BOUNDED RATIONALITY, SOCIAL LEARNING AND COLLECTIVE BEHAVIOR: DECISIONAL ANALYSIS IN A NESTED WORLD

Completed Research Paper

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Abstract

People are usually brought together in a social network to make synergetic decisions. This decision making process often involves information acquisition and social learning, which are essential to overcome individuals' bounded rationality. The performance of a society thus depends on the collective behavior of individuals. Besides information attributes, organizational properties often influenced such a decision process. In this article, we introduce a paradigm -- nested world -- that treats social network as a symbolic system. Based on this paradigm, we developed a research model to investigate how information attributes, social parameters, and their interactions influenced the performance of a social network. This research model was subsequently converted to a computational model for analysis and validation. Our findings suggested that informativeness, network density, social influence, and their interactions had significant influence on the performance of whole society. Besides these findigns, many interesting phenomenon were also observed, including significant social learning curve, U-shape decision speed, threshold of network density, and interchangeability between network density and social influence.

Keywords: Bounded rationality, social learning, decisional analysis, social network

Introduction

Human beings are characrterized by their bounded rationality (Simon 1957) and societies are characterized by their nestedness -- i.e., individuals are embedded in the web of relations and interactions (Borgatti 2009). The bounded rational individuals, nested together as an organism in a society, are always in dynamic evolution and exhibit interesting behaviors. They, sometimes, are rational enough to clarify rumors, but sometimes irrational to behave crazily as in a herd. Their collective behavior are sometimes powerful enough to trigger political changes such as Jasmine revolution in Tunisia, which was sparked by a short video shared on YouTube and spread rapidly via virtual communities in Facebook.

These behaviors exhibited by individuals in a nested society are believed to be related to hidden synergy resulted from the collective behavior of human beings. Synergy, in organization, is a gain in performance attributable to group interaction (Larson 2010). Synergy in a social network, however, is a hidden one, suggesting that synergy may not be compulsory or result in a predetermined goal. At most of the time, people in social network influence each other through information exchange, which may only resulted in cognitive synergy, but unnecessarily a consensus or a collective behavior.

Hidden synergy has been widely recognized and investigated in the fields of behavioral economics, financial market (Devenow and Welch 1996), labor market (Kubler and Weizsacker 2003), technology adoption (Duan et al. 2009; Walden and Browne 2002), innovation (Melissas 2005), real estate (Pierdzioch et al. 2010), politics (Bikhchandani et al. 1998) and legal issues (Farnsworth, 2007) in the past few years. In a nested world, how individuals make their decisions under hidden synergy thus to form collective behavior, and how collective dynamics evolve as a function of information distribution and network property are really an important research topics for investigation.

In order to analyze the dynamics of social networks, one of the methods is to treat network as an organism, and analyze their parameters at network level rather than individual level. The reason is that outcomes of social networks are determined by the collective behavior of individuals, rather than an individual. Tichy et al (1979) concurred with this reasoning and suggested that there are three sets of properties of networks that can be treated as determinants, namely, transactional content, nature of the link, and structural characteristics.

In this study, we adopted the perspective of information science by integrating individual judgmental process into social interactions, thus providing a paradigm to explain how collective behavior could be related with individual decision cues cognitively in the decision process. In this paradigm, we argue that the cognitive process of individuals make their decision cues highly correlated, thus conforming their behavioral in a social network. We also derived a research model from this paradigm for further investigation. In this research model, which was based on the foundations of decisional analysis (e.g., Banfield 1961; Pettigrew 1973) in social network, we have selected information as transactional content, social influence as nature of the link, and network density as structural characteristics. We examined how these parameters impact collective decisions separately as process and outcome.

The Paradigm of a Nested World

Whether society, a network formulated by individuals, can be treated as an organism arouses the interest of scholars from disciplines to trans-discipline. With the definition of organism, all organisms are capable of responses to stimuli, reproduction, growth and development, and maintenance of homoeostasis as a stable whole. Hence, if a society is treated as an organism, a society should have collective identity, intelligence, cognition and behavior.

According to self categorization theory, personal identity and social identy are different levels of self-categorization. Sociery should have its identity -- a collective self, which emerges as part of the normal variation in self-definition (Turner et al. 1994).

The collective intelligence has not been fully explored, even at the individual level. Of these limited investigations, Wooley et al. (2010), for example, have defined collective intelligence to be general ability of a group to perform a wide variety of tasks. They even demonstrated the existence of collective intelligence of human groups in their empirical research. As intelligence should be highly related with information processing at individual level, we claim collective intelligence should be highly related with information processing at network level. Information processing at network level includes information acquisition from the outside, information processing in individual mind and information exchange among individuals. Those processes comprise a symbolic system at social level.

Bounded Rationality and Social Learning

In the pursuit of perfection, psychologists create the term of rationality at individual level. They treat each individual as autonomy, and use the amount of benefit as a proxy of the degree of perfection. Rationality is defined as a behavioral strategy that individuals always choose actions that will maximize their benefit. In biology, rationality can be defined as fertilization in a growth game; in ecology, as surviving in a prey-predator game; in economics, as utility maximization in a tradeoff game; and in business, as profit maximization in the game of resource allocation.

Consider a fully rational agent without any constraint. She can always know what has happened, observe what is happening, and predict what will happen. Based on those, she has unbounded knowledge and cognition to choose a behavioral strategy without any constraint to maximize her own benefit.

Unfortuantely, in real life, there are always constraints on the performance and outcome of individuals and organizations. For example, a society will enforce constraints such as, laws, regulations, moral codes, and culture on people's behavior. These constraints on outcome and behavioral pattern provide equilibrium for the society.

Bounded rationality and the concept of equilibrium provide three real life constraints, namely cognitive constraint, outcome constraint and constraint on behavioral patterns. Simon (1957), recognizing various kinds of intrinsic constraints, proposed the concept of bounded rationality in his Nobel prize work, which suggested that human, though intended to be rational, sometimes failed to do so due to constraints, either intrinsic or extrinsic.

These constraints, along with the lack of ability and resources to arrive at the optimal solution in decision making, fostered bounded rationality. Hence, individuals in a society would not base their decisions purely on their own information, they also observe how others behave and infer information from their behaviors. This social learning behavior is a useful strategy to enhance individual's decision efficiency and effectiveness.

Social Learning and Conformity tendency

Social learning increases collaboration among individuals, which may consequently lead to conformity tendancy. Chamley (2003) suggested that social learning involves individuals' learning from the behavior of others and may lead to spectacular outcomes such as herding, fads, frenzies, crashes, and booms. Chamley (2003) even constructed a model to describe herd effect as a special case of social learning.

Herd behavior describes how individuals in a group can act together without planned direction. Observing the actions of others, people usually make the same choice, regardless of their own information. We assume human beings choose herd behavior because it will maximize benefit, though it may fail to do so. In this sense, herd behavior arises because of bounded rationality and social learning. More specifically, herd behavior due to bounded rationality can be considered as an imitation behavior to maximize the likelihood of achieving satisfactory payoffs for themselves with limited ability and available resources.

Informational cascades, one of the underlying mechanisms of herd behavior, support the argument of this bounded rationality. An informational cascade occurs when people observe the actions of others and then make the same choice, independent of their own private signals, that others have made (Bikhchandani et al. 1992). Herd could be rational as it maximizes the individual's *ex post* probability of success (Banerjee 1992). It explains herd effect in an information-based and cognitive way, rather than blind imitation.

Summary - Judgment and Collective Behavior

In the decision-making process, an individual will reveal her own preference only if her action aligns with private signal. Private signal and inferred signal serve as two cues for decision-making. Whether an individual reveal her own preference is determined by two factors in the cognitive and judgmental process. The first one is to what extent an individual is influenced by other's action, and the other one is an individual's confidence of private information. The confidence in self-judgment from private signal is further determined by informativeness, which reflects the quality of the information. The weight of signal inferred from other's action is determined by the social influence of each individual and how many people she is connected. The individual decision process nested together, thus form decisional dynamics of a society as illustrated in figure 1.

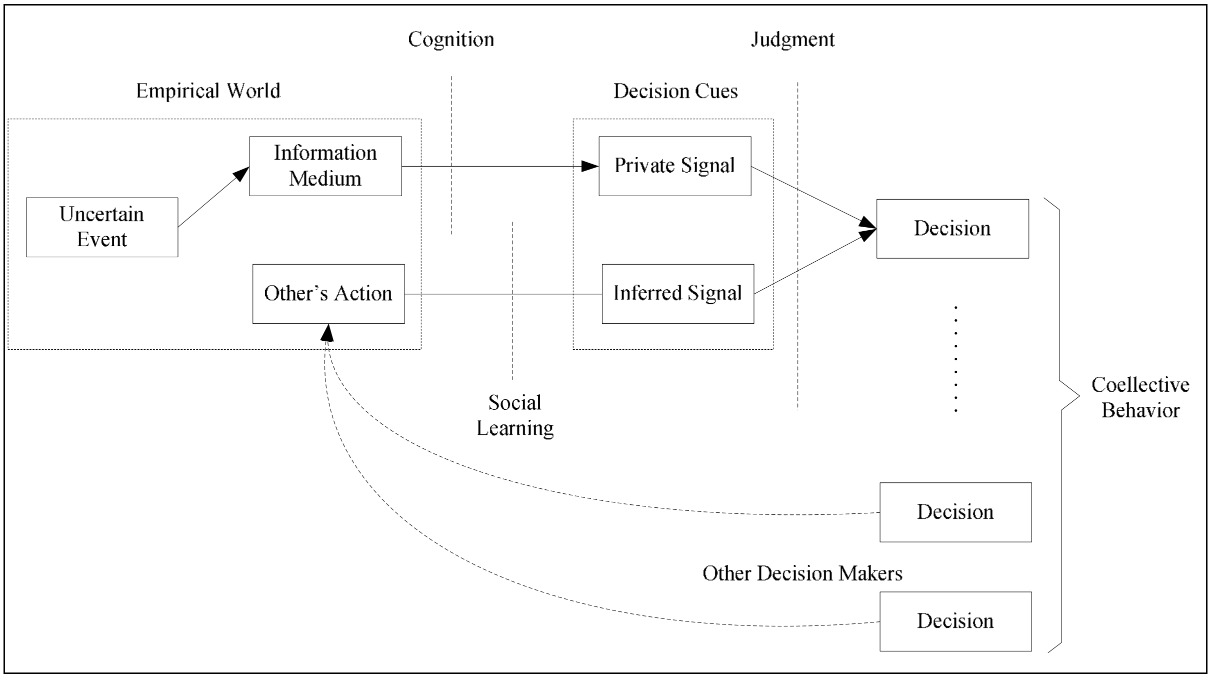

Figure 1. Social Network Organized as a Nested Symbolic System

Every decision-maker has two sources of information to support their decisions -- one directly acquired from uncertain event, and the other inferred from the actions of others. The two sources of information compete with each other at individual decision process. In a social network, not only people are nested, but also information and decision cues. This paradigm can be employed in any iterative decision-making process under hidden synery. Some of the representative contexts include financial market, investment, consumer choice, and etc.

Theoretical Framework

In order to evaluate the performance of the dynamics of social network more appropriaely, we need to develop some metrics suitable for the assessment of social network's performance. In the framework of the nested world proposed in Figure 1, we introduced a paradigm to treat society as a dynamic information processing organism. Any information system, either mechanical (e.g., computer, cell phone, PDA, and etc.) or symbolic (e.g., human brain, organization, society, and etc.), should have some metrics to evaluate their performance based on outcome and process. These metrics, which were derived as dependent variables of our research model, include decision quality, decision speed, fatal risk ratio, and energy efficiency. In our study, these metrics were tested against the effect of our independent variables, which include informativeness, network density, and social influence. The selection and explanation of our research variables are illustrated as follows.

Dependent Variables

Decision quality and decision speed

As the performance of a social network is determined by the collective behavior of individuals, the collective performance of a social network would be the cross-sectional collective performance of individuals in this social network at a specified time.

Social network as a symbolic system should have its learning process. Decision making in social network is an iterative process (Latané 1996), i.e., every individual update her belief and action in an iterative way. In this iterative process, all agents update their beliefs and actions, thus forming social dynamics analogous to the learning process of individuals. Therefore, this social dynamics can be viewed as the learning process of a social network. Like human brains, any symbolic system has a learning process, after which, the decision became stable. As social learning is a kind of bayesian one, social network should be non-exceptional to achieve steady state after all the individuals fully update their beliefs and actions.

In this study, we define the average performance of individuals, after the iterative process has achieved its equilibrium (Markov steady state), as decision quality. We also define the time consumed for the social dynamics to achieve equilibrium as decision speed.

Fatal risk ratio

Human society is an ecosystem that can not afford fatal risk, i.e., the performance of the society should not be below some threshold; otherwise the system will never sustain its development. In this study, fatal risk ratio is defined as the proportion of trials in which the decision quality is below some threshold, thus failing the social network. The threshold used is decision quality, which is set to 20% of the individuals in the society that have made the right choice. For each network pattern, we calcuate the fatal risk ratio by dividing the number of trials suffer from fatal risk by the total number of trials.

Energy efficiency

Energy efficiency describes how effective a social network can achieve a performance level as compared to its energy consumption. The energy consumption is comprised of two parts -- information cost and the energy consumed to maintain the social network (including stable topology and stable strength of social ties).

$$Energy\ Efficiency = \frac{Performance}{Information\ Cost + Maintainance\ Cost}$$

As information cost exists even when individuals are not organised as a network, therefore we considered information cost to be associated with individuals, rather than with the social network. In addition, the non-existence of a method to measure the interchange of information cost and maintainance cost forced our study to only consider a simplified function of energy efficiency by considering only performance and maintainance cost.

Independent Variables

Informativeness

Uncertainty is a state of having limited knowledge to exactly describe existing state or future outcome, more than one possible outcome (Hubbard 2007). In 1950s, there are two important articles (Shannon 1948; Blackwell 1951) about the essence of information which set far-reaching impact on broad range of disciplines. Although these papers adopted different approaches in their studies, they concurred that informativeness is the information's utility of reducing uncertainty. Although the formulas adopted by Shannon (1948) and Blackwell (1951) are different, they converged in their intepretation of information and uncertainty. In this study, we adopt Shannon (1948)'s concept of entropy as the measure of informativeness.

According to the concept of entropy to quantize information value, the value of information is determined by uncertainty reduction. Therefore, we use the concept of entropy to evaluate the uncertainty. Assume the state of the world is an element e from binary set *E= {-1, 1}*. We denote the unconditional probability distribution of the outcome as vector p, uncertainty entropy of event as

$$U(e) = -\sum_k p_k \log_2(p_k)$$

Informativeness, as the individual signal's utility of reducing uncertainty alone, can be evaluated in terms of the reduction of uncertainty entropy after getting individual signal.

$$u(s_i) = U(E) - U(E \mid s_i)$$

Network density

Network density is a statistical parameter to describe the topology of a network. It measures the relative number of ties in a network that link agents together. It is calculated as a ratio of the number of ties that exist in the network, compared to the total number of possible ties if every agent were tied to each other directly. In social network, it is referred to as, the proportion of people, on average, that an individual is directly connected to (Wasserman and Faust 1994).

In real life social network, network density should be within the range of (0, 1), which indicates that it is rarely possible for all the potential relations to exist and every individual should have more or less social relations. The reason why not all potential relations can exist is because of the fact that individual's resources (time, money, energy, and etc.) are limited, thereby constraining the expansion of their social relations. The reason why every individual have similar extent of social relations is that social activity is an important way to prove human-being's social existence. When network density goes to the extreme of zero, human society will disintegrate.

Social influence

Social influence is defined as a change in an individual's thoughts, feelings, attitudes, or behaviors that results from the interaction with another individual or a group. The likelihood of being influenced by another person is determined by the strength of social tie between each other. This process can cause initially randomly distributed attitudes and beliefs to become clustered or correlated. In each pair of autonomies, the social influence is usually asymmetric, because of different social status, fame, and etc.

Primary Investigation

Informativeness and collective decision-making

Informativeness is positively related with expected utility of the signal (Blackwell 1951). Expected utility of the signal is calculated by the payoffs in a statistical meaning. Recall our definition of the decision quality of social network as the average performance of individuals after the iterative process achieves equilibrium (Markov steady state). It indicates decision quality is a statistical measure of the individual's payoffs after information acquisition and social learning. Decision quality should be positively related with expected utility of the signal and the effectiveness of social learning. Therefore, we claim:

Hypothesis 1a: Informativeness and decision quality of the social network are positively related.

As informativeness is evaluated by uncertainty reduction, a more informative signal will leave decision-makers less uncertainty. Decision speed is a decreasing function of uncertainty level. First, uncertainty is negatively related with preference strength. While facing choice under uncertainty, the mean choice time is a negatively related with the strength of the preference (Dashiell 1937). Therefore, individual's mean choice time should be positively related with informativeness. Second, uncertainty is positively related to the time consumed for information retrieving and reasoning process (Townsend and Busemeyer 1993).

Thus the deliberation process to get a stable conclusion will cost less time for individuals under low level of uncertainty. When the social dynamics achieve equilibrium, all decision-makers in a social network get stable conclusions. Therefore, the time consumed for the social network to get equilibrium should be positively related to an individual's reasoning and learning time, which should be positively related to informativeness. Additionally, higher informativeness means the signals received by individuals are more likely to converge to the true state of the world. This convergence increases the deliberation speed of decision-making among interconnected individuals. Therefore, we claim:

Hypothesis 1b: Informativeness and the decision speed of social network are positively related.

Network density and collective decision-making

Social network, as an organism, should have responses to stimuli. Those stimuli are realized via individuals nested in the network. Individuals, through social ties, exchange their information in time series. Relational networks allow for coordination and information exchange between participants (Oliver 1991). Those exchange of information allow the refreshment of individual beliefs and actions, thus form a dynamic process, in which beliefs, judgment, norms are diffused across social network. Network density is an important factor that will determine the performance of social netowork, as it determines the number of relations.

As density increases, the number of social ties among decision makers grows, thus information exchange across the network becomes more effective. The efficiency of information exchange give each decision maker more informative signal set, thus reduce the uncertainty for each individual. Therefore the aggregated performance of individuals increases. At social level, it indicates the effectiveness of social learning is an increasing function of network density. Therefore, we claim:

Hypothesis 2a: Network density and the decision quality of social network are positively related.

Recall our definition of decision speed of social network as one divide by the unit-less time (number of iterations) for the social network to achieve equilibrium. The number of iterations depends on the steps of effective information diffusion, where information diffusion leads to change of beliefs and actions.

In a social network, information is diffused via two methods: direct diffusion and indirect diffusion (via neighbor's neighbor). Indirect diffusion is a time-consuming one, and direct diffusion costs less time. In a sparsely connected network, some sections of the network may be isolated. Individuals might have less communication channels with others. The lack of communication channel largely restricts information sources for social learning, hence resulting in more chance to stick to their own beliefs, or spend less iterations to update their beliefs before achieving stable conclusions. Thus sparsely connected social network has a merit of fast decisio-making due to the segregation of decision-makers.

As network density increases from sparse to moderate, many un-correlated individuals will be connected, thereby creating indirect connections. Former segregate sections are now connected, thus losing the merit of fast decision-making inherited from dictatorship and high degree of autonomy. Hence, when network density increases from sparse to moderate, it takes more time for social network to achieve equilibrium.

As network density increases from moderate to dense, the former indirect connection will have more chance to get direct social relation. Decision-makers will have more direct communication channels. As the number of indirect communication channels decreases, it will be more efficient for information to exchange across social network. This efficiency leads to a reduction of time consumed for social learning process. Thus social network will achieve equilibrium faster. Therefore, we claim:

Hypothesis 2b: Network density and the decision speed of social network have a U-shape relation.

Social influence and collective decision-making

Individual choice is influenced by the behavior of others. These behaviors constitute indirect information source other than information acquired directly from an uncertain event. Within the framework of social impact theory, the impact of this information source is determined by three factors: the number of others who make up that source, their immediacy, and their strength.

Dynamic social impact theory uses social impact to describe and predict the diffusion of beliefs through social systems (Latané 1996). Social structure is the result of individuals influencing each other in a dynamic and iterative way. The likelihood of being influenced by someone is determined by social ties between each other. This process can lead initially randomly distributed attitudes and beliefs to become clustered or correlated.

The aggregated interactions between each pair of individuals represent social ties in the social network. There is always finite set of interactions in a society. The resource, e.g., time, wealth, and etc., consumed to complete that interaction reflect how we should weight that behavior in formulating social ties. New technologies, such as video surveillance, e-mail, and "smart" name badges, offer a moment-by-moment picture of interactions over extended periods of time, providing information about both the structure and content of relationships (Lazer et al. 2009). Social influence is the process by which individuals make real changes to their feelings and behaviors as a result of interaction with others. People adjust their beliefs with respect to others to whom they feel influential because of similarity, majority, or expertise. Social influence is related with the dynamics of the social network, by determining how important individuals consider the signal inferred from the actions of others. Therefore, we claim:

Hypothesis 3a: Decision quality of social network is related with social influence.

Hypothesis 3b: Decision speed of social network is related with social influence.

Interaction effects

Information, as a special commodity for exchange, is transmitted and spreaded through connections in the social network. Network density determines the average connection exited in the social network, thus determine the number of exited path for information exchange. The social learning process is realized through information exchange. With relatively low informative signals, social learning will be more effective to improve the decision quality of a social network. As network density increases, the path for information exchange will increase, thus causing social learning effect to become significant. With relatively high informative signals, social learning will be less effective to improve the decision quality of the social network, as individuals themselves will have high decision quality. As network density increase, the path for information exchange will increae, but less effect of uncertainty reduction will be achieved through learning process. Therefore, we claim:

Hypothesis 4a: Informativeness will moderate the relationship between network density and decision quality of a social network.

More precisely, the strength of the relation between network density and decision quality is a decreasing function of informativeness.

In the process of information exchange, equilibrium is realized by confirmation and update of beliefs. Equilibrium is achieved while all the decision-makers confirm the state of the world, and insist her current belief at the next period.

Low informative signals provide the heterogeinity of signals among individuals. In a sparse network, individuals enjoy dictatorship, thus decision speed is high. In highly connected network, the heterogeinity of signals cost individuals much more time to confirm the state of the world, thus it is time-consuming for the social network to achieve equilibrium. Therefore, when the signal is less informative, the relationship between network density and decision speed is very strong.

When the signal is highly informative, the signals tend to be homogeneous. In a sparse network, individuals also enjoy dictatorship, thus decision speed is high, just like those under low informative settings. However, when the network is highly connected, the consequence will be slightly different. The homogeneous signals provide more chance for individuals to find their neighbors who hold the same belief. It takes much less time for them to confirm the state of the world as compared with low informative settings. Therefore, the relationship between network density and decision speed is weaker as compared with that under low informative settings. Conclusively, we claim:

Hypothesis 4b: Informativeness will moderate the relationship between network density and decision speed of social network.

More precisely, the strength of the relation between network density and decision speed is a decreasing function of informativeness.

The utility of information, despite its intrinsicl property – informativeness, is also determined by social influence, how strong an individual is influenced by her neighbors and to what extent an individual takes her neighbors' opinion into consideration. Social learning is realized through social relations, the effectiveness of social learning is determined by the total information individuals get and take into consideration. Thus, the effectiveness of social learning is determined by the total social influence an individual suffers from. The total social influence of an individual suffers from is further determined by the number of social ties and the strength of the social influence interchangeably. The number of the social ties is further determined by network size and network density. Therefore decision quality is determined by network density and the stength of social influence interchangeably. In a social network of relative low density, social influence will have higher impact on decision quality. As the network density increase, the impact of social influence on decision quality will decrease. Therefore, we claim:

Hypothesis 5a: Network density will moderate the relationship between social influence and decision quality of social network.

More precisely, the strength of the relation between social influence and decision quality is a decreasing function of network density.

In the process of information exchange, the likelihood that an individual will change her belief is determined by the collective social relations, which is determined by network density and social influence together. The likelihood of changing belief will further determine social network's speed of achieving steady state.

Low network density provides individuals less connections. Thus individuals are less likely to be influenced by others. When social influence is low, the influence of several connected other decision makers is low. Individuals will be more likely to insist their own beliefs. When the social influence is high, the influence of several connected other decision makers is high. Individuals will be more likely to follow the connected groups even the numer of connections is limited, and update her belief. Therefore, when the network density is low, the relationship between social influence and decision speed is very strong.

High network density provides individuals more connections. Thus individuals are more likely to be influenced by others. The aggregated influence of many connected other decision makers may be high enough to shift individual's belief. Therefore, when the network density is high, the relationship between social influence and decision speed is weaker. Conclusively, we claim:

Hypothesis 5b: Network density will moderate the relationship between social influence and decision speed of social network.

More precisely, the strength of the relation between social influence and decision speed is a decreasing function of network density.

Research Methodology

Based on the paradigm of the nested world, we develop a research model to investigate how informativeness, network density, and social influence, will influence the performance of social network, which is evaluated by the four metrics mentioned previously. In order to convert this theoretical model to an analytical one for further analysis, we build a computational model, and generate dataset through simulation. Simulation is a powerful tool not only in science & engineering, but also in social science & business (e.g., Lazer and Friedman 2007; Chang and Harrington 2006; Rivkin and Siggelkow 2003; Macy and Willer 2002). Due to the complexity of social network, we believe simulation based on computational model is a powerful tool to do social network analysis.

Computational Model

Social influence network theory involves a two-stage weighted averaging of influential opinions (Friedkin 1998). Actors start action with their own initial opinions. Then at each stage, actors form a "norm" opinion which is a weighted average of the other opinions in the group. Actors then modify their own opinion in response to this norm, forming a new opinion which is a weighted average of their initial opinion and the network norm. This theory utilizes mathematical models and quantifications to measure the process of social influence.

We construct the social network as Bayesian one, i.e., iterative process of decision making and belief update. The network has a size of 150 decision-makers, in which each pair of nodes has a probability of *p* to be connected directly. We choose the number of N=150 to align with Dunbar's (1992) number, a theoretical cognitive limit to the number of people with whom one can maintain stable social relationships (Dunbar, 1992). To ensure the robustness of the result, we also design the computational process with different network size, and the result is quite robust. We control for the average social influence and assign bidirectional social influences between each pair of connected decision-makers randomly, which are ranging from (0, 1) with truncated normal distribution. It conveys two concepts: First, inferred signal from any individual is less useful that private information; Second, social influence is heterogeneous. We generate the state of the world *e* from *E= {-1, 1}* with probability of 0.5 for each state, to represent an uncertain event. The state of the world will not change during the decision process, which is a reasonable assumption for short period learning process. Based on that event, we generate a signal from *s= {-1, 1}* for each individual as information acquisition. The information precision is constraint as *p (true) =p(s=E)*.

We denote sp_i as individual i's private signal, $si_{t,j}$ as inferred signal from agent *j* at time *t*, and $Inf_{i,j}$ as the social influence of *i* on *j*.

In order to turn decision makers to agents in the model, we made the following assumption about individual's mindset to get a simplified senario:

1. Deterministic mindset in decision-making process.

Deterministic mindset describes a psychological status that individuals will always follow their judgment regardless of how strong the evidence lead to that judgment is. In computational model, it is interpreted as agents always abide by their preferences, i.e., weak preference doesn't differ from strong ones.

2. Social influence in shaping judgment is linear.

Other's actions, through observation, will impact individual judgment. This impact is a linear function of social influence from others to individual.

3. Confidence in self information.

Agents always take their own information for higher weight while making judgment. This is reasonable for the reason that self information is concrete information acquired directly from uncertain event, and information perceived from other's action is an inferred signal with less meaning.

For specific individual *i* at time *t*, she will infer signal $si_{t,j}$ from her neighbors' action $a_{j,t}$

$$si_{j,t} = a_{j,t}$$

update her belief $b_{i,t}$ by Bayesian rule, according which the solution equals to linear additive form of private information and inferred information:

$$b_{i,t} = \begin{cases} sp_i, for\, i = 0; \\ b_{i,t-1}, for\, i \neq 0, if\ Sgn(b_{i,t-1} + \sum_{j}^{j\neq i} Inf_{j,i} si_{j,t-1}) = Sgn(b_{i,t-1}), or\, b_{i,t-1} + \sum_{j}^{j\neq i} Inf_{j,i} si_{j,t-1} = 0; \\ -b_{i,t-1}, for\, i \neq 0, if\ Sgn(b_{i,t-1} + \sum_{j}^{j\neq i} Inf_{j,i} si_{j,t-1}) = -Sgn(b_{i,t-1}) \end{cases}$$

and take action $a_{i,t}$

$$a_{i,t} = b_{i,t}$$

Individuals make decisions follow the rules iteratively. Steady state will always exist for first order Markov process. Assume a network with *N* nodes, and every individual in the network face choice from a complete choice set comprising of K strategies. The set of decision status will in all have K^N elements. Whenever the decision process exceeds the length of K^N+1, it will inevitably generate two collective behavioral states of the same state, i.e., the collective behavior will eventually achieve steady state given enough times of iteration.

The payoff will be determined at steady state. The payoff of each individual is determined by the rule:

$$payoff_{i,t} = \begin{cases} 1, if\ a_{i,t} = e; \\ -1, if\ if\ a_{i,t} \neq e \end{cases}$$

We take the average payoff of all the decision-makers as the collective performance:

$$performance(t) = \frac{1}{N}\sum_i payoff_{i,t}$$

Pattern Analysis

We randomly assign informativeness, network density and social influence within the range mentioned in table 1. We accumulate the data for 1097 patterns. For each of the patterns, we run 500 trials. For each trial, we run 50 iterations. Finally, we got 543,500 trials to do pattern analysis and model verification.

Table 1. Parameters for Decisional Analysis

Parameters	Range
Signal Precision	[0.55, 0.95]
Network Density	[0.1, 0.9]
Average Social Influence	[0.1, 0.9]

Pre-analysis of raw data

We compute the average performance of all the 500 trials under the same pattern. We record the number of iterations as unit-less time, and calculate the decision speed by dividing the times of iteration before average performance get stable. We record the average performance during Markov steady state as decision quality.

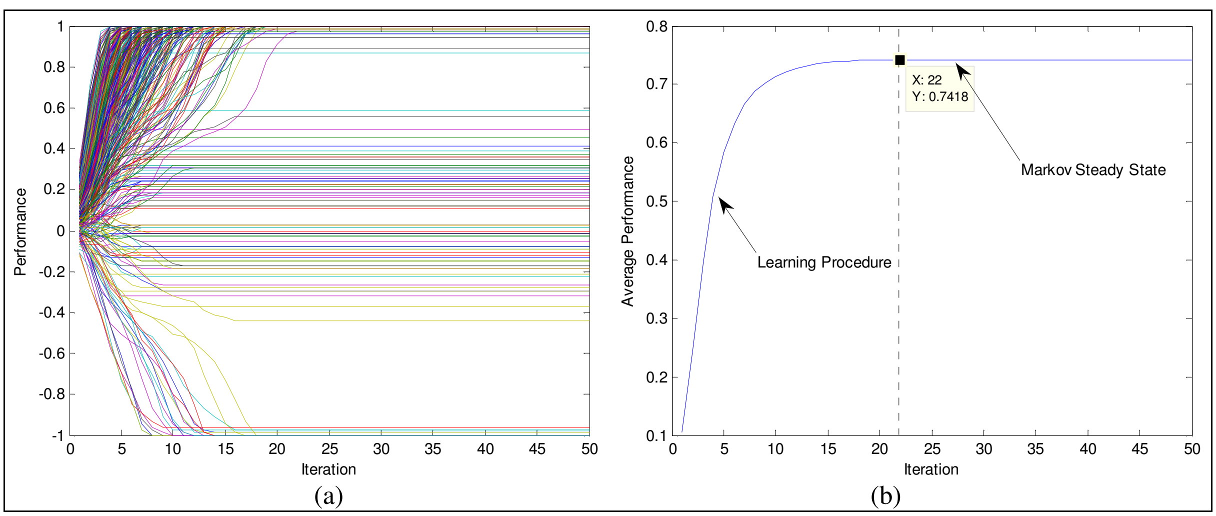

Figure 2. An illustration of one trial run and the average performance
(a) Several trials with finite iterations plotted. (b) The aggregated performance of each trial

The increasing performance indicates a social learning process. The flat line after several iterations indicates that the average performance becomes stable. We find the social learning curve to be significant.

The social learning curve in figure 2(b) reflects statistical aspect of social learning. In some cases, social learning can be harmful. It is illustrated in figure 2(a) as the decreasing performance in the iterative process. After the pre-analysis, we get dataset of 1097 cases for further analysis. The descriptive statistics and correlation is illustrated in table 2 & 3.

Table 2. Descriptive Statistics

Variable	N	Min	Max	Mean	S.D	Var
Informativeness	1097	.0072	.7136	.2561	.2212	.049
Network Density	1097	.1000	.9000	.5041	.2413	.058
Social Influence	1097	.1000	.9000	.5084	.2399	.058
Decision Quality	1097	.0959	1.0000	.8970	.2025	.041
Decision Speed	1097	.0200	.5000	.2900	.1446	.021
Fatal Risk Ratio	1097	.0000	.1460	.0090	.0310	.001
Energy Efficiency	1097	.0369	44.9307	1.7526	2.7346	7.478

Table 3. Correlation Matrix of the Key Variables

Variable	1	2	3	4	5	6	7
1. Individual Info							
2. Collective Info	.410***						
3. Network Density	-.020	-.009					
4. Social Influence	-0.10	.009	.000				
5. Decision Quality	.345***	.457***	.542***	.082**			
6. Decision Speed	.553***	.373***	.505***	-.004	.307***		
7. Fatal Risk Ratio	-.325***	-.902***	-.006	-.005	-.431***	-.290***	
8. Energy Efficiency	.293***	.170***	-.224***	-.423***	-.069*	.275***	-.135***

*p<0.05 **p<0.01 ***p<0.001; Info *abbre.* for informativeness.

We use two kinds of method to reveal the pattern. In order to find basic patterns, we use regression analysis to verify the basic model. In order to uncover some patterns not suitable to be reported by linear equation, we use 3D-mesh plot and contour map.

Regression analysis

In order to prevent multi-colinearity and observe more clearly how each independent variables result in the variance of the decision quality and speed, we use z-score of each variable for regression analysis. The results reported in table 4 & 5 are standardized coefficient.

Table 4. Parameter Estimation of Decision Quality

D.V. : Decision Quality	Model 1	Model 2	Model 3	Model 4
Informativeness	.359***	.351***	.355***	.355***
Network Density	.548***	.559***	.560***	.562***
Social Influence	.086***	.098***	.097***	.096***
Informativeness×Network Density		-.299***	-.299***	-.298***
Network Density×Social Influence			-.090***	-.091***
Informativeness×Social Influence				-.057**
Ajusted R Square	.426	.516	.523	.526
Sig F. Change	.000	.000	.000	.009

* p<0.05 ** p<0.01 *** p<0.001

Model 3 is the best model to explain the relationship between decision quality and independent variables, as model 4 increases only 0.3% to explain the variance of decision quality, and the significant level of the

F-statistic is 0.009, although significant, but uncompatable with the other 3 models, which are all smaller than 0.001.

Table 5. Parameter Estimation of Decision Speed

D.V. : Decision Speed	Model 1	Model 2	Model 3	Model 4	Model 5
Informativeness	.564***	.556***	.560***	.554***	.559***
Network Density	.521***	.525***	.520***	.519***	.521***
Social Influence	-.010	-.009	-.003	-.004	.159***
Network Density^2		.185***	.189***	.187***	.187***
Informativeness×Network Density			.141***	.139***	.144***
Network Density×Social Influence				.128***	.121***
Network Density^2×Social Influence					-.209***
Ajusted R Square	.577	.611	.630	.646	.665
Sig F. Change	.000	.000	.000	.000	.000

* p<0.05 ** p<0.01 *** p<0.001

Model 5 is the best model to explain the relationship between decision speed and independent variables. Because of decision speed as function of Network Density is U-shape, the relationship between decision speed and social influence has been suppressed in model 1~4. The moderation effect of Network Density on the relationship between social influence and decision speed is a U-shape rather than linear. After the U-shape moderation effect adds to model 5, the R^2 change is 1.9% with a significant level < 0.001.

After verification, we could find that the hypotheses form final model as illustrated in figure 3.

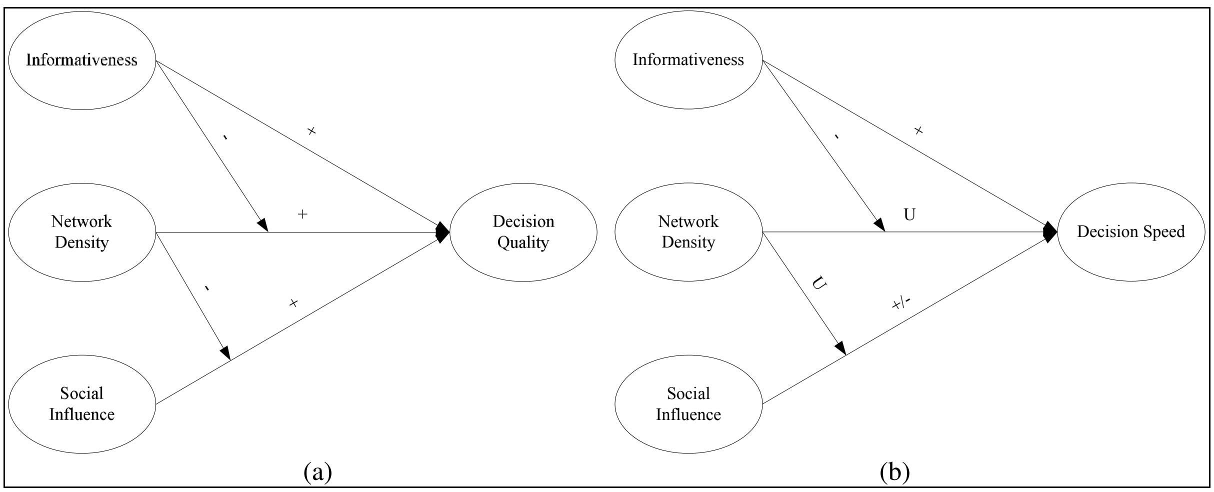

Figure 3. Final Result (a) Determinants of decision quality. (b) Determinants of decision speed

Futher pattern analysis

In order to have more intuitional results, we use 3D-mesh plot and contour map to reveal the patterns of how network density and social influence could influence the performance metrics. The outcome metrics in relation to the network properties are plotted as dot in the figure. The fitted estimation is plotted as color map.

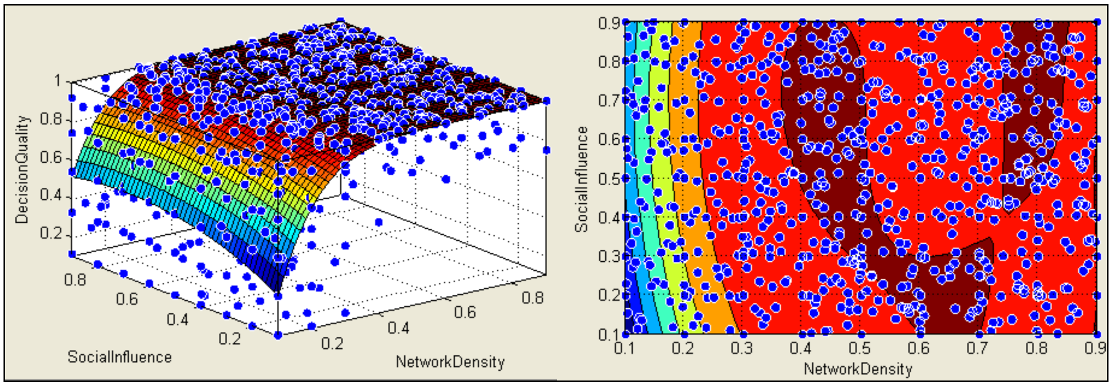

Figure 4. Decision quality as a function of network density and social influence

Blue to red indicate decision quality from low to high. Social influence and network density are interchangeably in driving decision quality. The marginal utility in driving decision quality is decreasing. We could see clearly that there is a threshold at network density of 0.2~0.3, above which the decision quality maintain stable. There is a significant point from which increasing network density will not improve the performance. Thus, we claim the bounded rationality of the social network: Beyond some specific network density, the decision quality will be constraint by cognition and the ability of information acquisition.

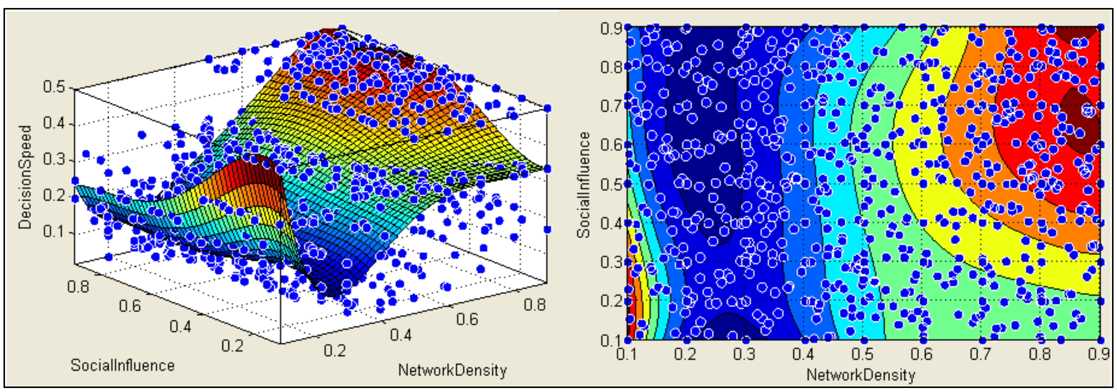

Figure 5. Decision speed as a function of network density and social influence

Blue to red indicate decision speed from low to high. In low density area, decision speed is primarily determined by network density. In high density area, social influence and network density are interchangeably in driving decision quality, and the marginal utility in driving decision quality is decreasing.

After comparison the perpendiculars in the contour map, we find that the x-y vector of the perpendiculars in low/medium/high network density areas changed significantly. Not only changed in strength, but also in direction. The moderation effect of network density on the relationship between social influence and decision speed is obvious.

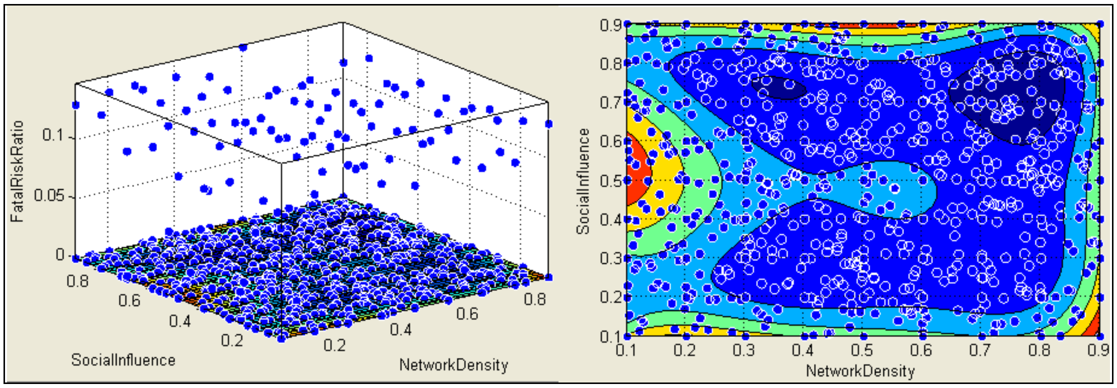

Figure 6. Fatal risk ratio as a function of network density and social influence

Blue to red indicate risk from low to high. Through the contour map, we could find that the areas suffter from relatively high fatal risk ratio are those have either extremely low/high network density or extremely low/high social influence.

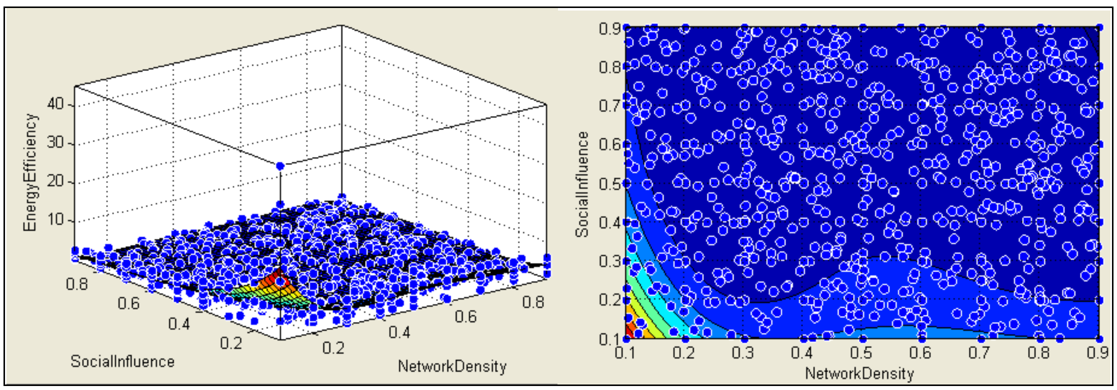

Figure 7. Energy efficiency as a function of network density and social influence

Blue to red indicate energy efficiency from low to high. The energy efficiency is monotone with network density and social influence.

Conclusion

With integration of the individual judgment process, social impact theory and information economics, we construct a framework named as the nested world. The framework provides an information based view of how information and decision cues are nested together to drive collective behavior.

The essence of this paradigm is to convey the concept that individual level bounded rationality leads to social learning, which leverages the bounded rationality at individual level. Through social learning, individuals get inferred signal weighted by social influence. Inferred signals serve as another source of decision cues other than private signal. Those individuals nest together and form a social level intelligence. The interpretation of decision in a nested world exhibits strong heritage from Nexwell's work unified theories of cognition (Newell 1990), which suggests that human are symbol systems, and intelligent systems are built up on multiple levels of systems.

Based on the computational model built from this paradigm, we find social learning curve to be significant, and there is threshold, at which the response of social performance as a function of network density changed significantly. It is encouraging to find this threshold. As people always find it time-consuming to maintain social relations, this threshold suggests that a satisfactory social performance may not really need us to be fully connected. Also, the relationship among informativeness, network density, social influence and performance metrics has been verified. Another result is that, like speed-accuracy tradeoff effects of human-beings (Townsend and Busemeyer 1993), social network has its tradeoff between decision quality and decision speed.

Implication

Social network has its intelligence in leveraging the bounded rationality of individuals. However, the intrinsic constraint lies in information acquisition and cognition, set a threshold from which the effect has been suppressed. This suppression in turn make the social network seems like an organism has its own boundary of rationality. In this sense, social network conveys two ideas about rationality: First, it leverages the bounded rationality of individuals; Second, the cognitive constraint makes social network operate like a dynamic organism own bounded rationality at social level.

Social learning makes the whole society response to stimulus as a huge intelligent organism. Sometimes social decision process is fast, and sometimes the process is relatively slow. The decision making process under synergy is highly comparable with the deliberation process of human brain. If we refer to the literature of biology, anthropology and sociology, and take the terminology that the decision quality of each level of organism is related with the benefit of that level. Cell has its benefit as copy itself. Organ has its benefit as maintain alive; animal has its benefit as survival and fertilization; individual, as the basic components of society, has its benefit of living and growth; and society has its own benift as social welfare. We take the existence just under that level as autonomy, to claim that the rationality at each level is determined by the collective intelligence at that level.

When the society chooses its structure, it is in somewhere a balance of high decision quality, high decision speed, high energy efficiency and low risk ratio. We could find moderately nested world is not only an existing phenomenon supported by the hypothesis of six degree of separation, but also has its merit in supporting the performance of human society. If someone argues that Darwin's Theory of Evolution could be used to explain the natural selection of human society more than species, we are more than eager to vote for it.

Providing an analytical method to evaluate the performance of social network, we have also tried to bridge the gap between micro behavioral economic theory and macro evaluation of social network.

From micro perspective, we take decision makers' belief and behavioral pattern into consideration at individual level. The process of social learning maximizes the probability of making best choice, i.e. minimize decision-maker's uncertainty. From macro perspective, we nest those decision-makers through social influence, thus provide a social level view of the learning outcome. The social level performance might stand for macroeconomic fluctuation. The risk analysis mentioned in further pattern analysis of social network also may help to evaluate the risk caused by herd behavior under specific social structures.

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