

EXPLORATORY MODELING OF ENSEMBLES FOR TESTING DECISION THEORY PARADIGMS

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ABSTRACT

Purely textual or mathematical representations suffer from intractability and vagueness respectively, making the rigorous comparison of theories, or of paradigmatic approaches, virtually impossible in traditional social science. Computational models provide an unprecedented ability to represent and test social theory. Different theories, represented as algorithms, can be tested alone or against one another *in silico* and in any combination imaginable. The advantages of this new capability are counteracted by the burden of trying to compare the effects of so many combinations of theoretical elements. Exploratory modeling systematically searches large parameter spaces of an ensemble of different models, and identifies models with the most explanatory power. This approach is used when competing models are characterized by “deep uncertainty” in their parameters and variables. Social scientists’ often disagree strongly on what variables are relevant or what values parameters should have in social scientific theories. Therefore exploratory modeling provides a tool that can enhance scientific decision-making. I provide an example of exploratory modeling for testing the validity of decision theories from rational choice, sigmoid utility, bounded rationality, and prospect theory paradigms. Political alliance formation in an Irian Jaya tribe is used as an empirical test case. In this case, exploratory modeling provides a way of comparing the validity of theories derived from different paradigms, and also suggests new hypotheses that may better explain the data.

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

INTRODUCTION

Traditional representations of theory in the social sciences rely on textual descriptions or mathematical representations. Textual descriptions suffer from the ambiguity of natural language. Mathematical modeling forces a rigor upon social theories, but many social phenomena are too complex or path dependent to allow tractable solutions (Holland, 1998). Furthermore, when theories from different paradigms (for example rational choice vs. bounded rationality) incorporate different variables and assumptions, it may be impossible to represent them in the same mathematical framework. Computational approaches in the social sciences are more rigorous than text but more flexible than mathematical formulations, and so appear to present a workable compromise for representing social theory (Sallach, 2003). An advantage of computational social science (CSS) is that seemingly incommensurable theories can be represented algorithmically and placed in the same simulation environment where their implications can be explored and their relative explanatory power compared. Rigorous testing of these competing theories would involve a thorough search of all potential variables and parameters.

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The promise of CSS comes, however, at a cost. While it may be possible to represent competing theories and varying parameter levels in a computational framework, the resulting space of possibilities (theory space) can be infinite. Realistic theories may possess hundreds or thousands of variable combinations. Furthermore, if the theories differ on the value of continuously varying parameters, the resulting parameter spaces can be infinite. Exploratory modeling is a potential solution to this problem, and employs an ensemble of models representing different theories that is explored for the set of models that may best represent the state of scientific knowledge (Bankes, 1993).

In this paper, I will present an application of exploratory modeling for testing competing decision theories that are derived from very different paradigms. 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.

EXPLORATORY MODELING

Bankes (1993) proposed exploratory modeling as an aid for decision makers who are very uncertain about their models of the world. Scientists are often ignorant about some phenomena because they happen too infrequently (nuclear catastrophes, meteor strikes, class 5 hurricanes). In other cases, paradigmatic differences are so great that scientists cannot agree on how to approach an explanation (economic behavior, the evolution of human behavior, causes of terrorism). Low probability events and scientific controversies are characterized by “deep uncertainty,” or ignorance of what variables and causal relationships hold or what parameters may characterize complex systems (Bankes, 2002:7263). Exploratory modeling provides a potential method for comparing models characterized by deep uncertainty.

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.

The technical details of how to search vast parameter spaces are open to discussion, but sampling strategies such as Monte Carlo and Latin Hypercube sampling (Kleijnen, 1997), patient rule induction methods (PRIM) (Lempert, et al., 2006), the use of neural networks (Bankes, 1993), and genetic algorithms (Miller, 1998) have been used or proposed. 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 and Frederick, 2003). 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). The omniscience implied by these assumptions is an overstatement of human capabilities (Gigerenzer and Selten, 2001; Klein, 2001). The assumption of strict self-interest has also been strongly criticized and demonstrated to be limited in its applicability (Fehr and Schmidt, 1999). 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). 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). The Arrow-Pratt measure of risk aversion measures an individual's risk sensitivity. It is calculated as: $AP = -W''/W'$, Where W is a wealth distribution function estimated, in this case, based on Kapauku men's wealth. Positive values indicate risk aversion and negative values indicate risk proneness. In the model's coordination game the risky choice is to cooperate, so the Join probability is altered as a proportion of an individual's risk proneness to the overall risk proneness of the population (Kuznar and Kobelja, 2006a). The most risk prone individuals always join, the least never 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. These functions adjust the Nash optimum join probability by weighting it, or by adjusting the game's payoffs according to the disutility of losses or utility of gains. 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.

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). Note that this does not represent all of the possible and scientifically reasonable ways that these theories might be combined. Instead, this reflects the state of debates among social scientists. The theory space that results from cross-comparison of these 24 models is a 24X24 matrix of 576 outputs, indicating how rapidly the theory space of an ensemble can grow. 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)

Several metrics were used to evaluate the efficacy of each model, including: the squared error of predicting the number of coalitions, the squared error of predicting mean coalition size, and the squared error of predicting the frequency distribution of coalition sizes (see Kuznar and Kobelja, 2006b). The best models predicted coalition number and size within 10-12% of the observed metric (number of coalitions, coalition size), whereas poor models typically predicted metrics to only 30-40%.

Most models did not perform very well, and for brevity are not presented here. Six models performed well, including the Nash optimum (N), sigmoid utility (S), 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. Four models showed the most promise, including SG, PT, sP3, and sC2. The naïve agent conformism 2 model (nC2) is included in this analysis as a typical example of a poor model. Models are compared by examining differences in their squared errors from actual data. Models that are statistically significantly different from the poor nC2 model provide especially close fits to the original data (Table 2).

Table 2. Model Performance in the Kapauku Simulation.

Model Comparisons	Metric Differences p-value		
	No. Coalitions SE	Mean Coalitions SE	Coalition Size Distribution SE
NC2 – SG	0.003	0.003	0.000
NC2 – PT	0.005	0.003	0.001
NC2 – sP3	0.005	0.026	0.000
NC2 – sC2	0.003	0.007	0.000
SG – PT	0.827	0.509	0.159
SG – sP3	0.694	0.990	0.331
SG – sC2	0.397	0.713	0.007
SP3 – sC2	0.494	0.616	0.015

The four best models fit the data much better than the vast majority of models as represented by naïve conformism 2 (nC2), with each model showing very strong and statistically significant differences from the poorer model on all metrics. The best of all the models, smart conformism 2 (sC2) additionally demonstrated statistically significantly better fits to the distribution of coalition sizes than either the sigmoid group (SG) or smart prestige bias 3 (sP3) models.

I would caution against concluding that the best fitting model, sC2, is confirmed and its competitors falsified, since it outperformed on only one metric presented here, and provided fits closer by a factor of at most 5%. 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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