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Meta-Sanctions Game on Complex Networks

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Abstract—Although incentive systems are effective for resolving social dilemmas, most studies consider interactions with no structures. This unnatural assumption is worth a loosen for dealing with real situations. Groupware, for example, is an effective form of media for knowledge sharing and active open communication. How should groupware in which vast amounts of beneficial content are provided and active discussion be designed? The behavior of information in such a medium resembles social dilemma games because users voluntarily post beneficial information that creates media values. Here, we show the evolution of cooperation in social dilemma games with incentive systems on networks. Our results reveal that spatial structures tend to prevent from promoting cooperative regimes and that a scale-free network can promote the cooperation while even a complete network cannot in specific parameters.

1. Introduction

Groupware is an effective form of media for knowledge sharing and active open communication. However, a player who participates in groupware has an incentive to free-ride on contributions of others whereas only beneficial information creates media value. Using public good game framework, cooperative behavior corresponds to providing beneficial contents on groupware, and non-cooperative behavior corresponds to not providing them. It is well-known that defective regimes are dominant in public good games. This theory suggests that actual groupware might provide incentives to encourage cooperative behaviors because they have appropriate contents. One of the effective systems to encourage cooperative behaviors in the public-goods game is meta-sanctions games. While Toriumi et al. [11] show that cooperative regimes are dominant in several meta-sanctions games, they assume that participants in a groupware play in a complete network. However, the relationships via an official or unofficial communication channels in a real groupware do not form such a complete network. Here, we deal with meta-sanctions games on several social networks and analyze an influence of such structures on the evolution of cooperation using agent-based simulations.

2. Related Works

Many researchers continue to focus on the evolution of cooperation in public-goods games. Some have granted sufficient ability to those playing public-goods games to remember their direct experiences [3] or indirect experiences [7] using tags [9] or reputation systems [8].

Other researchers [1] [6] have devised another sort of game that promotes cooperation by explicitly incentivizing players. Rewards and penalties are important incentives for the evolution of cooperation [2]. Galan [5] exposed the vulnerability of the meta-norms game proposed by Axelrod [1]. They demonstrated its dynamics with different types of selection mechanisms and concluded that meta-norms cannot be sustained in wide parameter spaces for long runs.

We address a meta-sanction game that integrates reward, punishment, meta-reward, and meta-punishment [10][4][11]. Using this game, we capture a bird's-eye view of the effect of meta-sanctions (rewards and punishments) on the evolution of cooperation.

3. Meta-Sanctions Games

3.1. Public-goods Games

Here, we defined cooperative behavior as C, and defective behavior as D. When users cooperate, they incur costs. Let κ_0 be the cost for C, let ρ_0 be the benefit for other users, and let N_0 be the number of other linked users who cooperated. For simplicity in our model, D users do nothing without any cost, and the other users get nothing. The payoff of the cooperators is represented as $-\kappa_0 + \rho_0 N_0$, and the expected payoff of the defectors is represented as $\rho_0 N_0$.

3.2. Generalized Meta-Sanction Games

A sanction system is a scheme that promotes cooperation in public-goods games. Rewarding cooperators and punishing non-cooperators are external incentives for players who cooperate in the games.

We employ a generalized meta-sanction game [10][4][11] as a generalized model of the sanctions in public-goods games. This scheme is an extension of Axelrod's meta-norms game [1] and devises not only punishments of defects but also the configurations of

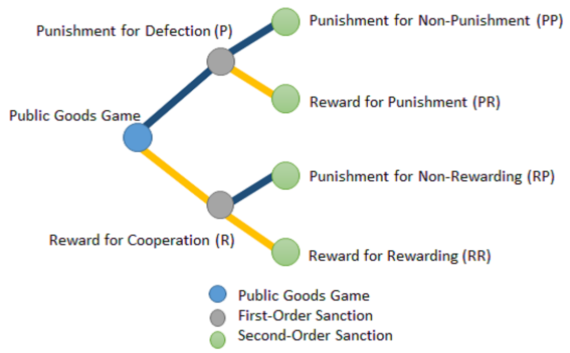

Figure 1: Meta-sanction game

meta-sanctions, including punishments and rewards. The original generalized meta-sanctions game do not employed network structures.

The following six systems are the sanctions in our meta-sanction game:

- Punishment of defectors (System P)
- Reward for cooperators (System R)
- Punishment of free-riders who punish defectors (System PP)
- Reward for punishers who punish defectors (System PR)
- Punishment of non-rewarding of cooperators (System RP)
- Reward for rewarders who compensate cooperators (System RR)

Since those who play meta-sanction games incur costs and accrue benefits for their actions, we set parameters. As mentioned in Section 3.1, a cooperator pays κ_0 in a public-goods game, and all of the connected players receive ρ_0. κ_1 is the cost when performing System P and the cost when performing System R. Likewise, κ_2 is the costs when performing Systems PP, PR, RP, and RR. The benefits of sanctions ρ_1, and ρ_2 are defined using the same rule. Since these costs and benefits include not only pecuniary matters but also psychological aspects, $\kappa_t < \rho_t$ is possible.

3.3. Basic Framework of Meta-Sanction Game

As shown in Fig. 1, a meta-sanction game has trilaminar parts that consist of the part of a public-goods game in which the player strategies are *defect* and *cooperate*. In a first-order sanction game, the player strategies are *punishing defectors* and *rewarding cooperators*. In part of a second-order sanction game, the player strategies are *punishing free-riders for using first-order sanctions* and *rewarding first-order sanction performers*.

We define all 25 possible configurations of meta-sanction games in Fig. 2. The name of the game type represents the system name of the deepest level of sanctions. System B is defined as a game with both Systems

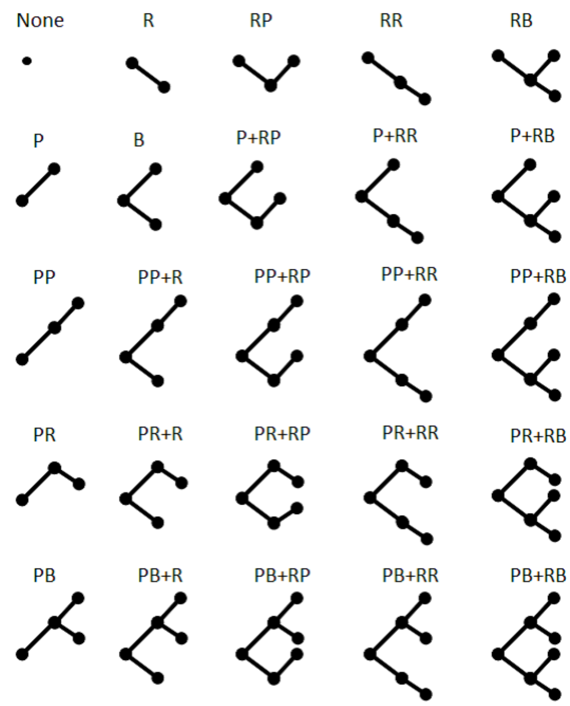

Figure 2: 25 possible configurations of meta-sanction games

P and R at the same level of sanctions. For example, the PB+R-type game has Systems P, R, PP, and PR.

3.4. Simulation Procedure

We set a model that consists of N agents as users in a groupware system. The simulation flow proceeded as follows:

1. **Public-goods game phase:** Each agent plays the public-goods game and either provides beneficial knowledge (cooperation=C) or does nothing (defect=D).
2. **First-order sanctions phase:** Each agent decides whether to perform first-order sanctions on the actions of all linked agents in the public-goods game phase.
3. **Second-order sanctions phase:** Each agent decides whether to perform second-order sanctions on the actions of all linked agents in the first-order sanction phase.
4. **Learning phase:** Each agent evolves his own strategy, as explained below.

Each agent repeatedly plays the meta-sanction game and evolves its own strategy to maximize profit in the learning phase. By analyzing our model, we clarified what types of game structures are likely to facilitate cooperation. See details in Toriumi et al.[11].

Table 1: Network Index

	Nodes	Links	L	C	r	R^2	γ
Complete Network	20	200	1.000	1.000	-	-	-
Random	168	1680	1.956	0.117	-0.020	0.020	-
Small World	168	1680	2.344	0.543	-0.018	0.153	-
BA	168	1625	2.003	0.227	-0.051	0.715	-1.652
CNN	168	1680	2.669	0.586	0.010	0.517	-0.554
Facebook Network[1]	168	1656	2.425	0.557	0.084	0.503	-0.597

Table 2: Payoff Parameters

$\rho_0 = 1.0$	$\kappa_0 = 1.0$
$\rho_1 = 0.5$	$\kappa_1 = 0.5$
$\rho_2 = 0.25$	$\kappa_1 = 0.25$

4. Meta-Sanctions Game on Complex Networks

In this paper, we consider the meta-sanctions games on complex networks as shown in Table 1 and reveal that network structures give an influence on the evolution of cooperation.

In Table 1, ”Node” represents the number of nodes, ”Links” represents the number of links, ”L” represents the average path lengths, ”C” represents the cluster coefficients, ”r” represents the assortativities, ”R^2” represents the power-law determination coefficients, and ”γ” represents the power indexes.

5. Simulation Results

Using an agent-based simulations, we perform the meta-sanctions games on six complex networks shown in Section 4. Table 2 shows payoff parameters of the model.

Figures 3 to 8, respectively, show the cooperation rates on a complex network, a random network, a small-world network, a BA network, a CNN network, and a Facebook network. On the one hand, cooperation regimes never emerge on the complex, random, regular, and small-world networks in a condition shown in Table 2. This is consistent with the result of Toriumi et al.[11]. On the other hand, our simulation reveals that cooperation regimes dominate on the BA, CNN, and Facebook networks. The latter networks have a common feature; their structures have a power law distribution. An important insight of our simulation is that a meta-sanctions game on a power law network can expect to reach cooperative regimes while it cannot on even a complete network.

6. Conclusion

In this paper, we test that the cooperation rates depend on the network structure in a meta-sanctions game. As a result, a meta-sanctions game on a power law network has a path to cooperative regimes in a specific parameter while it cannot on the other types including a perfect graph.

Future works will clarify some specific features on a network structure that contribute promoting cooperation.

Acknowledgments

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	None	R	RP	RR	RB
None	0.024	0.034	0.114	0.021	0.206
P	0.031	0.022	0.039	0.027	0.137
PP	0.220	0.047	0.158	0.021	0.314
PR	0.022	0.035	0.236	0.053	0.127
PB	0.045	0.026	0.118	0.056	0.029

Figure 3: Result of complete network

	None	R	RP	RR	RB
None	0.020	0.034	0.126	0.028	0.123
P	0.097	0.132	0.264	0.109	0.272
PP	0.400	0.387	0.445	0.362	0.400
PR	0.097	0.133	0.249	0.110	0.228
PB	0.339	0.290	0.432	0.344	0.374

Figure 4: Result of random network

	None	R	RP	RR	RB
None	0.018	0.033	0.214	0.041	0.189
P	0.128	0.115	0.279	0.136	0.235
PP	0.348	0.388	0.442	0.353	0.424
PR	0.094	0.135	0.310	0.121	0.271
PB	0.313	0.380	0.360	0.346	0.371

Figure 5: Result of small-world network

	None	R	RP	RR	RB
None	0.016	0.040	0.316	0.571	0.629
P	0.107	0.141	0.365	0.781	0.618
PP	0.497	0.408	0.557	0.631	0.796
PR	0.977	0.132	0.785	0.824	0.771
PB	0.902	0.329	0.887	0.770	0.835

Figure 6: Result of BA network

	None	R	RP	RR	RB
None	0.024	0.033	0.378	0.710	0.462
P	0.074	0.101	0.328	0.829	0.460
PP	0.565	0.364	0.604	0.494	0.608
PR	0.962	0.082	0.483	0.850	0.751
PB	0.825	0.320	0.630	0.787	0.777

Figure 7: Result of CNN network

	None	R	RP	RR	RB
None	0.020	0.036	0.614	0.623	0.528
P	0.122	0.140	0.551	0.750	0.636
PP	0.716	0.380	0.577	0.593	0.688
PR	0.972	0.181	0.747	0.693	0.763
PB	0.861	0.381	0.650	0.837	0.674

Figure 8: Result of Facebook network

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