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IPIM: An Effective Contribution-Driven Information Propagation Incentive Mechanism

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ABSTRACT The wide diffusion of information in social networks can be exploited to solve searching-for-a-target (SFT) problems including those of missing individuals. Incentive mechanisms that promote active individual participation can be designed to favor a clear propagation direction to help efficiently find a target. However, the existing incentive research rarely focuses on a clear propagation direction based on a specific goal. Thus, we propose an effective contribution-driven information propagation incentive mechanism (IPIM) that exploits ego networks to solve the SFT problem. First, we use an all-pay auction-inspired model to determine the propagation of alters in each ego network. We then propose a novel algorithm, the node propagation utility, based on effective contributions, to focus the propagation toward the target rather than searching indiscriminately and inefficiently. The theoretical analyses and simulation results indicate that IPIM guarantees the truthfulness, individual rationality, and budget feasibility. The simulations are conducted based on real and public social datasets. The IPIM shows increased efficiencies of 951.18 % of success rate, of 215.65 % in propagation hops, and of 514.41 % in participation scale, compared with a typical incentive mechanism. In conclusion, the IPIM shows significant value in the potential application in SFT.

INDEX TERMS Incentive mechanism, social network, information propagation, ego network.

I. INTRODUCTION

In recent years, social networks have evolved into unprecedented platforms of information diffusion. They characteristically consist of a set of ego networks that form potential connections between individuals. An ego network, which is a micro-social network, consists of direct links between an "ego" and its "alters," and the interactions among numerous ego networks can cause wide information diffusion. This provides a convenient approach to solving specific problems, such as searching for missing individuals [1]. We call this kind of problem "searching for a target" (SFT), characterized by its reliance on information diffusion. The solution requires many participants to not only propagate information, but to also determine an appropriate propagation direction towards the target. However, individuals in a real social network are rational and selfish. Thus, to guarantee wide participation in the appropriate propagation direction, there must be an incentive mechanism.

Social network incentive research has typically focused on expanding the scale of participation or on improving participation in quality [2]–[4]. However, to solve the SFT problem, two main challenges remain. The first is determining which of several information providers can activate a candidate to receive information and, hence, contribute effectively to the platform in a way that avoids inefficient repetitions. The second is choosing an appropriate forward diffusion path to shrink the searching space and improve the efficiency of solving the SFT problem.

We call the first challenge a problem of repeated propagation. Most studies assume that nodes propagate information indiscriminately to all neighboring nodes. By discriminating between nodes, however, other studies have determined the probability that a given neighbor receives information from a given source node [5], [6]. Nonetheless, these studies do not consider the occurrence of propagation loops within the

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network and do not contribute efficiently to finding the target. Repeated propagation through a given node does not change the direction of propagation and suffered useless costs.

The second challenge is the problem of propagation direction. Current research into incentives of social networking rarely considers determining a particular path in better accordance with reality. For example, most of studies search the whole social network to find a specific people without considering the direction of propagation. Those work can find the target using a flooding way, but also lead to a high CPU cost.

Therefore, we propose a novel information propagation incentive mechanism (IPIM) to solve the SFT problem. IPIM utilizes the features of ego networks to provide participants an exchange for some ''propagation costs'' to promote the active and wide-ranging propagation of different participants.

We put forward an all-pay auction-inspired model to address the repeated propagation problem. All-pay auction gives all bidders the chance to make a bid amount for the item, and only the using bidder is allocated the item being auction. Based on the characteristics of ego networks, we define ''common alters'' as nodes that receive information successively from different egos. These egos can then be regarded as bidders for the common alters. The winner of this auction, being the only ego to the common alter, thus contributes to the search for the target.

Regarding solving the propagation direction problem, we offer the concept of effective contribution to consider appropriate nodes gradually approaching the target. Concretely, we introduce two indices: propagation effectiveness and propagation contribution to evaluate the effective contribution of participants. More specifically, propagation effectiveness is used to predict the probability that an ego can activate its alter. To activate an alter, it must be willing to receive and to propagate incoming information from its ego. The propagation contribution is used to evaluate the distance between a node and the target. Thus, we can determine which nodes are more likely to effectively find the target, based on their effective contributions, further determining the appropriate propagation path.

Based on solving the two problems, we further propose an algorithm, the node propagation utility (NPU), for calculating the propagation utility of nodes. It is the motive power of nodes' propagation. Moreover, the IPIM guarantees wide and well-targeted information diffusion, which guarantees truthfulness, individual rationality, and budget feasibility. In summary, the main contributions of our work are as follows.

First, we propose an incentive mechanism, IPIM, it capitalize on the properties of ego networks to promote wide diffusion of information for an efficient solution of the SFT problem.

Second, an all-pay auction-inspired model is to address to solve the repeat propagation problem. In detail, we model propagation between the information receiving candidate (i.e., alter) and its multiple information providers (i.e., egos) as an all-pay auction. Only the winner can activate the common alter and contribute positively toward finding the target.

Third, we promote the concept of effective contribution to solve the propagation direction problem, consisting of propagation effectiveness and propagation contribution, which has significant impact on evaluating nodes' abilities to find the target. We can then determine the appropriate participants and obtain the optimal propagation path.

The remainder of the paper is structured as follows. In Section II, discusses the related work. Section III describes in detail the IPIM design. Section IV is the mechanism analysis. To study the performance of IPIM, we conduct comprehensive experiments, and discuss the results in Section V. Finally, we give concluding remarks in Section VI.

II. RELATED WORK

Incentive mechanisms are adopted to provide incentives for individuals to actively participate in different ways at their own expense. This has been widely applied in computer science and sociology, including delay-tolerant networks [7], opportunistic networks [8], wireless-sensor networks [9], crowd sensing [10], and social networks [11]. Most incentive mechanisms are usually based on a game model [12], [13] or an auction model [14], [15].

Two kinds of mechanisms address the incentive problem: ''user–platform'' and ''user–user''. In ''user-platform'' mechanisms users usually activated by platform. Most studies use the ''user-platform'' mechanism, especially in the context of crowd sensing. For example, Zhao focused on an online incentive mechanism and designed schemes to recruit mobile users under budget constraints [16]. Fang designed an incentive mechanism based on prices and subsidies in sharing platforms to attract participants while lowering payouts [17]. In the user-platform model, participants are recruited independently. However, in our work, information propagation among participants is utilized to find the target, effectively adopting the user–user model. Interaction incentive is therefore highly relevant to our work.

The user–user incentive study emphasizes cooperation between users, as featured in opportunistic networks, social networks, etc. The issue of node selfishness in opportunistic networks has been studied for several years, and several incentive schemes have been proposed to stimulate data exchange between nodes [18]. For example, Wu proposed a scheme named ''Vbargain'' (an incentive scheme based on oriented pricing), aiming to stimulate mobile users and collaboratively deliver video data [8]. However, this is different from social networks, which consist of a set of ego networks and emphasize direct relationship and contacts. In opportunistic networks, data transmissions usually occur in a state of non-connection and movement, using a form of storage-carrying-forwarding to deliver data. Data must also be forwarded using node encounters to a destination, making information propagation unstable and reducing the probability of finding the target. Obviously, there is a fundamental difference in user–user incentive, as considered in opportunistic networking and in our work.

Research on incentives in social networks also focuses on cooperation between nodes, depending on the links. Feng *et al.* proposed a social tie-based incentive scheme to deal with the selfish problem of cooperative spectrum sensing in distributed cognitive radio networks [19]. Gan *et al.* proposed a novel game-based incentive mechanism for multi-resource sharing, where users were motivated to share their idle resources in a conditional voluntary mode [20]. However, they neglected the differentiation analysis of node ability and relationship between nodes, and they did not choose an appropriate propagation path. Considering this problem, Doo and Liu proposed a probabilistic approach to studying how incentives can be utilized to boost diffusion of influence [6]. In particular, they defined an influence diffusion probability for each node instead of assuming a uniform probability prior to formulating rewards in terms of two factors: efforts and benefit. Nevertheless, contrasting our own work, this scheme evaluated the node reward based only on the number of affected neighbors and how much contribution they could make. Their work thus focuses on the number of propagators. In contrast, we analyze the distance between the propagation nodes and the target, providing a greater bearing on the direction than the scale of propagation. Moreover, this scheme does not consider repeated propagation to a given node, which affects the contribution and propagation of the platform. Thus, it is not suitable for solving the SFT problem.

Generally, our work is a kind of user–user incentive mode. Differing from an opportunity network with storage-carrying-forwarding, our work uses more stable social relations as propagation media. It takes on the characteristics of social networks, but it still differs from existing research on social network incentives. Specifically, our proposal is solving the SFT problem by evaluating the ability of each node to find a target, rather than simply expanding the scale of participation. Thus, we can determine the appropriate propagation direction.

III. MECHANISM DESIGN

Our incentive mechanism, IPIM, is designed to solve the SFT problem, as shown in FIGURE 1. The mechanism is based on a series of ego networks, consisting of focal nodes (i.e., egos), nodes that are directly connected to it (alters), and the ties, if any, between the alters. The purpose of our mechanism is promoting active propagation at nodes that will increase the likelihood of finding the target in the most economical and efficient manner. Of course, each alter has its own ego network. The active participation of an increasing number of nodes can therefore result in wide diffusion of information via success-ego networks, thereby enhancing the efficiency of finding the target.

There may exist repeated propagations in any ego network, reducing the efficiency of target-finding. Repeated propagation requires that a common alter may receive the same information many times from its egos. This does not

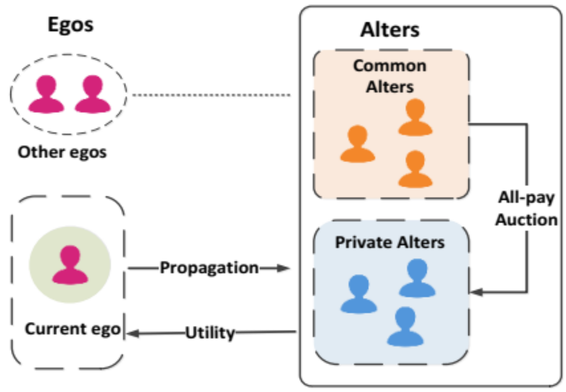


FIGURE 1. Incentive mechanism design.

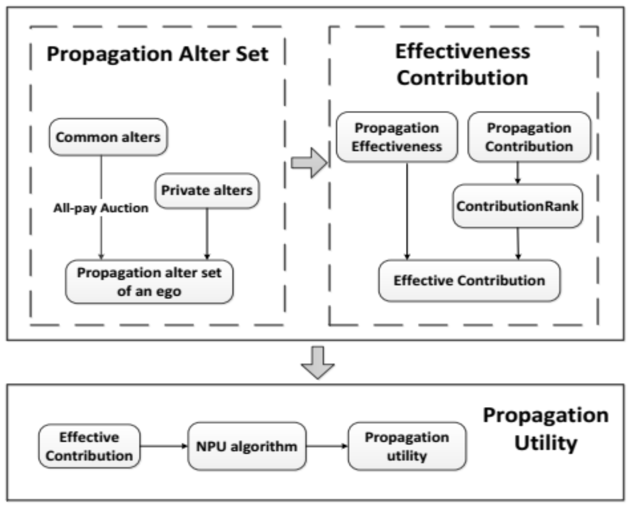


FIGURE 2. IPIM framework.

contribute to solving the SFT problem and it also reduces the willingness of information recipients to participate [21]. This is a challenge for many egos, who may be the only activator (i.e., information source) to a certain alter (i.e., information receiver).

We focus on efficiently finding the target. Thus, where or to whom should information be propagated to locate the target? To answer, we should evaluate the effective contribution of nodes to find the target. Because utility is the original motive of individual participation, it is positively related to reward, but only when nodes can obtain positive rewards during information propagation. Thus, calculating node utility to maximize participation scale while balancing total propagation cost is also a challenge.

Thus, there are three challenges in our work: solving the repeated propagation problem; solving the node effective contribution evaluation problem; and solving the node utility problem. For these, the IPIM has three corresponding parts: propagating the alter set; effective contributions; and propagating utility. The framework of IPIM is shown in FIGURE 2.

The propagation alter set is based on the all-pay auction model for determining the unique activator of common alters. Egos linking to the common alters are regarded as bidders, bidding for the common alters. Each ego bids, and the one making the highest effort bid wins the common alter and is rewarded. We then determine the set of winning egos in terms of the common alters allocated to them and their private alters as propagation alter sets.

An effective contribution is proposed to evaluate the ability of nodes in the propagation set to find the target. It consists of two indicators of propagation effectiveness and propagation contribution. The former represents the willingness of an alter to receive information from the ego and propagate it. This can be predicted in the current ego network by considering historical interactive data. The latter is used to evaluate the nodes' propagation contribution to solving the SFT problem. We propose a ContributionRank method for determining the distance (i.e., the contribution to the task of finding the target) between any propagation node and the target.

Propagation utility is based on the number of alters to which an ego can propagate. From the entire network, the more alters the ego propagates to, the higher the likelihood of finding the target. Thus, the more utility the ego can provide. In detail, we combine the propagation contribution with propagation effectiveness to yield a joint probability distribution for a Bayesian analysis. By considering the whole network, a prior and a posterior distribution can be obtained, corresponding respectively to the situations before and after an ego has propagated. The differences between these two distributions reflect the utility of the ego and determine the corresponding reward. The more alters to which the ego propagates, the greater its utility and the greater the reward. We describe the three parts of IPIM more specifically, as follows.

A. PROPAGATION ALTER SET

The propagation alter set consists of alters to which the ego can propagate to, or activate, in its own ego network. However, an alter may link to many egos (i.e., activators) in multiple networks. As explained before, repeated propagation by any node does not contribute to finding the target. Therefore, the sole activator of a certain alter is determined competitively among the various egos sharing this alter. Only by being the sole activator for a common alter can the ego enlarge the set of propagation alters and be rewarded. This concept resembles an auction, where many bidders compete for the same reward. Propagation between egos and their common alters can therefore be modeled as an all-pay auction. The number of bidders, unknown to the competitive egos, is denoted as n and obeys the Poisson distribution [22]. The auction framework is described as follows.

1) Denote J^* as a set of common alters, $J = \{1,2,\ldots j, \ldots, t\}$, linked to a set of egos I, where $I = \{1, 2, \ldots i, \ldots, n\}$ and $|I|$ defined as size of I, distributed across multiple ego networks.
2) The strategy of an ego node, i, determines how much effort, z_i^j, to make when competing for a common alter j. The incentive, given at the end of the auction, takes the form of a monetary prize to reward the ego who has made the greatest effort, $max_{i\in[1,n]} z_i^j$. This value is denoted, $z_{1,n}^j$, following the conventional notation in order statistics.
3) The prize is adaptive according to the $z_{1,n}^j = max_{i\in[1,n]z_i^j}$ ego's contribution, $\mathrm{M}(i)$, which is known to all. Each ego, i, also incurs a cost for its effort, defined as $h\left(z_i^j\right)$, where $h(\cdot)$ is some modulator function.
4) Egos are risk-averse and characterized by a von Neumann–Morgenstern (vNM) utility function, $u(\cdot)$ [23]. Each ego strategically determines z_i^j to maximize its own auction utility $u_{i,j}$. We define the auction utility of an ego as follows.

Definition 1: Each ego's auction utility for a common alter j is defined as the difference between its prize and the cost incurred:

$$\begin{cases} u_i^j = \left(M(i) - h\left(z_i^j\right)\right), & if\ z_i^j = z_{i,n}^j, \\ u_i^j = \left(-h\left(z_i^j\right)\right), & otherwise \end{cases} \tag{1}$$

The expected utility $E_u\left(z_i^j\right)$ is

$$E_u\left(z_i^j\right) = \left(M(i) - h\left(z_i^j\right)\right) P(win) + \left(-h\left(z_i^j\right)\right)(1 - P(win)) \tag{2}$$

where $\mathrm{P}(win)$ represents the winning probability, defined as follows.

Lemma 1: From the full-probability formula, the probability that an ego, i, wins a common alter, j, in the all-pay auction is

$$\begin{aligned} \mathrm{P}\left(z_i^j\right) &= \sum_{n=1}^{+\infty} P\left(z_i^j \mid n\right) P(n) \\ &= e^{-\lambda}\left(e^{\lambda F\left(z_i^j\right)} - 1\right) / F\left(z_i^j\right) \end{aligned} \tag{3}$$

where $\mathrm{F}\left(z_i^j\right)$ is the distribution function of z_i^j.

Proof: The effort cost, $h\left(z_i^j\right)$, is positively related to z_i^j. The probability distribution function of, z_i^j is $\mathrm{F}\left(z_i^j\right)$, and the probability density function is $\mathrm{f}\left(z_i^j\right)$. If there are n competitive egos, the probability follows the Poisson distribution: $\mathrm{p}(n) = \lambda^n * e^{-\lambda}/n!$. The winning probability, $\mathrm{P}(win)$, is given by the full probability formula,

$$\begin{aligned} \mathrm{P}(win) &= \sum_{n=1}^{\infty} p\left(z_i^j \mid n\right) p(n) \\ &= \sum_{n=1}^{\infty} F^{n-1}\left(z_i^j\right) \frac{\lambda^n}{n!} e^{-\lambda} \\ &= \sum_{n=1}^{\infty} \frac{\left(F\left(z_i^j\right)\lambda\right)^n}{n!} e^{-\lambda} / F\left(z_i^j\right) \\ &= \left(\sum_{n=0}^{\infty} \frac{\left(F\left(z_i^j\right)\lambda\right)^n}{n!} - 1\right) e^{-\lambda} F^{-1}\left(z_i^j\right) \end{aligned} \tag{4}$$

We can get $\mathrm{P}(win) = \left(e^{\lambda F(z_i)}\right) e^{-\lambda} F^{-1}(z_i)$ by using Taylor series and obtain the optimal effort, $z_i^{j^*}$, of ego i to its common alter, which can maximize its auction-utility. We then have another lemma of $z_i^{j^*}$:

Lemma 2: For a given ego, the optimal effort to win the common alter, j_t^*, is $z_i^{j^*}$, with the cost defined as follows. ($\underline{z_i^j}$ is lower bound of z_i^j)

$$h\left(z_i^{j^*}\right) = \int_{\underline{z_i^j}}^{z_i^j} M(i) e^{-\lambda} F^{-1}\left(z_i^j\right) F'\left(z_i^j\right) \times \left(\lambda e^{\lambda F\left(z_i^j\right)} - F^{-1}\left(z_i^j\right) e^{\lambda F\left(z_i^j\right)} + F^{-1}\left(z_i^j\right)\right) dz_i^j \tag{5}$$

Proof: As $E_{u_{i,j}} = \left(M(i) - h\left(z_i^j\right)\right) P(win) \left(-h\left(z_i^j\right)\right)(1 - P(win))$, the optimal effort, $z_i^{j^*}$, of participants, is the optimal strategy in equilibrium. It is also the solution of $\max E_{u_{i,j}}$. The envelope theorem is applied to parameter z_i^j. When the expected r utility is maximized, then $\partial E_{u_{i,j}} / \partial z_i^j |z_i^j = z_i^{j^*} = 0$, yielding the solution,

$$h'\left(z_i^{j^*}\right) = M(i) e^{-\lambda} F^{-1}\left(z_i^{j^*}\right) F'\left(z_i^{j^*}\right) \times \left(\lambda e^{\lambda F\left(z_i^{j^*}\right)} - F^{-1}\left(z_i^{j^*}\right) e^{\lambda F\left(z_i^{j^*}\right)} + F^{-1}\left(z_i^{j^*}\right)\right) \tag{6}$$

Owing to the personal minimum effort, $\underline{z_i^j}$, we consider that the current ego give up competition (i.e., $\mathrm{h}\left(\underline{z_i^j}\right) = 0$ if no other competitions). Then,

$$\begin{cases} h'\left(z_i^{j^*}\right) = M(i) e^{-\lambda} F^{-1}\left(z_i^{j^*}\right) F'\left(z_i^{j^*}\right) \\ \quad \left(\lambda e^{\lambda F\left(z_i^j\right)} - F^{-1}\left(z_i^j\right) e^{\lambda F\left(z_i^j\right)} + F^{-1}\left(z_i^j\right)\right) dz_i^j \\ h\left(z_i^j\right) = 0 \end{cases} \tag{7}$$

with the solutions,

$$h\left(z_i^{j^*}\right) = \int_{\underline{z_i}^j}^{z_i^j} M(i) e^{-\lambda} F^{-1}\left(z_i^j\right) F'\left(z_i^j\right) \times \left(\lambda e^{\lambda F\left(z_i^j\right)} - F^{-1}\left(z_i^j\right) e^{\lambda F\left(z_i^j\right)} + F^{-1}\left(z_i^j\right)\right) dz_i^j$$

Here, the prize function, $\mathrm{M}(i)$, is the reward gained by the ego if it succeeds in winning the common alter. It is defined as

$$M(i) = (|KL(p_i || p_i + q_t)|)\, k = (|p_i \log(p_i / p_i + q_t)|)\, k \tag{8}$$

where k is the reward for the contribution, p_i and q_t are the contributions of ego i and common alter t, respectively. Further details on $\mathrm{M}(i)$ will be provided in Subsections III.B. and III.C. Thus, the function of $\mathrm{h}\left(z_i^{j^*}\right)$ can be defined as

$$\begin{aligned} h\left(z_i^{j^*}\right) &= \int_0^{(|p_i \log p_i/(p_i+1)|)k} m e^{-\lambda} F^{-1}(m) F'(m) \times \left(\lambda e^{\lambda F(m)} - F^{-1}(m) e^{\lambda F(m)} + F^{-1}(m)\right) dm \\ &= \int_0^{|p_i \log p_i/(p_i+1)|k} e^{-\lambda} \left[(\lambda - T/m) e^{m\lambda/T} + T/m\right] dm, \\ \mathrm{T} &= |\mathrm{n} \log n / (n+1)|\, \mathrm{k}, \end{aligned} \tag{9}$$

where $m \in M(\cdot) \,|\, \{0, |p_i \log p_i / (p_i + 1)|k\}$, a valuation of bidders' rewards for common alter. $F(m)$ is the distribution function of m, satisfying the uniform distribution in $0\sim T$. Here, N is the total number of participants.

We then obtain the optimal effort of each competitive ego. According to the auction rules, only the ego having given maximum effort wins the common alter. Thus, we can obtain the final propagation alter set of an ego.

B. EFFECTIVE CONTRIBUTION

The key of propagation-based IPIM is selecting an appropriate propagation direction to shrink the SFT searching space. An effective contribution is proposed to evaluate the ability of nodes in the propagation alter set to find the target. Integrating with the "effective contribution", we can obtain the appropriate propagation nodes and choose an optimal diffusion path to reach the target more efficiency. "Effective contribution" consists of two indicators of propagation effectiveness and propagation contribution. Specifically, propagation effectiveness is used to predict the probability that an ego can activate its alter. The propagation contribution is used to evaluate the distance between a node and the target.

1) PROPAGATION EFFECTIVENESS

Our mechanism considers a graph for each ego network, $\mathrm{G} = <\mathrm{I}, \mathrm{J}, \mathrm{R}>$, where I is the set of egos and J is the set of propagation alters. R represents not only the direct links between egos and alters, but also the edge of effectiveness propagation between them. Propagation effectiveness is defined as follows.

Definition 2: A soft parameter, $\theta_{ij} \in [0, 1]$, is used to measure the propagation effectiveness between ego i and alter j. It is defined as the probability that j receives information and is willing to continue propagation:

$$Pr\left(S_{ij} = s|\theta_{ij}\right) = \left(\theta_{ij}\right)^s \left(1 - \theta_{ij}\right)^{1-s} \tag{10}$$

Each ego, $i \in I$, has a set of alters, with whom information can be directly exchanged. We denote the information transferred from i to j as $s_{ij} \in \{0, 1\}$, which initialize with a random value. According to Definition 2, which is a Bernoulli distribution parameter, we can calculate the posterior distribution, $\mathrm{p}\left(\theta_{ij}|S_{ij} = s\right)$, by Bayes' rule:

$$p\left(\theta_{ij}|S_{ij} = s\right) \propto Pr\left(S_{ij} = s|\theta_{ij}\right) * p\left(\theta_{ij}\right) \tag{11}$$

Because the Beta distribution is the conjugate prior of the Bernoulli distribution, the posterior becomes Beta

$(a_{i0}+1, b_{i0})$ if $S_{ij}=1$ or Beta $(a_{i0}, b_{i0}+1)$ if $S_{ij}=0$. Thus, if alter j successfully receives and propagates information, r_1, from ego node i of 1 or r_0 of 0, the posterior will become

$$p\left(\theta_{ij} \mid s_i\right) = Beta\left(a_i^0 + r_i^1, b_i^0 + r_i^0\right) \quad (12)$$

This yields the propagation effectiveness between the ego and any of its associated alters in the ego network. We qualify information propagation from node i to j as effective only when θ_{ij} reaches a certain threshold. For the winning alter, j, we obtain $\theta_{ij}=1$.

2) PROPAGATION CONTRIBUTION

The propagation contribution of a node can be quantified as the distance between the target and its IPIM. It represents the possibility of finding the target on that particular node. In practice, the alters in the propagation alter set of an ego contribute variably to propagation and thus bring different rewards to the ego. To evaluate the propagation contribution of alters, in accordance with the PeopleRank concept [24], we use node out-degree to characterize nodes as important when they are linked to many other nodes. Meanwhile, there is a heightened probability of two people being acquainted if they have one or more other acquaintances in common [25]. Similarity indicates the group of nodes depending upon common contacts or interests that can be measured by the ratio of common links (e.g., contact, interest, and neighbors) between individuals [26]. The higher the similarity shared by a node and the target, the more opportunities they have to encounter. We therefore evaluate the node contribution in a 2-dimensional perspective, defined by the node out-degree and similarity. These quantities constitute a 2-dimensional coordinate space, the points in which represent the distance from a node to the target. This method is ContributionRank, and the contribution of a node is thus given by

$$CR(i) = (1 - sim(i, tar)) + sim(i, tar) \sum\nolimits_{j \in J} (CR(j) / |J|) \quad (13)$$

where i ∈ I are the propagation nodes, J is the set of alters of i, and $sim(i, tar) \in [0, 1]$, is the attribute similarity between i and the target, which can be derived by the following intersection operation.

$$sim(i, tar) = \frac{|att(i) \cap att(tar)|}{|att(tar)|} \quad (14)$$

$att(\cdot)$ represents the set of node attributes, and the numerator equals the number of common attributes between node i and the target.

Based on the ContributionRank method, another parameter, $\vartheta_j \in [0, 1]$, is introduced to quantify the contribution of propagation alters. We divide ϑ_j into 5 levels as, [0,0.2), [0.2,0.4), [0.4-0.6), [0.6,0.8), and [0.8,1], in order of increasing likelihood of an alter to achieve the target, reflecting the likelihood of the reward that can be gained by the ego. Considering individual rationality, the propagation cost incurred by an ego should be less than the reward. We define the alter bringing $c \cdot k$ reward, correspond to level c($c = 1, 2, \ldots, 5$), the propagation cost is q, as a constant. ($k > q$)

Similarly, the contribution, ϑ_j, is a multinomial distribution, drawn from a known Beta prior distribution. Assuming θ_{ij} and ϑ_j are independent, the prior joint distribution is the product of two Beta distributions. Thus, for a given alter j taken from the propagation alter set, the posterior distribution can be calculated using Bayes' rule:

$$p\left(\theta_{ij}, \vartheta_j | S_{ij} = s\right) \propto Pr\left(S_{ij} = s \mid \theta_{ij}, \vartheta_j\right) p\left(\theta_{ij}, \vartheta_j\right) \quad (15)$$

The distribution parameters, θ_{ij} and ϑ_j, are updated by the approximation method. With the prior distributions of θ_{ij} and ϑ_j being Beta(a_{ij}, b_{ij}) and Beta(c_j, d_j), respectively, the joint posterior distribution conditioned on the observed $S_{ij} = s$ is approximated by the product of two independent Beta distributions with modified parameters.

The values of $a_{ij}(s)$, $b_{ij}(s)$, $c_j(s)$, and $d_j(s)$ are calculated using historical interactive data, by setting the multiple moments of θ_{ij} and ϑ_j equal in the true posterior, p $\left(\theta_{ij}, \vartheta_j | S_{ij} = s\right)$, and its approximation.

Thus, for any node, we define the propagation effectiveness and the propagation contribution as the two propagation indices, which are both means for calculating rewards.

C. PROPAGATION UTILITY

In an ego network, the propagation utility of the ego is based on the number of alters it can activate and how much contribution they make. The alter can also be the ego in its own ego network and activate its alters to gain the reward. The more alters it activates, the higher utility it brings and greater reward it gets. The node utility is defined as follows.

Definition 3: (Node Utility) The node utility is defined as the Kullback–Leibler divergence between the initial and final distributions of the propagation contribution in the whole network.

$$u(i, r)\{j\} = E_{S_{ij}} \left| KL\left(p^{r-1}\left(\theta_{ij}, \vartheta_i\right) || p^r\left(\theta_{ij}, \vartheta_j\right)\right) \right| \quad (16)$$

where r represents the propagation hop for the current ego, such that r-1 is the previous hop, for which the current ego network has not yet added. The Kullback–Leibler divergence between two distributions, corresponding to the states before and after the ego propagate to alters, represent the utility of this ego to help find the target.

Suppose that, in the current ego network hop, r, the distribution of θ_{ij} and ϑ_j is $p^r\left(\theta_{ij}, \vartheta_j\right) = Beta\left(a_{ij}, b_{ij}\right) * Beta\left(c_j, d_j\right)$. Node j is an alter in iteration, r-1, and becomes the ego in hop r. When the current ego, successfully propagates information to its alters, the ego is included in the r-1 network. By assessing each alter in the private propagation alter set, we obtain a new ego network, for which the distribution of contribution is influenced by the newly added alters. Obviously, this influence is brought by the current ego, because alters are added according to this new ego. Thus, we use relative entropy to calculate this distribution difference. It can be interpreted as measuring the propagation utility of the current ego. In Subsection III.B., we define k as being the reward obtained for a unit contribution level. The total reward, R (i), gained by the current ego, i, and the total cost of platform, C (p), can therefore be calculated as

$$\begin{cases} R(i) = k * \sum_{j=1}^{m} u(i, r)\{j\}, \\ C(p) = \sum_{i=1}^{N} R(i) \end{cases} \tag{17}$$

where m is the size of the set of propagation alters for ego i.

N is the total number of participants in the network.

IV. MECHANISM ANALYSIS

Usually, the incentive mechanism must satisfy the following Characteristics [27].

1. Truthfulness. Owing to selfishness, nodes strategically determine their efforts to maximize their own utility, hindering the platform from finding the target with lower payments. To maximize utility, a node will disclose its effort truthfully.
2. Individual Rationality. To incentivize nodes to participate in information propagation, their costs must be covered by the reward, satisfying individual rationality.
3. Budget Feasibility. Budget feasibility guarantees that the mechanism can be implemented in practice while satisfying the basic requirement.

We proved that our mechanism guarantees truthfulness, individual rationality, and budget feasibility.

A. TRUTHFULNESS

The mechanism is truthful only if truthful node's reward is greater than or equal to that of the untruthful node. In our mechanism, only if each node does its best to propagate information to its alters will it create more utility. Moreover, the propagation alter set of our mechanism is truthful if and only if the winning ego allocation is monotonic, and each winning ego is paid the threshold payment [27].

Lemma 3: If the ego, i, pays effort z_{i1}^{j}, making i become a winner, i pays effort $z_{ik}^{j}\left(z_{ik}^{j} > z_{i1}^{j}\right)$ and is still the winner.

Proof: Assume that the ego set is $I = \{1, 2, \ldots\ldots n\}$. The degree of effort of the ego, i, is $z_{i*}^{j} = \left\{z_{i1}^{j}, z_{i2}^{j}, \ldots, z_{in}^{j}\right\}$. Because of the allocation strategy, it always chooses the hardest player as the winner $= z_{1,n}^{j}$. If i is the winner, then $z_{i1}^{j} > z$ where $z \in \left\{z_{x}^{j} \mid x = 1, 2, \ldots n \text{ and } x \neq i\right\}$; if i pays effort z_{ik}^{j}, i will also be the winner, because $z_{i*}^{j} > z_{i1}^{j} > z$.

Lemma 4: Each winner pays its best effort.

Proof: Let each ego know the reward function, M (i),to become a winner and maximize its own profit. It will pay the best effort.

Let z_{ik}^{j} be the best effort, $z_{ik}^{j} = \underset{z_{ix}^{j} \in Z_{i*}^{j}}{arg\ max}\left\{E_u\left(z_i^j\right)\right\}$. Consider the following two situations.

Case 1: If ego i pays effort $z_{ik'}^{j}\left(z_{ik'}^{j} < z_{ik}^{j}\right)$ according to the allocation strategy, and $z_{ik'}^{j} < z_{lk}^{j} < z_{ik}$, then ego l becomes the winner and ego i loses the opportunity to become a winner.

Case 2: If ego i pays effort $z_{ik'}^{j}\left(z_{ik'}^{j} > z_{ik}^{j}\right)$ and $z_{ik'}^{j} > z$, then i will be a winner, and i is still a winner after paying effort, z_{ik}^{j}. According to the utility function, $u_i^j = M(i) - s_{ij}h\left(z_i^j\right)$, the utility of paying $z_{ik'}^{j}$ and z_{ik}^{j} are, respectively, $u_i^{j'} = M(i) - s_{ij}h\left(z_{ik'}^{j}\right)$ and $u_i = M(i) - s_{ij}h\left(z_{ik}^{j}\right)$. As h $\left(z_i^j\right) \propto z_i^j$, and M (i) remains unchanged, then $u_i^{j'} < u_i^j$.

Thus, ego i will pay its best effort in the competition, and our mechanism satisfies truthfulness.

B. INDIVIDUAL RATIONALITY

The utility of a node should be nonnegative to satisfy its individual rationality, such that is its reward, R (i), will be equal or greater than its propagation cost, q (i).

For a propagator, i, we can regard its utility calculated by two parts. In the all-pay auction, it may get M (i) if it wins. During propagation, if it propagates to its alters, it will get a utility of L (i). In our mechanism, the sum of M (i) and L (i) is the total utility. In an all-pay auction, there are three cases of propagator.

Case 1: When propagator i calculates utility $M(i) - h\left(z_i^j\right) \leq 0$ before the auction, according to the optimal effort, propagator i quits the auction.

Case 2: If it is not the winner, it is probably caused by weak risk aversion, the most common type in real life, not a restrictive assumption. Thus, it accepts utility $-h\left(z_i^j\right)$ when it does not win the auction.

Case 3: If it wins the competition, the utility is $M(i) - h\left(z_i^j\right) > 0$.

In the above three cases, individual rational is expressed in the auction process.

Similar to propagation, for the intrinsic of propagator i, we have defined that the lowest reward of per contribution is k, which is higher than its propagation cost q. For a node, i, it will obtain the utility of $(k - q) * \Delta Con$, where ΔCon is its effective contribution. Thus, our mechanism expresses individual rational.

C. BUDGET FEASIBILITY

In our mechanism, the budget of the platform can be expressed in terms of the sum of the reward of each propagator. Because we have defined that the reward of a propagator i as R (i) in (17), where m is the size of i's propagation alter set J, and

$$u_i = |KL[p_i||(p_i + q_i)]| = |p_i \log p_i / (p_i + q_i)| \tag{18}$$

The cost of the platform is u_p:

$$\begin{aligned} u_p &= \sum_{i=1}^{n} |KL[p_i||(p_i + q_i)]| \\ &= \sum_{i=1}^{n} |p_i \log p_i / (p_i + q_i)| \end{aligned} \tag{19}$$

where n is the number of propagators. Thus, there is a theorem that explains the budget feasibility of the platform.

Lemma 5: When the number of propagators reaches a certain amount in the whole network, the increasing degree of cost in platform will tend to be flat.

Proof: For a propagator, i, its utility is u_i, which is defined in (18), as $\partial_{ui}/\partial_{qi} > 0$, and the $\partial^2_{ui}/\partial^2_{qi} < 0$, the utility of propagator i, to the platform becomes a convex function. The consequential reward is provided by the platform and for propagator i, if it propagates to its alter j, letting j continues to propagate. The increasing utility of the network is Δu_{ij}, where u_{ij} represents the total contribution after i propagates to j. Given, if $\Delta u_{ij} < \Phi$, where Φ is a minimum value that tends to 0, then the utility will no longer increase for the whole network. Then, node j will not participate in propagation. Obviously, the propagation will be in a finite state over the whole network. Thus, the platform cost will be flat.

V. SIMULATIONS

Simulations are designed to evaluate the IPIM. First, because IPIM is mainly involved in promoting the active participation of the nodes, solving the SFT problem gets better. We use the public datasets provided by Stanford [28] to verify our incentive mechanism. Thus, with increased participation, the efficiency of solving the SFT problem grows even higher. Second, we construct an optimization objective function that combines multiple factors (positive and negative). Thus, we obtain the optimal effectiveness threshold for solving the SFT problem. This threshold is θ_{ij} we previously defined in Subsection III.B. to control the number of effective propagators. It is calculated using two different public data sets [29], [30]. Finally, on the basis of optimal threshold, we compare our mechanism to the PSI algorithm, described in a related work [6].

A. DATASET DESCRIPTION

To evaluate the impact of the propagation scale on solving the SFT problem, we analyze two datasets from Facebook and Google+, which are public social network datasets provided by Stanford [28]. The Facebook dataset consists of a whole social graph, including 10 ego networks. In Google+, the social graph consists of 132 ego networks. These networks are defined by lists of edges that connect pairs of anonymous user IDs.

We use two real and public social datasets to compare typical incentive mechanisms different from Facebook and Google+. They show interactive data among individuals, which is suitable for comparison. In a "communication-1 ego network" [29] or Data A, we find user interaction and evaluation information for their friends over a period of 18 months. "Facebook-like social network" [30] is Data B. Tables 1 and 2 show the properties of these datasets.

TABLE 1. Datasets of facebook and Google+.

Data Resources	Nodes	Edges	Inactive Nodes	Ego Networks	Property
Facebook	4039	88234	0	10	Undirecte
Google+	107614	57345	5343	132	Directed

TABLE 2. Datasets of two real social networks.

Data Resources	Nodes	Edges	Active Nodes	Ego Networks	Property
Data A	235	668	184	119	Directed
Data B	652134	1899	59835	1899	Directed

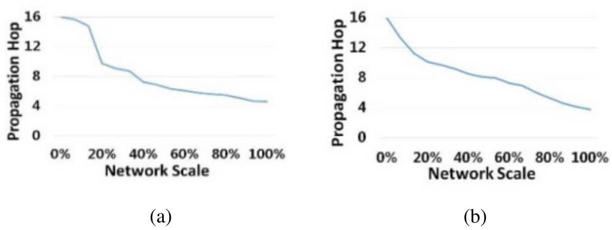


FIGURE 3. Influence on propagation hop with (a) Facebook and (b) Google+.

B. INFLUENCE OF PROPAGATION SCALE ON IPIM

The main purpose of IPIM is to incentivize people to propagate information to solve the SFT problem better. In theory, the more people who participate, the more likely it is to find the target. Therefore, to verify IPIM, we measure the efficiency of solving SFT problem with a participation or propagation scale as a parameter. Here, efficiency is embodied in propagation hops and success rates. A propagation hop indicates that the set of the propagation nodes should not only have high effectiveness contribution, but also a reduction of information propagation hops, thus reducing the finding time. The minimal number of propagation hops represents high speed and high efficiency of propagation to find the target. Success rate shows that we can successfully find the target via IPIM and reflect it in the form of a probability. For Facebook and Google+, we set the percentage of alters that each ego can propagate to as 5 %. Thus, it propagates 20 times over the whole scale of the network. To see clearly, we show the results by 20 % divisions in the figures.

1) INFLUENCE ON PROPAGATION HOP

Propagation hop is used to express the number of propagated ego networks from the initial node to the target, when the location is unknown, less hops means can find the target efficiently. In each dataset, we select an initial node (i.e., original information holder) randomly, and let it find the target. This node propagates information to its alters. Then, the alters propagate the information to more alters in multiple ego networks. Thus, the information repeats propagation until the target is found. We conduct 1,000 tests with different propagation scales and record the average of propagation hops as the final result.

Experimental results are shown in FIGURE 3. The average hops appear in the range of 4-16 for Facebook and in the range of 3-16 for Google+. Obviously, with the increasing number of propagators at the network scale, the hops become smaller and trends to steady, proving that the efficiency of SFT problem-solving gets higher.

2) INFLUENCE ON SUCCESS RATE

We count the total number of successes to find the target in each group of experiments. For each group, we also select the initial node randomly and begin with it to propagate to its alters. We test 1,000 times in each group and record the average success times as the result.

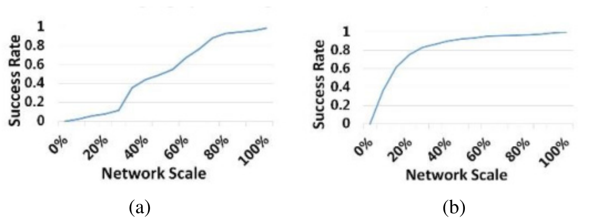


FIGURE 4. Influence on success rate with (a) Facebook and (b) Google+.

The results of the experiment are shown in FIGURE 4. The average success rate appears in the range of 0.050–0.987 for Facebook and in the range of 0.020–0.996 for Google+. Obviously, with the increase of the number of propagators, the success rate also increases, better solving the SFT problem.

With the increasing propagation scale, the target can be found faster with a higher success rate. Therefore, the design idea of IPIM, which promotes nodes' active participation, is effective.

C. INFLUENCE OF EFFECTIVE THRESHOLD ON SFT

In our mechanism, we propose a concept of propagation effectiveness and use the parameter, $\theta_{ij} \in [0, 1]$, to measure the propagation effectiveness between ego i and alter j. Only when the value of θ_{ij} reaches a certain threshold, θ_c, can we conclude that the information propagation between node i and j is effective. Thus, θ_c determines the number of alters to which each ego can propagate. It further determines the total number of propagators. Thus, a method is needed for determining a suitable threshold.

To get the optimal value of θ_c, we construct an optimization objective function, $\pi(\theta_c)$:

$$\pi(\theta_c) = \partial_1 f_1(\theta_c) - (1 - \partial_1) f_2(\theta_c). \tag{20}$$

Here, $f_1(\theta_c)$ represents positive factors of $\pi(\theta_c)$. Its value will increase with the increasing value of $f_1(\theta_c)$. Correspondingly, $f_2(\theta_c)$ represents negative factors of θ_c.∂_1 and $(1 - \partial_1)$ are their weights, respectively. If θ_c is the demand of evaluating the effectiveness of solving the SFT problem, concretely, $f_1(\theta_c)$ includes the factors of the number of propagation hops, the number of propagators, and the success rate. $f_2(\theta_c)$ can be the platform cost. Then, we analyze the relationship between θ_c and these factors. We show the result of Data B in FIGURE 5, because it covers more relationships than Data A. Thus, the result is more universal. Certainly, the results of Data A are consistent with data B results. We will not give details here. All results are obtained via data-fitting.

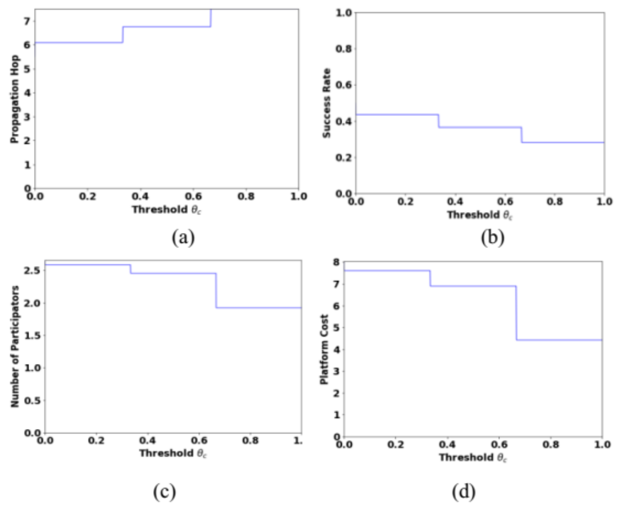


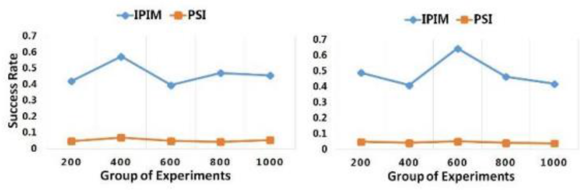
FIGURE 5. Relationship between factors and effectiveness threshold for Facebook-like social network.

From FIGURE 5, we can see that there is a positive correlation between propagation hop and θ_c. Additionally, there is a negative correlation between success rate, number of propagators, platform cost, and θ_c. Here, negative correlation means that the bigger the θ_c, the smaller the factor value. Positive correlation is just the opposite. Thus, we combine three negative factors and the only positive correlation factor in the same coordinate system. To balance the objective function, the intersection point of the two lines corresponds to the optimal threshold, θ_c^*, which best satisfies the demand of solving SFT.

With IPIM, the optimal threshold we obtained is 0.33. From FIGURE 5, the factors affecting solving the SFT problem are not very sensitive to the threshold, θ_c, There is no obvious change in the value of any factor in a threshold interval. Factor values do not change because of small changes in threshold. Therefore, the optimal threshold is scientific and effective in theory.

D. COMPARISON

Lastly, we compare the PSI [6] incentive mechanism, which de-fines an influence diffusion probability for each node instead of uniform probability and proposes formulation reward effects in terms of two factors: effort and benefit. We compare the participator scale of propagation information, where the propagation hops and the success rate are found in three data sets. These three indicators directly affect the efficiency of solving the SFT problem. The higher the success rate, the greater the number of participants and the better the efficiency. We test 1,000 groups in each data set. In each group, we test 100 times and record the average as a group result. To clearly show the results, we take 200 groups as a unit and record the average value as final. Thus, each point in the figures represents the average of the results

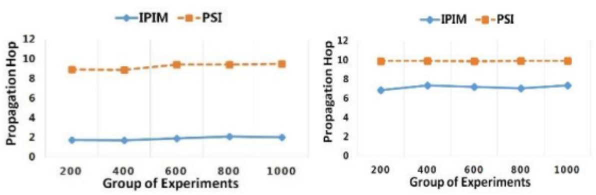


(a) (b)

FIGURE 6. Results of the success rate of IPIM and PSI in two datasets. (a) Data A. (b) Data B.

TABLE 3. Mean and variance of success rate of IPIM and PSI in two datasets.

Success Rate	(IPIM) Mean	(IPIM) Variance	(PSI) Mean	(PSI) Variance
Data A	0.5630	0.2464	0.0495	0.0090
Data B	0.4460	0.2473	0.0462	0.0093



(a) (b)

FIGURE 7. Results of the propagation hop of IPIM and PSI in two datasets. (a) Data A. (b) Data B.

TABLE 4. Mean and variance of propagation hop of IPIM and PSI in two datasets.

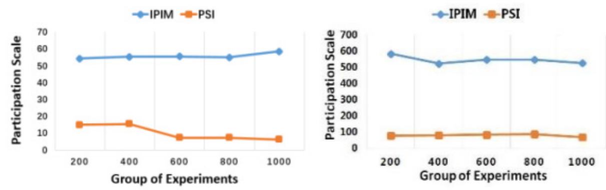
Propagation Hop	(IPIM) Mean	(IPIM) Variance	(PSI) Mean	(PSI) Variance
Data A	1.8746	0.4681	9.2502	0.8223
Data B	7.1720	10.3147	9.8865	0.0543

of 200 groups, and the value of each group is the average of the results of the 100 tests. Thus, the value of each point represents the average value of the 200 × 100 tests.

The results of the success rate comparison are shown in FIGURE 6. IPIM and PSI found the target in 563 and 50 groups, respectively, in the communication-1 ego network (Data A). In the 1,000 tests of Data B, IPIM and PSI found the target in 446 and 46 groups, respectively. The mean and variance of the two types of searches are listed in Table 3.

The results of propagation hops are shown in FIGURE 7. In Data A, the average hop of IPIM was from 2 to 4, whereas in PSI, it was from 8 to 10. In Data B, the average hop of IPIM as from 6 to 8, whereas in PSI, it was from 8 to 11. The mean and variance of the two types of searches are listed in Table 4.

The results of the participation scale are shown in FIGURE 8. From Data A, the average participation scale of the IPIM mainly appears in the range of 40-to-60, indicating the real number of participants propagating to find the target. Whereas, PSI mainly appears in the range of 0-to-20. The participation scale of IPIM is larger than PSI in two datasets. The mean and variance of the two types of searches are listed in Table 5.



(a) (b)

FIGURE 8. Results of the participation scale of IPIM and PSI in two datasets. (a) Data A. (b) Data B.

TABLE 5. Mean and variance of participation scale of IPIM and PSI in two datasets.

Participator Scale	(IPIM) Mean	(IPIM) Variance	(PSI) Mean	(PSI) Variance
Data A	55.6119	11.5187	10.1198	4.3746
Data B	546.7554	1775.7140	80.4937	2982.841

From the table, the success rate is 11.37 times higher in the IPIM search, rather than PSI in data A. It is 9.65 times higher in Data B. This result indicates that the IPIM performs better than PSI in terms of success rate. Nevertheless, IPIM frequently fails to find the target. For example, it fails in 437 groups on Data A and in 554 groups on Data B. Two reasons for this failure are the control of propagation effectiveness and the selection of inactive nodes for propagation. Both datasets have inactive nodes, and when information is propagated to only these nodes in a certain hop, information will stop diffusing. Thus, the IPIM and PSI searches all fail under such conditions. This scenario explains the emergence of failures in certain groups of IPIM experiments. In terms of the mean value, the IPIM takes fewer hops to find the target than the PSI approach, thereby reducing hops 79.73 times in Data A and 27.46 times in Data B. Comparing experiments, the IPIM better measures node effectiveness to propagation and selects the most appropriate nodes, thus reducing hops. In IPIM, hops taken are generally much smaller than in PSI, but cases still exist where hops in IPIM are close to those in the PSI approach. Such large differences between these cases and the average adds to the variance of IPIM.

Statistics indicate that the participation scale is larger by 449.54% (Data A) and 579.28% (Data B) in IPIM than in PSI. Therefore, we can conclude that IPIM is better than PSI in terms of participation scale. Thus, IPIM has a stronger incentive impact on the SFT problem than PSI. Under the same propagation conditions, IPIM propagates to more individuals faster, thus enhancing the efficiency of SFT problem solving.

VI. CONCLUSION

In this paper, we proposed an effective contribution-driven IPIM, which exploits ego networks to overcome the SFT problem. First, we used an all-pay auction to determine the propagation alters of each ego. Based on this, we proposed a novel algorithm, NPU, to evaluate nodal propagation rewards according to their effective contributions. This enabled us to provide propagation direction to the target instead of propagating randomly with low efficiency. Theoretical analysis and simulation results indicated that the IPIM guaranteed truthfulness, individual rationality, and budget feasibility. Finally, we verified the effectiveness of our mechanism using public social network datasets. Compared with typical algorithms, our results showed that our mechanism was more advantageous in solving the SFT problem.

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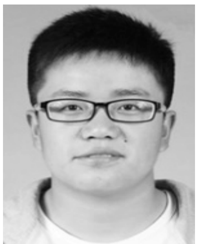

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