SISTER: A SYMBOLIC INTERACTIONIST SIMULATION OF TRADE AND EMERGENT ROLES

by

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DEDICATION

This is dedicated to my three lovely children, Sonny, Lana, and Anna, to my mother, Jean Christenson, and to the memory of my father, James Vakas.
I would like to thank the many friends and supporters who have helped me obtain this degree. I’d like to thank Glenn Tarbox, Steven Luce, and Summer Allen of Object Sciences Corporation for granting me the flexibility I needed to complete this dissertation. I’d like to thank my director, John Grefenstette, who spent a lot of time on my behalf and contributed many of the best ideas herein. I could not have done this without you. I’d like to thank my committee members, Kenneth DeJong, Harold Morowitz, Claudio Cioffi-Revilla and my former advisor, Larry Hunter, for their support and many good suggestions. Finally, I thank my personal mentors, both past and present: the late Jim Hoffman, Kevin Lacobie and Ben Goertzel. Thank you for imaginative conversations, for your encouragement and appreciation, and most of all, for being inspirations, teaching me to aspire to truth.
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SISTER: A SYMBOLIC INTERACTIONIST SIMULATION OF TRADE AND EMERGENT ROLES

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SISTER, a Symbolic Interactionist Simulation of Trade and Emergent Roles, captures the fundamental social process by which macro level roles emerge from micro level symbolic interaction. SISTER may be used for the computational social science objective of modeling social coordination in human societies, or for the artificial intelligence objective of coordinating coevolving agents in artificial societies. The knowledge in a SISTER society is held culturally, suspended in the mutual expectations agents have of each other based on signs (tags) that they read and display. In this study, this knowledge includes how to create complex goods. The knowledge of coordinating their creation arises endogenously. A symbol system emerges to denote these tasks. In terms of information theory, the degree of mutual information between the agent’s signs (tags) and their behavior increases over time. In SISTER societies, mutual information
can grow endogenously and be maintained robustly, even when agents die and are replaced, or are spread out over space.

The SISTER society of this study is an economic simulation, in which agents have the choice of growing all the goods they need by themselves, or concentrating their efforts in making more of fewer goods and trading them for other goods. They induce the sign of an agent to trade with, while at the same time, they induce a sign to display. The signs come to mean sets of behaviors, or roles, through this double induction. A system of roles emerges, holding the knowledge of social coordination needed to distribute tasks amongst the agents. This knowledge is maintained despite the stresses of the death and dislocation of individual agents.

This dissertation contributes to artificial intelligence by demonstrating how agents may divide their labor in a task endogenously. It shows how a complex endogenous communication system can develop to coordinate a complex division of tasking. It also shows that with a SISTER algorithm in which agents die, coevolving systems can avoid convergence and continue to grow in knowledge. With the SISTER algorithm, robot societies can robustly continue to maintain their symbols and roles despite death and distance.
1. Introduction

Artificial Intelligence has much to offer the social sciences and the social sciences have much to offer artificial intelligence. The new interdisciplinary field of computational social science bridges the gap between artificial intelligence and the social sciences. An important goal of computational social science is to distill the fundamental social processes which bring order to society. Such a distillation can be used to support theories in the social sciences by computer simulation, or be used to coordinate intelligent agents for distributed AI (Epstein and Axtell, 1996). The motivation of this study is to use social theory to distill the fundamental social processes of society computationally, so that they may be used in artificial intelligence and in social science.

The specific process that this study seeks to distill computationally is the formation of roles. According to computational social scientist Kluver, role formation is a fundamental process: “the motor of socio-cultural evolution is this: creative individuals generate new knowledge that becomes institutionalized in certain roles” (Kluver et al, 2003). The computer simulation of this study will use principles of social science to distill this process, and then demonstrate that these roles serve to create, coordinate, and preserve knowledge in society, whether the society be a human society or a society of intelligent agents. The principles of society are mainly drawn from the field of interpretive social science, particularly from the field of symbolic interactionism in
microsociology. Thus the title of this computer simulation is SISTER, a Symbolic Interactionist Simulation of Trade and Emergent Roles.

1.1. Problem Statement

The primary goal of this study is to demonstrate that the emergence of a system of roles is a sufficient condition for the creation, coordination, and preservation of knowledge in an artificial society.

In particular, this study demonstrates the emergence of a system of the roles reflecting a division of labor in a bartering society. Each agent in this multi agent simulation comes to have a set of tasks that other agents expect it to perform based on an endogenously developed role. Each role is part of a system of roles that agents perform for the good of the whole. A system of roles is to be differentiated from a system of tasks allocated on an individual level. Roles are sets of tasks that are independent of the particular individuals performing them. Agents can recognize other agents on the basis of their role, or on an individual basis. The hypothesis of this study is that agent societies in which agents recognize each other based on roles have more capacity to create, coordinate, and preserve knowledge than agent societies in which agents recognize each other as individuals. The particular type of knowledge that they create, coordinate and preserve is the knowledge of how to make composite goods, or goods that are composed of other goods. The amount of knowledge that a society is holding is measured in amount of mutual information, a concept from information theory. It is shown that
societies with role based recognition have greater utilities from trade than societies based on roles, and that this is correlated with the amount of knowledge in society. This result is shown to be robust under the stresses of the death of agents and agent separation in space.

1.2. Literature Review

In this review, the literature of the social sciences that is relevant to the fundamental processes of society will be presented first. Then the recent literature of computational social science will be reviewed in light of its degree of adherence to the principles discussed in the social science literature review.

1.2.1. Social Sciences Literature Review

Parsons, a major classical sociologist, theorizes that the source of order in society is the “double contingency” (Parsons, 1951). That is, each agent in society is simultaneously a subject of interpretation and an interpreter. It is both an interpreter of symbols, and a symbol at the same time. Luhmann also explains social order with Parsons’ double contingency (Luhmann 1984). He theorizes that social structures are structures of mutual expectations, or what he called “expectation expectation” (Luhmann, 1984). “Expectation expectation” is the concept of agents taking into account what other agents expect of them in their behaviors. Luhmann theorizes that all macro level social order ultimately comes from the expectation expectations of individuals (Luhmann
1984). Parsons believes that social order emerges from this double contingency by means of a shared symbol system (Parsons, 1951).

When Parsons and Luhmann theorize that social order ultimately comes from individual interactions, they infer a micro-macro link, with expectation expectations on the micro level, and social structure on the macro level. Micro-macro integration is the subfield of sociology which examines how phenomena on the micro level, such as expectation expectations, can emerge into macro level social structures. Our explorations of the process of social emergence are well informed by the theorists of micro-macro integration.

James Coleman, a major sociologist, theorizes on the micro-macro link. He notes that it is a common mistake to explain macro level phenomena with simple aggregation on the micro level. According to Coleman, simple aggregation is not an adequate micro-macro link (Coleman, 1994). For example, Coleman believes that Max Weber’s *The Protestant Ethic and the Spirit of Capitalism* (Weber, 2001) is a poor micro-macro theory because it tries to explain a social system, capitalism, with an aggregation of propensities to conduct derived from religious beliefs, such as thrift (Coleman, 1994). Capitalism is not a property of a homogeneous group of people; rather it is a system of interdependencies between heterogeneous groups. Coleman believes that an adequate micro-macro theory must address the process by which a homogeneous group of people differentiates into a system of relations between heterogeneous groups (Coleman, 1994). It is an interesting mental exercise to figure out a process by which Parsons’ ideas about social order can be made to fit Coleman’s ideas about the micro-macro link. Parsons
believes that double contingency on the micro level results in social structures on the macro level by means of a shared symbol system. To combine this process with Coleman’s micro macro theory, a system of relations between classes of persons has to be included. These ideas may be combined if a symbol system that denotes relations between roles emerges from micro level double contingency. This makes sense from the standpoint of other theorists as well. Symbolic Interactionist Peter Berger believes that roles and symbols of roles are important to the creation of social order (Berger and Luckman, 1966).

George Ritzer is one of the major micro-macro integration theorists in sociology. He believes that micro-macro integration can not be dealt with apart from the subjective-objective continuum. (Ritzer, 1999). That is, any theory of micro-macro integration in sociology must include both subjective and objective components. In the social sciences, theories of the subjective component of interaction are found in interpretive social science, or the subfield of symbolic interactionism in sociology (Ritzer, 1999). Theories of the objective component of interaction are found in microeconomics. It makes sense to include both as a way of grounding interactions based on symbols in the practicality of life, motivating their existence and giving them meaning. SISTER includes ideas from microeconomics and microsociology in its model of the fundamental social process. In computational social science, it is more common to find the use of microeconomic interactions, so this literature review will concentrate on the unique thing that SISTER has to offer, which is the modeling of interactions from microsociology.
Microsociology and interpretive social science in general have much to say about Parsons’ double contingency and shared symbol systems. They describe processes of symbolic interaction and interpretation of symbols. Interpretive social science comes from the school of philosophy called Hermeneutics (Winograd, 1997). It influences sociology in the symbolic interactionist and phenomenological schools, and economics in the Austrian school. Hermeneutics is a school of philosophy arising out of questions translators of the Bible have about preserving the meaning of texts across different circumstances of life (Winograd, 1997). They see a paradox about people. People can only understand the world through their own context: information can not be directly copied from one person to another, but is understood differently by those in different contexts. Yet they still come to understand each other through institutions and language. People invent their own meanings, yet they share meaning (Winograd, 1997). This hermeneutic paradox is essentially a restatement of Parsonian double contingency, or “expectation expectations” as Luhmann calls it. As the expectation expectations that people have of their symbol system turn into a consensus, then the subjective interpretations of individuals become objective.

In sociology, the symbolic interactionists look deeply into the process by which expectation expectations emerge a solution to the hermeneutic paradox by means of a consensus on a shared symbol system. Symbolic interactionists claim that institutions and language are generated from the interplay of subjective perspectives on the individual level (Berger and Luckman, 1966). In other words, shared meaning is an emergent property. The lower order process from which meanings emerge is the display and
reading of signs. According to phenomenologist Peter Berger, this occurs in a three phase dialectic of externalization, objectivation and internalization (Berger and Luckman, 1966). When we act upon our ideas, we externalize. Once we have done something in the public realm, it becomes separate from ourselves: this is the process of objectivation. Once it is separate from ourselves, it can come back and change ourselves and others: that is internalization (Berger and Luckman, 1966). These objectivations are signs that tell us what to expect from each other. They become habitualized and interlocked into a web of meanings that make sense together. This is how we create our ideas. In the process, we create ourselves.

An important special case of this is our categorizations of people, called roles. When our ideas about people are objectified, and these objectivations change others, this is the process of self fulfilling prophecy. The lower level process is that we change ourselves to meet others expectations of us. From this emerges different types of people, or different roles. Roles are essential to establishing social order (Berger and Luckman, 1966). SISTER models this process by which roles are formed and the hermeneutic paradox is resolved.

The Austrian school of economics uses the ideas of interpretive social science to explain economic behavior (Prychitko, 1995). Austrian economists believe that the best orderings of society are not imposed from the government but arise spontaneously and unintentionally from the acts of people looking out for themselves. Austrian economist Frederick Hayek coined the phrase “spontaneous order” (Hayek 1952) to mean that an
economy self organizes into institutions. One example of these is the institution of money, which Austrian economist Carl Menger called a "miracle." Money is considered a prime example of an organic institution: unintentionally, through the barter of goods, arises a standard of trade to help everyone trade better (Menger 1981). Adam Smith speaks of such institutions in terms of an "Invisible Hand" in appreciation of their complexity (Smith, 1994). Some examples of economic institutions are the division of labor, price and money. These institutions come to exist through interpretation on the individual interaction level. SISTER models the emergence of the institutions of the division of labor, price, and money, from the interpretation of signs on the individual level. This study focuses on the emergence of roles reflecting a division of labor.

1.2.2. Computational Social Sciences Literature Review

This overview of the recent computational social science literature will classify computational social science models according to how much they include of the basic principles of society overviewed in the previous section. All agent based models of computational social science have some kind of emergence, and may be categorized according to how close that emergence is to the emergence of sociological theory. The type of emergence in the model will be compared to the criteria that micro macro sociologists give. Models of emergence will be examined for whether they meet Coleman’s criteria of forming a heterogeneous system. Then, subjective components will be looked at more specifically, on the basis of how close a model of emergence is to encoding a solution to the hermeneutic paradox through the reading and display of signs,
double contingency, or expectation expectations. Figure 1 illustrates the classes of computational social science models.

Figure 1. An organization of models according to their fidelity with micro macro sociology theory. Heterogeneous agents with adaptive roles fit Berger’s and Coleman’s theories of social emergence (Berger and Luchman, 1966; Coleman, 1994)

In order for a model to meet Coleman’s criteria of the differentiation into a system, agents must change from homogeneous to heterogeneous over time. Agent based models of computational social science can be divided into homogeneous and heterogeneous. Homogeneous agents can either have fixed or adaptive behaviors. In models of heterogeneous agents, agent roles in relation to each other can be either fixed or adaptive, that is, they have preprogrammed heterogeneity, or their heterogeneity emerges endogenously. The type in which roles emerge endogenously is closer to a differentiating system than those that are fixed.
Models of emergence in homogeneous agents with fixed behaviors demonstrate what macro-level patterns that emerge when micro-level interactions are all of the same type. One of the earliest, most important models of homogeneous agents with fixed behavior is Shelling’s model of residential segregation (Shelling, 1978). In this model, Shelling shows that even racially tolerant individuals form segregated communities. He puts agents on a 2-D lattice representing housing locations, and lets them settle where they prefer. If the agents want to stay in neighborhoods where a majority of the neighbors are of their own race, and tolerate a minority of neighbors being another race, they still form communities consisting solely of one race or the other. Some more recent works with homogeneous agents and fixed behavior include Pahl-Wostl and Ebenhoh’s work on adaptive tool boxes (Pahl-Wostl and Ebenhoh, 2004). They came up with a method to extract regularities from experimental data on altruism, and to show that, when computational agents act according to these regularities, they display the same patterns as in the experimental data. In another model of homogeneous fixed agents, Wang and Thorngate explored the implications of a social theory, Heider’s balance theory, for groups larger than three (Wang and Thorngate, 2003). Groups under size three can be solved with mathematical analysis. In this model, agents try to locate themselves next to other agents that they like, and avoid agents that they dislike on an individual basis. Upper level patterns of separation into groups were explored as in Shelling’s model. Susaki and Box explored another social theory, von Thunen’s location theory, by giving agents the same rules, and seeing where they locate themselves around a “city” (Susaki and Box, 2003). The price of the land is calculated globally, and agents find the optimal
space for themselves and occupation given this calculation. They start out in the city, but
then form concentric circles of land use around it as in Thunen’s location theory. The
agents become different in the sense that they exist in different parts of an upper level
pattern, but they each follow the same fixed rules in the formation of that pattern.

Agents can come to differ in their behaviors by adapting to their environment. However, if the agents are all adapting together toward the same optimal behaviors, then they are still homogeneous, with adaptive behaviors. For example, agents which are part of the same genetic algorithm population are not usually forming a system of different behaviors for themselves, but converging towards the same optimal behaviors. This is because convergence is an intrinsic property of genetic algorithms.

Work that involves simple optimization, and most of the work to date on emergent language and tags falls under the category of homogeneous and adaptive. Axelrod’s work on the iterated prisoner’s dilemma is homogeneous and adaptive. Agent strategies for playing the prisoner’s dilemma game on an iterated basis are encoded in a single GA. The best strategy is found to be a Tit-for-tat strategy. It is the single strategy best for all homogeneous agents (Axelrod, 1997). Kluver and Stoica have a model of the social network problem similar to the models of Shelling and of Wang and Thorngate (Shelling, 1978, Wang and Thorngate, 2003, Kluver and Stoica 2003). They let the agents decide how to optimize their position amongst agents that they like and don’t like with adaptive methods instead of simple rules, making them homogeneous and adaptive. Their methods included both genetic algorithms and neural networks.
The work on emergent communication is relevant to symbolic interactionist ideas about the emergence of social order from the reading and display of signs. However, most work in lexicon development assumes that an ontology already exists, and agents try to map random signs into this ontology (Perfors 2002). Oliphant and Batali have a model in which agents try to send signals they hear most often sent or most often interpreted for a meaning (Oliphant and Batali, 1997). However, since the ontology already exists, a meaningful symbol system itself does not emerge, only a mapping. Other work is more grounded in meaningful activities. For example, Werner and Dyer have a model of blind males who move towards female stationary female listeners by interpreting the meaning of the sounds they emit (Werner and Dyer, 1992). The ones that reproduce are the ones that develop a shared lexicon. In the end, the entire population comes to share a lexicon. However, these agents reproduce in the same genetic algorithm population. Since convergence is a property of genetic algorithms, the method used ensures that they must eventually have the same lexicon. Steels has a model of Robot communication in which robots develop shared lexicons by indicating to each other objects on a table and grunting (Steels 1999). They demonstrate a solution to the hermeneutic paradox in that they come to share meaning despite their differing perspectives, in this case, different views of objects on a table.

There is a body of work in which agents identify each other by means of tags. Hales used tags for grouping in an iterated prisoner’s dilemma problem, showing that agents that would interact with each other because they are part of the same group will cooperate (Hales 2002). Riolo, Cohen, and Axelrod extended this model to show that
agents will donate to another agents that wear a sign that is similar to its own sign (Riolo, Cohen, and Axelrod, 2001). This shows that signs come to indicate group identifications. However the agents were still homogeneous in that they all behaved in the same way, with loyalty towards ones own group.

Computational Social Science models are more complex when their agents are heterogeneous, that is, they have differing behaviors. There are many models where a variety of agents are put together to explore what patterns emerge. These are the models of heterogeneous agents with fixed roles.

Many of these models are less based in social science and more based in game theory. Such models seek to explore different what happens when different action strategies are put together. These include Scheutz and Schermerhorn’s model of evolutionary stable strategies in stopping games (Scheutz and Schermerhorn, 2004). They apply the concept of an evolutionary stable strategy (Maynard-Smith 1982) to games in which opponents signal to each other about whether they will leave food or fight with each other for it. This paper examines how different combinations of strategies pay off. Bhavnani has a model of agents based on Axelrod’s model of cultural influence (Axelrod, 1997; Bhavnani, 2003). In Axelrod’s model, agents decide to act with other agents based on differences of cultural tags. If they act with each other, they become more alike. Bhavnani used Axelrod’s cultural tags to model differences between civicness in modern Italy. Agents are given traits similar to those in cultural regions in Italy, and degree of civicness is measured as agents interact with each other over time.
There are several models that look at the best strategies for playing the stock market, including a couple that model fundamentalist market strategies vs. chartist strategies (Takahashi and Terano, 2003; Sallans et al 2003), and one that sees how agents who incorporate option value when forming their trading prices fare (Sapeinza, 2003).

There are many other recent models that look at combinations of different strategies in fixed heterogeneous agents. Albino Carbonara and Giannoccaro have a model of industrial districts, with both cooperation and competition in it. It explores vertical cooperation between buyers and suppliers, and horizontal cooperation between competitors, who learn to interact with each other (Albino, Carbonara, and Giannoccaro, 2003). Etienne, LePage, and Cohen have a model of the strategies of stakeholders in an ecological scenario of a pine invasion. They model strategies based on interviews of stakeholders such as sheep farmers and foresters (Etienne, LePage, and Cohen, 2003). Srbljinovic et al have a model of ethnic mobilization in Yugoslavia, where each agent has its own ethnicity, its own grievances, an ability to hear the grievances of others and its own loyalty to its ethnic group. It also can hear calls for mobilization over the radio. It shows that mobilization happens quicker amongst agents with greater social networks.

Other heterogeneous fixed models have less to do with game theory and more to do with the social sciences. They include Hales and Edmond’s model that extends the Riolo, Cohen, and Axelrod’s model of indirect reciprocity. Hales and Edmonds give agents different skills, and show that agents donate resources that they don’t have the skill to use to agents with a similar tag (Hales and Edmonds, 2003). Epstein and Axtell
have a model of the transmission of culture through tags, which basically involves the spreading of culture and behavior through the copying of tags of neighboring agents (Epstein and Axtell, 1996).

Several of the models of heterogeneous fixed agents stem from the work of Conte and Castelfrachi. Conte and Castelfranchi have done extensive work in the area of normative reputation and its effects on aggression (Conte and Castelfrachi, 1995). In Conte and Castelfarchi’s model, agents interact with each other, and keep track of the behavior of other agents. If they have communication skills, and tell agents about aggressors, then the amount of aggressive interactions decreases as agents refuse to interact with aggressors (Castelfranchi, Conte and Paolucci, 1998). Younger explores the implications of this model for clusters of agents representing families with sharers (Younger 2003) and with stealers (Younger 2004). Caldas and Coelho apply the idea of sanctions to a game in which agents can contribute to a pot, announce their contribution, and are paid in proportion to their announced contribution (Caldas and Coelho, 1999). However, the announcement can be false. In this set up, agents learn to lie. However, if they are sanctioned for lying with a penalty, they learn to tell the truth. The model is extended to a scenario of agents with varying amounts of power who can vote for rules. Agents with power end up voting for their own benefit, and not according to the group. Both this and the normative reputation models are contrary to Hayekian spontaneous order models in which social order arises naturally (Hayek, 1952).
These more “social” models use coercion to cause social order, whether that coercion be through individual enforcement of order or through law enforcement of order. They are not as purely organic as order arising from Luhmann’s “expectation expectations,” in the natural symbolic interaction of everyday life (Luhmann, 1984). These models do not emulate the interpretive paradigm, because they are based on imitation. According to Conte and Dignum, in these models, “conventions, norms regularities, social structures and patterns of any sort (segregation, discrimination, opinion formation) are said to emerge from agent’s imitation of either the most successful, the most frequent, or simply the closest behaviors” (Conte and Dignum, 2003). This imitation is contrary to the interpretive paradigm, where agent’s interpretation of signs are done solely from their individual experiences. If every agent interprets signs from its own experiences, then the signs have every agent’s contribution when they come to have shared meaning. In contrast, if only one agent has a behavior which is imitated, and then enforced, the chances for that behavior to be modified by each individual that use it are fewer. To have every agent affect each other, a more coevolutionary model is needed. Coevolution of agent expectations upon agent expectations leads to an organic emergence of both convention and of heterogeneous agents.

Models with heterogeneous agents that have agents with emergent roles include both standard computational social science models and models of basic social processes. Klugl and Bazzan have a model in which has agents coevolve heuristics to react to traffic forecasts and come to adjust to each other (Klugl and Bazzan, 2004). Pajares, Lopez and
Hernandez have a model in which firms coevolve production rules of product strategies, that reproduces general economic patterns (Pajares, Lopez and Henandez, 2003).

Some more ambitious models of basic social processes include Kluver’s model of socio-cultural evolution through roles (Kluver, 2002). This is not an implemented model as much as a theory on how to design a computational model. In this theory, agents have a knowledge base and a position in society that represent their role in society. Agents coevolve their roles from interactions with each other, and through this process institutionalize their behaviors. Dittrich Kron, and Banzhaf also have a model of the basic social processes of Parsons’ double contingency and Luhman’s expectation expectations (Parsons, 1951; Luhmann, 1984; Dittrich, Kron and Banzhaf, 2003). Dittrich et al however abandons Parsons’ theory that a shared symbol system is responsible for the emergence of social order (Parsons, 1951). Dittrich calls this “impossible” and asks “how can a a dyad presuppose and develop a shared symbol system at the same time?” (Dittrich, Kron and Banzhaf, 2003). In Dittrich’s model, agents are hard coded to take into account what they perceive as other agents expectations of them in their decisions, and this, they say, predictably leads to social order. The agents read and display signs, each looking at what happened in the past and the predictability of one sign following another. The predictability is measured in entropy. They were able to obtain social order for didactic situations, but the meaning of signs rapidly decreases for numbers of agents above two. If agents are allowed to put themselves in each other’s shoes in their predictions, order is improved, but only slightly (Dittrich, Kron and Banzhaf, 2003).
Dittrich et al leaves the modeling of the basic social process as an open question. Dittrech et al’s abandonment of the shared symbol system as the solution to social order is premature. Coevolution may be used to solve this type of “chicken and egg” problem. SISTER uses coevolution to bring about a consensus on the symbol system. The symbol systems in Dittrich’s model did not become wide spread because they based agent’s expectations of each other on individual recognition. SISTER proves that role recognition has a significantly higher mutual information level (less entropy) and thus the signs have significantly more meaning in larger groups. SISTER solves both Dittrich’s and Kluver’s open questions by combining their models, basing the double contingency on roles (Duong 1996).

SISTER, the program of this thesis, is related to another adaptive heterogeneous model of symbolic interaction: the authors model of status symbols, racial prejudice and social class (Duong, 1991; Duong and Reilly, 1995). In this model, a symbol system emerges as employee agents induce the meaning of the signs they display at the same time that employer agents induce the meanings of the signs they read. Some of these signs can not be changed: they are the racial characteristics. Some must be bought with money from past employment, like a suit, and some signs can change freely, like a fad. Employees induce what sign they display on the basis of what gets them employed while employers induce what signs they should hire on the basis of the degree of talent that employees with those signs had in the past. This amount of talent is hidden during the employment interview. Employees with less talent are layed off and put back in the population of the unemployed in greater numbers than the talented. Agents of this
simulation each have a Hebbian neural network to interpret signs with. An interesting result is that signs come to have the same meaning to all of the employers even if they are incorrect. Talent distributions are the same according to race, but race comes to mean a lack of talent in an employer’s mind, if it becomes associated with a cheap suit. If one race gets caught in such a vicious circle of not being able to get hired because they as a group have cheap suits, then that race is a social class. If talented employees learn to buy expensive suits to differentiate themselves from those that lack talent, and employers also learn to hire those with more expensive suits, then those suits became status symbols (Duong, 1991; Duong and Reilly, 1995).

In a later simulation, Axtell, Epstein and Young show emergent classes of agents based on race by having agents bargain based on what they expect other agents to bid. This model uses an induction based on fixed signs similar to the one in the author’s model of racial prejudice: signs are induced by the reader only, and come to have meaning through coevolution of expectations (Duong 1991; Duong and Reilly, 1995; Duong, 1996; Axtell, Epstein, and Young 2001). The individual recognition runs of SISTER use signs induced by the reader only, but the role recognition runs use a double induction of signs (Duong 1996). This “double induction” of signs is the micro level of a Parsonian system and is the same thing as a double contingency. Coevolution facilitates the modeling of the double induction and the resultant emergent symbol system which Parson theorizes as the source of social order.
2. Specific Aims and Methods

2.1 Specific Aims

SISTER simulates the emergence of institutions, with the upper and lower levels of the simulation based on social theory. The basis of the lower level is microsociological and microeconomic rules. In accordance with interpretive social science, agents see signs through their senses and are closed with respect to meaning, and yet still share meaning. They do not copy other agent’s signs, but learn which signs to display through their own experiences. In accordance with micro-macro social theory, the upper level is a system of roles. These emergent roles are important to the continuity of a culture of agents. The emergence of a system of roles is shown to be one of a set of sufficient conditions for the creation, coordination, and preservation of knowledge in an agent society. This knowledge is held in the mutual expectations that agents have of each other based on their roles, in line with Parsons’ and Luhmann’s theory of social systems (Parsons, 1951; Luhmann, 1984).

Several questions are answered to demonstrate that an emergent system of roles facilitates the creation, coordination, and preservation of knowledge in society. First, it is determined whether agents can learn to trade based on role recognition alone, as opposed to individual recognition. That is, if agents are not recognized as individuals, but as a
member of a role by agents seeking other agents to trade with, can these agents still learn networks of trade? The difference between individual recognition and role recognition is the difference in going to “Joe” to trade some beans for oats opposed to going to “an oat farmer” to trade beans for oats. Once this question is answered, then it is asked whether role-based recognition is better than individual recognition in helping agents to learn complex cultural knowledge. In this case, the complex cultural knowledge is how to make a composite good. Once this baseline is established, it will be determined whether a system of roles helps agent cultural knowledge of assembling a composite good to be maintained over time under the stress of death and rebirth. Finally, it will be determined whether roles help maintain cultural knowledge over geographical distance.

2.2 Methods

SISTER is a simulation not of a modern economy, but of a simple barter economy, where no wealth may accumulate from day to day. Agents produce in the morning, trade in the afternoon, and consume at night, leaving nothing for the next day. It is assumed that agents seek to have eight goods in equal amounts, and as much as they can get of them. Agents can produce some or all of the goods as they please, but these activities cost effort. An agent has only limited efforts to spend, but if efforts are concentrated on making fewer of the goods, then more will be made. This simulates the benefits of specialization, also known as economies of scale. By this design the agents will be happier if they make lots of one good and trade it away for the others, however, it is up to the agents to learn how to trade. They develop institutions in the process of
learning how to trade, and their institutions are solutions to the problem of how to trade. They start out the simulation completely ignorant of what to produce, what to trade, how much to trade, and whom to trade it with, and what sign they should present to others to tell who they are. The knowledge they come to have to get to the answer, the development of interlocked behaviors and shared meanings prerequisite to that answer, are the emergent institutions. This study focuses on just one of these institutions: the emergence of a division of labor. Other institutions that the agents develop are price and money.

The subjective micro-level rules come from the principles of interpretive social science as found in phenomenological and symbolic interactionist sociology. The agents follow a basic principle of interpretive social science: they are closed with respect to meaning. They can not read the minds of other agents, but can only read signs through their senses. They each have their own private inductive mechanism with which they perform the symbolic interactionist task of inducing what signs they should display and the meaning of signs that they read. Their inductive mechanisms are autonomous in the sense that they are not seeded with information from other inductive mechanisms. With these inductive mechanisms, the agents interpret the signs they display solely from the context of their individual previous experiences, never copying another agent’s sign. Yet despite this autonomy, the signs emerge shared meaning. This is in accordance with the hermeneutic paradox of our inventing our own meaning and yet sharing meaning. As in the symbolic interactionist paradigm, the signs come to have meaning as is pragmatic for the agents in the function of their “everyday life”. The signs they learn to read and
display are signs of whom to approach to make a trade with and what to display to attract trade. The meanings that the signs come to have are roles in a division of labor. This is in accordance with phenomenological sociologist Peter Burger’s emphasis on the importance of roles and symbols of roles as a mechanism of organizing behavior. To learn how to trade, every agent must learn his role in terms of what goods to produce or assemble, and have general knowledge of the other roles in the society so that he may know who to trade with.

Tests of the importance of roles to the continuity of culture are performed. In the initial experiment, all goods are simple produce, harvested directly from the environment. In subsequent experiments, agents have the option of making composite goods, or goods that are made with more than one simple good. Agents learn to solve the more complex problem of which goods to put together to increase their utility. The ability of the agents to collectively learn how to make these composite goods is compared in agent societies where role symbols are used, and in societies where individual recognition is used. The ability of agent societies to carry this knowledge over time and over geographical distance is compared.

2.2.1. Design of SISTER

SISTER is a simulation of daily habits of trade in a bartering society. Every agent learns a plan of harvesting, cooking, trade, and a sign to display for a single day of the simulation. Each agent has a limited number of efforts that it learns to allocate between harvesting, cooking and trading of goods. It allocates these efforts to specific goods to
harvest or cook, and specific trade plans to perform. At the beginning of the day, agents harvest according to their production plans. They may harvest a few of each good, or more of some and less of others as their plans dictate.

Next, agents trade. All agents have both active and passive trade plans that are activated if agents devote the right amount of effort to them. Each trader follows its plans for active trading, by seeking out agents to trade with that display signs closest to the ones in their trade plans. If the passive trader has a corresponding trade plan and both the active and passive trader have the goods, then the trade takes place. See figure 2 for an illustration of corresponding trade plans. If the scenario simulates a spatial distribution of agents, then agents have to pay for active trades in proportion to another agent’s Manhattan distance on a grid. If the scenario simulates composite (cooked) goods, then an agent must have all the components of a good before it can trade that good (Lacobie, 1994). An agent may trade to get the ingredients of a recipe, cook it, and trade it away.
Figure 2. Corresponding Trade Plans. Agents trade with agents who have corresponding trade plans and are wearing the correct sign.

In the evening, the agents consume all of their goods, and judge their trade plans for the day solely on their satisfaction with what they consume that night. If the scenario simulates death and rebirth, then agents are periodically subjected to a small chance of losing all of the knowledge in their inductive mechanisms, and gaining a new id.

The agents motivation for trade lies in the encoded microeconomic rules. This simulation encodes two concepts from micro economics: the nature of the agent efforts and the nature of agent needs. The nature of agent efforts is that if agents concentrate
their efforts on fewer activities, they are able to be more productive than if they spread their efforts out over more activities. This simulates the benefits of specialization, or economies of scale. The nature of agent needs is that agents seek an even spread of several goods, and as much as they can get of them. It is as though each of the goods is one of the four essential food groups, and they seek a balanced diet of those goods.

Economies of scale are encoded by setting the efforts devoted to an activity to an exponent, whether that activity is a particular trade, the harvesting of a good, or the combining of goods (cooking):

\[ activity = Ke^c \]

The number of specific activities an agent may complete is equal to a constant for that type of activity, \( K \), times the efforts designated to that particular activity, \( e \), raised to an effort concentration factor for that type of activity, \( c \). For example, if the trade constant is 0.5 and the trade concentration factor is 3, and an agent devotes 2 efforts to trade 4 units of oats for 3 units of peas, then there are \( 0.5(2^3) = 4 \) such trades it can make. If the activity is a trade, the concentration of effort might mean that the agent has invested in a cart to make an active trade, or in storage to make a passive trade. If the effort is harvesting, it might mean that the agent has put in the investment to harvest a particular good well. If the effort is composing goods (cooking), the agent may have invested in training to learn how to cook a particular type of food. Whatever activity it is,
this equation means that putting a little more effort into the activity will make it much more productive.

The nature of an agents desires are encoded with the Cobb-Douglas utility function. At the end of the day, each agent consumes all of its goods. How happy an agent is with its trade plans is judged solely by the Cobb-Douglas utility function of the goods an agent consumes:

\[
\text{utility} = \prod_{i=0}^{n} \text{good}_i^{\text{weight}_i}, \text{where} \sum_{i=0}^{n} \text{weight}_i = 1.0
\]

“Good” is the amount of a good that an agent consumes, n represents the number of different goods, and weight is a measure of how much each individual good is desired. All of the weights add up to one. Each agent has a minimum of one of each good given to it. This is a standard utility function in economics. If all of the weights are the same, it makes it so that agents want a spread of all different types of goods, and as much as they can get of them. The agents want a spread of goods in the same sense that people need some of each of the four food groups. For example, if an agent has eight units each of two of the four food groups, his happiness is $8^{0.25} \times 8^{0.25} \times 1^{0.25} \times 1^{0.25} = 2.82$. If the goods are more spread amongst the food groups, and the agent has four units of each of the four food groups, then its happiness is $4^{0.25} \times 4^{0.25} \times 4^{0.25} \times 4^{0.25} = 3.48$. The agent would rather have four of four goods than eight of two goods. With this equation both the spread of goods and the amount goods are important. In this study, the weight for
each good is equal, so that differences in outcome can not be attributed to uneven utility values for individual goods.

The equations for effort and utility make it to the agents advantage to concentrate their efforts on making fewer goods so that they can make more of them, and then trading them for the rest of the goods, so that they can have an even amount of many goods. Agents may choose to make all of the goods for themselves until they learn how to trade them. In order to learn to trade the goods, the agents must learn to read each others signs and to display the correct sign. This is done according to the rules of interpretive social science. Agents never copy another agent’s interpretation of a sign, but rather interpret and display signs solely according to its own utility. To simulate Parsons’ double contingency, the sign is double induced: both the sign to seek for a trade and the sign to display on ones self are learned (Parsons, 1951). These signs come to have common meaning as the agents differentiate themselves. As in Parsons’ theory, the ordering of society comes through a shared symbol system, and as in Berger’s and Coleman’s theory, that ordering is a system of roles (Parsons, 1951; Berger and Luckman 1966; Coleman, 1994).

In the role recognition treatment, the passive trader displays a sign that its genetic algorithm has learned, but in the individual recognition treatment, the passive trader displays a unique identification tag. The ability to change the sign is the only difference between the two treatments. In the role recognition treatment, the sign that an agent displays for its passive trades comes to represent that agent’s role. That sign starts out
random, but comes to signify a role when all the agents that have learned to display the same sign have similar behaviors. Figure 3 illustrates agents that have differentiated into roles denoted by a learned tag that they display in common. In both the individual recognition treatments and the role recognition treatments, an endogenous differentiation of the agents occurs. However, when recognition is based on the role sign, several individuals become replacements for each other in their behavior, while if it is based on unique identification, agents learn to interact on an individual basis. In the role recognition scenario, an agent who wants to make an active trade can teach (that is, exert “selective pressure” on) many different agents who can replace each other to make a trade. In an individual recognition treatment, an individual can only teach one agent to make a trade.
Agents differentiate into roles. Roles are designated by tags, learned from an agent’s individual GA. Different agents which have the same tag are said to be members of the same role if the agents who display the same tag also have the same behaviors. These tags are individually learned by each GA, but come to mean the same set of behaviors.

For example, let’s call the goods of a role recognition scenario oats, peas, beans, and barley. Suppose an agent in the simulation has produced more oats and fewer beans. Suppose also that he displays a random sign to attract trade, and another agent with more beans and fewer oats guesses the meaning of that sign by coincidence while trying to trade his beans for oats. Both agents are satisfied with the trade and the sign; they
remember this, and repeat it. The more the trade is repeated, the more it becomes a stable thing in the environment for other agents to learn. Since an agent with an active trade plan is looking for any agent who displays a particular sign, then any agent can get in on the trade just by displaying the sign. The agents come to believe that the sign means “oats,” in the sense that if an agent displays the sign accidentally, the other agents will ask him to sell oats. This will put selective pressure on that agent to make and sell oats. At the same time, other agents who produce oats will benefit from learning the oat sign so as to attract trade. After a while, the society divides into roles, with groups of agents displaying the same sign and having the same behavior. If a new agent comes into the simulation, then to participate in trade he must learn the sign system already present. The signs are a guide to his behavior: when he displays a sign, the other agents pressure him to have the corresponding behavior. Thus a sign creates expectations of behavior, in accordance with Luhmann’s model of expectation expectations.

If composite goods or “cooking” is in the scenario, then agents must have all of the goods that a composite good is made of before it can trade that good. In a scenario with composite goods, agents have to know more to make trades in that good than they have to know in simple scenarios. They have to know to either harvest or purchase the goods that a composite good is made of, in addition to having to know who would buy the composite good. If a newly inserted agent displays the sign of one who sells a composite good, then it learns the component parts of the good when other agents come to it to sell those components. An agent is thus trained in how to perform his roles by the expectations of the agents in roles that interact with that role. For example, suppose
that in a SISTER society, the harvested goods were corn and lima beans, and the composite good was succotash, made from corn and lima beans. Suppose the agent who discovers succotash puts up a sign that she sells succotash. She buys lima beans and corn from lima bean and corn farmers, and finds that she has much business when she sells her succotash to the local diner, that uses her succotash to compose some of their dinner entrées. Through experience, our inventor of succotash has learned who sells the components of her good, lima beans and corn, as well as who buys the components of her goods, local diners. New agents who want to sell succotash now do not have to relearn all of that, because as soon as they put up a sign that says they sell succotash, lima bean and corn marketers start to call them. The new agent, because of the other agent’s expectations, figures out how to make succotash if he didn’t know before. If he only knows about the lima beans when he starts to display his sign, he will quickly learn about the corn. This is because he will feel selective pressure to buy corn. It will make the succotash better as far as the diners are concerned, and will give him more business. And it will be easy to buy because corn agents are constantly asking him to buy it. If it comes to be to his advantage, he will learn it. This is how the knowledge of how to make composite goods is held in the mutual expectations of agents. The mutual expectations that the agents have of the roles allows individuals to take advantage of what other individuals have learned in previous interactions. The knowledge of the society is held in the mutual expectations of the symbol system, as in Parsons’ an Luhmann’s theories (Parsons, 1951; Luhmann, 1984).
The reason that role systems can hold more information about how to make cultural products is that agents can replace one another and can learn from the expectations that other agents have of their replacement class. This is how they become trained to do their role. However, this training is not all encompassing: what they do is ultimately connected to their utility. They can reject trades if it is not to their advantage, for example, if they find that succotash tastes better with tomatoes than with lima beans.

2.2.2. The Implementation of SISTER

SISTER uses the methods of coevolution of genetic algorithms to implement the double induction of the signs. The use of genetic algorithms is not essential. The author implemented a symbolic interactionist simulation with neural networks previously (Duong, 1991; Duong and Reilly, 1995). In this simulation, employers induce the meaning of signs employees displayed in terms of their talent, while at the same time employees induced the meanings of the signs they displayed in terms of their income. However, these meanings were “coevolved” and held in the mutual expectations of Parsons’ and Luhmann’s theories, just as the signs in SISTER are (Parsons, 1951; Luhmann, 1984).

Genetic Algorithms are an inductive mechanism of artificial intelligence invented by John Holland (Holland, 1975). Genetic Algorithms mimic the induction that occurs naturally in Darwinian evolution. A genetic algorithm consists of a population of chromosomes, which are usually strings of ones and zeros. These ones and zeros are “genes” and represent possible solutions to a problem of optimization. Each
chromosome is judged with a fitness operator, that rates the solution it represents according to how well it solves the problem. Then, in accordance with Darwinian survival of the fittest, a reproduction operator is applied that lets the more fit contribute to the next generation in greater numbers than the less fit. One typical reproduction operator is the roulette wheel, where chromosomes contribute to the next generation in proportion to their fitness. This is the reproduction operator used for SISTER. These chromosome parents contribute to the next generation through a crossover operator, in which roughly half of each parent’s genes are contributed, the degree of mixture being determined by the number of “crossover points.” The number of crossover points in SISTER, along with other parameters of the genetic algorithm, is listed in figure 5. Finally, a mutation operator is applied, which randomly flips a small percentage of the genes, to introduce some diversity. The resultant offspring become the next generation, to be judged again by the fitness operator. As this cycle repeats the genes on the chromosomes converge towards a common solution, which is the solution to the optimization problem. Genetic Algorithms are a method of soft computing, along with neural networks and fuzzy logic, meaning that they are robust, that they can deal with uncertainty, and can give a pretty good or satisficing answer to problems too difficult to find an optimal answer to (Holland, 1975).

If the fitness of one genetic algorithm population depends on the behaviors encoded in at least one other genetic algorithm population, then the populations are coevolving (Potter and De Jong, 2000). SISTER is a program of coevolution, because the signs and behaviors of an agent are only good for it if the agents it interacts with have
corresponding expectations of signs and behaviors. In SISTER, each chromosome in an agent’s genetic algorithm population represents a plan of trade for a single day. It interacts with one other chromosome from each agent, for a single day of trading. All the first chromosomes of each agent’s genetic algorithm interact for the first day, then all the second chromosomes interact for the second day independently of the first, and so on. In the experiments of this thesis, each agent has 1000 chromosomes, so there are 1000 days in which each agent’s chromosomes interact with the other agent’s chromosomes, and 1000 days in which their fitness are judged, before the agents reproduce. The agents’ genetic algorithm populations reproduce separately and without seeding from each other. Then a new population of 1000 chromosomes is available for the next 1000 days of trade. The fitness function with which each chromosome is judged is the Cobb Douglass utility function of what goods that trade plan brought that agent after a day of trading. Figure 4 shows the activity cycle for these coevolving agents.
For 1 to i generations  //reproduction occurs every n days
{

For 1 to n chromosomes  //each chromosome represents a plan for one day
{

- Harvest goods in amounts according to plan.
- Trade goods with traders displaying signs closest to those in the plan.
- Consume goods and rate plan.
}

- Genetically recombine plans in private GA.
- If birth and death of agents is simulated, randomize the genomes of m agents.

Figure 4. SISTER simulation loop for individual agents. Every day, an agent implements a plan of harvesting and trading on a single chromosome. After it has used all of its chromosomes, its genetic algorithm reproduces, and it has a new set of plans. If death is implemented, some small percentage of agents have the genes of their genetic algorithms randomized, and they are given a new identification tag.

The number of bits in a single chromosome depends on the parameter values for the number of efforts and trade plans. See figure 5 for the parameters of the runs of SISTER in this study.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Agents</td>
<td>16</td>
</tr>
<tr>
<td>Population Size of GA in each agent</td>
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</tr>
<tr>
<td>Number of Crossover Points</td>
<td>4</td>
</tr>
<tr>
<td>Number of Bits in a Chromosome</td>
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</tr>
<tr>
<td>Mutation Rate</td>
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</tr>
<tr>
<td>Number of Efforts</td>
<td>128</td>
</tr>
<tr>
<td>Number of Trade Sections</td>
<td>16</td>
</tr>
<tr>
<td>Number of Goods</td>
<td>8</td>
</tr>
<tr>
<td>Constant of Harvesting</td>
<td>0.001</td>
</tr>
<tr>
<td>Constant of Trade</td>
<td>1</td>
</tr>
<tr>
<td>Constant of Cooking</td>
<td>1</td>
</tr>
<tr>
<td>Harvesting Effort Concentration Factor</td>
<td>3</td>
</tr>
<tr>
<td>Trading Effort Concentration Factor</td>
<td>3</td>
</tr>
<tr>
<td>Cooking Effort Concentration Factor</td>
<td>3</td>
</tr>
<tr>
<td>Number of Possible Amounts to Trade</td>
<td>4</td>
</tr>
<tr>
<td>Cobb-Douglas weight</td>
<td>0.125</td>
</tr>
</tbody>
</table>

Figure 5. Parameters common to the experiments of this study.
In a single chromosome, the sections for efforts come first. The number of efforts each agent is given per day is a parameter of the simulation: for this study, agents have 128 efforts each. There are four bits per effort: the first bit tells if this effort is to be devoted to trade or production. If it is production, the next three bits tell which good: otherwise they tell which one of a maximum of 16 trade plans are used. For this study, 8 trade plans are passive and 8 trade plans are active. The first bit is a gene switch since it controls the expression of the trade plans in another part of the chromosome. It serves to maintain diversity: when the trade is inactive, the trade section gains diversity through mutation, while it tends to lose diversity when it is active under the influence of natural selection. There are 16 trade plans after the effort sections. Each trade plan encodes a good to give, an amount to give, a good to receive, an amount to receive, an a sign to seek in a trade partner. Finally, the sign section encodes a sign to display to attract traders. We expect these signs to come to have meaning as the simulation progresses. Figure 6 shows the agent’s knowledge representation. Figure 7 illustrates the meaning of a chromosomal trade plan.
<table>
<thead>
<tr>
<th>Chromosome section</th>
<th>Bits</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Efforts</td>
<td>1</td>
<td>Production or trade?</td>
</tr>
<tr>
<td></td>
<td>2-4</td>
<td>Which good to produce or trade plan to activate</td>
</tr>
<tr>
<td>Trade Plans</td>
<td>1-3</td>
<td>Good to give</td>
</tr>
<tr>
<td></td>
<td>4-6</td>
<td>Amount to give</td>
</tr>
<tr>
<td></td>
<td>7-9</td>
<td>Good to receive</td>
</tr>
<tr>
<td></td>
<td>10-12</td>
<td>Amount to receive</td>
</tr>
<tr>
<td></td>
<td>13-16</td>
<td>Sign of agent to seek trade with</td>
</tr>
<tr>
<td>Role Tag</td>
<td></td>
<td>The meaning of the bits on the tag emerges</td>
</tr>
</tbody>
</table>

Figure 6. Knowledge Representation in SISTER, in an 8 good Scenario. A single chromosome has bits which represent efforts, trade plans and a tag. How many effort sections and trade plans in a single chromosome is a parameter of the simulation. A chromosome represents a single day of trade.
Figure 7. Illustration of a chromosomal trade plan section. One section on the chromosome of an agent encodes an active trade plan in the string, 0110010010001001, while a chromosome on the passive agent encodes a passive trade plan in the string 001000011001.

2.2.3 Roles and Mutual Information

To measure the amount of knowledge held in a society, the concept of mutual information, from information theory, is used. Mutual information is a measure of the information contained in a sign. If there is only one sign, and the agents that display it have several different behaviors, that sign indicates nothing. Conversely, if all sorts of signs all mean the same behavior, then those signs indicate nothing.
If \( p(x) \) is the probability (frequency) of occurrence of a sign and \( p(y) \) is the probability (frequency) of a behavior, then mutual information is a measure of the correspondence of symbols to behaviors in a system (Shannon 1993):

\[
MutualInformation_{x,y} = \sum_{x} \sum_{y} p(x, y) \times \log_2 \frac{p(x, y)}{p(x)p(y)}
\]

If there are many signs that mean many different behaviors, then the mutual information of a system is high. For example, if every agent that sells apples displays sign 1 and every agent that sells pears displays sign 2, then there is more information than if all agents display sign 1 and sell both pears and apples, or if some agents that sell apples display sign 1 and other agents that sell apples display sign 2. Mutual information is shown to correlate with utility.

Figure 8 shows an example of a trade scenario of trade with a high mutual information content, and two examples of trade scenarios with a low information content. Each table shows the number of trades made for all agents displaying a particular sign. In the high mutual information scenarios, different signs indicate different behaviors. In the low mutual information scenarios, a sign can mean many different behaviors, and many signs can mean the same behavior.
Figure 8. Mutual Information of Example Trade Scenarios. The rows indicate the number of a type of good sold. P(y), or the frequency of trade in a good, is determined by dividing the number of times a goods is sold in a row by the total number of trades. The columns indicate the sign displayed. P(x), or the frequency of the display of a sign, is determined by dividing the number of times a sign was displayed for a trade in a column by the total number of trades. P(x,y) is the frequency of co-occurrence of a particular sign and trade.
2.3 Tasks

This study describes four experiments to test the sufficiency of roles as one the ingredients for the creation, coordination, and preservation of knowledge. These experiments are designed to explore the following specific hypotheses:

2.3.1 Hypothesis of the first experiment: Agent societies that employ role-recognition (but not individual-recognition) will learn how to trade at least as well as agent societies that employ individual-recognition.

In this experiment, SISTER is run with agents that display and read a freely changeable sign to use in seeking another agent for trade. It is shown that, in the role recognition treatment, a system of roles has formed in which signs are used for the purpose of trade, with different signs meaning different trades. The performance task is for agents to increase their utility of eight simple goods that can be farmed or traded. This experiment shows the evolution of bartering behavior of simple harvested goods. Agents in both the role recognition treatment and the individual recognition treatment learn to produce fewer kinds of goods and trade them away for other goods. However, the agents in the role recognition treatment learn to do it better, with higher utilities. Experiments are performed with 16 agents, eight goods, and 1000 chromosomes per agent over 1500 generations, for 20 runs for each treatment.
In all experiments, average utility is used to assess how well a society of agents trades. In SISTER, this is the same as average fitness. A t-test is done on the average utility over a run, as well as for every corresponding cycle in a run. This t-test compares the role recognition treatment to the individual recognition treatment. The t-test measures how unlikely it is that the individual recognition treatment is as good as the role recognition treatment given all of the data from the 20 experiments. If the probability is below 5%, then we have significant evidence that agents in societies that use role recognition generally have higher utilities than agents in societies that use individual recognition.

Another test done in all the experiments is a t-test for difference in mutual information between the treatments, to check if the increase in utility is due to an increase in mutual information. A correlation between mutual information and utility is taken to support the hypothesis that the reason behind improved trade is the better information of the role treatments.

2.3.2 Hypothesis of the second experiment: Agent societies that employ role-recognition (but not individual-recognition) will learn how to assemble and trade more complex goods than agent societies with individual-recognition alone.

This is similar to the first experiment, except that two of the eight goods are composite goods. Good 6 is composed of good 0 and good 1, and good 7 is composed of
good 2 and good 3. Since the Cobb-Douglas utility function is the fitness function, it is in the agents best interest to get these composite goods in their spread of goods. The Cobb-Douglas utility function makes it so that an agent wants a spread of all of the goods. However, a composite good is a particularly good deal because, in the parameters of this study, it costs less to make than harvesting a new good.

2.3.3 Hypothesis of the third experiment: When birth and death is introduced into agent societies, those with role recognition have greater continuity of knowledge of how to make complex goods than societies with only individual recognition.

This experiment is similar to the second experiment except that a complexity is added: While the number of agents remains the same, agents are periodically killed and replaced by randomizing their chromosomes. The death rate is tested at several values, a 0.001 chance of death resulting in a complete turnover of agents in about every 1000 cycles, a 0.002 chance of death resulting in a turnover of agents in about every 500 cycles, and a 0.005 chance of death resulting in a turnover of agents in about two hundred cycles. The tests are all on how well an agent does after one turnover, so the cycle lengths tested are different. Additionally, a 5 bit sign is used to represent the 16 agents rather than a 4 bit sign, in order to give new “names” to the new agents that arise in the system. A 5 bit sign represents 32 different unique names for the individually recognized agents, who must display their unique name in their sign. 32 unique names are needed if all of the agents will die and be replaced about once.
2.3.4 Hypothesis of the fourth experiment: When an agent society is distributed geographically such that trade over distance costs more, knowledge of how to trade complex goods is spread more easily when agents have role recognition than when they have individual recognition.

This experiment will be like 2.3.3, except the complexity added will be a geographically based cost of trade, instead of birth and death. Agents looking for active trade will have to pay more for trade over distance. Efforts must be devoted for a trade in the simple scenarios (one unit of effort for each trade) but in this experiment, the number of units of effort required increases with Manhattan distance between the agents in a 4 by 4 grid. In spatial scenarios, a store four blocks away costs four times as much to reach as a store one block away. Agents can only travel to make a trade as far as they have efforts devoted to making that trade. For simplicity, the goods that an agent sells as a passive trader remain in the same location throughout the simulation. An agent has a “store,” through which it can sell goods in a single stable place, even though it travels to make purchases. An agent’s “store” remains in the same location for passive trading, but the agent himself must travel to other stores for active trading. For example, a tomato farmer may have set up shop on 5th street, and can still sell tomatoes passively from 5th street even though he has to walk to 8th street to the corn stand to actively trade his tomatoes for corn. The farther the store, the more efforts must be devoted. Costs of 1 effort per grid block, 2 efforts per grid block, and 3 efforts per grid block are tested.
3. Results for the Simple Scenario

3.1 Results

In this simple scenario of 16 agents with 8 primitive goods, the role recognition treatment does better than the individual recognition treatment at a confidence level of over 99%. The average individual recognition utility is 148.5 as compared to 164.5 for role recognition agents. For the parameters of this study, utility values are actually 1,485,000 and 1,645,000, but we report utility in units of 10,000. For the set of parameters of this study, 130 is a utility level of agents who make every thing for themselves without trade. Mutual information does not differ significantly between the treatments. Average mutual information is 0.36 for the individual recognition treatment as compared to 0.22 for role recognition treatment. The confidence level for a correlation between mutual information and utility is above 99% for both the role recognition treatment and the individual treatment. The correlation between utility and mutual information in the individual recognition treatment is 0.68, as compared to a 0.56 correlation for the role treatment. Figure 9 shows the scatter plots of the mutual information as compared to the utility.
Figure 9. Scatter plot of Utility vs. Mutual Information for the simple scenario. Scatter plots for the role recognition treatment and the individual recognition treatment. Individual $r = 0.68$, Role $r = 0.56$. The data do not form a “diagonal line” very well, indicating a weak correlation. The equation of the trendline for the role recognition scenario is approximately $y = 23x + 163$. The equation of the trendline for the individual recognition scenario is approximately $y = 19x + 142$.

Figure 10 shows a graph of the average utility, in twenty averaged runs, for both treatments. There is a yellow vertical bar in every cycle when a t-test shows a significant difference between the mean of the individual recognition runs and a mean of the role recognition runs. It is completely yellow between the two treatments because in every corresponding cycle, there is over a 99% confidence level in a difference between means.
Figure 10. Simple scenario average fitness. The utility of the agents is averaged for the 20 runs of the role recognition treatment and for the individual recognition treatments. The yellow vertical lines indicate places where a t-test shows a significant difference between treatments, which is true for every 10 cycles, making the space between the role and individual lines completely yellow. There are 1000 days of trade per “cycle.” Each cycle is one generation of the agent’s genetic algorithms.

3.2 Discussion

It may seem counter intuitive that a role recognition society would do better than an individual recognition society, because the role recognition treatment seems to be a harder learning problem. Role recognition requires a double induction: agents have to induce what sign they will display in addition to inducing what signs to seek in trade.
Agents of the individual recognition treatment only have to induce what sign to seek in trade. However, the reason that trade spreads through the role recognition society more easily is that an active agent may approach any agent of a role for a single trade plan, a one to many relation, whereas the active agent can only approach a single individual for a trade plan if it is in the individual recognition society. In a system of roles, agents can substitute for each other, but in a individual recognition system, they can not. As a result, a single agent in a system of role puts selective pressure on more agents, spreading its influence wider.

This simple run is the only one that shows no significant difference between the mutual information of the individual treatment and the role treatment. The average mutual information of 0.36 for the individual recognition is not significantly different from the average mutual information of 0.22 for the role recognition treatment. When the complexities of a composite good, death, and space are added in, the mutual information is always significantly greater in the role treatment. Perhaps this is because this simple scenario is too “easy” for both treatments. An individual recognition scenario can have as much mutual information as a role recognition scenario if only one agent is required to sell each good, and the society learns the identity of that agent. The measure of mutual information does not take into account the number of trades. A system where only half of the agents are trading can have as much mutual information in it as a system where all of the agents are trading. Therefore, increases in the role recognition treatment over the individual recognition treatment can be the result of an increase in the volume of trade that occurs in the role recognition treatment. However, we are still certain at the 99%
confidence level that there is a correlation between utility and mutual information in this simple scenario.

This experiment is partially successful at showing that a society with role recognition is better at creating, coordinating, and preserving knowledge than an individual recognition society. We are sure that the role recognition treatment does better than the individual recognition treatment in trade, and have rejected the null hypothesis that agent societies that employ role-recognition (but not individual-recognition) trade at equal average utilities as agent societies that employ individual-recognition. However, because we are not sure of the difference in mutual information between the treatments, we can not attribute this increase to the ability of the role treatment to hold more knowledge. The contrast of what we can show in the simple scenario vs. the complex scenario is instructive. The contrast is of not being able to show a difference in mutual information in the simple scenarios, to being able to show a strong difference in the complex scenarios. This is consistent with the idea that role recognition is robust in the presence of stresses to a society, while individual recognition fails in the presence of stress.
4. Results for the Composite Good Scenario

4.1 Results

In this scenario, two of the goods are composed of other goods: good 6 is composed of goods 0 and 1, and good 7 is composed of goods 2 and 3. In order to sell a composite good, an agent has to obtain the goods that it is composed of through harvesting or through trade. If it is through trade, then more complex social networking is required than in the simple scenario. A t-test comparing the individual treatment average utilities in the simple and the complex scenarios shows that the complex scenario is harder for the individual agents at the 92% confidence level. Average utility actually increases for the role recognition agents in the complex scenario as compared to the simple, meaning that the complex scenario is easier for them, however the difference is not significant. This is consistent with the idea that the role recognition agents are better able to take on stress and hold more information than the individual recognition agents.

Figure 11 shows the average utilities of both treatments over twenty runs each, again, with so many significant differences in utility as to make the area between the lines yellow with vertical bars indicating a 99% confidence level has been reached. A visual inspection shows the greater difference in utility. Individual recognition average utility decreases from 148 in the simple goods scenario to 140.5 in the composite goods scenario (significant at the 92% level), while role recognition average utility increases from 164.5 in the simple scenario to 166 in the composite goods scenario. There is
certainty at the 99% confidence level that the role recognition utilities are better than the individual recognition utilities in the composite goods scenario.

![Complex Scenario Average Fitness](image)

Figure 11. Composite good scenario average fitness. The utility of the agents is averaged for the 20 runs of the role recognition treatment and for the individual recognition treatments. The yellow vertical lines indicate places where a t-test showed a significant difference between treatments, which is true for every 10 cycles, making the space between the role and individual lines completely yellow.

The average mutual information in the role recognition treatment almost doubles, from 0.22 in the simple scenario to 0.40 in the composite good scenario, while the mutual information in the individual recognition treatment halves, from 0.36 in the simple to 0.17 in the composite good scenario. However, these differences across scenarios are not
at significant levels of confidence. The difference between the average mutual information of the role recognition treatment and the individual recognition treatment is at the 92% confidence level. The correlation between utility and mutual information in the individual treatment is 0.37, and is significant at the 94% level, while the correlation in the role treatment is 0.72. The level of confidence in the correlation between utility and mutual information in the role treatment exceeds the 99% level. Figure 12 shows a scatter plot diagram between mutual information and utility, showing a tighter correlation than in the simple scenario.
4.2 Discussion

The t-tests show that there is a significant difference between the role recognition treatment and the individual recognition treatment in terms of utility and in terms of mutual information. The agents in the role recognition scenarios were able to trade better than the agents in the individual recognition scenarios, and their symbol systems held more meaningful information than the symbol systems of the individual recognition scenarios. Furthermore, there is a significant correlation between the utility of the agents...
and the mutual information in the role recognition scenario, implying that the reason that the agents were able to trade better is because of their knowledge-rich symbol systems. A society with high mutual information would have many different roles. It has many agents displaying different tags, with those displaying the same tag having the same behavior, and those displaying different tags having different behaviors. Individual recognition societies can have high mutual information if every agent, each of which has a different sign, has a different behavior. High mutual information means a lot of knowledge, and role recognition societies use their greater amounts of knowledge to trade better.

This experiment shows that role recognition is superior to individual recognition in the creation and coordination of knowledge. The trades of role recognition agents have a higher utility than the trades of individual recognition agents in a more complex scenario, and it is probably (above the 90% confidence level) because of the greater amount of knowledge, as measured in mutual information, that the role society can create. The knowledge that mutual information measures is knowledge of social coordination. A composite good scenario requires more social coordination than a simple scenario, because an agent has to know both who to buy goods from to make a composite good and who to sell the composite good to. In an individual recognition scenario, this must be learned for every individual with the composite good. In a role recognition scenario, this coordination becomes part of the agent culture for other agents to "get in on." In SISTER as in real life, new interactions between individuals are informed by past interactions between other individuals through roles. In a role
recognition society, the knowledge is held culturally. It is distributed in the mutual expectations that agents have of other agents based on roles. This knowledge transcends the individual member of a role, as will be made clear in the next experiment, where cultural knowledge dies with individuals in the individual recognition scenarios, but continues on in the role recognition scenarios. This experiment has shown that more knowledge is created and coordinated in a role recognition society than an individual recognition society. The next experiment will show that knowledge is better preserved in a role recognition society than in an individual recognition society.
5. Results for the Death Scenario

5.1 Results

In this scenario, agents have the composite goods of the last scenario, but they have added on a small chance of dying at the end of each cycle. When an agent dies, the genetic algorithm that forms its trading plan is randomized, and the agent gets a new name. Thus this scenario has to use 5 bits for an agent’s sign, rather than 4, in order for the individual recognition agents to have enough new names in stock. This is disadvantageous for the individual recognition because it becomes harder to induce their exact name. The death rate is tested at 0.001, 0.002, and 0.005, with 20 runs for each treatment. The comparison point is the average time when a population would completely turn over. This point occurs at a different cycle number for the different death rates. So the comparison point is cycle 1000 for the 0.001 death rate, cycle 500 for the 0.002 death rate, and cycle 200 for the 0.005 death rate.

Figure 13 shows a control run, with a 5 bit sign, where death is zero. It is just like the runs in the composite good experiment. The figure shows a single median run (as opposed to an averaged run) for both the individual and role treatments, for illustrative purposes. Note that the points at 200, 500, and 1000 cycles are roughly equivalent: most of the learning occurs before cycle 100. Note also that learning is basically monotonic. It increases for the role run, and does not decrease for the individual run, in the absence of death. Figures 14, 15, and 16 show median individual and role treatment runs for the three death treatments with different death rates. Note that they are non monotonic, and
have periods of low utility to be recovered from. This happens when crucial agents die, and new agents have to learn the culture. Note also the ability of the role treatments to recover from these perturbations and grow, while the individual treatments may recover from the perturbations, but do not grow further. This is consistent with the idea that the role treatment is better able to recover from the stress of death.

Figure 13. Death scenario control median fitness. Thousand cycle control runs for the death scenario including the median fitness role recognition run and the median fitness individual recognition run. They have zero death rates. Note the monotonic nature of the curves as compared to the median runs with positive death rates.
Figure 14. Death rate 0.001 median fitness. Median fitness runs for role and individual recognition treatments in scenarios with a death rate of 0.001. Note the waves that the death causes.
Figure 15. Death rate 0.002 median fitness. Median fitness runs for role and individual recognition treatments in scenarios with a death rate of 0.002. Note the waves that the death causes.
Figure 16. Death rate 0.005 median fitness. Median fitness runs for role and individual recognition treatments in scenarios with a death rate of 0.005. Note the waves that the death causes.

Figures 17, 18, and 19 are the average utility version depictions of these runs. Note that there are no waves in the averaged versions because they have all been averaged out. They have vertical bars for every place that a t-test shows a significant difference above the 99% level, which again, is at every point (after initial growth) despite the variation caused by the utility waves. However, the means become closer as the death rate increases. This is evidence that the role recognition treatment is starting to break down in its ability to hold the culture. The average utility is significantly greater in the role recognition treatment, at over the 99% confidence level, than in the individual
recognition treatment. Average utilities of the role treatments, for death rates 0.001, 0.002, and 0.005 are 145, 133, and 125. Average utilities of individual treatments are 127, 121, and 115. These show that increasing death rates are harder on both individual and role utilities at above the 99% confidence level. Figure 20 shows these results in tabular format.

Figure 17. Death rate 0.001 scenario average fitness. The utility of the agents is averaged for the 20 runs of the role recognition treatment and for the individual recognition treatments. The yellow vertical lines indicate places where a t-test showed a significant difference between treatments. The waves caused by death are averaged out.
Figure 18. Death rate 0.002 scenario average fitness. The utility of the agents is averaged for the 20 runs of the role recognition treatment and for the individual recognition treatments. The yellow vertical lines indicate places where a t-test showed a significant difference between treatments. The waves caused by death are averaged out.
Figure 19. Death rate 0.005 scenario average fitness. The utility of the agents is averaged for the 20 runs of the role recognition treatment and for the individual recognition treatments. The yellow vertical lines indicate places where a t-test showed a significant difference between treatments. The waves caused by death are averaged out.
Figure 20. Results for the death scenario. Utility is higher in the role treatment than in the individual treatment. Role mutual information actually increases under the stress of death.

Death flattens the trade and mutual information in all of the treatments for the individuals. The control run for the individual treatment, which has 5 bits, does not have much trade, but has more than zero. This is reflected in the average mutual information scores of the 1000 cycle control, 0.14, as compared to the death rate 0.001 treatment, 0; the 500 cycle control, 0.27, as compared to the death rate 0.002 treatment, 0.04; and the 200 cycle control, 0.34 as opposed to the death 0.005 treatment, 0. These decreases in mutual information from the control are all significant above the 98% confidence level. In contrast, the average mutual information in the role recognition runs actually increased from the control; however this increase is not significant. This is reflected in the average mutual information scores of the 1000 cycle control, 0.665, as compared to the death rate 0.001 treatment, 0.715; the 500 cycle control 0.794, as compared to the death rate 0.002 treatment, 0.858; and the 200 cycle control, 0.65 as opposed to the death 0.005 treatment,
The difference between the average mutual information of the role recognition treatment and the individual recognition treatment is significant above the 99% level.

In the role treatment, average utility is correlated with average mutual information in death rates 0.001, 0.002 and 0.005 at values 0.43, 0.36 and 0.50. These results are significant above the 95% level except for the 0.36 value, which is significant above the 90% level. Individual recognition values are too low to have correlations. Figure 21, 22 and 23 show the utility vs. mutual information scatter plots that may be used to see the strength of the correlation.
Figure 21. Scatter plot of utility vs. mutual information for the death 0.001 scenario. Scatter plots for the role recognition treatment and the individual recognition treatment. Role $r = 0.43$. Individual treatment mutual information is zeroed by death, and role showed robustness with this somewhat diagonal line. The equation for the trendline of the role recognition treatment is approximately $y = 17x + 142$. 

$y = 17.042x + 141.67$
Figure 22. Scatter plot of utility vs. mutual information for the death 0.002 scenario. Scatter plots for the role recognition treatment and the individual recognition treatment. Role $r = 0.36$. Individual treatment mutual information is nearly zeroed by death, and role showed robustness with this somewhat diagonal line. The equation for the trendline in the role treatment is approximately $y = 9x + 135$. The equation for the trendline in the individual treatment is approximately $y = 23x + 130$. 

\[
y = 23.178x + 129.89 \quad y = 8.6886x + 135.32
\]
Figure 23. Scatter plot of utility vs. mutual information for the death 0.005 scenario. Scatter plots for the role recognition treatment and the individual recognition treatment. Role $r = 0.50$. Individual treatment mutual information is zeroed by death, and role showed robustness with this somewhat diagonal line. The equation of the trendline for the role treatment is approximately $y = 11x + 125$.

5.2 Discussion

This experiment supports the hypothesis that role recognition does better than individual recognition in preserving knowledge, that is, in keeping up the knowledge that a society holds under a stress. When an agent dies in a individual based recognition society, all the social coordination associated with its place in society is lost. If an agent dies in a role recognition society, even if there is only one agent in that role at a time,
other agents in the society or new agents may adjust their sign and receive the selective pressures to adjust their behaviors to the dead agent’s niche.

This finding contributes to artificial intelligence, because it shows a way to keep a coevolving society of agents learning new things. When new agents are brought into a society, they can bring change to the society more readily than old agents that have already-converged genetic algorithms directing them. Thus, death is a type of macro level mutation for coevolving systems. Death enables roles in the society to readjust to each other, change as the need arises, and complexify. If role recognition makes agents robust in the face of death, then it can help keep the diversity up in a coevolving system when used in concert with death. This finding further contributes to artificial intelligence in that robot agents in the real world will die by accident, and role based recognition is a way to keep the knowledge that they have accumulated alive socially despite their accidental death.

Role recognition is superior to individual recognition of agents in preserving knowledge because the agents serve as replacements for each other. Roles form robust replacement classes of agents, which enable the preservation of the knowledge of society, even when individual members of a class die. Role classes also promote the creation of knowledge, not only because agents within a role class may learn from each other’s experiences. This experiment has shown that role recognition, in conjunction with death, facilitates the creation of knowledge through the diversity that death and birth bring to a society. Roles coordinate knowledge across generations.
6. Results for the Spatial Scenario.

6.1 Results

In this scenario, agents with the same composite goods as the second experiment are distributed over space, so that the cost of making a trade goes up in proportion to the traders’ Manhattan distance in a 4 x 4 grid. Agents have two locations: a store, from which they hang their sign, if they choose to engage in passive trading, and the location of their buying agent, that travels around from store to store to make active trades. While death is logically more of a stress on the individual recognition treatments, space is more directly a stress on the role recognition agents. If individuals are ever to do better than roles, it seems that the scenario where they would do better would be a spatial scenario, where agents are too far apart to benefit from replacing each other. If there is too much space between a seller of barley on one end of the grid and a seller of barley on the other, how can one agent’s transactions benefit from another’s transactions?

In this experiment, three levels of spatial separation are studied, at a cost to get to an adjacent grid of 1 unit of effort, 2 efforts, and 3 efforts. These levels will be known as spatial-1, spatial-2, and spatial-3. The results show that these are hard on the agents, because the utility values of both the individual recognition treatments and the role recognition treatments decrease at a confidence greater than the 99% level between
spatial-1 and spatial-2. The difference is not significant for between spatial-2 and spatial-3.

Figure 24 shows a median run, to show that it does not have the waves of low utility that the death experiments have. Figures 25, 26, and 27 show the average utilities of the runs with each cost of trade. There is a large decrease between spatial-1 and spatial-2, and less of a decrease between spatial-2 and spatial-3.

Figure 24. Spatial-1 median fitness. In the spatial-1 scenario, median runs of the role treatment and the individual treatment are presented to show their monotonic nature.
Figure 25. Spatial-1 average fitness. The role recognition treatment and the individual recognition treatment show a significant difference at every value with a vertical bar.
Figure 26. Spatial-2 average fitness. The role recognition treatment and the individual recognition treatment show a significant difference at every value with a vertical bar.
Figure 27. Spatial-3 average fitness. The role recognition treatment and the individual recognition treatment show a significant difference at every value with a vertical bar.

Figure 28 shows the results for the spatial scenario in tabular form. In spatial-1, the role recognition agent’s utility is higher than the individual recognition agent’s utility at the 99% confidence level, with individual recognition runs having an average utility of 139 while the role recognition runs have an average utility of 159. Average mutual information is better in the role treatment at above the 99% confidence level, with individual treatments averaging 0.26 for mutual information, and role recognition treatments averaging 0.71. Utility correlates with mutual information for the individual recognition treatment at 0.67, and for the role treatment at 0.48. The correlation is
significant above the 99% confidence level. Figure 29 shows a scatter plot of the mutual information vs. utility, to illustrate the level of correlation for spatial-1.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Cost of Trade</th>
<th>Average Utility</th>
<th>Treatment Mutual Information</th>
<th>Correlation Utility and Mutual Info</th>
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<td>0.48</td>
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<td></td>
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<td></td>
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<td></td>
<td>Spatial-3</td>
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<td>0.05</td>
<td>N/A</td>
</tr>
</tbody>
</table>

Figure 28. Results for Spatial Scenario. Utility is higher in the role treatment than in the individual treatment. Role mutual information is higher than Individual mutual information as well.
Figure 29. Scatter plot of utility vs. mutual information for spatial-1. Scatter plots for the role recognition treatment and the individual recognition treatment. Role r = 0.48, Individual r = 0.67. The equation of the trendline for the role recognition treatment is approximately $y = 17x + 160$. The equation of the trendline for the individual recognition treatment is approximately $y = 32x + 136$.

In spatial-2, the role recognition agents still trade better the individual recognition agents, but at the 90% confidence level. The individual treatment has an average utility of 133 while the role recognition treatment has an average utility of 139. The difference in average mutual information is significant at the 93% level, with the individual treatment having an average mutual information of 0.1, and the role treatment having an average mutual information of 0.28. The role recognition treatment has a drastically reduced amount of information that its symbol system can hold, as compared to spatial-1.
However, the correlations between mutual information and utility are very strong, with a 0.68 for individual runs and a 0.79 for the role recognition runs. Both correlations occur at above the 99% confidence level. The difference in mutual information between the individual treatment and the role treatment is above the 99% level as well. This indicates that the mutual information is responsible for what little utility that the runs are able to muster. Figure 30 shows a scatter plot of the mutual information vs. utility, to illustrate the level of correlation for spatial-2.
Spatial-2 Correlation

Figure 30. Scatter plot of utility vs. mutual information for spatial-2. Scatter plots for the role recognition treatment and the individual recognition treatment. Role $r = 0.79$, Individual $r = 0.68$. The equation for the trendline of the role recognition treatment is approximately $y = 31x + 137$. The equation for the trendline of the individual recognition treatment is approximately $y = 20x + 135$.

Spatial-3 has no significant results with mutual information. The average mutual information of the individual treatments is 0.05 while the role recognition treatment is 0.12. This is the first experiment we have seen with no correlation between utility and mutual information. It means that the role recognition treatment did not use its symbol system to improve its utility over the individual recognition treatment. Figure 31 shows a scatter plot of the mutual information vs. utility, to illustrate the level of correlation for
spatial-3. A look at the nature of the trades gives us a clue to why. Now that the agents are spatially arranged, we can look at pictures of what is going on.

Figure 31. Scatter plot of utility vs. mutual information for spatial-3. Scatter plots for the role recognition treatment and the individual recognition treatment. Correlations are not significant. The equation for the trendline of the role recognition treatment is approximately \( y = 4x + 147 \). The equation for the trendline of the individual recognition treatment is approximately \( y = 136 \).

We present a spatial illustration of the last day of trade in sample runs for both treatments in every cost of trade scenario. Most of the illustrations are of the median run
for the role and the individual average mutual information. However, the best mutual
information for the role and the individual treatments are included in figures 32 and 33, to
illustrate what can happen. The best role treatment has an average utility of 164. The
agents have a utility of 174 and a mutual information of 1.831 on the last day of this run.
In these illustrations, the color of a square indicates an agent’s sign, and the different
shapes on the arcs between agents indicate the different goods that are traded. The shape
located on an agent represents the good it receives in a trade. In this scenario, we have 5
different signs with exactly 5 different behaviors. Agents 2 and 4 both display the same
sign (purple) and both have similar behavior. They buy good 2 and sell good 1 at a ratio
of 3 to 2. Agents 1 and 9 both display the yellow sign, and have the same behavior.
They buy composite good 7 and sell composite good 6 at a ratio of 4 to 3. Agent 3 buys
the same goods and sells the same composite goods, but sells them at a different price, a
ratio of 1 to 2. He has the orange sign. Agent 6 buys 2 and sells 3 at an even ratio, with a
red sign, and agent 0 buys 1 and sells 0 at a 3 to 2 ratio. Agent 3 is able to get another
price for its goods because it is located distantly from the other stores that sold the same
goods. It is the equivalent to a “convenience store”. Note also how agents selling
complex goods have to set up trade relations with agents selling their components (if they
don’t harvest the goods themselves). There is much to learn from utility, price and
distance with SISTER.
Figure 32. Best mutual information in role recognition treatment for spatial-1. Agent “stores” are placed in fixed locations on a 4 X 4 grid. Colors represent different displayed signs. These agents have different behaviors for the displayed signs, meaning they have differentiated into roles. The shapes represent goods traded. In this run, both the yellow and the orange roles trade in the two composite goods, but the orange charges a different price and has different local customers than the yellow. Agents with complex goods have complex networks of trade needed to obtain the right components.
Figure 33 shows the best individual treatment mutual information. It doesn’t involve the complex goods as the best role treatment does. However, it does have two different signs with two different behaviors. The agent 2 (purple) sells 0 and buys 1, while agent 10 (yellow) buys 3 and sells 2.
Figure 33. Best mutual information in individual recognition treatment in spatial-1. Two of the agents have learned different roles, but they have not spread to other agents. No complex goods are traded.

Figure 34 shows the median run for the role treatment in the spatial-1 scenario. Its mutual information is 0.628, even though it actually has better utility than the best role.
treatment mutual information. This run’s last scene utility is 186, while the best mutual information run’s is 174.
Figure 34. Median mutual information in role recognition treatment in spatial-1. Three roles have formed. An interesting thing about this run is that good three has become a standard of trade, that is, money has emerged. Money emerges in 55% of the role scenarios. It makes the mutual information lower because agents trade in money regardless of their sign. Although this is the median mutual information run, it is the best utility run of spatial-1, perhaps because of the emergence of money.
The lower mutual information implies that some of the agent having different signs have some of the same behaviors, and some of the agents with the same sign have different behaviors. However, on the whole, signs have meanings. Most agents displaying the yellow and purple signs have the behavior of buying 3 and selling 2 at a 3 to 4 ratio. Most agents with yellow also buy 3 and sold 4 at a 3 to 4 ratio. Agents with the purple sign all buy 2 and sell 4 at a 2 to 1 ratio, while one of the agents with the purple sign and the red sign agent buy 1 and sell 3 at a 1 to 3 ratio.

This is a very interesting scenario because it shows that one of the goods, number 3, has become the standard of trade. This explains why the mutual information is lowered in such a high utility scenario. Money has emerged in this scenario. Agents use good 3 to get other goods that they want. But money is a strategy that lowers mutual information, because it means that agents, regardless of the sign they display, have the same behavior. It is not unique to this scenario, in fact, significant amounts of trades that get re-traded occur in 55% of the role composite good scenarios and in 35% of the individual treatments for the simple composite goods of the second experiment. These trades in goods that get re-traded, or exchange trades, indicate the emergence of money. It shows that SISTER, in keeping the principles of social science closely, has emerged many different institutions and has a lot to offer as an economics simulation.

Figures 35 through 39 are all scenarios of zero mutual information. However, the role society still does better than the individual society. This is because the role runs can still spread a single kind of store throughout the society. However, a single sign that
means something has no mutual information, because it is not a system of signs that can mean different things. The commonness of zero mutual information in the higher cost of trade scenarios shows that these were severe stresses to both the individual treatments and the role treatments.
Figure 35. Median mutual information (of zero) in individual recognition treatment of spatial-1.
Figure 36. Median mutual information (of 0) of role recognition treatment in spatial-2. Even though the mutual information is zero, it does better than the individual recognition treatment because many traders have taken on that one role.
Figure 37. Median mutual information (of 0) in individual recognition treatment of spatial-2.
Figure 38. Median information (of 0) of role recognition treatment spatial-3.
Figure 39. Median mutual information (of 0) of individual recognition treatment of spatial-3.
6.2 Discussion

This experiment shows that knowledge can be preserved over space in role recognition societies better than in individual recognition societies. A role allows adjacent agents to learn from each other's experiences, and this causes information to spread over distances. This experiment, like that last one, demonstrates that knowledge in a role society can be preserved in the face of stress. Roles help cultural knowledge to have continuity over geographical distances as well as over generations.
7. Summary of Contributions

7.1 Contributions

This dissertation contributes to computational science in three basic ways. It contributes the demonstration of a hypothesis about roles, it contributes the system used to demonstrate the hypothesis, and it contributes a methodology to measure that system. More specifically, the first contribution is a:

- Demonstration that an emergent system of roles is a sufficient condition for the creation, coordination, and preservation of knowledge in an artificial society.

The consistent advantage that the role recognition agents have in trade over the individual recognition agents correlates with a consistently higher amount of mutual information in the role recognition agents’ symbol systems. This result shows that more knowledge was created in the role recognition treatment than in the individual recognition treatment, and that this knowledge was useful in coordinating trade. In the last two experiments, stresses were placed on the agents. The role recognition treatment showed the robust ability to preserve knowledge despite the stress of death and space, while the individual recognition treatments lost all knowledge in their symbol systems under these stresses.

The second contribution is of the simulation itself:
Demonstration of a multi-agent simulation of heterogeneous, adaptive agents, including economic assignment of credit, emerging communication, and emergent tasking

SISTER shows how tasking and communication amongst agents can develop endogenously. The emergent communication system facilitates a complex coordination of tasking between coevolving agents that is at the same time not preprogrammed. Their assignment of credit is based on price in individual trades, as opposed to an auction. This is a unique way to assign credit in a coevolving system.

The use of mutual information to measure a system of roles by measuring the correspondence between signs and behavior

This dissertation demonstrates the use of mutual information to measure the amount of differentiation of agents into a system of roles. Mutual information measures this systemization by measuring the amount of knowledge contained in the symbol system that controls the coordination of agents based on role signs. The more complex the system of roles and interrelations between agents, the more information contained in their symbol systems.
7.2 Conclusion

Institutions and roles are some of the most basic concepts of social science. However, theories of these basic concepts can only be conjecture as long as social scientists do not have access to the same sort of experimentation that physicists and chemists do. Theories of social science are based on statistics of observations in a world that can not hold all else the same: thus these statistics can not effectively tease out cause. At most, such statistics can only demonstrate necessity. If one historical phenomenon always precedes another, this is evidence of necessity; however, without the ability to do experiment, there is no way to prove sufficiency. Computer simulation provides a complementary functionality to real world observation: it can prove sufficiency, but not necessity. Since proving causation is a matter of proving both sufficiency and necessity, a combination of real world observation and computer simulation can make the social sciences more than a matter of conjecture. Computational Social Science is an important emerging tool for teasing out social causation, and this work seeks to model the most fundamental concepts of social science.

This thesis addresses questions about the relation of roles to culture. It asks what effect these generalizations of people have on the accumulation of knowledge in society. It asks how roles help to institutionalize knowledge and help knowledge to grow, how complex relations between people help to meet complex needs. To answer these questions, the SISTER algorithm is used (Symbolic Interactionist Simulation of Trade and Emergent Roles). SISTER is a program incorporating coevolution, in which agents each have their own genetic algorithm (GA), whose fitness is ultimately determined by
the genetic algorithms of other agents. These GAs evolve tags that come to indicate a set of behaviors associated with a role. Roles are nowhere defined in the simulation and exist in no one place, but rather are suspended in the mutual expectations of the coevolving agents. These mutual expectations emerge endogenously and are expressed through signs with emergent meanings. All institutional knowledge is distributed in these subtle mutual expectations. Specifically, it is hypothesized that an agent society with role-based recognition can create, coordinate, and preserve knowledge better than an agent society without roles.

SISTER is a simulation of the basic social process: the emergence of macro-level social institutions from micro-level symbolic interactionism. Intelligent object-oriented agents induce what sign they should display and the meanings of signs that they read. From this displaying and reading of signs, they come to have shared meanings despite the fact that they do not copy each other and only see from their own contexts. That is, agents never observe another agent’s situation and try to display those other agents signs. Imitation plays no role in the spreading of culture. Instead, symbol interpretations are reinvented in every agents individual circumstances. As Piaget said, “to learn is to invent.” These shared meanings become the agents’ own symbol system, and enable them to behave in synchrony and cooperation.

SISTER simulates a differentiation into the roles of a division of labor in an economic system (Duong, 1996). In SISTER, initially homogenous agents differentiate into the heterogeneous agents reflecting a division of labor. Roles solve the problem of
how the agents may work together to increase their utility. In previous results with SISTER (Duong 1996), the solution to this problem was simple: instead of making all goods for themselves, agents learned how to make fewer goods and trade them for other goods. However, these results did not adequately show the importance of roles to the continuance and increase of the knowledge that the agents held. This study addresses a more complex problem with the introduction of composite goods, or goods made from other goods. Composite goods require more social coordination than goods simply harvested. Spatial (geographical) complexity, and temporal complexity is included in the model so as to adequately differentiate between the knowledge-holding capacities of social systems with emergent roles and the knowledge-holding capacities of social systems without them. This gives evidence to the importance of roles to cultural continuity, that is, the creation, coordination, and preservation of knowledge.

Cultural continuity and the suspension of knowledge in mutual expectations are concepts that are difficult to measure exactly. To get at these concepts, we need a measure for the amount of knowledge that a society holds. In this study, the amount of knowledge held by a society is measured with a fundamental measure of information theory: mutual information. Mutual information measures the amount of information contained in signs. The culture of this simulation passed on through its symbol system is the knowledge of how to coordinate the agents in the making and trading of complex goods. Mutual information measures the amount of knowledge suspended in mutual expectations by measuring the correspondence between the sign the agents display and their behaviors. If all agents displaying a sign exhibit the same behaviors, then that sign
indicates one of the emergent roles of the system. This study tests the effectiveness of a society based on role recognition in preserving knowledge of task coordination under the stress of the death of agents, and separation over distance.

In order to test that effectiveness, a society that uses role recognition is compared to the alternative, a society that uses individual recognition. The experiments with role recognition include agents who seek to trade with other agents wearing a sign. The passive trader induces the sign he wears while the active trader induces the sign to trade with. The experiments with individual recognition include agents who seek to trade with an individual, whose name the active trader induces. Each individual’s name is unique and unchangeable.

We compare the average utilities of societies based on individual recognition with the average utilities of societies based on role recognition. Our results show that agents in a role based society can trade better than agents in societies based on individual recognition. We address the hypothesis that this occurs because the role-based society holds more knowledge about trade coordination than the societies based on individual recognition. Results in Chapter 3 show that the amount of mutual information is higher in the treatment with roles than in the individual recognition treatment. Furthermore, we establish a positive correlation between the amount of mutual information and the amount of utility. These result are repeated under various death rates and various geographical distances, to determine whether role recognition increases the ability of a society to hold knowledge of social coordination in its symbol system under these types
of stress. It is shown that roles help a society to hold cultural knowledge despite the death of a culture’s individual members or their spatial separation.

Our first implementation of SISTER (Duong 1996) was the first coevolution program to show an endogenous differentiation of agents into roles. By adhering to the principles of social science in a simple design, many economic institutions emerge from runs of the first implementation of SISTER, such as money, price, and the roles of a division of labor. These institutions emerge naturally and need further study concerning the conditions under which they emerge. This study focuses on the emergence of a role based division of labor.

While many computational social science models use game theory or ad hoc social models to emerge norms, SISTER adheres very closely to the principles of sociology. SISTER is not about spatial issues and outer territorial behaviors, but about the same topics that sociology is about, symbolic interaction, roles, and institutions. SISTER is a distillation of the basic social process, of the emergence of macro level institutions and language from micro level symbolic interaction. Nowhere in this simulation does one agent copy the sign of another agent. They only induce what signs to read and display based on what practical benefit that all of their signing, producing, buying and selling gets them at the end of the day. This “closure with respect to meaning” and this practicality are in accordance with the micro sociological theory of symbolic interactionism. This study demonstrates that these signs can come to have similar meaning to all agents, needing only an indirect fitness measure based on the
utility of goods consumed to reward for an interpretation. Thus, this simulation is the first to address hermeneutic paradox that people only learn from their own experiences, and yet share meaning on the social level. Most other models of language emergence either use imitation, or they use a single genetic algorithm to get agents to come to a consensus on the symbol system. Since convergence is intrinsic to these methods, they beg the hermeneutic question.

SISTER contributes to computational social science by integrating aspects of many different theories. SISTER implements Kluver’s concept of a socio-cultural engine based on roles (Kluver, 2002). It models Berger’s ideas about the importance of roles to social order (Berger and Luckman, 1966). At the same time, it models Parsons’ ideas of a “double contingency” as the basis of social order, through consensus on a symbol system (Parsons, 1951). Cultural knowledge exists in the mutual expectations agents have of each other, as in Luhmann’s model (Luhmann, 1984). SISTER does this while adhering to the micro macro integration sociologist’s ideas of what an emergence should be, including Coleman’s idea that it should be a system of roles (Coleman, 1994), and Ritzer’s idea that it should include both micro economics and micro sociology in concert (Ritzer, 1999).

SISTER unites all of these social theories in one socio-cultural engine. In this engine, roles are concepts of how agents should behave, suspended in the mutual expectations agents have of agents displaying the role’s sign. This suspension in mutual expectations is what carries cultural knowledge over time and space. It is the basic social
process, and it explains cultural continuity. Existing in something so subtle as mutual expectations, a system of roles enables knowledge in society to be held and to complexify. Individual identities can form a simple system, but in order to simulate society, we need a more complex system formed through institutionalization of role

A role comes in handy in all complex situations where knowledge accumulates and is handed down through generations. In simulations where the patterns of behavior are complex, the role sign guides an agent to a group of behaviors. For example, if an agent has one behavior of a role, he would be pressured to display a sign to indicate that behavior to others. Once he displays that sign he is pressured to have the other behaviors that go along with the role as well. This is the process by which knowledge is held in the mutual expectations of agents (Duong 1991). This is cultural, not individual, dissemination of knowledge. SISTER distills the process of self fulfilling prophecy, an important concept of symbolic interactionism (Berger and Luckman, 1966). The place of the members of society are determined and redetermined by the distributed expectations of the other members based on signs. This study shows that holding knowledge in mutual expectations not only helps agents to learn more complex tasks, but it helps them to learn them robustly, even though every member of a society dies, and even when they are separated over space.

This study is a contribution to computational social science, but it equally contributes to artificial intelligence. Accurate models of social coordination through roles and emergent symbol systems can help to coordinate coevolving agents
endogenously, as the need arises. Endogenous coordination is important to deal with unexpected situations. The SISTER algorithm can help robot societies to remain intelligent robustly, despite the death and dislocation of individual members. This study shows how agent societies can not only withstand the deaths of individual agents, but how death can help an agent society as a whole to continue to grow in knowledge. SISTER demonstrates how to distribute knowledge in the mutual expectations of agents, in coevolving distributed AI societies. It clearly shows that a role based division of labor with emergent signs can hold complex knowledge in an agent society better than individual recognition, especially when the stresses of death and space are placed on the society. It doesn’t matter whether that society is a society of persons or of robots. If we are talking about robots, then this is a work of artificial intelligence, using the basic principles of society to coordinate artificial intelligence programs endogenously.
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Curriculum Vitae

Deborah Vakas Duong was born in Washington D.C. She earned her bachelors degree in Sociology/Anthropology and Mathematics/Computer Science at Virginia Commonwealth University and her masters degree in Computer Science at the University of Alabama at Birmingham. With this dissertation she will earn her Ph.D. in Computational Sciences and Informatics at George Mason University. Her major is in Computational Social Science. She has three children, Sonny, Lana and Anna.