ENSEMBLE COMPUTING IN AGENT-BASED MODELING FOR TRANSCENDING PARADIGMATIC BOUNDARIES IN DECISION THEORY – UNDERSTANDING TRIBAL POLITICS

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ABSTRACT

The data outputs of agent-based models are extremely complex and that complexity is compounded by the uncertainty surrounding model parameters. Ensemble computing utilizes sets of models with varied parameter setting to explore the potential worlds a model could produce. This uncertainty is compounded when different models appear to derive from different scientific paradigms. I present a framework in which models derived from different paradigms are placed in an ensemble, whose varied outputs allow exploration of the various strengths and weaknesses of different decision theoretic paradigms. Specifically, theories and models derived from rational choice theory, risk sensitivity theories, social psychology, prospect theory, bounded rationality and culture norm theories are compared. Empirical data on political alliances in a patrilineal New Guinea tribe are used to measure the relative effectiveness of different theories. While ensemble computing can test competing hypotheses, its best use is in identifying the key elements any theory must have to be explanatory and predictive. This work applies to research on decision making and traditional tribal politics, including in regions of the world in turmoil such as Sudan, Somalia, Iraq, and Afghanistan.

Keywords: exploratory modeling; ensembles; decision theory; theory testing

INTRODUCTION

This paper is a follow-up to a modeling study of coalition formation in a New Guinea tribal village [Kuznar, 2006]. The evolution of coalitions among men in this village was used to test the efficacy of theories of political and economic decision-making drawn from rational choice, prospect theory, bounded rationality and risk sensitivity paradigms. The preliminary study identified four models that performed particularly well, sigmoid group (SG), full prospect theory (PT) (including effects of probability weighting, loss aversion and framing), and the smart agent prestige bias (sP3) and smart conformism 2 (sC2) models. In this paper, I present the results of more rigorous validation metrics that allowed finer discrimination among the competing theories.

In this paper, I present the results of more robust metrics used for exploring the strengths and weaknesses in decision theory models. The empirical case example used to test these models concerns the evolution of political alliances among men in a tribal village of New Guinea (present day Irian Jaya). This case provides an example of how exploratory modeling may enhance scientific evaluation, offers a preliminary test of decision theories, and suggests future hypotheses.

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EXPLORATORY MODELING

In exploratory modeling, the breadth of scientific ideas is captured in an ensemble of alternative models, rather than a single comprehensive model [Bankes, 2002:7264; Lempert, et al., 2006; Kleijnen, 1997]. Then, the resulting parameter space from these alternatives is searched for models that explain phenomena or models that are robust against perturbations of their parameters [Lempert, et al., 2006]. Exploratory modeling has been used for applied purposes such as weather forecasting [Palmer, 2000] and policy analysis [Bankes, 1993]. Since social scientists often propose theories derived from different paradigms, exploratory modeling may assist them in dealing with their own deep uncertainty. I present a relatively simple case where 24 decision models, derived from several different paradigms, are tested against one another to explore their relative explanatory power. I concentrate on only versions of the models that correspond to specific published propositions. A full exploration of each model's parameters and variables would require the use of the more sophisticated sampling strategies enumerated above.

MODELING THE KAPAUKU OF IRIAN JAYA (NEW GUINEA)

The Kapauku are a tribal people who live in the highlands of Irian Jaya. Their economy is based on growing yams and raising pigs, they control territories that contain their farmland and villages, they have cultural norms of patrilineal descent, and they practiced extensive warfare in the first half of the 20th century. The anthropologist Leopold Pospisil made detailed and extensive observations of Kapauku economy and politics during the decade of the 1950's, and he published data on the individual economics and political affiliations of the 55 adult men who comprised the political network of the Kapauku village of Botekubo [Pospisil, 1963, 1972]. Two prominent features of Kapauku culture are men's obsession with wealth acquisition and the intensely political nature of men's lives. Kapauku political coalitions center around *tonowi* (wealthy men), who are both economically successful and politically powerful [Pospisil, 1963:11, 48]. I use Pospisil's data on individual men's wealth and political affiliations to test competing theories of decision making by simulating men's decisions with theorized decision rules and examining which rules produce Kapauku-like alliances.

I have developed a general computational model of risk-taking in which agents interact via a coordination game with an optimal Nash mixed strategy of probabilistically cooperating and defecting with partners [Kuznar, et al., 2006]. This general model was adapted to represent the political behavior of the 55 men in Botekubo. The simulation begins with each man in his own alliance, and coalitions evolve as men join or defect on one another according to programmed decision models. Competing decision models are evaluated based on the speed and accuracy with which alliances structurally similar to those observed in Botekubo form.

DECISION THEORY

The field of decision theory is divided among several different paradigmatic lines, including traditional (canonical) rational choice, various bounded rationality approaches, and prospect theory. Sigmoid utility represents another alternative, in part derived but also departing from rational choice [Kuznar, 2007]. Each paradigm gives rise to numerous specific theories.

Rational Choice

Core elements of rational choice include the assumptions that individuals have full knowledge of their preferences and resources, that individuals maximize their utility, and that individuals are selfish [Cowell, 1986:Chapter 4]. Nash optimal solutions to competitive or cooperative interactions assume rational capabilities and so represent rational choice decision models.

Sigmoid Utility

Sigmoid utility theory maintains that an individual's position in a wealth distribution influences that individual's sensitivity toward risk [Kuznar, 2002; Friedman and Savage, 1948; Kuznar, 2007]. Individuals on the cusp of a class boundary, where increases in social rank (climbing the social ladder) bring large increases in wealth and status, are expected to be risk prone, or to take chances. I have applied this approach to understanding various forms of political behavior from voting, to political coups, to rebellions, to modern day terrorism [Kuznar and Frederick, 2003; Kuznar, et al., 2006; Kuznar, 2007]. Since joining a group of unknown individuals carries risk, risk prone individuals are more likely to join, and risk averse individuals are least likely to join. This approach is derived from rational choice, but departs by being particularly sensitive to others' payoffs and by allowing envy at others' well-being (rather than greed for one's self) as a motivator.

Group Affiliation

Social psychologists argue that small group dynamics can override selfish motives, especially in extremely risk-prone groups that tend to become highly socially isolated [Atran, 2003]. Therefore, the social psychological effect of small group dynamics on members of a group will be the reverse of the effects on individuals regarding risk sensitivity. Agents' probability of joining with non-members will be inversely proportional to their group's risk sensitivity; members of highly insular groups never join with outsiders. By using sigmoid utility theory and Arrow-Pratt measures, this model combines elements of sigmoid and small group psychology paradigms.

Prospect Theory

Prospect theory [Kahneman and Tversky, 1979, 2000] is a collection of propositions about human decision making that are derived from and empirically supported by experimental studies. Prospect theory's three core propositions are that people systematically distort probabilities (overestimating low probabilities and underestimating high probabilities), that people are loss averse (experiencing twice the disutility of a loss than the utility of an equal gain), and that framing profoundly affects decision-making with people (people are risk prone when considering losses and risk averse when considering gains) [Kahneman, 2000]. Prospect theorists have derived mathematical functions for probability weighting [Prelec, 2000:77] and the disutility of loss aversion [Tversky and Fox, 2000:104; Tversky and Kahneman, 1992:57] and I use these functions to model probability weighting (PW) and loss aversion (LA) respectively. I model framing (FR) by recording whether an agent's wealth has increased or decreased, assigning an adjusted Nash optimal join probability for agents in a frame of gains or the reciprocal probability for agents in a frame of decreases.

Prestige Bias

Prestige bias is the imitation of those with higher social status [Boyd and Richerson, 1985], and is a simple heuristic proposed by bounded rationality theorists. Prestige bias theories fail to specify the scales at which it operates. Therefore, I modeled prestige bias at different scales including imitating a higher-status partner (Prestige 1, P1), imitating the household patriarch (Prestige 2, P2), imitating the wealthiest member of a coalition (Prestige 3, P3), and imitating the wealthiest member of the society (Prestige 4, P4).

Conformist Transmission

Conformist transmission refers to the copying of normative behavior in a society [Boyd and Richerson, 1985], and is another bounded rationality decision heuristic. As with prestige bias theory, conformist transmission theory offers no guidance as to what social norms are copied, those of a neighborhood, a tribe, a nation, or the global village. Consequently, I developed alternative models of conformist transmission including conformism to one's household (Conformism 1, C1), to one's alliance (Conformism 2, C2), and to the entire society (Conformism 3, C3). Models assuming that probabilities were drawn on a [0,1] interval (naïve agents) vs. probabilities that bracketed the Nash optimum (smart agents) were run for both the prestige bias and conformism models. The models that bracketed the Nash optimum combine elements of quasi-rational choice with bounded rationality.

Validation Metrics

Evaluating the goodness of fit of computational models is challenging. To date, many validations consist of producing graphical outputs (or often 2-dimensional geographic maps) that look like some stylized fact the researchers are modeling [Kohler, et al., 2005; Lansing, 1993; Kuznar and Sedlmeyer, 2005]. Some computational methodologists label this "viewgraph validation," and point out that while intuitive visual aids can be a useful starting point for validating models, they fall short of rigorous and thorough validations of the model [Kleijnen, 1995; Oberkampf and Trucano, 2002; Oberkampf, et al., 2004].

It is necessary to use quantitative measures of a model's performance in order to evaluate the degree to which different models are successful and in what ways [Oberkampf, et al., 2004]. Simulation researchers use Thiel's Inequiality Coefficient (TIC) to compare model and empirical outputs and have expanded it to incorporate multiple dimensions of goodness of fit [Murray-Smith, 1998; Kheir and Holmes, 1978]. The single-dimension metric is calculated as:

$$TIC = \frac{\sqrt{\sum_{i=1}^{n}(y_i - z_i)^2}}{\sqrt{\sum_{i=1}^{n} {y_i}^2} + \sqrt{\sum_{i=1}^{n} {z_i}^2}} = \frac{n_{yz}}{d_y + d_z}$$

Where y_i is an empirical measure, z_i is a model output that corresponds to the empirical measure, *i* indexes the *i*th model run, and *n* is the number of runs. We use Thiel's Inequality Coefficient to compare the number of coalitions generated by a model and mean coalition size to Pospisil's data. Its values vary from 0 to 1, with 0 indicating a close fit (no difference). The normalized values of the TIC allow comparison of different models and different performance variables.

Point measures like means, variances and TICs are commonly used and provide one means of evaluating goodness of fit. However, one can have identical means drawn from very different data distributions. The Kolmogorov-Smirnov *D* – Statistic provides a non-parametric test for the equality of distributions [Blalock, 1979:266-269]. Models that produce statistically significantly different data distributions clearly perform poorly, and models with large *p* – values produce data distributions statistically indistinguishable from actual data.

RESULTS

An ensemble of 24 models represents the basic propositions of these theories, derived from four paradigms (rational choice, sigmoid utility, small group social psychology, prospect theory) (Table 1). Each model was run 100 times, and 10 model runs were selected from each run for analysis of how quickly the model converged to alliances similar to those empirically observed in the tribe. The performance of each model at iteration 15 was used to standardize the comparisons.

Table 1. Relationship between Decision Theoretic Paradigms and Decision Models Tested in Kapauku Simulation.

Paradigms	**Models**
Rational Choice	Nash optimum (N)
Modified Rational Choice	Sigmoid utility (S)
Modified Rational Choice / Social Psychology	Sigmoid utility+Group affiliation (SG)
Prospect Theory	Probability weighting (PW), Loss aversion (LA), Framing effects (FR), PW+LA, PW+FR, LA+FR, PW+LA+FR
Bounded Rationality	naïve Prestige bias 1 (nP1), naïve Prestige bias 2 (nP2), naïve Prestige bias 3 (nP3), naïve Prestige bias 4 (nP4), naïve Conformism 1 (nC1), naïve Conformism 2 (nC2), naïve Conformism 3 (nC3)
Bounded Rationality / quasi-Rational Choice	smart Prestige bias 1 (sP1), smart Prestige bias 2 (sP2), smart Prestige bias 3 (sP3), smart Prestige bias 4 (sP4), smart Conformism 1 (sC1), smart Conformism 2 (sC2), smart Conformism 3 (sC3)

Four models provided close fits to empirical data, including sigmoid utility (S), sigmoid group affiliation (SG), smart conformism 2 (sC2), and loss aversion (LA). These results differ from an earlier effort that did not use Theil's Inequality coefficient and Kolmogorov-Smirnov. In that earlier study [Kuznar, 2006], a prestige bias model and the full prospect theory model also performed well. The results from using more robust metrics are more discriminating. They also are more discriminating among the well-performing models. Two models consistently performed well across all metrics, and they were the sigmoid utility (S) and smart conformism 2 (sC2).

Table 2. Model Performance in the Kapauku Simulation.

Model	TIC Coalition Number	TIC Mean Coalition Size	Difference from Actual Coalition Number	Difference from Actual Coalition Size	No. Distribution Matches per 20 runs	Kologorov-Smirnov mean p-value
Nash	0.118	0.105	3.35	0.55	**15**	**0.258**
Sigmoid	**0.074**	**0.066**	**1.40**	**0.24**	**15**	0.252
Group Affiliation	**0.095**	**0.085**	**2.30**	**0.39**	11	0.199
Prestige I	0.109	0.096	3	0.50	13	**0.310**
Prestige II [0,1]	0.267	0.252	11	1.37	1	0.024
Prestige III [0,1]	0.240	0.220	9.2	1.21	4	0.072
Prestige IV [0,1]	0.242	0.223	9.35	1.22	1	0.034
Prestige II [0.3,0.9]	0.145	0.128	4.2	0.64	14	**0.275**
Prestige III [0.3,0.9]	0.150	0.141	5.15	0.81	13	0.173
Prestige IV [0.3,0.9]	0.245	0.225	9.5	1.23	3	0.050
Conformism I [0,1]	0.204	0.181	7.1	0.99	5	0.112
Conformism II [0,1]	0.248	0.240	10.2	1.32	0	0.019
Conformism III [0,1]	0.213	0.192	7.7	1.07	7	0.172
Conformism I [0.3,0.9]	0.130	0.113	3.15	**0.47**	13	0.202
Conformism II [0.3,0.9]	**0.083**	**0.073**	**2**	**0.35**	**15**	0.230
Conformism III [0.3,0.9]	0.120	0.107	3.4	0.55	**16**	0.181
PW (probability Weighting)	0.171	0.163	6.2	0.94	10	0.199
FR (Framing)	0.210	0.199	8	1.12	7	0.079
LA (Loss Aversion)	**0.090**	0.103	**1.7**	0.49	**17**	**0.371**
PW FR	0.187	0.175	6.8	1.00	5	0.088
FR LA	0.365	0.365	17.95	1.80	0	0.004
PW FR LA	0.284	0.271	12.1	1.45	3	0.042

(Full Prospect Theory)						
Mean	0.181	0.169	6.58	0.896	8.5	0.152
s.d.	0.077	0.075	4.15	0.422	5.9	0.106
Threshold	**<0.104**	**<0.094**	**<2.43**	**<0.474**	**>14.4**	**>0.258**

A more fruitful approach is to explore new hypotheses by asking what the successful models had in common. Successful models had two characteristics in common: 1) agents behaved in a quasi-optimal manner by selecting strategies that did not deviate far from Nash optimality, and 2) agents were not homogenous in their decisions. Therefore, the specific models derived from four different paradigms might not so much accurately represent reality as much as capture some essential elements that a model must have to be valid.

CONCLUSION

Computational models provide new and flexible capabilities for representing social theories from different paradigms. Exploratory modeling using ensembles of models provides a method by which competing theories can be tested. The result of the testing may not be a single correct answer, but insights into what essential elements better theories must contain. In the Kapauku case, theories related to rational choice, prospect theory, and bounded rationality each has some merit. In particular Kapauku men appear to have a general sense of what an optimal political strategy is, they may be imitating one another to refine their strategies, and their decisions appear to be conditioned by prospect theory biases, risk sensitivity, and group pressures to conform. Exploratory modeling with ensembles provides a method for more systematically searching the implications of these theories and suggesting new hypotheses that may aid in the search for more comprehensive and valid theories.

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