Between Trust and Performance: Exploring Socio-Economic Mechanisms on Directed Weighted Regular Ring with Agent-Based Modeling

Gao, Lin

16 April 2017

Between Trust and Performance: Exploring Socio-Economic Mechanisms on Directed Weighted Regular Ring with Agent-Based Modeling

Gao, Lin*

16th April 2017

Abstract: This paper explores the evolution of interaction and cooperation supported by individuals' changing trust and trustworthiness on directed weighted regular ring though agent-based modeling. This agent-based model integrates fragility of trust, interaction decision, strategy decision, payoff matrix decision, interaction density and information diffusion. *Marginal rate of exploitation* of original payoff matrix and *relative exploitation degree* between the original and mutated payoff matrices are stressed in trust updating; influence of observing is introduced via *imagined strategy*; relation is maintained through *relation maintenance strength*. The impact of 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 on the sum of number of actual interaction and cooperation of all agents are probed on the base of a baseline simulation, respectively. Under the experimental design and parameter values selection in this paper, it is found that basically as degree of embeddedness in social network, proportion of high trust agents and probability of information diffusion in neighbors increase, as mutation probability of payoff matrix, conflict in mutated payoff matrix and probability of information diffusion in non-neighbors decrease, interaction and cooperation perform better.

Keywords: Trust, directed weighted regular ring, agent-based modeling, 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.

The micro interactions can be and are often modeled by games, such 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) 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. One possible disadvantage of this method is that given the payoff structure, it cannot distinguish the different degrees of influences on an agent of trust-increasing and trust-decreasing

* Institute of Institutional and Innovation Economics (iino), University of Bremen. Hochschulring 4, WiWi, Room 2.13, 28359, Bremen, Germany. E-mail: lingao@uni-bremen.de

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 has rarely been considered into formal models.

Trustworthiness, as an inseparable aspect of trust research, can be 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 payoff difference between a unilateral cooperation and a unilateral defector 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 link weights. (Newman, 2004) Strength of social ties is a significant characteristic of social relationships. 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, as a methodology (Niazi and Hussain, 2011), 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; Elsner *et al*, 2015, Chapter 9; Chen *et al*, 2015; Caiani *et al*, 2016, among others) 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 useful insights in research of the decline of trust.

Section 1 enumerates some interested parameters and their concrete meaning in my agent-based model. Section 2 describes the experimental design in detail. Section 3 presents results. Section 4

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

concludes.

1 Interested parameters

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 neighbors Number of neighbors in my model refers to 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. What is more meaningful, social embeddedness can also be 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.[1] 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 It 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 means the proportion of individuals whose trust is equal to or higher than 2/3 in the whole population.[2] This is a parameter to represent the whole trust status in a society.

Probability of interaction information diffusing in neighbors It 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 diffusing in non-neighbors It 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

[1] It is simply not be distinguished so much between utility payoff and monetary payoff in this paper; they can be distinguished in different actual and concrete situations.

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

2.1 Artificial society and network structure

Consider an artificial society with n agents. The set of all agents is denoted by a finite set $N = \{a_i \mid 1 \leq i \leq n,\ i \in N^+\}$ with the subscripts representing the unique identity of a given agent. All agents are arranged on a 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. Let $Neig_i$ be a_i's neighborhood, then $Neig_i^C = N - Neig_i - \{a\}$ represents a_i's non-neighbor set. All agents can memorize their neighbors' identity but cannot memorize that of non-neighbors.

2.2 Initialization of agents' attributes

Some important attributes of agents and their initialization are stressed here, even though there exist some other attributes. Their specific usage will be illustrated in 2.3 in detail.

2.2.1Trust and trustworthiness

Both trust and trustworthiness are float numbers in range [0, 1].[1] If an agent's trust is equal to or higher than 1/2, 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, 1/2) and [1/2, 1] follows uniform distribution in corresponding ranges, respectively. That is,

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

$Tr_{i,init}$ is agent a_i's initial trust. r_i^{tr} is a pseudo random number 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,

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

$Trw_{i,init}$ is a_i's initial trustworthiness.

2.2.2 Probability of information acquisition

Information acquisition here means that an agent acquires others' interaction information via non-interaction ("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: 1) probability of acquiring information from his neighbors p_i^{IAN}; 2) probability of acquiring information from his non-neighbors p_i^{IANn}. They are both randomly chosen from uniform distribution in range [0, 1]

[1] Direct relationship between an agent's trust and his own trustworthiness is not presupposed. This is also in accordance with an experimental research of Kiyonari *et al* (2006) which suggests that trust does not beget trustworthiness (Kiyonari *et al*, 2006).

and do not change across time.

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

2.2.3 Weights of four kinds of information sources

It is assumed 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, and 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] Specifically, we set the weights of four kinds of information sources as follows (see Table 1):

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

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

2.2.4 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 time period. A neighbor to whom a_i assigns larger unilateral link weight is with higher probability to be chosen. All weights that an agent assigns to his neighbors sum up to 1. In the first time period, each neighbor of a_i is assigned with equal weight by a_i and with equal probability to be chosen as a potential interaction partner if a_i's choosing scope is within neighbors.

2.3 Micro-level process

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

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 2.3.1), 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 2.3.2); 3) all agents one by one modify their unilateral link weights for the next time period (described in 2.3.3).

2.3.1 Interaction, information diffusion and trust-updating

1) Interaction decision for active potential interactions

For each sub-period τ ($\tau \in \mathrm{N}^+$ and $\tau \leq Req_{i,t}^{Inte}$) in time period 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. 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: 1) It equals number of potential interactions with neighbors $Num_{i,t}^{PI,N}$ plus number of potential interactions with non-neighbors $Num_{i,t}^{PI,Nn}$, or 2) it equals a_i's *active* interaction requests $Num_{i,t}^{API}$ plus interaction requests from others (*passive* interactions) $Num_{i,t}^{PPI}$.

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.

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's willingness to interact which is 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.

[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.

3) Pure strategy decision

Applying which pure strategy for the forthcoming actual interaction is determined by the agents' trustworthiness. If a random number chosen from uniform distribution in range [0, 1] is smaller than an agent's trustworthiness, his strategy will be "Cooperate"; otherwise, his strategy will be "Defect". Hence, each agent is actually using a mixed strategy.

4) Payoff matrix mutation

The actual interaction process is modeled by non-cooperative and symmetric prisoners' dilemmas. [1]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[2]:

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

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

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

[1] Even though a classical game "Prisoners' dilemma" in game theory is adopted, strategy updating (trustworthiness updating in this paper) is not directly associated with comparison of utility function in this paper.

[2] It is not specified in this paper whether the payoffs are utility or monetary payoffs, not it involves the comparability of cardinal utility or ordinal utility; they become more concrete and meaningful in specific situations more or less. However, the meaning behind is obvious in real world.

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 $\boldsymbol{A}$.

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} 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 $\boldsymbol{A}$.

Due to the specific conditions that $\boldsymbol{A}$ and $\boldsymbol{A}^{mut}$ should satisfy in this paper, it is assumed 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 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: a) 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; b) 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, a) is for trustworthiness updating and b) is for unilateral link weights updating.

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, other 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,

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

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

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

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.

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}. What an observing agent will get informed about others' interaction is a) the strategy combination, that is whether the observed interaction is "mutual cooperation", "unilateral defection" or "mutual defection"; b) the relationship between the observed interacting parties, namely "mutual neighbors" or "mutual non-neighbors" and c) 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.)

• 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.)

ii) Quantitative trust-updating

Quantitative trust-updating is based on a certain amount ΔTr^{Base} which equals 0.005 much exactly an agent will update his trust hinges on a) *marginal rate of exploitation* of payoff matrix $\boldsymbol{A}$ (namely, $MRE^{\mathrm{A},C/D}$), b) *relative exploitation degree* of $\boldsymbol{A}^{mut}$ compared to $\boldsymbol{A}$ (namely, $RED^{Amut\,/A}$), and c) 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 1).

Table 2. Trust-updating directions

Information acquiring method	**Strategy**		**Trust-updating direction**	
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		↓	----

- 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}.

2.3.2 To update self’s trustworthiness

Agents’ updating of their own trustworthiness 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 the highest number of passive potential interactions from neighbors $Num_{j_0,t}^{PPI,N}$ in the current time period. If $Num_{j_0,t}^{PPI,N}$ is larger than a_i’s own number of passive potential interactions $Num_{i,t}^{PPI,N}$ and if j_0’s number of actually interaction is not 0, a_i would switch his trustworthiness to a_{j_0}’s cooperation rate of $R_{j_0,t}^{C} = \frac{Num_{j_0,t}^{C}}{Num_{j_0,t}^{AI}}$ $\left(Num_{j_0,t}^{AI} \neq 0\right)$ 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

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

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

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

$R_{j_0,t}^{C}$ 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.

2.3.3 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

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

$R_{ij,t}^{C_j}$ 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_i^{Neigs} is a_i's number of neighbors. α is the default cooperation rate estimation and equals 0.2 which is used as a proxy for $R_{ij,t}^{C_j}$ 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:

$$lw_{ij,t+1} = p_{ij,t+1,\tau}^{API} = \frac{R_{ij,t}^{C_j} + \delta}{\sum_{j=i-\frac{Num_i^{Neigs}}{2}}^{i+\frac{Num_i^{Neigs}}{2}} \left(R_{ij,t}^{C_j} + \delta\right)} = \frac{R_{ij,t}^{C_j} + \dfrac{1}{Num_i^{Neigs}}}{\sum_{j=i-\frac{Num_i^{Neigs}}{2}}^{i+\frac{Num_i^{Neigs}}{2}} \left(R_{ij,t}^{C_j} + \dfrac{1}{Num_i^{Neigs}}\right)}$$

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

$lw_{ij,t+1}$ 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 *relation maintenance strength* which is a constant and whose direct purpose is matrix completion since denominator of each element may be zero. It can also be used for: a) 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; b) 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 $\delta = lw_{ij,t=1} = \frac{1}{Num_i^{Neigs}}$, 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. Change of link weights reflects heterogeneity of links.

3 Results and analysis

Parameter values are listed in Table 3. Numbers or matrices for compared parameters in Table 3 with a short horizontal line underneath are the parameter values used in baseline simulation. Comparison of candidate values of each parameter is based on base-line simulation. For every parameter value portfolio under investigation, I am interested in the evolution of 1) the sum of number of actual interaction of all agents $\sum_{i=1}^{100} Num_{i,t}^{AI}$, 2) the sum of number of cooperation of all agents $\sum_{i=1}^{100} Num_{i,t}^{C}$ and 3) the difference between them.[1] All simulations in this paper are implemented 800 runs.

3.1 Baseline simulation

Before comparison of some parameter values are presented, let us have a quick look at the baseline simulation. Figure 1 illustrates the baseline simulation with the min, max, median and mean of 800 simulation runs. In the baseline simulation, median and mean values of both $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ of 800 runs decrease first and then soar. The distance of their max values and min values are gradually spanning the how range. Median of the differences between $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ decreases first then enlarges and then shrinks again, while its mean is relatively stable.

3.2 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 parameters having the same value with those in the baseline simulation. The results of 800 runs are exhibited in Figure 2. Under the experience design in this paper, $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ perform better (have higher values) as degree of embeddedness in social networks. In the worst situation of se = 0.6, median of both $\sum_{i=1}^{100} Num_{i,t}^{AI}$

[1] Since each interaction involves 2 agents and each time period contains 20 sub-time periods, the max values of $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ is 4000.

Table 3. Parameter values

Parameters	Value / Candidate values
Unchanged parameters	
Network size	100
Number of immediate neighbors	6
Boundary between low trust and high trust	1/2
Original payoff matrix	$\begin{bmatrix} 3 & 1 \\ 4 & 2 \end{bmatrix}$
Base of trust updating (ΔTr^{Base})	0.005
Default cooperation rate estimation (α)	0.2
Relation maintenance strength (δ)	1/6
Number of time periods	50
Number of sub-time periods	20
Number of simulation run	800
Compared parameters	
Degree of embeddedness in social network (se)	0.6, 0.7, 0.8, 0.9
Mutation probability of payoff structure (mppm)	0.0, 0.1, 0.2, 0.3
Mutated payoff structure (Amut)	$\begin{bmatrix} 3 & -3 \\ 8 & 2 \end{bmatrix}, \begin{bmatrix} 3 & -2 \\ 7 & 2 \end{bmatrix}, \begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}, \begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}$
Proportion of high trust agents (pht)	0.6, 0.7, 0.8, 0.9
Probability of information diffusion in neighbors (pidn)	0.7, 0.8, 0.9, 1.0
Probability of information diffusion in non-neighbors (pidnn)	0.00, 0.05, 0.10, 0.15

Note: The abbreviations in the parentheses for the six compared parameters are what will be used in legends in graphics

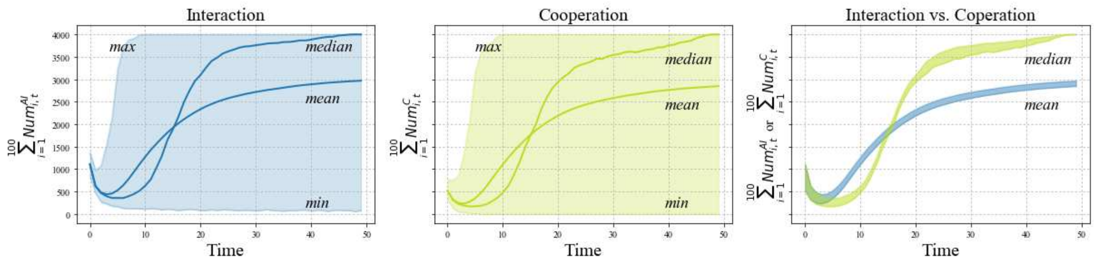

Figure 1. Baseline simulation.

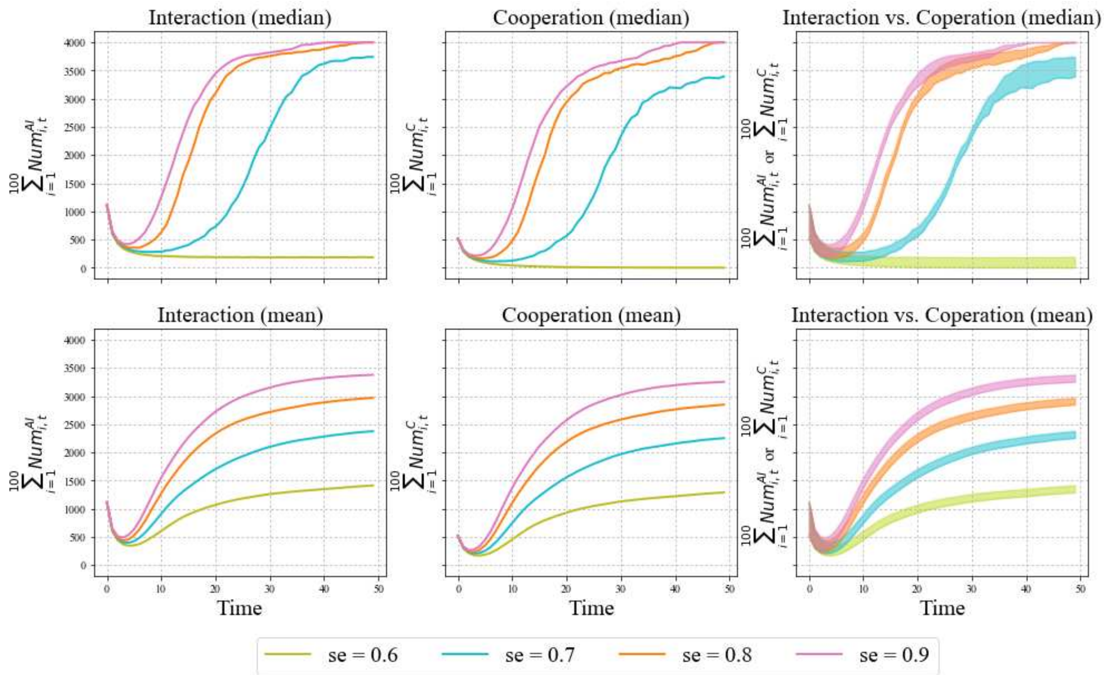

Figure 2. Comparing degrees of embeddedness in social networks.

and $\sum_{i=1}^{100} Num_{i,t}^{C}$ of 800 runs even collapse.

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 the interactions with each neighbor, and more values of cooperation rate estimation for each neighbor, and more chances for him to update trustworthiness, which avoid being locked in low trustworthiness trap. Learnt trustworthiness, then, is reflected on interactions. Degree of embeddedness in social network represents an opposite of mobility to some extent. Thus, as social mobility accelerates, both trust and trustworthiness decrease and may collapse.

As to the relatively stable gap between mean of $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ of 800 runs, 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.

3.3 Mutation probability of payoff matrix

Four candidates are compared for mutation probability of payoff matrix, namely 0.0, 0.1, 0.2 and 0.3 with the other parameters having the same value with the baseline simulation. The results are shown Figure 3. Both $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ soar even with different speed. They perform better for mppm = 0 and 0.1 than for mppm = 0.2 and 0.3.

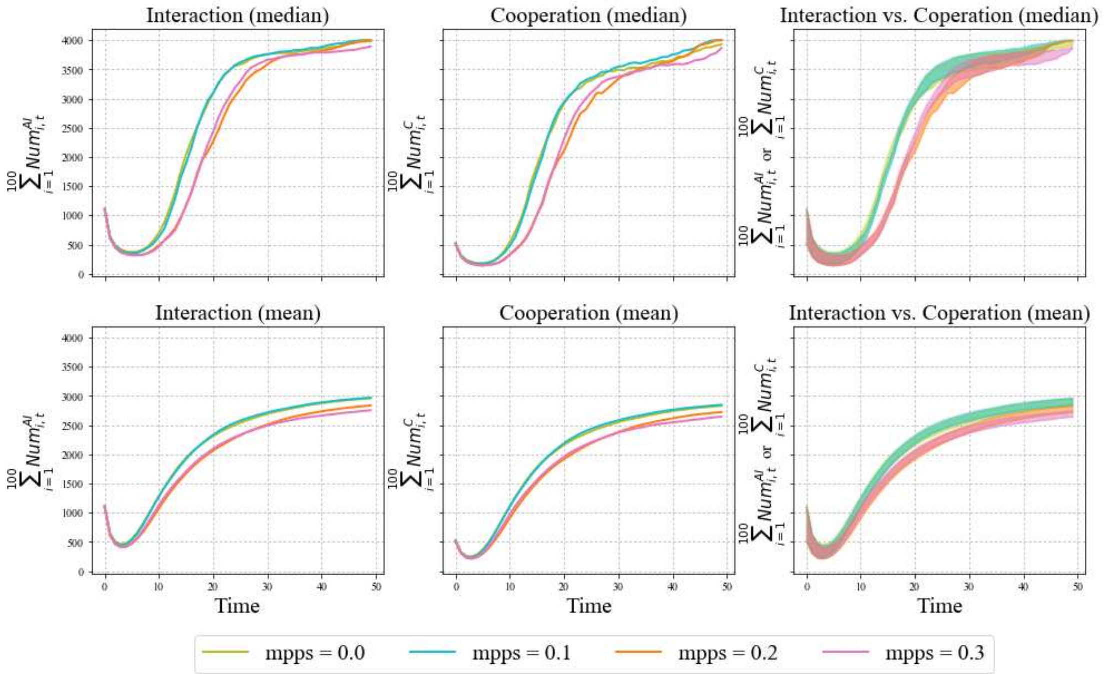

Figure 3. Comparing mutation probabilities of payoff structures.

The reason why $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ increase under all candidates of mutation probability of payoff matrix is that mppm 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 learns 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 a unilateral cooperative party than the original payoff matrix. Therefore, it takes more time for trust to recover and arise when mppm is higher, *ceteris paribus*.

3.4 Mutated payoff matrix

Four different candidates are compared for mutated payoff matrix, namely $\begin{bmatrix} 3 & -3 \\ 8 & 2 \end{bmatrix}$, $\begin{bmatrix} 3 & -2 \\ 7 & 2 \end{bmatrix}$,

$\begin{bmatrix} 3 & -1 \\ 6 & 2 \end{bmatrix}$ and $\begin{bmatrix} 3 & 0 \\ 5 & 2 \end{bmatrix}$ with the other parameters having the same values with the baseline simulation. The results are presented in Figure 4.

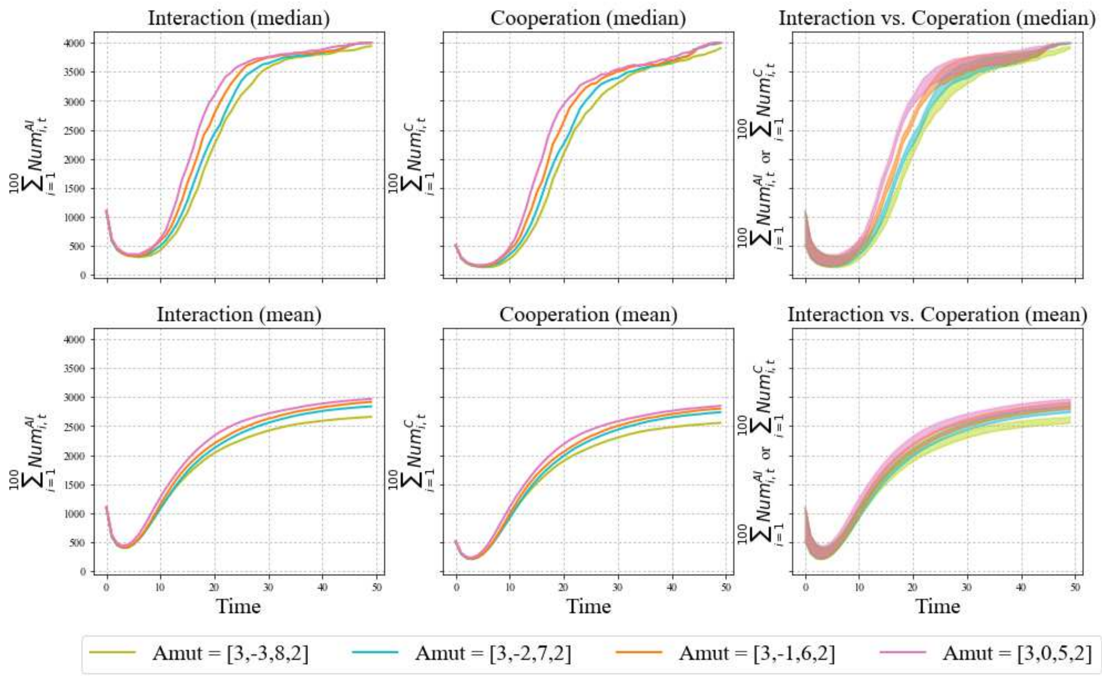

Figure 4. Comparing mutated payoff matrices.

As the conflict between a unilateral cooperator and a unilateral defector narrows, both $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ soar with a faster speed. It is because *relative exploitation degree* (RED) amplifies the degree of trust-decreasing as *ex post* conflict of mutated payoff matrix gets stronger, which causes trust to decrease more severe for a unilateral cooperator, *cetera paribus*.

3.5 Proportion of high trust agents

Four candidates are compared for proportion of high trust agents, namely pht = 0.6, 0.7, 0.8 and 0.9 with other parameters taking the same value with the baseline simulation. The results are exhibited in Figure 5.

The impact of pht is relatively vague, since the figure contradicts our intuition that higher proportion of high trust agents could result in better performance and faster take-off speed. Except the exception of pht = 0.9, we can roughly say that both $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ soar faster as pht increases. Since when pht = 0.9, $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ still perform very well and shares the same pattern with other candidates, this may not be a problem.

3.6 Probability of information diffusion in neighbors

Four candidates are compared for probability of information diffusion in neighbors, namely pidn = 0.7, 0.8, 0.9 and 1.0 with other parameters taking the same value with baseline simulation. Results are shown in Figure 6. Roughly, under the experimental design and parameters value selection, as probability of information diffusion in neighbors gets larger, both $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$

take off faster.

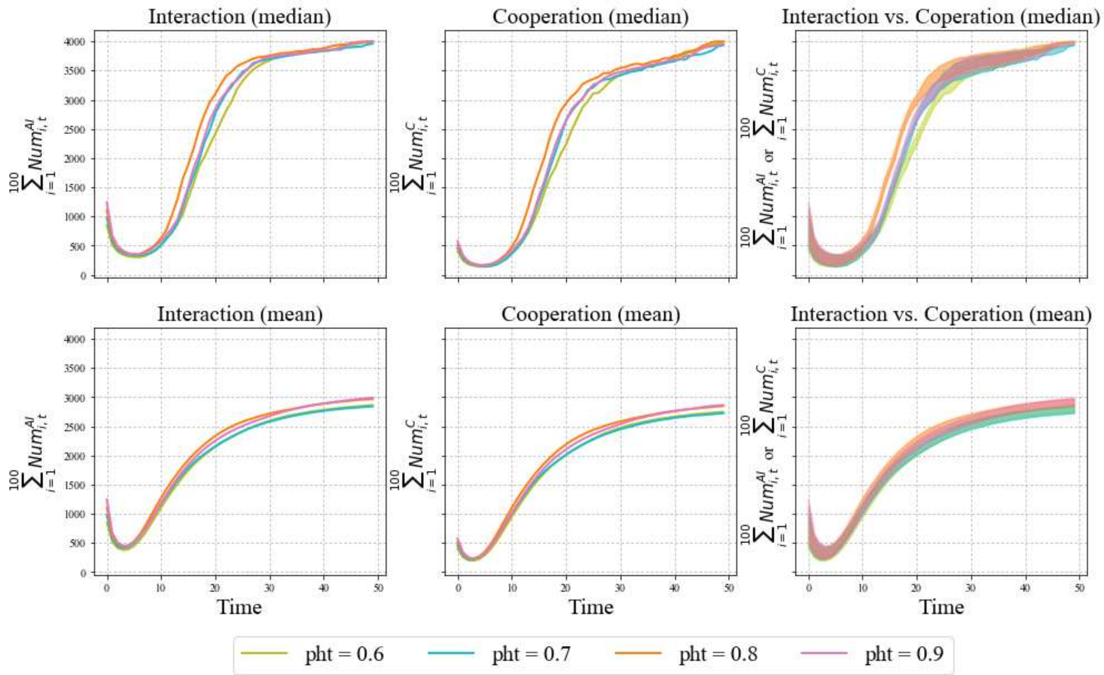

Figure 5. Comparing proportions of high trust agents.

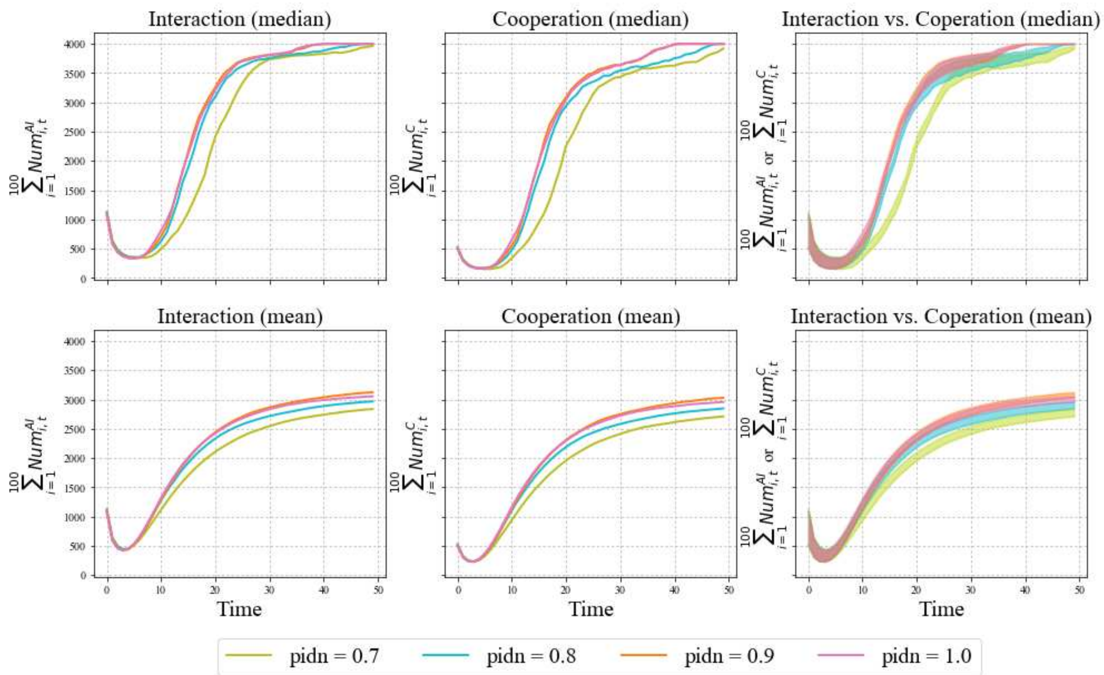

Figure 6. Comparing probabilities of information diffusion in neighbors.

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.

However, it should be mentioned that the impact of information diffusion, both in neighbors and non-neighbors, is a subtle issue. The decisive factor of information diffusion may not be the probability but the nature of event getting diffused, namely whether the observed event is a trust-increasing one or a trust-decreasing one. As pidn increases, both the chances of observing trust-increasing events and trust-decreasing events rise, while 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 $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ 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 soar. The impact of information diffusion is embodied more obviously for non-neighbors which is analyzed below.

3.7 Probability of information diffusion in non-neighbors

Four candidates are compared for probability of information diffusion in non-neighbors, namely pidnn = 0, 0.05, 0.1, 0.15 with other parameters sharing the same value with baseline simulation. Results are plotted in Figure 7. It can be seen that $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ is more sensitive to probability of information diffusion in non-neighbor than in neighbors. As probability of information diffusion in non-neighbors gets larger, $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ take off slower. In the worst situation of pidnn = 0.15, median of $\sum_{i=1}^{100} Num_{i,t}^{AI}$ and $\sum_{i=1}^{100} Num_{i,t}^{C}$ of 800 runs even collapse.

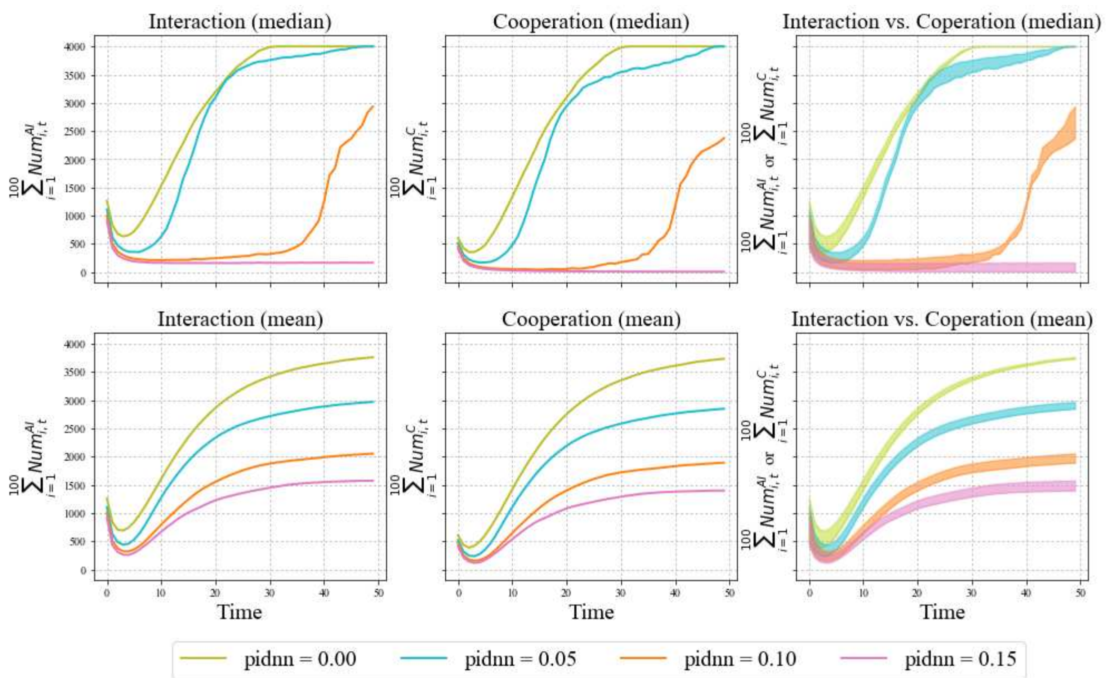

Figure 7. Comparing probabilities of information diffusion in non-neighbors.

As mentioned above, the decisive factor of information diffusion lies in the nature of event getting diffused, namely whether the observed event is a trust-increasing one or a trust-decreasing one.

This kind of impact is amplified for information diffusion in non-neighbors.

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 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 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*; relation is maintained through *relation maintenance strength*.

This paper probes the impact of 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 in socio-economic process on the sum of number of actual interactions and number of cooperation of all agents on the base of a baseline simulation. Under the experimental design and parameter values selection in this paper, basically as degree of embeddedness in social network, proportion of high trust agents[1] and probability of information diffusion in neighbors increase and as mutation probability of payoff matrix, conflict of mutated payoff matrix and probability of information diffusion in non-neighbors decrease, simulation performs better.

Acknowledgement

I wish to express my sincere gratitude to China Scholarship Council (CSC) for financial support, my parents Wenfu Gao and Yingchun Gao for love and support, Torsten Heinrich for seminar "Simulation Models" in University of Bremen, and Wolfram Elsner, Torsten Heinrich, Rebecca Schmitt and Tong-Yaa Su for comments.

References

Axelrod, R.M., 1997. The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration. Princeton University Press.

Axelrod, R.M., 1984. The Evolution of Cooperation. Basic Books, New York.

[1] There is an exception in the impact of proportion of high trust agents, as mentioned above.

Banisch, S., Lima, R., Araújo, T., 2012. Agent based models and opinion dynamics as Markov chains. Social Networks, Vol.34, pp.549-561.

Caiani, A., Godin, A., Caverzasi, E., Gallegati, M., Kinsella, S., Stiglitz, J.E., 2016. Agent Based-Stock Flow Consistent Macroeconomics: Towards a Benchmark Model. Journal of Economic Dynamics & Control, Vol.69, pp.375-408.

Chen, S.-H., Chie, B.-T., Zhang, T., 2015. Network-Based Trust Games: An Agent-Based Model. The Journal of Artificial Societies and Social Simulation, 18(3)5, <http://jasss.soc.surrey.ac.uk/18/3/5.html>.

Elsner, W., Schwardt, H., 2015. From Emergent Cooperation to Contextual Trust, and to General Trust: Overlapping Meso-Sized Interaction Arenas and Cooperation Platforms as a Foundation of Pro-Social Behavior. Forum for Social Economics, Vol.44, No.1, pp.69-86.

Elsner, W., Heinrich, T., Schwardt, H., 2015. The Microeconomics of Complex Economies: Evolutionary, Institutional, Neoclassical, and Complexity Perspectives. Elsevier, Amsterdam.

Geanakoplos J., Axtell, R., Farmer, J.D., Howitt, P., Conlee, B., Goldstein, J., Hendrey, M., Palmer, N.M., Yang, C.-Y., 2012. Getting at Systemic Risk via an Agent-Based Model of the Housing Market. American Economic Review, Vol.102, No.3, pp. 53-58.

Gilbert, N., 2008. Agent-Based Models. Series: Quantitative Applications in the Social Sciences. SAGE Publications, No.153.

Gowdy, J., Mazzucato, M., van den Bergh, J.C.J.M., van der Leeuw, S.E., Wilson, D.S., 2016. Shaping the Evolution of Complex Societies. In: Wilson, D.S., Kirman, A. (Eds.), Complexity and Evolution: Toward a New Synthesis for Economics. The MIT Press, Cambridge, Massachusetts/ London, England, pp.327-350.

Kim, W.-S., 2009. Effects of a Trust Mechanism on Complex Adaptive Supply Networks: An Agent-Based Social Simulation Study, The Journal of Artificial Societies and Social Simulation, 12 (3) 4, <http://jasss.soc.surrey.ac.uk/12/3/4.html>.

Kiyonari, T., Yamagishi, T., Cook, K.S., Cheshire, C., 2006. Does Trust Beget Trustworthiness? Trust and Trustworthiness in Two Games and Two Cultures: A Research Note. Social Psychology Quarterly, Vol. 69, No. 3, pp. 270-283.

Macy, M.W., Skvoretz, J., 1998. The Evolution of Trust and Cooperation between Strangers: A Computational Model. American Sociological Review, Vol.63, No.5, pp. 638-660.

Macy, M.W., Willer, R., 2002. From Factors to Actors: Computational Sociology and Agent-Based Modeling. Annual Review of Sociology, Vol. 28, pp. 143-166.

Newman, M.E.J., 2004. Analysis of Weighted Networks. Physical Review E 70, 056131.

Niazi, M., Hussain, A., 2011. Agent-based Computing from Multi-agent Systems to Agent-based Models: A Visual Survey. Scientometrics, Vol. 89, No. 2, pp. 479-499.

Pyka, A., Fagiolo, G., 2005. Agent-based Modelling: A Methodology for Neo-Schumpeterian Economics. In: Hanusch, H., Pyka, A. (Eds.), The Elgar Companion to Neo-Schumpeterian Economics. Edward Elgar, Cheltenham.

Seltzer, N., Smirnov, O., 2015. Degrees of Separation, Social Learning, and the Evolution of Cooperation in a Small-World Network. The Journal of Artificial Societies and Social Simulation, 18(4)12, <http://jasss.soc.surrey.ac.uk/18/4/12.html>.

Slovic, P., 1993. Perceived Risk, Trust, and Democracy. Risk Analysis, Vol.13, No.6, pp.675-682.

Tesfatsion, L., Judd, K.L. (Eds.), 2006. Handbook of Computational Economics Volume 2: Agent-Based Computational Economics. Elsevier, Amsterdam.

Tran, T., Cohen, R., 2004. Improving User Satisfaction in Agent-Based Electronic Marketplaces by Reputation Modelling and Adjustable Product Quality. AAMAS'04: Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems (Washington, DC, USA), IEEE Computer Society, pp. 828-835.