2012

Modeling collective dynamics of social systems: Incorporating various social mechanisms into agent-based models

Dene L. Farrell

MODELING COLLECTIVE DYNAMICS OF SOCIAL SYSTEMS: INCORPORATING VARIOUS SOCIAL MECHANISMS INTO AGENT-BASED MODELS

BY

DENE LEO FARRELL

BS, Binghamton University, 2006

THESIS

Submitted in partial fulfillment of the requirements for
the degree of Master of Science in Systems Science
in the Graduate School of
Binghamton University
State University of New York
2012

Accepted in partial fullfillment of the requirements for
the degree of Master of Science in Systems Science
in the Graduate School of
Binghamton University
State University of New York
2012

JUNE 28, 2012

Dr. Hiroki Sayama, Advisor
Departments of Bioengineering and Systems Science and Industrial Engineering, Binghamton University

Dr. Harold W. Lewis III, Advisor
Department of Systems Science and Industrial Engineering, Binghamton University

Dr. David Sloan Wilson, Advisor
Departments of Biology and Anthropology, Binghamton University

Dr. Craig Laramee, Advisor
Department of Bioengineering, Binghamton University

ABSTRACT

Agent-based models (ABM) are becoming increasingly used for social simulation experiments. Various aspects of social interaction are modeled with ABM in various ways. When considering collective dynamics in social systems a modeler may need to shift focus between evolutionary, socio-topographical, or cognitive issues of a system. I present three original papers demonstrating complex behavior arising from collective dynamics in ABM simulations focusing on evolutionary and cognitive mechanisms.

The first report demonstrates the coupled emergence of cooperation and selfish punishment behavior in groups of individuals playing an iterated public goods game. ABM is implemented here to describe an evolutionary system and test game theory hypotheses about one possible avenue for the evolution of altruism. The focus lies on a search for evolutionarily stable strategies within a global population over time. Single agents are determined by phenotypic propensities towards altruism and punishing. An emergence of the correlation between punishing and cheating is paired with the emergence of a high rate of altruism. Selfish punishment in this case can be seen as a second level form of altruism, as altruistic punishment is typically seen. The model presented does not account for cognitive mechanisms, but demonstrates an evolutionary explanation for collective dynamics of altruism in game theory terms.

The second report demonstrates the effects of mental modeling within groups of decision makers. In this report we shift our focus from evolutionary mechanisms to cognitive mechanisms, particularly the effects of remembering information received from others in conversation and the resulting change in one's own world view due to adjusting for the information received from others. In this case we are investigating how differences in interactions between agents will lead to differences in group problem solving performances. We seek the effects of varying the memory parameter and find a sharp threshold, passing which leads to similar individual perceptions of problem space and consequently suboptimal exploration of all possibilities in problem space. This model demonstrates no evolutionary mechanisms, as it asks questions only pertaining to cognitive mechanisms of the agents.

The third report demonstrates a synthesis of evolutionary and cognitive mechanisms. Simulated discussants in a team approaching a problem act as an evolutionary environment for the evolution of ideas. Cognitive mechanisms are translated into evolutionary operators. Individuals perform evolutionary operators on a population of ideas at the disposal all participants in the team. Investigated are the evolutionary behaviors of various groups with various compositions of propensities towards certain evolutionary operators. We find that certain combinations of operators are drastically more effective than others at discovering optimal solutions and that proper balance between selective and creative operators is important for finding good solutions.

These studies are but three of many ways to implement ABM for social modeling. In the last section I discuss further possibilities for synthesizing multiple social mechanisms within ABM simulations of social systems. In some cases it is best to simply choose one approach from another, but as simulations are increasingly called upon to model more complex scenarios in which many disparate mechanisms are simultaneously paramount, reconciling separate dynamics that span more than one theoretical basis is becoming a crucial skill for creating meaningful models.

DEDICATION

For my mother and father. I love you.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Hiroki Sayama. I have greatly appreciated his personal and professional advice.

I would like to thank my parents for supporting me during undergraduate and graduate years.

I would like to thank David Sloan Wilson and Omar Eldakar for their collaboration on several projects including our research on Selfish Punishment.

I would like to thank the Binghamton University Bioengineering Department for the support and guidance given by all faculty and staff members. I especially appreciate the assistance of Ellen Madison in all matters imaginable.

I am grateful to the New England Complex Systems Institute for my visits during the 2006 ICCS, the 2007 summer session, and the acceptance of my presentation into the 2007 ICCS.

I thank all friends and family that have helped in many forms of support they have offered throughout my years of education.

Thanks to Hal Lewis for helping me bring this work to completion.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Basic Description of ABM

Agent based models include any model demanding the abstraction of an agent. An agent is a set of information that performs actions based on a set of rules and may change it's own set of information based on the events it participates in. All of these things fall under the umbrella of ABM: A checker game; a genetic algorithm; virtually any video game; and countless models of real systems such as economic models in which agents represent single actors participating in an economic system. Since ABM uses one-to-one analogues of the system modeled, they are intuitive and technically simple. Since ABM often demonstrates complex phenomena through repetitive computer simulations it is often conceptually difficult to predict outcomes. ABM is often used to explore iterated interactions between agents that, despite being well-defined would be intractable for analytical methods, especially in game theory and evolutionary theory scenarios [4, 15, 2, 43].

ABM is useful when modeling systems with complex agents or where interactions between agents are complex. It often proves the best approach when interactions are discontinuous, nonlinear, or carry historicity. Similarly, when spacial relations are important, keeping track of moving parts is easiest in an ABM construct. It is useful for systems consisting of heterogeneous or hierarchically ordered populations of agents. It is useful for modeling systems with nontrivial or dynamical topologies such as network based systems. In short, ABM is basically useful for making models that fail to be captured by traditional equation-based models.

Since ABM is such a new and broad field, there are areas of controversy such as the need for universal methodologies [42, 24, 37] and validation methods [21]. At the same time there seems to be much consensus that ABM is the best simulation technique for accurately describing social phenomena [14, 15, 21], and is expected to become the default platform for social computational models [12]. There are multiple avenues for implementing models from various levels of baseline complexity. Besides programming from scratch, there exist libraries and frameworks such as Swarm and Repast, visual ABM coding environments such as NetLogo and StarLogo, and scripting programming environments such as Mathematica and Matlab.

While much work is needed on developing universal methodologies and techniques allowing for comparisons across models, ABM has undeniably demonstrated great progress in producing explanatory models. ABM is often cited in or the basis for exciting, new dynamical systems and complex systems theory explanations for anomalous things such as complex features [31], altruism [20, 13], culture [38, 1], language [3, 25] and higher-level intelligence [9].

Sociality, Evolution, and ABM

The presence of sociality in an evolutionary system changes how selection pressures relate to an individual's behavior. In social systems individuals affect others in ways besides direct competition; the fitness of all individuals within a social group are tied together because they all share some conditions defined by the boundaries of the social group [44]. Evolutionary game theory has been useful for illustrating models of social strategies in evolutionary systems and often times the best format for models is ABM when dealing with complex systems. Since evolutionary theory is algorithmic in nature (Darwin, after-all, was able to describe biological evolution without access to the micro-level mechanisms), evolutionary systems often loan themselves well to computational simulation [36].

The dove-hawk game, for example, demonstrates a contest of two strategies vying for a resource [34]. Doves share and do not fight, while hawks fight and do not share. Hawks, when meeting a dove take all of a resource, and when meeting another hawk take half of a resource on average while also paying a cost of fighting. Doves meeting doves simply split the resource evenly. In a well mixed population the evolutionary dynamics can be described analytically using frequency dependent fitness equations. A single equilibrium point of a certain distribution of populations can be analytically found. If the cost of fighting is high, then the hawk is a self limiting strategy due to the high negative effect of homogeneous interactions.

As spatial interactions come into play, the mathematics become more complicated and in some cases untenable. When agents are placed in groups that are competing on the group-level, for example, it may become necessary to turn to ABM to examine the effects of both local relative fitness of individuals within groups and the global fitness of groups between groups. Often times multiple evolutionary stable strategies (ESS) can be demonstrated in such cases.

ABM has been especially useful for social simulation because it best portrays social systems made of agents and interactions of complex qualities. I will briefly describe in what way it was adapted for each specific system investigated in the three studies presented. It will be demonstrated in what way ABM was used to model the following systems: (1) The evolution of a self limiting strategy; (2) Emergence of shared mental models of problem spaces; (3) The evolution of an ecology of ideas.

1.1 Evolution of a self limiting strategy

In Chapter 2 we study the emergence of an ESS that is self limiting (selfish punishers) and dependent upon the existence of non-punishing altruists. Selfishness as a trait alone is typically viewed as negative behavior regarding group fitness. Studies concerned with the evolution of sociality and altruism usually investigate mechanisms that limit selfishness such as models focusing on punishment mechanisms [45, 46, 22, 19, 18, 7, 17, 23, 16]. Punishment, however, is often costly and therefore second-order altruism [45, 5, 6, 16]. We study a polymorphous strategy within which an individual behaves selfishly in first order interactions, but behaves altruistically in second order interactions by punishing other cheaters.

We created an Agent Based Model in the programming language of Mathematica. In our simulation a large population of individuals is divided into ephemeral groups of size N. Groups play a public goods game. There are two rounds of activity. First, individuals have an opportunity to contribute a portion of their endowment to a central fund that is doubled and evenly redistributed to all group members. Second, Individuals have an opportunity to contribute part of their endowment to a central fund that increases the chance of ejecting cheaters from the group. All individuals have inherited propensities to cooperate and to punish. Each trait is modeled as a number between 0 and 1 in increments of 0.1. We find that a negative correlation between altruism and punishment emerges, representing groups of non-punishing altruists with selfish punishers.

1.2 Emergence of shared mental models of problem spaces

Problem solving is becoming more and more a collective activity in which neither groups nor problems are divisible into separable subsystems [26]. Techniques for demonstrating group level behaviors are emerging from several disciplines [1, 33, 30, 29]. New analysis techniques are being developed in the psychology and organizational behavior literature [11, 47, 26] that focus on multiple levels of interaction between individuals. Evolutionary biology, likewise, is turning to multilevel selection theory [44, 40, 35] for explanations of anomalous behaviors such as altruism and sociality.

The theory of social situatedness [32, 39] recognizes that an individual requires a social and cultural environment to develop intelligence to have an arena within which to apply intelligence. Socially situated intelligence is becoming well represented, notably in AI and ALife literature [8, 28, 10, 41, 25]. These models often make use of Theory of Mind (ToM), where ToM is one agent's ability to perceive the thoughts of the other to some degree.

In Chapter 3 we investigate the effects of ToM on groups of agents in non-competitive settings, as opposed to the typical evolutionary system in which an agent can get an edge on another by predicting the other's actions. We study the dynamics of collective decision making with regards to various interaction protocols and various possibilities for mental model formation.

We created an ABM construct that simulated groups of individuals negotiating multidimensional optimization problems. Individuals each have imperfect information and are limited to local information retrieval. Through conversation individuals share information with each other and come to consensus on best solutions. As agents share information, however, focus closes in on the region of discussion leaving large regions in the problem space unexplored.

1.3 Evolution of an ecology of ideas

Similarly to the previous chapter, we address collective decision making again in Chapter 4. In this case, however, we focus on modeling both evolutionary dynamics and cognitive mechanisms of individuals in groups. Leadership, psychology and organizational behavior disciplines have studied collective dynamics of groups in decision processes, but they often fail to account for nonlinear processes, high-dimensional problem spaces and non-trivial social structure [26]. ABM is a well suited format for modeling such circumstances. Dynamical modeling studies have considered complex problem spaces [27], but not in addition to complex social interactions.

In Chapter 4 we model team decision making dynamics by simulating an evolving ecology of ideas in an environment described by the conversational propensities of team members. Several cognitive mechanisms are mapped to evolutionary mechanisms and are in this way applied to a progressive process of decision making. We use an ABM format in order to capture the complexity of individuals and their interactions. We demonstrate various evolutionary dynamics captured by various mixtures of propensities towards certain selective and creative actions.

1.4 References

[1] A. Acerbi and D. Parisi. Cultural transmission between and within generations. *Journal of Artificial Societies and Social Simulation*, 9(1), 2006.

[2] R. Axelrod. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton Univ. Press, Princeton, NJ, 1997.

[3] J. H. Barkow, L. Cosmides, and J. Tooby. *The Adapted Mind: Evolutionary Psychology and the Generation of Culture*. Oxford University Press, New York, 1992.

[4] E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(10):2780–7287, 2002.

[5] S. Bowles and H. Gintis. Homo reciprocans. *Nature*, 415:125–128, 2002.

[6] S. Bowles and H. Gintis. The evolution of strong reciprocity: cooperation in heterogeneous populations. *Theor. Popul. Biol.*, 65:17–28, 2004.

[7] R. Boyd, H. Gintis, S. Bowles, and J. Richerson. The evolution of altruistic punishment. *Proc. Natl. Acad. Sci.*, 100:3531–3535, 2003.

[8] R. A. Brooks, C. Breazeal, M. Marjanovic, B. Scassellati, and M. M. Williamson. The cog project: Building a humanoid robot. *Lecture Notes in Computer Science*, 1562:52–87, 1999.

[9] R. W. Byrne and A. Whiten. *Machiavellian Intelligence: Social Expertise and the Evolution of Intellect in Monkeys, Apes and Humans*. Oxford University Press, Oxford, UK, 1988.

[10] C. Castelfranchi. Modelling social action for ”ai” agents. *Artificial Intelligence*, 103:157–182, 1998.

[11] S. Dionne, H. Sayama, D. Farrell, and E. Carroll. Evolutionary perspective on group decision making: A within- and between-groups simulation. paper submitted, 2007.

[12] B. Edmonds, C. Hernandez, and K. G. Troitzsch. *Social Simulation: Technologies, Advances and New Discoveries (Premier Reference)*. Information Science Reference, Hershey, PA, 2007.

[13] O. T. Eldakar, D. L. Farrell, and D. S. Wilson. Selfish punishment: Altruism can be maintained by competition among cheaters. in revision process for the Journal of Theoretical Biology, 2007.

[14] J. M. Epstein and R. Axtell. Agent-based modelling: Understanding our creations. *The bulletin of the Santa Fe Institute*, pages 28–32, 1994.

[15] J. M. Epstein and R. L. Axtell. *Growing Artificial Societies: Social Science from the Bottom Up*. MIT Press, Cambridge, MA, 1996.

[16] E. Fehr. Don’t lose your reputation. *Nature*, 432:449–450, 2004.

[17] E. Fehr and U. Fischbacher. The nature of human altruism. *Nature*, 425:785–791, 2003.

[18] E. Fehr, U. Fischbacher, and S. Gachter. Strong reciprocity, human cooperation, and the enforcement of social norms. *Hum. Nat.Int. Bios.*, 13:1–25, 2002.

[19] E. Fehr and S. Gachter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[20] E. Fehr and S. Gaechter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[21] N. Gilbert. *Agent-Based Models*. Sage Publications, London, UK, 2007.

[22] H. Gintis. Strong reciprocity and human sociality. *J. Theor. Biol.*, 206:169–179, 2000.

[23] H. Gintis, S. Bowles, R. Boyd, and E. Fehr. Explaining altruistic behavior in humans. *Evol. Hum. Behav.*, 24:153172, 2003.

[24] D. Hales, J. Rouchier, and B. Edmonds. Model-to-model analysis. *Journal of Artificial Societies and Social Simulation*, 6(4), 2003.

[25] T. Ikegami and G. Morimoto. Chaotic itinerancy in coupled dynamical recognizers. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 13(3):133–1147, 2003.

[26] N. L. Kerr and R. S. Tindale. Group performance and decision making. *Annual Review of Psychology*, 55:623–655, 2004.

[27] M. Klein, P. Faratin, H. Sayama, and Y. Bar-Yam. Protocols for negotiating complex contracts. *IEEE Intelligent Systems*, 18(6):32–38, 2003.

[28] H. Kozima, C. Nakagawa, and H. Yano. Can a robot empathize with people? *International Journal "Artificial Life and Robotics"*, 8:83–88, 2004.

[29] J. S. Lansing. “artificial societies” and the social sciences. *Artificial Life*, 8:270–292, 2002.

[30] N. Lazaric and A. Raybaut. Knowledge creation facing hierarchy: the dynamics of groups inside the firm. *Journal of Artificial Societies and Social Simulation*, 7(2), 2004.

[31] R. E. Lenski, C. Ofria, R. T. Pennock, and C. Adami. The evolutionary origin of complex features. *Nature*, 423:139–144, 2003.

[32] J. Lindblom and T. Ziemke. Social situatedness and artificial intelligence: Vygotsky and beyond. *Adaptive Behavior*, 11(2):79–96, 2003.

[33] I. Lustick. Agent-based modelling of collective identity: testing constructivist theory. *Journal of Artificial Societies and Social Simulation*, 3(1), 2000.

[34] J. Maynard-Smith. Evolution and the theory of games. 1982.

[35] N. Nicholson. Evolutionary psychology: Toward a new view of human nature and organizational society. *Human Relations*, 50:1053–1078, 1997.

[36] R. T. Pennock. Models, simulation, instantiations, and evidence: the case of digital evolution. *Journal of Experimental and Theoretical Artificial Intelligence*, pages 1362–3079, 2006.

[37] D. Phan and F. Amblard. *Agent-Based Modelling and Simulation in the Social and Human Sciences*. The Bardwell Press, Oxford, UK, 2007.

[38] P. J. Richerson and R. Boyd. *Not By Genes Alone : How Culture Transformed Human Evolution*. University Of Chicago Press, December 2004.

[39] D. J. Siegel. *The Developing Mind: How Relationships and the Brain Interact to Shape Who We Are*. The Guilford Press, NewYork, 1999.

[40] E. Sober and D. S. Wilson, editors. *Unto others: The evolution and psychology of unselfish behavior*. Harvard University Press, Cambridge, MA, 1998.

[41] M. Takano and T. Arita. Asymmetry between even and odd levels of recursion in a theory of mind. In L. M. Rocha, L. S. Yaeger, M. A. Bedau, D. Floreano, R. L. Goldstone, and A. Vespignani, editors, *Artificial Life X: Proceedings of the Tenth International Conference on the Simulation and Synthesis of Living Systems*, Amsterdam, NL, 2006. The MIT Press.

[42] U. Visser and D. L. DeAngelis. A standard protocol for describing individual-based and agent based models. *Ecological Modeling*, 198:115–126, 2006.

[43] J. W. Weibull. *Evolutionary Game Theory*. MIT Press, Cambridge, MA, 1996.

[44] D. S. Wilson and E. Sober. Reintroducing group selection to the human behavioral sciences. *Behavioral and Brain Sciences*, 17(4):585–654, 1994.

[45] T. Yamagishi. The provision of a sanctioning system as a public good. *J. Pers. Soc. Psychol.*, 51:110–116, 1986.

[46] T. Yamagishi. Seriousness of social dilemmas and the provision of a sanctioning system. *Soc. Psych. Q.*, 51:32–42, 1988.

[47] F. J. Yammarino, S. D. Dionne, J. U. Chun, and F. Dansereau. Leadership and levels of analysis: A state-of the-science review. *The Leadership Quarterly*, 16:879–919, 2005.

Chapter 2

Selfish punishment: Altruism can be maintained by competition among cheaters

Published in the Journal of Theoretical Biology

Volume 249, Issue 2, 2007 Nov 21, Pages 198-205

Omar Tonsi Eldakar[1], Dene Leo Farrell[2], David Sloan Wilson[3]

[1]Department of Biological Sciences, Binghamton University, Binghamton, NY 13902-6000, USA [2]Department of Bioengineering, Binghamton University, Binghamton, NY 13902-6000, USA [3]Department of Anthropology, Binghamton University, Binghamton, NY 13902-6000, USA

Abstract

Altruistic punishment refers to a class of behaviors that deters cheating at a cost to the punisher, making it a form of second-order altruism. Usually, it is assumed that the punishers are themselves solid citizens who refrain from cheating. We show in a simulation model that altruism and punishment paradoxically become negatively correlated, leading to a form of selfish punishment. Examples of selfish punishment can be found in organisms as diverse as wasps, birds, and humans.

2.1 Introduction

Altruism is famously difficult to evolve because of potential exploitation by cheaters. Punishment can potentially deter cheating, but it often requires time, energy and risk. The term altruistic punishment refers to a class of behaviors that deters cheating at the expense of the punisher, qualifying as a form of second-order altruism in comparison to first-order altruists who do not punish [15, 13, 11, 4, 10, 16, 9]. The cost of punishing cheaters, along with the cost of being cheated, make it difficult to explain altruistic punishment as an evolutionary stable strategy [2, 3, 9]. This report suggests another way that altruism can be maintained; by cheaters who punish other cheaters.

The concept of selfish punishment was suggested to us by an empirical study on humans showing that individuals most likely to punish cheaters were also most tempted to cheat [7]. This seems hypocritical in moral terms but makes sense as a behavioral strategy because cheaters decrease the fitness of everyone in their groups, including other cheaters. A negative correlation between punishment and altruism might exist if cheaters have an even greater incentive than altruists to get rid of other cheaters. A few theoretical models have addressed this possibility [20, 24], but it needs to be explored more fully, especially in the context of the public goods games used by experimental economists to study the dynamics of cooperation in human social groups [12, 13, 16].

Our model suggests that when the propensity to cooperate and the propensity to punish are modelled as independent traits, a negative correlation between altruism and punishment robustly evolves, although the size of the correlation varies with parameters such as group size, duration of the group, and the cost of punishing others.

2.2 Methods

The program was implemented in Mathematica and is available from the authors upon request. We composed an N-person evolutionary game theory model that emulates one of the standard public goods games in experimental economics [12]. The model begins with an infinite population of individuals that vary in their propensity for altruism (A) and punishment (P). These traits are modelled as two variables that initially vary uniformly and independently between 0 and 1 at 0.1 increments. A large number (T) of groups of size N are formed at random. Members of each group play multiple rounds (R) of a two-phase public goods game. During phase 1, each individual is given an endowment (E) and allowed to contribute a proportion to a central fund, which is doubled and distributed equally to all members of the group. The remainder is retained by the individual at its initial value. Each individuals (i) altruism trait determines the proportion of its endowment that it contributes (A_i) and withholds $(1 - A_i)$. Individual payoffs at the end of phase 1 can be represented by Eq. (1), where the profits earned for a given individual (pay_i) is calculated by adding the individuals share of the public fund $2E(\sum_{j=1}^{N} A_j)/N$ to the portion of the endowment the individual selfishly withheld from group donation $E(1 - A_i)$. Individuals maximize their own payoff by withholding all of their endowment $(A = 0)$, but this strategy minimizes the payoff for the group, resulting in the classical prisoners dilemma situation:

$$pay_i = E(1 - A_i) + \frac{2E(\sum_{j=1}^{N} A_j)}{N} \tag{2.1}$$

During phase 2, individuals are allowed to contribute resources to detect and punish those who were stingy during phase 1 (the cheaters). Each individual is assumed to know the total contribution of other group members but not the contribution of each individual. Investing in punishment results in a probability that the least altruistic member of the group (other than oneself) will be detected and excluded from subsequent rounds of the game, to be replaced by another individual drawn randomly from the same population as the original members. This is biologically reasonable if we assume that not everyone can get into groups and that the remainder forms a waiting list for replacements. The fact that the replacements play fewer rounds than the original members is immaterial because they still contribute to fitness differentials in the total population, based on how they play the game during the remaining rounds.

The amount that an individual invests in punishment is based on three factors, as shown in Eq. (2). The first term (P_i) represents the individuals static punishment trait. The second term $(\sum_{j=1,j\neq 1}^{n-1} 1 - A_j)/(N-1)$ represents the average amount of cheating that took place among other members of the group. The third term (C) represents the amount required to detect the worst cheater with certainty:

$$punC_i = P_i \frac{\sum_{j=1,j\neq 1}^{n-1} 1 - A_j)}{(N-1)} C \tag{2.2}$$

A maximum of two individuals can be removed during any particular round of the game; the worst cheater, based on the efforts of the other group members, or the next worst cheater, based on the efforts of the worst cheater. The probability that the worst cheater will not be detected by a given member of the group i is

$$esc_i = 1 - P_i \frac{\sum_{j=1,j\neq 1}^{n-1} 1 - A_j)}{(N-1)} \tag{2.3}$$

The probability that the worst cheater will be detected and removed by any member of the group is

$$rem_{all} = (1 - \prod_{i=1}^{n-1} esc_i)D \tag{2.4}$$

where the worst cheater is not included in the calculation. The term D gives the probability that the cheater can be removed, once detected. When $D = 1$, the probability of detection is equal to the probability of removal. When $D = 0$ then removal is impossible, regardless of detection. The probability that the next worst cheater is removed is similar to Eq. (4), with only the worst cheater included in the calculation. The idea of the worst cheater removing the second worst cheater makes sense for two reasons. First, by removing the second worst cheater, the worst cheater reduces the amount of cheating perceived by the group, effectively weakening the strength of punishment (decreasing the middle term in Eq. (2)). Second, despite the punishment efforts of the group there remains uncertainty that the worst cheater will be banished. Therefore, by removing the next worst cheater, the worst cheater increases its likelihood of remaining in later rounds. The other $(N - 2)$ members are safe during a particular round of the game but can become vulnerable if replacements make them one of the worst two cheaters in subsequent rounds. After the game is played for a number of rounds (R) within each group and for a large number (T) of randomly formed groups, each individual is assigned a fitness based on its total earnings and a baseline fitness value (B), representing the fact that fitness is not determined entirely by the interactions that take place during the game. Fitness is then summed for each strategy-type accounting for both abundance and fitness, deriving a cumulative fitness value for each combination of altruism and punishment (121 types). These cumulative sums are then normalized to sum 1, representing the frequency of each strategy type following asexual reproduction in direct proportion to fitness, which become the new frequencies of the 121 types in the infinite population for the next round of group formation. It should be noted that asexual reproduction is interpreted loosely in terms of the replicator dynamic of evolutionary game theory, which includes any process that causes the most successful strategies to increase in frequency in the population [14].

Table 2.1: List of model parameters and default values

Variable	Baseline value	Definition
A	(0-1) at 0.1 increments	Proportion of endowment allocated to the group fund
C	40	Maximum cost of punishment
D	0.5	Efficiency of removal of a cheater upon detection
E	50	Resources allocated to each player at the beginning of each round of play
M	10^{-4}	Mutation rate
N	4	Group size
P	(0-1) at 0.1 increments	Propensity to punish
R	6	Number of rounds played per generation
T	10^{4}	Number of groups per simulation

Mutations in the altruism and punishment traits were assumed to occur with a frequency of (M) and took place during the asexual reproduction stage. In one set of simulations, a type was assumed to mutate into any other type with equal probability, resulting in all types potentially being present in the population at a low frequency. In another set of simulations, mutations were assumed to deviate by a value of ± 1, which means that a given type could be completely absent from the population.

Simulations were run with 2 alternate scenarios of initial population frequencies. The first began with all combinations of the altruism (A) and punishment (P) traits in equal proportions. The second began with the population fixed for $A = 0$ and $P = 0$ to see if altruism and punishment could evolve from mutation frequencies.

To summarize (1) Groups are most productive when everyone invests their entire endowment, (2) in the absence of punishment, individuals are most productive within each group when they withhold their own investment; (3) punishment can cause cheating to become disadvantageous; (4) punishment is costly for the punisher; and (5) the altruism and punishment traits are initially uncorrelated. Our prediction is that a negative correlation (cheaters more likely to punish) will develop on the basis of the model dynamics. The parameters and their default values are listed in Table 1.

2.3 Results

2.3.1 Initial conditions

A representative simulation run with the initial population consisting of an even distribution of all possible combinations of altruism and punishment is shown in Fig. 1 (see legend for parameter values). The most stingy individuals are quickly removed from the population by punishment (generation 20), followed by the elimination of most punishers due to the cost of punishment (generation 50). Variation in both the altruism and punishment trait is maintained at equilibrium, with a negative correlation between the two traits representing a stable equilibrium of altruistic non-punishers and selfish punishers, as we predicted (generation 100). Fig. 2 shows that the equilibrium is maintained over the long term, although coupled oscillations between the frequencies of the two traits and their covariance take place over shorter time scales. Unlike altruistic punishers, selfish punishers possess the ability to recoup the cost of punishment through their exploitation of altruists within groups.

Fig. 3 shows a comparable run in which the initial population consists entirely of selfish non-punishers $(A = 0, P = 0)$. Remarkably, the same equilibrium is established, although a large number of generations is required. If the capacity for punishment is eliminated by setting D to zero, altruism does not evolve from this starting point. To see how selfish punishment promotes the evolution of altruism, consider a single selfish punisher in a given group. By expelling the most selfish individuals, which are replaced by randomly chosen

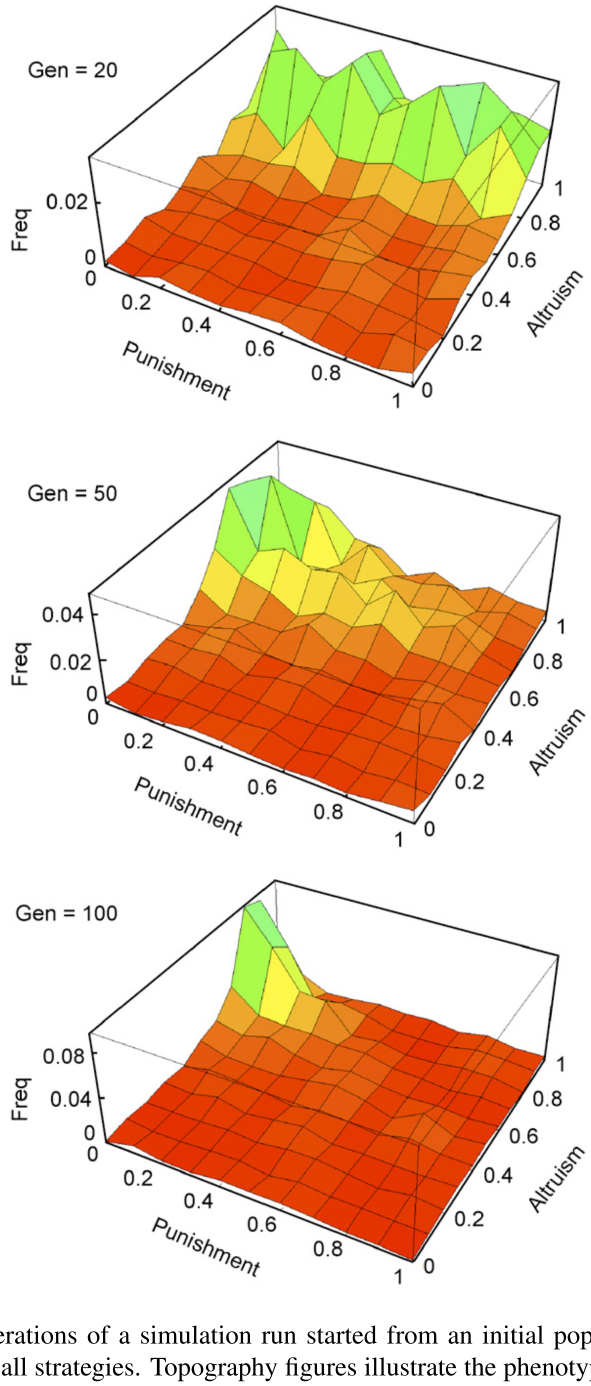


Figure 2.1: Selected generations of a simulation run started from an initial population composed of even population distribution of all strategies. Topography figures illustrate the phenotypic distribution of the population, demonstrating the reduction of cheaters (generation 20), then the reduction of altruistic punishers (generation 50), and a negative correlation between altruism and punishment at equilibrium (generation 100). This run consisted of 1000 groups of $N = 4$ individuals created at random from the total population every generation. Within each group, the game was played for $R = 6$ rounds. The maximum cost of detecting and excluding a cheater was $C = 80$ % of ones endowment and the efficiency of removal of a cheater upon detection was $D = 0.5$.

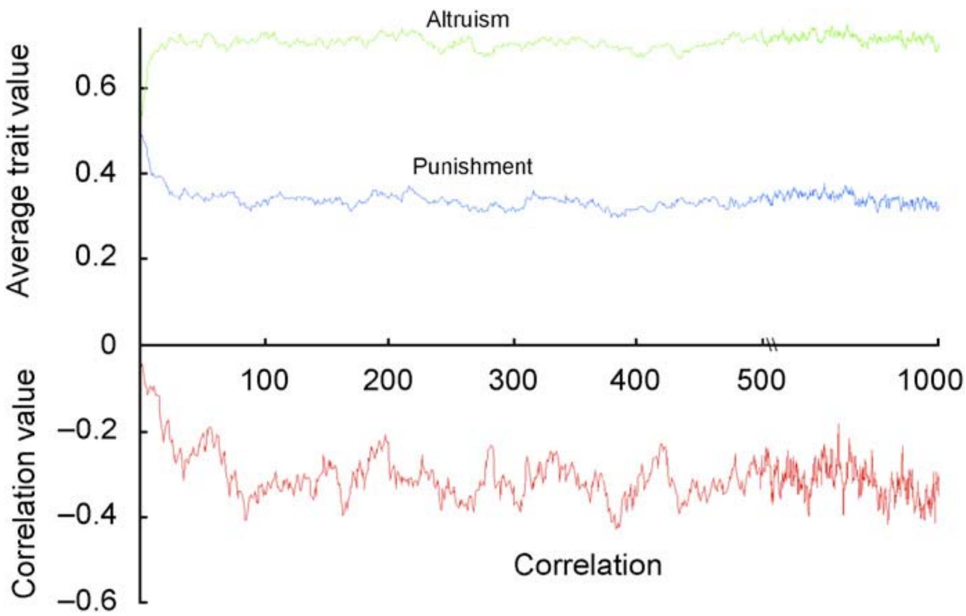


Figure 2.2: Time-series graph of a selected simulation showing the average trait values of the population for altruism and punishment over 1000 generations along with the emerging negative correlation between the two traits. Parameter values are the same as Fig. 1.

members of the total population, the punisher increases the average degree of altruism within the group. Altruists now benefit from each other and the selfish punisher recovers the cost of punishment by exploiting the altruists during subsequent rounds. Of course, this will only work if there is a sufficient frequency of altruists in the total population. Although the simulation run begins with $A = 0$, a mutation rate of $M = 10^{-4}$ results in a selectionmutation balance of approximately 7 % of the population with $A > 0$, which is sufficient for the concentrating effect of punishment to take place. A large number of generations is required for the selectionmutation balance to establish itself, accounting for the time required for altruism to evolve in Fig. 3. An implication is that altruism will not evolve from a starting point of $A = 0$ when the mutation rate (M) is sufficiently low or the cost of punishing (C) is sufficiently high, which we will demonstrate below.

Now that we have described the dynamics of the model during a single simulation run, we will vary single parameters of the model while keeping the others at their default values (shown in Table 1 and Fig. 1).

2.3.2 Cost of punishment

The cost of punishing others is modelled by the parameter C, which represents the proportion of the endowment that is required to detect a cheater with certainty. Fig. 4 shows that the equilibrium levels and altruism and punishment decline as C is increased, although they remain at moderate levels even at the highest value of C. The lower part of Fig. 4 shows that the correlation between the altruism and punishment is close to zero when punishing others is nearly cost-free, but becomes increasingly negative when punishing others becomes costly. Thus, our model suggests that the concept of selfish punishment is especially relevant when punishing others is costly.

2.3.3 Group size

The equilibrium levels of altruism and punishment also decline with group size (Fig. 5), although remaining at moderate levels even at the highest value tested. The negative correlation between altruism and punishment reaches its lowest value at a value of $N = 7$ and then rises slightly. These trends reflect a number of factors. When $N = 2$, the concept of a public good is not applicable because an individual must punish if there is to be any punishment of its single partner. At high values of N, the capacity to punish is limited by round length. Only a maximum of two cheaters can be removed during each round, which means that when group size exceeds round length, intermediate cheaters are immune to punishment.

2.3.4 Round length

When groups exist for only a single round of play, punishment cannot maintain altruism and both traits go to zero, except for mutations, as shown in Fig. 6. The positive correlation between the two traits when $R = 1$ is based on the fact that most individuals have values of zero for both traits while a few (the mutants) have positive values of both traits. Punishment becomes increasingly effective at maintaining cooperation as round length increases. At the highest value of R tested, an average value of approximately 0.4 for the punishment trait maintains altruism at close to its maximum value. Round length has an indirect effect on the cost of being punished and the benefits of excluding cheaters from ones group. When cheaters are excluded from their group, they keep their earnings but sit out the remaining rounds of the game. This cost becomes increasingly severe as R increases, especially relative to those who remain in the game. Thus, increasing R is similar to decreasing the cost of punishing cheaters, causing the correlation between altruism and punishment to decrease, as in Fig. 4.

2.3.5 Mutations

For simulations that began with an equal distribution of all types, model results were not affected by the two assumptions about mutations within the range of $M = 10^{-2}$ - 10^{-7}. For models that began with $A = 0$, $P = 0$, a sufficiently small mutation rate (given either assumption) can prevent the frequency of altruists at mutationselection balance from achieving the threshold required for the concentrating effect of punishment to take place. Similarly, when the cost of punishment is increased (C), a corresponding increase in mutation rate is required for altruism to evolve from a mutation frequency.

2.4 Discussion

Punishing others requires time, energy, and risk, just like any other trait. In dyadic interactions, the costs and benefits of punishing a cheater can be calculated in a straightforward fashion because the punisher is the sole beneficiary of the punishment [5]. In larger groups, the benefits of punishment are shared by other members of the group who do not share the costs, creating a public goods problem that increases with the cost of punishing others. The proverbs It takes a thief to catch a thief and there is no honor amongst thieves imply that no one is better at finding a cheater than another cheater and that cheaters themselves interact competitively. Cheaters might have a number of special advantages for detecting and excluding other cheaters, such as familiarity with cheating strategies or experience at fighting. These special advantages are not included in our model. Instead, we made the conservative assumption that altruism and punishment are separate and (initially) uncorrelated traits. An extreme altruist is just as capable of detecting and excluding cheaters as an extreme cheater. Nevertheless, a negative correlation between the altruism and punishment traits robustly develops based on the model dynamics.

One way to interpret selfish punishment is as an entirely selfish strategy whereby cheaters maintain and protect flocks of cooperators for their own advantage, similar to the way that the mafia offers protection for a price. Alternatively, selfish punishment can be regarded as a division of altruistic labor, with some individuals providing the first-order public good of cooperation and others providing the second-order public good of punishment, similar to the way that human communities support a police force. Division of labor evolves because altruistic punishers suffer a double cost whereas selfish punishers in the same group are compensated for the cost of punishment by being exempted from cooperation during the first round. Regardless of how it is interpreted, selfish punishment can cause altruism to evolve and be maintained at a high frequency without the problems usually associated with altruistic punishment. There is a threshold frequency of altruism that must be crossed before altruism can be positively selected, but it is sufficiently low that mutationselection balance is sufficient, at least for certain combinations of M and C. See Wilson and Dugatkin (1997) for a discussion of the problem of origination for the evolution of altruism in models that assume quantitative variation vs. discrete traits.

The correlation between selfishness and punishment becomes increasingly strong as the cost of punishing others (C) increases. Examples of low-cost punishment in human social interactions include gossip and collective decisions that cannot be opposed because the group is so much stronger than any particular individual (see Sober and Wilson, 1998, Chapter 5 for ethnographic examples from a random sample of cultures). In these cases, punishment and altruism should remain uncorrelated. The effects of group size and round length can also be interpreted in terms of public benefits and private costs. Increasing group size makes punishment ineffective because at most only one cheater can be removed during each round of the game. Increasing round length enables more cheaters to be excluded and increases the differential between those who are excluded and those who remain.

Nakamaru and Iwasa (2006) model of selfish punishment considers four discrete strategies; altruistic punisher (AP), altruistic non-punisher (AN), selfish punisher (SP) and selfish non-punisher (SN). The interactions are dyadic and punishment causes ones selfish partner to pay a fine at an expense to the punisher. Individuals exist on a two-dimensional lattice and interact either with their four nearest neighbors (lattice model) or with four individuals chosen at random from the total population (completely mixing population). In both cases, individuals compete with their four nearest neighbors based on their payoffs, either in terms of survival (score-dependent viability model) or reproduction (score-dependent fertility model). The SP strategy can invade and persist in some of these conditions but not others. As in our model, it can facilitate the evolution of altruistic strategies by virtue of its negative effect on other punishers.

Our model allows gradations of altruism and punishment, assumes interactions in randomly formed groups of size N rather than dyadic interactions on a lattice, and is intended to emulate the public goods games that experimental economists use to study altruism and punishment in human social interactions. Given these assumptions, we observe a robust negative correlation between altruism and punishment, although the magnitude of the correlation varies with the parameter values. Obviously, these two models only begin to explore the different kinds of social settings and population structures in which selfish punishment might exist as a successful behavioral strategy [21, 23, 24].

Considerable evidence for altruism maintained by competition among selfish individuals exists for nonhuman species, from insects to vertebrates. Wenseleers et al. describe a corrupt policing strategy in tree wasps Dolichovespula sylvestris, where workers that police other workers lay their own eggs [25]. Scrub jays that tend to steal caches from other scrub jays are also more defensive of their own caches [8]. In addition to our empirical study on humans that inspired our simulation model [7], the history of medieval knights provides a potential historical example of selfish punishment. Much as the knights of old are revered in mythology and popular culture, the first Castellans are better described as selfish thugs who fought among themselves to exploit the defenseless, and therefore altruistic, peasants [1]. As Pope Gregory VII put it during the 11th century (quoted in Bisson, 1994, p. 42), Who does not know that kings and princes derive their origin from men ignorant of God who raised themselves above their fellows by pride, plunder, treachery, and murder?

In this human example and many non-human examples, the dynamics of altruism and punishment are complicated by power asymmetries such as social dominance [5, 6, 17, 18, 19, 22]. Our model shows that selfishness and punishment can become correlated even in the absence of power asymmetries and other factors that give cheaters an intrinsic advantage in punishing other cheaters.

2.5 Acknowledgements

We thank A.B. Clark, C. Laramee, D. Smail, T. Wenseleers, N. Prince and members of EvoS, Binghamton Universitys Evolutionay Studies Program, for helpful discussion.

2.6 References

[1] T. N. Bisson. The feudal revolution. *Past Present*, 142:6–42, 1994.

[2] S. Bowles and H. Gintis. Homo reciprocans. *Nature*, 415:125–128, 2002.

[3] S. Bowles and H. Gintis. The evolution of strong reciprocity: cooperation in heterogeneous populations. *Theor. Popul. Biol.*, 65:17–28, 2004.

[4] R. Boyd, H. Gintis, S. Bowles, and J. Richerson. The evolution of altruistic punishment. *Proc. Natl. Acad. Sci.*, 100:3531–3535, 2003.

[5] T. H. Clutton-Brock and G. A. Parker. Punishment in animal societies. *Nature*, 373:209–216, 1995.

[6] F. B. M. de Waal. Integration of dominace and social bonding in primates. *Q. Rev. Biol.*, 61:479–549, 1986.

[7] O. T. Eldakar, D. S. Wilson, and R. O'Gorman. Emotions and actions associated with altruistic helping and punishment. *Evol. Psychol.*, 4:274–286, 2006.

[8] N. J. Emery and N. S. Clayton. Effects of experience and social context on prospective caching strategies by scrub jays. *Nature*, 414:443–446, 2001.

[9] E. Fehr. Don't lose your reputation. *Nature*, 432:449–450, 2004.

[10] E. Fehr and U. Fischbacher. The nature of human altruism. *Nature*, 425:785–791, 2003.

[11] E. Fehr, U. Fischbacher, and S. Gachter. Strong reciprocity, human cooperation, and the enforcement of social norms. *Hum. Nat.Int. Bios.*, 13:1–25, 2002.

[12] E. Fehr and S. Gachter. Cooperation and punishment in public goods experiments. *Am. Econ. Rev.*, 90:980–994, 2000.

[13] E. Fehr and S. Gachter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[14] H. Gintis. *Game Theory Evolving*. Princeton University Press, Princeton, NJ, 2000.

[15] H. Gintis. Strong reciprocity and human sociality. *J. Theor. Biol.*, 206:169–179, 2000.

[16] H. Gintis, S. Bowles, R. Boyd, and E. Fehr. Explaining altruistic behavior in humans. *Evol. Hum. Behav.*, 24:153172, 2003.

[17] L. A. Giraldeau and T. Caraco. *Social Foraging Theory*. Princeton University Press, Princeton, NJ, 2000.

[18] S. Kim. For whom do we reciprocate? the effects of dominance relationships on the use of incentives in collective action. Unpublished manuscript, 2006.

[19] T. Monin and F. L. W. Ratnieks. Policing in queenless ponerine ants. *Behav. Ecol.*, 50:90–108, 2001.

[20] M. Nakamaru and Y. Iwasa. The coevolution of altruism and punishment: role of the selfish punisher. *J. Theor. Biol.*, 240:475–488, 2006.

[21] M. E. Price, L. Cosmides, and J. Tooby. Punitive sentiment as an antifree rider psychological device. *Evol. Hum. Behav.*, 23:203–231, 2002.

[22] L. M. Ruttan and M. B. Mulder. Are east african pastoralists truly conservationsits? *Curr. Anthropol.*, 40:621–652, 1999.

[23] M. Shinada, T. Yamagishi, and Y. Ohmura. False friends are worse than bitter enemies: altruistic punishment of in-group members. *Evol. Hum. Behav.*, 25:379–393, 2004.

[24] K. Sigmund, C. Hauert, and M. Nowak. Reward and punishment. *Proc. Natl. Acad. Sci.*, 98:1075710762, 2001.

[25] T. Wenseleers, A. Tofilski, and F. K. W. Ratnieks. Queen and worker policing in the tree wasp dolichovespula sylvestri. *Behav. Ecol. Sociobiol.*, 58:80–86, 2005.

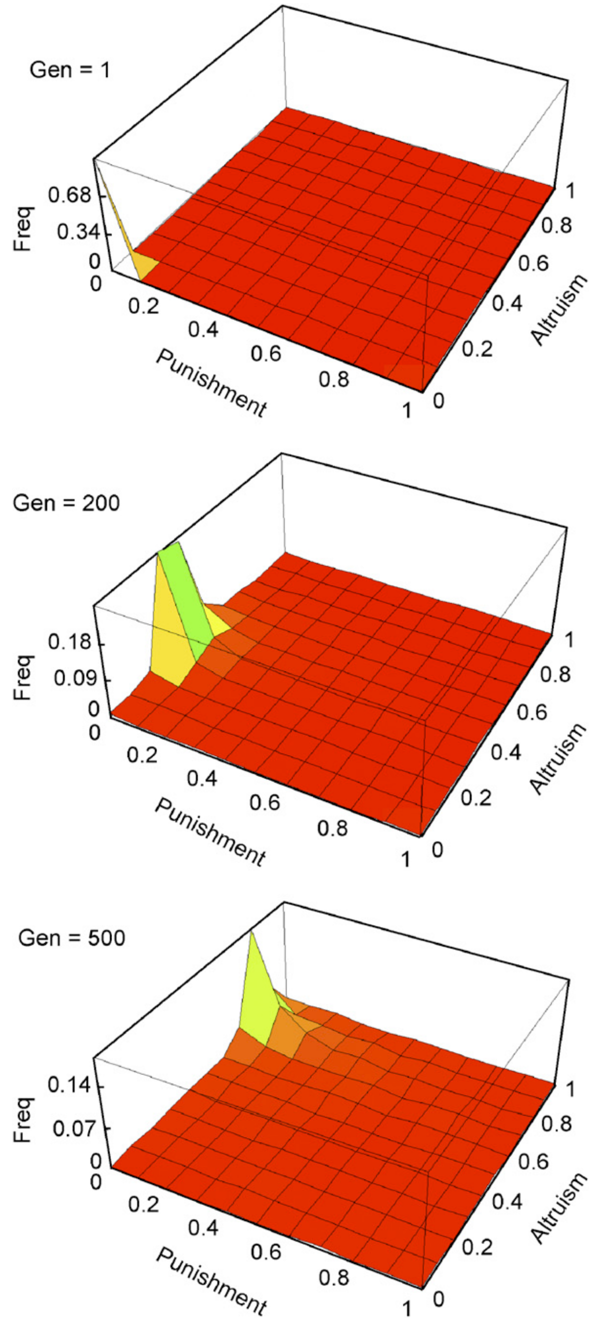


Figure 2.3: Selected generations of a simulation run started from an initial population composed of only the selfish non-punishing strategy. Topography figures illustrate the phenotypic distribution of the population, starting from the initial selfish non-punisher distribution (generation 1), then the increase of altruism in the population (generation 200), and the further increase of altruism (generation 300) until reaching a stable equilibrium depicted in Fig. 1. This run consisted of 1000 groups of $N = 4$ individuals created at random from the total population every generation. Within each group, the game was played for $R = 6$ rounds. The maximum cost of detecting and excluding a cheater was $C = 80\%$ of ones endowment and the efficiency of removal of a cheater upon detection was $D = 0.5$.

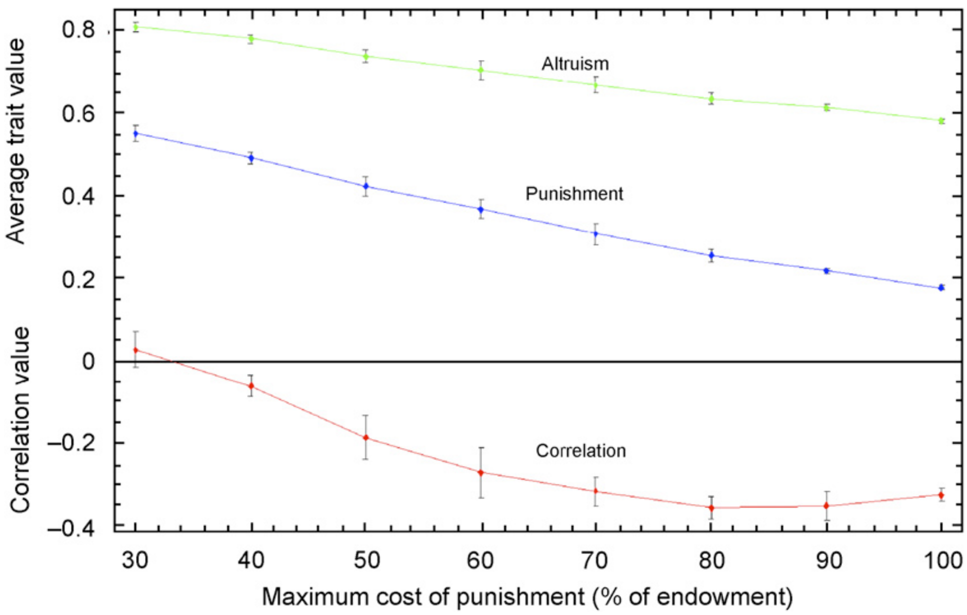


Figure 2.4: The average correlation between altruism and punishment as the cost of detecting and excluding cheaters (C) increases. Error bars indicate the range of five replicate simulations for each set of parameter values. A low cost indicates that the maximum probability of detecting and removing a cheater can be achieved with a low proportion of ones endowment. Within this range, the amount that an individual invests is based on the value of its punishment trait and the amount of cheating that took place during phase 1 of the game. Other parameter values are the same as Figs. 1 and 2.

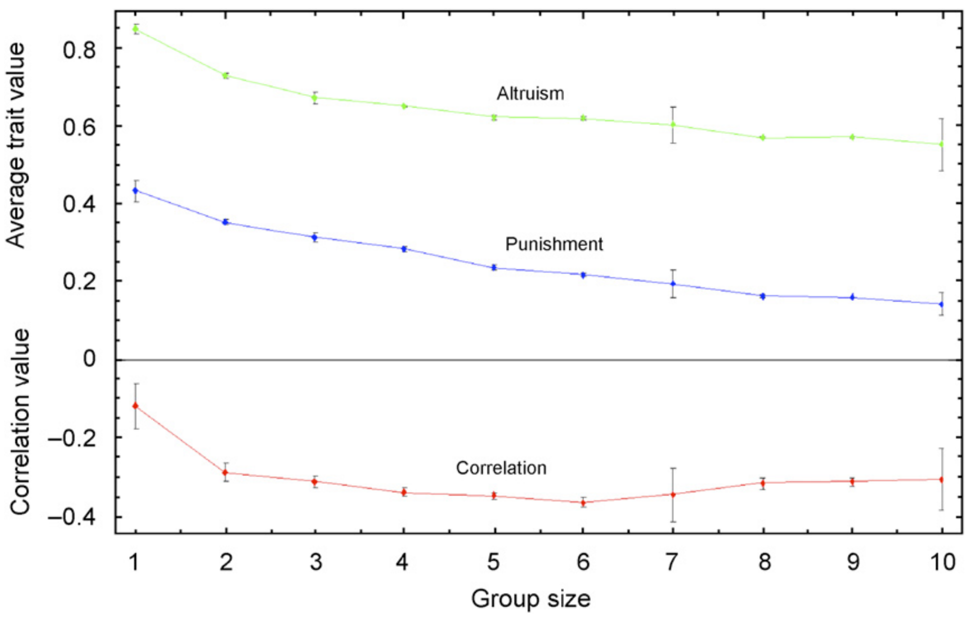


Figure 2.5: Levels of altruism and punishment decline however remain at moderate levels when increasing group size (N). The correlation between altruism and punishment declines with group size until its maximum value at group size $N = 7$ then begins to raises slightly. Error bars indicate the range of five replicate simulations for each set of parameter (N) values. Other parameters values are the same as Figs. 1 and 2.

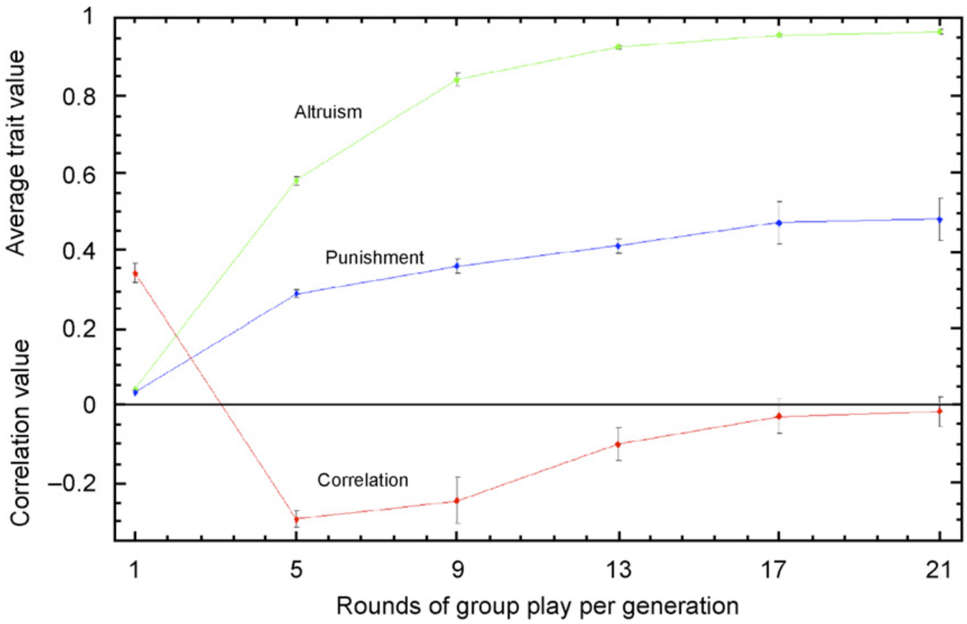


Figure 2.6: Levels of Altruism and punishment increase with increasing the number of rounds (R) of group play per generation. Altruism and punishment levels at parameter value $R = 1$ indicate that both cooperation and punishment are unsuccessful in one-shot games. These values increase in simulations of successively longer iterated games. The correlation between altruism and punishment approaches zero with increasing rounds of group play indicating less overall punishment (see text for explanation indirect effect of round length on punishment costs). Error bars indicate the range of five replicate simulations for each set of parameter (R) values. Other parameters values are the same as Figs. 1 and 2.

Chapter 3

The effects of mental model formation on group decision making: An agent-based simulation

Published in Complexity

Volume 16, Issue 3, January-February 2011, Pages: 49-57

Hiroki Sayama[1], Dene Farrell[1], Shelley D. Dionne[2]

[1]Department of Bioengineering, Binghamton University, Binghamton NY, 13902-6000

[2]School of Management, Binghamton University, Binghamton NY, 13902-6000

dfarrel1@binghamton.edu, sayama@binghamton.edu

Abstract

To identify limitations to group level intelligence and propose possible solutions, we investigate dynamics of group decision making processes on complex problems when individuals are capable of forming mental models of others based on the history of the group discussion. Our results suggest a counter-intuitive possibility that as the capacity of memory increases, the amount of information sharing may decrease far below the entire problem space. This is due to premature convergence of group discussion on a particular solution; incorporating knowledge from others into one's own world view creates a local agreement, leaving

unexplored diversities beyond the scope of discussion. The mechanisms stifling group level exploration and possible protocols for overstepping local optima are discussed.

3.1 Introduction

Problem solving in the 21st century increasingly draws on indivisible group efforts to address issues that are neither individual sized nor reducible to separable subsystems [8]. Collaborations no longer express additivity. Forming appropriate interaction architectures and protocols for groups has become a problem rivaling the original goals around which groups are formed. Mainstream, traditional science has tended to either focus on individuals as unique and separate, or on populations as probabilistic, leaving a large range of group behaviors neglected, much like newtonian mechanics and statistical mechanics fail to capture physical systems displaying organized complexity [23]. The appropriate response to both epistemological dilemmas has been to reevaluate the extents to which ordinary analytical methods and assumptions have been effective and develop new methodologies capable of addressing the unexplored range of behaviors.

A wave of innovative techniques for analyzing and demonstrating group level behavior is flooding the literature from several disciplines. Artificial societies science is a vanguard pioneer of group level intelligence, mapping out imaginative, theoretical [1, 14]; realistic, applied [12]; and paradigm widening, possibilistic [11] angles. Other areas such as organizational behavior [6, 26] and psychology [8] are showing renewed interest in multilevel analysis of group behavior; while some disciplines such as evolutionary biology [24, 20] and evolutionary psychology [16] have made regular use of mulitilevel selection theory as an explanatory implement for seemingly anomalous behavior such as altruism and sociobioloigal complexity.

Since the current extent of research grows rapidly and it is difficult to track and maintain historical and interdisciplinary coherence, it is instructive while developing methodologies to pay mind to the current cultural backdrop in which research is conducted. Common mistakes and overlooked opportunities reveal themselves readily and imminent issues to be addressed stand out more clearly.

Most techniques used to study intelligence share common limits due to underlying assumptions. It has been generally assumed that individuals can be addressed as separate pieces, each measured by some universal metric. It is worth noting that many popular general intelligence measures unequivocally have and continue to serve segregating and hegemonistic purposes [15]. In couching the framework of some group problem solving circumstance, in which the assumption of separability of actors is false, i.e. there is some amount of inherent socio-complexity, approaches treating individuals as interchangeable are neither useful nor feasible.

An alternative perspective considers the very idea of intelligence as rooted in collective phenomena. The concept has been developed in theories of social situatedness [13, 19] recognizing that an individual requires a social and cultural embedding to develop and display intelligence, and evolutionary social intelligence theory [3] that credits an environment of evolutionary adaptedness with inter-individual interaction as not only a necessary entailment of social interactions themselves, but the prime cause and basis of complex intelligence in humans.

Since the field of artificial societies is relatively new itself [17] there remains a scarcity of models representing sociality as a generative and central component of intelligent systems rather than an epiphenomenon [18] or teleological basis [5]. And, although the idea of socially situated intelligence is hardly novel [22], it is just recently claiming much interest in the sciences of the artificial, notably in AI and ALife communities both explicitly [2, 10, 4] and implicitly in models that explore collective behavior in groups of agents capable of Theory of Mind (ToM) [21, 7], where ToM may be defined as the ability to perceive another's intention to some extent.

ToM is typically associated with competitive settings. While the work cited above concerns coordinated behavior, evolutionary selection algorithms still pit agents against each other in a competition to reproduce and prolong existence into successive generations. In this context, ToM and joint attention are not directly applied to form a collaborative understanding of some mutual information, but rather to incite a group behavior that depends on a recursion of competitive feedback, which benefits all agents involved in a successful event.

Here we explore the relatively neglected area of entirely non-competitive constructs. Specifically, we address the problem of describing dynamical group decision making processes with respect to differing sets of interaction protocols. We present a model that simulates agents attempting to navigate multi-dimensional, continuous problem spaces9 with incomplete information of the world and each-other, and localized information retrieval from their own memories. As such, the formation of group cohesion does not develop from coincidental similarities, but arises from dynamic interactions of a heterogeneous mixture of actors, where commonalities of perception evolve out of redundancies in interactions.

Our results suggest a limitation to a group's exploration of a problem space as a consequence of recording previous discussion and mental model formation of others. Discussion becomes repetitive, addressing a limited scope of the problem space, within which individual models display within group homogeneity. Exploring hidden information in the regions beyond the scope of discussion becomes a nontrivial problem for groups demonstrating mental model formation. Some solutions in the past have been to separate agents in order that they not bias each other. For complex problem solving such methods are not plausible due to a non-decomposability of tasks. We suggest possible protocols of interaction for enhancing the problem space exploration while maintaining group structure and cohesion.

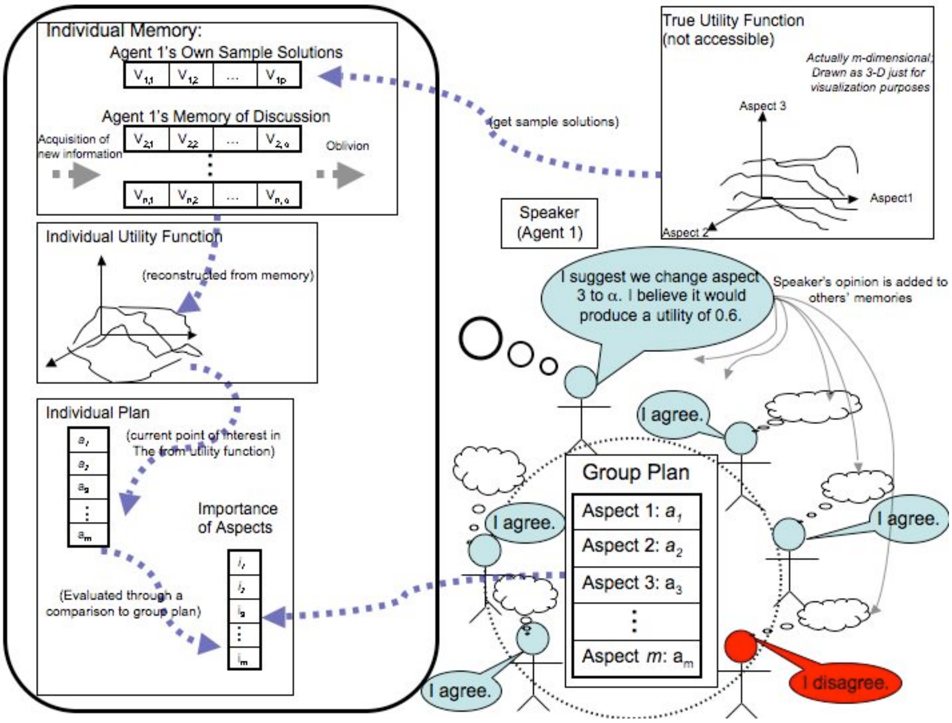


Figure 3.1: A schematic illustration of the model. A group consisting of n agents is lead in discussion by a speaker, while the role of which alternates cyclically at each round. There exists some true utility function (upper right inset) for which the group is tasked with maximizing. Individuals reconstruct models of the utility function with sample points and memory of information discussed by other individuals (upper left inset). $v_{1,j}$ $(j = 1, 2, ...p)$ denote sample points created separately for each individual at initialization. $v_{i,j}$ $(i = 2, 3, ...n, j = 1, 2, ...q)$ denote sample points acquired through discussion. p and q are the number of sample points at initialization and the capacity for memory, respectively. The oldest sample points are omitted as the new are included if capacity has been filled. With the individual utility function an agent performs a local search for optima, producing an individual plan with a specific value for each aspect of the problem, a_1 ... a_m. When considering which aspect to propose for incorporation into the group plan a speaker compares the expected difference in utility for each aspect. Proposals promising higher utility are ranked with higher importance values. The resulting list of relative importance values is a probability distribution for deciding on the aspect to be proposed, i_1 ... i_m. After a proposal individuals record the suggested plan as a point in their memory and vote on its acceptance to the group plan.

3.2 The Model

3.2.1 Overview

We present a model for illuminating the obstructive effects of mental models in relation to harnessing collective intelligence for complex tasks. We investigate group decision-making where individual actions derive from hardwired intelligence and circumstantial conditions. We charge groups with the task of solving multi-dimensional optimization problems. Individual perception of the problem space is unique, incomplete, noisy, and localized. One group solution, alterable only by a group consensus, coexists with individual solutions.

A schematic illustration of the model is shown in Figure 1. A group consisting of n individuals discusses a solution to an optimization problem in m dimensions. Each individual has a model of a true utility function reconstructed from sample points that may be either uniquely their own or gained through discussion. At the initialization of a group, each individual extracts p random sample points from the true utility function distorted by some noise, η, where the boundary conditions of $\eta \in [0, 1]$ describe pure fidelity and random noise. With the sample points they interpolate a model. Throughout discussion, proposals are recorded in the memories of others creating a secondary, dynamic source of sample points.

There exists one group solution and separate individual solutions. Each individual maintains a location in the problem space as their own solution. Individual solutions may be modified by adapting a proposal or by local searches spanning a small fraction of the entire space. Proposals address a single aspect in one of the m dimensions. When speaking to the group an agent ranks the importance of various aspects by comparison to the group plan. Those which would improve the utility of the plan are ranked highest.

A group votes on the acceptance of a proposal with some consensus function. If a large enough portion of the group agrees, then the group solution is modified by adopting the proposal. Individuals may accept proposals to change the group plan while not adopting the suggestion themselves if the difference between speaker and listener solution preferences are near in the problem space. If a listener adopts the speaker's proposal by adjusting their own solution however, it is assumed that they accept the proposal for the group plan as well.

3.2.2 Problem Space

Groups of n individuals form a model of their environment and attempt to decide on a single optimal plan. The environment is a multi-dimensional, nonlinear utility function that is only partially visible to individuals at a single point in time. Navigating the problem space entails searching in each dimension for a maximal solution. The utility function is a summation of a set of orthogonal sinusoids in *m* dimensions:

$$f(x_1, ..., x_m) = \sum_{i=1}^{m} \sum_{j=1}^{k} sin(\omega_j x_i) \tag{3.1}$$

where k is the number of superposed frequencies in a single dimension and frequencies are randomly generated such that $\omega_j \in [0, 50]$. The function, f, is normalized within the range of [0,1]. Agents are charged with the task of finding the maximal solution to f, for which they initially receive a limited set of randomly selected sample solutions.

3.2.3 Mental Model Formation

A mental model is created with an interpolating algorithm using inverse squared distances for localized weighted averages:

$$f'(v_u) = \frac{\sum_{\text{for all } i,j} f(v_{i,j}) \|v_{i,j} - v_u\|^{-2}}{\sum_{\text{for all } i,j} \|v_{i,j} - v_u\|^{-2}} \tag{3.2}$$

where the set of known solutions is used to guess the utility at some space vector, v_u.

In addition to existing in a common environment, agents share information about their own models through discussion. Speakers report their current proposal and the related utility value expected. Listeners save this information and treat it as one of their own sample points if they are assigned with a capacity for memory, $q \in \mathbb{N}$, that denotes the number of points shared in discussion an agent will remember for each other agent. q is the main parameter of interest in the results presented here.

If the process of sharing data is iterated, recursive models emerge that are similar to the behavior demonstrated by Theory of Mind [21, 7]. Since an agent models the environment with all points included in their memory, subsequent models are blends of the previous models of all members of a group. The iterative combination of models leads to a nontrivial reformation of all models and some amount of homogeneity within a limited region. Even for the case of a single memory space for discussion infinite recursion is realized through a continuous chain of hysteresis from one statement to the next.

3.2.4 Group Interactions

Individual and group solutions are randomly localized in the solution space. A round of group interactions is a sequence of events:

1. Individual, localized searches
2. Discussion of and potentially the altering of the group solution
3. Altering of individual solutions in response to shared information

We assume a human-like predicament of shortsightedness: in addition to having incomplete information, a single agent at any point in time may sweep only a tiny fraction of their own, modeled solution space. The scope of a local search, where s is the diameter of the space searchable, is confined to a small fraction of the entire problem space. Theoretically an individual might hill-climb across the entire space in a dimension within a single simulation.

Following local optimization, a speaker is randomly selected to discuss a single component of the group solution. In order to decide on a topic to discuss, individuals may rank each component of their m-dimensional solution as it separately relates to the plan. An expected change of utility to the group plan is calculated for each possible proposal, comparing utility values for of each potential plan with respect to the speaker's model. The topic of the proposal is chosen probabilistically in proportion to the relative expected increase of utility to the plan.

The speaker suggests some change in a certain dimension, m_i, to the existing plan, whereupon the remaining members vote as to acceptance or rejection of the change. There are two avenues for acceptance manifested in individual and social decisions. Individuals compare the suggested location to their current solution by way of their own model. If it appears to be a better solution they adopt the strategy themselves and as a modification to the group plan. In the case of an inferior suggestion an individual may still accept a proposal with some probability related to nearness to their own plan. The following is the algorithm performed when generating a decision for each listening group member:

Algorithm 3.2.1: ACCEPTQ(s_p, s_a)

---

if $f(s_p) - f(s_a) > 0$

then $\begin{cases} \text{Accept} \\ s_a \leftarrow s_p \end{cases}$

else if $r < e^{-(\Delta D^2)/T}$

then Accept

---

where s_p and s_a represent the proposed and an agent's own plan, respectively, r is a random number in [0,1], ΔD is the distance between the two plans, $\|s_p - s_a\|$, and T is a function of the time analogous to the temperature in an annealing system as described below. The *then* clause is executed in the case of both individual and social acceptance, otherwise the *else if* clause demonstrates the probability with which an individual accepts a proposal socially, while maintaining their own solution.

A group consensus is created from the set of votes by means of a parameterized fractional value. An accepted proposal is fully enacted, shifting the group solution for future discussion, otherwise no change is made.

3.2.5 Simulated Annealing

It has been demonstrated that time-differentiated exploration of a solution space for complex, multifaceted problems results in significantly superior results for pairs of semi-antagonistic agents attempting to negotiate mutually optimal contracts in comparison to paired hill-climbing strategies [9]. We implement a version of the simulated-annealing protocol pertinent to group dynamics. Simulated annealing facilitates a wide exploration of the solution space, while maintaining the general structure of a goal oriented group. The probability of an individual accepting a proposal socially is an exponential function of the distance from their own solution preference and the temperature:

$$\text{P(Accept)} = e^{(-\Delta D)^2/T} \tag{3.3}$$

where ΔD is the distance of their own position from a suggested solution as it is described in Algorithm II.1, and the temperature, T, is a linear function of the inverse of the proportion of the total time used

$$T(t_i, t_f) = \alpha \frac{t_f}{t_i}, \tag{3.4}$$

where t_i, t_f, and α are the present time, the final time, and a constant, respectively. Annealing is restricted to the social acceptance level, since implementation on the individual level of acceptance would lead to a premature convergence of all individuals for the low-dimensional solution space cases we concentrate on in the following section.

Algorithm 3.2.2: CONSENSUS(ν, t_i, t_f)

---

if $\frac{1+\nu}{n} > \frac{t_i}{t_f}$

  then make change to group solution

  else do not change group solution

---

where ν is the number of acceptance votes from listeners.

3.3 Results

The results presented share some common parameter settings. The diameter of local searches, $s = 0.01$; the number of sinusoids composing each dimension, $k = 5$; the number of sample points, $p = 20$; the constant of temperature, $\alpha = 0.05$; and noise, $\eta = 0.2$. The remaining parameters were varied: the number of agents, n; dimensions, m; simulation time, t_f; and memory size, q.

3.3.1 Memoryless Agents: Disparate Groups

Parameters: $m = 2, n = \{3, 6\}, q = 0, t_f = 100$

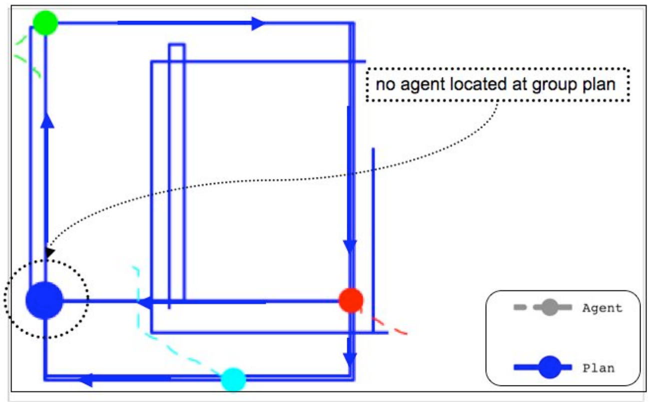
Without sharing information, trajectories generally do not tend to converge. Figure 2a shows a situation in which the coalition of two agents (green and red) has excluded a third (cyan) from contributing, and placed the solution in an area unknown to any agent. Figure 3a demonstrates the complete obviation of the group; the group solution resides at the location of a single agent while the entire group is dispersed in space. At the most, groups may generate a collective perception and decision by effecting the locality of individuals through interactions. If agents are separated, only relating to each other through proposals, not knowledge, then a greater exploration of the solution space ensues because they are unable to agree on one solution. The solution however, is not insured to be the optimal solution of all known in the group, or even an optimum for that matter.

3.3.2 Single Unit of Memory: Convergence

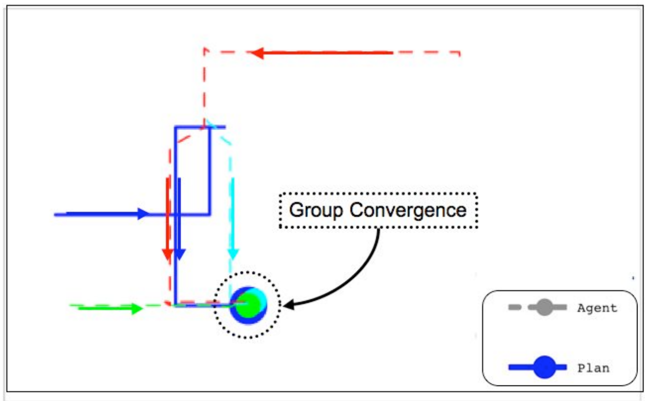
Parameters: $m = 2, n = \{3, 6\}, q = 1, t_f = 100$

When information is shared in a task oriented context, restrictions to the scope of discussion emerge. An agent stores one sample point mentioned by each other agent in discussion when $q = 1$. The most recently mentioned proposal always replaces previous memory. With this subtle difference we notice a dramatic shift in behavior. Groups often spontaneously converge on a highly discussed region and this prohibits a thorough exploration of all possible solutions. Figure 2b demonstrates one simulation in which such a convergence occurred. The stark difference in behavior between the two simulations shown in Figure 2 derives from a slight difference in conditions. Agents in Figure 2b have each been alloted one memory space for every other agent so that they may store the last reported value of a speaker and incorporate this into their own model of the world. This minimal condition leads to an infinite recursion of models like that seen in agents demonstrating a Theory of Mind.

A minimal amount of information in a relevant region is sufficient to produce coordinated behavior. For this model, groups of larger sizes than three typically fraction into subgroups, but converge for the subgroups



(a) $q = 0$



(b) $q = 1$

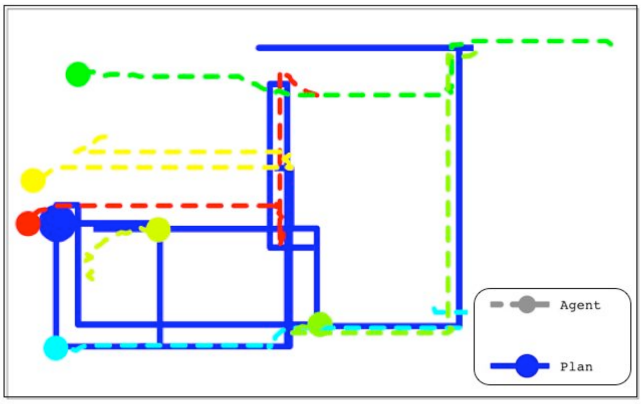
Figure 3.2: Trajectories of agents and group solutions in a simple, two-dimensional problem space. Individual agents' paths and the group solution are shown in dashed and solid lines respectively. Final positions are designated by points, the group solution being of a larger size. (a) All individuals resort to hill-climbing strategies without the sharing of information ($q = 0$). The final group plan is oscillating. (b) The group quickly converges on a single solution while sharing a minimal amount ($q = 1$). The final group plan is stable. Parameters: $m = 2, n = 3, q = \{0, 1\}, t_f = 100$

formed, with the group solution residing at one of the subgroups' locations as shown in Figure 3b.

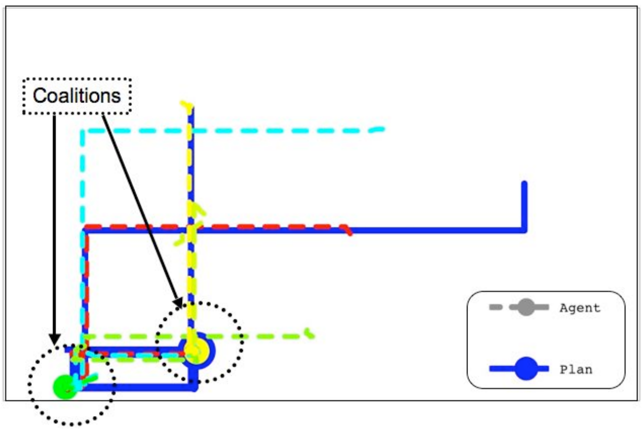
3.3.3 Formation of Shared Mental Models

Parameters: $m = 2, n = 2, q = 40, t_f = 100$

The emergence of shared mental models is represented in Figure 4 by the homogeneity of models in some region that appears to hold the solution to the problem. Initially, agents view an issue differently. The topology of Agent 1's model significantly evolves to resemble that of Agent 2, while the converse is true: Agent 2 moderates the gradient of the optimum in its own model. The regions nonadjacent to the area discussed change very little, with the differences between models becoming exasperated for some regions above the mutual solution area. Agents have the capacity to agree only within the range of discussed regions.



(a) $q = 0$



(b) $q = 1$

Figure 3.3: Formation of coalitions in large groups. Individual agents' paths and the group solution are shown in dashed and solid lines respectively. Final positions are designated by points, the group solution being of a larger size. (a) Larger groups are not necessarily more likely to form a coalition. This group demonstrates the same diffuse characteristic as the group of size $n = 3$ in Figure 2a ($q = 0$). (b) Two subgroups form around different local optima ($q = 1$). Parameters: $m = 2, n = 6, q = \{0, 1\}, t_f = 100$

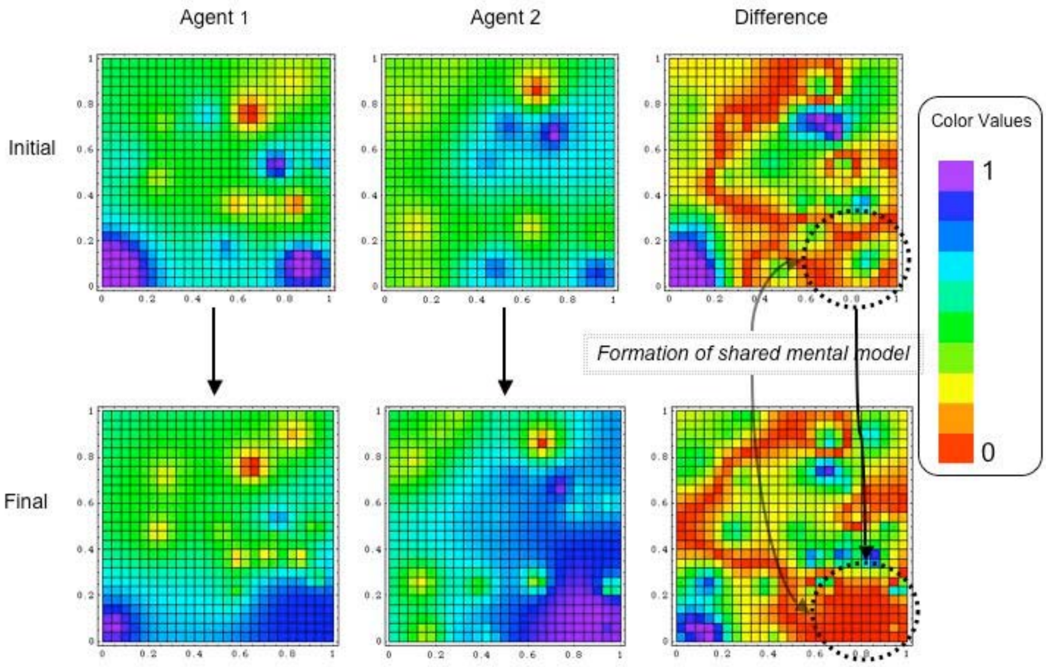


Figure 3.4: Utility functions perceived by two agents' and the formation of shared mental models. The legend on the right describes a function for mapping colors to utility values and differences between models. Two individuals come to agree upon a range of solutions in which they initially differed (top charts). After 100 time steps they have converged on a local maximum in the bottom left of the charts and shared the same expected values for local solutions. Parameters: $m = 2, n = 2, q = 40, t_f = 100$

A limitation to the total possible convergence of models is seen at approximately the the same capacity for memory, $q = 40$ in Figure 6.

3.3.4 Convergence with respect to Memory

Parameters:$n = 3, m = \{2, 8\}, q = \{0, 1...10\}, t_f = 200$

In low-dimensional problems, the capability to agree on a single group solution appears in conjunction with a decrease in exploration of the problem space. Figure 5a shows the sharp drop in the time it takes a group to converge on a plan with respect to memory. The performance with respect to the real function, f, remains the same in both cases. Exploration is offset by a lack of cohesion in the former case, and cohesion is offset by premature convergence in the latter. If convergence on a final plan were more gradual, then benefits of both group cohesion and a good exploration of the problem space might be demonstrated in a single group.

We investigated problems of higher dimensions, hoping to find, as it has been shown for humans [25], that complex group level dynamics are more relevant for problems of greater complexity. The results show the contrary.

Comparing behavior in higher dimensional problems to lower dimensional cases reveals curiously similar dynamics. Figure 5a shows the amount of total time used to converge on a group solution for a two-dimensional problem, where convergence is defined by the sum of the distances of agents' solutions from the group solution, as being below a threshold $D_{th} = 0.04$.

$$D_{group} = \sum_{i=1}^{n} \|s_i - s_{group}\| \tag{3.5}$$

For higher dimensional cases, groups fail to converge on a single solution. The metric of individual distances from the final group plan is used to measure group cohesion. Figure 5b shows D_{group} at for the final simulation time with respect to q. Although groups fail to agree on one solution, the introduction of memory has a similar influence to that of the two-dimensional case.

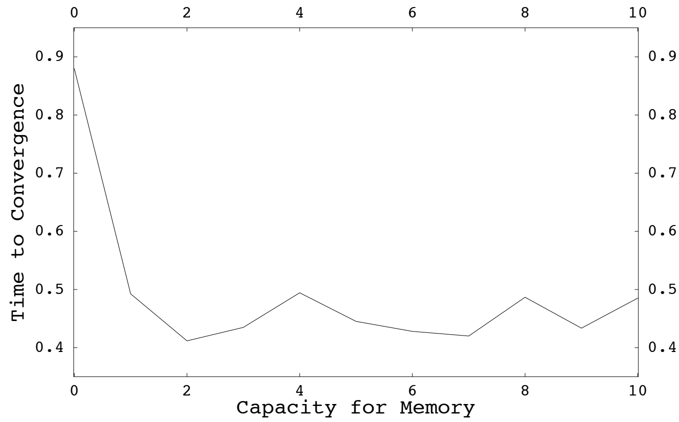
The property described in Figure 4 that is the most obvious culprit of the condition portrayed in Figures 5a and 5b. A quick convergence to a limited region of the solution space limits the amount to which agents can effect each other by sharing novel information. We might expect the same results in higher dimensional problem spaces based on the similar trend in Figures 5a and 5b.

3.3.5 Limitation of Information Sharing

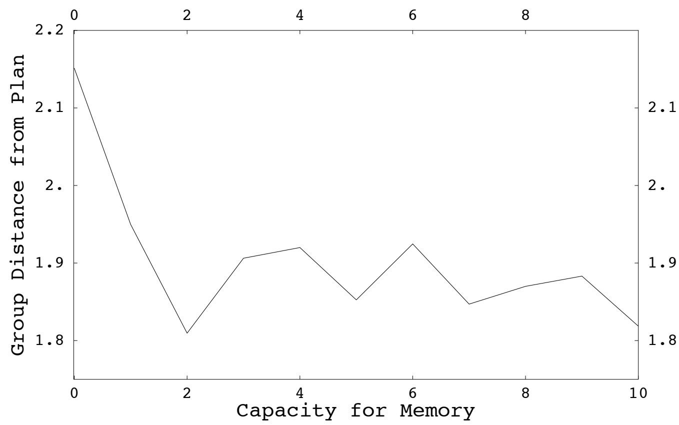
Parameters:$n = 3, m = 2, q = 100, t_f = 100$

Figure 6 shows the inability of a group to share one model of a problem despite the group acceptance of a single solution. The sharing of information is bounded because discussion does not leave the local area of the group solution once the solution is found. This condition may be a major limiting factor in groups of individuals that take a brute force approach to solving problems such that each individual learns more and groups work together for an extended period of time. If discussion is limited to a small region of the solution space, then all other information is neglected regardless of time and memory constraints.

We see illustrated in this last figure the essence of difficulties in problem solving with groups. Complex problems meriting the attention of humans do not lack more extensive descriptions or improved lookup mechanisms for retrieving existing information. The crucial issue is one of synthesis. The obstruction behind which lie the greatest advancements of human intelligence is a need for a dynamical awareness of existing and potential information along with the maintenance of fluid group cohesion throughout intelligent navigation of a problem space. Figure 6 demonstrates the prominence of this obstruction as a consequence of mental model formation in anthropomimetic groups.



(a) Time for Convergence in 2-D Problem Space



(b) Group Cohesion in 8-D Problem Space

Figure 3.5: Results of Monte Carlo simulations: convergence on a solution is shown for 2-D and 8-D problems. (a) The fraction of t_f needed for a group to come within a threshold distance, $D_{th} = 0.04$, to the group solution is shown as a function of memory capacity. Groups of explore a 2-D space. (b) The sum of all individuals' distances from the group plan. Groups exploring an eight-dimensional space are no longer converging on single solutions, but demonstrate a similar improvement with the introduction of memory. (In eight-dimensional, euclidean space, the longest distance that can be traced in a unit hypercube is $\sqrt{8} = 2.83$) Parameters: $n = 3, m = \{2, 8\}, t_f = 200$

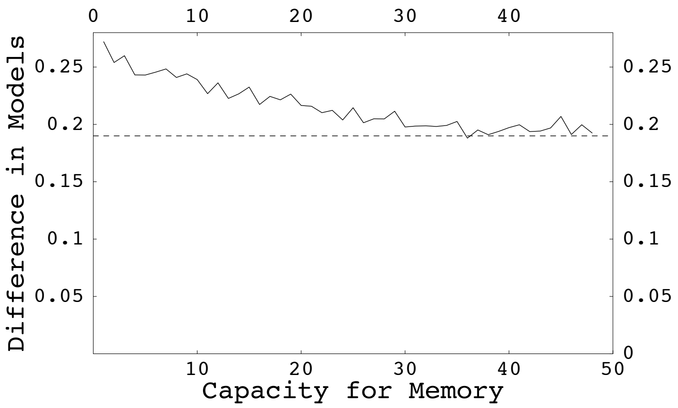


Figure 3.6: Results of Monte Carlo simulations: the average difference between any two members of a group is measured as the average difference in the value of a solution over a large set of randomly selected location (numerically equivalent to the integral of the difference of the two models). The dashed line, $y = 0.19$, is an approximation of the minimum heterogeneity in a group. Parameters: $m = 2, n = 3, q = 100, t_f = 100$

3.4 Discussion

Shared mental model formation in anthropomimetic groups demonstrates unique, counterintuitive behavior. For low-dimensional cases of any capacity for memory, discussion rapidly curtails exploration and produces a crowding of some solution region. The local area of the group solution is changed for all agents to express homogeneity when compared across individuals. Sameness of models and emergence of cooperation are simultaneously appearing phenomena, for which a direction of causality cannot be defined.

The nature of the shared mental model formation can be qualitatively described as smoothing and averaging differences in a highly discussed region, while leaving a high level of heterogeneity in undiscussed areas. Rapid convergence on solitary solutions are a result of both the arbitrary preference of one solution over unexplored others, and the avoidance of lower valued regions of a solution space. Our model indicates that large reserves for memory, exceeding an agent's own space for saving sample points, does not necessary lead to a better understanding of a large portion of the solution space, moreover in some conditions this will lead to a limited exploration of the limited knowledge that does exist.

The crucial limitation to collective intelligence lies in the antagonistic relationship between convergence and exploration. Convergence can be perceived here as a representation of the context of the communal information reservoir. A fuzzy boundary of the convergent region becomes the backdrop for a qualification of information. That which is used and accepted lies within, all else having been rejected. Without a framework for qualifying discussion, the group cannot process information. Individuals may discuss every slight detail of their knowledge with each other, but the interaction would be moot if lacking intelligence on the receiving end of the exchange.

In addition to the necessity for an implicit qualifier of information passing through group discussion, it's initial absence constrains creation to the scope of the actual conversation. The generation of meaning must be demonstrated through sequential, responsive acts of speaking and listening by individual agents, from which the backdrop pattern emerges. In the context of an optimization problem the appropriate pattern describes a convergence on an optimal solution. The probability of exploring possibilities beyond the area of convergence diminishes as consensus is reached and the border of the discussion region contracts.

Individual agents negotiate a differences in locality and mental models of the problem space. The introduction of mental models of others modifies the expression of these conflicts and shifts the balance between convergence and exploration. We explored the relationships between these opposing forces in attempts to form a framework for describing balance in the context of group level behavior. Assuming a limitation of perception as characteristic of human beings, agents are capable of sweeping only a small fraction of their models at once. Consequently, neither the capacity for memory nor increasingly accurate models may improve behavior after a certain extent. The protocol of interaction must be manipulated to change group behavior driven performance. For problems of higher dimensionality it may be necessary to employ the simulated annealing protocol on the level of *individual* acceptance for the development of a cohesive group centered on a single group solution.

3.5 Conclusion

To identify limitations to group level intelligence and propose possible solutions, we investigate dynamics of group decision making processes on complex problems when individuals are capable of forming mental models of others based on the history of the group discussion. Our results suggest a counter-intuitive possibility that as the capacity of memory increases, the amount of information sharing may decrease far below the entire problem space. This is due to premature convergence of group discussion on a particular solution; incorporating knowledge from others into one's own world view creates a local agreement, leaving unexplored diversities beyond the scope of discussion. The mechanisms stifling group level exploration and possible protocols for overstepping local optima are discussed.

Connecting groups of individuals by allowing not only reactive, but also cooperative generative relationships, in which every individual partly authors the perception of others in parallel to a group focus on solving a particular problem leads to dramatic changes in group behavior. The transition from solitary hill-climbers as in the case of Figure 1a to a group demonstrating premature convergence of a single solution is so sharply pronounced that a large range of behaviors in between remain unexplored. The possibility of simulating higher dimensional problems and implementing a strong simulated annealing protocol appears to be a promising direction for future research.

In order to encourage a more diverse discourse and the revealing of so-called "hidden information" [8], the protocol of interaction may need be manipulated, both to sustain some distance of opinions for the sake of maintaining an interesting conversation, and to overcome a repulsion to lower-valued solution areas in favor of a more thorough exploration of all possibilities. The eventual convergence on a solution is paramount in group problem solving, especially in the context of complex and nonlinear problems where the region between two competing strategies or coalitions of strategies is most likely not nearly as favorable as either solution itself.

3.6 Acknowledgments

1

We thank Ingeborg Majer O'Sickey, Don Gause, and Karthik Bharath for their contribution to the conceptual formation of this work.

3.7 References

[1] A. Acerbi and D. Parisi. Cultural transmission between and within generations. *Journal of Artificial Societies and Social Simulation*, 9(1), 2006.

[2] R. A. Brooks, C. Breazeal, M. Marjanovic, B. Scassellati, and M. M. Williamson. The cog project: Building a humanoid robot. *Lecture Notes in Computer Science*, 1562:52–87, 1999.

[3] R. W. Byrne and A. Whiten. *Machiavellian Intelligence: Social Expertise and the Evolution of Intellect in Monkeys, Apes and Humans*. Oxford University Press, Oxford, UK, 1988.

[4] C. Castelfranchi. Modelling social action for "ai" agents. *Artificial Intelligence*, 103:157–182, 1998.

[5] R. Conte and M. Paolucci. Intelligent social learning. *Journal of Artificial Societies and Social Simulation*, 4(1), 2001.

[6] S. Dionne, H. Sayama, D. Farrell, and E. Carroll. Evolutionary perspective on group decision making: A within- and between-groups simulation. paper submitted, 2007.

[7] T. Ikegami and G. Morimoto. Chaotic itinerancy in coupled dynamical recognizers. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 13(3):133–1147, 2003.

[8] N. L. Kerr and R. S. Tindale. Group performance and decision making. *Annual Review of Psychology*, 55:623–655, 2004.

[9] M. Klein, P. Faratin, H. Sayama, and Y. Bar-Yam. Protocols for negotiating complex contracts. *IEEE Intelligent Systems*, 18(6):32–38, 2003.

[10] H. Kozima, C. Nakagawa, and H. Yano. Can a robot empathize with people? *International Journal "Artificial Life and Robotics"*, 8:83–88, 2004.

[11] J. S. Lansing. "artificial societies" and the social sciences. *Artificial Life*, 8:270–292, 2002.

[12] N. Lazaric and A. Raybaut. Knowledge creation facing hierarchy: the dynamics of groups inside the firm. *Journal of Artificial Societies and Social Simulation*, 7(2), 2004.

[13] J. Lindblom and T. Ziemke. Social situatedness and artificial intelligence: Vygotsky and beyond. *Adaptive Behavior*, 11(2):79–96, 2003.

[14] I. Lustick. Agent-based modelling of collective identity: testing constructivist theory. *Journal of Artificial Societies and Social Simulation*, 3(1), 2000.

[15] A. Montagu, editor. *Race and IQ*. Oxford University Press, New York, 1999.

[16] N. Nicholson. Evolutionary psychology: Toward a new view of human nature and organizational society. *Human Relations*, 50:1053–1078, 1997.

[17] J.-P. Rennard. Artificiality in social sciences, 2006.

[18] P. J. Richerson and R. Boyd. *Not By Genes Alone : How Culture Transformed Human Evolution*. University Of Chicago Press, December 2004.

[19] D. J. Siegel. *The Developing Mind: How Relationships and the Brain Interact to Shape Who We Are*. The Guilford Press, NewYork, 1999.

[20] E. Sober and D. S. Wilson, editors. *Unto others: The evolution and psychology of unselfish behavior*. Harvard University Press, Cambridge, MA, 1998.

[21] M. Takano and T. Arita. Asymmetry between even and odd levels of recursion in a theory of mind. In L. M. Rocha, L. S. Yaeger, M. A. Bedau, D. Floreano, R. L. Goldstone, and A. Vespignani, editors, *Artificial Life X: Proceedings of the Tenth International Conference on the Simulation and Synthesis of Living Systems*, Amsterdam, NL, 2006. The MIT Press.

[22] L. Vygotsky. *Thought and Language*. MIT Press, Cambridge, 1975. Original work published in 1934.

[23] W. Weaver. Science and complexity. *American Scientist*, 36:536, 1948.

[24] D. S. Wilson and E. Sober. Reintroducing group selection to the human behavioral sciences. *Behavioral and Brain Sciences*, 17(4):585–654, 1994.

[25] D. S. Wilson, J. J. Timmel, and R. R. Miller. Cognitive cooperation: when the going gets tough, think as a group. *Human Nature*, 15(3):225–250, 2004.

[26] F. J. Yammarino, S. D. Dionne, J. U. Chun, and F. Dansereau. Leadership and levels of analysis: A state-of the-science review. *The Leadership Quarterly*, 16:879–919, 2005.

Chapter 4

Evolutionary Perspective on Group Decision Making

Published in the Proceedings of the Seventh International Conference on Complex Systems (ICCS2007)

Dene Farrell[1], Hiroki Sayama[1], Shelley D. Dionne[2], Francis J. Yammarino[2], David Sloan Wilson[3]

[1]Department of Bioengineering, Binghamton University, Binghamton NY, 13902-6000

[2]School of Management, Binghamton University, Binghamton NY, 13902-6000

[3]Departments of Biological Sciences and Anthropology, Binghamton University, Binghamton NY, 13902-6000

Abstract

Team decision making dynamics are investigated from a novel perspective by shifting agency from decision makers to representations of potential solutions. We provide a new way to navigate social dynamics of collective decision making by interpreting decision makers as constituents of an evolutionary environment of an ecology of evolving solutions. We demonstrate distinct patterns of evolution with respect to three forms of variation: (1) Results with random variations in utility functions of individuals indicate that groups demonstrating minimal internal variation produce higher true utility values of group solutions and display better convergence; (2) analysis of variations in behavioral patterns within a group shows that a proper balance

between selective and creative evolutionary forces is crucial to producing adaptive solutions; and (3) biased variations of the utility functions diminish the range of variation for potential solution utility, leaving only the differential of convergence performance static. We generally find that group cohesion (low random variation within a group) and composition (appropriate variation of behavioral patterns within a group) are necessary for a successful navigation of the solution space, but performance in both cases is susceptible to group level biases.

4.1 Introduction

Collective decision making is becoming more central and indispensable in human society as modern problems increasingly involve interactivity and inseparability within large scale tasks [4]. In high-tech product and software development, for example, the amount of workers participating in a design project can be in the order of thousands as a result of a products complexity exceeding an individuals capacity, which almost inevitably results in suboptimal outcomes [5]. More recently, online collective decision making among large populations of anonymous participants via computer mediated networks has been implemented for product rating and common knowledge base formation. Both individual behavior and the organizational structure greatly influence decision processes. The complexity of the processes is more manifested when constituents of groups are heterogeneous with regard to both their world views and behavioral propensities. Collective human decision making in such conditions is poorly understood, being one of the most significant challenges in the social sciences.

The leadership, psychology and organizational behavior/management disciplines have examined collective dynamics using both experimental and applied studies. They generally emphasize linear statistical relationships of team and individual level variables [4], without accounting for nonlinear processes, high-dimensional problem space and non-trivial social structure. Complex, nonlinear problem space has been considered in dynamical modeling studies [5], in which interdependence of aspects of problem are considered, but not nontrivial social interactions. Here we investigate collective decision making dynamics from a novel perspective by shifting the focus of agency from group members to potential solutions being discussed. The decision making processes are described using concepts in evolutionary theory, where evolution acts on a population of potential solutions through mechanisms of selection and variation as effected by human discussants. Group members thus serve both as an evolutionary environment and as implements of evolutionary action on a population of solutions. Within this context, several evolutionary operators can be mapped to human behaviors. Examples include replication (advocacy of an existing idea), subtractive selection (criticism against an existing idea), mutation (revision of an existing idea) and recombination (creation of a new idea by mixing existing ideas).

4.2 Model

4.2.1 Groups

We apply evolutionary framework to model simple group decision making processes within a small-sized, well-connected social network structure. We conduct multiple levels of analysis [1, 7] on how homogeneities or heterogeneities of world views/goals among the participating agents, as well as group-level behavioral patterns and biases, affect the decision making dynamics and the final outcomes [2].

When group members are heterogeneous in world views, differences between individual utility functions play a crucial role in determining the group dynamics; the relevant level of analysis is within groups. Each member acts as group parts [1] to achieve individual objectives. Conflicts of interest make the problem space more complex than that of groups consisting of homogeneous, world perspectives. On such complex landscapes there is more possibility for populations to become stuck at local optima, detrimenting the overall adaptiveness. Contingently, the importance of variation relates to escaping from the local optima in order to reach better solutions.

If group members are homogeneous in their world view, they behave as group wholes [1]; the relevant level of analysis is between groups. The population of solutions evolves to adapt to a single utility function shared by all the group members, so the problem space would be simpler than with heterogeneous groups. With little conflicts of interest, selection is relatively important to adaptiveness as speeding up the convergence of discussion. Variation still holds importance, especially with complex nonlinear problems.

Our model assumes that groups are initiated with a list of randomly generated ideas, whereupon they begin to perform a set of actions on the existing population of solutions repeatedly for a fixed number of iterations. Individuals always act in the same order and groups always demonstrate a full rotation. The number of actions on the population of solutions is a product of the number of group members, N, and the number of iterations, t.

In the population, there may be multiple copies of the same type of solution, which represents the relative popularity among group members. Each action is performed on a single copy of solution, not on an equivalence class of all solution replicates.

4.2.2 Utility Functions

Groups are situated in an M-dimensional binary problem space, with 2^M possible solutions. For a simulation, every solution has a utility value specified by a master utility function U that is unavailable to group members. Individuals perceive solution utility values based on their own utility functions U_j constructed by adding noise to U. We develop a semi-continuous assignment of utility values in the problem space in the following way. First, s representative solutions $S = \{v_i\}$ $(i = 1 \ldots s)$ are generated as random bit strings, where each v_i represents one solution made of M bits. One solution is assigned the maximum fitness value, 1, and another, the minimum fitness value, 0. The remaining $s - 2$ solutions are assigned a random real value between 0 and 1, ensuring that the entire range of utility values is from 0 to 1, for the sake of comparisons between simulation results. The utility values of all possible solutions in the domain of the master utility function are defined by interpolation using the utility values of representative solutions in S. We use the Hamming distance as a measure of dissimilarity between two bit strings. With this measure, the utility value of each possible solution not present in S is calculated as a weighted average of the utility values of the representative solutions calculated as follows:

$$U(v) = \frac{\sum_{i=1}^{s} U(v_i \cdot D(v_i, v)^{-2})}{\sum_{i=1}^{s} D(v_i, v)^{-2}} \tag{4.1}$$

where $v \notin S$ is the solution in question, $U(v_i)$ is the utility of a representative solution ν_i in S, and $D(v_i, v)$ is the Hamming distance between v_i and v. Each individual in a group will unconsciously have a different set of utility values for the possible solutions of the problem. Individual utility functions $U_i(v)$ $(j = 1 \ldots N)$ are generated by adding random noise to the master utility function so that:

$$U_j(v) \in [\max(U(v) - \nu, 0), \min(U(v) + \nu, 1)] \tag{4.2}$$

for all v , where ν is the parameter that determines the range of noise. Individuals do not access global maximum/minimum utility values, though they can retrieve a utility value from the function when a specific solution is given.

In addition to individual deviations from a common master utility function, we investigate the effect of common deviations from the true utility function, or group level biases. For simulating group level bias we introduce a new step in the generation of individual utility functions, in which the master utility function $U(v)$ differs from the original true utility function, $U_T(v)$. Specifically, a bias β is imposed on the true utility function both by flipping bits with probability 0.25 β per bit and adding a random number ranged

$[-\beta, \beta]$ to utility values. Solution sets are renormalized to the range $[0, 1]$. The master utility function is generated from the biased representative solution set. Subsequent methods follow as described above. Bias represents fidelity of information at the group level, where $\beta = 0$ denotes perfect information, and complete randomization is asymptotically approached as bias increases.

4.2.3 Evolutionary Operators

We identify six evolutionary operators representing individual behaviors reflecting selection or variation. Some operators use a preferential search algorithm to stochastically search the solution population, where r_p solutions are randomly selected and ranked according to their perceived utility values, and then the best or worst solution is selected depending on the nature of the operator being executed.

Replication. Replication adds an exact copy of a solution from the population of solutions back onto the list. Solutions are chosen for replication with the preferential search algorithm. Replication therefore can neither produce a novel solution nor remove one, but it gently sways the ecology of the population by increasing the popularity of favorable existent solutions. This represents an advocacy of a particular solution under discussion.

Random point mutation. Random point mutation adds a copy of a solution with point mutations, flipping of bits at each aspect of a problem with a probability p_m. The solution on which the operator acts is chosen from the active population with a preferential search algorithm (discussed in more detail below). This represents an attempt of making random changes to the existing ideas, reflected in asking what if questions. Random point mutations help escape local maxima of a utility function in the problem space when a utility function is nonlinear and many-peaked.

Intelligent point mutation. A solution is selected from the population with a preferential search algorithm. It makes several (r_m) offspring of the parent solution and selects that of the highest perceived fitness for addition to the population. This represents a proposal of an improved idea derived from existing ideas under discussion. The intelligent point mutation can be useful in maximizing a utility function with one maximum by climbing monotone gradients, but it may perform poorly in a complex utility landscape.

Recombination. Recombination chooses one solution at random and one with a preferential search algorithm. It then creates two offspring from the two parent solutions. Sexual reproduction is simulated with a multiple point cross-over recombination: parent solutions are aligned by aspects, for each of which there is a probability p_s of switching their contents. Of the two offspring, that of higher perceived utility is selected and added to the population. This represents a creation of a new idea from two existing ideas.

Subtractive selection. The preferential search algorithm is used to find the solution with the worst fitness, whereupon it is singled out and deleted from the population. This represents a criticism against a bad idea. Subtractive selection is the only operator that reduces the number of existing solutions and is therefore essential to groups attempting to attain convergence in the population distribution.

Random generation. Finally, random generation of solutions adds a randomly generated solution to the population. There is no use of an individuals utility function, nor any connection to the existing solutions on the table at that time. New solutions are generated utterly randomly. This represents a sudden inspiration of a totally unique idea that is unrelated to the existing ideas under discussion.

4.2.4 Simulation Settings

The following parameter settings were held constant for all simulations: group size $N = 6$; problem space dimensionality $M = 10$; number of sample solutions in the preferential search algorithm $r_p = 5$; number of offspring generated in the intelligent point mutation $r_m = 5$; random mutation rate per bit $p_m = 0.2$; probability of random switching in recombination $p_s = 0.4$; number of iterations $t = 60$. It was also assumed that groups were initialized with four random ideas. For each group, the noise parameter ν and the bias parameter β were varied from 0 to 1.2 by increments of 0.2.

4.2.5 Metrics of Group Performance

We use two separate performance metrics: the true utility of the mode solution at the end of group simulation and the convergence of solutions. Convergence is based on entropy

$$H = -\sum_{i=1}^{n} p(x_i) \cdot \log_2 p(x_i) \tag{4.3}$$

, where $p(x_i)$ is a normalized frequency of the i-th type of solutions in the population. Since the maximum possible value of H is M (this is the case when there are exactly $2M$ solutions in the population which are different from each other), $M - H$ is a quantitative measure that intuitively means the number of aspects of the problem on which the group has formed a cohesive opinion. For normality, we will use $(M - H)/M$ as the metric.

4.3 Results

We first conducted a within-group analysis examining effects of heterogeneity in world views (utility functions) within a group. Here we assumed group members were balanced behaviorally; in each iteration, they

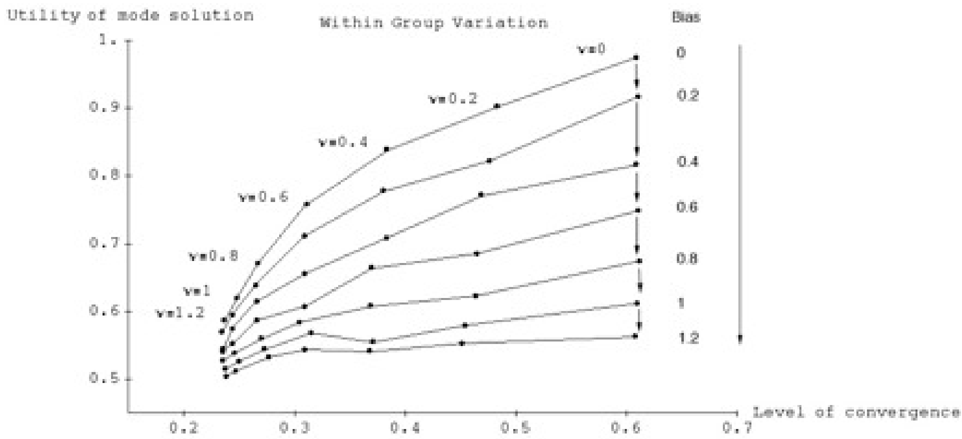


Figure 4.1: Simulation results showing the effects of within-group heterogeneity and group level bias. The level of convergence and the true utility value of mode solutions for several different noise levels are plotted. $\nu = 0$ represents the case of completely homogeneous groups, while larger values of ν represent more heterogeneous group cases and larger values of bias represent large discrepancies between group utility functions and true utility function.

randomly chose one of the six operators with equal probability. Figure 1 indicates the results with several different settings of within-group variation ν and group-level bias β, plotting them in a 2-D performance space using the two metrics described above.

Group-level bias affects the utility of group solutions while convergence is largely unaffected. On the other hand, within-group variation degrades both convergence and utility. Groups performed better in both performance metrics when they were homogeneous in their utility functions. As the groups members become more heterogeneous, the true utility value of the mode solution decreased and the final population of solutions after discussion became more diverse. The decrease of the true utility value was particularly drastic; in nonbiased conditions with no heterogeneity, the groups were able to find nearly perfect solutions for the problem (i.e., the utility close to 1). As the groups become more heterogeneous the utility achieved dropped to just above 0.5, meaning that there was no net improvement achieved during the group discussion. This was due to the conflicts of interest among the group members.

Contrary to other findings regarding heterogeneous groups outperforming homogeneous groups on creative and intellectual problem solving tasks [3, 6], our findings indicate the opposite, which may seem to support the negative relationship reported between both surface-level (i.e., demographic) and deep-level (i.e., psychological) diversity and group functioning and performance [2]. We must note here, however, that the diversity considered in this set of experiments is about the individual utility functions only, and not about the individual behavioral patterns.

In order to explore the effects of various compositions of individual behaviors, we ran another set of experiments using the same simulation model with different behavioral patterns assumed for different groups. In forming different group properties, we modeled only a handful of potential evolutionary operators/behaviors combinations. We modeled some operators singularly (e.g., random generation was the only operator within the group), and for other groups we combined two evolutionary operators to reflect increasing complexity of group behavior (e.g., recombination and intelligent point mutation). For the former cases group members were assumed to choose the designated operator for 95% of their total actions, with 1% for each of the other five operators. For the latter combined cases they were assumed to choose each of the two operators for 48% of their total actions (96% in total), with 1% for each of the other four operators. We limited our examination to eight group types: replication and subtractive selection (Group 1); subtractive selection and random point mutation (Group 2); replication and recombination (Group 3); recombination (Group 4); recombination and intelligent point mutation (Group 5); intelligent point mutation and random generation (Group 6); random generation (Group 7); and, finally, the balanced team we used in the previous experiment as a control (Group 0).

Figure 2 shows the results of the second set of experiments comparing group performances with different group properties, plotting them in the same 2-D performance space as used for Figure 1. The effect of group-level bias is similar to that seen in Figure 1. Among the groups examined, the balanced Group 0 case was the best in terms of the utility value of the mode solution. Interestingly, however, we saw a variety of different group performances achieved by groups with different properties, seen as a kind of wave front near the upper-right corner of the performance space.

We further noticed in Figure 2 that the groups that sit along this wave front were arranged roughly in the order of the balance between selection and variation in evolutionary operators; Group 1, which was the best in terms of the convergence but poor in the mode selection utility, used the combination of replication and subtractive selection, which are both selection-oriented operators. Group 2, the second best in convergence and second worst in mode selection utility within the wave front, used the combination of subtractive selection and random point mutation, which is more variation-oriented than Group 1. Along the way toward Group 0, we saw Group 3 (replication and recombination), Group 4 (recombination only), and Group 5 (recombination and intelligent point mutation), where the qualitative shift of balance of evolutionary operators from selection-oriented to variation-oriented can be seen. It is also notable that the random generation operators (used in Groups 6 and 7) were generally not working for improving group performance.

4.4 Conclusion

The application of the evolutionary paradigm is illuminating for studying collective decision making dynamics because it allows the researcher to remove themselves from the traditional teleology adopted in most

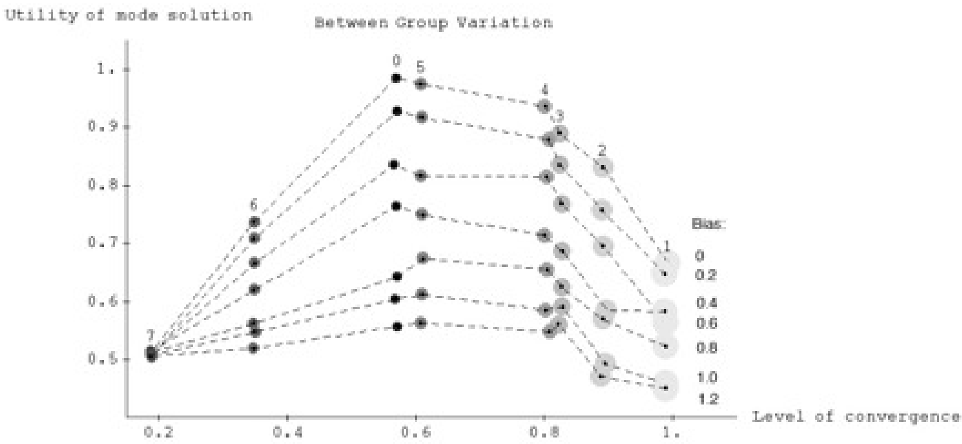


Figure 4.2: Simulation results showing the effects of group-level difference of behavioral patterns. The level of convergence and the true utility value of mode solutions under varying conditions of group-level behavioral patterns and bias are plotted. Group 0 is the balanced team that uses all of the six evolutionary operators with equal probability; Group 1 uses replication and subtractive selection mostly; Group 2 subtractive selection and random point mutation; Group 3 replication and recombination; Group 4 recombination only; Group 5 recombination and intelligent point mutation; Group 6 intelligent point mutation and random generation; and Group 7 random generation only.

simulations of human groups. We have portrayed group dynamics in a novel way by treating members of the group as constituents of an evolutionary environment in which populations of solutions evolve. In this new framework, we have characterized the properties of the population of solutions after discussion as quantitative metrics of the performance of a group. We demonstrated through simulations that heterogeneous groups with random variations in individual utility functions had a drop in both utility and convergence of solution populations compared to more homogeneous groups. We also demonstrated that variations in the compositions of individual behavioral patterns between groups resulted in a large spectrum of performance, in which groups well balanced between reductive and creative evolutionary forces yielded solutions that were highly adaptive by both performance metrics. All operators have a particular utility in appropriate circumstances, but we highlight that recombination operators are particularly important in that they demonstrate creative changes on large and small scales with a single mechanism, as are selection operators essential to promoting the best ideas by converging a solution population on the best solutions.

1

4.5 References

[1] F. Dansereau, F. J. Yammarino, and J. C. Kohles. Multiple levels of analysis from a longitudinal perspective: Some implications for theory building. *The Academy of Management Review*, 24(2):346–357, 1999.

[2] S. D. Dionne, A. E. Randel, K. S. Jaussi, and J. U. Chun. Diversity and demography in organizations: A levels of analysis review. *Research in Multi-Level Issues*, 3:181–229, 2004.

[3] D. H. Gruenfeld, E. A. Mannix, K. Y. Williams, and M. A. Neale. Group composition and decision making: How member familiarity and information distribution affect process and performance. *Organizational Behavior and Human Decision Processes*, 67:1–15, 1996.

[4] N. L. Kerr and R. S. Tindale. Group performance and decision making. *Annual Review of Psychology*, 55:623–655, 2004.

[5] M. Klein, P. Faratin, H. Sayama, and Y. Bar-Yam. Protocols for negotiating complex contracts. *IEEE Intelligent Systems*, 18(6):32–38, 2003.

[6] C. J. Nemeth. *Minority dissent as a stimulant to group performance*, pages 95–111. Sage, 1992.

[7] F. J. Yammarino, S. D. Dionne, J. U. Chun, and F. Dansereau. Leadership and levels of analysis: A state-of the-science review. *The Leadership Quarterly*, 16:879–919, 2005.

Chapter 5

Conclusions

Modeling social systems is dually problematic. Social systems are complex in themselves and the literature of scientific tools is disparate and often contradictory. I have worked towards reconciling modeling approaches focused on cognitive mechanisms and modeling approaches focused on evolutionary mechanisms. I demonstrated three original studies that have focused on one or both of the two mechanisms and we present arguments for creating a unified theory of social dynamics.

In the first study we demonstrated a new form of altruistic punishment, in which individuals who punish are also more likely to cheat. We use agent based modeling to simulate a repeated public goods game. We show that altruism and punishment become negatively correlated for a range of parameters, leading to selfish punishment. The study is a social simulation based entirely on assumptions of evolutionary mechanisms. All events are determined directly by phenotypes and genetic algorithms. We study the emergence of an selfish punishers that are dependent upon the coexistence of non-punishing altruists. Selfish behavior is generally considered simply a negative trait for group well-being. Most studies seek explanations for its suppression, such as studies investigating altruistic punishment [25, 26, 15, 12, 11, 5, 10, 16, 9]. Because punishment is often difficult to execute in reality it comes at a cost to the punisher and is therefore second order altruism [25, 3, 4, 9]. We were able to demonstrate a polymorphism that couples first order selfishness with second order altruism.

In the second study we investigated effects of mental model formation on collective decision making processes. Groups of individuals attempt to come to consensus on problems in complex problem spaces, where each individual possesses imperfect information, a limited scope of their own model of problem space, and a plastic view of the problem space varying depending both on original imperfect information and a memory of group solution suggestions. This model is based entirely on an interaction of cognitive mechanisms and hard-wired social dynamics. There is no genetic component. We explored mechanisms described in the theory of social situatedness [20, 22] and Theory of Mind (ToM) models [6, 19, 7, 23, 17]. Explanatory models for social situatedness and ToM usually assume evolutionary dynamics. We investigated the effects of ToM in noncompetitive scenarios where all agents work together to solve a single problem. We found that greater capacities for assimilating information from others can potentially lead to premature agreements and suboptimal explorations of problem space.

In the third and last study cognitive mechanisms are modeled as evolutionary mechanisms. We model team decision making dynamics. By treating people as an evolutionary environment within which ideas propagate and evolve, we are able to include cognitive and evolutionary mechanisms. We demonstrate that a process of collective decision making can work very much like an ecosystem over time, evolving an ecology of ideas and variably with respect to the propensities of team members towards various social actions. Studies recorded in the leadership, psychology and organizational behavior disciplines have investigated collective dynamics of groups in decision processes but they often focus on single variable statistics, failing to explore complex scenarios of social interactions and problem formats [18]. We implemented an ABM approach to study more complex scenarios.

In the ABM construct it is possible to develop models reconciling approaches focusing on cognitive and evolutionary mechanisms. I will briefly note that the effects of the two are not necessarily distinguishable: An evolutionary system may give rise to agents with capacity for cognitive interactions. An agent making a mental model of an other, for example, may arise as an emergent property of coevolving predator-prey species. Cognitive mechanisms included in the assumptions of a model, however, differ from evolutionary mechanisms in that they model thinking and its effects on the interactions between agents. One avenue to reconciling the two approaches was demonstrated in the third study, in which we created a reversal of the traditional evolutionary paradigm: actors with agency are, rather than the units upon which an evolutionary machine acts directly, considered part of an ecological environment in which decisions evolve and collective behaviors emerge. Additionally, as our understanding of cognitive mechanisms such as ToM greaten and as we are able to model such dynamics with greater ease we can begin to incorporate them into models focusing on the evolution of higher level social patterns, emergent patterns that would stand above basic cognitive mechanisms in a larger dynamical hierarchy.

5.1 References

[1] R. Axelrod. *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration*. Princeton Univ. Press, Princeton, NJ, 1997.

[2] E. Bonabeau. Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, 99(10):2780–7287, 2002.

[3] S. Bowles and H. Gintis. Homo reciprocans. *Nature*, 415:125–128, 2002.

[4] S. Bowles and H. Gintis. The evolution of strong reciprocity: cooperation in heterogeneous populations. *Theor. Popul. Biol.*, 65:17–28, 2004.

[5] R. Boyd, H. Gintis, S. Bowles, and J. Richerson. The evolution of altruistic punishment. *Proc. Natl. Acad. Sci.*, 100:3531–3535, 2003.

[6] R. A. Brooks, C. Breazeal, M. Marjanovic, B. Scassellati, and M. M. Williamson. The cog project: Building a humanoid robot. *Lecture Notes in Computer Science*, 1562:52–87, 1999.

[7] C. Castelfranchi. Modelling social action for ”ai” agents. *Artificial Intelligence*, 103:157–182, 1998.

[8] J. M. Epstein and R. L. Axtell. *Growing Artificial Societies: Social Science from the Bottom Up*. MIT Press, Cambridge, MA, 1996.

[9] E. Fehr. Don’t lose your reputation. *Nature*, 432:449–450, 2004.

[10] E. Fehr and U. Fischbacher. The nature of human altruism. *Nature*, 425:785–791, 2003.

[11] E. Fehr, U. Fischbacher, and S. Gachter. Strong reciprocity, human cooperation, and the enforcement of social norms. *Hum. Nat.Int. Bios.*, 13:1–25, 2002.

[12] E. Fehr and S. Gachter. Altruistic punishment in humans. *Nature*, 415:137–140, 2002.

[13] J. Ferber. *Multi-Agent Systems. An Introduction to Distributed Artificial Intelligence.* Addison Wesley, London, UK, 1999.

[14] N. Gilbert. *Agent-Based Models*. Sage Publications, London, UK, 2007.

[15] H. Gintis. Strong reciprocity and human sociality. *J. Theor. Biol.*, 206:169–179, 2000.

[16] H. Gintis, S. Bowles, R. Boyd, and E. Fehr. Explaining altruistic behavior in humans. *Evol. Hum. Behav.*, 24:153172, 2003.

[17] T. Ikegami and G. Morimoto. Chaotic itinerancy in coupled dynamical recognizers. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 13(3):133–1147, 2003.

[18] N. L. Kerr and R. S. Tindale. Group performance and decision making. *Annual Review of Psychology*, 55:623–655, 2004.

[19] H. Kozima, C. Nakagawa, and H. Yano. Can a robot empathize with people? *International Journal "Artificial Life and Robotics"*, 8:83–88, 2004.

[20] J. Lindblom and T. Ziemke. Social situatedness and artificial intelligence: Vygotsky and beyond. *Adaptive Behavior*, 11(2):79–96, 2003.

[21] J.-P. Rennard. Artificiality in social sciences, 2006.

[22] D. J. Siegel. *The Developing Mind: How Relationships and the Brain Interact to Shape Who We Are*. The Guilford Press, NewYork, 1999.

[23] M. Takano and T. Arita. Asymmetry between even and odd levels of recursion in a theory of mind. In L. M. Rocha, L. S. Yaeger, M. A. Bedau, D. Floreano, R. L. Goldstone, and A. Vespignani, editors, *Artificial Life X: Proceedings of the Tenth International Conference on the Simulation and Synthesis of Living Systems*, Amsterdam, NL, 2006. The MIT Press.

[24] J. W. Weibull. *Evolutionary Game Theory*. MIT Press, Cambridge, MA, 1996.

[25] T. Yamagishi. The provision of a sanctioning system as a public good. *J. Pers. Soc. Psychol.*, 51:110–116, 1986.

[26] T. Yamagishi. Seriousness of social dilemmas and the provision of a sanctioning system. *Soc. Psych. Q.*, 51:32–42, 1988.