We finally propose an application of Bayesian game-theoretic model to address the incentive mechanism for socially-aware crowdsensing. The contributions of this article are summarized as follows:

- We provide an introduction of socially-aware crowdsensing and discuss important issues arising from the network effects. Special attention is paid to an incentive mechanism as it is a crucial means of supporting sustainable and profitable crowdsensing services. Seminal works in the area are thoroughly reviewed.
- The proposed game theoretic model provides a unified framework for a strategic incentive mechanism design to support socially-aware crowdsensing. It formally takes social network effects in crowdsensing into account, aiming to optimize strategies of the self-interested service provider and users making rational decisions to achieve their individual objectives.
- It is widely accepted that information about social network effects is incomplete because of, for example, limited and inaccurate social data. Therefore, we present

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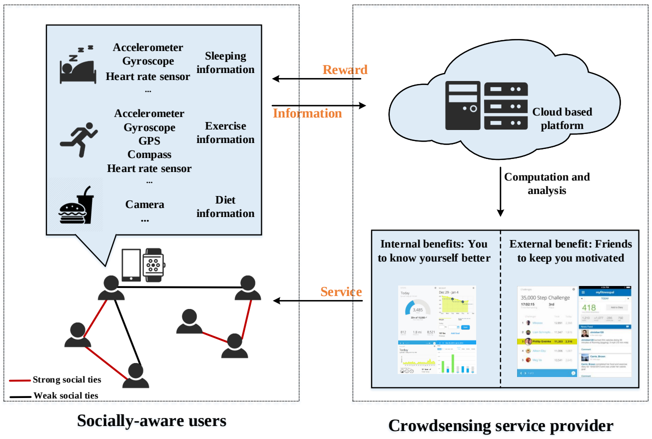

Figure 1: An illustration of a socially-aware crowdsensing application.

a Bayesian game model to address this incomplete information issue.

II. Overview of Socially-Aware Crowdsensing and Network Effects

Crowdsensing [3] provides a promising paradigm for achieving a flexible and scalable sensing coverage. In crowdsensing, users carrying portable smart devices are encouraged to participate in gathering local information and sharing knowledge. Typically, a basic crowdsensing system includes a cloud-based platform and a collection of crowdsensing users. The platform regulator, i.e., the crowdsensing service provider, can post a set of sensing tasks with different purposes, and the users are actively involved to perform the corresponding tasks [4]. In traditional crowdsensing, the quality of the aggregated services that a crowdsensing system can provide largely relies on the sensory information collected from a group of independent sensors or users.

Recently, many socially-aware crowdsensing services and applications have been introduced and used by a number of people. In socially-aware crowdsensing, social interactions or social ties among users through online platforms have a significant impact on the user's experience, as illustrated in Fig. 1. For example, in a health-related crowdsensing application, a user can join and upload his/her diet, exercise, heart rate or medical information. According to such information, the application can keep track of the user's physical condition Apart from being logged for the user, the information can be shared to other socially-connected users. Food consumption information can be shared among family members. Likewise, exercise activity information can be shared among friends. The user can benefit from the information shared by other users such as knowing calories of a certain type of food or being aware of upcoming exercise events. Additionally, the user will gain benefits when the information is used for data analytics, e.g., by the crowdsensing service provider, to give insights about his/her health conditions and offer fitness advice. The social ties and influence are interpreted as "social network effects" in the social network domain.

Due to such network effects, the participation of one user will attract his/her socially-connected users to participate in the same crowdsensing services. For example, if Alice shares her food information as well as health report from Foodstand in her Facebook post, it is more likely that her social friends notice and download the same application to join for collecting and sharing similar information in the service. In return, Alice can benefit from the participation of her socially-connected friends because of the enhanced accuracy in health report and fitness advice. To sum up, social network effects motivate users to actively participate in sensing activities, which can be exploited by crowdsensing service providers to improve their sensing campaigns. Some crowdsensing applications have already perceived such a commercial value. For example, DietSensor is encouraging its users to share their experience with their friends via Facebook. Despite its promising business potential, socially-aware crowdsensing still faces many challenges, such as:

- **Privacy Preservation:** Without appropriate privacy-preserving mechanisms, crowdsensing users are reluctant to participate because of their privacy concerns on personal information disclosure. In traditional crowdsensing, sensing information from the users is modified in order to protect their privacy, such as adding noise to the original data. Most of the existing research attempts assume independence among the information from different individuals in addressing the privacy-preserving information collection problem. Under this assumption, individual's information contributions will not cause privacy leakage to others.
  However, in socially-aware crowdsensing services, individuals who have social ties/influence may share some common or overlapped interests. Thus, the information correlation can cause privacy leakage to other individuals even though they do not contribute the information. In this regard, a malicious attacker may infer individual private information by exploiting such information correlations. In [6], the authors studied a privacy-preserving information collection problem with the consideration of information correlation and social relationship. Therein, the social relationship is assumed to be public knowledge, and the individual users' privacy loss under data correlation is characterized. However, social relationship may be kept private by users, and even be reported untruthfully in real crowdsensing applications. This can adversely affect information accuracy as well as quality and usefulness of crowdsensing services.
- **Massive Data Storage:** Existing crowdsensing services rely on the centralized cloud-based architecture, where users sense and report information to a central server for processing and performing analysis. Cloud-based crowdsensing service providers often suffer from limitations of the centralized architecture such as high operational cost, performance bottleneck, and a single point of failure/attack. For socially-aware crowdsensing, the peer-to-peer data sharing scheme leveraging the processing capabilities of smart devices is introduced in [5]. By

utilizing their social ties or links, users are encouraged to share information directly rather than to report and save it in the server. This can shift part of the storage function to the distributed users and thus alleviate data storage loads of the server.

- **Security:** Malicious users can launch different attacks to crowdsensing systems. One of the common attacks is the Sybil attack, where a dishonest user (attacker) illegitimately creates and uses multiple fake identities to gain benefits without extra efforts. For example, multiple fake users can generate falsified nutrition information about food from certain places. To address such an attack, users can cooperate with each other to detect and avoid misbehaving attackers in traditional crowdsensing services. Especially in socially-aware crowdsensing, social relationship can be used to identify fake users. For example, fake users usually have much stronger social ties only among themselves, compared to those with other parts of the population.
- **Incentive Mechanism Design:** Voluntary participation in crowdsensing may not be economically sustainable. This is due to the fact that mobile users need to consume their resources such as battery and network bandwidth to accomplish sensing tasks. To motivate the crowd to participate, it is natural that a monetary incentive is provided for compensating the users' cost. In a socially-aware crowdsensing system, social network effects can be seen as an extra incentive to boost the users' participation, which should be considered by the crowdsensing service provider. The authors in [7] focused on how network effects impact incentive mechanism design in maximizing a crowdsensing service provider's profit. However, only a simple homogeneous scenario is considered, i.e., identical social influence among all users, which is far from reality. In [8], the authors studied social impacts of heterogeneous users on incentive mechanism design. However, social ties/influence among users are assumed to be perfectly known by a crowdsensing service provider and all the users. This is not applicable to some of the real-world crowdsensing applications because of, e.g., limited and inaccurate social data [9]. Therefore, a study considering realistic assumptions on information about social ties/influence is needed.

III. Game Theoretic Incentive Mechanisms for Socially-Aware Crowdsensing with Incomplete Information

As discussed, in a socially-aware crowdsensing system, the crowdsensing service provider needs to properly design its incentive mechanism to motivate users by a reward to execute crowdsensing tasks. When the reward is high, more users want to participate and contribute. However, the high reward may lead to an exorbitant cost and redundant information. Moreover, the service provider and users can be self-interested, and make rational decisions towards their individual objectives. This makes a game theoretical approach naturally suitable to study their strategic decisions. Game theory provides a formal analytical framework with a set of mathematical tools to study complex interdependent interactions among rational players and predict their strategy choices [10]. Some of the game theoretic approaches/models applied to crowdsensing are reviewed in the following:

- **Stackelberg game:** A Stackelberg game [10] models a hierarchical, sequential decision making among players, i.e., a leader choosing its strategy before followers. In crowdsensing, a service provider, i.e., a leader, determines the total reward for users, i.e., followers. Given the reward, the users decide whether to perform sensing tasks to obtain the reward or not. In [13], the authors designed a uniform incentive mechanism for the situation in which all users receive the same reward. The unique Stackelberg equilibrium is validated, at which the profit of the service provider is maximized, and none of the users can improve its utility from performing sensing tasks by unilaterally deviating from its current strategy. In [11], the authors proposed a similar Stackelberg game model, but a discriminatory incentive mechanism is adopted that different users may receive different rewards.
- **Bargaining game:** A bargaining game [10] is adopted to analyze the situation in which players cooperatively try to make an agreement by negotiating or bargaining with each other. A typical solution is the Nash bargaining solution, which can ensure efficiency and fairness. In [12], the authors considered that a crowdsensing service provider bargains on reward allocation while users bargain on their participation. The incentive mechanism is characterized according to the supply-and-demand pattern of participation and reward, respectively, in the bargaining process.
- **Contract theory:** Contract theory [10] models the relation between a seller and buyers in the presence of asymmetric information. The buyers are characterized by types that are private information. The seller, called the contract designer, proposes a list of contract items. The buyers can only accept or reject the contract. In [13], the authors proposed a contract-based incentive mechanism for crowdsensing with task-reward contract items for different types of users. The cost of users is regarded as the type not known to the crowdsensing service provider. Thereafter, the optimal and feasible contract is then proposed, in which users of various types select one of the contract items to perform sensing tasks and receive the reward.

Although studies in the area of game theoretic incentive mechanism design for crowdsensing are rich, there are still open issues, such as:

- **Bounded rationality:** Practical modeling of users and provider behaviors in crowdsensing may be affected by the internal bounded rationality and external incomplete information. Consequently, the prediction of users' participation or the reward incentive can be intractable. Therefore, the actual decision-making process is not consistent with the one that we obtain using a traditional game-theoretic model with fully rational players. A more general theoretical model termed prospect theory from *behavioral economics* can be a suitable approach for analyzing human behaviors more psychologically accurately [14].

- **Complicated interactions among users:** In existing game-theoretic incentive mechanisms, complicated interactions among users are frequently missing and neglected. However, this may not be practical in some of the crowdsensing applications. For example, as aforementioned, one important feature of socially-aware crowdsensing is that the decision (participation) of one user is influenced by the decisions of other socially-connected users, and the interactions are mutual. As such, users' decisions are coupled with each other, complicating the users' decision making. Therefore, the non-cooperative game among the users also needs to consider such social network effects in socially-aware crowdsensing.
- **Incomplete information:** Most of the existing studies adopt game-theoretic modeling with complete information to investigate the incentive mechanism in crowdsensing. However, information is rarely complete and known by all players. For example, crowdsensing service providers do not know the exact preferences, information quality or potential malicious behaviors of users. This information is crucial in determining incentive mechanisms to reach providers' best strategies. Consequently, the uncertain behaviors from users may lead to inefficiency of incentive mechanisms. Some works adopt Bayesian game-theoretic methods that incorporate the probability theory to analyze the random behaviors with uncertain factors such as the participation cost [9]. However, the model for incomplete information about social tie/influence in socially-aware crowdsensing needs to be developed.

IV. Bayesian Stackelberg Game Approach for Socially-Aware Incentive Mechanisms with Incomplete Information

As mentioned above, incomplete information for decision making, complicated interactions of users, and incentive mechanism design for socially-aware crowdsensing have never been considered jointly. Therefore, in this section, we introduce an application of Bayesian game-theoretic model to reach the best decisions of a crowdsensing service provider and its users, when deeming social network effects as uncertain parameters.

A. System Model

We consider a mobile socially-aware crowdsensing system situation consisting of a crowdsensing service provider ("provider") and a set of mobile users ("users"). The provider requires the users to perform a certain type of sensing tasks, e.g., to capture and report physical exercise events. To do so, the provider announces an incentive, e.g., an offered reward, to motivate the users to participate in the services. Based on the information about the reward, the users individually decide how much efforts that they want to contribute by taking the social network effects into account. This rewarding and participating decision making process of the provider and users, respectively, can be inherently modeled as a hierarchical Stackelberg game [10], [11]. However, the information about the social network effects is rarely complete. Nevertheless, the distribution information, which captures the social network effects from the network interaction patterns, can be obtained through, e.g., historical information or long-term learning. Therefore, we abstract the distribution information of social network effects into a known probability distribution. This leads us to develop the Bayesian Stackelberg game model for analyzing the decision making by the provider and users in the socially-aware crowdsensing system.

B. Game Formulation and Analysis

Generally, Bayesian game is shown to be useful for modeling an incomplete information game in which the outcome of the game can be predicted by using Bayesian analysis [10]. The proposed Bayesian Stackelberg game model is composed of a set of *players*, i.e., the provider as the *leader* and N users as the *followers*. Here, the leader applies its strategy before the followers with the knowledge that the followers will choose their best strategies accordingly. The followers hence can observe the strategy of the leader. The *strategy* of the provider is the reward to offer, and that of the users is the service participation level (effort) that can be the sensing time or the amount of data uploaded. The *payoff* of the provider is the profit, and that of the users is the utility.

The utility function of a user consists of the following components:

- *Internal utility:* The user obtains a direct benefit, i.e., internal utility, from the participation of the crowdsensing services. For example, in a health-related crowdsensing application, the user can use the service to log his/her health-related information including food consumption and exercise activities. The service can also perform data analytics to the user such as calculating calories intake and suggesting exercise routine.
- *External utility:* The user obtains an indirect benefit, i.e., external utility, originating from social network effects. In socially-aware crowdsensing, the user can enjoy an additional benefit from participation levels of the other users. Given the example of the health-related application again, the user can benefit from the information about food consumption and exercise activities contributed or shared from the user's family members or friends. The degree or coefficient of social network effects is defined as the weight on the strategy, i.e., participation level, of the other users to the externality utility of the user. A larger weight, i.e., more influence, can increase the external utility of the user faster.

  For network effects, the concepts of in-degree and out-degree are adopted in the utility function of the user. The in-degree denotes the number of other users that the user influences. Conversely, the out-degree denotes the number of other users influencing this user. Consequently, the in-degree represents the user's influence and the out-degree represents the user's susceptibility to be influenced by other users. For each user, its social structure, i.e., the in-degree and out-degree, is private information. The user knows the exact social structure of itself, but the user is uncertain about the social structure of other users, e.g., because of the privacy protection. In this regard, only the probability distributions of in-degree and out-degree are commonly known.

- *Reward:* The user receives the reward from the provider which is proportional to the user's participation level.
- *Cost:* The cost is associated with the participation level, e.g., energy consumption and network bandwidth consumed.

The profit function of the provider consists of the following components:

- *Revenue:* The benefit obtained from the total aggregated contributions and service participation of all users can be regarded as the revenue.
- *Cost:* The cost of the provider is the total reward paid to users. As the provider has only the information on the probability distributions of in-degree and out-degree of users, it is better of the provider to apply a uniform reward, i.e., the same reward for all users, i.e., the uniform incentive mechanism.

The Bayesian Stackelberg game modeling the interactions among the provider and users works as follows. In the upper Stage I, the provider as the leader first determines and broadcasts the reward as an incentive to the user. In the lower Stage II, each user as a follower decides on its individual participation level based on the reward offered by the provider. The strategies of the provider and all users are determined under the incomplete information of social network effects, i.e., in-degree and out-degree of each user.

To obtain the solution, we analyze each stage of the proposed Bayesian Stackelberg game using the backward induction method [10]. The solution of this game is the Bayesian Stackelberg Equilibrium (BSE), defined as the point where the expected payoff of the provider (leader) is maximized given that the users (followers) adopt their best responses, i.e., the Bayesian Nash Equilibrium (BNE). Likewise, the BNE denotes the point at which each user seeks a strategy profile that maximizes its expected payoff given the belief on the strategies of other users and their degree distributions. At the BNE, each strategy is the best response to strategies of the other users, and no user can improve its payoff by changing its strategy unilaterally.

The BSE is able to jointly maximize the profit of the provider and the utility of each user in the presence of uncertain social network effects. In particular, in a real crowdsensing service, the characterization of the BSE has a practical significance, i.e., the provider and users can potentially reach a market agreement to trade sensing information. Note that the mathematical details of obtaining the BNE and BSE of the game and their analytical results, e.g., existence and uniqueness, are provided in [15]. For comparison, we also study the benchmark case where the provider knows both the in-degree and out-degree of any individual user. This case of complete information allows us to implement the discriminatory incentive mechanism, i.e., the provider can offer different rewards to different users.

C. Numerical Results

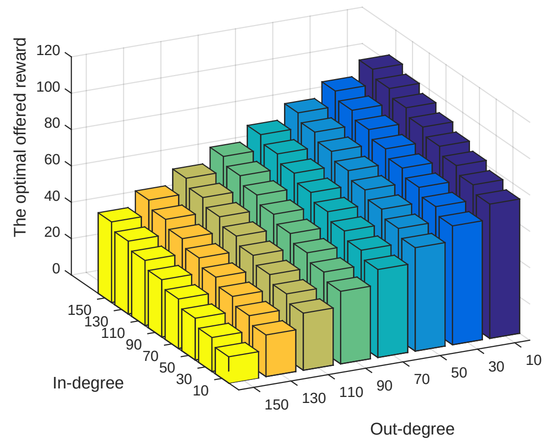

Figure 2: Illustration of the optimal offered reward with respect to different in-degrees and out-degrees.

We first evaluate the impact of the in-degrees and out-degrees of the users on the optimal offered reward from the provider. The in-degrees and out-degrees are randomly chosen from specific normal distributions. The means and variances for the in-degrees and out-degrees are denoted by (μ, σ_k^2) and (μ, σ_l^2), respectively. We vary the in-degree and out-degree of one particular user and observe the reward offered by the provider to that user. From Fig. 2, we observe that the optimal reward of the user increases with the increase of in-degree, but with the decrease of the out-degree. Recall that the user's in-degree represents its influence to other users, and the out-degree represents its susceptibility to be influenced by other users. Given the underlying social network effect, the more influential user, i.e., with higher in-degree, can encourage more other users to participate in the crowdsensing service. Therefore, the provider should increase the reward for this user. By contrast, the user with higher out-degree can be influenced by many other users. Therefore, it is not worth for the provider to increase the reward to this user, which may reduce the profit.

Next, we consider the uniform and discriminatory incentive mechanisms jointly. Fig. 3 shows that the optimal offered reward decreases when the mean value of in-degree and out-degree increases, i.e., social network effects become stronger. The reason is that as social network effects become stronger, the users can motivate each other to have a higher participation level. Consequently, the total utilities of the users become larger (Fig. 4(a)), and the provider can offer a less reward to save the cost and achieve a higher profit (Fig. 4(b)).

Additionally, we find that θ, i.e., the equivalent monetary worth of users' participation level, also has an impact on the users and the provider. It it shown that when θ increases, the provider should offer more reward to promote the users' participation level as shown in Fig. 3. Finally, we study the impact of the variance of in-degree and out-degree. When the variance decreases, the profit gained by the provider from the uniform incentive mechanism is close to that from the discriminatory incentive mechanism. The reason is that the heterogeneity of users' social network effects reduces

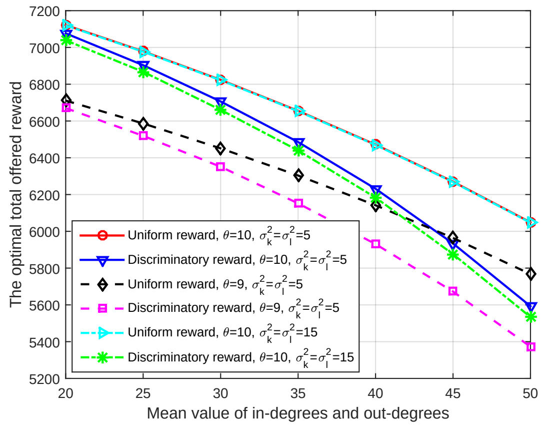

Figure 3: Impacts of mean value of in-degrees and out-degrees (μ) on the optimal total offered reward. (θ denotes the coefficient which translates users' participation level to the equivalent monetary worth, i.e., revenue, for the provider.)

when the value of variance decreases. Conversely, when the heterogeneity is higher, the provider can offer diverse rewards to the users allowing the provider to optimize its profit more efficiently. Nevertheless, although the discriminatory incentive mechanism performs better in terms of the provider's profit, it is practically difficult to implement in the real crowdsensing services, especially with a large number of users.

V. Conclusion

In this article, we have investigated a novel incentive mechanism for socially-aware crowdsensing by leveraging Bayesian game-theoretic model. First, we have briefly introduced the concept of socially-aware crowdsensing and emphasized on an important role of social network effects in the services. We have also highlighted some unique research challenges in socially-aware crowdensing services. We have discussed game theoretic incentive mechanisms for crowdsensing and outlined some open issues. Finally, we have proposed the application of Bayesian game-theoretic approach to reach the best decisions of the crowdsensing service provider and the users when the information of social network effects is incomplete. The approach is shown to improve the benefits of the crowdsensing service provider as well as those of the users. In our future research plans, we will consider the security issues in the design of incentive mechanisms for socially-aware crowdsensing.

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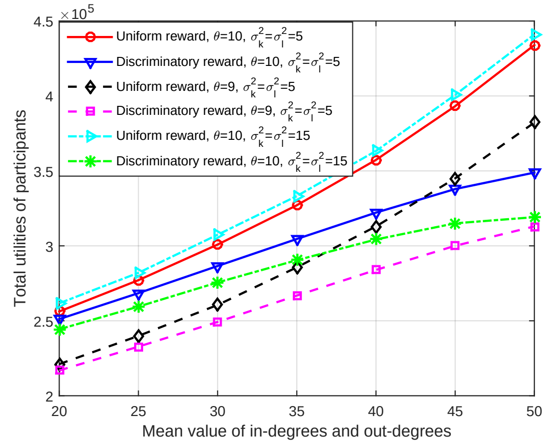
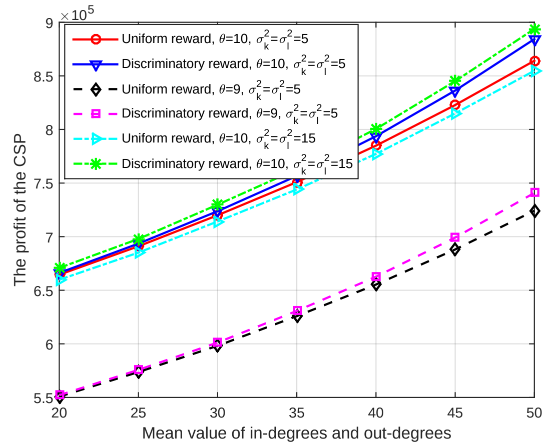


(a) Total utilities of participants



(b) Profit of the provider

Figure 4: Impacts of mean value of in-degrees and out-degrees (μ) on the total utilities of participants and the profit. (θ denotes the coefficient which translates users' participation level to the equivalent monetary worth, i.e., revenue, for the provider.)

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