# Selfishness, Cooperation and Topology Dynamics in Networks

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***Abstract*—We study the dynamics of a network of agents (players) under two models settings. In the first model, players (agents) extend heterogeneous cooperation levels to their partners and in the second, perfectly rational and selfish agents engage in an iterated Snowdrift Game and the evolution of the system suggests that cooperation emerges and prevails even when no external rules or norms for punishing defectors are imposed. Agents base their decisions purely on local information and the network rewiring rules are such that agents pair-up with only recommended co-players (this rules assumes the reason of perfect rationality). A cyclical behavior in the number of cooperators is observed in the second setting which is dependent upon its information update model parameter denoting the number of proactive agents in the population. The randomness (cyclic behavior in the number of cooperators) is lost when the number of agents who update proactively is small. Our results from the second model show that inspite of not imposing any societal norms, cooperation was prevalent in a rational population. We also present the simulation results of our first model (asymmetric cooperation system) and comment on some intersting observations where some agents are happy being exploited and some others exploit their co-players by leveraging on their degree of connectivity.**

## I. Introduction

Emergence and persistence of cooperation has been a subject of keen scientific interest, both from an evolutionary and behavioral standpoint. The prevalence of cooperation in many oragnizational structures led to many studies in this area, which explain its abundance (and its control parameters) by partly-rational behavior of agents, reciprocity parameters and spatial constraints. The Iterated Prisoner's Dilemma game [1] is generally taken as a representative social dilemma game to analyze this behavior. With slight modifications to its payoff matrix, some other games like Snowdrift game have also been used to understand the emergence of cooperation. Games like these have a small bias towards cooperation, which is believed to reflect real-life scenarios, and help to understand how agents are responsible for their environment of operation by their perfect (imperfect) information sets.

Extensive work has been done in this regard on an adaptive-network setting (to reflect an interplay of behavior and neighborhod of players in a network) with respect to various social dilemma games under many action profiles, strategy spaces and other imitation/replicator dynamics involving unconditional cooperation or defection from each agent participating in the game. Players either follow a strategy to earn higher payoffs in the game by either imitating the action profiles of their highest earning neighbors or incorporate a preset behavior like Tit-for-Tat, Grim, Pavlov, Always Cooperate, Always Defect or any other complex behavior. In all the strategy spaces, it was assumed that players either cooperate or defect fully and can have no intermediate stage of lending partial cooperation to their co-players[52]. In this work, we propose two game models (much in the light of the work done in [52]) on adaptive networks: in the first model, players (agents) are free to choose their co-players and can extend various levels of cooperation to their partners heterogeneously. In our second model, the players (agents) are perfectly rational and selfish. Though operating on unconditional cooperate or defect action profiles, players get to choose their co-players based on their local information only and this model aims to show that no external rules (like imitation dynamics or strategy space selection) are necessary for cooperation to evolve in a population of selfish agents.

Our first model is based on continuous adaptive networks where players (agents) extend asymmetric cooperation levels to their partners, all the while reinforcing and sustaining advantageous collaborations in the network. Our second model is based on a selfish society with no norms and regulations (to punish defectors) and absence of a global entity to provide players with network-wide information of the game state. Players greedily act upon their local information and follow no preset strategies. We intend to show that cooperation can still emerge in a perfectly rational and selfish population. We wanted to study the implications of this idea and also the dynamics of the network where agents extend asymmetric cooperation to their chosen partners. The paper is structured as follows: Section II presents the literature review. Our proposed models are presented in section III. Section IV reports our findings and finally, section V summarizes our conclusions.

## II. Literature Survey

Cooperation lays the foundation to form any complex social system. This draws on an interesting aspect that in spite of high costs incurred by a cooperating entity (agent), cooperation is to be seen in abundance in many organizational networks. The first ever study to understand cooperation among agents was done by Axelrod and Hamilton[1]. They analyzed the Prisoners Dilemma [2] game among various agents (in an evolutionary setting) under the basis that interaction among any two entities occur on a probabilistic basis. However the Prisoner's Dilemma which advocates "non-cooperation" as the best strategy contrasted popular "altruistic" real world scenarios where cooperation was prevalent. This gave way to the study of games giving a somewhat better payoff to cooperators even when others defect, like the Snow Drift game to model social scenarios[7].

They also studied issues pertaining to direct reciprocity and the effect, in general, of reciprocity in an asocial setting on evolutionary stable strategies. Many studies followed suit to understand the evolution of cooperation [3], [4]. Various other mechanisms such as kin selection [30], indirect reciprocity [29] and group selection [28], [27] have been proposed to explain the persistence of cooperation in networks. It has been ascertained in [6], [5] that if agents are spatially distributed (defined in an abstract sense), then such space constrained interactions promote cooperation among them. However, for some classes of social dilemma games (like Snowdrift game), the spatial structure was found to inhibit evolution of cooperation [7]. This spatial structure was often modeled by complex networks with nodes denoting the participating agents and links denoting pairwise interactions [8], [9], [10]. These works drew some direct correlations between the evolution of cooperation and the topology of the network. But they had assumed that the underlying topology was static.

In real social networks, however, the interaction games are based upon the behavioral aspects of agents and links form and get dissolved continuously with time. The decisions (behavior) taken by agents thus get affected by the topology of the network, which itself is changing with agents' decisions. This shaping and reshaping of decisions by agents, which in turn define their operating environment, charactertizing the topology of their network (Adaptive Networks) was studied in [11], [12], [13], [14], [15]. In the presence of adverse ties, it was shown that emergence of cooperation is faster when there is a mutual benefit involved with long lasting interactions as opposed to those where one of the players gets exploited [16], [17].

In an evolutionary setting however, strategy selection also plays an important role and various replicator dynamics ('imitate the best' tactic being very popular) come into play wherein only the fittest of the lot are chosen to plan another round of the dilemma game, until a stable population is achieved. Here, to overcome this selection filter, agents try to imitate the strategies of ther highest-payoff earning neighbors [18], [19]. Under this coevolutionary dynamics, the strategy chosen by an agent will affect both its payoff and its chances of being selected as the model to imitate by its neighbors [21], [20].

With reference to the evolutionary game setting under complex networks, it was shown that in Iterated Prisoner's Dilemma game [24] and single-shot Prisoner's Dilemma games [22], [23], the evolution of cooperation is enhanced by discrete rewiring of links by agents [25], formation and dissolution of links [26] and addition of new agents [31].

A study on Prisoner's Dilemma Interactions on Graphs with High Girth [33] showed that such graphs had iteractions which led to emergence of cooperation, whereas it was seen that for graphs with many cycles of length 3 or 4, defection spread more rapidly. Another interesting study was on "Phase Transitions" [34] in which the players (nodes) actually change their payoff matrix as the game progresses based on the eigenvalues of the payoff matrix. However, another study [35] shows that asymmetric Prisoner's Dilemma games don't favor cooperation.

This network setting also falls under the area of Network Exchange theory and Bargaining Models. In this area, however, there is an additional constraint that nodes (players) can only have limited collaborations and hence have to forego some of their neighbors' deals (or ask for better offers from neighbors by threatening to get a deal from some other player). Also, the agents are considered myopic (act on local information sets). Many models [40], [41], [42], [43] have been presented to predict the agreement patterns of the players and how the total generated wealth be distributed among them. Tardos and Kleinberg [44] also proposed a theoretical characterization (unique exchange setting) to the bargaining model proposed by [45] with respect to graph matchings. These studies assume a linear payoff function and we wish to observe the cooperation trends under non-linear functions , where the utility gets saturated with increasing investments over time. Our study also differs partly from the coalitional game settings (Shapely value, cores, etc.) and bargaining sets. This assumes that players can form coalitions among themselves. However, under imperfect information setting, and to evade computational costs, we aim to model the network on the invitation-basis (players get invited by other players to form a collaborative link) where players decide upon their cooperation scale upon receiving an invitation. We also divide the total reward evenly among the participating entities, which is a special case of Proportional Bargaining Solution [47].

In our study, we chose to analyze the interactions based on the Snowdrift Game (SD) [51]. This game has been proposed as an alternative (in Evolutionary Biology, Economics and Sociology literature) to the Prisoner's Dilemma (PD) game to understand cooperation for two major reasons: one was out of biological interest (the Snowdrift Game is equivalent to the Hack-and-Dove game) and the other due to some difficulties in assessing proper payoffs in IPD. The major difference between these two games is that the sucker's payoff in PD game (cooperator confronting a defector) is the lowest; while in SD, both the defectors yield lowest payoffs. Hence, there is a slight bias towards cooperation in SD. In addition to the inhibition of cooperation (due to spatial structure) in Adaptive networks [53], low connection-diversity in scale free networks [54], phase transitions and hysteresis behavior [55], suboptimal connectivity-density [56] and non-resonance type phenomena [57], there are some additional factors which affect the emergence of cooperation. Some of these mechanisms (factors) are: variations in strategy transfer capacities of agents [59], cost of punishments and rewards [61], memory effects [58] and random noise [60].

While many interesting observations have been made (on the emergence and sustenance of cooperation) on adaptive networks, the action profiles (either mixed or pure) considered in the previous work maintain that an agent either lends its cooperation fully or defects completely [48], [49], [50]. There are many scenarios where such an assumption wipes out many real-life social networks out of the cooperation study picture. There are many instances where people try to distribute their time and resources among their interactive partners and there is no pure cooperation or defection involved. Agents can choose their level of cooperation with their partners and can update their strategies (here, once the decision to cooperate gets fixed, the strategy is to come up with an optimal investment/cost for the cooperative link). This decision of asymmetric cost bearing by an agent towards its collaborative partners involves various factors such as how is its payoff increasing with its increasing investment, how are its partners reciprocating to its decisions, when can it afford to be completely selfish (i.e incur zero cost) while its partners bear all the cost of their collaboration, etc.

## III. Models

### A. Asymmetric Cooperation Model

*1) Assumptions and Setup:* We consider $N = 100$ agents engaged in bilateral collaborations. In this setup, an agent $i$ invests some resources (signifying cost or time) $c_{ij}$ towards agent $j$ and reaps some benefit $B(c_{ij}, c_{ji})$, where $c_{ji}$ is the investment $j$ makes in collaboration with $i$. They both incur a cost $C$, which is a function of their respective investments. In our analysis, we assumed $B$ to be a sigmoidal function which yields out increasing benefits with increasing costs and flattens as the investments go above a certain limit. The cost function $C$ is assumed to be linear. Thus, the payoff agent $i$ obtains in collaboration with $j$ at a certain time step is given by:

$$P_{ij} = B(c_{ij}, c_{ji}) - C(c_{ij}) \tag{1}$$

where $B(c_{ij}, c_{ji}) = \frac{6(c_{ij}+c_{ji})}{3+\sqrt{1+(c_{ij}+c_{ji})^2}}$ and $C(c_{ij}) = c_{ij}$.

The above functional forms for Benefit and Cost functions capture the characteristics of real-world collaborations: inefficiency of small investments, flattening of benefits at high investments and the ever increasing costs. A random graph is initialized with agents participating in various collaborations simultaneously. Initial investments for each collaboration (for each agent) are drawn from a normal distribution with $\mu = 0.5$ and $\sigma = 0.01$.

We assume the investments to be non-negative and impose no further restrictions on them. Every agent is free to make different investments in different partnerships.

*2) System Dynamics:* To specify the dynamics of the network, each agent tries to maximize its payoff from a collaboration using a gradient optimization rule:

$$\Delta c_{ij} = \frac{\partial P_{ij}}{\partial c_{ij}} \tag{2}$$

Note that this selfish strategy followed by each agent already induces investment changes (link weights) and results in the network changes. However, blindly following the above rule simply results in a gradual climb to the maxima of the payoff function for each player's investment. To make the dynamics more realistic, the concept of cooperation and defection is introduced. Cooperation in this setup refers to following the gradient optimization rule. Defection refers to reducing the investment by $\Delta c_{ij}$ when $\Delta c_{ij} > 0$ and reducing investment by $3|\Delta c_{ij}|$ when $\Delta c_{ij} < 0$.

*3) Defection Index:* Defection as can be seen is both a dominant as well as rational strategy. However, if both players in a link continually defect, the result will simply be a uniform descent to 0 investment from both players. In order to defer such an event, an incentive for cooperation is provided by introducing a global metric called a *Defection Index*. Each player $i$ at the start has a Defection Index $DI_i$ of 0. As the game progresses, the defection index for a player is increased by $3|\Delta c_{ij}|$ whenever he defects and decreased by $|\Delta c_{ij}|$ whenever he cooperates.

The game progresses in generations and time-steps which are described in detail below. At the start of a generation, each player $i$ has a tuple of defection probabilities $< p_{ij} >$ where $p_{ij}$ represents the probability with which player $i$ defects with player $j$. Additionally, players start with a random initial investment per existing partnership as described earlier. Within a generation, there are time-steps which capture the sequence of cooperations and defections in the ascent to the maxima. The probabilities $< p_{ij} >$ don't change within a generation. A generation ends when all partnerships reach the maxima (this is guarenteed to happen for reasonable values for $p_{ij}$). When a generation ends, the players update their defection probabilities based on the global defection indices of other players by this update rule :

$$p_{ij} = \frac{DI_i}{2 < DI >}$$

where $DI_i$ refers to the Defection index of the $i_{th}$ player and $< DI >$ refers to the average defection index of all the players. The very first generation starts with $p_{ij} = 0.5$ for all the players. The interesting thing to note here is that in any generation, all players defect against a particular player with the same probability. So, a player making selfish choices for a subset of his links and accruing a high defection index gets penalized by all players in the subsequent generation.

*4) Link Rewiring:* After a generation ends, the players again start a new generation with random investments. One noticeable change is that the topology of the network may be considerably different from that of its previous generation. The new generation typically witnesses broken partnerships as well as possibly new partnerships. The rule for breaking links for a player $i$ in partnership with player $j$ is based on $i's$ investment ratio ($IR_i$) in the link which is the ratio of his investment in the link to the total investment in that link,

$$IR_i = \frac{c_{ij}}{c_{ij} + c_{ji}}.$$

$IR_i$ when greater than $i's\ tolerance$ value $t_i = 0.65 + 1/N_T d_i$ (where $d_i$ is the degree of player $i$ and $N_T$ is a heuristic constant) results in $i$ breaking his link with player $j$ for the next generation. Similarly, for adding links, we have a probability $p_{LINK}$ with which links are randomly added in each generation.

In the above course of investment coordination, some agents end up exploiting their co-players in some collaborations and/or get exploited by others. Since each agent has a threshold value to tolerate the extent to which they get are willing to be exploited and since players with high degrees can afford to reduce their investments a little, thereby pushing their partners to put in more money (or time) to sustain the link (collaboration). With such dynamics, we get to see some players (agents) reaping higher payoffs than their neighbors and some collaborations have been reduced to almost a 'no-reciprocation' state, where one agent contributes around $90\%$ of the total investment while its partner extends only $10\%$ of the remaining link weight.

### B. Selfish Society Model

*1) Assumptions and Setup:* We assume that all the players are perfectly rational and act only upon their local information. No global moderator keeps track of the payoff values for the players. Players also have a memory of last 10 time-steps (they can remember the payoff from their co-players for 10 timesteps). Each player (agent) tries to maximize his/her expected payoff in the next time step. The Snowdrift game (Table I shows the payoff matrix for the two-player version) is played iteratively. The expected payoff for the next time step by a player is calculated by w.r.t his/her co-player's previous action. The change in the neighborhood of player $i$ from time $t$ to $t+1$ is denoted as $N_i(t) \rightarrow N_i(t+1)$. This change in neighborhood can occur when agent $i$ cancels and/or adds some links. Every agent can atmost cancel $\alpha$ links and add atmost $\beta$ edges. The neighborhood of $i$ after cancellation (addition) of $\acute{\alpha} \leq \alpha$ ($\acute{\beta} \leq \beta$) edges is denoted by $N_i^{\acute{\alpha}}(N_i^{\acute{\beta}})$. $P_i$ denotes the payoff of agent $i$.

| Player $i$ / Player $j$ | Cooperate | Defect |
|---|---|---|
| Cooperate | 1 | $1-r$ |
| Defect | $1+r$ | 0 |

TABLE I
PAYOFF MATRIX FOR A TWO-PLAYER SNOWDRIFT GAME WHERE $0 < r < 1$. ANY FORM OF SNOWDRIFT GAME CAN BE REDUCED TO THIS VERSION. WE USED $r = 0.8$ IN OUR SIMULATIONS.

Players can form links with those who are only two edges away from them. This assumption stems from the fact that players would accept incoming links from cooperative players who are recommened by their neighbors. Thus, players who cooperate can only form new links with their next to nearest neighbors. To capture the responsiveness of players, only selected players can rewire their links (maximum of $\alpha + \beta$ link configurations are possible) and each player is selected with probability $P_{selection}$ in each time step. The game is initialized with $N = 100$ nodes on a random graph with linking probability 0.1. Every player's state is randomly initialized either to cooperate or defect.

*2) System Dynamics:* To determine the action in the next time step, each player estimates his expected payoff using his neighborhood information as follows: since agent $i$ can form atmost $\beta$ links, it chooses its highest earning neighbor ($j$ as shown in the figure). To estimate the additional payoff ($P_i^{additional}$) he earns when he forms $\beta$ edges, it subtracts the payoff he earned from his and $j$'s common neighbors from $j$'s payoff to calculate how much profit $j$ is obtaining from uncommon neighbors. It then multiplies this value with the fraction $\frac{\beta}{N_{uncommon}}$, where $N_{uncommon}$ is the number of uncommon neighbors for $i$ and $j$.

$$P_i^{additional} = (P_j - P_i^{N_{common}})\frac{\beta}{N_{uncommon}} \quad (3)$$

$P_i^{N_{common}}$ denotes the payoff $i$ obtained from the common neighbors of $i$ and $j$. Thus at time step $t$, agent $i$ updates its action and neighborhood with probability $P_{selection}$. Once chosen to update, $i$ calculates its expected payoff in case of cooperation as

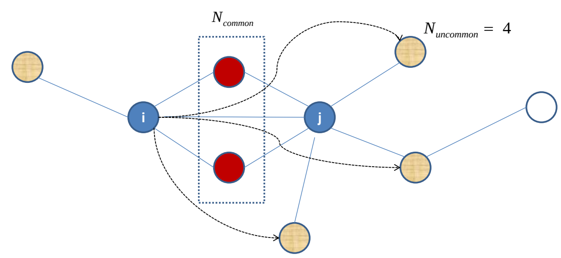


Fig. 1. Illustrating the neighborhoods of $i$ and $j$ at a certain time step. The players have 2 neighbors in common.

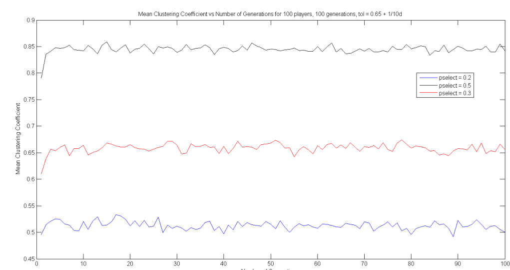


Fig. 2. Mean Clustering Coefficient for different values of $P_{LINK}$.

$$P^{cooperate}(t+1) = P_i^{additional}(t) + P_i^{N_i + N_i^{\acute{\beta}} - N_i^{\acute{\alpha}}} \quad (4)$$

and in case of defection as

$$P^{defect}(t+1) = P_i^{N_i - N_i^{\acute{\alpha}}} \quad (5)$$

where, $P_i^{N_i} + N_i^{\acute{\beta}} - N_i^{\acute{\alpha}}$ denotes the payoff of $i$ when it cooperates with its neighbors after deleting $\acute{\alpha}$ edges and adding $\acute{\beta}$ edges and $P_i^{N_i - N_i^{\acute{\alpha}}}$ denotes the payoff $i$ gets upon defecting with its neighbors after deleting $\acute{\alpha}$ edges. Agent $i$ defects in the next time step if $P^{defect}(t+1) \geq P^{cooperate}(t+1)$ and cooperates otherwise. If they both are equal, then it chooses to cooperate or defect randomly.

This sequence is performed simultaneously by all agents who have been selected for the update at time step $t$. Upon updating their neighborhood and actions for the next time step, the sequence is repeated again.

## IV. RESULTS AND DISCUSSION

### A. Asymmetric Cooperation Model

Figures 2 and 3 show the clustering coefficients and mean degree with varying $P_{LINK}$ values for 100 players over 100 generations of a particular simulation. Both mean degree and clustering coefficient increase with $P_{LINK}$.

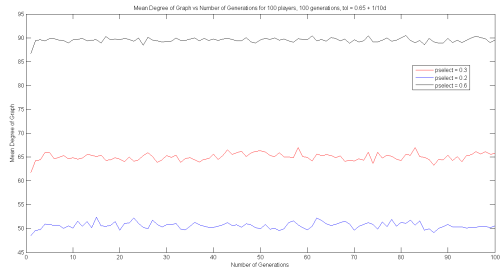

Fig. 3. Mean Degree for different values of $P_{LINK}$.

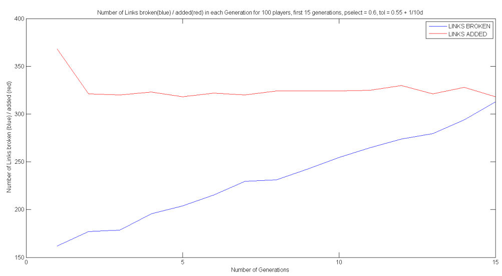

Fig. 4. Number of Links Broken/Added Post Stabilization (16-100 generations).

Figures 5 and 4 are the most interesting in terms of the Asymmetric model. These represent how the edges break and add over as generations progress. Since the random graph was initialized with a linking probability of 0.2, the network is initially sparse. However, the linking probability for adding edges over generations is $p_{LINK} = 0.6$ due to which the network starts becoming dense. Since the tolerance for each player is inversely proportional to their degree, players are reluctant to break many links in the initial generations (first 15). This is indeed the case for small real-world companies which have an initial desire to grow and acquire lots of partners without being eclectic. However, as players earn a decent degree distribution, the number of links broken roughly matches the number of links added. Moreover, since a player doesn't reform a link which he recently broke, this means that the links being added are all different from links being broken. This is

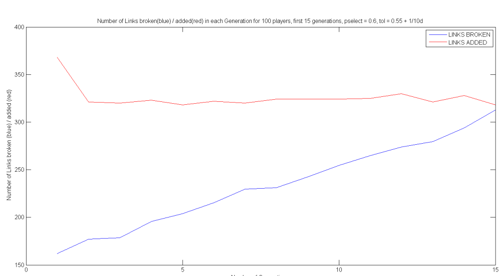

Fig. 5. Number of Links Broken/Added during Stabilization (first 15 generations).

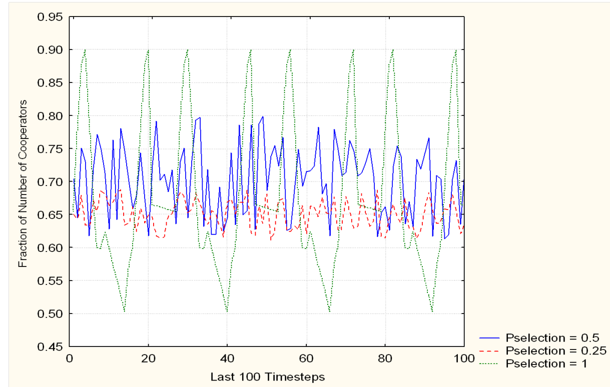


Fig. 6. Fraction of cooperators in the network for different values of $P_{selection}$. The regularity along the time series increases with $P_{selection}$

an interesting observation since the network has an equilibrium edge density but with rapidly varying topology which mimics real-world scenarios.

## *B. Selfish Society Model*

Figure 6 shows the time series of the fraction of cooperators with varying $P_{selection}$ values for the last 100 steps of a particular simulation. In each of our simulations, every agent can make atmost $\alpha + \beta$ link configurations where $\alpha = \beta = 6$. As can be seen, oscillations with high amplitude occur for high values of $P_{selection}$ and the oscillations dampen with decreasing $P_{selection}$. For $P_{selection} = 1$, the network is highly mercurial where the rise of about $40\%$ (in the number of cooperators) of the system size is observed in the first 5 time steps. As shown in Figure 7, the average degree of the network also shows similar behavior.

The reason for this oscillatory behavior of the system could be explained as: in the states corresponding to low fraction of the number of cooperators, the average degree has been reduced to an exten which motivates the agents to build up links again. In instances where some agents got disconnected, we relinked all of them to a randomly chosen agent. In the states where the fraction of the cooperators is high, the number of links start to break since for a rational agent whose neighbors are consistently cooperating, it starts to defect. This agent will defect as soon as the payoff it obtains by defecting with its neighbors exceeds the payoff it gets when cooperating with agents after adding $\beta$ edges:

$$P_i^d > P_i^c + \beta P_i^{additional} \tag{6}$$

where $P_i^d$ is the payoff $i$ obtains upon defecting with its neighboors and $P_i^c$ is the payoff it gets upon cooperating with its neighbors.

With $\beta = 6$, the links being added in each time step is comparatively high and hence the network will reach the maximum average degree very fast. With low $\alpha$ and $\beta$ values, the amplitudes of the oscillations reduced. Looking at the rewiring probability $P_{selection}$, it captures the notion of the willingness of the agents to react to new information and make link configurations. By lowering its value, the oscillations in

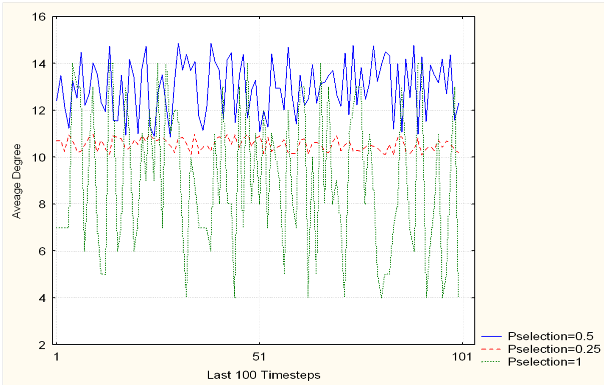


Fig. 7. Time-series of average degree of the network for different values of $P_{selection}$

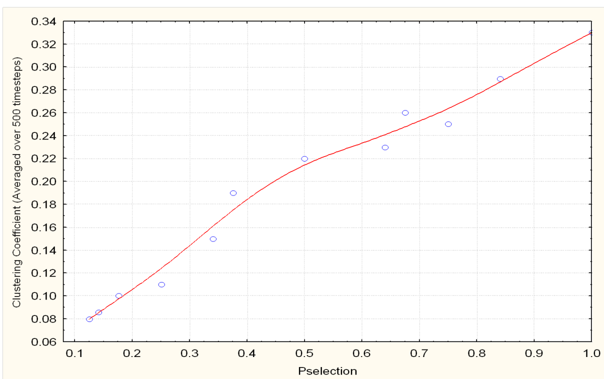


Fig. 8. Average values of the clustering coefficient for different values of $P_{selection}$

the number of cooperators and average degree get damped. Additionally, while lowering $P_{selection}$, the number of agents losing all their links also reduced accordingly suggesting the increasing stability of the network.

As for the dependence of number of cooperators in the network on $\alpha$ and $\beta$ values, it increased monotonically with increasing $\alpha$ and $\beta$ values. For $\alpha = \beta = 1$, the network presented a high degree of randomness with defectors dominating the whole population. We set $\alpha$ and $\beta$ values to be equal throughout our simulations. Figure 8 shows the average clustering coefficient of the network with varying values of $P_{selection}$. The $\alpha$ and $\beta$ values have been set to 6 in the simulation. Upon comparing some snapshots of the network with their equivalent random graphs shows that our network has higher clustering coefficients (an equivalent random graph can be obtained by calculating its linking probability from the number of edges of the network's snapshot; the expected clustering coefficient of a random graph is its linking probability). This observation can be easily explained as there is an additional mechanism to add more edges in our setting with the model parameter $\beta$ and suggests that our model illustrates a better cooperation sustaining network than an equivalent random graph.

## V. Conclusion

In this paper, we have proposed two models for the formation of asymmetric collaborative network of selfish agents (continuous adaptive networks) and an iterated Snowdrift game on an adaptive network involving selfish and perfectly rational agents whose decisions are based only upon their neighborhood information. Within this framework, some reasonable assumptions were made about agents' decisions inducing dynamics in the networks wherein cooperation is sustained in both the models and in particular, the levels of cooperation extended by agents in the first model increased with time. The degree of cooperation prevalent in both the systems relied heavily on the rewiring probability $P_{selection}$ and the nature of their payoffs. In the first model where we allowed agents to maintain different levels of cooperation, pevalence of high degree to investment coordination and cooperation extension can be seen as a precursor to a social norm. With limited information (and limited memory of 10 timesteps in the second model)in both the cases about the global nature of their networks, agents did coordinate to yield higher cooperation levels inspite of acting selfish and making rational decisions in every timestep. What goes beyond the presented work, but is worth the investigation is a study of similar cooperation-biased models under different benefit/cost functions with a quantitative discussion on their resource allocation strategies.

## VI. Acknowledgements

I would like to thank Venkataraman Santhanam (venkai@cs.umd.edu) for his valuable inputs and help in compiling the network metrics for the asymmetric-cooperation setting. I would also like to thank the authors of [52] for providing me the base for building my game model in examining the effect of selfishness of players on the network, at a global level. I am deeply thankful to Professor Aravind Srinivasan (srin@cs.umd.edu) and Professor Ashok Agrawala (agrawala@cs.umd.edu) for providing me with their insightful suggestions & several constructive discussions which helped me shape up this work.

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