A Dynamical System and Information Theory Approach to Norms and Behaviors

Qiankun Zhong

Department of Communication

qkzhong@ucdavis.edu

Abstract

Culture and Norms has a powerful influence on social action even when individuals do not deeply internalize its meanings. However, when people strategically follow norms in the social systems without internalizing the meaning, it will create an inconsistency in their beliefs and behaviors in different social contexts. This project aims to capture the difference between actions driven by internalized values and actions driven by strategic choice through agent based modeling and informational properties. The result of this study shows that the agents that do not internalize norms have a higher inconsistency and less memory in their action sequence.

Introduction

How culture and norms influence behaviors has always been a key question in social science. Some believe that culture functions as a form of collective beliefs and values that guided social actions (Schneider, 1976; LeVine, 1984). Others recognize culture as a form of self-referential system that defines what our actions will mean to others (Swidler,1986). Swidler used "semiotic code" to characterize this form of culture as a self-referential system of meanings where the meaning emerges from how people use it rather than its inherent values. This paper aims to capture the theoretical meaning of semiotic code through agent-based modeling and test its hypothesis through dynamical system and information theory analysis.

Social life is full of conflicting and competing cultural meanings, yet individuals have to bear the conflicts and make decisions on which meanings to take in their everyday social practices with each other. Semiotic code thus influences individuals' behavior by ordering the abundant conflicting cultural meanings into a few categories, simplifying the complicated decision-making process of meanings into a question of how individuals want to be interpreted by other people given those categories. Inconsistency between what people believe and what they think they should do causes inconsistency in their behavior. Of course, sometimes we will internalize the cultural experience of how others will internalize us (Mead 1967), however, the internalization is not necessary in influencing individual's behavior. Indeed, semiotic code can influence individuals' behavior in a much more direct way through publicly promoted norms even when individuals don't internalize it. For example, although many people don't believe that presents on Mother's Day is the only way to express children's affection for mothers, they will follow the publicly promoted semiotic code that if you love your mother you will buy a gift for her on that day.

Social context also plays an important role in the influence of semiotic code on individual behavior. In ambiguous social context, it's more difficult for people to infer and internalize the inherent cultural meanings. Instead, they will try to infer how they should act according to their reflection on each other. For example, in high-risk political situations, people will seize on coherent ideology, not because they truly believe the ideology but because the ideology provide a social organization which they can draw inference from to interact with others (Palmer 1989). This explains the emergence of political polarizations in uncertain situations – it is always easier to define allies and enemies than to define the cultural meanings behind a political event.

Stable social context, such as institutions, instead structures and constraints cultural meanings and provide a coherent strategy for individuals daily practices. The institutions at the same time also captures the dilemma between individuals' action and beliefs. In given institutionalized social context, even when individuals consciously disbelieve the dominant values and norms, they usually find themselves engaged with the dilemma as well. For example, although empirical evidence shows that that Americans do not really believe that the country provides equal opportunity for all (Mann, 1970; Kluegel and Smith, 1986; Swidler, 1992), but these beliefs are still prevelant throughout time, even among the dispriviliedged.

Understanding the difference how culture functions through internalization and through semiotic codes will help us understand better how norms influence individual's social behavior in different social context. Information theory and dynamical system provide an opportunity to measure how individuals access and store the information from norms and social interactions, which may help us reveal the "deep structure" of culture.

Dynamical system

I built a multi-agent system to simulate individual's behavior in different social context. To specify the theory of semiotic code and model how individual's behavior and beliefs are influenced by norms through social interactions and internalizations, I included the following assumptions:

(1) There are two ways people follow norms. The first is to internalize the value of the norm and follow the norm out of individual belief. The second is to strategically follow the norm based on one's perception about other people's beliefs.
(2) Individuals don't have full information about their opponents' belief, but they can make a guess according to the opponent's last social action with other individuals.
(3) All agents have a randomly assigned internal value about the norms, which influences how they make decisions and how much they are gratified from their social interactions. Agents who can internalize norms will keep updating their internal values after each interaction. Agents who only make strategic social actions will have a relatively fixed value.
(4) When two agents encounter each other and use the same strategy, they will gain a social benefit from the successful social interaction. When two agents encounter each other and use different social strategies, they will have a social lost from the conflicted social interaction. When an agent uses a strategy not aligned with their internal value, the agent will have an internal lost. When an agent uses a socially promoted strategy, the agent will gain a semiotic top-up benefit.

The global properties and individual properties are included in *Table 1*.

Table 1 Global and Agent Properties

Global properties	Agent Properties
• Number of agents • Proportion of agents that have the internalization function (value updating function) • A strategy (Strategy A) that follows the publicly promoted norm • A strategy (Strategy B) that doesn't follow the publicly promoted norm • Payoffs of social interaction, social conflict, internal cost and socially promoted norm top-up	• An internal value between [0,1]. The value is biased toward • Strategy at each time step • The function to updating their internal value and internalizing the payoffs

The model runs in 4 iterative steps:

(1) Two agents are randomly paired up. The model has a well-mixed population. Agents move randomly at each step and are randomly paired up with another agent within a distance of 1.
(2) Two agents decide on their optimal strategies based on the opponent's last move and their own values. *Table 2* presents the payoff matrix.

Table 2 Strategy Payoff Matrix

	Same as my behavior	**Different from my behavior**
Same Behavior as my value	Social Benefit	-Social Cost
Different Behavior from my value	Social Benefit – Internal Cost	-Social Cost– Internal Cost

(3) Two agents make the move and receive a payoff from the interaction. Because the two agents don't have full information about the opponent's belief, the payoffs they receive from the interaction may differ from the optimal payoffs they expected before the interaction.
(4) Agents with the internalization function will update their values with the payoffs from the interaction. If they play a socially promoted strategy and receive a positive payoff, their internal value will be updated more towards the socially promoted norm, otherwise, it will be updated more towards the other norm.

The model parameters are included in *Table 3*.

Table 3 Initial setting of parameter values

Parameter	**Value**
Number of agents	1000
Timesteps	100,000
Proportion of agents with beliefs bias towards the socially promoted norm	0.1 0.5 0.9
Proportion of agents that internalize norms	0.1 0.5 1
Social benefit	2
Social cost	2
Internal cost	2
Promoted norm top-up	1

Method

The multi-agent system is simulated in Java through SimStateSweep(See *Figure 1* and *Figure 2*). To capture the decision dynamics of agents with different initial internal values and internalization functions, I followed four agents with different traits (See *Table 4*) in all experimental conditions (3 proportion of socially-promoted-norm followers X 3 proportion of learners) and collected data of their strategies throughout 100,000 timesteps.

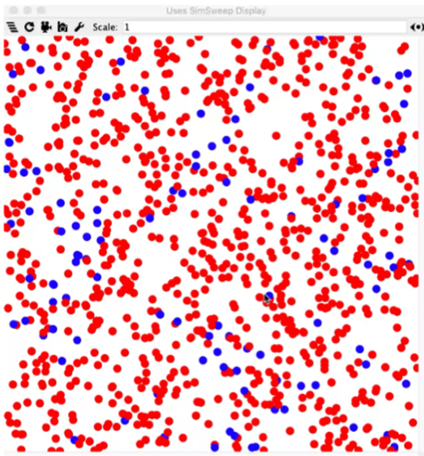


Figure 1 1000 agents with random movement are placed in the system*. At every timestep, two agents within 1 unit of distance will be randomly paired up and play. Blue agents are those who played a socially promoted strategy and red agents are those who played the other strategy. Figure1 presented a visualization of the system with a proportion of 0.1 socially promoted norm followers as the initial condition.*

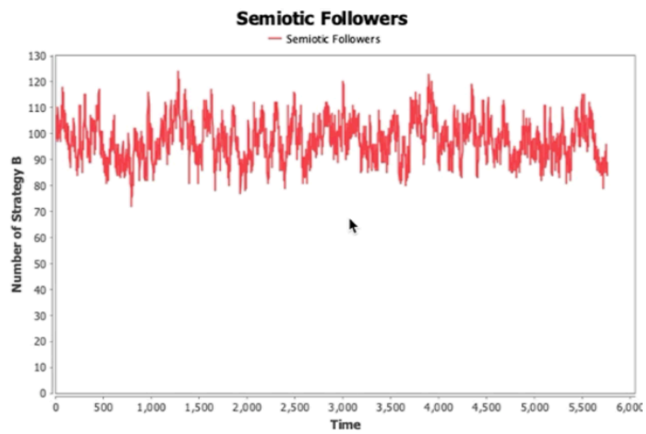


Figure 2 The number of agents play socially promoted strategy oscillates in the system*. How agents decide on the strategy is influenced by the proportion of socially promoted norm followers and the proportion of agents who internalize norms. Figure2 presented the strategy dynamics of of the system with a proportion of 0.1 socially promoted norm followers and a proportion of 0.1 learners as the initial condition.*

Table 4 Individual agents recorded in the simulation

	Learner	Non-learner
Socially-promoted-norm follower	Agent1	Agent3
Non-socially-promoted-norm follower	Agent2	Agent4

To measure the intrinsic inconsistency in agent decisions and learned information through internalization process, I calculated the entropy rate, excess entropy, binding information and statistical complexity of the agent strategy dynamics.

Entropy rate h_μ is the rate of increase with respect to L of the total Shannon entropy in the large-L limit (Crutchfield & Feldman, 2003). The entropy rate h_μ quantifies the irreducible randomness in sequences produced by a source: the randomness that remains after the correlations and structures in longer and longer sequence blocks are taken into account. In this multi-agent system, h_μ can be used to measure the inconsistency in agent decision sequence. If an agent's decision making is a stabilized process, we should expect a lower h_μ. Instead, if the agent's social action is inconsistent because they only strategically follow the norms, we should expect a higher h_μ.

Excess Entropy E can be interpreted in different ways. In this project, we understand it as the mutual information between the past and future (Cruthfield & Feldman, 2003). It measures the amount of historical information stored in the present that is communicated to the future. In this system, the updating internal value is a channel that stores the information of the past experience and influences future decisions. We can thus use E to measure the "internalization" or "learning" in agent behavior. Agents that internalize norms are expected to have a higher E than those that don't internalize norms.

Binding Information b_μ is the joint entropy minus all unshared information. In this project, I use b_μ to measure how much information is stored in the social interaction process.

Lastly, statistical complexity C_μ is a measure of structure (Crutchfiled & Feldman, 1997). It is the quantify of the informational size of the distribution over causal states. Thus, C_μ is the average amount of memory needed to optimally predict the process. In this system, I use C_μ to measure the structure in an agent's decision sequence. Similarly, we expect agents that internalize norms to have a higher $C_\mu$than those who don't.

Results

I compared the informational and computational statistics of the four agents' decision sequence across 9 conditions. Results show that non-learners have a higher entropy rate than learners only in conditions where the socially promoted norms are followed by the majority (See *Figure 3*). All agents have a higher entropy rate in conditions where socially promoted norm is dominant, except for agents who bias towards the socially promoted norm and also keep internalizing the norm (Agent1).

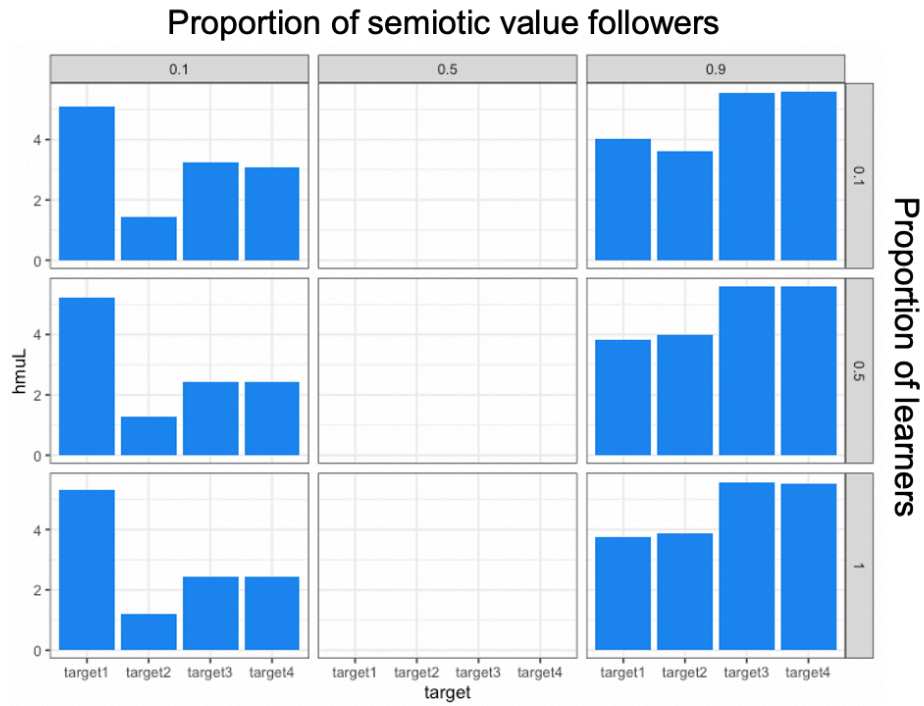
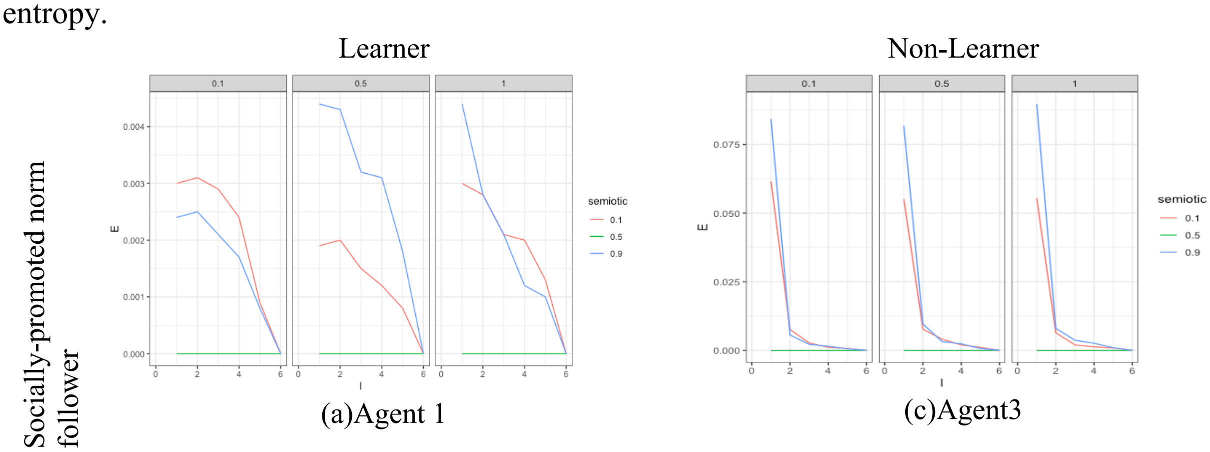


Figure 3 Internalizing agents have a higher entropy rate when the socially promoted norm is dominant *Each panel in this figure presents the excess entropy of one simulated condition. Each panel presents the excess entropy of the 4 agents: Target 1(socially-promoted-norm follower & learner), Target 2(non-socially-promoted-norm follower & Learner); Target 3(socially-promoted-norm follower & non-learner), and Target4 (non-socially-promoted-norm follower & non-learner). We found that non-learners only have higher entropy rate than non-learners in conditions where the socially promoted norm is dominant. The 3 empty panels in the middle column are the equilibrium condition, that's why the agents in those conditions all have an entropy rate of 0.*

I used the excess entropy E to measure the "internalization" or "learning"(See *Figure 4*). Non-learners have a sharp drop of excess entropy at block length 2, suggesting that the pattern of the sequence is mostly "learned" at step 2. This makes sense in my system, because for non-learners, only the opponent's last move influences their decisions. For Learners, there is more nuances in the relationship between excess entropy and the parameter values. Comparing *Figure* 4 (a) and (b), I found that the proportion of learners in the system (the panels) has a smaller effects than the proportion of socially-promoted-norm followers on the learning agent's excess entropy.



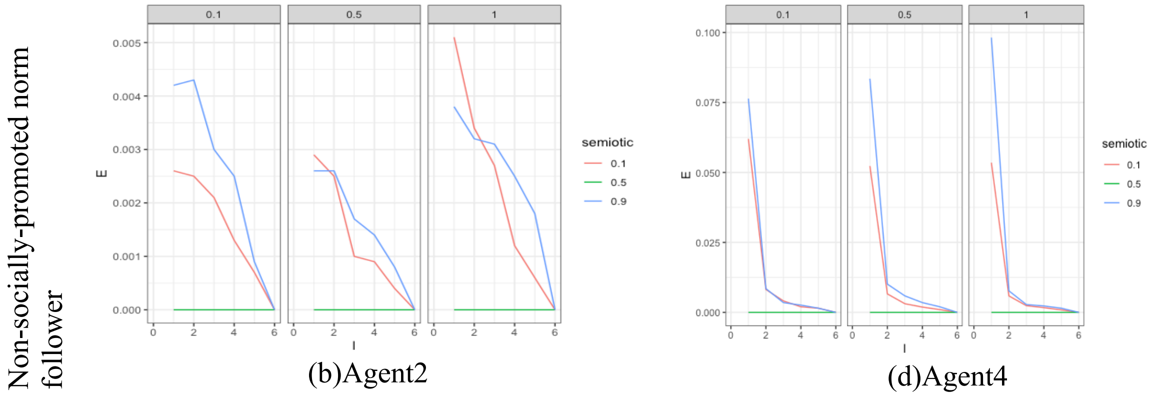


__Figure 4 Non-leaners have a faster drop in excess entropy than learners__ The four figures plot the excess entropy of the four agents I followed in the system. The three panels in each figure are the three conditions of different proportion of learners in the system. The colors of the line plots represent the proportion for socially-promoted-norm followers. For non-learner (c) and (d), we observe an immediate drop in E, because they don't store any information after 1 step and the only historical information that influences their decision making is the opponent's last move.

b_μ measures the stored information in the process. As expected, non-learners only store the most information at L=2, because their memory is only related to the history of length 1. Thus their b_μ will drop after L=2. For learners, there is a general increasing trend of binding information in regards to the block length.

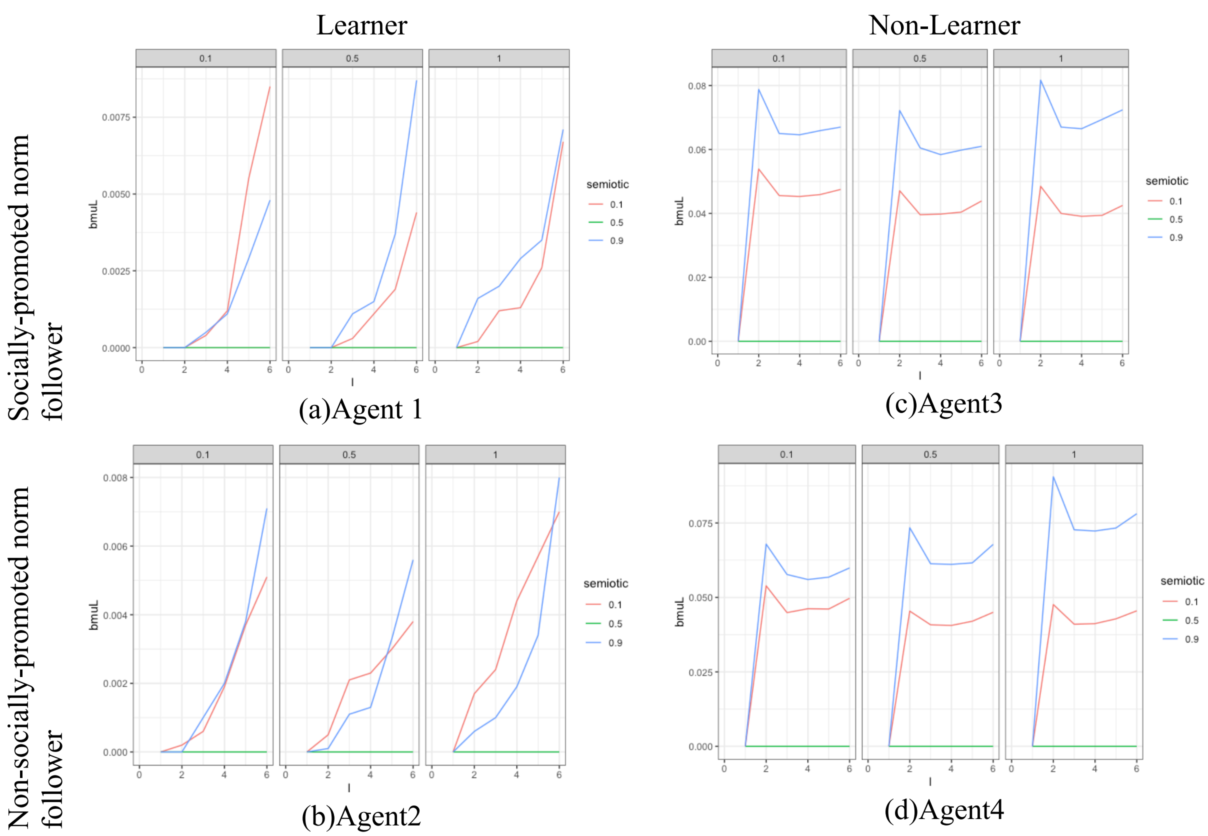


__Figure 5 b_μ for non-learners shows a clear drop after step 2 whereas it shows different increasing patterns for learners__ The layout of this figure is the same as figure 4. (c) and (d) shows that the binding information are mostly stored at L=2 and has a drop after L=2. Similar to the analysis of excess entropy, the pattern at L=2 reveals the non-learners' memory that they only *incorporate historical information one timestep back. For learners, there is a general increasing trend in regards to block length in all 9 conditions. For a condition with more learners, more information is stored in the process with the increase in block length comparing to the condition with fewer learners.*

Lastly, I calculated the statistical complexity of the decision sequence but the results show that all 4 agents have a C_μ of 0(see *Figure 6*). Two explanations can justify the 0 statistical complexity. First, the agents are programed with only one state (see *Figure 7*), which naturally result in $C_\mu = 0$. Second, single agents' movement and the opponents they encounter in each timestep is random, making the decision sequence close to a biased coin random process. For future analysis, the decision dynamics of the whole system (see *Figure 2*) might be more appropriate for causal state analysis.

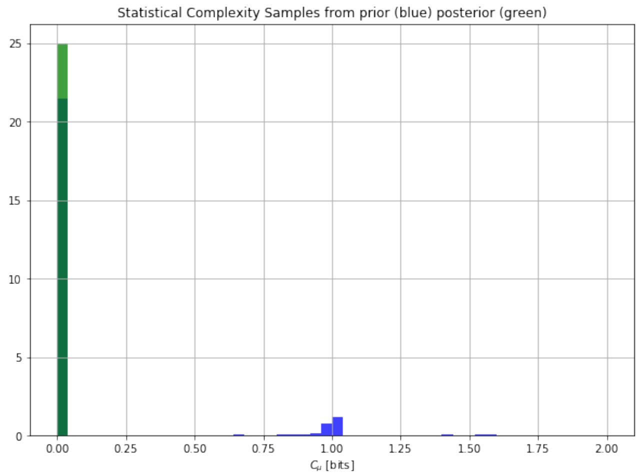


Figure 6 Statistical Complexity is 0 for all 4 agents' decision sequence

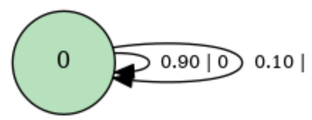


Figure 7 The epsillon machine of Agent 1's decision dynamics at a majority condition is similar to the biased coin process

Conclusion

To capture the inconsistency created by individual's belief and strategic action in following norms, I built a game theory multi-agent system to simulate agents' behavior under the influence of norms. I first used information theory and computational properties to analyze agents' decision dynamics. The results show that the agents that cannot internalize norms have a higher intrinsic randomness than those who internalize norms, supporting the hypothesis that strategically following the norm will lead to a higher inconsistency in people's behavior. Excess entropy and binding information were also used to assess the learning and internalization in the process. As designed in the multi-agent system, non-learning agents show a 2-step memory in the system, while the process of learning agents are more complicated. Both the proportion of socially-promoted-norm followers and the proportion of learning agents have an influence on the information stored in the learning agents' decision dynamic processes.

This report only presented a first attempt to explore this multi-agent model. For future work, I will complicate the model by programing the agents with multiple states and expanding the strategy pool. I will also conduct analysis on the aggregated agent behavior as system dynamics. Eventually, I will also explore the state changes of the system when the socially promoted norm switches from one strategy to another.

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