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Analysis of Individuals' Economic Behavior and Social Interactions in the Context of Prisoner's Dilemma Game: A Simulation Approach

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Abstract

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Starting from the traditional microeconomic concept of the individual's decision process, choices are made based on the concepts of rational behavior and utility maximization; however, several studies from the field of behavioral economics have questioned this traditional model and proposed complementary theories in order to understand and represent the decision-making process better.

To analyze the statements of behavioral economics related to bounded rationality present in the decision-making process and looking from individual to collective levels, this research offers a model using the techniques of computational economics, such as multi-agent based modeling, and the concepts of social and economic networks. The proposed model recreates a scenario of the game on networks using a modified version of the Prisoner's Dilemma game. The agent-based model in a social network simulation allows us to emulate individuals' economic behavior and social interactions with the purpose of studying particularities concerning game performance and outcomes.

The results of the present research demonstrate that in an artificial environment, it is possible to recreate the irrational behavior of individuals and compare it with rational behavior in a social scenario. The findings show that the outcome of the game has differences between rational and irrational behavior in terms of threshold point, conversion time, and transition of the dominant strategy. The application of this research can improve the design of policies and analyze their impact on the society.

Keywords: Behavioral Economics, Prospect Theory, Agent-Based Modeling, Prisoner's Dilemma, Game Theory, Game on Networks.

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Chapter 1. Introduction

1.1. Motivation and Background

Since the beginning of civilizations and along human history, individuals have constantly faced problems related to preferences, decisions, and choices. Decisions are involved in almost all our day to day activities and are influenced by the environment where we live and by other individuals. As a society, we deal with decisions that have impacts on our group. All the decisions that we make aim to achieve individual objectives, as well as collective objectives (Arrow, 1958).

Standard economic theory sets the individual's decision process as the base of economic models. The classic decision-maker model refers to a rational actor making decisions based on self-interest under the axiom of utility maximization. However, several authors have been arguing toward a behavioral economics perspective, where the individual is not alone during the decision-making process and other factors (such as environmental, psychological, sociological, and anthropological) have direct influence during this process. The drivers of evolutionary economics focus on two main social influences: the social context and cultural mental models (Gintis, 2009; Hoff & Stiglitz, 2016).

The decision-making process has several steps; first, the person has to evaluate his or her options in an intelligent decision process; second, select which option will be his or her preferred or likely action according to his or her cognitive reasoning; and finally, do the preferred action (Slovic, 1995). In this context, individual preferences and choices are the basics of an individual's behavior as a single player; however, individuals live in an environment and interact with other individuals. Looking from a micro to a macro perspective, social behavior is the association of each individual's behavior coexisting with others in a social context (Chen, 2016; Koohborfardhaghighi & Altmann, 2014a; Roberts, 2012).

1.2. Problem Description

The classic concept of microeconomics starts with Pareto's approach, which believes that preferences, choices, and utilities have an ordinal interpretation. That ordinal interpretation becomes inconsistent considering aspects such as beliefs, knowledge, uncertainty, and risk. However, a cardinal interpretation of expected utility, which was proposed by von Neumann and Morgenstern in 1944, has created a dilemma between economists. The expected utility approach gives us the option to include risk and uncertainty during the decision-making process (Machina & Viscusi, 2013; M. Peterson, 2009).

Risk and uncertainty are involved in most of the decisions that people make daily and those decisions have different types of biases and misjudgment. Daniel Kahneman and Amos Tversky have studied the irrational behavior of people, and from the psychology perspective, a statement of rational choice behavior is not enough to represent real human behavior, consequently, it has become an inconsistent model (Glimcher & Fehr, 2013; Kahneman, 2003).

Moreover, the classic economic model only considers a static environment and has avoided the reality of dynamic forces, where individuals can discover and learn how to make better decisions in an evolutionary environment. And looking beyond that, individuals interact with other individuals in a constantly changing ecosystem where belief and knowledge flows are present, as well as risks and uncertainties. Then, individuals need to know how to adapt in a changing world (Chen, 2016; Roberts, 2012).

The problem is that the standard microeconomic concepts are not enough to represent the decision-making process. Besides, game theory offers an opportunity to analyze how a decision made by one player infers other players' decisions. In this way, the Prisoner's Dilemma can be used to represent the real problems that people face, in general, but what happens if uncertainties are included, and moreover, when this game is played by a group of people?

1.3. Research Questions

The problematic described before related to the individual's decision-making process and its implications, makes us propose the following research questions:

1. What kind of model can be used to represent individuals' economic behaviors and social interactions?

2. How does the outcome of the Prisoner's Dilemma change by using prospect theory?

3. How can social network structures affect the overall performance of the Prisoner's Dilemma game?

1.4. Objectives

The main objective of this research is to represent the decision-making process and the impact of personal decisions on others in a social structure by using prospect theory.

The secondary objectives aim to use the proposed model in different network structures, analyzing the game's performance and outcomes in terms of decision threshold points and strategy adoption.

1.5. Methodology

During the past two decades, the literature of social and economic networks has been growing exponentially. These new concepts combined with behavioral economic and computational economic techniques offer the research community a better understanding of how individual decisions impact a group of individuals, as well as how beliefs and knowledge are propagated in a social network and what the consequences are for the individuals (Matthew O Jackson, 2014).

The methodology used in the present research sought to answer the three research questions described above. In this sense, six steps were proposed as follows:

1. Review the concepts of decision theory, specifically in terms of rational and irrational behaviors.

2. Investigate game theory concepts and find out how the Prisoner's Dilemma can be used to represent people's interactions.

3. Study the concepts related to games in networks and propose a model that can represent the individuals' decision-making process in a social scenario.

4. Design and implement the proposed model using agent-based modeling.

5. Simulate the model using two decision processes: expected utility (rational behavior) and prospect theory (irrational behavior), and compare the results.

6. Using different network structures, simulate the model and compare the performance.

The reason for using the Prisoner's Dilemma is because it is considered by psychologists and economists as a social dilemma that can represent different instances of human real life problems, where personal and social interests confront each other. "When I do what is best for me, and you do what is best for you, we end up in a situation that is worse for both of us" (Martin Peterson, 2015, p. 2).

The principal methodological tools are multi-agent based modeling and social networks. These two tools will provide enough resources to emulate the Prisoner's Dilemma game between individuals in a social group. The advantages of using both tools allow us to simulate different activities that people perform during the decision-making process (Heckbert, Baynes, & Reeson, 2010; Watts & Strogatz, 1998).

1.6. Contributions

For this research, we designed and analyzed a laboratory experiment of behavioral economics and games in networks. The proposed model has three components employed to represent the decision-making process and the impact of personal decisions on others.

The proposed model and results of this research can be used to design and test policies. In this context, policy makers should be able to consider factors like bounded rationality, repeated games, and network effects. Societies are formed by people, and they interact with others, forming social networks. Inside a social network, beliefs and knowledge are distributed and they will affect the performance and outcome of a new policy.

1.7. Overview of the Rest of the Paper

This paper is organized into five sections. Chapter 2 contains all the theoretical background used. Concepts and perspectives about economics, decision theory, utility, expected utility, and prospect theory are included in the first section of this chapter. The second part contains all the theories related to game theory and networks. The third part is related to the basic concepts of agent-based modeling.

Chapter 3 explains the proposed model. First, we describe the general framework, followed by an explanation of game mechanics as related to the decision process, interactions, and networks. The last section of this chapter analyzes an example using the proposed model.

Chapter 4 covers the simulation and results of the proposed model. The multi-agent scenario of the game in networks uses two decision processes (with and without prospect theory) and four kinds of networks (regular, random, small-world, and scale-free).

Finally, Chapter 5 comprises the conclusions, recommendations, and limitations of the present research.

Chapter 2. Fundamentals of the Model

2.1. Perspectives of Economics

Considering the diversity of social and natural science approaches to how an individual's decision-making process is performed, there are some similarities, as well as some differences, as detailed below:

- **Economic perspective:** Consumers choose from a complete list of products and services. Choices are selected based on the statement of utility maximization (rational choice) (Varian, 2014).

- **Evolutionary psychology perspective:** Decisions attempt to take a step forward from the current status to a better position. In this context, status quo is the baseline endowment for measuring the next level or position (Roberts, 2012).

- **Biological perspective:** The brain has a set of different modules, and each module has a specific function. Our brains have evolved to solve particular problems that our ancestors faced in earlier times (Roberts, 2012).

- **Social perspective:** People make decisions based on different factors, and one of these factors involves the decisions made by other individuals in the social group. People's beliefs and opinions can influence the decisions of others in a social group. Moreover, individuals with higher reputations or recognition are viewed as a model to follow (Arrow, 1994; Hoff & Stiglitz, 2016; Matthew O. Jackson, 2014).

- **Brain process perspective:** Two systems are recognized during the decision process in the brain. The first system, fast thinking or intuitive, uses a low cognition level and is connected to emotions, habits, and the association of events. The second system, slow thinking or reasoning, uses a high cognition level and can solve complex problems. The first system is monitored by the second system, but it does not work all the time during the decision process. Most of our decisions are delivered by the first system during our daily activities (Hoff & Stiglitz, 2016; Kahneman, 2003).

Looking at the perspectives mentioned lines above about how individuals make decisions, it seems complicated to fit all of them in a single static model used in traditional economic theory. However, theories in the fields of behavioral economics and neuroeconomics are available and can be useful for representing an individual's decision process.

2.2. Economic Representations

2.2.1. Preferences, Choices, and Utility

Starting from the traditional economic concept of the decision process, choices under certainty are made based on each individual's preferences, which are fixed, and utility maximization evaluation characterizes the decision process. This concept of rational choice behavior looks very simple, elegant, and idealistic, which is why it is the basis for microeconomic concepts. However, several studies have been done since Arrow (1958) where the traditional economic model has been questioned in order to understand better how the decision process works and what the variables around it are.

Considering the fact that people are different in aspects like age, gender, personality, beliefs, traditions, education, and so on, all these factors have an impact on their preferences. Preferences are also affected by the status quo of each person. People tend to make progress in their status quo, which changes preferences that are controlled by endogenous and exogenous variables (Gintis, 2009; Roberts, 2012).

In this context, preferences and choices are not fixed and they are dependent on different external variables related to natural, social, and cultural environments, where preferences can change over time and individuals have the ability to learn based on their previous experiences and others' experiences. Evolutionary theory suggests that people learn by doing and use past experiences as a source of knowledge to adapt their behavior. Nevertheless, people interact with others and these interactions influence the learning process as well as the concept of social knowledge suggested by Arrow (1958), creating a complex scenario. Finally, to add another element, the environment where people live can change over time. Therefore, uncertainties appear in the decision process scenario and it becomes more complex in a coevolutionary scenario (Gintis, 2009).

In studies done by Rubin (2003) and Pinker (2003), both showed that "humans are not good innate economists". They argued that we do not have the innate capacity to understand modern economics and perform a rational choice process in all our daily activities. As an analogy, we can look at how humans learn to speak and read. First, we learn to speak in an intuitive form because our natural environment helps us to learn automatically. Second, the ability to read is a feature that we need to be taught in order to learn it. Consequently, economics is more like reading; humans require a learning process to understand it and perform a rational choice process (Roberts, 2012).

2.2.2. Uncertainty and Risk in Economic Behavior

In all our decisions, uncertainty and risk are factors that are present most of the time. During our lives, we learn how to deal with these problems. Starting from the traditional economic perspective, preferences have an ordinal approach: an individual's preferences are ranked in a specific order of preference (1st, 2nd, 3rd, etc.). However, this approach is not consistent enough; therefore, a cardinal approach was suggested by von Neumann and Morgenstern in 1944 (Von Neumann & Morgenstern, 2007).

This has generated debates among economists about the traditional ordinal concept postulated by Pareto and the cardinal concept from von Neumann and Morgenstern. The expected utility concept arose with the cardinal approach, and after several discussions, it was accepted and proven that there is no inconsistency and that it can also be applied to the ordinal approach (assuming no risk nor uncertainty) (Machina & Viscusi, 2013).

Risk and uncertainty are present at individual's level, as same as, at market level; then, the analysis could become into complicated mathematical expressions and hard to deal with them. However, the complexity of the mathematical formulation has not been considered as a barrier. Thus, interpreting and analyzing these conditions in economic theory have been limited to using the basic concept of economic behavior.

2.2.3. Expected Utility

The expected utility concept presented by von Neumann and Morgenstern introduced the idea of how to represent an expected value in a choice that an individual faces. This basic representation tries to understand how individuals perceive the conditions of risk and uncertainty. Given a number of possible events, each event can be appraised by its value and occurrence probability. Equation 2-1 displays the expected utility concept (Von Neumann & Morgenstern, 2007).

$$E[u] = \sum_{i=1}^{n} u(x_i)p_i \tag{2-1}$$

Where: $E[u]$ is the expected utility, $u(x_i)$ is the utility of choice x_i , p_i is the probability that choice x_i happens.

Risk and uncertainty are represented in terms of probability. The occurrence probability of an event has been studied in the statistics field, where risk and uncertainty can be measured and evaluated. The complexity of probability depends on the event itself. For example, if a simple event like tossing a coin is going to be considered, then the probability of getting heads or tails is reduced to 0.5. And, if a reward is added for each outcome (heads or tails), then we can calculate the expected utility of the game.

Moreover, expected utility provides a subjective value for each possible choice and can be used to express a preference degree as more likely or more desirable. Therefore, the ordinal approach of preferences fits well in this cardinal approach.

Several studies done by neuroscientists have shown that the brain evaluates the expected utility values representing the different payoffs and selects the one that has the higher value. Therefore, the human brain has the ability to evaluate expected utilities (Gintis, 2009). But, as Kahneman and Tversky explained in prospect theory, perceptions about values and probabilities are biased (Kahneman, 2003).

2.2.4. Prospect Theory

The prospect theory proposed by Daniel Kahneman and Amos Tversky in 1979 was a compilation of their different psychological experiments. The theories behind this concept are opposed to utility maximization and the rational-agent model from traditional economics. The problems arise when people face risk and uncertainty. Under the rational-agent precept, individuals will seek and select the optimal choice, which maximizes its own utility. However, in practice this concept is not true at all; Kahneman and Tversky found that rational choice behavior is inconsistent from the psychology perspective (Kahneman, 2003).

Reviewing the psychological perspective first, the human mind has two main systems and both are used during the decision-making process. The first system is called "intuition" and the second system is called "reasoning." Both are close together and the first system is part of the second system; however, only one of them is used each time when a person faces a decision activity (Kahneman, 2003).

The intuition system has features such as fast thinking, effortless, associative, automatic, and emotional. This system works closely with the perception process of the mind. This system is also connected to an individual's habits. On the other hand, the reasoning system has other features like slow thinking, effortful, logical, controlled, and neutral. The reasoning system controls the intuitive system, but not all the time. Moreover, the reasoning system can detect failures or misconceptions made by the intuitive system. The second system does not work all the time because it depends on our mental capacity. The effortful process requires more mental resources and time to be completed (Kahneman, 2003).

However, individuals use fast or slow thinking depending on the circumstance. If an individual faces a decision process where utility is low, like buying groceries at the store, he or she will use the fast thinking system. On the other hand, if the decision implies a high utility level, like buying a new car, then he or she will use the slow thinking system. Looking at the precepts described earlier and relating them to the two systems, it is possible to say that the rational-choice agent concept does not fit well here (Hoff & Stiglitz, 2016).

When adding a new element, risk, the decisions become more complex. Uncertainty is present due to a lack of complete information during the decision process. In this case, the decision maker has to estimate the value of the possible outcomes based on his or her perceptions, and perceptions come from the environment where he or she is located. In this sense, perceptions are dependent on which framework is presented. The contrasts between the two states are evaluated by the decision maker and his or her decision is made based on the value of the expected outcomes (Fox & Poldrack, 2014).

Until this point, the expected utility concept fits well during the decision-making process, and it is possible to label that decision maker as "risk neutral." But, Kahneman and Tversky found after several experiments that individuals have "risk averse" and "risk seeking" behaviors. Again, these two findings contradict traditional rational behavior, which becomes an irrational behavior. In this case, the expected utility maximization concept looks inconsistent. Therefore, to explain these two risk postures, Kahneman and Tversky formulated the prospect theory. According to this theory, the utility function has two attitudes: one toward gains, and another toward losses. The subjective expected utility is shown in Figure 2-1 and Equation 2-2 (Fox & Poldrack, 2014).

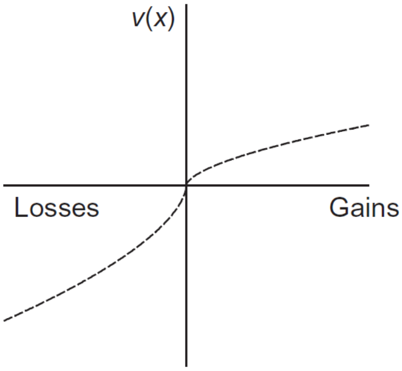

Figure 2-1. Value function, Prospect Theory (Fox & Poldrack, 2014, p. 535).

$$V(x, p) = w(p) * v(x) \tag{2-2}$$

Where: $V(\cdot)$ is the subjective utility, $w(p)$ is the probability weighted function, and $v(x)$ is the value function.

The weighted function represents the relevant probability or subjective probability perceived by the individual. Figure 2-2 shows the shape of this function, which has two main features: an overestimation of lower values and an underestimation of higher values.

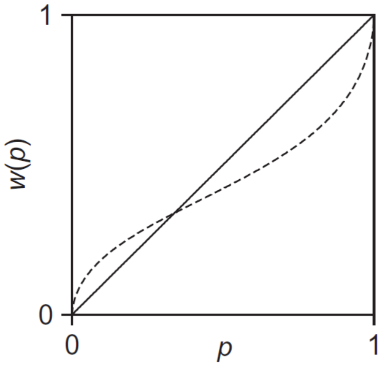

Figure 2-2. Probability weighting function, Prospect Theory (Fox & Poldrack, 2014, p. 535).

Combining these two functions, it is possible to explain the irrational behavior of individuals. Risk aversion behavior is present due to losses that are more painful than gains; individuals tend to avoid negative outcomes without evaluating the true value. Risk-seeking behavior is present when an individual overestimates the lower probability values. Moreover, the status quo point, located in the middle of gains and losses, is a preferred state because of risk aversion. Individuals avoid suffering losses and only seek gains. This precept is the foundation for the endowment effect proposed in behavioral economics. Under this theory, the relation between willingness to accept and willingness to pay is around two times (Fox & Poldrack, 2014; A. Tversky, Slovic, & Kahneman, 1990).

Finally, one extension of prospect theory is the cumulative prospect theory (CPT). In this case, the analysis is focused on decisions under uncertainty. Here, the decision process contains two possible outcomes. Cumulative prospect theory is represented in Equation 2-3 with two outcomes (Fox & Poldrack, 2014).

$$V(x,p;y) = w(p) * v(x) + [1 - w(p)] * v(y) \tag{2-3}$$

Where: $V(\cdot)$ is the subjective utility, $w(p)$ is the probability weighting function, and $v(x), v(y)$ are value functions.

According to several experiments done by Kahneman and Tversky, the utility value and probability weighting functions are possible to represent in formal expressions. Equation 2-4 is the value function and Equation 2-5 is the probability weighting function (Amos Tversky & Kahneman, 1992).

$$v(x) = \begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda|-x|^{\beta} & x < 0 \end{cases} \tag{2-4}$$

Where: $\alpha = 0.88$, $\beta = 0.88$, and $\lambda = 2.25$

$$w(p) = \frac{p^{\gamma}}{[p^{\gamma}+(1-p)^{\gamma}]^{\frac{1}{\gamma}}} \tag{2-5}$$

Where the value of gamma is $\gamma = 0.61$. Equation 2-5 is the probability weighting function (Amos Tversky & Kahneman, 1992).

2.3.Networks

A social network is a graphical representation of a social structure using a collection of nodes and links. Nodes are represented by people and links symbolize an interaction between two people. The social interaction is the way in which two people are connected or related to each other. This social interaction denotes that those two individuals have something in common and they share some information between them. The social network is an interdisciplinary science that mixes social sciences with mathematical models to understand how a group of individuals works (Abbasi & Altmann, 2010; M. Newman, 2010).

Networks have distinctive measures that represent their characteristics. The common measures for networks are:

- **Degree centrality:** The number of connections that each node has. The number of a node's connections can tell us the degree of influence that a specific node has in the network.
- **Eigenvector centrality:** The influence of each node relative to its connections with other nodes. The relative score that each node has represents how well that node is connected in the network.
- **Closeness centrality:** The distance of one node with respect to the others. If a node has a low value, this means that it is a central node, close to the others.
- **Betweenness centrality:** This refers to the measure of how many times the node is located as a bridge to connect other nodes or clusters in the network.
- **Clustering coefficient:** The frequency of small closed loops in the network. Clusters are small groups in the network.

In addition to these measures, networks are usually divided into four groups. The type of each group is based on its topology. The four main groups are:

- **Regular network:** This kind of topology follows a specific pattern in connecting one node with another and its structure looks well organized.

- **Random network:** Connections are made randomly without a prior definition or following a specific distribution. These networks do not follow any pattern or order.

- **Small-world network:** Developed by Duncan Watts and Steven Strogatz, this model refers to a specific feature of the small-world phenomenon. This model is characterized by high propagation speed due to its short path length (Watts & Strogatz, 1998).

- **Scale-free network:** Introduced by Barabasi-Albert, this model follows the power law distribution. The features of this kind of network are similar to most of the networks found in the real world, like the Internet, World Wide Web, power grids, airplane traffic, and so on (Barabási, 2016).

2.4. Game Theory

2.4.1. Definition of Games in Normal Form

Game theory is interested in the analysis of strategic interactions between players. Each player can have two or more strategies to be used during the game. The formal representation of game theory contains a payoff matrix of the game. This matrix has the reward values for each possible outcome. For example, if we have two players (A, B) with two possible strategies $(S1, S2)$, the payoff matrix will have four possible outcomes. Figure 2-3 depicts the payoff matrix for two players with two strategies.

Figure 2-3 corresponds to a symmetric game, where the payoff values are the same according to each strategy selected by each player. This representation is the basic shape used in game theory to analyze strategic interactions.

		Player A	
		S1	S2
Player B	S1	a, a	b, c
	S2	c, b	d, d

Figure 2-3. The payoff matrix of a general game.

Depending on the outcomes, each player can have a dominant strategy or not. A dominant strategy denotes a strong preference for being selected by the player because that strategy provides the higher reward or utility. When both players have dominant strategies, the game will reach an equilibrium (Shoham & Leyton-Brown, 2008; Varian, 2014).

2.4.2. Games Classification

Games are classified according to their main attributes. These main attributes rely on the primordial purpose of each game. From this perspective, games are classified into two main groups: cooperative and non-cooperative. Each group has its own characteristics and points of interest, which are used during the analysis of each game (Heifetz & Yalon-Fortus, 2012; Narahari, 2014).

a) Cooperative Games

This group of games is also called “social dilemma games.” Social dilemma games have a special element related to the social behavior and collaboration of the players. Here there are two possible behaviors, one is a “social interest” and the other is a “selfish interest.” Players can select a strategy according to their evaluation process.

At this point, different dilemmas can appear in order to distinguish which decision is better. Figure 2-4 shows the payoff matrix for social dilemma games.

	Player A	
Player B	Social interest	Selfish interest
Social interest	a, a	b, c
Selfish interest	c, b	d, d

Figure 2-4. The payoff matrix for social dilemma games (Heifetz & Yalon-Fortus, 2012, p. 28).

Again, one of the main concerns in this kind of game is collaborative behavior. Therefore, the analysis focus on understanding when both players cooperate. However, looking at the concept of rational behavior, individuals are selfish and make decisions based on their own personal interest under the axiom of utility maximization. In other words, each player seeks his or her own personal interest, regardless of others' interest. From the ethics perspective, Aviad Heifetz mentioned that: "when all behave selfishly, the outcome is bad for all. Therefore, it is logical and rational for each to contribute her share to common effort. This is because if everyone does so, all will be better off" (Heifetz & Yalon-Fortus, 2012, p. 26).

Different game schemes and dilemmas can be grouped in this category. The most common cooperative games analyzed in economics, biology, and social sciences are the Battle of the Sexes, the Chicken game, Stag Hunt, the Public Goods game, and Global Games.

A variation of the Prisoner's Dilemma game can be considered as a type of cooperative game. This kind of game has been studied extensively in the literature because of the many applications in economics and social sciences. Cooperative games have the strategic complements feature in networks due to their interest in collaborative behavior (Matthew O Jackson & Zenou, 2014).

b) Non-Cooperative Games

The second group contains non-cooperative games. Game analysis is fixated on the benefits of each player. These games do not have any form of commitment between players. Here, players have their own preferences for adopting strategies. Another feature of non-cooperative games is the presence of a conflict between the players. Thus, coalitions or cooperation agreements are not included. Here, the interest is in predicting the opponent's strategy and selecting the best strategy according to the payoff matrix. This behavior corresponds to the Nash equilibrium analysis (Heifetz & Yalon-Fortus, 2012; Narahari, 2014).

Games of competition, like rock-paper-scissors and zero-sum games are non-cooperative games. Evolutionary games can be considered part of this category because they emphasize determining which species will survive. One example of this type of game is the Hawk-Dove game (Heifetz & Yalon-Fortus, 2012).

2.4.3. Nash Equilibrium and Pareto Optimal

Dominant strategies and game equilibrium can be present or not in a game, but reaching equilibrium is not easy in most cases. In this context, two concepts are used to analyze the equilibrium point in a game. The first one is called the Nash equilibrium. It was introduced by John Nash in 1954, and described as follows: "if A's choice is optimal, given B's choice, and B's choice is optimal given A's choice" (Varian, 2014, p. 542). The second concept is called the Pareto optimal. This optimal point in the game follows Pareto's efficiency, and is reached when "there is no way to make someone better off without making somebody else worse off" (Varian, 2014, p. 15).

The analysis of both points, Nash equilibrium and Pareto optimal are used by players to select their preferences in the game. However, before both players play the game, they do not know what strategy will be adopted by their opponent. The players can only have some expectations about what the other player is going to do. And this is where the analysis of the Nash equilibrium can bring an advantage to the player to push the adversary to prefer one strategy or another. Games can be played once or several times, and strategic decisions can have an impact on the players' performance. For example, if our game is between two companies that are fighting over market share, the setup of an aggressive or passive market strategy will impact the performance of both companies. Then each company has to analyze its strategy and evaluate the opponent's strategy. In the end, both companies will earn benefits according to their decisions.

2.4.4. Pure and Mixed Strategy

Pure strategy refers to when a player fixes his or her strategy and is going to play all the games doing the same. Mixed strategy expresses a random behavior of the players to set their strategies. In this case, there is a probability of selecting each choice. Probabilities can be estimated and used to evaluate the dominant strategy, as well as the Nash equilibrium point (Shoham & Leyton-Brown, 2008).

In the presence of risk and uncertainty, each player needs to estimate the possible actions of his or her opponent. The player compares the possible outcomes from each strategy based on the likelihood probability that the opponent will perform the same or different strategy. The decision will be selected based on which strategy yields the higher value (Heifetz & Yalon-Fortus, 2012).

The strategic decision when a player prefers strategy a over strategy b can be represented as follows:

$$E[U(a;p)] \geq E[U(b;p)] \tag{2-6}$$

$$\sum_{i=1}^{n} u(a_i)p_i \geq \sum_{j=1}^{m} u\left(b_j\right)p_j \tag{2-7}$$

Where: $E[U(\cdot)]$ is the expected utility function, a, b are the possible strategies to adopt, p is the probability of strategy profile, and $u(\cdot)$ is the utility value.

2.4.5. Repeated Games

Repeated games occur when both players play the same game several times. In this case, each time they meet can be considered as a new game. The players' reputations are constructed based on their previous decisions, and reward or punishment policies can be applied. In this context, repeated games can be used by policy makers to modify people's behavior. Repeated games can lead an individual's interest to others' interests. Ostrom (1990) explained how societies design repeated game schemes to ensure that people pay attention to others' interests besides their own personal interests. Models that thrill the effects of personal interest on others are known as social capital. Karla Hoff and Joseph Stiglitz referred to social capital when they said, "societies that have constructed repeated games to sustain welfare-enhancing cooperation are said to have high levels of social capital" (Hoff & Stiglitz, 2016, p. 31).

2.4.6. The Prisoner's Dilemma Game

The Prisoner's Dilemma was introduced by Albert W. Trucker in 1950. At that time, John F. Nash, a graduate student at Stanford University, analyzed this peculiar dilemma in terms of non-cooperative games. However, this particular game has a dual impact: one from non-cooperative game analysis and the other related to cooperative games. The Prisoner's Dilemma has been a popular object of study due to its application to real life activities related to social problems, economic applications, political fights, and so on (Martin Peterson, 2015).

The special feature of this game is that it focuses on distinguishing two main strategies: confess and deny. The game presents a case where two bandits have been captured after they committed a crime. The authority in charge of this case gives two options, confess or deny their crime. When both cooperate to confess or deny their crime, they receive the same payoff, but when one of them defects, then they will receive different payoffs. Each prisoner is in a different room and they have to decide on their own; they cannot talk to each other. Figure 2-5 depicts the payoff matrix for the Prisoner's Dilemma game.

		Player A	
		Deny	Confess
Player B	Deny	-2, -2	-1, -20
	Confess	-20, -1	-10, -10

Figure 2-5. Payoff matrix of Prisoner's Dilemma game (Martin Peterson, 2015, p. 2).

The solution from a personal interest point of view is confessing to the crime. Regardless of any other decisions, the confess strategy looks better. If Player A chooses to confess, he or she can receive -1 or -10. If Player B denies, he or she will receive -20, otherwise he or she will receive -10. Then, Player B should confess as well (-10 for both). On the other hand, if Player A decides to deny, he or she can receive -2 or -20. Then Player B can deny and receive -2 or confess and receive -1. Again, Player B would be better off to confess. If we do the analysis in the other way, starting with Player B, the result is the same.

In analyzing this game, we can see that the dominant strategy is selecting the confess strategy. Nevertheless, the Nash equilibrium point is located when both players decide to deny. The Pareto optimal is located when both players decide to confess. This is when the dilemma arises regarding which solution is correct, the Nash equilibrium or the Pareto optimal.

If both players decide to pursue his or her personal interest, using rational choice behavior, then those actions will only benefit each individual. But, the game has another solution, which is when both players act together and choose deny. As Martin Peterson (2015) mentioned: "the actions that most benefit each individual do not benefit the group" and "when I do what is best for me, and you do what is best for you, we end up in a situation that is worse for both of us." This is the main reason that has made the Prisoner's Dilemma become one of the most relevant and studied games.

The Prisoner's Dilemma has grabbed the attention of scientists from different areas like economics, psychology, sociology, biology, physics, and so on. This game has different variants and applications; each one adapts the payoff matrix according to its reality. In general, the payoff matrix for the Prisoner's Dilemma game is shown in Figure 2-6. The main condition for the values is that it must have $a > b > c > d$. Also, it has to consider that $2b > (a + d)$ (Martin Peterson, 2015).

		Player A	
		Cooperate	Selfish
Player B	Cooperate	b, b	a, d
	Selfish	d, a	c, c

Figure 2-6. General Prisoner's Dilemma payoff matrix.

We mentioned that the prisoners are not able to talk to each other. However, we can consider the option where each prisoner makes a promise to his or her partner about his or her choice. Again, a dilemma arises when each prisoner evaluates his or her options and he or she can behave selfishly or not. Moreover, this game can be played several times in a repeated way. During repeated games, players can change their strategies one or more times according to their evaluations of the future next game. In this context, cooperative behavior can lead to reaching benefits in the long run.

2.4.7. Games on Networks

a) Introduction

Individuals make decisions all the time, from in the morning about breakfast until evening about which TV channel to watch. Most of these decisions are influenced by people around the decision maker. Hence, social networks play an important role at an individual's level as well as at a societal level. Beliefs and behavior can spread in a social group and influence people's decisions (Matthew O Jackson & Zenou, 2014).

People's consumption behavior has two components: one related to personal satisfaction, and one that reflects social consumption. People enjoy when others are consuming similar products or making similar decisions, for example, people like sharing and discussing their hobbies or common activities (Hoff & Stiglitz, 2016; Janssen & Jager, 2003).

In this context, strategic actions performed by individuals in a network will have an impact on the micro and macro level. Therefore, network structure matters, as well as individual preferences. Moreover, personal decisions will influence others' decisions.

b) Definitions

During the game, we consider the two main components, the players, and a network. The players are a finite set from 1 to n. Each player has connections, called links, with other players. Therefore, the network is formed by the players and their connections. The players' links symbolize an interaction between players. Players interact with their closest neighbors, and this represents a subnetwork (Matthew O Jackson & Zenou, 2014; Koohborfardhaghighi & Altmann, 2016a, 2016b).

c) Games

A game in a network is performed by players in a finite subset of subnetworks. In other words, the game is played in each subnetwork. Therefore, a player's utility depends on other players' decisions. Those other players are the neighbors and the rest of the players in the network. The decision in terms of a pure Nash equilibrium strategy depends on the expected payoffs. Games can be performed several times until the game reaches an equilibrium point (Matthew O Jackson & Zenou, 2014).

2.5. Agent-Based Computational Economics

2.5.1. Concept, Characteristics, and Principles

The concept of the agent comes from the artificial intelligence field. Here, an agent represents any living organism, like humans or animals, and also a group of individuals, like an organization or institution. This entity has the following characteristics (Shi, 2011):

- **Autonomy:** The agent controls its behavior according to its goals and intentions.
- **Interactive:** The agent can influence and be influenced by the environment.
- **Collaborative:** The agent is not alone in the environment, and it can interact with other agents (multi-agent system).

- **Communication:** The way that the agent exchanges information with other agents is called communication.

- **Longevity:** The agent has a "fairly long" time span.

In this sense, an agent can be considered as an autonomous entity located in a specific environment. The agent perceives or gets information about the environment through its sensors and uses that information to perform actions, and those actions involve the surrounding environment. Figure 2-7 illustrates the basic concept of an agent.

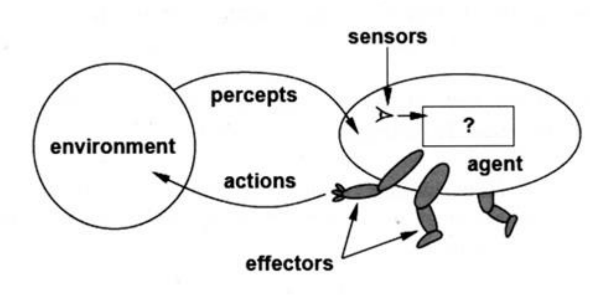

Figure 2-7. Agent model concept (Shi, 2011, p. 503).

The special feature of agent-based modeling is related to dynamic systems. The agent is able to change its goals according to the environmental conditions, and the environment can also change over time. In this sense, the agent performs a decision-making process based on rules and analytic functions. In a multi-agent system, each agent can perform different behavior depending on its own objectives; this allows us to represent heterogeneity among all agents in the system. Multi-agent systems are complex and hard to represent by traditional methods like differential equations, which are difficult mathematical expressions to handle (Heckbert et al., 2010; Railsback & Grimm, 2011; Shi, 2011).

2.5.2. Interactions, Emergent Patterns and Adaptive Behaviors

Interactions allow us to explore a phenomenon conceptualized from the micro to the macro level. Simple interactions at the individual level can deliver different results at the collective level. Interactions can represent economic processes like a specific market, or a complete industry, where agents exchange goods and services (Heckbert et al., 2010).

Emergent patterns refer to the representation of a collective behavior that is the result of individual actions. This feature provides researchers with the ability to analyze how collective patterns emerge or originate from a micro level. In this sense, a group of people can have a specific collective behavior based on the actions performed by each individual. This socioeconomic phenomenon can be represented and evaluated on both levels, micro and macro (Heckbert et al., 2010; Railsback & Grimm, 2011).

The adaptive behaviors feature has a special application to represent human behavior. Looking back at the classic assumption of rational choice behavior in economics, this representation has been questioned by new approaches from behavioral economics. Several experiments have demonstrated that people's behavior is not rational at all, and it adapts over time and according to the environmental conditions. Moreover, an individual's decisions are made using incomplete information under regimes of risk and uncertainty. Putting this all together, the human decision process is a dynamic complex system that depends on endogenous and exogenous factors. The dynamics of this behavior are based on two main principles: adaptation and learning. Humans adapt their goals according to the circumstance and also learn how to satisfy their needs. Therefore, as a methodological tool, the Agent-based modeling

(ABM) offers researchers the possibility to model and simulate the human decision-making process in an environment with other agents with whom they can establish social interactions and exchange information and/or resources (Gintis, 2009; Heckbert et al., 2010; Koohborfardhaghighi, Lee, & Kim, 2016a, 2016b).

2.6. Literature Review of Games on Networks and the Prisoner's Dilemma Game

In this subsection, we will present a brief look at some research related to games in networks, the Prisoner's Dilemma, and prospect theory. These three aspects are closely related to our research. The main idea of this summary is to show which aspects have been examined in the literature related to our research topic.

This literature review has five features: the game in networks model, game objectives, strategic decision process, networks used, and prospect theory. Tables 2-1 to 2-4 show the features and the corresponding references.

Table 2-1. Networks used literature review.

Network used	References
General (theoretical approach)	(Candogan et al., 2016; Corten et al., 2016; Ding et al., 2015; Dziubiński et al., 2016; Huang et al., 2015; Raub & Weesie, 1990; Rogers et al., 2015; Wu et al., 2005)
Regular (simulated)	(Ding et al., 2015; Huang et al., 2015)
Random (simulated)	(Buskens & Snijders, 2016; Fu et al., 2008; Szolnoki & Perc, 2009)
Small-world (simulated)	(B. J. Kim et al., 2002; Ono & Ishizuka, 2005; Wu et al., 2005)
Scale-free (simulated)	(Perc & Szolnoki, 2008; Wu et al., 2005)
More than one type of network (simulated)	(Cassar, 2007; Cimini & Sanchez, 2015; Ohtsuki et al., 2006)

Table 2-2. Game objective literature review.

Game Objective	References
Strategy adoption	(Buskens & Snijders, 2016; Cassar, 2007; Cimini & Sanchez, 2015; Ding, Wang, Ruan, & Xia, 2015; Dong, Li, Tao, & Zhang, 2015; Engel & Zhurakhovska, 2016; Haas, 2001; B. J. Kim et al., 2002; Nowak & May, 1993; Ono & Ishizuka, 2005; Perc, 2006; Szolnoki & Perc, 2009; Szolnoki & Szabó, 2007; Wu, Xu, Chen, & Wang, 2005)
Utility	(Candogan, Epitropou, & Vohra, 2016; Corten, Rosenkranz, Buskens, & Cook, 2016; Ding et al., 2015; Dziubiński, Goyal, & Minarsch, 2016; Huang, Cheng, Zheng, & Yang, 2015; Raub & Weesie, 1990; Rogers, Roth, Ullman, & Wu, 2015; Wu et al., 2005)
Other objective	(Ballester, Calvó-Armengol, & Zenou, 2006; Dolbear & Lave, 1966; Fu, Hauert, Nowak, & Wang, 2008; Goeree, Holt, & Palfrey, 2003; Nikolova & Stier-Moses, 2015; Ohtsuki, Hauert, Lieberman, & Nowak, 2006; Raub & Snijders, 1997)

Table 2-3. Strategic decision process literature review.

Strategic decision process	References
Fermi function (payoffs)	(Ding et al., 2015; Perc, 2006; Szolnoki & Szabó, 2007; Wu et al., 2005)
Normalized cumulative payoff	(B. J. Kim et al., 2002; Ono & Ishizuka, 2005; Szolnoki & Perc, 2009; Wu et al., 2005)
Expected utility	(Corten et al., 2016; Dziubiński et al., 2016)
Cost minimization	(Nikolova & Stier-Moses, 2015; Rogers et al., 2015)
Field experiment (empirical evidence)	(Dolbear & Lave, 1966; Engel & Zhurakhovska, 2016; Goeree et al., 2003; Raub & Snijders, 1997)
Other decision process	(Ballester et al., 2006; Buskens & Snijders, 2016; Candogan et al., 2016; Cassar, 2007; Cimini & Sanchez, 2015; Dong et al., 2015; Fu et al., 2008; Haas, 2001; Huang et al., 2015; Nowak & May, 1993; Ohtsuki et al., 2006; Raub & Weesie, 1990)
Using prospect theory (empirical approach)	(Dolbear & Lave, 1966; Engel & Zhurakhovska, 2016; Goeree et al., 2003; Haas, 2001; Raub & Snijders, 1997)

Table 2-4. Game model literature review.

Game on Network Model	References
Prisoner's dilemma game (cooperative)	(Buskens & Snijders, 2016; Cassar, 2007; Cimini & Sanchez, 2015; Corten et al., 2016; Ding et al., 2015; Dolbear & Lave, 1966; Engel & Zhurakhovska, 2016; B. J. Kim et al., 2002; Ono & Ishizuka, 2005; Perc, 2006; Raub & Weesie, 1990; Wu et al., 2005)
Prisoner's dilemma game/Evolutionary game (cooperative)	(Nowak & May, 1993; Szolnoki & Szabó, 2007; Wu et al., 2005)
Prisoner's dilemma game/Coevolutionary game (cooperative)	(Fu et al., 2008; Szolnoki & Perc, 2009)
Prisoner's dilemma game and Harmony game (cooperative)	(Huang et al., 2015)
Prisoner's dilemma game and Public Goods game (cooperative)	(Dong et al., 2015)
Other games (cooperative)	(Haas, 2001; Nikolova & Stier-Moses, 2015; Ohtsuki et al., 2006; Raub & Snijders, 1997; Rogers et al., 2015)
Other games (non-cooperative)	(Ballester et al., 2006; Candogan et al., 2016; Dziubiński et al., 2016; Goeree et al., 2003)

This literature review is useful for distinguishing between the different studies that have been done related to the game in networks, the Prisoner's Dilemma, and prospect theory. Nevertheless, there is a void in modeling and simulating the individual decision-making process in networks using prospect theory. This void will be filled with the present research.

Chapter 3. Model Description

3.1. Game Model Framework

The model has four main conceptual components: expected utility, prospect theory, the Prisoner's Dilemma game, and the game on networks. These four components and our model represent the decision-making process and the impact of personal decisions on others.

Three elements are used in our model to represent the decision-making process and the impact of personal decisions on other individuals.

- **Decision process:** Uses the expected utility and prospect theory.
- **Interaction process:** Repeated Prisoner's Dilemma game.
- **Game on Networks process:** Represents our model in a global setting.

In this context, the concept of games on networks conceptualized by Matthew O Jackson and Zenou (2014) is useful to include in our model. However, there are some particular details related to behavioral economics that make our model different than others.

3.1.1. Decision Process

An individual's decisions are based on maximizing the utility function by evaluating his or her personal interest and the possible actions performed by neighbors. The neighbors are the individuals with whom the decision-maker interacts, and his or her behavior is influenced by them.

The possible actions that others can do introduce uncertainty into the system. During the decision process, the individual has to estimate the possible actions that others might do. Then, utility becomes an expected value under uncertainty. Now consider that the individual has two choices (c, d); before making a decision, he or she has to evaluate each choice and then select the one with the expected higher return. To represent this decision criteria, we use the expected utility expressions as follows:

$$E[U(c)] = \sum_{i=1}^{n} u(c_i) * p(c_i) \tag{3-1}$$

$$E[U(d)] = \sum_{j=1}^{m} u(d_j) * p(d_j) \tag{3-2}$$

Where: $E[U(\cdot)]$ is the expected utility function, c, d are the possible strategies to adopt, p is the probability of strategy profile, and $u(\cdot)$ is the utility value.

If $E[u(c)] > E[u(d)]$, then c will be preferred over d; otherwise d will be selected.

The second approach to the decision process is using prospect theory. Cumulative prospect theory (CPT) is used in regimes under uncertainty. In these circumstances, the person faces a problem where two possible outcomes can happen. The prospect considers two options, where $V(\cdot)$ is the subjective utility, $w(p)$ the probability weighting function, and $v(x), v(y)$ are the value functions for each outcome.

$$V(x, p; y) = w(p) * v(x) + [1 - w(p)] * v(y) \tag{3-3}$$

Equation 3-3 represents the Cumulative Prospect Theory (CPT).

3.1.2. Interaction Process

The interaction process occurs between two players (X, Y) and two strategies (c, d). Our model is performed using a variant of the Prisoner's Dilemma. Each player can choose to behave as a cooperator or defector:

- **Cooperator ($\boldsymbol{c}$):** This player pays a cost (C) for every interaction and expects to receive something back.

- **Defector ($\boldsymbol{d}$):** This player has no intention to pay any cost and wants to receive some profit.

Considering our basic schema of two players (X, Y) and two strategies (c, d), the payoff matrix can be defined as follows:

Table 3-1. Basic schema of the payoff matrix (2x2).

	X-Defector	**X-Cooperator**
Y-Defector	$X = 0; Y = 0$	$X = -C; Y = C$
Y-Cooperator	$X = C; Y = -C$	$X = B; Y = B$

The condition in our model is when both players cooperate, they will receive a benefit (B). From the societal perspective, cooperator behavior favors social welfare, and a defector is a free rider.

Now, we will consider the expected utility concept in a scenario of repeated games for our model. The evaluation process of selecting one strategy or another will be reduced to calculate the expected value of each strategy. The equations for evaluating each strategy (cooperator or defector) are as follows:

$$E[U(c)] = p * u(c, d) + (1 - p) * u(c, c) \quad (3\text{-}4)$$

$$E[U(d)] = p * u(d, d) + (1 - p) * u(d, c) \quad (3\text{-}5)$$

Where: $u(\cdot)$ is the payoff value, and p is the probability of strategy profile based on the player's reputation.

Using prospect theory in the evaluation process is quite similar, but it requires calculating the utility value and weighted probability. The equations using prospect theory criteria are as follows:

$$W[V(c)] = w(p) * v[u(c, d)] + [1 - w(p)] * v[u(c, c)] \quad (3\text{-}6)$$

$$W[V(d)] = w(p) * v[u(d, d)] + [1 - w(p)] * v[u(d, c)] \quad (3\text{-}7)$$

Where: $v(u)$ is the utility value function, $w(p)$ is the weighted probability of strategy profile based on the player's reputation.

3.1.3. Game on Network Process

Our model will be tested with a game on networks, which has the following characteristics:

- A finite number of players during the game ($N = 100$).
- Four kinds of fixed networks ($N,\ g$): random, regular (4d lattice), small-world, and scale-free.

- Mixed strategy: choice under strategic uncertainty.
- Iterated game (multi-shot).

The game process has the following steps:

- Each player is surrounded by neighbors (y_i) who are cooperators (c) or defectors (d).
- Player x has to decide which strategy to use before each round.
- Each individual plays one game per neighbor.
- Both players ($x,\ y_i$) play the match and receive the corresponding payoffs.

The four networks are considered to be the most representative sort of networks. In Chapter 2, these networks and some properties were described. Now, we are going to summarize the characteristics of the four networks to be used.

a) Random Network

By definition, a random network does not follow any specific pattern when the links are placed. The algorithm used to create this network is simple: select each node of the network and make a link with a random node of the network. The randomness does not follow any specific distribution.

The properties of this random network are depicted in Figure 3-1.

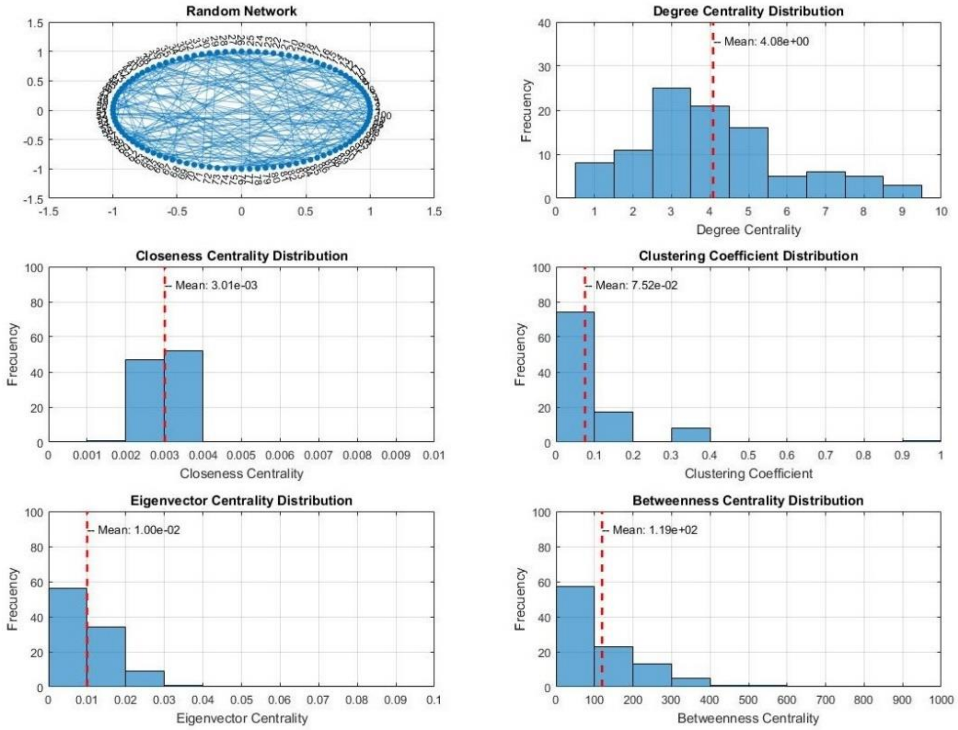

Figure 3-1. Random network properties.

The measure values of this network are summarized in Table 3-2 as follows:

Table 3-2. Random network measures.

Measure	Value
Mean Degree Centrality	4.08
Mean Closeness Centrality	3.01×10^{-3}
Mean Clustering Coefficient	7.52×10^{-2}
Mean Eigenvector Centrality	1.00×10^{-2}
Mean Betweenness Centrality	119.00
Average Path Length	3.41

b) Regular Network

By definition, a regular network is one that has a well-defined pattern structure. In this case, we used the concept of a lattice network; specifically, our regular network is a 4D lattice network. 4D refers to the four dimensions of Euclidean space ($\boldsymbol{R}^4$). This means that each node is connected to four other nodes. The rule for connecting nodes is the same for every node.

The properties of this regular network are depicted in Figure 3-2.

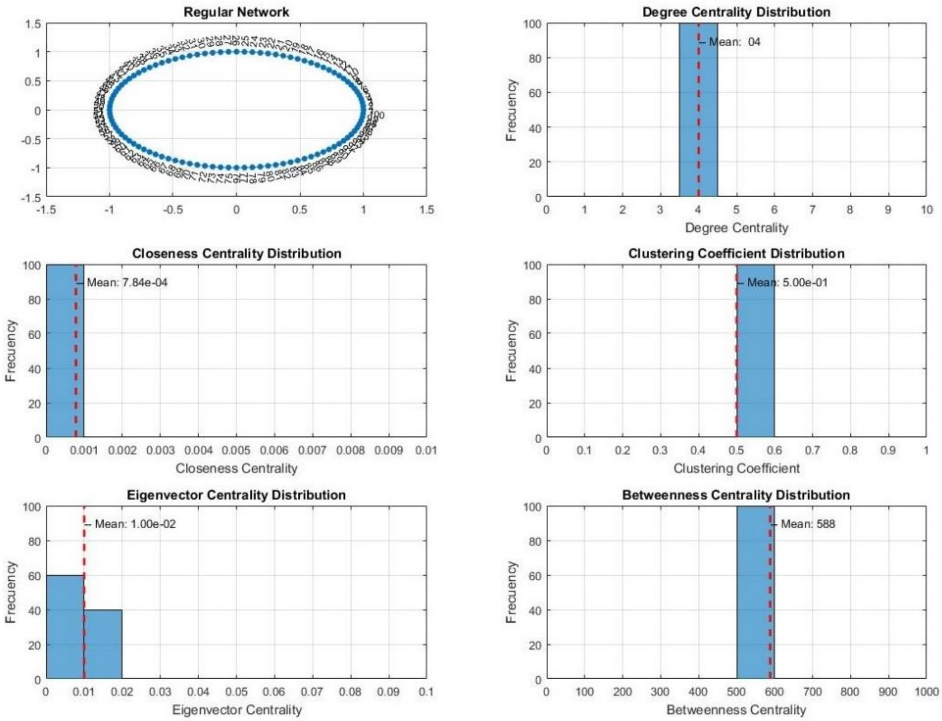

Figure 3-2. Regular network properties.

The measure values of this network are recapped in Table 3-3 as follows:

Table 3-3. Random network measures.

Measure	Value
Mean Degree Centrality	4.00
Mean Closeness Centrality	7.84×10^{-4}
Mean Clustering Coefficient	0.50
Mean Eigenvector Centrality	1.00×10^{-2}
Mean Betweenness Centrality	588.00
Average Path Length	12.88

c) Small-World Network

The small-world network uses the Watts-Strogatz model[1]. The model starts with a 2D lattice (two dimensions Euclidean space $\boldsymbol{R}^2$) and rewires some links with a defined probability ($p = 0.5$). The measure values of this network are resumed in Table 3-4 and Figure 3-3.

Table 3-4. Small-world network measures.

Measure	Value
Mean Degree Centrality	4.00
Mean Closeness Centrality	2.82×10^{-3}
Mean Clustering Coefficient	8.21×10^{-2}
Mean Eigenvector Centrality	1.00×10^{-2}
Mean Betweenness Centrality	129.00
Average Path Length	3.60

[1] Small-Network model proposed by M. E. Newman and Watts (1999).

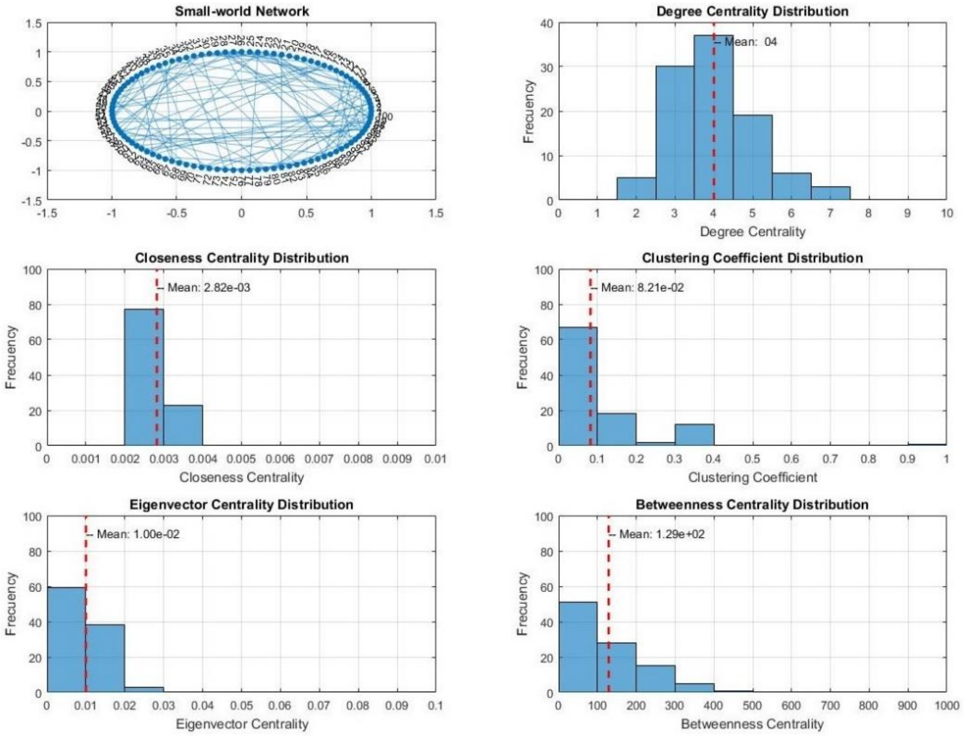

Figure 3-3. Small-world network properties.

d) Scale-Free Network

The last network is the scale-free, and it uses the Barabasi-Albert model[2]. This model employs a different construction method. The method starts with a few connected nodes and adds links to other nodes following a power law distribution.

---

[2] Scale-free model proposed by Albert and Barabási (2002).

The measure values of this network are resumed in Table 3-5 as follows:

Table 3-5. Random network measures.

Measure	Value
Mean Degree Centrality	3.94
Mean Closeness Centrality	3.57×10^{-3}
Mean Clustering Coefficient	1.74×10^{-1}
Mean Eigenvector Centrality	1.00×10^{-2}
Mean Betweenness Centrality	929.00
Average Path Length	2.88

The properties of this random network are depicted in Figure 3-4.

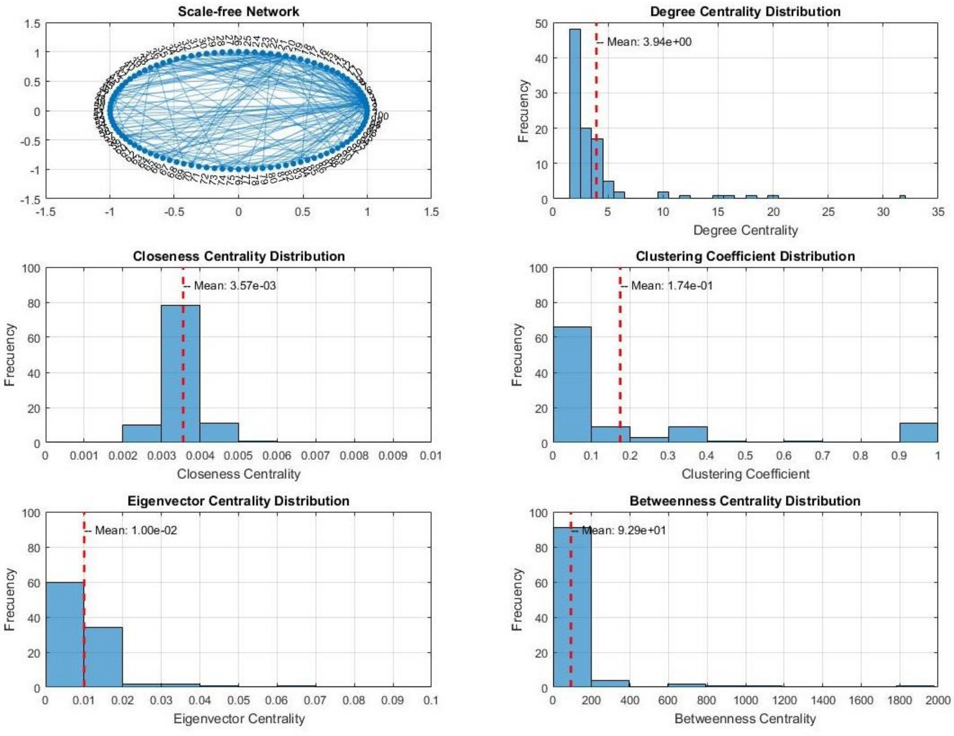

Figure 3-4. Scale-free network properties.

3.2. Example Analysis

As an example analysis of our model, we propose a simple network structure formed by five nodes and four links, where node x is connected to all other nodes around it. This network topology is illustrated in Figure 3-5. This basic network topology was used as the initial state for our analysis. For now, we are going to focus on node x and its neighbors in the game.

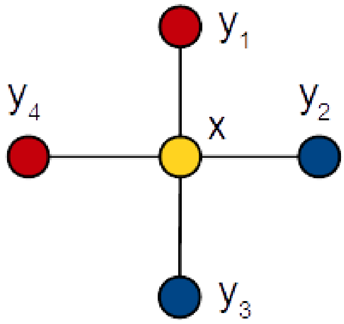

Figure 3-5. Model analysis of a basic network topology.

The evaluation process starts when node x looks at its four neighbors (y_1, y_2, y_3, y_4) and uses the reputation of each neighbor to estimate the possible outcome of the match. Thus, node x is going to play four rounds each match. The number of rounds per match is delimited by the degree centrality (k). Therefore, we generalize the number of rounds per match as k. One of the game conditions is that before each match, the player can select which strategy he or she is going to use for the whole match. Consequently, each strategy profile is the expected utility summation of using that strategy against all the neighbors. At the end, both strategy profiles are compared and the one with the highest value will be selected. The equations to be used are as follows:

$$E[U(c)] = \sum_{i=1}^{k} E[U(c, p_i)] \tag{3-8}$$

$$E[U(d)] = \sum_{i=1}^{k} E[U(d, p_i)] \tag{3-9}$$

Considering that the payoff matrix is fixed and is the same for every match, the expression is as follows:

$$E[U(c, p_i)] = p_i * u(c, d) + (1 - p_i) * u(c, c) \tag{3-10}$$

$$E[U(d, p_i)] = p_i * u(d, d) + (1 - p_i) * u(d, c) \tag{3-11}$$

Where: p_i is the probability of strategy profile of each player based on his reputation, and the payoff values are $u(c, d) = -C$; $u(c, c) = B$; $u(d, d) = 0$; $u(d, c) = C$.

Now we are going to make a couple of assumptions in our example. First, we assume that the four neighbors have the same reputations, which means they have similar probability ($p_i = p$).

One point of interest in a game on networks lies in finding the threshold point. The threshold point is when a player decides to choose one strategy and reject the other. Let us say that being a cooperator is preferred over being a defector. Then, the expected utility of the cooperator strategy should be higher than the defector strategy. Equation 3-12 represents this preference.

$$E[U(c, p)] > E[U(d, p)] \tag{3-12}$$

Using equations 3-10 and 3-11 in 3-12, the benefit-cost ratio is expressed as follows:

$$\frac{B}{C} > \frac{1}{1-p} \tag{3-13}$$

The second assumption for our analysis is that probability has the value of $p = 0.5$. Using this probability value, the benefit-cost ratio should be higher than two ($B/C > 2$). The calculated expected utility values for both strategies are:

Table 3-6. Expected utility of strategy profiles.

	B=2; C=1	**B=2.1; C=1**
$E[U(c)]$	2.0	2.2
$E[U(d)]$	2.0	2.0

As we can see in Table 3-6, when the ratio of benefit-cost is greater than two, the expected utility value of being a cooperator is higher than being a defector. Therefore, we assume that player x should set his or her strategy to be a cooperator. In this case, that response is the best strategy for the game.

Now we use the prospect theory for our analysis. Using Equations 3-6 and 3-7, and the same criteria as before, it is possible to have an expression that represents the benefit-cost ratio in terms of weighted probability. However, in this case, that probability is the weighted function of prospect theory. The benefit-cost ratio is shown in Equation 3-14.

$$\frac{B}{C} > \left\{1 + \lambda * \left[\frac{w(p)}{1-w(p)}\right]\right\}^{\frac{1}{\alpha}} \qquad (3\text{-}14)$$

The weighted probability for $p = 0.5$ is $w(p) = 0.42$, and the benefit-cost ratio is $B/C > 3.01$. Table 3-7 shows the subjective values for the evaluation process of each strategy.

Table 3-7. Subjective utility of strategy profiles.

	B=3.0; C=1	**B=3.1; C=1**
W(c)	2.31	2.49
W(d)	2.31	2.31

Comparing the results from Tables 3-6 and 3-7, the threshold point using prospect theory is higher than without it. This difference corresponds directly to the subjective bias about probabilities and prospect values. As prospect theory states, higher probabilities are underestimated. Besides, subjective utility values (gains and losses) affect and produce the risk aversion phenomena.

This analysis can be generalized for different kinds of networks, such as regular, random, small-world, and scale-free. The threshold point determines when one strategy is better to be selected in order to maximize the outcome.

Chapter 4. Simulation and Results

4.1. Agent-Based Model Description

Before starting the simulation analysis, this section describes the model created in NetLogo software. The ODD protocol (Overview, Design concepts, and Details) is used to describe the design and functionalities of our model. This protocol was developed by experienced modelers, and it is used as a standard for Agent-based modeling (ABM) analysis. It results in an organized and quick description of the model and its features (Railsback & Grimm, 2011).

The ODD protocol has seven elements arranged in three sections. The seven elements are described in relation to our model design as follows:

4.1.1. Purpose

First, the model aims to represent human economic behavior when people face a decision problem under the conditions of uncertainty. In this case, the decision is about which strategy should be adopted by each individual in the modified Prisoner's Dilemma game in a defined network.

The decision process has two variants: one is based on rational behavior and the second uses irrational behavior. Our second purpose is to compare the outcome of the game using both decision processes. Third, using the precept that repeated games can lead to change the individual's preferences; then, we are looking at how the strategy adoption changes over time in different network structures.

4.1.2. Entities, State Variables, and Scales

The entities in our model are two. One is the individuals and the second is the connections or links between them. Hence, individuals and their connections form a social network structure. The model analysis includes four types of social networks: regular, random, small-world, and scale-free. These four networks are fixed during the whole game. The four networks were created in Matlab using the corresponding algorithms.

The agent's state variables are two. Each individual can select one of two available strategies each time. The strategies are cooperator (blue color) and defector (red color).

In this case, scales do not have any particular meaning, because there is no consideration of the physical location of the individuals in the network. Besides, the values of cost and benefit are referential values. This means that no monetary scale is used. Our interest is to discover the benefit-cost ratio and nothing else. Moreover, the time scale is undefined. Each game or interaction can be days, weeks, or months. Again, there is no specific interest in time value; however, during the analysis of the social dynamics, the beliefs' spread speed and conversion time are considered from a general perspective.

4.1.3. Process Overview and Scheduling

The dynamics of our model are basically three. First, each individual evaluates the expected utilities of each possible strategy (being a cooperator or a defector). To calculate the expected utility, it is necessary to know two values: the payoff and the probability of the strategy profile. The payoff matrix is fixed during all the games and is known by all the players. The probability of the opponent's strategy depends on his or her reputation. Reputation measures how many times the player acts as a defector.

After evaluating the expected utilities, the second step consists of each individual setting his or her strategy for each round of the game. This process just consists of comparing the expected values and selecting which has the higher value.

The last step lies in the game. Here, each individual has k opponents, who are the linked neighbors. The game is played between two players and they compare their strategies and receive the outcome according to the payoff matrix.

These three steps are performed each round. This means that an individual selects his or her strategy each time before the next round of games. In this way, the decision made by each individual involves two aspects: one comes from the payoff matrix and the second is from the linked neighbors.

4.1.4. Design Concepts

In this section, we explain how the model was implemented, detailing the following aspects:

- **Basic principles:** Three main principles rule the model. First, the agent decision process can use one of two concepts: the expected utility evaluation or prospect theory evaluation. Each evaluation is based on the theories explained in Chapters 2 and 3. The second principle relies on the game. A modified version of the Prisoner's Dilemma game is used to evaluate the strategies of each player and deliver the outcomes. The third principle is the social network. The environment is a multi-agent system where agents are connected with others, shaping a social structure.

- **Emergence:** Emergence rests on which strategy becomes dominant in the network. The dominance of one strategy among the individuals depends on the incentives and interactions between them.

- **Adaptation:** Each agent selects his or her strategy each time before each round of the game. That selection aims to be the best option for the agent at that moment. Hence, agents adapt their preferences according to the circumstances.

- **Objectives:** The object for all the agents is the same, select the best strategy that seems to yield the higher outcome and play the game.

- **Learning:** Agents by themselves do not do any learning activity. The game could be considered a learning process from a macro level perspective. The group of individuals can perform better, in terms of collaborative behavior, if most of them have selected the cooperative strategy.

- **Prediction:** Agents make a prediction when they calculate a strategy's expected utility. This prediction is simple and it is only valid for the coming round of games.

- **Sensing:** The sensing process of agents is seeing the strategy profile of each of the neighbors. The strategy profile depends on the personal reputation of each agent.

- **Interaction:** The interaction between agents corresponds to playing the game. Each time, two agents face each other in the game and receive the corresponding payoff.

- **Stochasticity:** The random process in our model corresponds to set the initial strategy profile of all the players. This process does not follow any formal distribution.

- **Collectives:** Collectives are modeled as a social group of individuals. Our model uses four types of social networks.

- **Observation:** In our model, the world displays all the agents, the social links, and the player's strategy. The red color represents a defector strategy and the blue color a cooperative strategy.

4.1.5. Initialization

The setup of our model depends on five variables. These five variables are described as follows:

a) Benefit, a positive number $B = \{1, \ldots, 10\}$.

b) Cost, a positive number $C = \{1, \dots, 10\}$.

c) Network (N, g), a graph with a fixed number of nodes $N = \{100\}$; and a defined network structure (g = random, regular, small-network, scale-free). The finite network is represented as an adjacency matrix. This predefined matrix is loaded from a file.

d) Initial population strategy ($D = \{1, \dots, 100\}$; $C = 100 - D$), the population of cooperators (C) and defectors (D) are randomly distributed without any preference.

e) Prospect theory (Boolean variable true or false), used to select which decision process is going to be used by all the agents.

All five variables have to be selected before the game simulation. These variables remain fixed during the whole simulation. The simulation stops when one of the strategies becomes dominant (all the agents have the same strategy) or the number of steps reaches one thousand (1000).

4.1.6. Input Data

There is no input data in our model. The data generated by the model depends on the five variables described before.

4.1.7. Submodels

The submodels used in the program are divided into three groups. The groups and corresponding submodels are as follows:

a) Setup group

- Load network matrix: This sub-process loads the adjacency matrix of the selected network.

- Nodes initialization: Here all the variables used for each agent are initialized.

- Initial strategy distribution: The initial strategy is randomly distributed in all the nodes.

b) Run process group

- Strategy evaluation: Each agent evaluates the expected utility that he or she guesses to receive using each strategy.

- Strategy update: Based on the strategy evaluation, each agent selects the strategy that seems to yield the higher value.

- Play the game: Each agent plays the game with each neighbor and both players receive the corresponding payoff.

c) Support group

- Payoff matrix: This process builds the payoff matrix based on the cost and benefit values.

- Prospect payoff matrix: When the prospect theory evaluation process is activated, the payoff matrix is recalculated based on the equations mentioned in Chapter 2.

- Data collection: The simulated data is collected for a posterior analysis of the results.

4.2. Expected Utility and Prospect Theory Outcome Analysis

First of all, the analysis starts with the results of the example given in Chapter 3. Resuming that analysis in Table 4-1, it is possible to distinguish that the prospect theory decision process requires a higher benefit-cost ratio than expected utility. The reason for this is due to the biased perception of value and probability. Briefly, we can state that is possible to see risk aversion behavior. Therefore, a higher incentive (benefit B) is required to make the same decision.

Now, we take a look at our results in the case of a regular network. The reason of this selection was due to its well-defined structure that is similar to our example analyzed in Chapter 3.

Table 4-1. Example analysis summary.

	Expected Utility (EU) decision process	
	B=2; C=1; p=0.5	B=2.1; C=1; p=0.5
E[U(c)]	2.0	2.2
E[U(d)]	2.0	2.0
	Prospect Theory (PT) decision process	
	B=3.0; C=1; p=0.5	B=3.1; C=1; p=0.5
W(c)	2.31	2.49
W(d)	2.31	2.31

The setup for our simulations is as follows:

- Network (N, g): regular network $(N = 100)$.

- Initial population strategy $(C = 50, D = 50)$.

Figure 4-1 shows the population strategy selection and the benefit-cost ratio.

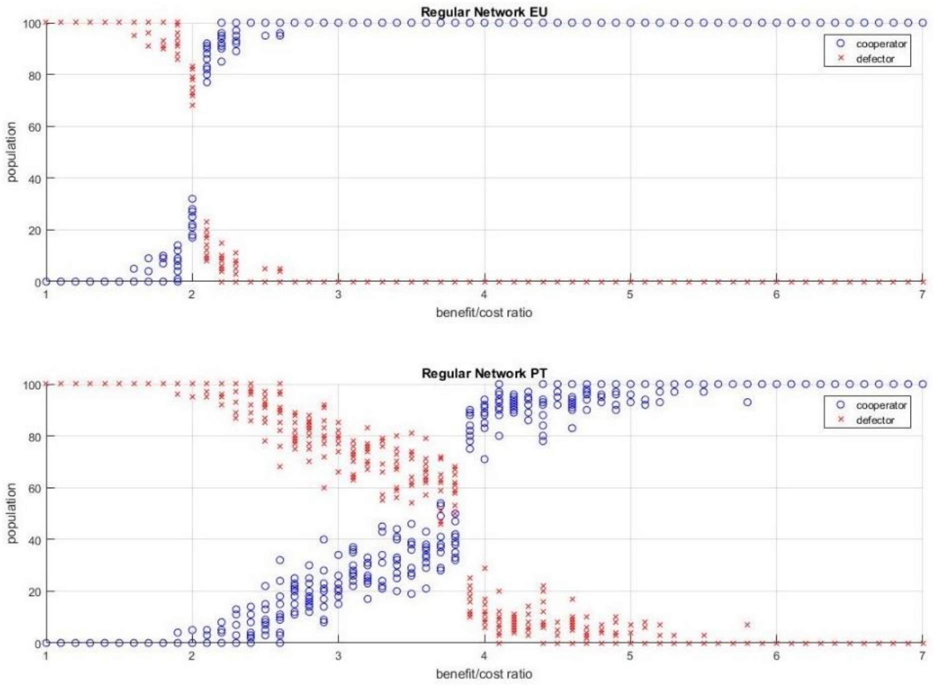

Figure 4-1. Regular network population strategy selection and benefit-cost ratio.

The results in Figure 4-1 denote the difference in the benefit-cost threshold ratio. Remember, this threshold denotes when selecting one of the two strategies is the best option. In the case of expected utility, the threshold point is clear when the benefit-cost ratio is two. On the other hand, the threshold point goes to the right when the benefit-cost ratio is 3.8. Moreover, the transition from the majority of defector behavior to the majority of cooperator behavior has an "S" shape similar to the logistic "SI epidemic model"[3]. This means that the transition requires a process since

[3] SI Epidemic model is a typical mathematical representation of how a disease can spread in a network. (M. Newman, 2010)

the new belief is inserted into a subgroup and it will spread in the network. Here, the benefit-cost ratio has the persuasive power to change the behavior in the population.

Another interesting result is about the time that is needed to reach a majority of one strategy. Figure 4-2 depicts the result analysis of conversion time (100% population) and benefit-cost ratio. Conversion time means how many rounds the game needs to be played to reach a majority.

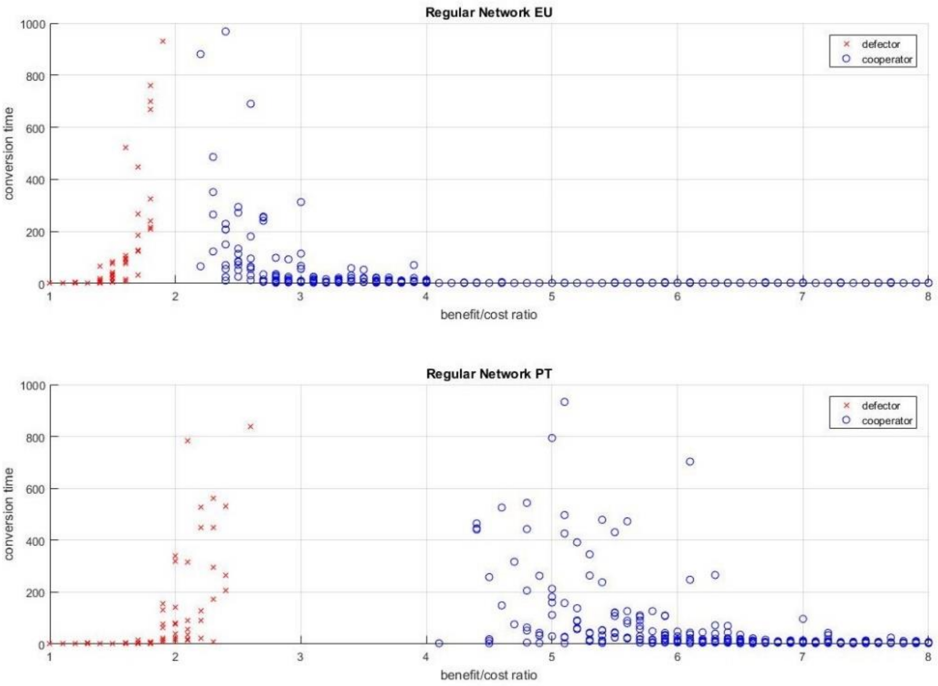

Figure 4-2. Regular network conversion time and benefit-cost ratio.

First, we analyzed the expected utility decision process. In this case, the benefit-cost threshold point (B/C = 2) is the boundary between a majority of defectors or cooperators. When the benefit-cost ratio is near the threshold point, the conversion time rises. This means that beliefs have resistance to being distributed in the network. The resistance lies when subgroups with the same strategy are formed in the network.

Those groups present a cohesive force that is resistant to a new belief (Matthew O Jackson & Zenou, 2014; K. Kim & Altmann, 2015). Figure 4-3 depicts how subgroups with the same strategy or belief are formed.

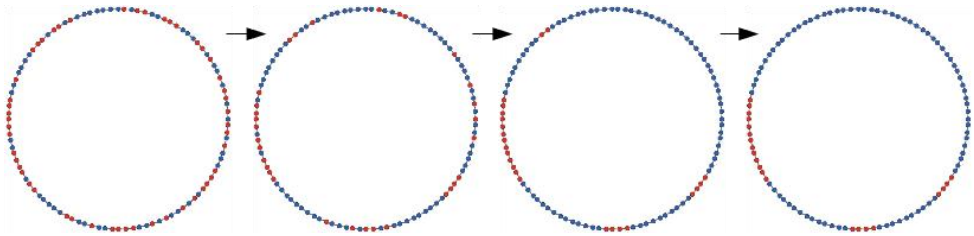

Figure 4-3. Subgroups formation in a regular network.

In the case of the expected utility process decision, the gap to reach a strategy majority is wider than the expected utility process. This effect corresponds to risk-averse behavior. Again, subgroups of individuals with the same strategy are formed and this cohesive force creates a resistant force.

The transition of one strategy into another requires effort in terms of time and incentives (benefit/cost ratio). In the case of a regular network, changes are slow and systematic due to the network's structure. The diffusion of a belief in a network depends on degree distribution and other factors (M.O. Jackson, 2010; Koohborfardhaghighi & Altmann, 2014b).

4.3.Network Structures Performance Analysis

The second part of our result analysis aims to compare the different network structures. Our study has four network structures: random, regular, small-world, and scale-free. All of them have one similar characteristic: the mean degree value, which is around four. First of all, the main measure values of our four networks are resumed in Table 4-2.

Table 4-2. Networks measure values.

Network	Mean Degree Centrality	Mean Cluster Coefficient	Average Path Length
Random	4.08	7.52 $\times 10^{-2}$	3.41
Regular (4D-lattice)	4.00	50.00 $\times 10^{-2}$	12.88
Small-world (Watts-Strogatz)	4.00	8.21 $\times 10^{-2}$	3.60
Scale-free (Barabasi-Albert)	3.94	17.40 $\times 10^{-2}$	2.88

First, we will present the results using the expected utility decision process. Figure 4-4 shows the population strategy adoption and benefit-cost ratio of the four networks. Figure 4-5 depicts the conversion time and benefit-cost ratio.

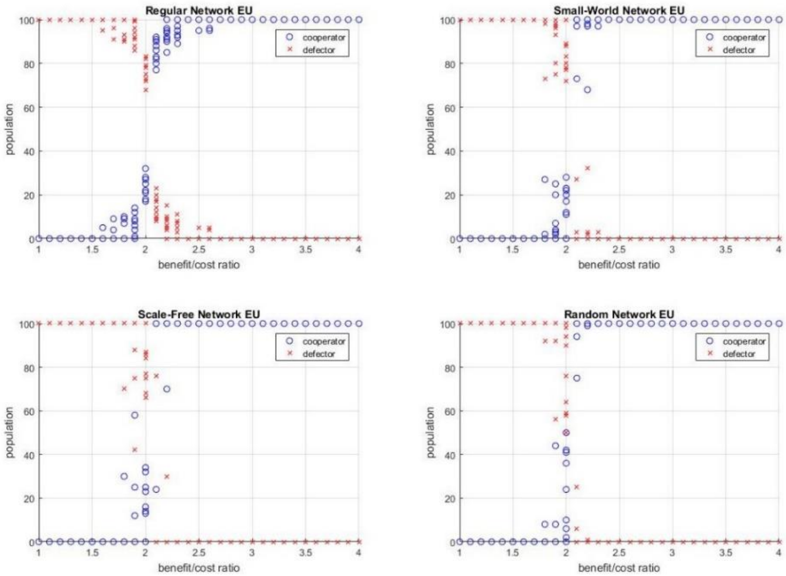

Figure 4-4. Networks population and benefit-cost ratio using Expected Utility (EU) in the decision process.

Observing the results in Figure 4-4, the first finding is that all the networks have the same threshold point, located at the value of two (benefit-cost ratio). Moreover, three of the four networks (small-world, scale-free, and random) have a similar transition shape between one strategy majority to the other. The regular network has a strong "S" shape because of its own network characteristics, such as degree distribution and average path length.

According to Barabási (2016), one feature of scale-free networks is the epidemic transmission speed. This kind of network has a robustness to random internal failures, but it is fragile to intentional attacks. Looking at the average path length, the scale-free network has the lowest value.

The second part of the analysis includes the conversion time required to reach a majority in one of the two strategies. Figure 4-5 shows the conversion times and benefit-cost ratios of our four networks. Here, again, the time increases at the threshold point (benefit-cost ratio equals 2). However, in the case of the scale-free network, the time is shorter compared with the other networks. On the other hand, the regular network has higher conversion time values and the transition gap is wider. Once more, the epidemic transmission speed for the scale-free network is lower, confirming its own characteristics (Barabási, 2016).

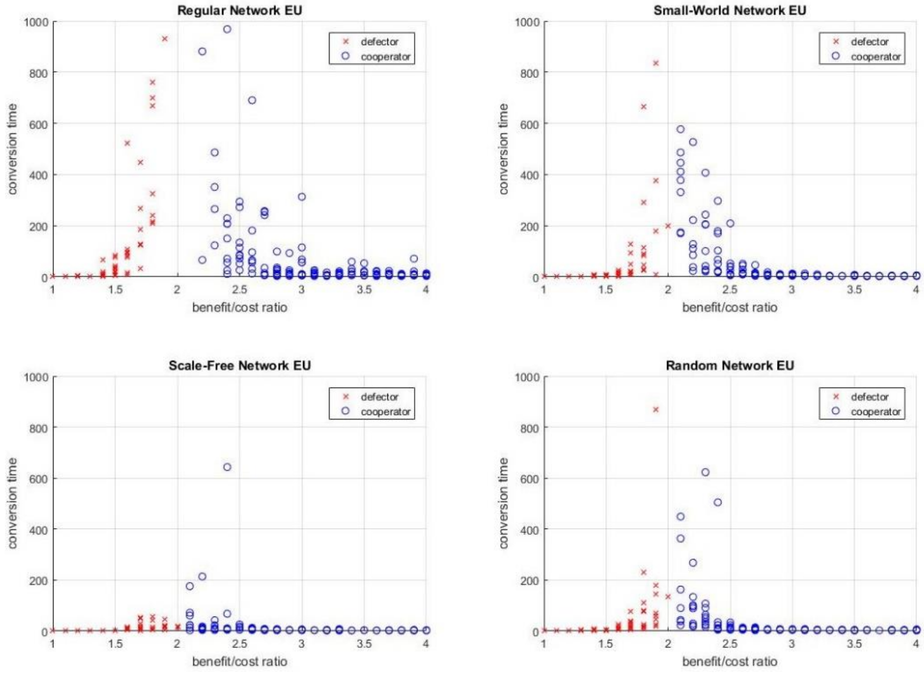

Figure 4-5. Networks conversion time and benefit-cost ratio using Expected Utility (EU) in the decision process.

The third part of our analysis corresponds to reviewing the results using prospect theory during the decision process. The results will be presented in two figures. Figure 4-6 describes the population strategy selection and the benefit-cost ratio.

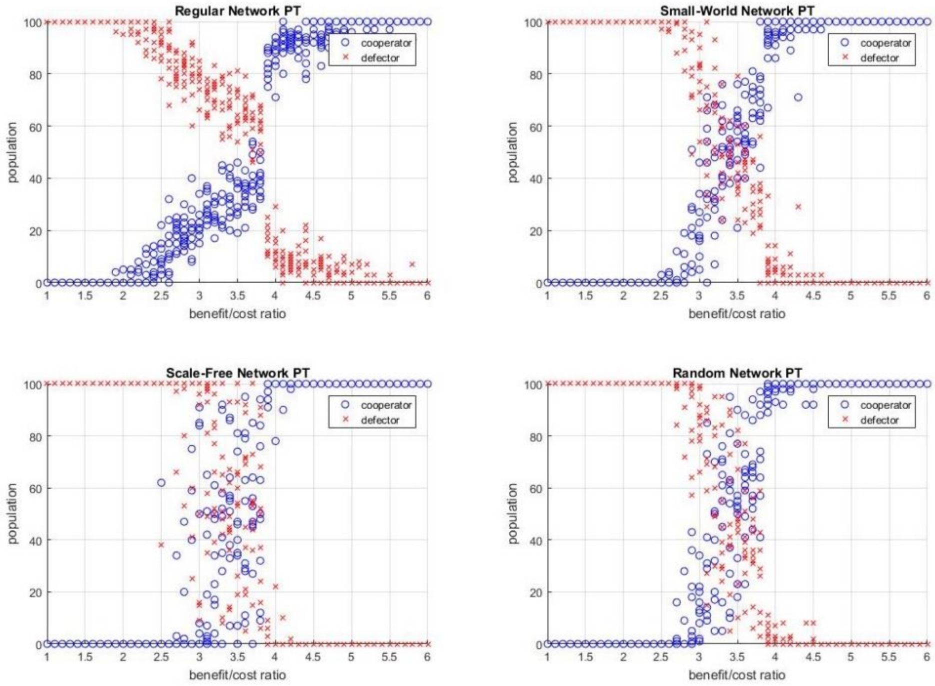

Figure 4-6. Networks population and benefit-cost ratio using Prospect Theory (PT) in the decision process.

Looking at Figure 4-6, the threshold point location is quite similar for three of the four networks. Specifically, the regular network has that point located at the value of 3.8 of benefit-cost ratio. On the other hand, for the scale-free, small-world, and random networks, the threshold point is around 3.5. Again, the transition of one dominant strategy into the other has an "S" of the logistic function. However, due to the decision process using prospect theory, the transition of one dominant strategy into the other is not as clear as in the case of expected utility. The risk aversion effect makes the threshold point higher and also affects the conversion from defector to cooperator majority.

Moreover, Figure 4-7 displays the conversion time and benefit-cost ratio. In that figure, we can observe that the regular network has the wider threshold point compared to the others. Again, our interest lies in the scale-free network, because it shows the narrowest and shortest conversion time of the majority of one strategy into the other.

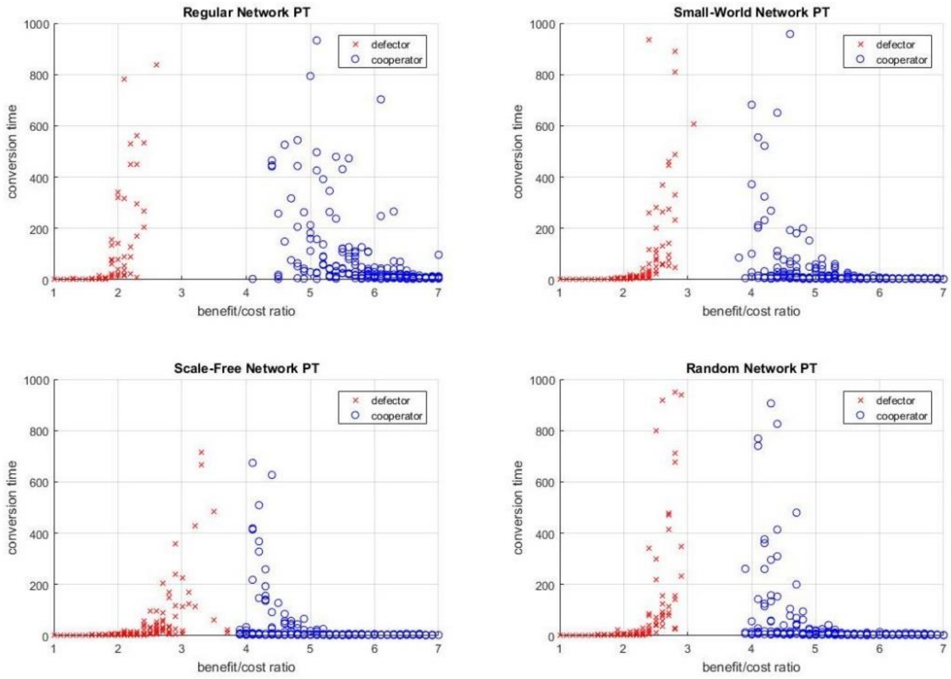

Figure 4-7. Networks conversion time and benefit-cost ratio using Prospect Theory (PT) in the decision process.

The last section of our analysis shows the initial population and benefit-cost ratio required to reach a majority of one strategy. Figure 4-8 depicts the four networks and the two decision processes in two subgraphs.

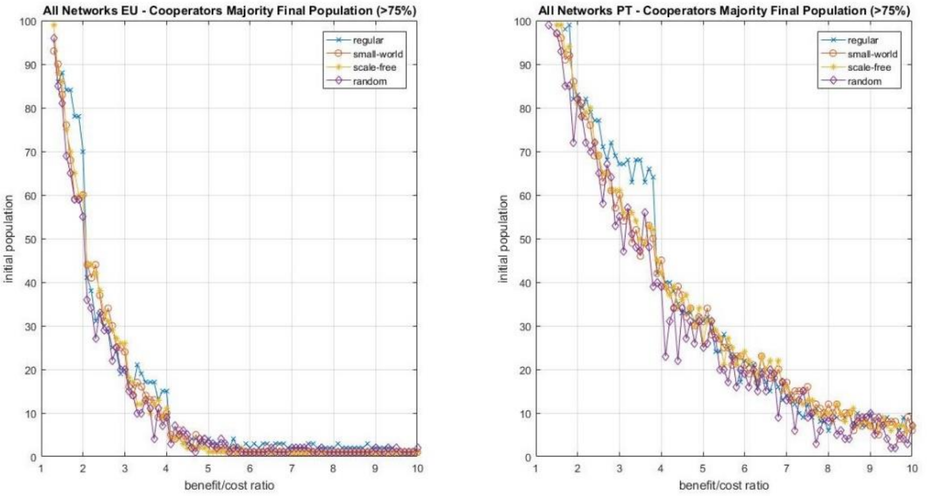

Figure 4-8. Initial population and benefit-cost ratio required for reaching a majority of one strategy.

In Figure 4-8, it is possible to distinguish the relationship between the initial population and the benefit-cost required to reach a majority level in one of the two strategies. This means that the benefit-cost ratio can be set up by looking at the number of individuals that follow a certain strategy. There are slight differences between the network type; but the gap is more visible using prospect theory during the decision process.

4.4.Model Application

The Prisoner's Dilemma game has different applications in the field of economics. One real life application of the present research on the Prisoner's Dilemma game on networks is the public transportation systems. Citizens of a neighborhood or city have to decide if they will use the public transport system. If they do not use it, they will use a private car. Here, a social dilemma arises and the local government will try to develop a policy to solve problems related to public transportation and traffic congestion (M. Peterson, 2009).

The steps to follow to use our proposed model are as follows:

1. Economic analysis of the social problem in terms of benefit-cost ratio.
2. Social network structure construction based on people's interactions.
3. Decision process, interaction process, and the selection of a game in a network.
4. Simulation of the model in the social network.
5. Results analysis and implications of the new policy.

Chapter 5. Conclusions and Recommendations

5.1. Conclusions

The model proposed in our study to represent individuals' economic behavior and social interactions involves three components. The three components are the decision process, the interaction process, and the game on networks process. The decision process has two options: the expected utility process, which aims to simulate rational behavior; and using prospect theory to imitate irrational behavior. The interaction process uses a modified version of the Prisoner's Dilemma game. The Prisoner's Dilemma game gives us the option of selecting one of two strategies, being a cooperator or a defector. The game on networks process is used to place all the components in a social structure. Hence, we can represent the decision-making process of individuals in a group using an agent-based modeling methodology.

The simulation results have shown that the performance of the Prisoner's Dilemma game is different in the four analyzed networks. The differences involve the conversion time and the transition from one dominant strategy to the other one. The "S" shape logistic function has a different slope for each network. The scale-free network has the steeper slope and the regular network has a gradual slope. In terms of conversion time, the regular network has the higher and wider value and the scale-free network is faster and narrower. The conversion time and majority transition are related to the characteristics of each network, such as degree centrality distribution and average path length. However, the threshold point of the benefit-cost ratio remains constant in all the network structures.

Comparing the outcomes using prospect theory and expected utility during the decision process, the simulation results of the game have differences in terms of threshold point, conversion time, and transition of a dominant strategy. Using prospect theory, the threshold point is higher and responds to risk aversion behavior. Risk aversion behavior also affects the conversion time and transition of a dominant strategy. These two values also increase and respond to the irrational behavior of the agents.

In terms of utility level, when the majority of the population exhibits cooperative behavior, the whole group achieves higher levels of utility and welfare. Agents with a high degree of centrality achieve high utility levels. However, the present study has no specific objective to measure that level of utility.

The results of the present research demonstrate that in an artificial environment, using agent-based modeling is possible to recreate the irrational behavior of individuals and compare it with rational behavior in a social scenario. The findings show that the outcome of the game has differences between rational and irrational behavior. Additionally, network structure matters and can affect the results of the game.

The implications of this research are connected to policy makers. Ostrom (1990) found that in using policies with repeated games, an individual's selfish interest can transform into a collective interest. But, if we do not take into account the differences that exist between rational and irrational behavior during games on networks, policies might fall out and will not yield the expected outcome. Risk aversion behavior is present during decisions and it will lead to undesired results. However, if we consider that irrational behavior is present, and the social network structure matters, the implementation of a new policy can yield the expected outcome.

Policy makers should pay attention to the fact that individuals have irrational behavior. A new policy to boost a public service might fail during the initial steps. This can occur in terms of benefit-cost ratio, enforce time, or where it is better to start the project (social network location). These questions can be addressed if the policy makers consider the bounded rationality and the social network effects that can create interference when a policy is put in force.

Behavioral economic theories give us the opportunity to look at individuals as they are. The classic concepts of microeconomics are good enough to represent our behavior, but they have some limitations that can be solved using the modern techniques of computational economics such as agent-based modeling and social networks analysis.

5.2. Recommendations

Agent-based modeling gives us the opportunity to model and simulate dynamic complex systems that are difficult to deal with using other methodologies such as elaborate and hard equation systems. The use of the ODD protocol helps a lot during the design, implementation, and simulation process of the model. Therefore, using this protocol is recommended when this methodology is used.

5.3. Model Limitations and Future Research

The model and the game on networks proposed in the present research have some limitations:

- The model has two components, a theoretical approach to the decision-making process and simulation in an artificial environment. The interactions process and network used are based on conceptual models from game theory and networks, respectively.
- The four kinds of networks used are the representative types of networks in the literature. A real network was not included in the present research.
- The decision process is under a regimen of uncertainty related to the strategy profile. There are only two variables involved during the decision-making process.
- The agents have a naïve cognitive process. There is no learning method included in the decision process.
- The network structure stays static during the whole game. The present model does not include any coevolutionary process.
- The model and simulation do not include any analysis on the utility level because the utility level is directly related to the strategy adoption.

The future research implications include solving some of the limitations of the present research related to the learning process, coevolutionary environment, utility level analysis, and real network analysis.

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Appendix A

Agent-based model software code (NetLogo v5.3.1)

```
extensions
[
  nw
  matrix
]
globals
[
  payoffs
  w-payoffs
  alpha
  beta
  lambda
  gama
  conversion-time
  f1?
]
turtles-own
[
  strategy
  utility
  degree
  mem-utility
  blue-neighbors
  red-neighbors
  red-X
  blue-X
  p
  wp
  wo
  W-red
  W-blue
  opponent-vect
  A
  B
  red-history
  blue-history
  red-rep
  prob-vect
]
to setup
  ca
; Variables initialization
  set alpha 0.88
  set beta 0.88
  set lambda 2.25
```

```
  set gama 0.61
  set w-payoffs matrix:make-constant 2 2 0
  set payoffs matrix:make-constant 2 2 0
  set-default-shape turtles "circle" ; set the default shape for all nodes
  set conversion-time 0
  set f1? false
; Payoffs matrix definition
  payoffs-matrix
; Prospect theory flag check
  ifelse (prospect? = true)
  [ pospect-payoffs-matrix ]
  [ set w-payoffs matrix:copy payoffs]
  show (word "m1:" payoffs)
  show (word "m2:" w-payoffs)
; Data files initialization
;  data-file-init
;  final-data-report-init
; Load adjacency matrix
  load-matrix
; Network nodes initialization
  init-nodes
; Nodes strategy initialization
  set-initial-strategy
  set-current-plot "Degree distribution"
  histogram [ degree ] of turtles
  reset-ticks
end

to load-matrix
    if (network-type = "REG2")
  [    nw:load-matrix "matrix-REG2.txt" turtles links ]

    if (network-type = "RAN1")
  [    nw:load-matrix "matrix-RAN1.txt" turtles links  ]

    if (network-type = "WS1")
  [    nw:load-matrix "matrix-WS1.txt" turtles links  ]

    if (network-type = "BA1")
  [    nw:load-matrix "matrix-BA1.txt" turtles links  ]

end

to init-nodes
  ; create nodes, set size, color and plot them
  ask turtles
  [
    set size 4
    set strategy false
    set color (gray + 2)
    set utility 0
    set mem-utility []
    set degree (count link-neighbors)
```

```
    set blue-neighbors 0
    set red-neighbors 0
    set red-X 0
    set blue-X 0
    set p 0
    set wp 0
    set wo 0
    set red-history 0
    set blue-history 0
    set red-rep 0
    set prob-vect []
    set opponent-vect [who] of link-neighbors
  ]
  layout-circle (sort turtles) max-pxcor - 3
end

to set-initial-strategy
  while [(count turtles with [strategy = "red"]) < red-strategy-initial-number]
  [
    ask one-of turtles
    [ if (strategy != "red")
      [ set strategy "red"
        set color red
        set red-history 1
        set red-rep 1 ]
    ]
  ]
  ask turtles
  [ if (strategy != "red")
    [ set strategy "blue"
      set color blue
      set blue-history 1 ]
  ]
  show (word "reds:" count turtles with [strategy = "red"])
  show (word "blues:" count turtles with [strategy = "blue"])
  show (word "Mean degree:" mean [degree] of turtles)
end

to go
  evaluate-strategy
  update-strategy
  play-game
;  file-open "test-output.csv"
;  ask turtles [ data-file-input ]
;  file-close
  set-current-plot "Social Welfare distribution"
  histogram [ utility ] of turtles
  if (f1? != true)[
    if ((count turtles with [strategy = "red"] = count turtles) or (count turtles with
[strategy = "blue"]) = count turtles)
    [ set conversion-time (ticks + 1)
      show(word "Conversion time: " conversion-time)
      set f1? true
```

```
      stop
    ]
  ]
  tick
  if ticks >= 1000
  [
    ;show (word "reds:" count turtles with [strategy = "red"])
    ;show (word "blues:" count turtles with [strategy = "blue"])
    show (word "Social Welfare: " mean [ utility ] of turtles)
    ;show (word "Mean degree:" mean [degree] of turtles)
    stop
  ]
end

to evaluate-strategy
  ask turtles [
  ifelse (count link-neighbors = 0)
  [ stop ]
  [
  set W-red 0
  set W-blue 0
  set prob-vect [red-rep] of link-neighbors
  ]
  let i 0
  let l1 length prob-vect
  while [l1 > i]
  [
    set p (item i prob-vect)
    ifelse (prospect? = true)
    [ set wp ((p ^ gama) / (((p ^ gama) + (1 - p) ^ gama) ^ (1 / gama))) ]
    [ set wp p ]
    set W-red (W-red + wp * (matrix:get w-payoffs 0 0) + (1 - wp) * (matrix:get w-
payoffs 1 0))
    set W-blue (W-blue + wp * (matrix:get w-payoffs 0 1) + (1 - wp) * (matrix:get w-
payoffs 1 1))
  set i (i + 1)
  ]
 ]
end

to update-strategy
  ask turtles[
  ifelse (W-blue > W-red)
  [ set strategy "blue"
    set color blue
    set blue-history (blue-history + 1) ]
  [ set strategy "red"
    set color red
    set red-history (red-history + 1) ]
  set red-rep (red-history / (red-history + blue-history))
  ]
end
```

```
to play-game
ask turtles [
  set A 0
  set B 0
  let l2 length opponent-vect
  let j 0
  while [l2 > j]
  [
    let opponent (item j opponent-vect)
    let my-strategy strategy
    let opp-strategy [ strategy ] of turtle opponent
    ifelse (my-strategy = "red")
    [
      ifelse (opp-strategy = "red")
      [ set A matrix:get payoffs 0 0
        set B matrix:get payoffs 0 0 ]
      [ set A matrix:get payoffs 1 0
        set B matrix:get payoffs 0 1 ]
    ]
    [
      ifelse (opp-strategy = "red")
      [ set A matrix:get payoffs 0 1
        set B matrix:get payoffs 1 0 ]
      [ set A matrix:get payoffs 1 1
        set B matrix:get payoffs 1 1 ]
    ]
   set utility (A + utility)
   ask turtle opponent
   [set utility (B + utility)]
   set j (j + 1)
  ]
]
end

to payoffs-matrix
  let V gain-value
  let C cost-value
  matrix:set payoffs 0 0 0
  matrix:set payoffs 1 0 C
  matrix:set payoffs 0 1 (- C)
  matrix:set payoffs 1 1 (V)
end

to pospect-payoffs-matrix
  let n 0
  set n (item 0 (matrix:dimensions payoffs))
  let i 0
  while [i < n]
  [
    let j 0
    while [j < n]
    [
      matrix:set w-payoffs i j (prospect-value (matrix:get payoffs i j))
```

```
      set j j + 1
    ]
    set i i + 1
  ]
end

to-report prospect-value [x]
  ifelse (x >= 0)
  [    report (x ^ alpha)  ]
  [    report ((abs(x) ^ beta) * (- lambda))  ]
end

to data-file-init
  if (file-exists? "test-output.csv") [carefully [file-delete "test-output.csv"] [print error-
message]]
  file-open "test-output.csv"
      file-type "tick,"
      file-type "id,"
      file-type "strategy,"
      file-type "red-neighbors,"
      file-type "blue-neighbors,"
      file-type "degree,"
      file-type "red-X,"
      file-type "blue-X,"
      file-type "wp,"
      file-type "W-red,"
      file-type "W-blue,"
      file-type "utility,"
      file-type "opponent-vect,"
      file-type "A,"
      file-type "B,"
      file-type "red-history,"
      file-type "blue-history,"
      file-type "red-rep,"
      file-type "prob-vect,"
  file-close
end

to data-file-input
  file-print " "
  file-type ticks            file-type ","
  file-type who              file-type ","
  file-type strategy         file-type ","
  file-type red-neighbors    file-type ","
  file-type blue-neighbors   file-type ","
  file-type degree           file-type ","
  file-type red-X            file-type ","
  file-type blue-X           file-type ","
  file-type wp               file-type ","
  file-type W-red            file-type ","
  file-type W-blue           file-type ","
  file-type utility          file-type ","
  file-type opponent-vect    file-type ","
```

```
  file-type A                file-type ","
  file-type B                file-type ","
  file-type red-history      file-type ","
  file-type blue-history     file-type ","
  file-type red-rep          file-type ","
  file-type prob-vect        file-type ","
end

to final-data-report-init
  if (file-exists? "final-output.csv") [carefully [file-delete "final-output.csv"] [print error-
message]]
  file-open "final-output.csv"
  file-type "run-number,"
  file-type "node,"
;  file-type "utility,"
  file-type "degree,"
  file-type "red-initial,"
  file-type "red-final,"
  file-type "b/c-ratio,"
  file-type "conversion-time,"
  file-type "prospect,"
  file-type "network,"
  file-close

end

to final-data-report
  file-open "final-output.csv"
  file-print " "
  file-type behaviorspace-run-number              file-type ","
  file-type [who] of turtles                      file-type ","
;  file-type [utility] of turtles                 file-type ","
  file-type [degree] of turtles                   file-type ","
  file-type red-strategy-initial-number           file-type ","
  file-type count turtles with [strategy = "red"] file-type ","
  file-type gain-value                            file-type ","
  file-type conversion-time                       file-type ","
  file-type prospect?                             file-type ","
  file-type network-type                          file-type ","
  file-close
end
```

초록

죄수의 딜레마 게임 측면에서의 개인의 경제행동과 사회 상호작용 분석: 시뮬레이션 방법을 이용하여

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개인의 의사 결정 과정에 대한 전통적인 미시 경제 개념에서 시작하여 선택은 합리적인 행동과 효용 극대화의 개념에 기초하여 이루어진다. 그러나 행동 경제학 분야의 여러 연구에서 의사 결정 과정을 더 잘 이해하고 대표하기 위해이 전통적인 모델과 보완 이론에 의문을 제기했다.

이 연구는 의사 결정 과정에 존재하는 제한된 합리성과 관련된 행동 경제학의 진술을 분석하고 개인적 관점에서 집단적 차원으로 바라보고자, 다중 에이전트 기반 모델링과 같은 전산 경제학 기법, 사회 및 경제 네트워크,

죄수의 딜레마 게임의 수정 버전을 사용한 모델을 제시한다. 소셜 네트워크 시뮬레이션에서 에이전트 기반 모델은 게임 성능 및 결과에 관한 특수성을 연구 할 목적으로 개인의 경제적 행동과 사회적 상호 작용을 모방 할 수있게 한다.

본 연구의 결과는 인공 환경에서 개인의 비합리적 행동을 재창조하고 사회 시나리오에서의 합리적 행동과 비교할 수 있는 가증성을 제시한다. 연구 결과에 따르면 게임의 결과는 임계점, 전환 시간 및 지배 전략의 전환과 관련하여 합리적이고 비합리적인 행동의 차이가 있음을 시사한다. 이 연구의 향후 응용 방안은 정책 설계를 개선하고 사회에 미치는 영향 분석이다.

주요어: 행동 경제학, 전망이론, 에이전트 기반 모델링, 죄수의 딜레마, 게임 이론, 네트워크 게임.

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