Establishing Cooperation in Highly-Connected Networks Using Altruistic Agents

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***Abstract*—This paper addresses the importance and challenges of establishing cooperation among self-interested agents in multiagent systems (MAS). We study MAS operating on highly-connected random and scale-free (SF) networks. However, we emphasize SF networks as these are prevalent in society and nature. Existing imitation-based approaches for cooperation have been shown to not fare very well in these highly-connected networks. Motivated by studies that show the advantage of altruistic privacy buddies in online social networks to provide better privacy guarantees in highly-connected networks, we present a stochastic influencer altruistic agent (StIAA) mechanism for cooperation. In StIAA, a small proportion of altruistic agents which irrespective of their payoff, always cooperate with their neighbors are introduced into a network of self-interested agents that try to maximize their payoff by imitating the wealthiest agents in their neighborhood. To determine optimality of their action choices, the self-interested agents imitate the cooperative action of their altruistic neighbors (should there be one) with a small exploration probability. We show, both analytically and experimentally, that StIAA leads to significantly higher cooperation in highly-connected networks than the existing imitation-based approaches. We also conduct a comprehensive study on the performance of StIAA and the results indicate that it is both robust and scalable.**

I. Introduction

One of the enduring challenges in networked multiagent systems (MAS) is to establish cooperation among the self-interested agents for achieving a common goal [1], [2], [3], [4]. Traditionally, the Prisoner's Dilemma (PD) game has been used as an abstract interaction model to capture the tension between the personal and social goals of these agents. Some simple imitation based approaches have been shown to enhance the likelihood of cooperation when the agent interaction is constrained by the underlying network topology such as scale-free (SF) networks [5], [6]. In SF networks the node degree follows power-law distribution independent of the scale of the network, a feature suitable for large-scale MAS. Also the SF structure is robust against self mutation and environmental perturbation. It is observed that many real-world SF networks, such as social networks, are highly-connected exhibiting large average connectivity [7], [8], [9]. For instance, the average connectivity of a node in the Facebook network is reported to be 190 [10]. It has been shown that imitation based rules (e.g., *imitate-best-neighbor (IB)* [1] and *stochastic imitate-random-neighbor (SA)* [5][1]) that facilitate cooperation in random networks and *sparsely-connected* SF networks (average degree is 4) are unable to establish cooperation in highly-connected SF networks [11]. Also, there exists a strong theoretical argument based on natural selection showing that high-connectivity among the nodes in SF networks results in diminished or no cooperation [12]. However there are many instances where it is critical to establish cooperation in highly-connected networks. For example, achieving consensus among the online social network (OSN) application users about acceptable privacy settings for individual applications is a key challenge [13].

In OSNs such as in Facebook (highly-connected SF network), while self-interested agents always try to optimize privacy setting policies of the third-party applications, it has been shown [13] that the existence of special agents (altruistic agents) who act as privacy buddies (or self-deployed policy-recommender forums) [14] with better knowledge about the app functionalities and requested permissions help provide better privacy guarantees. We use this idea to motivate our solution approach where a small percent of agents behave as altruistic agents (those who always cooperate) work towards biasing the self-interested agents to converge to a consensus that optimizes privacy settings of the entire network. In this paper, we describe our multiagent-based solution approach to establish distributed cooperation in the user community. The central research question we address is: *how to establish cooperation in MAS operating on highly-connected SF networks?*

We propose the design of a heterogeneous MAS composed of both the altruistic and self-interested agents and show that it performs significantly better in *highly-connected* SF networks. Our stochastic influencer altruistic agent (StIAA) mechanism is motivated by a novel definition of *cooperation* [15] in which the otherwise competing agents decide to aid each other. Our goal is to determine the conditions under which such cooperation thrives. In other words, we try to bias the self-interested behavior of the agents to make them cooperate with each other. To do this, we introduce a small proportion of altruistic agents in a self-interested society (similar to the influencer agents

[1]Henceforth these two approaches are referred as IB and SA respectively.

in [16], [17]). The altruistic agents are designed to always cooperate with their neighbors while the self-interested agents may cooperate or defect since their objective is to maximize their utility by imitating the strategy of the wealthiest agents in their neighborhood. However, since agents in SF networks typically only have partial-observability of their environment (access only to information about immediate neighborhood), it is possible that the self-interested agents may get stuck in a local maxima. Therefore, we enable these agents to determine the optimality of their strategies by stochastically trying the strategy of the altruistic agents in their neighborhood with a small exploration probability [2]. By manipulating the self-interested behavior of the large majority of the population, the altruistic agents are able to facilitate cooperation. We analytically show that this probabilistic exploration creates a cluster of cooperators in SF networks that helps to foster the evolution of cooperation. Our comprehensive empirical study substantiates this claim.

Previously altruistic agents were used in the context of coordination game [16], [17] whereas in this work we use the notion of altruism to solve a cooperation game. Both games are structured as 2-person 2-choice symmetric games to model the common problem of social norm emergence from a game-theoretic perspective [18]. While coordination game is suitable to model *conventional norm* problems (no conflict in interest between the individual and collective interests), cooperation game is used to model *essential norm* emergence problems in which conflict exists between agent's self-interest and collective interest [19]. We believe the cooperation game studied in this paper captures more complex multiagent interactions.

Exploration in the strategy space is a standard approach in evolutionary game theory which alone is unable to solve the cooperation problem. Similarly it has been shown that network reciprocity by itself is not sufficient to guarantee cooperation [20]. We propose a novel and ingenious mechanism that uses limited altruism, exploration in strategy space and network reciprocity in an innovative way to solve the complex problem of cooperation in highly-connected SF networks.

By maintaining cooperation, the altruistic agents try to influence their neighbors to cooperate. We show that cooperation thrives when at most one neighbor of each altruistic agent reciprocate them in each iteration. To make this applicable to real world settings, these reciprocator agents are chosen stochastically. More specifically, we don't require the entire agent society to reciprocate the few altruistic agents which could be very expensive. Instead, only some of them should stochastically reciprocate their altruistic neighbors (should there be one) for a short duration (current round of the PD game) while the majority follow the imitation-based rule. We analytically show that this limited amount of "network reciprocity" [1] creates a cluster of cooperators in SF networks that helps to evolve cooperation. We show this through a comprehensive empirical study.

In summary, we hypothesize that cooperation could emerge and be sustained in self-interested networked societies with the help of only handful of altruistic agents, and that it does not necessarily require the concerted effort of the entire society. The main contributions of this paper are:

- Proposing a heterogeneous system design approach that is composed of a large majority of self-interested agents and a small proportion of influencer altruistic agents.
- Showing both analytically and experimentally that our approach performs significantly better than the baseline imitation based approaches in promoting cooperation in highly-connected SF networks.
- Demonstrating the robustness and scalability of StIAA.

The remainder of this paper is organized as following. First, we discuss the relevant literature in the Section II. Then we present our proposed StIAA mechanism in Section III followed by an extensive computational study in Section IV. Finally, Section V presents conclusion with a summary of our observations and discussion of future work.

II. Related Works

Two imitation based approaches has been shown to evolve cooperation in a society of self-interested agents when the interaction of the agents has a network structure. In [1] the memoryless agents use the *imitate-best-neighbor* (IB) action update rule while playing repeated PD game with their neighbors in a two-dimensional grid. According to this deterministic rule, each agent imitates the action of the wealthiest agent (including itself) in the next round. It has been shown that cooperation evolves over a wide range of payoff parameters and the final fraction of cooperators is independent of the initial fraction. In [5], agents use the *stochastic imitate-random-neighbor* (SA) action update rule to facilitate cooperation in moderately-connected SF networks. According to this stochastic imitation rule, for each agent i one neighbor j is chosen randomly. Then if j's payoff is larger than i's payoff, i imitates j's strategy with a probability. SA increases the final fraction of cooperators with the heterogeneity of the degrees. However, both of these state-of-the-art imitation based approaches fail to facilitate cooperation in highly-connected SF networks [11].

One significant approach towards solving the cooperation problem in **highly-connected** SF networks used the evolution of social network of interactions as well as the evolution of strategies [21]. These two evolutions follow different time-scales and it has been shown how this variation could affect the process of cooperation evolution. However, the cost of link rewiring is not included in the payoff calculation of the agents.

Another study presented in [2] used a single coalition emergence approach for achieving full cooperation in a MAS. They developed a centralized leader based coalition formulation model over complex networks where the agents pay an amount of tax to their leaders in order to join a coalition. They have shown that their distributed information sharing consensus mechanism effectively reduces the tax rate imposed by the leader. However, both the leader tax collection and information sharing require maintenance of network wide multi-hop communication which would incur overhead cost. Moreover, they do not investigate the variation of topological features and its impact on their algorithm.

A network growth model based on an evolutionary preferential attachment algorithm is pursued in [22]. The fitness of each node is defined as proportional to the accrued payoff from the PD game. New nodes are preferentially linked with the high fitness existing nodes and play the PD game with its neighbors accordingly. The resultant network is shown to be heterogeneous with the SF property. This work provides a useful understanding about how the microscopic dynamics could lead to the coevolution of the structure and the macroscopic behavior of the SF network. However, the emergence of *full cooperation* seems to be impossible if the payoff for the temptation to defect is larger than the payoff for the reward.

Commitment based approaches have been used to facilitate the emergence of cooperation [3], [4]. In [3], agents interactions are captured using a non-iterated PD game. This work is based on an unstructured population with random interactions among the agents that use a social learning model and mutation for strategy adaptation.

A parallel thread of research involves studies by physicists on the issue of cooperative behavior among selfish agents over complex networks in the framework of evolutionary game theory. It has been shown in [23] that the growth and preferential attachment rule of the SF network significantly enhance the cooperative behavior. An investigation on the effect of high clustering to enhance cooperation over the SF network is provided in [24].

The use of influencer altruistic agents in our approach is inspired by some previous works [16], [17]. They addressed the problem of forming a social convention while we address the cooperation problem. Also these works used a small number of inflexible "influencer-like" agents and agent interactions are modeled using coordination games.

Although most of the works on the evolution of cooperation underscore the importance of the SF degree-distribution in promoting cooperation, their investigation is limited only to the low-connectivity SF networks domain (except [21]). On the other hand, we try to establish cooperation in SF networks that exhibit higher connectivity. Moreover, unlike these works, our proposed MAS is composed of heterogenous agents that include both the self-interested and altruistic agents.

III. Stochastic Influencer Altruistic Agent (StIAA) Mechanism

In this section we present our proposed Stochastic Influencer Altruistic Agent (StIAA) mechanism.

A. The Interaction Model

The agent interactions in the MAS are purely local and are constrained by an undirected SF graph $G(V, E)$ where V is the set of vertices (or nodes) and $E \subseteq V$ x V is the set of edges. Each node corresponds to an agent[2]. The numbers of nodes are referred by n. Once the graph or the network is formed by the agents it becomes fixed. Two nodes v_i and v_j are neighbors if $(v_i, v_j) \in E$. The neighborhood $N(i)$ is the set of nodes adjacent to v_i. That is, $N(i) = \{v_j | (v_i, v_j)\} \in E \subset V$ and $|N(i)|$ is the degree of node v_i. The adjacent agents (within single-hop distance) are defined as the *neighbors*. The SF graph is generated using the Barabasi-Albert model [25].

[2]Throughout the paper, we use agent and node interchangeably.

B. The Cooperation Game

The agent interactions in the MAS are purely local and are constrained by an undirected SF graph. The agent interactions are captured by a *2-person* Prisoner's Dilemma (PD) game. Every agent is equipped to play this game with each one of its neighbors and their interactions are represented by the network links. The agents start playing the PD game after the network is formed and we consider the final network as a closed system.

Agent i's payoff is denoted by $u(i, j)$ which agent i obtains by playing a PD game with its neighbor j. After every round of the game, the payoff received by playing the PD game with the neighbors gets accumulated and the accumulated payoff is defined as $\sum_{j=1}^{m} u(i, j)$, where j refers to the neighbors of i. In each round of the game agents use a fixed strategy for all of its neighbors, which is either to cooperate (C) or to defect (D). In a *2-person* PD game setting these two strategies intersect at four possible outcomes represented by designated payoffs: R (reward) and P (punishment) are the payoffs for mutual cooperation and defection, respectively, whereas S (sucker) and T (temptation) are the payoffs for cooperation by one player and defection by the other. The payoff matrix is represented by Table I. For the PD game, the payoffs satisfy the condition $T > R > P > S$ and for iterated PD's we require $T + S < 2R$.

Similar to the previous approaches, such as [5] and [1], we assume that agents are able to access the state of the immediate previous round from their neighbors. The state information include accumulated payoff and the action. These information is provided by the neighbors upon agents' request. We also assume that the communication channel is error-free. Since the agent communication is limited only within their local neighborhood, we do not consider the cost associated with their communication.

TABLE I
Payoff Matrix for the Prisoner's Dilemma Game

	C	D
C	(R,R)	(S,T)
D	(T,S)	(P,P)

Agent Types: The heterogeneous agent society is composed of two types of agents: (i) rational self-interested agents (SIAs) that always try to maximize their payoff and (ii) influencer altruistic agents (IAAs) that always cooperate with their neighbors.

C. Stochastic Influencer Altruistic Agent (StIAA) Mechanism

The large majority of the agents in our proposed MAS are self-interested, and therefore, they try to maximize their payoff by using the IB action update rule. According to this rule, each agent imitates the action of the wealthiest agent (including itself) in the next round. We introduce a small proportion of influencer altruistic agents at random locations that always cooperate with their neighbors. The idea of influencer agents is inspired by the influencer fixed strategy agents in [17], [16]. These IAAs broadcast their presence in their neighborhood to motivate the SIAs to reciprocate them. As mentioned earlier, the rational SIAs that increase their payoff by always adopting the action of their wealthiest neighbors may get stuck into local maxima due to partial observability of their network. Therefore, we enable them to determine the optimality of their action choice (pareto-optimality) by trying the action of their neighbor IAAs with a small exploration probability $p_{explore}$.

In the following, we provide an analytical argument on why the proposed StIAA mechanism performs better in SF networks.

D. Analytical Discussion on StIAA's Performance in SF Networks

In SF networks, due to the degree-heterogeneity, some agents have high-degree connectivity while the majority of the agents have low-degree connectivity. As a consequence, the high-degree nodes or the hubs always reap higher accumulated payoffs as compared to their low-degree neighbors. If the majority of the neighbors of a hub node are cooperators, then it generates high payoff by cooperating but even higher payoff by defecting. Let us consider two hubs which are cooperator and defector (h_C & h_D) respectively. Since initially cooperators and defectors are distributed uniformly in the network, these hubs should have approximately equal number of cooperator (n_C) and defector (n_D) neighbors, i.e., $n_C \simeq n_D \simeq z/2$, where z is the average node degree of the hub. Therefore, the accumulated payoffs (ACP) of the two hubs should be: $ACP(h_C) = n_C * R + n_D * S \simeq z/2 * (R + S)$ and $ACP(h_D) = n_C * T + n_D * P \simeq z/2 * (T + P)$. Since $T + P > R + S$, the fitness of the defector hubs would be larger than that of the cooperator hubs. This is the reason why defection prevails when solely the imitation based strategies are pursued.

However, irrespective of the strategies adopted by the hubs, their accumulated payoffs are always greater than their low-degree neighbors. Let us consider a low-degree neighbor of a hub that may act as a cooperator (k_C) or a defector (k_D), and its accumulated payoff is $z_1/2 * (R + S)$ (when it cooperates) or $z_1/2 * (T + P)$ (when it defects), where z_1 is the average degree of this node. In SF networks, since the average degree of the hubs are much larger than the that of the low-degree nodes, i.e. $z >> z_1$, $ACP(h_C)$ or $ACP(h_D)$ is always larger than $ACP(k_C)$ or $ACP(k_D)$.

Previously it has been shown that when the agents follow the IB or SA state update rule, the behavior of the high-degree nodes or the hubs determine the asymptotic state of the network [11]. A defecting hub can lead its imitating neighbors towards defection. We find a remedy to this problem in a mechanism called "network reciprocity" that is able to resist or eliminate the invasion of the defectors [1]. According to this mechanism, if the cooperators are able to form clusters in which they mutually help each other, then cooperation evolves and sustains in the network. We now discuss how our StIAA based approach increases the likelihood of the hubs to form clusters of cooperators and thereby facilitates cooperation.

In StIAA, the influencer altruistic agents (IAAs) persuade their neighbors to cooperate. According to StIAA, the defector hubs that follow the IB state update rule may at some stage explore and reciprocate the strategy of its IAA neighbor. After becoming cooperators hubs would incur highest accumulated payoff as compared to their low-degree neighbors and thus would influence them to adopt its current action of cooperation. The hubs are interconnected due to the *age-correlation* among the nodes in the Barabasi-Albert model of SF networks. At one time-step of the iterative game it is possible that multiple interconnected hubs adopt (through exploration) the cooperative action of the IAAs in their neighborhood in the current round and thereby could lead the entire network towards evolving cooperation.

We use a small SF network as depicted in Figure 1 to illustrate this phenomenon. In (a) all agents are self-interested (SIAs) except one IAA. In the current round three SIA's act as defectors while one SIA cooperates. The accumulated payoff of the hub would be the largest (2T+2P) in its neighborhood and therefore its neighbors would adopt its defection strategy in the next round leading the network towards a defection state. The IAA alone is not able to resist this invasion of the defectors. However, since the SIAs try the action of their IAA neighbor with a small exploration probability, the hub may adopt the cooperative action of the IAA in one time-step as in (b). Again its accumulated payoff would be the largest and, as a consequence, its SIA neighbors would adopt its cooperation strategy. Thereby the entire network would evolve into a cooperation state in (c). However, it is important to note that if one of the neighbors of the hub (other than the IAA) is another hub that has adopted the action of defection, the cooperative hub may imitate its action and the network would turn into all-defectors. To resolve this problem both the hubs need to explore the action of the IAA in the current round. Our simulation results indicate that this indeed happens in one of the time-steps as the network uses many iterations to finally converge into a majority cooperative state.

E. Algorithm for StIAA Mechanism

Algorithm 1 describes our StIAA mechanism. Initially the strategies (Cooperate or Defect) are randomly assigned among the agents and the IAAs are randomly selected; then agents play the PD game with their neighbors and compute the accumulated payoffs (Lines 1.4 - 1.13). Then (Lines 1.6 - 1.13) the SIAs try the action of their IAA neighbor with a small probability $p_{explore}$. Otherwise the SIAs update their strategies according to the IB action update rule. This process repeats (Lines 1.4 - 1.15) over multiple rounds and leads the network into a cooperation state. Since the updating of the actions depend on the local neighborhood, we implement *synchronous update* in which the entire society updates their

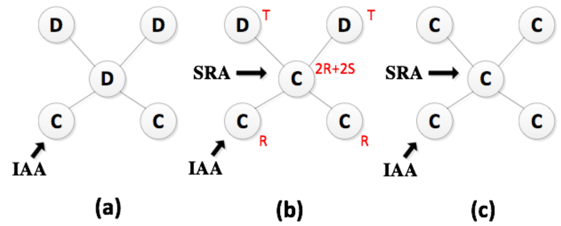


Fig. 1. **StIAA facilitating cooperation in a SF network:** (a) One influencer altruistic agent (IAA) and four self-interested agents (SIA) of which three SIAs, including the hub, behave as defectors; (b) based on payoff differentials, the hub SIA might try IAA's cooperation strategy and act as a stochastic reciprocator agent (SRA) (c) all of the SIAs adopt the cooperation strategy of the hub SRA by following the imitate-best-neighbor (IB) state update rule.

Algorithm 1: Stochastic Influencer Altruistic Agent (StIAA) Mechanism

```
    Require: Accumulated payoff is transparent only to the
             neighbors
1.1  begin
1.2      randomStrategySelection()
1.3      randomIAAselection()
1.4      playPDGamewithNeighbors()
1.5      computeAccumulatedPayoff()
1.6      for each agent i:= 1 to n do
1.7          r ← randomDouble()
1.8          if r < p_explore AND neighborOfSIA(i)==IAA
             then
1.9              i reciprocates the IAA
1.10         else
1.11             i follows the IB rule
1.12         end
1.13
1.14     end
1.15 end
1.16 iterate (Lines 1.4 - 1.13)
```

states simultaneously in discrete time-steps that gives rise to a discrete-time macro-level dynamics.

IV. Simulation and Results Analysis

We conduct simulations with the following goals: (i) compare the performance of our proposed StIAA mechanism to two state-of-the-art imitation based approaches, e.g., IB and SA and then (ii) perform a comprehensive empirical study on the performance of StIAA by varying the percentage of the initial number of cooperators, percentage of IAAs and the temptation payoff values.

A. Network Topology

The agents are situated on a connected topology that constrains the communications to the immediate neighbor set. An edge between two nodes of the network indicates that the agents interact and play the PD game.

The experiments are conducted on SF topologies of varying average degrees. In addition to this, we study the performance of StIAA in random networks (RNs) as compared to the performance of the IB and SA action update rules over RNs.

The SF topologies are generated using the Barabasi-Albert model. The minimum node degree is varied from 1 to 25 such that average node degree z lies between 2 to 50.

The random networks (RNs) are generated first by adding a random node with every node in the network. This ensures that no node is isolated. Then we add links between two randomly selected nodes. The number of these randomly added links is varied to create networks with varying z in the range of 2 to 50.

B. Simulation Setup

Our network consists of 1000 agents represented as nodes in both the SF and random networks. **A majority cooperation state (MCS) is defined as the one in which 90% or more agents cooperate with each other** [26]. In order to investigate the scalability of StIAA, we conduct experiments on 5000 agents SF networks as well.

The IAAs maintain their cooperation strategy during the course of the simulation. These agents not only behave altruistically (being always cooperative), but also try to influence their neighborhood agents to become altruistic (cooperative). We consider only 5% IAAs to be the approximate upper bound (the same reported in [16]). For most of our experiments we maintain this value. However, this number is varied within the range of 1% to 7% to observe how it affects the performance of StIAA. Similar to [2], the exploration probability $p_{explore}$ is set to 0.05. However, for higher connectivity networks, this value is increased to 0.1 for getting better performance.

The following values for the PD payoff matrix are used in the simulations: R = 1, P = 0.1 and S = 0. Hence, the incentive to defect, T, is restricted to $1 < T < 2$. For most of our experiments we use the value 1.1 for the temptation payoff. However, this value is varied within the range 1.1 to 1.9 to investigate its effect on the performance of StIAA.

All the results reported are averages over 100 realizations for each network. Each simulation consists of 10,000 time-steps where a time-step refers to a single run of Algorithm 1.

C. Simulation Results

Comparison of the Existing Imitation based Approaches with StIAA: Figure 2(a) and 2(b) show the performance of the IB, SA and StIAA for various average degree random and SF networks respectively. The network size is limited to 1000 agents. For each average degree category we created 100 network instances and used the three approaches to observe the process of evolution of cooperation. In SF networks, when the average degree is smaller (z in the range of 4 to 5), the SA performs better than the IB. However, as the average degree increases, both IB and SA fail to establish MCS. A similar pattern can be observed in random networks in which larger average degree result in increasingly less or no cooperation.

In sparse SF and random networks ($z \approx 2$), the StIAA does not converge into MCS (as also observed in case of IB and SA). However, for average degree between 4 to 30, StIAA converges to MCS in almost all instances with $p_{explore}$ set to 0.05. However, when the average degree lies in the range of 40 to 50, this low value of $p_{explore}$ does not lead to MCS. Our results indicate that by increasing this value to 0.1, the likelihood of cooperation in these highly-connected SF networks can be significantly increased.

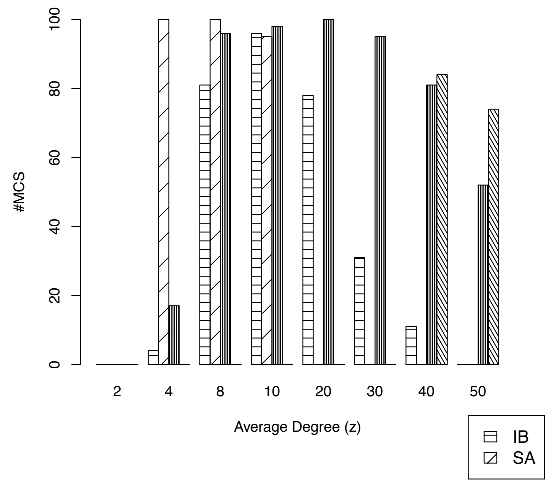
The performance of the StIAA in random networks is not as good as in SF networks. The main reason for this relatively poor performance is that RNs do not have the benefit of skewed degree-distribution. In SF networks, because of age-correlation among the hub nodes, StIAA facilitates the formation of clusters of cooperators that help to evolve cooperation. On the other hand, unlike SF networks, in random networks the degree of the nodes are not very large nor are they intricately connected. As a consequence, clusters of cooperators are less likely to be formed. However, StIAA significantly outperforms IB and SA in random networks.

D. Empirical Analysis of StIAA

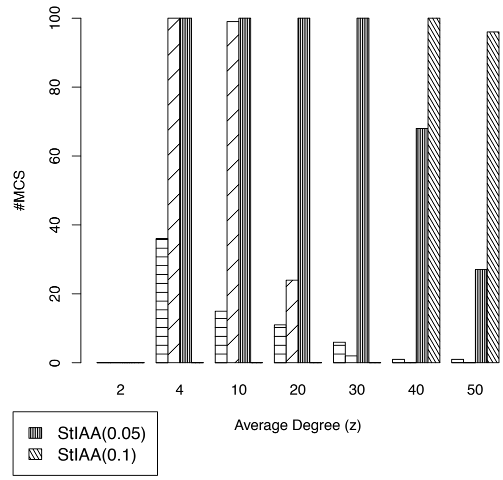
In order to perform a comprehensive analysis of the performance of StIAA mechanism in SF networks, we vary the following parameters: (a) percentage of the initial number of cooperators (%Coopp), (b) temptation payoff values (T) and (c) percentage of the IAAs (%IAA).

Variation of % of Initial Cooperators: Table II shows the effect of the variation of the initial percentage of cooperators for various levels of the temptation payoff values. First, consider the situation when the temptation payoff value is set to 1.1 (columns 3, 6, and 9). The results indicate that when the initial percentage of cooperator is very low (10%), even in the most highly-connected networks ($40 < z < 50$) likelihood of cooperation is high. For example, in networks with $z \approx 50$, exploration probability of 1.1 establishes cooperation in 72% instances. With the increase in the percentage of initial cooperators, as in 30% and 50% cooperator networks, MCS occurs 90% and 96% times respectively. Therefore, it appears that the variation in the percentage of initial cooperators does not affect the cooperation evolution process very much when temptation payoff is as low as 1.1. StIAA is able to evolve cooperation even if the initial fraction of cooperators is very small (e.g., 10%). Therefore, it is **robust** against the perturbation in the number of cooperators and can transform a majority defector society into a cooperative one.

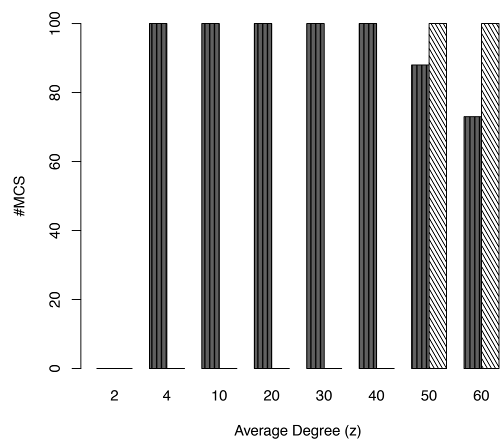
Variation of Temptation Payoff: However, when the temptation payoff increases beyond 1.1, even with 50% initial cooperators the network does not evolve towards cooperation (columns 10 and 11) in very large neighborhoods (where z is approx. $40 \sim 50$). In other words, the performance of StIAA is sensitive to the payoff value of temptation. We may need to increase both the IAAs and exploration probability to facilitate cooperation where benefit of temptation is high.



(a) RN Network



(b) SF Network (Small)



(c) SF Network (Large)

Fig. 2. Plot of average degree (z) vs. number of times each mechanism successfully converges into a majority cooperation state (#MCS) over 100 simulations; temptation payoff=1.1, initial cooperators=50%, IAA=5%.

TABLE II

EFFECT OF THE VARIATION OF VARIOUS PARAMETERS IN 1000 AGENTS SF NETWORKS. FOR EACH VARIATION, THE TABLE SHOWS THE NUMBER OF TIMES THE NETWORK SUCCESSFULLY CONVERGES INTO A MAJORITY COOPERATION STATE (#MCS) AMONG 100 SIMULATIONS. THE AVERAGE DEGREE IS ROUNDED TO THE NEAREST INTEGER VALUE.

		Variation of % of Cooperators & Temptation Payoff (T) (%IAA = 5)								
		%Coop=10			%Coop=30			%Coop=50		
		T=1.1	T=1.5	T=1.9	T=1.1	T=1.5	T=1.9	T=1.1	T=1.5	T=1.9
z	$p_{explore}$	#MCS	#MCS	#MCS	#MCS	#MCS	#MCS	#MCS	#MCS	#MCS
2	0.05	0	0	0	0	0	0	0	0	0
4	0.05	100	27	0	100	27	1	100	28	100
10	0.05	100	100	100	100	100	100	100	100	100
20	0.05	100	100	100	100	100	100	100	100	100
30	0.05	99	62	6	100	73	14	100	78	12
40	0.05	20	0	0	56	1	0	68	5	0
	0.1	100	54	1	100	68	3	100	67	3
50	0.05	0	0	0	7	0	0	27	0	0
	0.1	72	0	0	90	1	0	96	0	0

		Variation of % of IAAs (%Coop=50, T=1.1)		
		%IAA=1	%IAA=3	%IAA=7
z	$p_{explore}$	#MCS	#MCS	#MCS
2	0.05	0	0	0
4	0.05	99	100	100
10	0.05	97	100	100
20	0.05	68	100	100
30	0.05	29	89	100
40	0.05	19	29	92
	0.1	32	99	100
50	0.05	11	24	26
	0.1	21	52	100

Variation of % of IAAs: Columns 12-14 of Table II shows the effect of various percentage of IAAs for a fixed 50% initial cooperators and 1.1 temptation payoff value. It can be seen that for smaller density of IAA (1% to 3%) StIAA does not always converge into MCS beyond medium average connectivity networks (where $z > 20$). In case of 1% IAA the convergence scenario is not satisfactory when the average degree increases. Even with relatively large value of $p_{explore}$ (= 0.1), performance does not improve much. The improvement is not significant in case of 3% IAA. On the other hand, although 7% IAA provides better result, its difference with 5% IAA is not significant (columns 9 and 14). In other words, 5% IAA is a reasonably small number to maintain good performance. Therefore, we use this percentage as the **upper bound for the IAAs**.

Scalability of StIAA: In order to study the **scalability** of StIAA, we investigate its performance on 5000 agents SF networks with varying degrees within the range 2 to 60. Figure 2(c) shows that the performance of StIAA is even better than 1000 agents SF networks. For example, when the average neighborhood size becomes larger (such as when z is between 40 to 50), more than 80% times MCS occurs. We further increase the neighborhood size ($z \approx 60$), and observe that more than 70% instances StIAA converges into MCS. With an increased exploration rate ($p_{explore} = 0.1$), convergence rate is 100% even in very high average degree networks.

The Challenge of Sparse Networks: Figure 2 and Table II show the challenge of establishing cooperation in *sparse networks* (where $z \approx 2$). Neither IB and SA, nor StIAA perform well in these networks. Due to low-connectivity, many agents in these networks has only one neighbor. As a consequence, most of the time stochastic reciprocation approach fails to find neighbors that would reciprocate the IAAs. This makes the resistance of the defectors difficult and results in degraded performance of StIAA.

V. CONCLUSIONS AND FUTURE WORK

It this paper, we have presented a stochastic influencer altruistic agent (StIAA) mechanism that is able to establish cooperation in MAS operating on **highly-connected** RN and

SF networks. We introduced a small proportion of influencer altruistic agents (IAAs) in the self-interested society. The IAAs, irrespective of their payoff, always cooperate with their neighbors while the self-interested agents (SIAs) try to maximize their payoff by imitating the wealthiest agent in their neighborhood. In order to check the optimality of their actions, the SIAs try the cooperative action of their IAAs (should there be one) with a small exploration probability. We have conducted a comprehensive simulation on the performance of StIAA. Our main findings are as follows:

- StIAA performs significantly better in highly-connected RN and SF networks than the existing state-of-the-art IB and SA action update rules.
- We determine realistic upper bounds for the percentage of the IAAs (only 5%) to ensure cooperation.
- StIAA is **robust** as it is able to evolve cooperation in societies that initially has very small fraction of cooperators.
- At higher temptation payoff level, the network cannot resist defectors. We may need to increase both the IAAs and the exploration probability.
- StIAA is **scalable** in that increasing the size of the network does not degrade its performance.

We believe our IAA based approach would be appropriate for highly-connected OSNs where "privacy buddies" [13], [14] playing the role of influencer agents could establish and enhance cooperation.

In addition to this, we identify the problem of establishing cooperation in sparse networks (where average degree ≈ 2). As future work, we intend to address the cooperation problem in other network types ranging from sparse to large neighborhoods.

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