Privacy Preservation in Location-based Advertising: A Contract-Based Approach

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Abstract

Location-based advertising (LBA) is rapidly developing with the surging popularity of mobile devices and the advances in localization techniques. However, many LBA applications aggressively collect users' location data without providing clear statements on the usage and disclosure strategies of such sensitive information, which raises severe privacy concerns. Existing privacy preservation mechanisms normally require modifications at the user side or provide limited protection. To overcome these limitations, we propose an LBA system to leverage insensitive users to broadcast location-based ads to the privacy-sensitive users around them. To reward the privacy-insensitive users for delivering the ads, we design a number-reward contract scheme, in which a set of ad broadcast reward plans is offered to different insensitive users that select the most suitable plans based on their utilities. In addition, we derive optimal contract designs in both complete and incomplete information scenarios. Simulations are carried out to verify the theoretical analysis. The results show that a win-win situation is achieved, where every entity involved has an increased utility.

Keywords: Location-based advertising (LBA), Privacy, Contract Theory

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1. Introduction

Location-based advertising (LBA) makes use of user location information and pushes location related advertisements (ads) to users' mobile devices. It is one type of targeted advertising, where an ad broker is responsible for sending ads to users based on users' locations and preferences. Significant attention has been paid to LBA due to its user-tailored feature, which makes it efficient in terms of converting users that read the ads into buyers [1, 2]. One of the first LBA services was launched by ZagMe in Britain in late 2000 [3, 4]. Registered users could receive ads and promotion information in the form of text messages when they were in certain shopping malls. Nowadays, with the advances in mobile device and localization techniques, LBA is no longer limited to SMS-based format and users can receive ads automatically without the need to activate the service manually when they reach certain areas. Many users welcome LBA on account of the convenience it brings. It makes shopping easier when the ads that are related to the brands in the shopping mall are shown on their mobile devices. These factors together with the surging popularity of mobile devices are contributing to the rapid growth of LBA [5].

Although LBA systems improve the efficiency of advertising, severe privacy issues arise with these systems. Nowadays, the growing privacy threats of sharing location-related information is becoming a concern of both users and governments [6]. Such privacy threats come from the fact that many advertisers aggressively collect location data without clear statements about how to use the data and whom the data will be shared with. Untrusted advertisers that have access to users' location data may sell such personal information to third parties without user's permission [7]. Moreover, malicious adversaries with criminal intent could pose a threat to individual security and privacy. Being aware of such risks, users may not allow LBA systems to access their sensing data, which in turn disables the functionalities provided by LBA, and thus, causes inconvenience to the users.

To retain the benefits brought about by LBA, it is essential to incentivize users to adopt the LBA systems. Existing efforts have focused on privacy preserving mechanisms to encourage users to be involved in the LBA systems. These mechanisms either require modifications at the user side [8, 9] or modify user statistics [10, 11] to hide their information from advertisers and ad brokers. However, these changes made on the LBA systems provide privacy protection at the cost of the benefits of advertisers or ad brokers. The advertisers may be dissatisfied by the modifications at the user side, as these modifications make them unable to track the accurate click count, which normally determines their payments [12]. Similarly, ad brokers may not be in favor of modifying user statistics as it compromises the accuracy of delivering personalized ads, which undermines the ad brokers' profits. With these disadvantages in mind, advertisers and ad brokers would naturally tend to refuse the adoption of these systems, which hinders the promotion of these privacy-preserving mechanisms in the LBA systems. The target of this paper is to fill this gap by providing an LBA framework that frees the systems from these modifications and can thoroughly preserve the private information of sensitive users.

Our key observation is that there are insensitive users (IUs) that are not concerned about their location privacy [13], and we can leverage these IUs to assist the ad dissemination without revealing the location information of sensitive users (SUs). In particular, the ad broker can directly send location related ads to IUs, who forward the ads to surrounding SUs. As such, SUs can enjoy these ads without leaking their location information to advertisers or ad brokers.

To realize the above vision, several challenges should be addressed. The first challenge is how to motivate different IUs to forward ads to SUs around them. IUs need to spend energy and communication resources to forward ads to surrounding SUs. Moreover, IUs have different numbers of surrounding SUs, which determines the types of IUs. Without proper incentive mechanism design for versatile types of IUs, IUs may not be willing to assist the ad dissemination. To motivate IUs, we propose a rewarding scheme for IUs using contract theory, which is an effective tool to discuss how the incentive compatible mechanism in a monopoly market when asymmetric information exists [14]. In our scenario, the asymmetric information is types of IUs. Our key idea is to offer the right contract items so that all IUs have the incentive to select the optimal contract according to their types. In particular, we characterize the necessary and sufficient conditions for feasible contract, and further design a number-reward contract scheme that is optimal under both complete and incomplete information scenarios.

Another challenge stems from the privacy leakage when counting the number of viewers for each ad. Ad viewer counting is essential for advertisers and ad brokers for the billing process, while SUs deem ad click behaviors as private information and may not want them to be disclosed. To address this predicament, we introduce an entity named *publisher*. Instead of direct sending ads to IUs, the ad broker sends ad identifiers (IDs) to IUs and then IUs broadcast the IDs to SUs around them. Users can extract the ads from the publisher based on the ads' IDs. As such, the publisher can count the number of viewers for each ad and moreover the number of ads forwarded by every IU. These two numbers are important, because the ad broker charges advertisers based on the first number and rewards IUs based on the second number.

The main contributions of this paper are threefold. First, we propose a contract-based framework to motivate different types of IUs to broadcast ads to surrounding SUs. We analyze the necessary and sufficient conditions for feasible contract, and design an optimal framework. Second, our LBA system preserve users' privacy without compromising the billing processing. Finally, we conduct numerical simulations to validate the proposed framework under different scenarios, and the results demonstrate that our system can reach a win-win situation, where every entity involved has an increased utility.

The rest of the paper is organized as follows. In Section 2, we describe the system model and define the utility functions of the ad broker and IUs respectively. In Section 3, we formulate the problem using contract theory and analyze the contract design in complete and incomplete information scenarios. We present the simulation results in Section 4. Related works are reviewed in Section 6. We summarized the paper in Section 7.

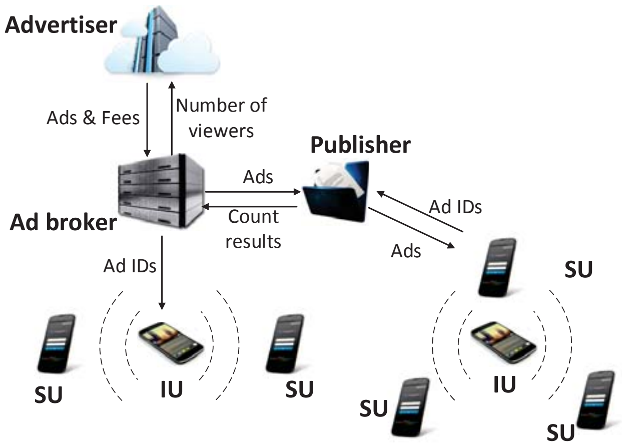

Figure 1: System Structure

2. System Model

In this section, we first describe the LBA system architecture. Then, we discuss the system model and define the utility functions of the ad broker and IUs.

2.1. System Overview

System architecture. Figure 1 shows the system structure. Our location-based advertising system is comprised of a set of advertisers, an ad broker, a publisher and a group of users. All entities are assumed to be rational and selfish, and merely care about their own utilities.

Advertisers and the ad broker. Advertisers and the ad broker are considered to be semi-honest, that is, they correctly follow the protocols defined in the system, yet attempt to learn private information from their received data. Advertisers send their ads to an ad broker, who is responsible for matching ads with users based on user location information. In this work, we mainly focus on the interactions among the ad broker and users. To match ads with users, the ad broker needs user location information, which is deemed private [15].

Users. Users are divided into SUs and IUs according to their sensitivities to location information. SUs are concerned about their privacy and by no means can the ad brokers push customized ads to these users directly. Differently, IUs are insensitive to their privacy and enjoy the convenience brought about by location-based services. Therefore, the ad broker can send location related ads to IUs. It is worth noting that our system model is consistent with these real-world platforms such as iAd and AdSense to push ads to users. In addition, if users store their interest profiles locally on their smartphones, the phones can then automatically filter out uninterested ads without bothering the users. We also assume that there is no click fraud, as click fraud can be addressed by existing solutions [16, 17].

We categorize IUs into different types according to the total number of SUs around. Formally, the type of IUs is defined as

Definition 1 (Type of IUs)**.** *An IU is a type-s user if there are s SUs within its communication range.*

Our system leverages IUs to send location-based ads to SUs around them. The model of using IU to forward ads to SUs is motivated by geographic social networks, such as Foursquare, Twitter (nearby tweets), in which users can receive messages from nearby users to find places of interest or topics in the local region. After receiving ads from the ad broker, IUs broadcast the ads to SUs around them by available wireless access networks (e.g. LTE broadcast, WiFi or Bluetooth). The ad broker motivates IUs by paying them based on the number of ads they forward to SUs. As IUs only broadcast ad IDs while SUs never communicate with IUs, the privacy of SUs is preserved from untrusted IUs.

The publisher and Ad ID. Users can extract and view the ads from the publisher. The publisher is a content provider on the Internet that sits in the middle of the ad broker and users for ad delivery and click counting. It can be either one global provider or multiple local providers corresponding to local shopping malls or stores, whose load can be balanced according to existing

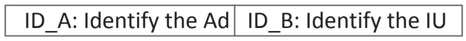

Figure 2: Format of an ad ID

techniques in content delivery networks [18].

To correctly count the number of viewers for each ad, the number of ads delivered by every IU without compromising the SUs' privacy, we design a mechanism as shown in Figure 1. Instead of sending the ads, the ad broker send ad IDs to the IUs. Then, the IUs broadcast these ad IDs to the surrounding SUs. Along with an ad ID, the ad title or tags are also sent to SUs. Alternatively, SUs can cache all ad titles associated with IDs using prefetching, and then map received ad IDs to corresponding ad titles [9]. SUs decide whether they are interested in an ad based on its title or tags, and interested SUs need to request the full content from the publisher based on the ad ID. Certainly, different ads have different IDs. Even for the same ad, the ad broker sends different IDs to different IUs. In this way, the publisher can count the number of ads disseminated by different IUs as well as the number of viewers for each ad. Figure 2 shows the design of the ad ID. One ID is composed of two segments, ID_A and ID_B. ID_A is used to identify the ad and ID_B is used to identify the IU. Thus, when the ad publisher receives an ID, it will return the corresponding ad based on ID_A, add to the number of viewers for this ad, and meanwhile add to the number of ads delivered by the IU whose identity is ID_B. The number of bits assigned to each segment can be decided by the total number of ads and the total number of IUs respectively. The publisher does not know which SUs requested ads as the ad ID can only identify the ad and the IU that distribute the ad, while the SU is anonymous.

2.2. Utility Functions

In our model, we denote the cost of broadcasting once for an IU as c, which is related to the energy consumption of the mobile devices. For simplicity, we assume that one SU can only receive the broadcasts from the nearest IU. Due to lossy channel and high collision probability in dense user environments, one time broadcasting can only successfully deliver the ad to a subset of surrounding SUs. We denote p as the probability that one broadcasting successfully delivers the ad to an interested SU. Therefore, for an IU with s surrounding SUs, the number of SUs that will fetch ads from the publisher after the first broadcast is $p \cdot s$. Then, the number of SUs that fetch ads from the publisher after the second broadcast is $p \cdot (1-p) \cdot s$ as there are $(1-p) \cdot s$ SUs left that have not fetched any ads. Thus, after the qth broadcast, the number is $p \cdot (1-p)^{q-1} \cdot s$. To forward n ads in total, the number of broadcasting (l) the IU needs can be calculated by the following equation

$$p \cdot s + p \cdot (1-p) \cdot s + ... + p \cdot (1-p)^{l-1} \cdot s \geq n. \tag{1}$$

And we have

$$l = \left\lceil \frac{\lg(1 - \frac{n}{s})}{\lg(1-p)} \right\rceil. \tag{2}$$

Hence, the total cost of forwarding n ads for an IU that has s SUs around is

$$v(s,n) = c \cdot \left\lceil \frac{\lg(1 - \frac{n}{s})}{\lg(1-p)} \right\rceil. \tag{3}$$

After delivering n ads to SUs, the IU gets a reward r from the ad broker. Thus, the payoff (utility) for a type-s_i IU is

$$u_i = r - c \cdot \left\lceil \frac{\lg(1 - \frac{n}{s_i})}{\lg(1-p)} \right\rceil. \tag{4}$$

We consider user types in an ascending order, i.e. $s_1 < s_2 < ... < s_T$. The higher the user type, the lower the cost and the higher the payoff. We assume that IUs are selfish and rational, so they aim to maximize their own utilities. Thus, the number of ads a type-s_i IU will deliver is

$$\alpha(s_i) = \arg\max_n \left\{ r - c \cdot \left\lceil \frac{\lg(1 - \frac{n}{s_i})}{\lg(1-p)} \right\rceil \right\}. \tag{5}$$

Obviously, IUs of the same type will adopt the same strategy. We denote the set of all user types as $\mathscr{S}$. By adopting this mechanism, the profit (utility) of the ad broker is

$$\Phi = \sum_{s_i \in \mathscr{S}} (A \cdot n_i - r_i) \cdot M_i, \tag{6}$$

where M_i is the number of type-s_i users, A is the revenue received from advertisers for delivering one ad to end users, n_i is the number of ads a type-s_i IU will forward and r_i is the reward that the ad broker pays to IU for sending n_i ads. The first part $\sum A \cdot n_i \cdot M_i$ is the total revenue increased and the second part $\sum r_i \cdot M_i$ is the total reward paid to IUs.

Our problem is to optimize the ad broker's utility in Equation 6, given user strategies as shown in Equation 5, which is to optimize their own strategies. We will discuss the problem in Section 3.

3. Contract Formulation and Design

In this section, we first formulate the system model as a contract and discuss the incentive compatible and individual rational constraints for a feasible contract. Then we analyze the contract design under complete and incomplete information scenarios respectively.

3.1. Design Rationale

Contract theory is initially applied in supply chain to provide incentives to all entities in the chain [19]. The basis of contract theory is to coordinate production quality/quantity and pricing so that the decentralized supply chain behaves nearly or exactly the same as the integrated one. These features of contract theory makes it suitable for our framework. In our framework, one ad broker needs to motivate different types of IUs, who make their decisions in a distributed manner. Specifically, we design proper contracts to coordinate the types of IUs and ad dissemination rewards. This is similar to the coordination between production quality/quantity and pricing in supply chain: the types of IUs determine their effectiveness of ad dissemination, which can be considered as the quality of ad dissemination; similarly, the number of broadcasting corresponds to the production quantity in supply chain.

A major advantage of contract theory is it can be used to address the information asymmetry issue. In our framework, the types of IUs cannot be observed by the ad broker, and thus become the asymmetric information. We analyze the contract-based framework under both complete and incomplete information scenarios. Under the complete information scenario, the ad broker knows the user type of every IU. Analogous to online social network (e.g., Facebook, Twitter) settings [20], the privacy preference can be determined by the initial settings when a user enters the LBA system. The number of surrounding users can be estimated based on carrier sensing in Wi-Fi. In particular, an IU estimates the number of surrounding users by counting the number of MAC addresses it can hear during carrier sensing. Then, the number of SUs is estimated by subtracting the number of IUs from the number of all users. Alternatively, we can also adopt a similar protocol to count the number of SUs without leaking their identities based on [21]. Under the incomplete information scenario, the ad broker has no access to user type information of every IU, but knows the distribution of the user types.

Detailed user type determination process is presented in Algorithm 1. It takes two steps: 1) IU and SU determination (line 2), and 2) IU type determination (lines 3-8). The type of device (IU or SU) can be determined by the initial settings in the LBA system. By toggling the location service setting, users can decide whether allow the service provider to access their location information. Then, an IU estimates the number of surrounding users by counting the number of MAC addresses it can hear during idle listening. Then, the number of SUs is estimated by subtracting the number of IUs from the number of all users.

3.2. Contract Formulation

In the presence of asymmetric information, which is the user type in our case, contract theory studies how the ad broker constructs contractual arrangements. The ad broker proposes a contract which clarifies how the reward of an IU is related to the number of ads it forwards. The contract is a set of number-reward pairs, denoted by $\xi = \{(n_1, r_1), (n_2, r_2), ..., (n_T, r_T)\}$. Each IU chooses

Algorithm 1 User Type Determination

```
while A new user u_i enters the LBA system do
    u_i selects the type of device (IU/SU), and uploads its type to the ad broker;
    if u_i type is IU then
        u_i performs idle listening for time T;
        u_i counts the number of different MAC addresses N during T;
        u_i fetches location data of other IUs, and computes the number of surrounding IUs N_IU;
        u_i computes the number of surrounding SUs N_SU − N − N_IU;
    end if
end while
```

the number of ads n_k to deliver and get a reward of r_k once he or she has finished the task, that is there are totally n_k SUs that fetch ads from the publisher by IDs broadcasted from this IU.

For a feasible contract, the utility of every IU must be non-negative. Otherwise, IUs, whose utilities are negative, will opt-out of joining this system and not broadcast any ads at all. Hence, the contract should satisfy the individual rationality (IR) constraints, defined as follows.

Definition 1 (*IR : Individual Rationality*):

$$r_i - c \cdot \left\lceil \frac{\lg(1 - \frac{n_i}{s_i})}{\lg(1-p)} \right\rceil \geq 0, \forall s_i \in \mathscr{S}. \tag{7}$$

Moreover, IUs of any type must have their preferred contract itemsets, i.e. a type-s_i IU prefers to deliver n_i ads to SUs and obtain a reward of r_i over any other choices. That is, a feasible contract must be incentive compatible (IC), defined as follows.

Definition 2 (*IC : Incentive Compatibility*):

$$r_i - c \cdot \left\lceil \frac{\lg(1 - \frac{n_i}{s_i})}{\lg(1-p)} \right\rceil > r_{i'} - c \cdot \left\lceil \frac{\lg(1 - \frac{n_{i'}}{s_i})}{\lg(1-p)} \right\rceil, \forall s_i, s_{i'} \in \mathscr{S}. \tag{8}$$

To sum up, a feasible contract must be incentive compatible (IC) and individual rational (IR), and vice versa any contract that satisfies the IC and IR constraints is feasible.

The optimal contract $\xi^* = \{(n_i^*, r_i^*)\}$ for the ad broker is the one that maximizes its utility in Equation (6), that is

$$\{(n_i^*, r_i^*)\} = \arg\max_{(n_i, r_i)} \sum_{s_i \in \mathscr{S}} (A \cdot n_i - r_i) \cdot M_i. \tag{9}$$

Therefore, we need to solve Equation (9) subject to the IC and IR constraints. Next we discuss how to design the optimal contract in complete and incomplete information scenarios.

3.3. Contract Design under complete information

In this subsection we discuss the scenario where the ad broker has complete information about IUs. It knows the user type of each IU. Therefore, the ad broker can treat every IU separately and offer a type-dependant contract to it: (n_s, r_s) for type-s IUs. Since for every IU there is only one customized contract item, we do not need to discuss the IC constraint in this circumstance. For the IR constraint, it must be satisfied as an equality.

Lemma 1: If the ad broker has complete information of s_i for every IU$_i$, the optimal contract offered to IU$_i$ satisfies

$$r_i^* - v(s_i, n_i^*) = r_i^* - c \cdot \left\lceil \frac{\lg(1 - \frac{n_i^*}{s_i})}{\lg(1-p)} \right\rceil = 0. \tag{10}$$

Proof. We prove it by contradiction. We assume that the optimal contract (n_i^*, r_i^*) makes $r_i^* - v(s_i, n_i^*)$ greater than zero. If we set $r_i^{'} = r_i^* - (r_i^* - v(s_i, n_i^*))$, the contract still satisfies the IR constraint and will increase the utility of the ad broker. Therefore, $(n_i^*, r_i^{'})$ is a better contract than (n_i^*, r_i^*), which contradicts the assumption that (n_i^*, r_i^*) is optimal. $\square$

Thus the problem is relaxed to

$$\max_{\{(n_i, r_i)\}_{s_i \in \mathscr{S}}} \quad A \cdot n_i - r_i, \tag{11}$$

$$\text{s.t.} \quad r_i - v(s_i, n_i) = 0. \tag{12}$$

By solving this problem, we have the following results.

Algorithm 2 Designing feasible and optimal contract in complete information scenario

for each user type s_i **do**

$n_i^* = s_i + \frac{c}{A \cdot \lg(1-p)}$;

$r_i^* = c \cdot \frac{\lg \frac{-c}{A \cdot s_i \cdot \lg(1-p)}}{\lg(1-p)}$;

end for

Proposition 1: Under complete information, the optimal contract (n_i^*, r_i^*) offered by the ad broker to a type-s_i IU is

$$\begin{cases} n_i^* = s_i + \frac{c}{A \cdot \lg(1-p)}, \\ r_i^* = c \cdot \frac{\lg \frac{-c}{A \cdot s_i \cdot \lg(1-p)}}{\lg(1-p)}. \end{cases} \tag{13}$$

Proof. The first derivative of $\varphi_i = A \cdot n_i - r_i$ is $\frac{\partial \varphi_i}{\partial n_i} = A - \frac{dr_i}{dn_i}$. For simplicity, we approximate Equation (10) to $r_i = c \cdot \frac{\lg(1-\frac{n_i}{s_i})}{\lg(1-p)}$. Thus when $\frac{\partial \varphi_i}{\partial n_i} = 0$, we can get the result in Equation (13). Accordingly, $\frac{\partial^2 \varphi_i}{\partial n_i^2} = \frac{c}{\lg(1-p)} \cdot \frac{1}{(n_i - s_i)^2} < 0$. Thus (n_i^*, r_i^*) is the optimal contract set the ad broker will offer to a type-s_i IU. $\square$

As such, the social surplus, that is defined as the aggregated utility of the ad broker and the IUs, is

$$\Upsilon(s_i, n_i) = A \cdot n_i - \left\lceil \cdot \frac{\lg(1 - \frac{n_i}{s_i})}{\lg(1-p)} \right\rceil. \tag{14}$$

We can see that the contract set given in Equation (13) also maximizes the social surplus. Therefore, the solution is efficient. With the seller, that is the ad broker in our case, taking all the surplus while the buyers, that are the IUs, getting no surplus, this solution is called perfect price discrimination.

3.4. Contract Design under Incomplete Information

In this subsection, we analyze the contract design under incomplete information. The ad broker only knows the distribution of user type instead of the exact user type of every IU. Thus, it should offer the same contract items to all the IUs. Designing the contract under incomplete information is much more challenging compared to the former scenario.

3.4.1. Feasible Contract

We suppose there are totally T different types of IUs, denoted as $s_1, s_2, ..., s_T$. As analyzed above, the same type of IUs will choose the same contract item. To solve the problem in Equation (9), which is subjected to the IR and the IC constraints, we first study the necessary and sufficient conditions for a feasible contract.

Lemma 2 (*First necessary condition*): A feasible contract $\xi = \{(n_t, r_t)\}$ satisfies the following condition: $n_i > n_j$ if and only if $r_i > r_j$.

Proof. We first prove that if $n_i > n_j$, then $r_i > r_j$. According to the IC constraints, we have that for a type-s_i user $r_i - v(s_i, n_i) > r_j - v(s_i, n_j)$. That is $r_i - r_j > v(s_i, n_i) - v(s_i, n_j)$. In addition, $v(s, n) = c \cdot \frac{\lg(1-\frac{n}{s})}{\lg(1-P)}$, which is obviously a strictly monotone increasing function with regard to n (note that $\lg(1 - P) < 0$). Hence we have

$$r_i - r_j > v(s_i, n_i) - v(s_i, n_j) > 0, \tag{15}$$

that is $r_i > r_j$.

Next we prove that if $r_i > r_j$, then $n_i > n_j$. Similarly, according to the IC constraints, we have $r_j - v(s_j, n_j) > r_i - v(s_j, n_i)$. That is

$$v(s_j, n_i) - v(s_j, n_j) > r_i - r_j > 0. \tag{16}$$

Hence $v(s_j, n_i) - v(s_j, n_j) > 0$. As analyzed above, $v(s, n)$ is strictly monotone increasing. Thus, $n_i > n_j$. □

This lemma shows that when an IU delivers ads to more SUs, it must receive higher rewards.

Lemma 3 (*Second necessary condition*): A feasible contract $\xi = \{(n_t, r_t)\}$ satisfies the following condition: if $s_i > s_j$, $n_i \geq n_j$.

Proof. We prove it by contradiction. We assume that there are two contract itemsets $(n_i, r_i), (n_j, r_j)$ such that $s_i > s_j$ but $n_i < n_j$. According to the IC constraints, we have

$$\begin{cases} r_i - v(s_i, n_i) > r_j - v(s_i, n_j), \\ r_j - v(s_j, n_j) > r_i - v(s_j, n_i). \end{cases} \tag{17}$$

Adding the two equations, we get

$$v(s_i, n_j) - v(s_i, n_i) - v(s_j, n_j) + v(s_j, n_i) > 0. \tag{18}$$

As $v(s, n)$ is a differentiable function, we can do the following calculation.

$$\begin{aligned} & v(s_i, n_j) - v(s_i, n_i) - v(s_j, n_j) + v(s_j, n_i) \\ = & \int_{n_i}^{n_j} v_n(s_i, n) \mathrm{d}n - \int_{n_i}^{n_j} v_n(s_j, n) \mathrm{d}n \\ = & \int_{s_j}^{s_i} \int_{n_i}^{n_j} v_{sn}(s, n) \mathrm{d}n \mathrm{d}s \\ = & \int_{s_j}^{s_i} \int_{n_i}^{n_j} \frac{c}{\lg(1-P)} \cdot \frac{1}{(n-s)^2} \mathrm{d}n \mathrm{d}s < 0 \end{aligned} \tag{19}$$

The last line stands because $s_i > s_j$, $n_j > n_i$ and $\frac{c}{\lg(1-P)} \cdot \frac{1}{(n-s)^2} < 0$, which is in conflict with Equation (18). Thus, all the contract items should follow the condition that if $s_i > s_j$, $n_i \geq n_j$. □

From this lemma, we can see that a higher type IU will choose to deliver ads to more SUs. This is reasonable as a higher type IU has more surrounding SUs and it is easier to forward more ads.

The above two lemmas show the following necessary conditions for a feasible contract:

$$n_1 \leq n_2 \leq ... \leq n_T, \text{ and } r_1 \leq r_2 \leq ... \leq r_T \tag{20}$$

We have $r_i = r_{i+1}$ when and only when $n_i = n_{i+1}$, which can be inferred from lemma 2. Next we discuss the sufficient conditions for a feasible contract.

Lemma 4: A contract $\xi = \{(n_t, r_t)\}$ is feasible when it meets the following conditions.

- $n_1 \leq n_2 \leq ... \leq n_T$,
- $0 \leq v(s_1, n_1) \leq r_1$,
- and for all $i = 2, 3, ..., T$,

$$r_{i-1} + A \leq r_i \leq r_{i-1} + B, \tag{21}$$

where $A = v(s_i, n_i) - v(s_i, n_{i-1}), B = v(s_{i-1}, n_i) - v(s_{i-1}, n_{i-1})$.

Proof. We prove it by induction. We suppose $\xi_k = \{(n_1, r_1), (n_2, r_2), ..., (n_k, r_k)\}$ is a subset of ξ and is a contract for the first k types of IUs.

We first prove that ξ_1 is feasible. As there is one contract set for ξ_1, we only need to verify that it satisfies the IR constraints. From the second condition in this lemma, we have $r_1 - v(s_1, n_1) \geq 0$. Therefore, ξ_1 is feasible.

Then we suppose that ξ_k is feasible and verify that ξ_{k+1} is also feasible under this assumption. We first prove that ξ_{k+1} meets IC constraints, i.e. for $\forall i = 1, 2, ..., k$

$$\begin{cases} r_{k+1} - v(s_{k+1}, n_{k+1}) > r_i - v(s_{k+1}, n_i), \\ r_i - v(s_i, n_i) > r_{k+1} - v(s_i, n_{k+1}). \end{cases} \tag{22}$$

From the left-hand side of Equation (21), that is $r_{i-1} + A \leq r_i$,we have

$$r_{k+1} \geq r_k + v(s_{k+1}, n_{k+1}) - v(s_{k+1}, n_k). \tag{23}$$

As ξ_k is feasible, the IC constrains for type-s_k IU must be satisfied, i.e.,

$$r_k - v(s_k, n_k) \geq r_i - v(s_k, n_i), \ \forall i = 1, 2, ..., k. \tag{24}$$

Combining Equation (23) and (24), we get

$$\begin{aligned} &r_{k+1} - v(s_{k+1}, n_{k+1}) \\ \geq &r_i - v(s_{k+1}, n_k) + v(s_k, n_k) - v(s_k, n_i). \end{aligned} \tag{25}$$

Additionally, Equation (19) implies that

$$v(s_k, n_k) - v(s_k, n_i) > v(s_{k+1}, n_k) - v(s_{k+1}, n_i). \tag{26}$$

Thus, we have

$$r_{k+1} - v(s_{k+1}, n_{k+1}) > r_i - v(s_{k+1}, n_i), \tag{27}$$

which proves the IC constraints for type-s_{k+1} IUs, i.e. the first Equation in (22). Next we prove the second Equation in (22), i.e. the IC constraints for type-s_i $(i = 1, 2, ..., k)$ IUs with regards to type-s_{k+1} IUs. From right side of Equation (21), we have

$$r_k + v(s_k, n_{k+1}) - v(s_k, n_k) \geq r_{k+1}. \tag{28}$$

As ξ_k is feasible, we have

$$r_i - v(s_i, n_i) \geq r_k - v(s_i, n_k), \ \forall i = 1, 2, ..., k. \tag{29}$$

Combining the above two equations, we have

$$\begin{aligned} r_i - v(s_i, n_i) &\geq r_{k+1} - v(s_i, n_k) + v(s_k, n_k) - v(s_k, n_{k+1}) \\ &\geq r_{k+1} - v(s_i, n_k) + v(s_i, n_k) - v(s_i, n_{k+1}) \\ &= r_{k+1} - v(s_i, n_{k+1}). \end{aligned} \tag{30}$$

Thus, we have proven that ξ_{k+1} satisfies the IC constraints. Next we prove that it also satisfies the IR constraints. As ξ_k is feasible, all the type-s_i $(i = 1, 2, ..., k)$ IUs meet the IR constraints. Thus, we only need to prove that for the type-s_{k+1} IUs, the following condition is satisfied.

$$r_{k+1} - v(s_{k+1}, n_{k+1}) \geq 0. \tag{31}$$

Obviously, $v(s, n)$ is a strictly monotone decreasing function with regard to s, which means $v(s_{k+1}, n_i) < v(s_i, n_i)$. Together with Equation (27), we have

$$\begin{aligned} r_{k+1} - v(s_{k+1}, n_{k+1}) &\geq r_i - v(s_{k+1}, n_i) \\ &\geq r_i - v(s_i, n_i) \geq 0. \end{aligned} \tag{32}$$

The last line is the IR constraints for type-s_i IUs. Thus ξ_{k+1} satisfies the IR constraints.

Up to now, we have proved that i) ξ_1 is feasible and ii) if ξ_k is feasible, ξ_{k+1} is feasible when the conditions in this lemma hold. Thus, $\xi = (s_i, n_i)$ is feasible under these conditions. □

Actually, lemma 4 is also a necessary condition of a feasible contract, which can be proved by a similar process in this proof. Due to space limitation, we do not show it here.

3.4.2. Optimal Contract

In this subsection, we derive the optimal contract based on the lemmas above. We analyze it in two steps. First we discuss the optimal rewards $\{r_t\}$ for different types of IUs when $\{n_t\}$ are feasible and fixed. Then we find the optimal assignments of the number of ads to be delivered by different types of IUs, i.e. $\{n_t\}$.

From lemma 3 we know that for a feasible contract, $n_1 \leq n_2 \leq ... \leq n_T$ as $s_1 < s_2 < ... < s_T$. We first tackle the problem as follows.

$$\max_{r_i} \sum_{i=1}^{i=T} (A \cdot n_i - r_i) \cdot M_i, \tag{33}$$

where the rewards satisfies the conditions in lemma 4.

Proposition 2: For a feasible contract $\xi = \{(n_t, r_t)\}$ whose $\{n_t\}$ are fixed and $n_1 \leq n_2 \leq ... \leq n_T$, the unique optimal rewards $\{r_t^*\}$ are

$$r_t^* = r_{t-1}^* + v(s_t, n_t) - v(s_t, n_{t-1}). \tag{34}$$

Proof. Obviously the contract designed in this lemma meets the conditions in lemma 4. Therefore, it is a feasible contract.

To prove that Equation (34) maximizes the utility of the ad broker, we only need to prove that it minimizes $\sum_{i=1}^{i=T} r_i \cdot M_i$ as $\{n_i\}$ are fixed. We prove it by contradiction. Suppose that there exists a feasible set of $\{r_i^{'}\}$ such that

$\sum_{i=1}^{i=T} r_i^{'} \cdot M_i < \sum_{i=1}^{i=T} r_i^{*} \cdot M_i$. Then there must exist at least one reward $r_k^{'} < r_k^{*}$. From Equation (21) in lemma 4, we have

$$r_k^{'} - v(s_k, n_k) + v(s_k, n_{k-1}) \geq r_{k-1}^{'}. \tag{35}$$

Thus, we have

$$\begin{aligned} r_{k-1}^{*} &= r_k^{*} - v(s_t, n_t) + v(s_t, n_{t-1}) \\ &> r_k^{'} - v(s_k, n_k) + v(s_k, n_{k-1}) \geq r_{k-1}^{'}. \end{aligned} \tag{36}$$

Continuing this process, we finally get $r_1^{'} < r_1^{*} = v(s_1, n_1)$, that is $r_1^{'} - v(s_1, n_1) < 0$. The IR constraints for type-s_1 IUs are violated. Therefore, there does not exist such a set of $\{r_t^{'}\}$ and $\{r_t^{*}\}$ maximizes the utility of the ad broker.

Then we prove that $\{r_t^{*}\}$ is unique. We assume that there exist another feasible set $\{r_t^{'}\} \neq \{r_t^{*}\}$ and $\sum_{i=1}^{i=T} r_i^{'} \cdot M_i = \sum_{i=1}^{i=T} r_i^{*} \cdot M_i$. There must exist at least one $r_k^{'}$ which is smaller than r_k^{*}. With the same process as above, we can prove that it is impossible to have such a set of $\{r_t^{*}\}$. Therefore, the rewards assignment $\{r_t^{*}\}$ is unique.

To sum up, $\{r_t^{*}\}$ given in Equation (34) is optimal and unique. $\square$

With the result in proposition 2, we can further analyze the optimal setting of $\{n_t\}$.

Proposition 3: The optimal $\{n_t^{*}\}$ which maximizes the ad broker utility is given by

$$n_t^{*} = \arg\max_{n_t} (AM_t n_t - M_t v(s_t, n_t) - \alpha_t \sum_{i=t+1}^{T} M_i), \tag{37}$$

where $\alpha_t = v(s_t, n_t) - v(s_{t+1}, n_t)$.

Proof. From Equation (34) in proposition 2, we get

$$r_t^{*} = v(s_1, n_1) + \sum_{i=1}^{t} \beta_i, \quad \forall t = 1, 2, ..., T, \tag{38}$$

Algorithm 3 Designing feasible and optimal contract in incomplete information scenario

for each user type s_t **do**

  $n_t^* = \arg\max_{n_t}(AM_t n_t - M_t v(s_t, n_t) - \alpha_t \sum_{i=t+1}^{i=T} M_i)$, where $\alpha_t = v(s_t, n_t) - v(s_{t+1}, n_t)$;

  while exists $n_k, n_{k+1}, ..., n_{k+q}$ that do not follow $n_k \leq ... \leq n_{k+q}$ **do**

    for $i = k; i \leq k+q; i++$ **do**

      $n_i = \arg\max_n \sum_{t=k}^{t=k+q}(AM_t n_t - M_t v(s_t, n_t) - \alpha_t \sum_{j=t+1}^{j=T} M_j)$;

    end for

  end while

  $r_t^* = v(s_1, n_1^*) + \sum_{i=1}^{i=t} \beta_i$, where $\beta_i = v(s_i, n_i^*) - v(s_i, n_{i-1}^*)$;

end for

where $\beta_i = v(s_i, n_i) - v(s_i, n_{i-1})$. Hence, the utility of the ad broker is

$$\Phi = \sum_{t=1}^{T}(An_t - v(s_1, n_1) - \sum_{i=1}^{t} \beta_i)M_t. \tag{39}$$

Rearranging the items in the above equation to make items related to n_t together, we have

$$\Phi = \sum_{t=1}^{T}(AM_t n_t - M_t v(s_t, n_t) - \alpha_t \sum_{i=t+1}^{T} M_i), \tag{40}$$

where the only variable is n_t. Thus by solving Equation (37), we can get an optimal contract that maximize the ad broker's utility. □

So far, the contract we design satisfies the second and third conditions in lemma 4. To make it feasible, it should also satisfies the first condition, that is $n_1 \leq n_2 \leq ... \leq n_T$. However, there is no guarantee that the $\{n_t^*\}$ in proposition 3 satisfies this condition. Suppose there is a subset $n_k, n_{k+1}, ..., n_{k+q}$ that does not follow the rule. We can adjust it by setting

$$n_i = \arg\max_n \sum_{t=k}^{k+q}(AM_t n_t - M_t v(s_t, n_t) - \alpha_t \sum_{j=t+1}^{T} M_j), \tag{41}$$

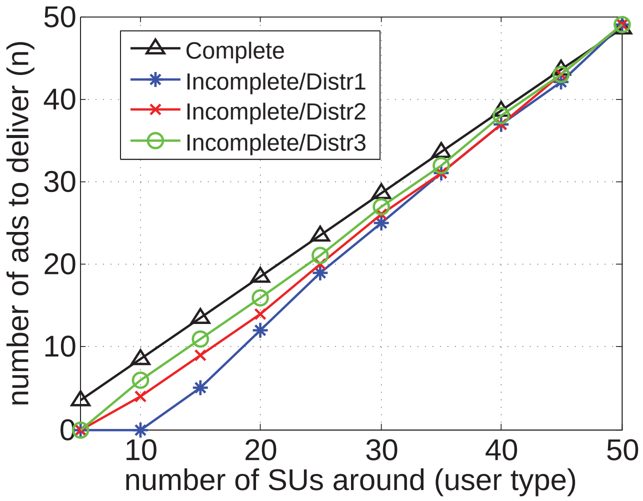

Figure 3: Optimal numbers of ads to be delivered

where $i = k, k+1, ..., k+q$. After this adjustment, $n_k = n_{k+1} = ... = n_{k+q}$, which can be proved by proposition 3 in [22]. Thus, the adjusted subset meets the requirements from lemma 4.

To sum up, we can design the feasible and optimal contract in steps shown in Algorithm 3.

4. Simulation

In this section, we first introduce the simulation setup and then present the simulation results to show the optimal contracts in complete and incomplete information scenarios and analyze the utilities of the ad broker and IUs.

4.1. Simulation Setup

Table 1: User type distribution (N=220 users in T=10 types)

s_i	1	2	3	4	5	6	7	8	9	10
Distr. 1	4	8	12	16	20	24	28	32	36	40
Distr. 2	22	22	22	22	22	22	22	22	22	22
Distr. 3	40	36	32	28	24	20	16	12	8	4

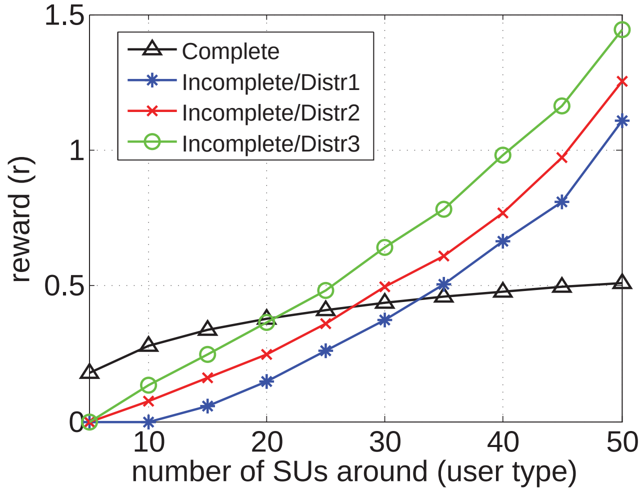

Figure 4: Optimal rewards

We implement the proposed framework using MATLAB. The simulation methodology conforms to existing privacy-preserving LBA proposals [9, 23] as well as contract theory mechanism designs [22]. In our simulations, there are totally $T = 10$ types of IUs. A higher type user has more SUs around it. Specifically,there are $5i$ SUs around type-s_i IU. We discuss three possible distributions for IU types as summarized in Table 1. Unless otherwise stated, the probability of fetching ads for an SU $P = 0.5$, the average revenue of sending ads to one user $A = 0.1$, and the cost of one broadcast $c = 0.1$. Note that we also vary these parameters in certain figures to evaluate their impacts on the performance.

4.2. Simulation Results

We first present the optimal contract under different distributions for the complete and incomplete information scenarios. Figure 3 shows the optimal number of ads to deliver, i.e. n, for different types of users, and Figure 4 shows the corresponding optimal rewards. When the ad broker has complete information about IU type, it will offer a type-tailored contract set to each IU. Thus, the contract is independent on the user type distribution. We find that under complete information, the ad broker will stimulate the IUs to deliver more

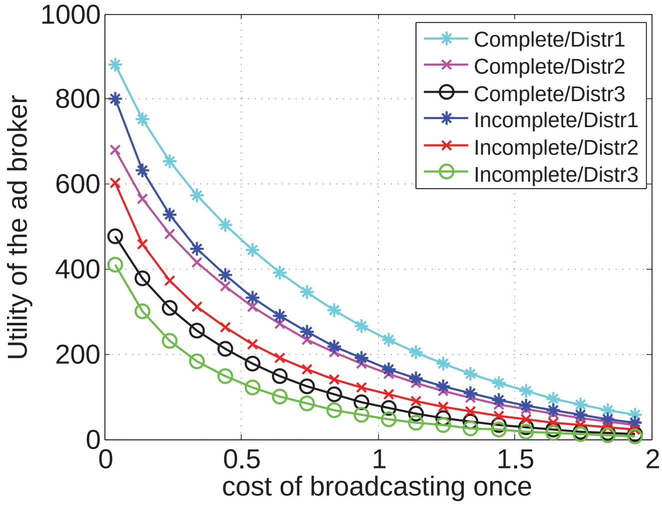

Figure 5: Utility of the ad broker

ads with a relatively low reward especially for higher type IUs. This shows that information is valuable, by which the ad broke can offer perfectly discriminating price and get all the social surplus(as analyzed in section 3.3 and verified below).

In the presence of incomplete information, the ad broker has to offer the same contract to all the IUs. We find that when there is a larger portion of high type IUs, the ad broker loses interest in the low type IUs and tends to give more motivation to high type users as they are more lucrative. Oppositely, with more low type IUs, the ad broker has to make use of these low type ones. In this case, the ad broker has to pay higher rewards to motivate low type IUs to deliver more ads as the efficiency of ad delivery is lower for these IUs. By low efficiency, we mean that as there are fewer SUs around, the audience of the broadcast is smaller, and fewer SUs will receive ad IDs and ultimately fetch ads from the publisher.

Next we discuss the utilities of the ad broker and all the IUs. From Figure 5, we find that the ad broker always gain higher utility in complete information scenario no matter how the IU types are distributed. This verifies our theoretical analysis, which shows that the ad broker gains all the social surplus and maximizes it. In the same scenario (the complete or incomplete information scenario), the ad broker gains the highest utility in distribution 1 and the least in distribution 3. This result agrees with the one shown in Figure 4, which indicates that the ad broker needs to pay out higher rewards in distribution 3. Paying higher rewards means lower utility for the ad broker. In Figure 6, we find that the IUs will get no utility in the complete information scenario as analyzed in section 3.3. Although in distribution 3, every IU receives higher rewards, the total utility of all IUs is still lower. This is because most IUs are lower types whose rewards are lower than the higher types.

Figure 7 presents an intuitive image about the utilities. Case a,b,c show the utilities under distribution 1,2,3 respectively. For every case, the left-hand one corresponds to the complete information scenario and the right-hand one illustrates the incomplete information scenario. The sum of the ad broker utility and IU utilities is the social surplus. Obviously, with more higher type IUs, the social surplus is higher as under this distribution more SUs are likely to receive ad IDs and fetch ads from the publisher. In the incomplete information scenario, as the IUs preserve their private information, that is their user types, the ad broker has to leave some utilities for the IUs to reach its own optimality. This information asymmetry also leads to a decrease in social surplus as the ad broker can not offer perfectly discriminate rewards to different types of IUs.

We also study how the change in parameters influences the utilities. Figure 5 and Figure 6 show that with the increase in the cost of broadcasting once, i.e. c, the utility of the ad broker decreases and the total utility of IUs will first increase and then decrease. From Equation (13), we know that in the complete information scenario when c increases, n will decrease and r will increase, that is the ad broker will have less ads delivered but pay higher rewards. Therefore, its utility will decrease, which is similar in the incomplete information case. For IUs, with the increase in cost, their rewards also increase. Thus, there exists an optimality for them. As for parameter p and A, that is the probability an SU will fetch ads from the publisher when receiving ad IDs and the revenue of delivering ads to one more user, the utilities of the ad broker and IUs will

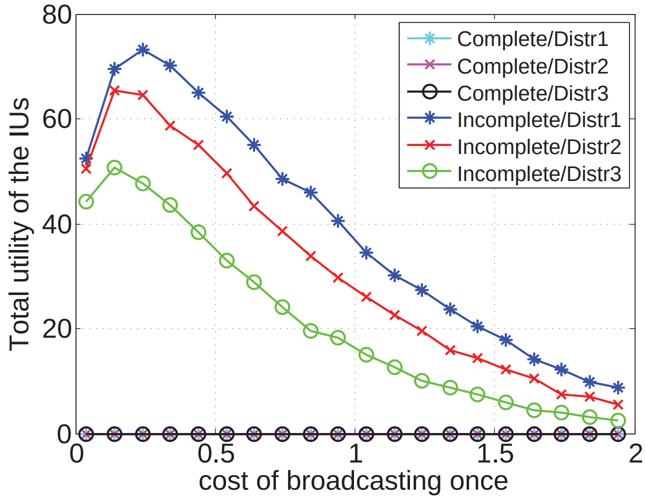

Figure 6: Total utility of the IUs

increase, respectively. The trend is simple and obvious. Due to space limitation, we do not show the numerical result here.

Finally, we compare our proposed LBA system with the traditional one. Figure 8 illustrates the states of the ad broker and the IUs in terms of their utilities. In traditional LBA system, the ad broker can only push ads to IUs. In our simulation model, there are totally $N = 220$ IUs and the average revenue of sending one ad is $A = 0.1$. As such, the revenue of the ad broker is 22 at most, and this is also the profit (utility) of the ad broker as it does not need to pay IUs for forwarding ads. In this case, the utilities of the IUs are zero. The red dot in Figure 8 represents the state in traditional system (it is independent in terms of the information completeness and user distribution). The purple dot represents the state in our proposed system under different scenarios and user distributions. It is obvious that our system can increase the utility of at lease one party. Specifically, in the presence of incomplete information, the utilities of the ad broker and the IUs both increase. As such, a win-win situation is achieved and both parties have the incentive to take part in our new system.

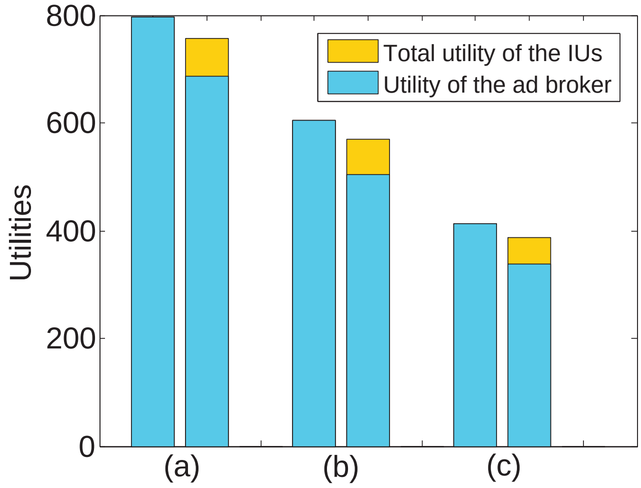

Figure 7: Utilities

5. Discussion

This section discusses some practical considerations of the proposed framework.

5.1. Provisioning for Pure SU systems

An essential observation in our framework is that there exists both IUs and SUs in the LBA system. Existing surveys and investigations [24, 25, 20] have shown that there are still quite a large portion of people who deem location information insensitive. Therefore, the case where all users are SUs is very rare.

In the extreme case of pure SU systems, our contract framework still works by integrating it with existing economic compensation mechanisms. It has been reported that have reported that users are willing to trade their private information for money [26, 27]. The economic compensation mechanisms that pay users for revealing their personal information have already been widely considered in the literature [24, 25, 28]. Additionally, many companies, including Bynamite, Yahoo, and Google, are also engaging in the purchase of users' private information in exchange for monetary or non-monetary compensation [29, 27].

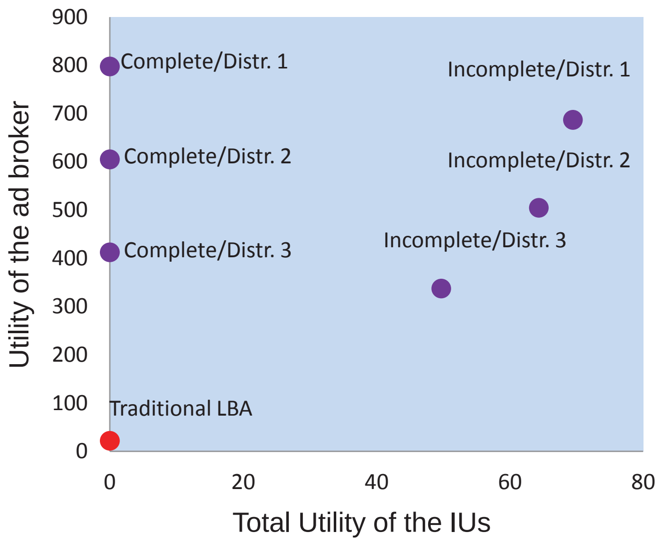

Figure 8: Comparison between traditional LBA and proposed LBA

Therefore, we can replace the role of IU in our framework with the SUs who are willing to trade their location information for money.

5.2. Deployments Considerations

Our framework can be easily extended to existing LBA systems. Existing LBA systems contain advertisers, an ad broker, and users, while our framework introduces an extra party, i.e., the publisher. In practice, the publisher can be the local shopping malls, or the network provider who deploys the ad networks, such as iBeacons. In practice, there are third parties that have already deployed iBeacons for cooperative shopping malls to deliver ads to customers. In such a system, the publisher shares profit with the shopping malls. The LBA system can be deployed as dedicated Ad networks such as iBeacon, or atop existing Wi-Fi infrastructures that deliver ads through local access points. At the customer end, customers can install the LBA app in their smartphones, such as GroupOn and Macy's.

6. Related Work

Location-based advertising is one type of targeted advertising. There are some existing works that discuss the transparency properties and privacy problems of targeted advertising or location-based advertising. Chen. et al [2] take a measurement study to reveal the correlations between format of advertisement, privacy, brand credibility and consumers' attitudes. THe results show that customers are more willing to accept LBA with less personal information revealed, which motivates our design in the privacy preservation aspect. Bin et al. [30] reveal that the majority of the targeted advertisements are related to *travel and tourism* and *shopping*. Among these categories, location information is the most essential one. Subhankar et al. [1] point out that location information is sensitive and location-based advertising should be on a permission basis. Based on the privacy problem disclosed in the existing works, we exploit the way to make the most out of location-based advertising in the presence of privacy issues. The industry now allows users to set their advertising profile and opt-out of being tracked. One example is Google's ad preference setting. However, as shown in [31], there are still non-compliance instances and it is inconvenient to use. Protocols like Do Not Track have been proposed to regulate online tracking [32]. Although main browsers today are supporting these protocols, the compliance is not compulsory.

There are some existing works that provide privacy preserving solutions. Fawaz et al. [33] propose a privacy-preserving LBA framework in which users form a cooperative group to request ads without leaking their identities. Artail et al. [21] extend the framework by adding a billing system without a third-party. MobiAd [34] provide privacy-preserving LBA by caching ads locally on users' phones, and reports the clicks via a Delay Tolerant Networking (DT-N) protocol. Our work differs from [33, 21, 34] in two aspects: i) We focus on scenarios, e.g., shopping mall, where users move frequently and request ads instantly while they require users to tolerate tens of seconds delay to form cooperative groups; ii) Our focus is to design an incentive mechanism that motivates selfish advertisers, ad brokers, and users to adopt the LBA system, while they focus on developing comprehensive secure protocols without systematic analysis on incentive mechanisms. Privad [8, 17] introduce a new entity, referred to as dealer, which is responsible for transmitting the communication between the ad broker and users anonymously. The ad broker and the dealer have incomplete information respectively. User private information is preserved as long as the two parities do not collude with each other. Murali et al. [9] propose to use statistically falsified user information for ad targeting. An approximation algorithm is discussed for this system and they claim that the performance is close to optimal. Adnostic [35] uses a cryptographic system to preserve user privacy. The privacy problem is discussed by economic incentives in [28], where users are aware of their privacy leakage and compensated for it. In all these systems, user profiles are kept locally in their own devices. Ad filtering takes place at the user side, that is user devices choose the ads their owners may be interested in according to the local profile. This solution requires caching a lot of ads locally. Obliviad [23] retrieves private information based on safe hardware and mixes electronic tokens to preserve clients' private profiles. There are also works that specifically discuss preserving location privacy. One solution is to collectively change the pseudonyms of the mobile nodes in mix zones [36]. Another category enables the users to set the information they are willing to share with third parties [10, 11]. For example, instead of accurately telling the ad server its location, the user may be willing to reveal the fact that he or she is in a certain city, which is a larger region. These solutions are either complicated to implement or still leaking private information to some extent.

LBA essentially belongs to location-based services (LBSs). Numerous techniques have been proposed for preserving privacy in LBSs. Spatial cloaking and anonymization are widely adopted [37, 38, 39], where a value provided by a user is indistinguishable from those of $k-1$ other users within a spatial region to provide privacy guarantee. Private information retrieval (PIR) is leveraged [40] to secure users' location information. However, privacy preservation techniques for LBS have focused on location privacy, while ad click behavior protection is not considered. Additionally, they compromise location estimation accuracy [37, 38, 39], or prevent click counting [40], which hinders the benefits of advertisers and ad brokers, thereby making them unwilling to adopt these systems.

In this paper, we leverage contract theory, which is an extensively discussed topic in economics, into location-based advertising. Contract theory studies how to coordinate the quantity/quality and price so as to maximize the seller's payoff in the presence of asymmetric information [14]. There are complete contracts and incomplete contracts. For the former one, all possible states and their consequences should be specified. Incomplete contracts proposed by Oliver Hart et al. [41] discuss the contract construction when complete information is impossible.

7. Conclusion

In this paper, we propose an LBA framework where insensitive users are leveraged to send ads to the sensitive users around them. In particular, we introduce the publisher and design an ad ID to count the number of viewers for each ad as well as the number of ads delivered by every insensitive user, and meanwhile guarantee the privacy of sensitive users. In addition, we design a number-reward contract to motivate the insensitive users to deliver ads. Numerical results demonstrate that our proposed system can guarantee higher utilities compared with the traditional LBA system. A win-win situation is achieved and both the ad broker and the users have the incentive to participate in our LBA system.

Our theoretical and numerical studies provide some implications on future LBA systems. Our contract-based approach reveals that by rewarding users to forward ads, both users and ad brokers are motivated. As such, we can achieve a win-win situation. For future work, we plan to extend our proposed system to social networks, where users can be leveraged to forward the ads that they receive and are interested in. In this way, ads can reach more audiences and social network participants can get recommended ads from their friends. The influential power of a forwarded ad will be studied.

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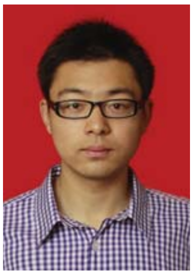

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