Trust and Performance: Exploring Socio-Economic Mechanisms in the "Deep" Network Structure with Agent-Based Modeling

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Abstract: This paper extends the concept of interaction platforms and explores the evolution of interaction and cooperation supported by individuals' changing trust and trustworthiness on directed weighted regular ring network from the angle of micro scope by using agent-based modeling. This agent-based model integrates several considerations below via a relatively delicate experimental design: 1) a characteristic of trust is that trust is destroyed easily and built harder (Slovic, 1993); 2) trustworthiness may be reflected on both strategy decision and payoff structure decision; 3) individuals can decide whether or not to be involved in an interaction; 4) interaction density exists, not only between neighbors and strangers (Macy and Skvoretz, 1998), but also within neighbors; 5) information diffusion. In this agent-based model, *marginal rate of exploitation* of original payoff matrix and *relative exploitation degree* between two payoff matrices are stressed in their influence of trust-destroying; influence of observing is introduced via *imagined strategy*; relationship is maintained through *relationship maintenance strength*, and so on. This paper treats number of immediate neighbors, degree of embeddedness in social network, mutation probability of payoff matrix, mutated payoff matrix, proportion of high trust agents and probabilities of information diffusion within neighborhood and among non-neighbors as important aspects happening on interaction platforms, and the influences of these factors are probed respectively on the base of a base-line simulation.

Keywords: Trust, trustworthiness, directed weighted regular ring network, agent-based modeling, marginal rate of exploitation, relative exploitation degree, imagined strategy, relationship maintenance strength, number of neighbors, degree of embeddedness in social network, mutation of payoff matrix, information diffusion, social mobility, institutional quality, evolution of interaction, evolution of cooperation

Introduction

Trust as a lubricant permeates almost every aspect of social and economic life. It typically functions on human individuals and is reflected in their social and economic interactions. From the individuals' perspective, different personal experiences (including direct interaction experiences and observation experiences) may drive different trust of individuals. At the same time, individuals' diverse traits may lead to that their trust gets influenced to different degrees by even the same trust-influencing events. Put another way, individuals would not react to the same degree to external information; there exist people more easily being influenced. Thus, trust is heterogeneous across individuals in a given population, and is more or less subjective.

The micro interactions (interactions of individuals) can be and are often modeled by games, such

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as Prisoners' Dilemmas or coordination games *et cetera*. Cooperation in dilemma-like payoff structure is a remarkable research topic in game theory. (e.g., Axelrod, 1984/2006) In research of trust by modeling micro interactions by non-cooperative Prisoners' Dilemmas, diachronic share of cooperation in the whole society (number of cooperation over population size) is often adopted as a measure of (social) trust. This method actually treats global share of trustworthy behaviors as equal to (social) trust and has reasonability, to some extent. However, some possible disadvantages accompany, at the same time. For example, given the payoff structure, this method cannot distinguish the different degrees of influences on an agent of trust-increasing and trust-decreasing events. It implies trust-decreasing events have an equivalent impact with trust-increasing events (even with very opposite directions). But generally speaking, trust is produced harder but can be destroyed easily. Slovic (1993) also states, "It (Trust) typically created rather slowly, but it can be destroyed in an instant by a single mishap or mistake"; the "fragile" nature of trust may, added by Slovic (1993), result from human psychological disposition to regard trust-destroying news as more credible. (Slovic, 1993) However, this characteristic of trust, which contributes to research of decline of trust, has rarely been considered into formal models.

Trustworthiness, as an inseparable aspect of trust research, is reflected not only on the chosen strategy, but also on the chosen payoff structure. Given a payoff structure, unilateral defection destroys partners' trust; when an individual enlarges the interest conflict in the original payoff structure, his unilateral defection probably to a larger extent destroys his partners' trust than in the original payoff structure. Imagine a situation that a consumer is going to buy baby formula. The bad situation he has known or he can imagine is that at worst the formula is not worth the price he has paid. However, the consequence turns out to be that the baby of the consumer gets very sick after drinking the formula. The game is still the same one, namely "buying baby formula", however the payoff structure does not consistent with the original one. Thus, it can be said that social trustworthiness also mirrors institutional quality: in a society with a relatively perfect institutional system, probably less events destroying public trust happen.

Additionally, people do not definitely participate in a potential interaction. They can make a decision not only on which strategy and payoff structure to use in an interaction, but also on whether or not to be involved in an interaction (Macy and Skvoretz, 1998). Trust, therein, is a crucial factor to enable interactions. (Elsner and Schwardt, 2015)

As to interactions, the probability of encountering different persons is not the same, which is a salient characteristic of social interactions. The random-pairing mechanism actually implies equal probability of meeting any other in the whole simulated population. Macy and Skvoretz (1998) argue that random-pairing and one-shot Prisoners' Dilemma experiments overlook "the embeddedness of the game in social networks". (Macy and Skvoretz, 1998) High degree of embeddedness, in the paper of Macy and Skvoretz (1998), means high probability to reencounter each other. Thus, players, in their paper, are endowed with two types of relationships, namely neighbors and strangers, and interactions with neighbors are set with high degree of embeddedness while interactions with stranger with low embeddedness. (Macy and Skvoretz, 1998) This is a much more realistic pairing mechanism since interactions are locally dense in individuals' interaction network.

Interaction density exists, both between neighbors and strangers and within neighbors. Hence, even within neighborhood, interactions also always accompany partner selections. Besides that one's relationships with others are with "to exist or not to exist", they are also with different (unilateral) link weights. When an individual has an opportunity to interact with one of his neighbors, he probably would like to interact with those relatively trustworthy.

Interactions are a relatively direct experience while non-interactions (for simplicity, observations[1]) provide another way to get others' interaction information. Information both from direct interactions and observations is channels that an individual gets to know about the status of the whole society. An obvious phenomenon about information diffusion in contemporary era is that its channels get more, its coverage gets larger and its speed gets faster. Besides traditional mass media, the technological support of improving information technology and internet access, the popularization of personal computers and mobile terminals, the emergent new media and the diverse on-line social platforms extremely largely improve the probability that an individual acquires information. Information acquired through observations (here means non-interactions) which is about others' interactions and contains information of others' trustworthiness in the society shapes the information receivers' trust.

It has been realized that taking individuals' heterogeneity into account in economic researches coincides with evolutionary thinking. Gowdy *et al* (2016) argue that the average behavior of representative agents is one of the causes that make the modern economics non-evolutionary. (Gowdy *et al*, 2016, p 327) Modeling heterogeneity is the very strength of agent-based modeling (ABM) and is also the core difference between ABM and other methodologies, such as systematic dynamics. ABM places "a strong emphasis on heterogeneity and social interactions". (Banisch, Lima and Araújo, 2012) So far, ABM gets more and more adopted in research in different fields and different topics of social sciences. (e.g., Axelrod, 1997; Macy and Willer, 2002; Tran and Cohen, 2004; Pyka and Fagiolo, 2005; Tesfatsion and Judd (Eds.), 2006; Gilbert, 2008; Geanakoplos *et al*, 2012; Chen *et al*, 2015; Spaiser and Sumpter, 2016) Research on trust with agent-based modeling also emerges. (e.g., Kim, 2009; Chen *et al*, 2015)

In this paper, agents' heterogeneity is reflected on three main aspects below: 1) agents' trust (namely, their willingness to participate in a potential interaction in this paper) and their trustworthiness (i.e., their probability to cooperate in an actual interaction in this paper); 2) agents' capabilities of acquiring others' interaction information both from his neighbors and non-neighbors, respectively; 3) agents' trust-updating weights of different acquired interaction information (of mutual neighbors or mutual non-neighbors, and from personal interactions or observations). As to social interactions, an interaction contains (at least) the decision-makings below: 1) whether to initiate (or participate in) a potential interaction; 2) which partner to choose if the potential interaction is within neighborhood; 3) which (pure) strategy to use in the actual interaction; 4) which payoff matrix to apply.

The aim of this paper is to explore the evolution of interaction and cooperation supported by individuals' changing trust and trustworthiness on a directed weighted regular ring network under different conditions of environment from the angle of micro scope via designing an agent-based model. Additionally, what is presented in the experimental design in this paper also provides

[1] For simplicity, we use "observations" to refer to all non-interactive ways of acquiring others' interaction information.

useful insights in research of the decline of trust.

Section 1 explains and extends the concept of “deep” network structure and enumerates some aspects reflecting “deep” network structure, information diffusion and institutional quality which are important for the micro process of the agent-based model in this paper. Section 2 describes the whole agent-based simulation in detail. Section 3 presents the simulation results, including influence of some selected single parameters based on a base-line simulation and a comparison of 2 societies. Section 4 is a short presentation about some enlightenment on institutional emergence. Section 5 concludes.

1 “Deep” network structure

The title of this paper gives special stresses on “‘deep’ network structure”. This concept tightly relates the conception of “meso”-sized interaction platforms and arenas in several papers of Elsner and Elsner *et al*. (e.g. Elsner, 2007; Elsner and Heinrich, 2009; Elsner, 2010; Elsner and Heinrich, 2011; Elsner and Schwardt, 2014; Elsner and Schwardt, 2015) In their papers, Elsner and Elsner *et al* accentuate the size dimension of the interaction platforms and arenas. Elsner (2007) argues that meso level, i.e. mid-sized groups, is a proper level on which institutional or structural emergence take places. (Elsner, 2007) Elsner *et al.* (2009) further dig into the co-evolution of an institution and the size of its carrier group by using a supergame of prisoners’ dilemma from a population perspective. (Elsner and Heinrich, 2009) However, argue Elsner and Schwardt (2015), “it (size of interaction arenas) is not about absolute size in terms of overall population but the ‘inner’ size structure of interaction arenas”. (Elsner and Schwardt, 2015)

The word “structure” usually refers to a kind of spatial or proportional arrangements. How different interaction platforms are arranged generates a structure. Despite the size dimension, it is the interdependent individuals’ micro interaction processes that are carrying on on these interaction platforms. That a particular individual interacts across different platforms means different interaction platforms may contain some (at least one) same individuals; these platforms therefore overlap. Inspired by Elsner and Schwardt (2014), Dai (2015) classifies interaction platforms into four types, namely political platforms, economic platforms, social platforms and international platforms. (Dai, 2015, p 100-102) However, I would like to provide another way of considering interaction platforms and, at the same time, the overlapping of interaction platforms. Note that this is not even a roughly exhausted classification of interaction platforms; it just provides different *angles* of thinking and understanding overlapping interaction platforms.

Geographical-location-related platforms Geographical adjacency increases the probability of interaction. As an individual moves to different geographical locations, he encounters different interaction partners. Faster mobility enlarges chances of encountering more strangers.

Social-roles-related platforms Multiplicity of a human’s social roles also provides possibilities of the overlap of interactions platforms. For example, a female can be both a mother and a teacher at the same time. As a mother, she interacts with her children and other people related to her responsibility of a mother; as a teacher, she interacts with her students, others teachers and other staff in her school.

Events-related platforms Interaction platforms can vary depending on different events that an individual deals with. When an individual is involved in an event, he enters the platform and interacts with others also involved in the event; when the event finished, the platforms dismisses. Thus, different events offer different interaction platforms.

Technology-based platform This kind of platforms is mainly for distinguishing from realistic social interaction networks. Supported by modern information technology, various on-line social platforms emerge, such as Facebook, Twitter, LinkedIn. In China, there are on-line social networks like Sina Weibo, and instant communication softwares like Tencent QQ and WeChat. These on-line social platforms overlap with realistic social networks and provide communication at any time anywhere. However, what is remarkable about on-line social platforms is that they supply more opportunities of communicating with and getting information about a lot more strangers.

Treating an interaction platform as a conceptual brace in this paper, we also take into account what have been mentioned in the introduction, such as the different interaction densities both between neighbors and non-neighbors and within neighborhood, the different influences of trust-decreasing and trust-increasing events, information acquired via both interactions and observations and institutional quality *et cetera* when considering the environment of and what is happening on an interaction platform in order to better describe and understand the socio-economic mechanism on this "deep" network, rather than focusing on the size dimension. Before presenting experimental design, it is necessary to figure out some parameters and their meaning that we use to explore socio-economic processes underlying trust in our agent-based simulation. In a word, they are all about with whom to interact and how, essentially.

Number of immediate neighbors Number of neighbors in our simulation is how many direct, or immediate, or one-degree separated neighbors an individual has. The probability of a given neighbor is chosen as an interaction partner is higher if an individual has fewer neighbors *ceteris paribus* if the choosing scope is within his neighborhood.

Embededness in social network Inspired by Macy and Skvoretz (1998), embeddedness in one's social network here refers to the probability that a potential interaction will be with an immediate neighbor (one-degree separated neighbor) and is represented by a real number within range [0, 1]. Thus, 1 minus means social embeddedness degree is the probability that a potential interaction will be with a non-neighbor. What is more meaningful, social embeddedness is used to indicate social mobility.

Mutated payoff matrix Mutated payoff matrix is a mutated version of the original and popular payoff matrix. Interactions are modeled as symmetric non-cooperative prisoners' dilemmas in this paper. The original and the mutated payoff matrix have the same payoff values for pure strategies against themselves, while have different payoff values for pure strategies against the different pure strategies. The mutated payoff matrix is endowed with a larger interest conflict and is used as an ingredient of indicating *relative degree of exploitation* of the mutated payoff matrix over the original payoff matrix.

Mutation probability of payoff structure Mutation probability of payoff structure is the probability that the original payoff matrix is changed to the mutated payoff matrix by the initiator of a potential interaction on condition that the initiator has decided to play "Defection" in the forthcoming actual interaction. This is an indicator for institutional quality in this paper.

Proportion of high trust individuals Proportion of high trust individuals in the whole population in this paper is the proportion of individuals whose trust is equal to or higher than 2/3 in the whole population.[1] This is a parameter to represent the whole trust status in a society.

Probability of interaction information diffusion in neighbors Probability of interaction information diffusion in neighbors is the probability that the interaction information, including the strategies and payoffs of the interaction parties, get spread in agents who are neighbors of either of the interaction parties.

Probability of interaction information diffusion in non-neighbors Probability of interaction information diffusion in non-neighbors is the probability that the interaction information, including the strategies and payoffs of the interaction parties, get spread in agents who are neighbors of neither of the interaction parties.

2 Experimental design

2.1 Artificial society

Consider an artificial society with n agents. The set of all agents is denoted by a finite set $N = \{a_i \mid 1 \leq i \leq n, i \in \mathrm{N}^+\} = \{a_1, a_2, a_3, \ldots a_i \ldots, a_{n-1}, a_n\}$ with the subscripts representing the unique identity of a given agent. As shown in set N, the identities, namely the ids of agents, are represented by continuous non-negative integers from 1 to the population size of the simulated artificial society.

2.2 Self's social network structure

After all agents are instantiated with a unique identity, they are arranged on a network of directed weighted regular ring sequentially with an equal number of neighbors. a_i's neighbors are those who are nearest to him on the ring. On "ring" networks, the two agents with the smallest id and the largest id are next to each other. Thus, the agents' ids are joined head to tail.

Additionally, let $Neig_i$ be a_i's neighborhood (here means a_i's set of immediate neighbors with 1 degree separated in this paper) and $Neig_i^C = N - Neig_i - \{a\}$ represent a_i's non-neighbor set. As soon as the ring network structure is generated, a "memory" list consisting of one-dimension arrays, which is for unilateral ink weights updating, is created for each agent with which an agent can memorize the id of his neighbors, the times of cooperation that each of his neighbors applies to him in a current period, and his times of actual interactions with each of his neighbors in a current period. Subsequently, the non-neighborhood can be accordingly achieved. Before agents interact, the order of each agent's neighbor list and non-neighbor list, and agent list (containing all agents) are shuffled.

2.3 Initialization of agents' attributes

In this part, some important attributes and their initialization are stressed, even though there are still some other attributes in the initialization process of agents. The specific use will be illustrated

[1] The trust level in this paper is a real number within range [0, 1).

in 2.4 in detail.

2.3.1 Initialization of trust and trustworthiness

Each agent's trust is generated as a float number in range [0, 1). If an agent's trust is equal to or higher than 2/3, he is treated as a high trust agent. An agent with probability p^{HTr} (namely proportion of high trust individuals in the whole population) is initialized as a high trust agent. Agents' trust in ranges [0, 2/3) and [2/3, 1) follows uniform distribution in corresponding ranges, respectively. That is,

$$Tr_{i,init} \sim \begin{cases} \mathrm{U}\left(\frac{2}{3}, 1\right) & \text{if } r_i^{tr} \in [0, p^{HTr}) \\ \mathrm{U}\left(0, \frac{2}{3}\right) & \text{if } r_i^{tr} \in [p^{HTr}, 1) \end{cases}$$

$Tr_{i,init}$ is agent a_i's initial trust. r_i^{tr} is a pseudo random number (namely, a sample value of a random variable following uniform distribution in range [0, 1)). p^{HTr} is proportion of high trust individuals in the whole population.

Similar with trust, one's trustworthiness is a float number randomly chosen from uniform distribution [0, 1). Namely,

$$Trw_{i,init} \sim \mathrm{U}(0, 1)$$

$Trw_{i,init}$ represents agent a_i's initial trustworthiness

Additionally, what should be pointed out here is that, as shown above, it is not assumed in advance any direct relationship between an agent's trust and his own trustworthiness.[1]

2.3.2 Initialization of probability of information acquisition

Information acquisition here means that an agent acquires others' interaction information via non-interaction (namely, observing hereinafter, for convenience). An agent's probability of information acquisition indicates his capability to obtain and his attention paid to others' interactions.

Each agent has two probabilities of information acquisition: one is about information acquired from neighbors p_i^{IAN}; the other is about information acquired from non-neighbors p_i^{IANn}. They are both randomly chosen from uniform distribution in range [0, 1) and do not change across time. That is,

$$p_i^{IAN} \sim \mathrm{U}(0, 1)$$

$$p_i^{IANn} \sim \mathrm{U}(0, 1)$$

Now, let a_i be an observing agent. When a piece of interaction information gets diffused within the

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[1] In this paper, an agent's trust and his own trustworthiness is not directly related because I have not found literature writing about that, to the best of my present limited knowledge.

neighborhoods of two interaction parties, as long as one of the two interaction parties is the observing agent's neighbor, the observing agent would following p_i^{IAN} observe; when the piece of interaction information gets diffused within non-neighborhoods of the interaction parties, if neither of the two interaction parties is the observing agent's neighbor, the observing agent would following p_i^{IANn} observe.

2.3.3 Initialization of weights of four kinds of information sources

We assume that there are four kinds of information sources on which an agent can depend to adjust his trust: 1) interactions with neighbors, 2) interactions with non-neighbors, 3) observing interactions between two mutual neighbors (that is, the two interacting parties are mutual neighbors), 4) observing interactions between two mutual non-neighbors.

Let w_i^{Neigs} denote a_i's weight of information about mutual neighbors, let w_i^{Nneigs} be a_i's weight of information about mutual non-neighbors, let w_i^{Inte} represent a_i's weight of information acquired through interactions and let w_i^{Obs} indicate a_i's weight of information acquired via observations. All of an agent's four weights are randomly chosen from uniform distribution on range [0, 1) and do not change across time. The weights of four kinds of information sources in trust-updating is four linear combinations of either w_i^{Neigs} or w_i^{Nneigs} and either w_i^{Inte} or w_i^{Obs}.[1] That is, the weight of interacting with neighbors in a_i's trust-updating is a linear combination of w_i^{Neigs} and w_i^{Inte}; the weight of interacting with non-neighbors in a_i's trust-updating is a linear combination of w_i^{Nneigs} and w_i^{Inte};the weight of observing interactions between two mutual neighbors in a_i's trust-updating is a linear combination of w_i^{Neigs} and w_i^{Obs}; the weight of observing interactions between two mutual non-neighbors in a_i's trust-updating is a linear combination of w_i^{Nneigs} and w_i^{Obs}. Specifically, we set the weights of four kinds of information sources as follows (see Table 2.3-1):

Table 2.3-1 Weights of four kinds of information sources in a_i's trust-updating

	$w_i^{Inte} \sim \mathrm{U}(0,1)$	$w_i^{Obs} \sim \mathrm{U}(0,1)$
$w_i^{Neigs} \sim \mathrm{U}(0,1)$	$0.5 * (w_i^{Inte} + w_i^{Neigs})$	$0.5 * (w_i^{Obs} + w_i^{Neigs})$
$w_i^{Nneigs} \sim \mathrm{U}(0,1)$	$0.5 * (w_i^{Inte} + w_i^{Nneigs})$	$0.5 * (w_i^{Obs} + w_i^{Nneigs})$

2.3.5 Initialization of unilateral link weights

Unilateral link weights are what an agent, say a_i, depends on to actively choose a neighbor as a potential interaction partner when his scope of choosing is within neighborhood, and unilateral link weights do not change within a time period. The neighbor to whom a_i assigns larger unilateral link weight is with higher probability to be chosen. Let $LW_{i,t}$ be the set of unilateral link weights that a_i holds for all his neighbors in time period t. We set

$$LW_{i,t} = \{lw_{ij,t} | a_j \in Neig_i, 0 \le lw_{ij,t} \le 1 \text{ and } \sum_j lw_{ij,t} = 1\}$$

[1] Here an implicit assumption is that w_i^{Neigs}, w_i^{Nneigs}, w_i^{Inte} and w_i^{Obs} are mutually independent.

and set

$$p_{ij,t,\tau}^{API} = lw_{ij,t} \quad (0 \le \tau \le Req_{i,t}^{Inte} \text{ and } \tau \epsilon \mathrm{N}^{+})$$

Therein, $lw_{ij,t}$ the unilateral link weight that a_i assigns to his neighbor a_j in time period t. It equals $p_{ij,t,\tau}^{API}$, the probability that a_i actively chooses his arbitrary neighbor a_j as a potential interaction partner when neighborhood is a_i's choosing scope in sub-time period τ of time period t. Note that $lw_{ij,t} \neq lw_{ji,t}$, since the network structure is a directed weighted graph in this paper, as aforementioned.

Initially, an agent's unilateral link weights follow discrete uniform distribution, which means that in the first time period, each neighbor of a_i is with probability $\frac{1}{Num_i^{Neigs}}$ (Num_i^{Neigs} is the number of a_i's neighbors) to be chosen as a potential interaction partner by a_i. That is, initially,

$$p_{ij,t=1,\tau}^{API} = \mathrm{P}\{Partner_{i,t=1,\tau}^{API} = a_j \,|PT_{i,t=1,\tau}^{API} = 0\} = \frac{1}{Num_i^{Neigs}} \quad (a_j \in Neigs_i;\ 0 \le \tau \le Req_{i,t}^{Inte} \text{ and } \tau \epsilon \mathrm{N}^{+})$$

$Partner_{i,t=1,\tau}^{API}$ represents the partner that a_i actively chooses as his potential interaction partner in sub-time period τ of time period t=1. $PT_{i,t=1,\tau}^{API} = 0$ represents the condition that the partner type of the chosen potential interaction partner is a neighbor ("neighbors" is represented by 0 and "non-neighbors" by 1). The specific mechanism agents update their unilateral link weights for the next time period when a time period ends will be introduced in detail in section 2.4.3.

2.4 Micro-level process

Each time period contains $\tau = Req_{i,t}^{Inte}$ sub-time periods ($Req_{i,t}^{Inte} = 20$ in this paper). The micro-level process in each time period contains three main tasks: 1) all agents one by one have an opportunity to actively make an interaction request (described in 2.4.1), and this rotation repeats for $Req_{i,t}^{Inte}$ times; 2) all agents one by one update their trustworthiness (namely probability to cooperate in each actual interaction) for the next time period (described in 2.4.2); 3) all agents one by one modify their unilateral link weights for the next time period (described in 2.4.3).

2.4.1 Interaction, information diffusion and trust-updating

1) Interaction decision for active potential interactions

For each sub-period τ ($\tau \in \mathrm{N}^{+}$ and $\tau \le Req_{i,t}^{Inte}$) in time step t, every agent, in turn in a shuffled order, has an opportunity to actively make an interaction request to others. Whether an agent will grasp the opportunity and enter the next step of choosing a potential interaction partner is determined by his willingness to interact, namely his own trust in this paper. That is, a_i with a probability equal to his trust continues to choose a potential interaction partner.

Before we go further, I would like to talk about *potential interactions*. A potential interaction is acquired whenever an agent has an opportunity to interact, however has not yet actually interacted. Thus, number of potential interactions of an agent i in time period t can be calculated in two different ways. The first way is:

$$Num_{i,t}^{PI} = Num_{i,t}^{PI,N} + Num_{i,t}^{PI,Nn}$$

$Num_{i,t}^{PI}$ represents a_i's number of potential interactions within time period t. $Num_{i,t}^{PI,N}$ represents a_i's number of potential interactions with his *neighbors* in time period t. $Num_{i,t}^{PI,Nn}$ represents a_i's number of potential interactions with his *non-neighbors* in time period t.

However, as we notice, an agent's number of potential interactions also equals his *active* interaction requests and interaction requests from others (*passive* interactions).Thus, the second way to calculate an agent's number of potential interactions within time period t is:

$$Num_{i,t}^{PI} = Num_{i,t}^{API} + Num_{i,t}^{PPI} = Req_{i,t}^{Inte} + Num_{i,t}^{PPI}$$

$Num_{i,t}^{API}$ represents a_i's number of active potential interactions in time period t. $Num_{i,t}^{PPI}$ represents a_i's number of passive potential interactions in time period t. According to the setting in this paper, $Num_{i,t}^{API} = Req_{i,t}^{Inte} = 20$.

2) To choose a potential interaction partner

Following Macy and Skvoretz (1998), in this paper the degree of embeddedness in social network is also assumed. Degree of embededness in social network, as a parameter, is represented by a float number in range [0, 1). When a_i is going to actively propose an interaction request, his potential interaction partner will be chosen either from his neighborhood with probability equal to degree of embeddedness in social network or from his non-neighborhood with probability equal to 1 minus degree of embeddedness in social network.[1]

If a_i's potential interaction partner is definitely going to be chosen from neighborhood, which neighbor on earth will be chosen hinges on a_i's unilateral link weights assigned to his neighbors. On contrast, if a_i's potential interaction partner is definitely outside his neighborhood, a non-neighbor will be randomly chosen among a_i's non-neighbors with equal likelihood. That is,

$$p_{ij,t,\tau}^{PI} = \begin{cases} lw_{ij,t} & \text{if } a_j \in Neigs_i \\ \dfrac{1}{Num_i^{Nneigs}} & \text{if } a_j \in Neigs_i^C \end{cases}$$

$p_{ij,t,\tau}^{PI}$ represents the probability that a_i chooses a_j as his potential interaction partner in sub-time period τ of time period t. If a_j belongs to a_i's neighbors, the probability that a_j is chosen is $lw_{ij,t}$; if a_j belongs to a_i's non-neighbors, the probability is $\frac{1}{Num_i^{Nneigs}}$. Num_i^{Nneigs} is the number of a_i's non-neighbors. If the former $(a_j \in Neigs_i)$, a_j's number of passive potential interactions (namely, passive potential interactions) from neighbors in the current time period increases by 1.[2] Namely,

$$Num_{j,t}^{PPI,N} \leftarrow Num_{j,t}^{PPI,N} + 1 \quad \text{if } a_j \in Neigs_i$$

[1] "Degree of embededness in social network" here only represents the probability that an agent encounters a neighbor in a potential interaction; it does not represent an agent's subjective willingness to interact with a neighbor.

[2] The number of passive potential interactions with non-neighbors is not counted.

Number of passive potential interactions from neighbors is counted for trustworthiness updating in 2.4.2. Whether a_i's chosen potential interaction partner a_j (either a neighbor or a non-neighbor) would like to participate in the interaction then depends on a_j willingness to interact determined by a_j's own trust. Only if a_j agrees to interact, the interaction will actually happen, and a_i and a_j enter the next step of strategy decision; otherwise, the actual interaction won't happen.

3) Pure strategy decision

Applying which pure strategy for the forthcoming actual interaction is determined by the agents' probability of cooperation, namely their own trustworthiness in this paper. If a random number chosen from uniform distribution in range [0, 1) is smaller than an agent's trustworthiness (probability to cooperate), his strategy will be "Cooperate"; otherwise, his strategy will be "Defect". Hence, each agent is actually using a mixed strategy. That is,

$$PS_i \leftarrow \begin{cases} 0 & \text{if } r_i^{stra} \in [0, Trw_{i,t}] \\ 1 & \text{if } r_i^{stra} \in (Trw_{i,t}, 1) \end{cases}$$

PS_i represents the pure strategy that agent a_i would use in a forthcoming actual interaction. "0" represents "Cooperation" and "1" "Defection". r_i^{stra} is a pseudo number following uniform distribution in range [0, 1). $Trw_{i,t}$ is agent a_i's trustworthiness in time period t.

4) Payoff matrix mutation

The actual interaction process is modeled by non-cooperative and symmetric prisoners' dilemmas. Denote matrix $\boldsymbol{A}^g$ as a general form of payoff matrixes of prisoners' dilemma and set

$$\boldsymbol{A}^g = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

a_{11} is an agent's payoff when both he and his partner apply strategy "Cooperation"; a_{12} is an agent's payoff when he alone uses strategy "Cooperation" while his partner uese strategy "Defect"; a_{21} is an agent's payoff when he plays strategy "Defect" and his partner plays strategy "Cooperation"; a_{22} is an agent's payoff when both players apply strategy "Defect". Then, the elements of payoff matrix $\boldsymbol{A}^g$ should satisfy $a_{21} > a_{11} > a_{22} > a_{12}$ and $a_{11} > \frac{a_{21}+a_{12}}{2}$ for a game to be a prisoners' dilemma.

What is more important for trust-updating later in this paper, we define *marginal rate of exploitation* (MRE) of a given payoff matrix $\boldsymbol{A}^g$ as

$$MRE^{\mathrm{Ag},C/D} = \frac{a_{11} - a_{12}}{a_{21} - a_{11}}$$

$MRE^{Ag,C/D}$ represents *marginal rate of exploitation* of pure strategy "Defection" to pure strategy "Cooperation" under payoff matrix $\boldsymbol{A}^g$. It measures how much a defector can gain from deviating one unit of payoff from pure strategy "Cooperation" on the loss of his game partner who is a cooperator. *MRE* is positive.

Consider two symmetric prisoners' dilemmas with $\boldsymbol{A}$ and $\boldsymbol{A}^{mut}$ having different numerical payoffs:

$$\boldsymbol{A} = \begin{bmatrix} a_{11}^A & a_{12}^A \\ a_{21}^A & a_{22}^A \end{bmatrix} \quad \text{and} \quad \boldsymbol{A}^{mut} = \begin{bmatrix} a_{11}^{Amut} & a_{12}^{Amut} \\ a_{21}^{Amut} & a_{22}^{Amut} \end{bmatrix}$$

Therein, $\boldsymbol{A}^{mut}$ is a mutated version of $\boldsymbol{A}$. Thus, the *marginal rate of exploitation* of payoff matrix $\boldsymbol{A}$ is:

$$MRE^{A,C/D} = \frac{a_{11}^A - a_{12}^A}{a_{21}^A - a_{11}^A}$$

Besides the general conditions a prisoners' dilemma should satisfy, $\boldsymbol{A}$ and $\boldsymbol{A}^{mut}$ in this paper also satisfy $a_{11}^{Amut} = a_{11}^A$, $a_{22}^{Amut} = a_{22}^A$, $a_{21}^{Amut} > a_{21}^A$ and $a_{12}^{Amut} < a_{12}^A$ to ensure that the mutated payoff matrix $\boldsymbol{A}^{mut}$ enlarges the exploitation degree of unilateral defection compared to the original payoff matrix $\boldsymbol{A}$, and to have comparability as well. At the same time, we denote *relative exploitation degree* (RED) of payoff matrix $\boldsymbol{A}^{mut}$ over $\boldsymbol{A}$ as

$$RED^{Amut/A} = \frac{a_{21}^{Amut} - a_{12}^{Amut}}{a_{21}^A - a_{12}^A}$$

Relative exploitation degree is constructed to measure to which degree a mutated payoff matrix $\boldsymbol{A}^{mut}$ enlarges the interest conflict of the original payoff matrix $\boldsymbol{A}$. Both marginal rate of exploitation and relative exploitation degree are for trust updating in 6) in 2.4.1. Numerically, $\boldsymbol{A} = \begin{bmatrix} 3 & 1 \\ 4 & 2 \end{bmatrix}$ in this paper and $\boldsymbol{A}^{mut}$ is a parameter with different candidate values. For example, when $\boldsymbol{A}^{mut} = \begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}$, we get

$$MRE^{A,C/D} = \frac{a_{11}^A - a_{12}^A}{a_{21}^A - a_{11}^A} = \frac{3-1}{4-3} = 2$$

$$RED^{Amut/A} = \frac{a_{21}^{Amut} - a_{12}^{Amut}}{a_{21}^A - a_{12}^A} = \frac{5-0}{4-1} = \frac{5}{3}$$

Payoff matrix decision comes after pure strategy decision. The initiator (the *active* interaction party) of a potential interaction has an exclusive right to unilaterally change payoff matrix from $\boldsymbol{A}$ to $\boldsymbol{A}^{mut}$ with probability p^{Amut} which is a parameter in this paper, on condition that the initiator has already decided to apply "Defection" for this forthcoming actual interaction.[1] As long as no payoff matrix mutation happens, the interaction will carry on with the original payoff matrix $\boldsymbol{A}$. That is,

$$PM_{i,t,\tau} = \begin{cases} A & \text{if } r^{PM} \in [0, p^{Amut}] \\ A^{mut} & \text{if } r^{PM} \in (p^{Amut}, 1) \end{cases}$$

$PM_{i,t,\tau}$ represents a_i's payoff matrix decision for his active potential interaction in sub-time period τ in time period t. r^{PM} is a pseudo random number. Due to the specific conditions that $\boldsymbol{A}$ and $\boldsymbol{A}^{mut}$ should satisfy in this paper, we suppose that when active actor chooses $\boldsymbol{A}^{mut}$: 1) the passive actor cannot discover he is under $\boldsymbol{A}^{mut}$ unless the passive actor plays "Cooperation"; 2) observers cannot

[1] Even though mutation probability is very small in nature (e.g., Seltzer and Smirnov, 2015), it is not set that small in this paper.

either detect their observed interaction is under $\boldsymbol{A}^{mut}$ unless the observed interaction is unilateral defect.

5) To play the game

After pure strategies and payoff matrix for the forthcoming interaction have been decided, the two interaction parties begin to play the game. What each of both interacting parties should record through each actual interaction in a current time period is two aspects: i) counting his own actual interactions (including both active ones and passive ones) and "Cooperation" (no matter what pure strategy his partner uses) no matter whether his partner is a neighbor or a non-neighbor; ii) counting actual interactions happening with each of his neighbors and "Cooperation" that each of his neighbors applies to *him* according to his neighbors' identity. All these are reset to zero at the beginning of every time period (not sub-time period). Therein, i) is for trustworthiness updating in 2.4.2; ii) is for unilateral link weights updating in 2.4.3.

Formally, in each actual interaction, for purpose of i),

$$Num_{i,t}^{AI} \leftarrow Num_{i,t}^{AI} + 1$$

$$Num_{i,t}^{C} \leftarrow Num_{i,t}^{C} + 1 \qquad \text{if } PS_i = 0$$

$Num_{i,t}^{AI}$ represents the times of a_i's actual interactions in time period t. $Num_{i,t}^{C}$ represents the times that a_i uses "Cooperation" in time period t. For purpose of ii),

$$Num_{ij,t}^{AI} \leftarrow Num_{ij,t}^{AI} + 1 \quad \text{if } a_j \in Neigs_i$$

$$Num_{ij,t}^{C_j} \leftarrow Num_{ij,t}^{C_j} + 1 \quad \text{if } a_j \in Neigs_i \text{ and } PS_j = 0$$

$Num_{ij,t}^{AI}$ represents the times of a_i's actual interactions with his neighbor a_j in time period t. $Num_{ij,t}^{C_j}$ represents the times that his neighbor a_j applies "Cooperation" to a_i in time period t.

6) Diffusion of interaction information (Observed by others)

It is possible that others who are not interacting parties get informed of the situation and result of an interaction. Except the two interaction parties, say a_i and a_j, the agents in the artificial society are separated into two sets: one is the union-neighbor set $UNeig_{ij}$ in which the agents are neighbors of either of the interaction parties; the other is set $DNeig_{ij}$ in which agents are neighbors of neither of the interaction parties. Thus, when the interaction parties a_i and a_j are mutual neighbors,

$$UNeig_{ij} = Neig_i \cup Neig_j - \{a_i, a_j\}$$

$$DNeig_{ij} = N - (Neig_i \cup Neig_j)$$

When the interaction parties a_i and a_j are mutual non-neighbors,

$$UNeig_{ij} = Neig_i \cup Neig_j$$

$$DNeig_{ij} = N - \left(Neig_i \cup Neig_j\right) - \{a_i, a_j\}$$

The probability that the interaction information of a_i and a_j diffuses in these two interacting parties' neighborhoods $UNeig_{i,j}$ is p^{IDN}, and the probability diffusing in their non-neighborhoods $DNeig_{i,j}$ is p^{IDNn}. Both p^{IDN} and p^{IDNn} are random numbers following uniform distribution in range [0,1) and act as parameters whose influence will be investigated under four different candidate values.

Then, the interaction information of a_i and a_j starts "diffusing" separately in $UNeig_{i,j}$ and $DNeig_{i,j}$. Whether an outside agent a_k (an agent who is not one of the interacting parties) will get informed of the just happening interaction depends on whether he belongs to $UNeig_{i,j}$ or $DNeig_{i,j}$, and his own probability of information acquisition from neighbors p_k^{IAN} and from non-neighbors p_k^{IANn}. That is,

$$p_k^{GI} = \begin{cases} p_k^{IAN} & \text{if } a_k \in UNeig_{ij} \\ p_k^{IANn} & \text{if } a_k \in DNeig_{ij} \end{cases}$$

p_k^{GI} is the probability that an outsider a_k gets informed of a piece of interaction information between a_i and a_j. What an observing agent will get informed about others' interaction is 1) the strategy combination, that is whether the observed interaction is "mutual cooperation", "unilateral defection" or "mutual defection";2) the relationship between the observed interacting parties, namely "mutual neighbors" or "mutual non-neighbors" and 3) the specific payoff matrix, that is whether the payoff matrix is a mutated one. Note that $\boldsymbol{A}^{mut}$ can only manifest itself in the situation of unilateral defection because $\boldsymbol{A}^{mut}$ has the same values with $\boldsymbol{A}$ in situations of "mutual cooperation" and "mutual defection" according to the settings in this paper.

7) To update self's trust

i) Trust-updating directions (qualitative trust-updating)

Changes of trust have three directions: increase, decrease and remain unchanged. In order to clarity how trust changes and when, it is necessary for us to at first distinguish trust-increasing events, trust-destroying events and trust-invariant events. This is analyzed from two angles: interacting agents and observing agents.

• Interacting agents

For the two interacting agents, in the situation of mutual cooperation, both agents' trust increase; in the situation of unilateral defection, the cooperative agent's trust decreases while the defective agent's trust remains unchanged; in the situation of mutual defection, both agents' trust keeps invariant. (Also see Table 2.4-1)

• Observing agents

For an observing agent, he first images which (pure) strategy he would have applied if he had been in the interaction. An observing agent's imagined pure strategy with probability equal to his trustworthiness is "Cooperation". If his imagined (pure) strategy is "Cooperation", his trust will increase when he observes mutual cooperation, and his trust will decrease when he observes unilateral defection or mutual defection. If his imagined (pure) strategy is "Defection", his trust will not change. (Also see Table 2.4-1)

Table 2.4-1 Trust-updating directions

Information acquiring method	**Strategy**		**Trust-updating directions**	
Interaction	self	partner	self	partner
	C	C	↑	↑
	C	D	↓	----
	D	C	----	↓
	D	D	----	----
Observation	Observed strategy combination		Observer's imaged strategy	
			C	D
	Mutual cooperation		↑	----
	Unilateral defection		↓	----
	Mutual defection		↓	----

ii) Quantitative trust-updating

Quantitative trust-updating is based on a certain amount ΔTr^{Base} which equals 0.05. How much exactly an agent will update his trust hinges on 1) *marginal rate of exploitation* of payoff matrix $\boldsymbol{A}$ (namely, $MRE^{\mathrm{A},C/D}$), 2) *relative exploitation degree* of $\boldsymbol{A}^{mut}$ compared to $\boldsymbol{A}$ (namely, $RED^{Amut\,/A}$), and 3) a_i's own weights for four kinds of information sources (the four possible combinations of either w_i^{Neigs} or w_i^{Nneigs} and either w_i^{Inte} or w_i^{Obs} shown in Table 2.3-1).

• Interacting agents

Assume a_i interacts with his neighbor a_j. If both a_i and a_j apply "Cooperation",

$$Tr_i \leftarrow \min(Tr_i + 0.5 * \left(w_i^{Neigs} + w_i^{Inte}\right) * \Delta Tr^{Base}, 1)$$

If a_i unilaterally uses "Cooperation" under payoff matrix $\boldsymbol{A}$,

$$Tr_i \leftarrow \max(Tr_i - 0.5 * MRE^{A,C/D} * \left(w_i^{Neigs} + w_i^{Inte}\right) * \Delta Tr^{Base}, 0)$$

If a_i unilaterally uses "Cooperation" under payoff matrix $\boldsymbol{A}^{mut}$,

$$Tr_i \leftarrow \max(Tr_i - 0.5 * RED^{Amut/A} * MRE^{A,C/D} * \left(w_i^{Neigs} + w_i^{Inte}\right) * \Delta Tr^{Base}, 0)$$

When a_i's interaction partner is a non-neighbor a_j, w_i^{Nneigs} should replace w_i^{Neigs}. At the same time, a_j should also update his trust according to the same rule.

• Observing agents

Assume a_k observes the interaction between two mutual neighbors a_i and a_j. If both a_i and a_j apply "Cooperation" and a_k's imaged pure strategy is also "Cooperation",

$$Tr_k \leftarrow \min(Tr_k + 0.5 * \left(w_k^{Neigs} + w_k^{Obs}\right) * \Delta Tr^{Base}, 1)$$

If not both a_i and a_j apply "Cooperation", when a_k's imaged pure strategy is "Cooperation" and the observed payoff matrix is not $\boldsymbol{A}^{mut}$,

$$Tr_k \leftarrow \max(Tr_k - 0.5 * MRE^{A,C/D} * \left(w_k^{Neigs} + w_k^{Obs}\right) * \Delta Tr^{Base}, 0)$$

If not both a_i and a_j apply "Cooperation", when a_k's imaged pure strategy is "Cooperation" but the observed payoff matrix is $\boldsymbol{A}^{mut}$,

$$Tr_k \leftarrow \max(Tr_k - 0.5 * RED^{Amut/A} * MRE^{A,C/D} * \left(w_k^{Neigs} + w_k^{Obs}\right) * \Delta Tr^{Base}, 0)$$

When a_k observes an interaction happening between two mutual non-neighbors, w_k^{Nneigs} should replace w_k^{Neigs}.

2.4.2 To update self's trustworthiness

Agents' updating of their own trustworthiness (namely their probability of cooperation in an interaction) is considered as a process of strategy learning. We constrain the objects of an agent's strategy-learning within his neighbors. Every agent updates his trustworthiness near the end of a time period. What needs to be done for an agent a_i is searching out his neighbor, say a_{j_0}, with highest number of passive potential interactions $Num_{j_0,t}^{PPI,N}$ in the current time period. If $Num_{j_0,t}^{PPI,N}$ is larger than a_i's own times of passive potential interactions $Num_{i,t}^{PPI,N}$, a_i would switch his trustworthiness to a_{j_0}'s cooperation rate of $R_{j_0,t}^{C}$ in the current time period t and take it as his (mixed) strategy for the next time period; otherwise, a_i would maintain his current trustworthiness over to the next time period. The reason why the base of strategy learning is set at agents' cooperation rate of a current time period t rather than agents' probability of cooperation in an interaction is that it is assumed that an agent's probability of cooperation in an interaction is not observable for other agents while his cooperation rate is, on contrast.

Formally, let $Neig_i$ represent the set of a_i's neighbor set in which his strategy-learning candidates are in time period t and a_j be an arbitrary element in $Neig_i$. The agent a_{j0} with the highest number of passive potential interactions in the current time step t in $Neig_i$ satisfis

$$j_0 = \text{argmax}_j\{\, j \mid Num_{j,t}^{PPI,N}, a_j \in Neig_i\}$$

Thus,

$$Trw_{i,t+1} = \begin{cases} R_{j_0,t}^{C} & \text{if } Num_{j_0,t}^{PPI,N} > Num_{i,t}^{PPI,N} \\ Trw_{i,t} & \text{otherwise} \end{cases}$$

Therein

$$R_{j_0,t}^{C} = \frac{Num_{j_0,t}^{C}}{Num_{j_0,t}^{AI}} \quad \left(Num_{j_0,t}^{AI} \neq 0\right)$$ [1]

$R_{j_0,t}^{C}$ represents agent j_0's cooperation rate in time period t, $Num_{j_0,t}^{C}$ represents agent j_0's total times of cooperation in time period t and $Num_{j_0,t}^{AI}$ represents agent j_0's total times of actual (not potential) interactions in time period t.

2.4.3 To update self's unilateral link weights

At the end of each time step t, each agent updates his unilateral link weights for the next time step t+1. At first, a_i evaluates each of his neighbor's cooperation rates only to *him* according to

$$R_{ij,t}^{C_j} = \begin{cases} \dfrac{Num_{ij,t}^{C_j}}{Num_{ij,t}^{AI}} & (Num_{ij,t}^{AI} \neq 0) \\ 0.2 & (Num_{ij,t}^{AI} = 0) \end{cases} \qquad (a_j \in Neigs_i)$$

$R_{ij,t}^{C_j}$ represents a_i's evaluation on his arbitrary neighbor a_j's cooperation rate to *him* in the end of time period t. $Num_{ij,t}^{C_j}$ is the times that a_i's neighbor a_j applies "Cooperation" to a_i in time period t. $Num_{ij,t}^{AI}$ is the times of a_i's actual interactions with his neighbor a_j in time period t. ($Num_{ij,t}^{C_j}$ and $Num_{ij,t}^{AI}$ have been introduced in 5) in 2.4.1.) Num_{i}^{Neigs} is a_i's number of neighbors. 0.2 is used as a proxy of $R_{ij,t}^{C_j}$ whenever a_i has no actual interaction records of his neighbor a_j in time period t.

Then a_i updates his link weights for the next time period t+1 according to the mechanism below:

---

[1] $Num_{j_0,t}^{AI}$ will be definitely larger than 0 if $Num_{j_0,t}^{PPI,N} > Num_{i,t}^{PPI,N}$, since the lower limit of an arbitrary agent's $Num_{i,t}^{PPI,N}$ is zero.

$$lw_{ij,t+1} = p^{API}_{ij,t+1,\tau} = \frac{R^{C_j}_{ij,t} + \delta}{\sum_{j=i-\frac{Num^{Neigs}_i}{2}}^{i+\frac{Num^{Neigs}_i}{2}} \left(R^{C_j}_{ij,t} + \delta\right)} = \frac{R^{C_j}_{ij,t} + \frac{1}{Num^{Neigs}_i}}{\sum_{j=i-\frac{Num^{Neigs}_i}{2}}^{i+\frac{Num^{Neigs}_i}{2}} \left(R^{C_j}_{ij,t} + \frac{1}{Num^{Neigs}_i}\right)}$$

$$(a_j \in Neigs_i, 0 \le \tau \le Req^{Inte}_{i,t} \text{ and } \tau \in \mathrm{N}^+)$$

$lw_{ij,t+1}$ represents the unilateral link weight that a_i assigns to his neighbor a_j for the next time period. $p^{API}_{ij,t+1,\tau}$ represents the probability that a_i actively chooses his neighbor a_j as his potential interaction partner when a_i should choose an potential interaction partner within his neighborhood in any sub-time period τ of time period t+1. What is more, we define δ as *relationship maintenance strength* which is a constant and used for: 1) controlling to which degree a relationship is maintained over to the next time period even if an agent's neighbor defects in all actual interaction between them in the current time period; 2) and at the same time for an agent to attach enough importance on neighbors' cooperation rate in the actual interactions between them in the current time period. The link-weights updating rule is created like this because embeddedness in social network is an interested parameter in this paper and, hence, it is undesirable to totally delete any relationship forever. In this paper, we set $\delta = lw_{ij,t=1} = \frac{1}{Num^{Neigs}_i}$, namely a_i's initial unilateral link weight to his arbitrary neighbor a_j, in order to keep consistence with the fact that, generally, a neighbor is with less probability to be chosen in a larger neighborhood

3 Results and analysis

Simulations are constrained within an artificial society of 100 agents and with an original payoff matrix of $\begin{bmatrix} 3 & 1 \\ 4 & 2 \end{bmatrix}$, and focus on the influence of seven parameters, namely number of immediate neighbors, degree of embededness in social network, mutation probability of payoff structure, mutated payoff matrix, proportion of individuals with high trust in population, probability of information diffusion in neighbors and probability of information diffusion in non-neighbors. The candidate values of each parameter of interest are listed in Table 3-1:[1]

Table 3-1: Candidate values of each parameter of interest

Parameters	Candidate values
1) Population size (ps)	<u>100</u>
2) Number of immediate neighbors (nn)	4, <u>6,</u> 8, 10

[1] The abbreviations of these terms in section 3 are not the same as the mathematical symbols in section 2. The abbreviations in this section are used for annotations in simulation figures.

3) Degree of embededness in social network (se)	0.6, 0.7, 0.8, 0.9
4) Mutation probability of payoff structure (mpps)	0.1, 0.2, 0.3, 0.4
5) Original payoff matrix (***A***)	$\underline{\begin{bmatrix} 3 & 1 \\ 4 & 2 \end{bmatrix}}$
6) Mutated payoff matrix ($\boldsymbol{A}^{mut}$)	$\underline{\begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}}, \begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}, \begin{bmatrix} 3 & -2 \\ 7 & 2 \end{bmatrix}, \begin{bmatrix} 3 & -3 \\ 8 & 2 \end{bmatrix}$
7) Proportion of individuals with high trust in population (pht)	0.6, 0.7, 0.8, 0.9
8) Probability of information diffusion in neighbors (pidn)	0.6, 0.7, 0.8, 0.9
9) probability of information diffusion in non-neighbors (pidnn)	0.1, 0.2, 0.3, 0.4

Note: Numbers or matrixes with a short horizontal line underneath are the parameter values used in base-line simulation.

For every parameter value portfolio under investigation, we are interested in the evolution of two variables: person-time of interaction and person-time of cooperation. Person-time, in this paper, is the sum of every individual's number of some record (such as, actual interaction and cooperation) in a time period. Formally,

$$PersonTime_t^{AI} = \sum_{i=1}^{100} Num_{i,t}^{AI}$$

$$PersonTime_t^{C} = \sum_{i=1}^{100} Num_{i,t}^{C}$$

$PersonTime_t^{AI}$ is the person-time of actual interactions within time period *t* which equals the sum of each agent's number of actual interactions in time period *t*. $PersonTime_t^{C}$ is the person-time of "Cooperation" within time period *t* which is the sum of each agent's number of "Cooperation" in time period *t*. Both are in range [0, $2 * Req_{i,t}^{Inte} * PopulationSize$], namely [0, 4000].[1] “Person-time” is adopted because multiple interactions within a time period are allowed for each agent and every agent is actually using a mixed strategy rather than a fixed pure strategy in a time period, and additionally, it is the impact of interaction information that is important for both interacting agents and observing agents.

Since there are very large potential combinations of parameter values, we will explore the influence of each parameter of interest based on a base-line simulation.

3.1 Base-line simulation

The results of base-line simulation are shown in Figure 3.1-1 and Figure 3.1-2. From Figure 3.1-1 and Figure 3.1-2, two variables of interest (namely, person-time of interaction and person-time of cooperation, respectively) undergo a process of approaching to the largest possible value and the distribution of these two variables of interest are largely skew to the left especially in the first 10 time periods.

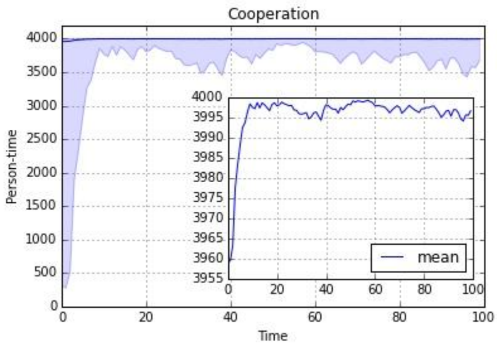


Figure 3.1-1

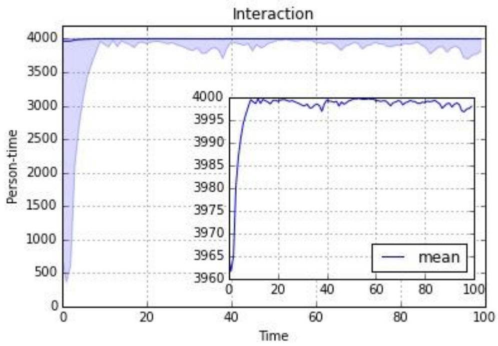


Figure 3.1-2

Figure 3.1-1 and Figure 3.1-2 Base-line simulation. Figure 3.1-1 Evolution of person-time of interaction (minimum, mean and maximum). Figure 3.1-2 Evolution of person-time of cooperation (minimum, mean and maximum). Both run 100 times. The blue lines in both big figure and the small figure are the mean values of 100 simulation runs. The light blue shadow in the big figure is the area between minimum and maximum values of the 100 simulation runs.

3.2 Number of immediate neighbors

Four different values of number of neighbors, namely nn=4, 6, 8 and 10, with the other parameters having the same value with those in the base-line simulation. The simulation results are shown from Figure 3.2-1 to Figure 3.2-3. From Figure 3.2-1 and Figure 3.2-2, number of immediate neighbors does not exhibit monotonous influence on the two variables of interest: when nn=6 and 10, the two variables of interest situate at high level and rapidly approach to the largest possible values; when nn=4, at lower middle level; when nn=8, at very low level. Additionally, when nn=8, cooperation collapses.

- Impacts on trust

[1] $PersonTime_t^{AI}$ and $PersonTime_t^{C}$ are in range [0, $2 * Req_{i,t}^{Inte} * PopulationSize$] rather than in range [0, $Req_{i,t}^{Inte} * PopulationSize$] because each actual interaction contains two players.

Each agent is a representative of a mixed strategy. On the condition that agents' trustworthiness (probability to cooperate) is invariant within a time period, given a particular actual interaction partner, the probabilities of increasing and decreasing personal trust are therewith determined. When nn is relatively small, the probability to meet the same neighbor is relatively high, *ceteris paribus*. The more times an agent meets the same neighbor, the less probability that he encounters diverse mixed strategies, and the stronger the impact of a particular neighbor's trustworthiness on his trust-updating, and the more certain his two trust-updating directions. Thus, encountering the same neighbor reinforces trust-updating directions: the more trustworthy a neighbor, the more opportunities an agent increases trust; the less trustworthy a neighbor, the more chances an agent decreases trust. This influence of number of neighbors on trust therefore is a double-edged sword similar to putting all eggs into one basket. More neighbors offer possibility of dispersing risk of being locked in local environment of trustworthiness constructed by neighbors.

• Impacts on trustworthiness

More neighbors result in less actual interactions with each neighbor and, hence, fewer samples of evaluating the cooperation rate of each neighbor within a time period. This, however, tends to cause polarized evaluation of neighbors, and the "first impression" becomes very important. For example, if an agent carries on one actual interaction with a neighbor, the neighbor's cooperation rate can only be 0 or 1. On contrast, if an agent conducts four times of actual interactions with a neighbor, the neighbor's cooperation rate can be five values, namely 0, 1/4, 2/4, 3/4 and 1. For example, assume an agent a_i's trustworthiness is 1/4 and the trustworthiness of his neighbor a_j who receives the most potential interaction requests is 3/4. In the former situation, a_j interacts once in total in a time period and cooperates. a_j's evaluated cooperation rate will be 1 and a_i will update his trustworthiness to 1. In the latter situation, a_j interacts four times and cooperates three times. a_j's evaluated cooperation rate will be 3/4 and a_i will update his trustworthiness to 3/4. For another example, assume an agent a_i's trustworthiness is 1/4 and the trustworthiness of his neighbor a_j who receives the most potential interaction requests is 2/4. In the former situation, a_j interacts once and defects. a_j's evaluated cooperation rate will be 0 and a_i will not update his trustworthiness and stick to 1/4. In the latter situation, a_j interacts four times and cooperates twice. a_j's evaluated cooperation rate will be 2/4 and a_i will update his trustworthiness to 2/4. This may to some extent explain why the behaviors of the two variables of interest when nn=8 and nn=10 are quite different.

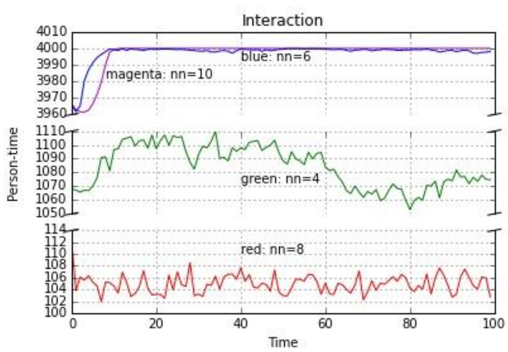


Figure 3.2-1

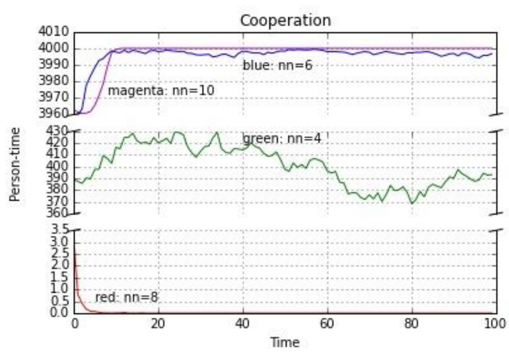


Figure 3.2-2

Figure 3.2-1 and Figure 3.2-2 Comparison of different values of number of immediate neighbors. Figure 3.2-1 Evolution of mean person-time of interaction. Figure 3.2-2 Evolution of mean person-time of cooperation. Both run 100 times.

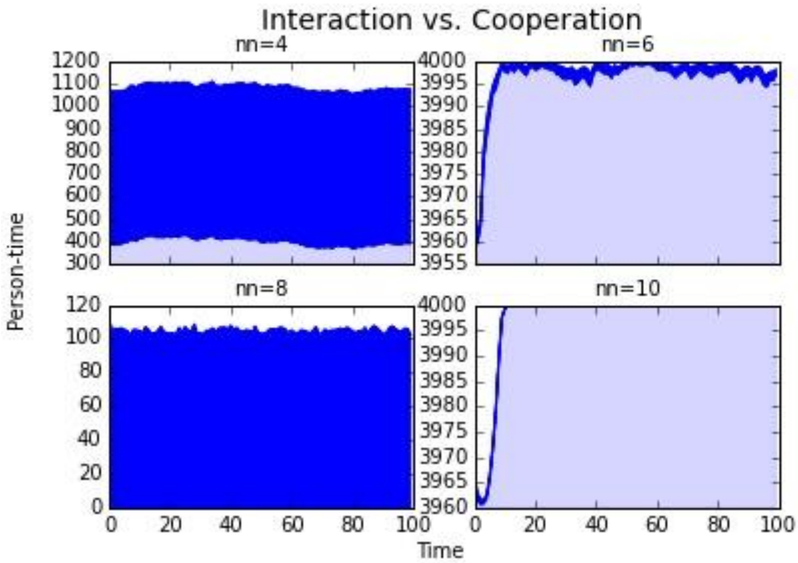


Figure 3.2-3[1] Comparison of different values of number of immediate neighbors. Difference between mean person-time of interaction and cooperation. Run 100 times.

3.3 Degree of embeddedness in social network

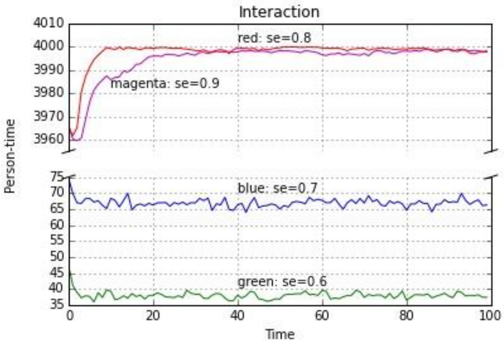
Four different values are compared for degree of embeddedness in social network, namely se=0.6, 0.7, 0.8 and 0.9 with the other six parameters having the same value with those in the base-line simulation. The simulation results are exhibited from Figure 3.3-1 to Figure 3.3-3. From Figure 3.3-1 and Figure 3.3-2, when se=0.8 and 0.9, two variables of interest situate at high level and approach to largest possible value within 20 time periods. On contrast, when se=0.6 and 0,7, the two variables of interest locate very low and mean person-time of cooperation even touches zero. In Figure 3.3-3, when se=0.8 and 0.9, the difference between mean person-time of interaction and that of cooperation is very small; however, when se=0.6 and 0.7, the gap is relatively large. What is more, the gap between person-time of interaction and cooperation exists all the time for all the four candidate values, and the difference is relatively stable.

The principle behind somehow shares the same vein with the impact of number of immediate neighbors on the two variables of interest. When degree of embeddedness in social network is higher, interactions more likely happen within neighborhood, *ceteris paribus*. Thus, when degree of embeddedness in social network is higher, on one hand, an agent's trust-updating relates stronger to his fixed neighbors' trustworthiness; on the other hand, an agent has more samples of their neighbors, and more values of cooperation rate and more chances for him to update trustworthiness, which avoid being locked in low trustworthiness trap. Learnt trustworthiness, then, is reflected on interactions. As aforementioned, degree of social embeddedness is an indicator of

[1] The relatively dark blue shadow is the difference between mean person-time of interaction and that of cooperation of 100 simulation runs, while the light blue shadow is the area of mean person-time of cooperation of the 100 simulation runs. The same with Figure 3.3-3, Figure 3.4-3, Figure 3.5-3, Figure 3.6-3, Figure 3.7-3, Figure 3.8-3.

social mobility in this paper. Thus, as social mobility accelerates, both trust and trustworthiness may collapse.

As to the relatively stable gap between mean person-time of interaction and that of cooperation, it may be attributed to: 1) Information acquisition capability. Assume an agent whose current trust is low. If his information acquisition capability via observing (both neighbors and non-neighbors) is at the same time low, then he has fewer chances to increase trust and will always not participate in actual interactions. 2) Unilateral link weights updating. An agent's most defective neighbor has less likelihood to be chosen as a potential interaction partner if other neighbors are more cooperative.



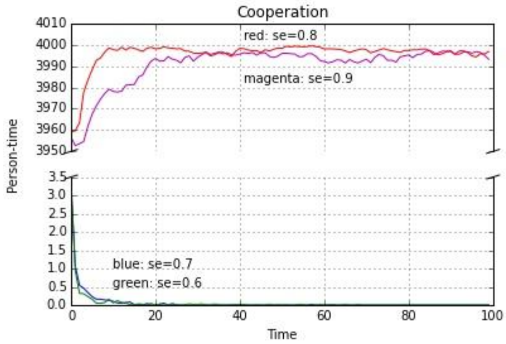


Figure 3.3-1 Figure 3.3-2

Figure 3.3-1 and Figure 3.3-2 Comparison different values of degree of embeddedness in social network. Figure 3.3-1 Evolution of mean person-time of interaction. Figure 3.3-2 Evolution of mean person-time of cooperation. Both run 100 times.

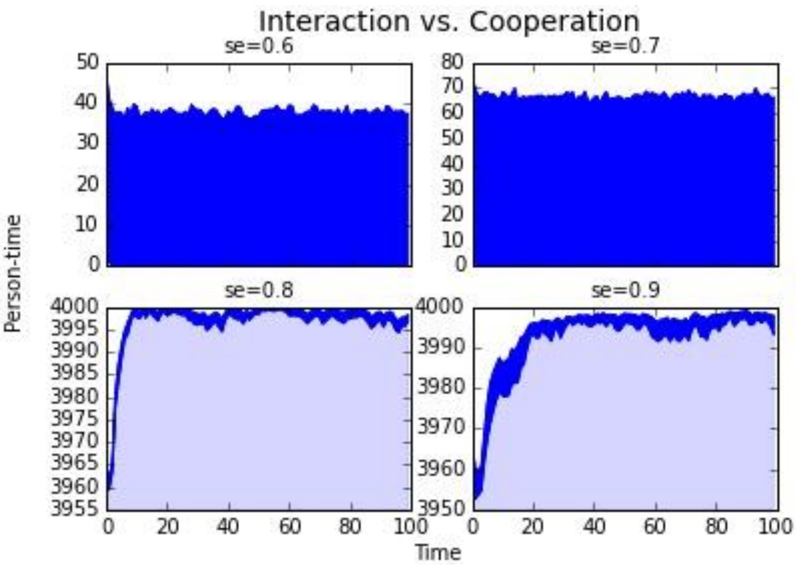


Figure3.3-3 Comparison of different values of degree of embeddedss in social network. Difference between mean person-time of interaction and cooperation. Run 100 times.

3.4 Mutation probability of payoff structure

Four different values are compared for mutation probability of payoff structure, namely 0.1, 0.2, 0.3 and 0.4 with the other six parameters having the same value with that in the base-line simulation. The simulation results are shown from Figure 3.4-1 to Figure 3.4-3. From Figure 3.4-1 and Figure 3.4-2, both the two variables of interest increase and approach to the largest possible value under different parameter values of mutation probability of payoff structure. When mpps=0.1, 0.2, and 0.3, two variables of interest soar within about 10 time periods, while mpps=0.4, increase does not take place until about the 20th time period. Again, from Figure 3.4-3, the gap between mean person-time of interaction and that of cooperation is small and relatively stable.

The reason why two variables of interest increase under all candidate values of mutation probability of payoff structure is that mpps is a conditional probability. That is, it is the probability of the original payoff matrix being changed to a mutated one by an initiator of a potential interaction on condition that the initiator has already decided to play "Defection" in the forthcoming actual interaction, as mentioned before. Therefore, as agents learn to be more trustworthy, they choose fewer times of "Defection" for actual interactions. Consequently, the probability of changing payoff matrix also gets lower. Because payoff values of a mutated payoff matrix enter trust-updating via *relative exploitation degree* (RED), a mutated payoff matrix renders trust-decreasing more severe for an unilateral cooperative party than the original payoff matrix. Therefore, it takes more time for trust to recover and arise when mpps is higher, *ceteris paribus*.

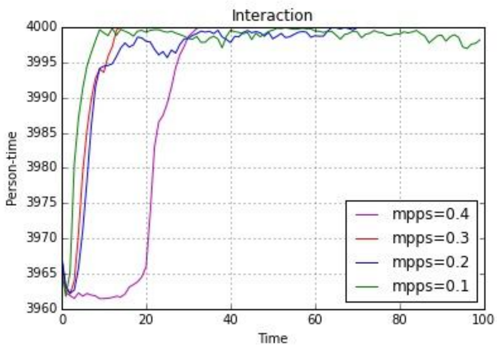


Figure 3.4-1

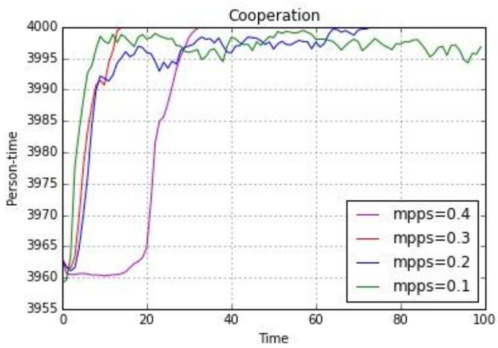


Figure 3.4-2

Figure 3.4-1 and Figure 3.4-2 Comparison different values of mutation probability of payoff structure. Figure 3.4-1 Evolution of mean person-time of interactions. Figure 3.4-2 Evolution of mean person-time of cooperation. Both run 100 times.

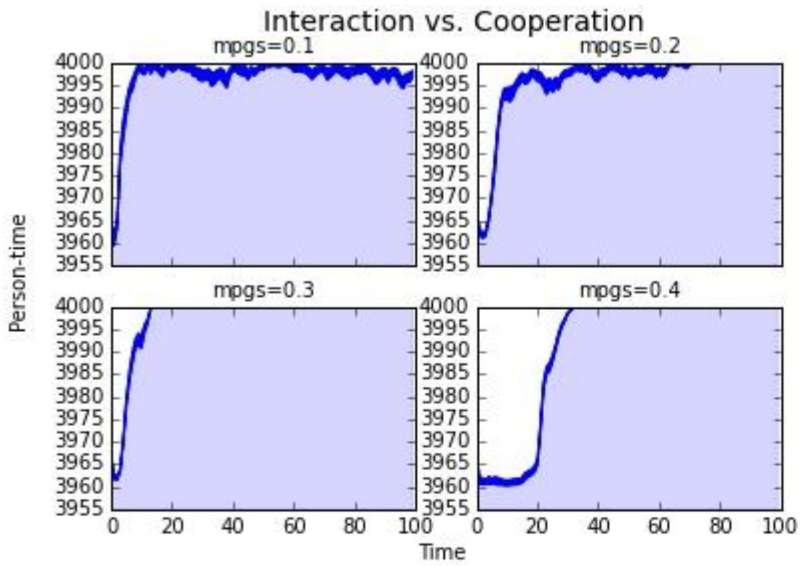


Figure 3.4-3 Comparison of different values of mutation probability of payoff structure. Difference between person-time of interaction and cooperation. Run 100 times.

3.5 Mutated payoff matrix

Four different candidates are compared for mutated payoff matrix, namely $\begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}$, $\begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}$, $\begin{bmatrix} 3 & -2 \\ 7 & 2 \end{bmatrix}$ and $\begin{bmatrix} 3 & -3 \\ 8 & 2 \end{bmatrix}$ with the other parameters having the same values with those in the base-line simulation. The simulation results are presented from Figure 4.5-1 to Figure 4.5-3. From Figure 4.5-1 and Figure 4.5-2, both the two variables of interest increase under different candidates of mutated payoff matrix. However, as *ex post* interest conflict of mutated payoff matrix enlarges, the two variables of interest move downward almost as a whole. From 4.5-3, the gap between mean person-time of interaction and cooperation under $\boldsymbol{A}^{mut}$=$\begin{bmatrix} 3 & -2 \\ 7 & 2 \end{bmatrix}$ and $\begin{bmatrix} 3 & -3 \\ 8 & 2 \end{bmatrix}$ is obviously larger than under $\boldsymbol{A}^{mut}$=$\begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}$ and $\begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}$. It is because *relative exploitation degree* (RED) amplifies the decrease of trust as *ex post* interest conflict of mutated payoff matrix gets stronger, which causes trust to decrease more severe for a unilateral cooperator, *cetera paribus*.

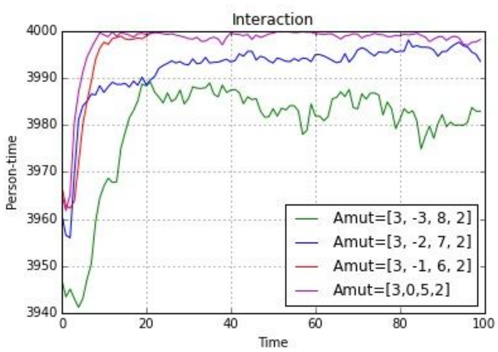


Figure 3.5-1

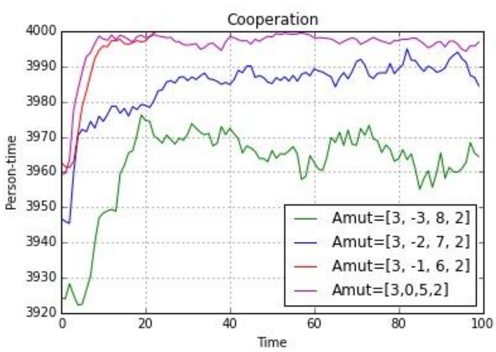


Figure 3.5-2

Figure 3.5-1 and Figure 3.5-2 Comparison of different candidates of mutated payoff matrix. Figure 3.5-1 Evolution of mean person-time of interaction. Figure 3.5-2 Evolution of mean person-time of cooperation. Both run 100 times.

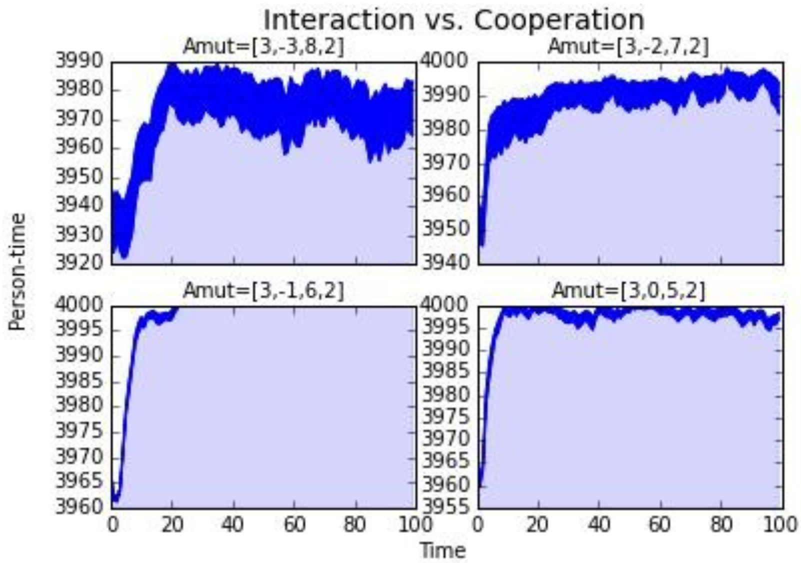
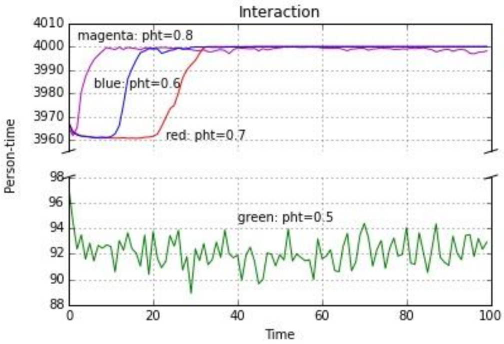


Figure 3.5-3 Comparison of different candidates of mutated payoff matrix. Difference between mean person-time of interaction and that of cooperation. Run 100 times.

3.6 Proportion of high trust agents

Four different values are compared for proportion of high trust agents, namely 0.5, 0.6, 0.7, 0.8 with the other parameters having the same value with those in the base-line simulation. Results are shown from Figure 4.6-1 to Figure 4.6-3. In Figure 4.6-1 and Figure 4.6-3, when pht=0.6, 0.7, 0.8, the two variables of interest locate at high level and increase to the largest possible value. However, when pht=0.5, the two values lie at very low level and cooperation collapses. Additionally, for each variable of interest, similar patterns are achieved respectively under pht=0.6, 0.7, 0.8, even though the taking-off time-points are not monotonously increase as pht decreases. In Figure 4.6-3, when pht=0.6, 0.7 and 0.8, the gap between mean person-time of interaction and that of cooperation is quite small, nearly entirely coincides. On contrast, when pht=0.5, even though there are still a certain amount of actual interactions, no cooperation exists at all. The impact of pht somehow shares a common point with that of mpps, since, roughly speaking, they both generate a horizontal movement as parameter value changes, which is in contrast with the impact of $\boldsymbol{A}^{mut}$ that causes vertical movement.

According to the experimental design in this paper, an agent updates his trust in response to his latest encountering event, either a personal interaction or an observation, on the base of his latest trust level. Hence, an agent's initial trust and the continuous shocks of trust-influencing events of same direction to a large degree affect his personal evolutionary path of trust, *ceteris paribus*. An agent's trust is reflected on his willingness of interaction. The higher an agent's trust, the more possible he would participate in a potential interaction. Higher proportion of high trust agents, equivalent to more skewness to the left of trust distribution among population, therefore definitely results in universal improvement of the willingness of interaction among population. Whereas a small quantity of actual interactions cannot provide enough information of others' trustworthiness, the whole artificial society gets stuck in vicious circle of low trust trap.



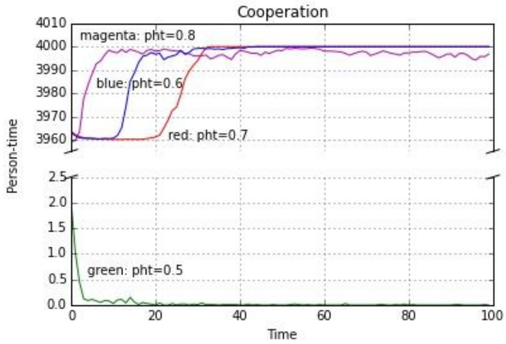


Figure 3.6-1 Figure 3.6-2

Figure 3.6-1 and Figure 3.6-2 Comparison of different values of proportion of high trust agents. Figure 3.6-1 Evolution of mean person-time of interaction. Figure 3.6-2 Evolution of mean person-time of cooperation. Both run 100 times.

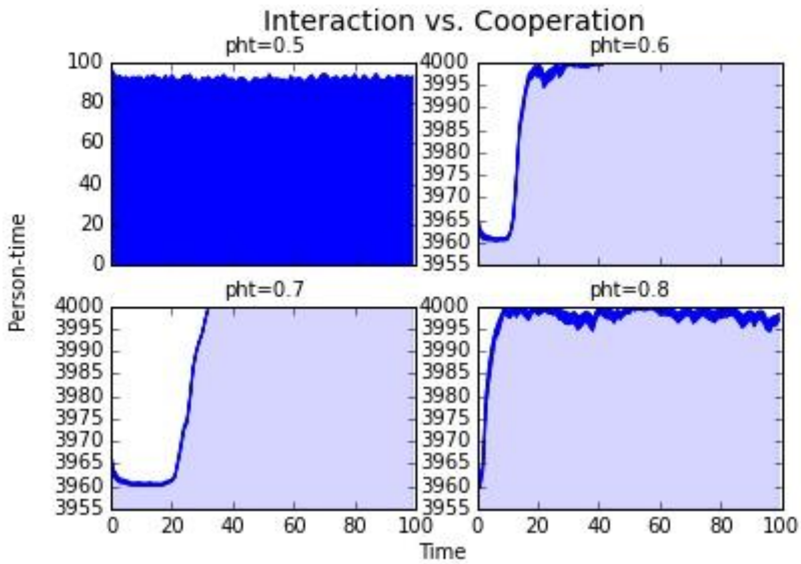


Figure 3.6-3 Comparison of different values of proportion of high trust agents. Difference between mean person-time of interaction and that of cooperation. Run 100 times.

3.7 Probability of information diffusion in neighbors

Four different values are compared for probability of information diffusion in neighbors, namely 0.5, 0.6, 0.7 and 0.8, with the other parameters having the same value with those in the base-line simulation. Results are exhibited from Figure 3.7-1 to Figure 3.7-3. In Figure 3.7-1 and Figure 3.7-2, when pidn=0.5, 0.7 and 0.8, two variables of interest situate at high level. Specifically, when pidn=0.8, the three variables soars first, then when pidn=0.5. Both when pidn=0.5 and 0.8, the two variables approach the largest possible value. When pidn=0.7, the two variables do not develop as well as those when pidn=0.5 and 0.8. On contrast, when pidn=0.6, the two variables locate at low level. In 3.7-3, when pidn=0.5 and 0.8, the gap between mean person-time of interaction and cooperation is smaller than that when pidn=0.7, and a lot smaller than that when pidn=0.6.

As aforementioned, observing is an important channel of acquiring information about others' interactions and, at the same time, trust-updating. A characteristic of information diffusion within neighborhoods is that informational coverage is relatively small but informational arrival is relatively frequent. That is, the impact of information diffusion within neighborhoods is mainly local. Therefore, agents are more likely to have heterogeneous information via observing neighbors. As pidn increases, both the chances of observing trust-increasing events and trust-decreasing events rise. However, trust-decreasing events have larger impacts on agents' trust than trust-increasing events. Thus, the effect of a certain amount of trust-decreasing events needs a more quantity of trust-increasing events to compensate. That is, the impact of pidn on the two variables of interest may depend on the number contrast between trust-increasing events and trust-decreasing events. Only when trust-increasing events are observed as many times as enough can the two variables of interest locate high and soar. Specifically, when pidn is very high (e.g., 0.8), both trust-increasing and trust-decreasing events get very frequently spread and, what is more important, a preponderance of trust-increasing events overwhelm trust-decreasing events. So do when pidn is medium high (e.g., 0.5). However, when pidn is either not extremely high or medium high (e.g., 0.7, especially 0.6), an absence of absolute number advantage of trust-increasing events over trust-decreasing events causes the two variables not to perform quite well.

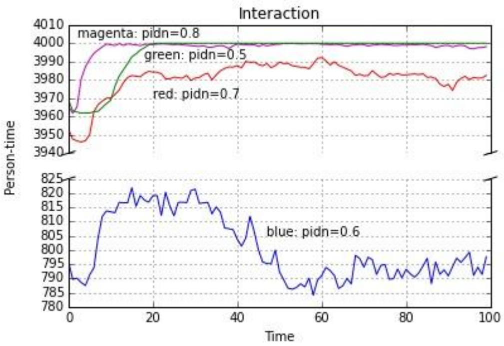


Figure 3.7-1

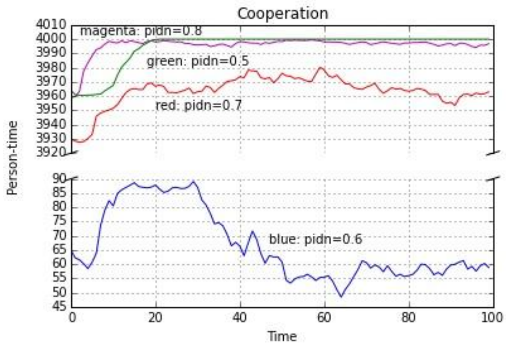


Figure 3.7-2

Figure 3.7-1 and Figure 3.7-2 Comparison of different values of probability of information diffusion in neighbors. Figure 3.7-1 Evolution of mean person-time of interaction. Figure 3.7-2 Evolution of mean person-time of cooperation. Both run 100 times.

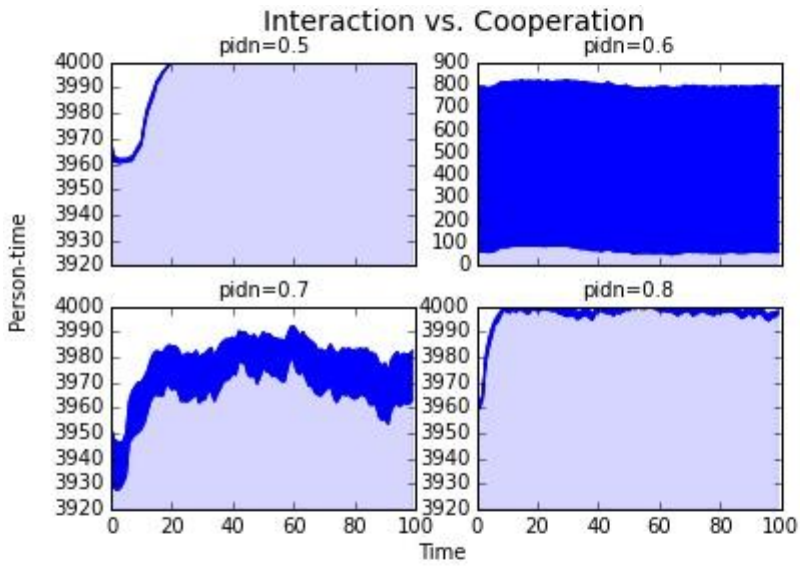


Figure 3.7-3 Comparison of different values of probability of information diffusion in neighbors. Difference between mean person-time of interaction and that of cooperation. Run 100 times.

3.8 Probability of information diffusion in non-neighbors

Four different values are compared for probability of information diffusion in non-neghbors, namely 0.1, 0.2, 0.3 and 0.4 with the other parameters having the same value with those in the base-line simulation. Results are presented from Figure 3.8-1 to Figure 3.8-3. In Figure 3.8-1 and Figure 3.8-2, when pidnn=0.1 and 0.4, two variables of interest situate high and increase to the largest possible value within about 10 time periods; when pidnn=0.3, locate at lower middle level; when pidnn=0.2, lie at very low level and cooperation collapses. In Figure 3.8-3, when pidnn=0.1 and 0.4, the gap between mean person-time of interaction and that of cooperation is very small. On contrast, when pidnn=0.2 and 0.4, the difference is large, especially when pidnn=0.3.

The principle behind is largely similar with that of the impacts of pidn. What is different here for pidnn is that the impact of information diffusion among non-neighbors is relatively global and agents are more likely to have homogeneous information via observing non-neighbors.

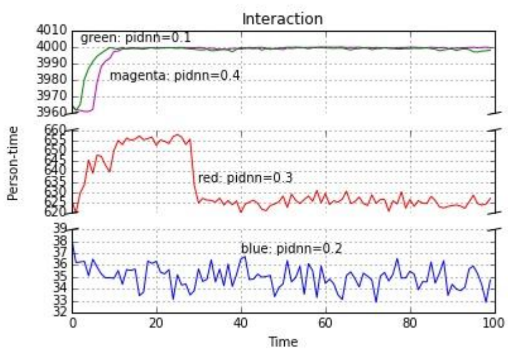


Figure 3.8-1

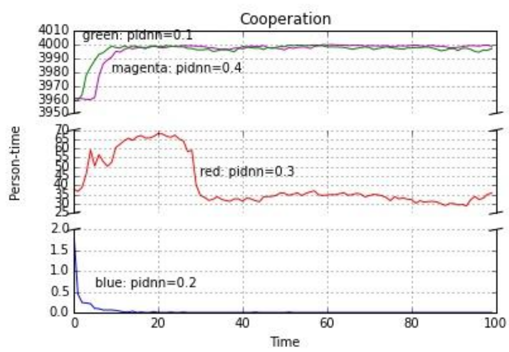


Figure 3.8-2

Figure 3.8-1 and Figure 3.8-2 Comparison of different values of probability of information diffusion in non-neighbors. Figure 3.8-1 Evolution of mean person-time of interaction. Figure

3.8-2 Evolution of mean person-time of cooperation. Both run 100 times.

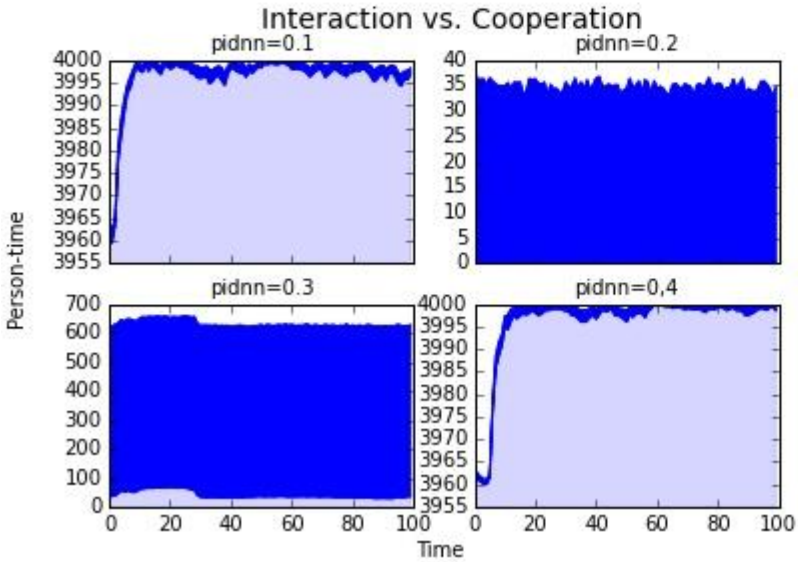


Figure 3.8-3 Comparison of different values of probability of information diffusion in non-neighbors. Difference between person-time of interaction and that of cooperation. Run 100 times.

4 Conclusion

This paper explores the evolution of interaction and cooperation, supported by individuals' changing trust and trustworthiness respectively, on a directed weighted regular ring network from the angle of micro scope by using agent-based modeling. This agent-based model takes into account agents' heterogeneity on: 1) trust and trustworthiness; 2) capabilities of acquiring information from neighbors and non-neighbors; 3) weights of different kinds of information sources. It also integrates several considerations below via relatively delicate experimental design: 1) a characteristic of trust is that trust is destroyed easily and built harder (Slovic, 1993); 2) trustworthiness may be reflected on both strategy decision and payoff structure decision; 3) individuals can decide whether or not to be involved in an interaction; 4) interaction density exists, not only between neighbors and strangers (Macy and Skvoretz, 1998), but also within neighbors; 5) information diffusion.

This agent-based model regard trust as the decisive factor of willingness to interact and trustworthiness as the decisive factor of probability to cooperate, and applies somehow relatively novel and plausible trust-updating, trustworthiness-updating and link-weight-updating mechanism. *Marginal rate of exploitation* of original payoff matrix and *relative exploitation degree* between two payoff matrices are stressed in their influence of trust-destroying; influence of observing is introduced via *imagined strategy*; relationship is maintained through *relationship maintenance strength*, and so on.

This paper extends the concept of interaction platforms: interaction platforms can be geographical-location related, social-roles related, events related and technology based. It also treats number of immediate neighbors, degree of embeddedness in social network, mutation probability of payoff matrix, mutated payoff matrix, proportion of high trust agents and probabilities of information diffusion within neighborhood and among non-neighbors as important aspects happening on interaction platforms, and the influences of these factors are probed respectively on the base of a base-line simulation of the agent-based model in this paper.

It should be figured out here that the results somehow may only fit the experimental design and parameter values in *this* paper. However, several ideas in the experimental design provide important inspiration for further research on trust (such as, decline of trust), which is the most important contribution of this paper.

Acknowledgement

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