2010

Verification, Validation, and Accreditation (VV&A) of Social Simulations

Duong, Deborah

Verification, Validation, and Accreditation (VV&A) of Social Simulations

Deborah Duong
Augustine Consulting, Inc.
Naval Postgraduate School
Monterey, CA 93943
dvduong@nps.edu

Keywords:

Validation, Irregular Warfare, Verification, Conceptual Model, Agent-Based Model, System Dynamics, Bayesian networks, causation, correlation, social science, modeling

ABSTRACT: This paper discusses the VV&A of social simulations by an examination of uncertainty, correlation, and cause in social processes in general and in social simulation methodologies in particular. Standards of scientific investigation for social simulation are presented, and different methodologies of social simulation are examined for the degree to which they can implement the standard. Methodologies examined include Bayesian networks, system dynamics models, reactive agent-based models and cognitive agent-based models. Standards for the accumulation of knowledge in social science through refutation of conceptual models are presented, and how they may be objectively evaluated using computational technologies of ontologies and optimization under soft constraints.

1. Introduction

Many practitioners of social simulation criticize the military Verification, Validation and Accreditation (VV&A) process as missing the mark in terms of capturing an understanding of the value of these simulations. It is widely believed that the subjective criteria of validation, such as “face validation,” are often misapplied by subject matter experts (SMEs) who are unfamiliar with the concepts of the new field of Computational Social Science. What is needed is a new set of objective criteria that give the military decision maker confidence in social simulation. In the interest of developing appropriate objective criteria, we examine what validation is, why we need it, and how differences from physics based simulation require different validation techniques. Objective methods for validation which follow the Statics and Computer Science principle of “separation of the testing set from the training set” against data that the model has not been trained on, are presented.

2. Uncertainty in Social Science Simulation

Simulations to be used for scientific purposes, such as analysis, are meant to inform us about new situations, such as what might happen if the commander tries a new Concept of Operations (CONOPS). Decision makers use simulations to anticipate the effects of actions and give predictive insights with a great amount of uncertainty. This is opposed to simulation for training purposes, which can be purely descriptive and does not need to generalize to unforeseen situations. Perhaps the most distinguishing characteristic of social simulation is its greater uncertainty as compared with physics simulations. This uncertainty comes from many different factors, including the disagreement among social scientists about the nature of the social environment, the lack of consensus on how to represent the social environment in a computer, and the relative lack of experimental controls in data collection in the social sciences. But even in a best-case scenario for social analysis, with accurate social theories and new technologies for computational representation and data gathering, there would still be uncertainty in social analysis because of the uncertainty intrinsic to the social world. Human beings are the symbolic species, and symbols are by nature arbitrary. This arbitrariness makes detailed prediction impossible: we would not expect a simulation of the emergence of language, for instance, to come up with the exact phonemes in Japanese, because that is arbitrary. However, good social theories direct us to what falls into patterns and what is arbitrary. In other words, good theories and techniques give us greater knowledge of what the intrinsic uncertainties are and what patterns we can expect to see. As long as the commander has confidence in what the uncertainties are, he can make rational decisions in the same way that a gambler can make rational decisions given knowledge of the intrinsic uncertainties in a game of cards. Even if uncertainty is high, with say a 60% chance of success, he can make a rational allocation of resources instead of accepting the risks from doing nothing, which could be greater.

VV&A is meant to inform the analyst how correct a tool is likely to be for a given situation so that a rational decision may be made. The commander needs an objective measure of how much a simulation matches social correlative data and an understanding of how well the simulation will generalize to the new CONOPS situation. Accreditation of conventional simulations tells under what conditions a tool falls within acceptable credibility limits. However, with social simulation, the results are less certain. Typical levels of certainty for physics based scientific experiments in which "all else is held the same" may be 90% or greater, while typical levels of certainty for a social theory may be at the 60-70% level. In the complex adaptive system (CAS) of society, scientists do not often have the option to "hold all else the same," to tease out cause in a way that raises the certainty levels, because of ethical restraints on experimentation with human beings. This in turn prevents the development of theory that characterizes the correct variable levels that would also raise the certainty. The goal of computational social science is to use computer simulation to do the analyses that cannot be done by direct experiment, to develop better theories and guide us towards accurate patterns to look for. Computer simulation experiments have some advantage over real world experiments: they can not only "hold all else the same" better than real world experiments, but they can also analyze how groups of phenomena interact with each other, in vicious and virtuous cycles, something social scientists can only conjecture about without CAS analysis techniques. The computer also offers a way for the causal analysis of social theory to be compared to real world correlational social data on a large scale, to offer an objective measure of the degree to which the simulation matches correlational data. This measure is not only the VV&A that the commander needs to determine risk, it is also an essential step in the iterative improvement of theory which constitutes science. As George Box noted, science is an iterative process between theory which directs experiment, and statistical analysis of experimental data which directs theory [1]. In order for such an iteration to work with science, a correspondence between the simulation data and the real world data must be drawn. Computer science offers the technology of ontologies with which to draw the correspondence between causal simulation data and real world correlational data.

The capacity to match simulation to corresponding real world data and obtain objective measures of fit is essential to the practice of computational social science for the advancement of theory, but the commander does not have to wait for the improvement of theory for the measure of uncertainty to be useful. This is because we can now take all types of uncertainty into account, including epistemic uncertainty, which is uncertainty because we do not know something, and intrinsic uncertainty, or uncertainty that is part of the system studied. Better science can reduce the epistemic uncertainty of a system, at the same time it describes the intrinsic uncertainty of a system, but both epistemic and intrinsic uncertainty can be measured and used in a risk calculation. As an example, suppose that a gambler bets on a game of craps with someone he suspects of dishonesty. The gambler knows that half of the time, when he suspects someone of dishonesty, he is right. This uncertainty in the credibility of the gambling partner is epistemic uncertainty, or uncertainty because he does not know if his partner is cheating or not. However, the probability of the actual role of a fair dice can go into his calculation of risk with which he decides whether to play and how much to bet. The comparisons of the results of simulations to data done in the VV&A process, using the principle of separation of the testing set from the training set, tells the total uncertainty. Even if that uncertainty is now high, it is useful to commanders in a world of risks that can result from both action and inaction.

In fact, the best way to treat the multitude of theories in the social sciences is as another form of uncertainty. Because of limited resources, few social theories are typically used in analysis of Irregular Warfare (IW), but that is not the best way to test CONOPS given disagreement in the social sciences. It is better to compare CONOPS against all schools of social thought, as long as social scientists disagree on which theories are the most accurate. The same thing should be done with epistemic uncertainty that is done with all uncertainty in the testing of CONOPS: the CONOPS that are found to be the most robust in the most plausible scenarios are the most successful CONOPS. Whether the random variates of stochastic discrete event conventional simulations are averaged to show the success of CONOPS, or the different scenarios of different social theories are individually compared, robustness of CONOPS is still the measure.

3. The Principle of the Separation of the Testing Set from the Training Set

If a commander wants to use a simulation in a new situation and have confidence in its correctness, that simulation must have been tested with situations that the simulation has never seen before that are not very different from the situation that he wants to use it in. In computer science and statistics, we call this the principle of separating the testing set from the training set: the data that modelers use to develop the model is as different as the data used to test the model as the data the simulation is to be used on. Before the simulation is put into use, it should be tested with "surprise" data, to test the ability to generalize. Social science simulation is no different from physics based simulation in this respect: both the social theory and the physical theory deal with phenomena with some intrinsic randomness, however, physics theory is more general and agreed upon because physics theory guides us well as to what to measure and what to ignore. Perhaps the greater uncertainty in the social world prevents us from finding accurate patterns in social science, but how we will know that we have found those more accurate patterns can only be by the generality of the applicability of the theory. The idea that there are no general patterns in the social world is false, because we as humans see patterns and use them to navigate the social world all of the time. Analysis techniques have the potential to give us different, more objective views of general patterns. We know we want to see generally applicable patterns, so we need to use our technologies to help us discover those patterns.

The way that we obtain patterns in science is through accurate theory of causal relations. Computer simulations are causal models, as opposed to statistical correlational models or rule-based models. We could make models that describe the outer phenomena, such as a plastic model plane that does not fly describes the way a plane looks, but theory of cause is needed to be useful in science or in any analysis. We know a theory of cause is correct because it is both parsimonious and general. For example, the Ptolemaic theory of the solar system is neither parsimonious nor general, that is, it takes much space to describe what phenomena occurs with what other phenomena, much of that phenomena is double counted, and it cannot be used from any other viewpoint but Earth's. However, the Copernican theory is much more succinct and can be used in other solar systems as well. We need more accurate causal models to make models that generalize to new situations and pass tests of the separation of the testing set from the training set.

As a result of their different degree of agency and causality vs. descriptiveness, different simulation methodologies have different abilities to find accurate and general patterns.

4. Causation and Correlation in the CAS Methodologies of Social Science Simulation

The commander's CONOPS are a type of social intervention, and to test our CONOPS, we would want to know about how alternative interventions interact with the present social system, to find the higher order effects that SMEs and statistical methods alone cannot foresee. To do this, we need to look at the existing social structures, and what might break down or repair them.

Social structures come in the form of institutions. Adam Smith saw social institutions as the "invisible hand" through which a miracle can occur: the miracle of individuals acting purely in their own interest creating a society which is good for the whole [2]. Such optimistic views describe societies that are in virtuous cycles. If the emergence of good social institutions out of utility-maximizing individual acts is a natural process, then places in the world in need of international interventions are in the midst of the breakdown of that process, places where individuals seeking their own benefit create dysfunctional patterns, places which are stuck in vicious cycles. Virtuous and vicious cycles are both kinds of dynamic structures, complex adaptive system terminology for structures that exist because a series of events cause each other. The best models of the effects of international interventions would model first principles that explain why the individual seeking personal utility sometimes results in the good of all, and sometimes results in dysfunctional patterns. They would address the relation between structure and agency. Countries that are hotspots of world conflict are often caught in vicious cycles that are often not volitional on an individual level. For example, the worse critics of corrupt practices are often those that feel compelled to engage in them [3]. A good model of corruption will explain coercive social forces where individuals that maximize their personal utility are drawn into vicious cycles in which their behavior harms each other, instead of the virtuous cycles of Adam Smith's free market. The purpose of a model would be to detect and guide intervening actions at tipping points, points where actions make a difference as to whether social institutions enter and leave virtuous and vicious cycles. If action at these tipping points is missed, then future corrective action could be far more difficult or impossible to perform.

If the purpose of the model is to find the effect of international interventions on a social environment, a correlative or a rule based model alone cannot do this. In order to find the levers, cause, rather than correlation, must be modeled. As in the Ptolemaic model, with descriptive correlation it is nearly impossible to avoid double counting phenomena, resulting in a model that is "muscle bound," only giving an outwardly plausible result for a very limited set of data. The purpose of a simulation model is to model from first principles, computing out the implications from the assumptions as they apply to a particular scenario. In order to do this, a simulation must model cause, which in a simulation is a walkthrough of the process by which phenomena come to be correlated when looked at from the outside. In machine learning techniques, which are based on correlation, it does not matter how the output prediction is derived from the input: in most cases it is a black box. However, in a simulation model it does matter how the phenomena of interest is derived from the assumptions: the derivation must be a process that corresponds to a conceptual model of a real world process. This conceptual model is a social theory, but one that is detailed enough to define the causal processes that correspond to the real world as represented in a computer simulation.

5. Descriptive Methods

Some methods stand between the purely correlational statistical methods and causal models, including system dynamics models and Bayesian networks. These methods have the capability of describing cause; however, causal explanations are not generated by the models themselves. What these models lack can be made up by using them as part of hybrid systems with other models that do generate causal explanations. System dynamics models are differential equation models that correspond to a conceptual model as is required in social simulation models. However, in system dynamics models, the relation between variables is modeled, but the reasons for these relations are seldom described. The relation between variables is set up beforehand and cannot change as the model is run. The models describe that the value of one variable goes up while another goes down, but they do not explain why. system dynamics models thus tend to stay at a single level of description.

Bayesian networks can also represent cause, but their structure is either of causal patterns designed by a modeler, or of correlational links learned from data. Bayesian networks are a method of determining the likelihood of system state based on the condition of other system states in conditional probability tables.

Both methodologies, because of their descriptive, correlational nature, have a tendency to over-fit the data, whether this over-fitting occurs during construction by humans or when the structure is machine learned. Data is over fit when an incorrect model can generate real world data in one or very few instances only, and is not able to forecast any excursion from this limited set. Over fitting occurs when there are too many variables that may be adjusted to each other, making a system so flexible that it does not resist our incorrect ideas about the system's nature. There are an infinite number of incorrect ways to model a data set, and less flexible techniques which actually walk through a simulation, such as agent based modeling, are better at alerting us to failure. In any case, the practice of separating the testing set from the training set will show when over-fitting has occurred, and should be used to test the effectiveness of any model against data it has not seen, before it is put in actual use.

Because they are basically descriptive in nature, Bayesian networks and system dynamics models tend to lack parsimony, having many variables that form many hypotheses. A myriad of hypotheses puts the analysis at risk in that they often lead to the double counting of phenomenon and incorrectness as a result. Too many hypotheses at once lead to the greater uncertainty which puts a scientifically rigorous analysis in question. The uncertainty from multiple hypotheses of cause is a greater problem in the deterministic, hand-constructed system dynamics models. A Bayesian net with the wrong causal structure may not generalize well, but it does have a distribution of answers while a system dynamics model with the wrong casual structure comes up with only a single (wrong) answer. In operations research, uncertainty in models is dealt with through trying out all the possibilities in proportion to their plausibility, as modeled with random draws from probability distributions, and then examining the likely outcomes, drawing a confidence interval given those uncertainties. This is viable, even with a system with lots of uncertainty in it, because the number of runs depends on the variance of output variables rather than the variance inside the model. Even with much variance inside the model, an output variable may have much less variance, requiring a reasonable number of runs for the development of a confidence interval. To deal with uncertainty in what is usually a deterministic system dynamics model, we would have to include all of the alternative hypotheses that are represented in the myriad equations, something that Bayesian networks do but system dynamics models do not. That is, when we are uncertain of a relation between variables as expressed in an equation, we should run several different plausible equations in a systems dynamics model. Unfortunately, this is a practice that is not easy and not followed, making system dynamics models deterministic rather than stochastic, and contrary to some of the basic principles of analysis in operations research.

Deterministic system dynamics techniques do not deal with the development or consequences of heterogeneity, but rather address only "average" entities of any class. For example, they cannot model a social network by themselves: they cannot relate a particular father to a particular son. The best systems dynamics models can do is relate averaged fathers to averaged sons. If events that occur at the tails of distributions are important, as in complex social phenomena, then models that average the entities miss those important events. For example, actors that influence society may perform infrequent (outlier) events with significant consequence to the population.. This is a significant problem, because, while any one entity is expected to be average, in most systems it is very unlikely for all the entities to be average.

The descriptive nature of Bayesian networks and system dynamics models presents an even more basic problem for modeling an analysis of the results of our interventions in a society: the epistemological problem of bias –,running a scientific experiment so that the answer to the question is in the question itself. If the relations between the variables and the structure of a model is basically static, as in Bayesian networks and system dynamics models, then answers to questions about the relations between variables (such as the relation between an international intervention and crime or corruption in the state) come from the assumptions of the model, as opposed to being computed from first principles. To contrast, the agent based method of computing out the implications of first principles recombined in different scenarios, does not put the answer to the question in the question, and is more similar to traditional operations research analysis of problems. It is of prime importance in validating a model that the input is separated from the output, and does not follow directly or obviously from it; however, in this stage of irregular warfare analysis this fundamental principle is often neglected.

6. Methods Involving Emergence

Agent-based models (ABMs) model individuals with agency that perceive and act in their environment based on goals, and have a level of description in addition to the agent level, the social level. In contrast to system dynamics models, ABMs explain how phenomena at a single level of description relate to each other through a type of indirection, known as emergence. With ABMs we may walk through the lower level process that causes the relation, because agent based models have more than one level of description. In agent based systems, the phenomena of emergence are simply the patterns created as the assumptions are walked through, and these patterns do not exist before the simulation is run, not even in the mind of the modeler. True emergence implies creation of patterns, "dynamic structures," by the dynamics of the model and thus non-predetermined results. This non-predetermination of result is important to the basic principle of non-bias in science, of not putting the answer to the question of an experiment in the question itself. To contrast, in system dynamics models, the relationship between variables is designed by the modeler before the run of the simulation, and is thus more descriptive than computing from first principles. The upper level of description in an agent based model is the social institutions, the patterns of virtuous or vicious cycles through which individual motivation affects social processes and social processes affect individual motivation. Agent based models can find higher order effects because they model how individuals learn new behavior patterns based on goals when an intervention to their environment is made, individuals that react not only to the intervention, but to the other individuals reacting to the intervention, and so on.

Agent based modeling is applicable to causal models in the two main types of social theory: objective and subjective. One example of an objective social theory is the general equilibrium theory model from economics. Even if a social theory is completely objective and materialistic, and the choices of the agent are subconscious to the agent, that social theory is still enacted through an agent. The process by which human action happens is always through human agency, so that even social theories that are materialistic in nature, for example those that use non-human phenomena such as the natural environment to predict human behavior, are still best simulated with agents in order to model cause. A social theory may be behaviorist and ignore what is not measurable in the conscious or subconscious mentation of the agent, but, if is a complete theory, it will still explain the process by which human beings bring about the correlation between the environment and their behavior patterns. Thus objective theories of the social environment, for example cultural materialist theories, can be simulated with either the simpler correlational methods such as statistical, machine learning, and system dynamics methods; or the more complex causal methods such as agent based methods. Social theories which have simplifying assumptions made to enable a less complex analysis, such as general equilibrium theory's assumption of perfect information in economics, can still be modeled with agents that obey those simplifying assumptions. Agents with simple rules, also called "reactive agents," are adequate for such an analysis. However, if the method does not require simplification, it is very informative to drop simplifying assumptions to compare the outcome to that of analyses which require the simplifying assumptions. Epstein and Axtell's Sugarscape is an example of an agent based model of economics that uses reactive agents to drop the simplifying assumption of perfect information in general equilibrium theory, so that the implications of bounded knowledge may be explored [4].

To contrast, the more subjective social theories, such as those of the interpretive paradigm, should only be simulated with the more complex causal methods of the agent based modeling paradigm. In subjective social theories, perception and interpretation determine behavior, and so to walk through the causes of phenomena in subjective social theories those subjective phenomena are modeled through an agent's interpretation of its environment. Models of subjective social theory, to capture the complexities of interpretation, require agents that have cognitive abilities. These "cognitive agents" have the ability to perceive and learn an interpretation, and are more complex than the “reactive agents” that are adequate for objective social theory models.

One example of a subjective social theory that could be modeled a number of ways is “the New Institutional Economics” (NIE), the economic theory that institutions form from the collective effects of individual behaviors of agents intending to reduce the uncertainty of the outcomes in their social interactions [5]. Models of the theory of the NIE therefore should include cognitive agents which learn how to reduce their uncertainty. One method of modeling NIE is with cognitive agents that learn using a neural network [5]. Although a neural network is a method of machine learning, which can predict social phenomena in a simple correlative manner as a standalone, the situation is more complex when there are individual neural networks in every agent of a cognitive agent simulation. The same is true with other machine learning techniques such as Bayesian networks or genetic algorithms: they are simple when used in standalone version, but complex when used as the mind of single agents in a multi-agent simulation. System dynamics models have been used for agent cognition as well. No matter the particular model of cognition, when agents adapt to each other, they engage in a “coevolution” from which new institutions emerge, new ways that agents learn to behave in reaction to an intervention.

The NIE describes a process whereby agents approach equilibria, as in general equilibrium theory, but the knowledge they gain as institutions form while they seek the equilibria acts to move the equilibria, and this is the engine of social change. If we were to describe the approach to equilibria in terms of feedback, from systems theory, it would be negative feedback. Agents converge upon an institution when there is nothing they can do to better themselves because their self interests motivate them to act towards one another in ways that dampen change, just as a thermostat uses feedback to keep the temperature constant. If we were to describe the formation of new equilibria as a side effect of the NIE approach to equilibria in systems theory terms, it would be positive feedback. Agents complexify, accumulating new institutions in a hierarchical manner as the new institutions give them new motivations to optimize, resulting in growth. If we were to model NIE with both agent-based and system dynamics models, the system dynamics model would capture these positive and negative feedback processes in a static manner, describing how institutions work once they already exist, rather than how they come to be. To contrast, agent-based systems would walk through the processes by which these new social structures form. The birth of institutions is of more than historical importance, because the structures of CAS are dynamic, existing only because they are continually “coming to be.” Agent based models capture the dynamism of structures which only exist because they are continually generated, and thus have a higher fidelity to CAS theory.

Another property that gives agent based models the potential to be highly valid is their concreteness. One common problem in social models is what some call “squishy variables,” or nebulous social qualities that have no real measure in the world. Modelers who use this technique often say they care about the direction of the variable, but forget to consider that the direction is sensitive to the magnitude in methods such as system dynamics. It is better to base social models on measurable, countable indicators, such as the standard variables of economics: gross domestic product, and even something like consumer confidence, where there exists a method to determine the values of variables in the real world.

Because agent based models are simulations that walk through assumptions, their input data tend to be more countable and obtainable in principle than the data of the techniques which emulate cognitive maps. Because they compute from first principles, their data is endogenously generated, so that they tend to need less initialization data. Rather, agent based models have relatively fewer assumptions but the higher order effects of those assumptions are emphasized, resulting in emergent phenomena, or new phenomena generated from the computation of the implications of the relatively few assumptions. Agent based simulations have an epistemological soundness based on Occam’s razor: if a few assumptions, known to exist on an individual (micro) level, generate many patterns known to exist on a social (macro) level, then we have a good, parsimonious explanation. If the pattern is true across scenarios, including for data that the model has never seen before, then we can begin to say we have a validated model. Agent based models are more resistant to incorrect theorizing by virtue of the fact that agent based modeling is less flexible than correlative methods, having to walk through a process that corresponds to a theory to get to its results. Because they are inflexible, we know what valid models look like: a few known micro-level assumptions computing out many known macro-level patterns, and doing so in general and for unseen data sets. However, the hard part is knowing how to be successful.

The phenomenon of emergence, or the endogenous generation of structure, has implications for the traceability of cause in agent based models. It is often difficult to trace the cause of emergent upper level patterns in agent based models because the relations between variables are not set up before hand, as in many Bayesian net models and all system dynamics simulations, but rather occur because of the dynamics in the simulation. However, tracing cause is doable, and may involve debugging and statistical techniques.

As described earlier, agent based simulations come in two kinds: reactive and cognitive. Reactive agents have a few static rules that determine their behavior, and different macro-level patterns emerge from different starting conditions. In contrast, cognitive agents can learn and change the rules by which they behave. Learning is important for the simulation of the emergence of institutions, because it allows feedback from macro level patterns down to micro level behaviors, a phenomenon known as "immergence." The upper-lower feedback of immergence is essential for the true emergence of new practices that are computed from the simulation's assumptions rather than being predetermined by the modeler beforehand. How new practices might arise is exactly what we are looking for when we test socially oriented CONOPS such as measures against corruption.

Reactive simulations are adequate for testing the consequences of policy on existing structures. Some agents lie halfway between the cognitive and the reactive types. Reactive agents may include simple memory based on past interactions, or they may be part of a machine learning algorithm called a genetic algorithm, where the group of agents as a whole has a "species memory" of past interactions.

Agents that are part of a genetic algorithm can learn new social structures as a group. They do not learn through their own experiences, as an autonomous agent would, but they learn by the experience of the "species," the group of agents that they reproduce with. Agents with better strategies reproduce in greater proportion, so that the entire species converges upon strategies that work. John Holland[6] invented genetic algorithms as simulations of biological evolution, but others have used this technique to simulate the emergence of social strategies. These strategies are recognized rules of social interaction, or institutions. There has been much research in the field of Computational Social Science on the learning of institutions by playing the games of game theory iteratively using genetic algorithms. Axelrod's Iterated Prisoners Dilemma (IPD) was the first such study where the strategy of cooperation emerged in agents that could receive a more immediate benefit from cheating [7]. The IPD is viewed as a general formula for the emergence of social behavior, which is relevant to the study of the breakdown of institutions that the analyst needs to take into account in the testing of CONOPS.

True cognitive agents have the advantage of autonomy, of perceiving their environment and acting upon their perceptions of their individual experiences. The genetic algorithm technique and simple reactive agent learning techniques are not as scientifically rigorous because the phenomena that are under investigation are artifacts of the method. Social institutions are the phenomena in question, defined as common patterns of behavior. Genetic Algorithms in simple reactive learning agents work by replication, and convergence is a property of genetic algorithms. If you use a method that can produce the answer you seek no matter what model you use, then it offers no resistance to false models, and does not in fact come to a reasonable result because of the model, but because of a side effect of the method. In other words, to explain common behavior patterns by copying, we put the answer to the question in the question itself. Rather, for scientific rigor, agents should have the choice of having differing behaviors, and a theory of institutions should address why sometimes agents act in unison and sometimes do not. Autonomous agents, which are not coerced to copy but act only according to their utility based on their individual perceptions, have that choice.

7. Principles of Verification, Validation, and Accreditation for Social Models

To pass a validation, a social model should adequately separate the input from the output so that relations are developed within the simulation that were not there to begin with, be parsimonious and general enough so that the testing set may be separated from the training set, be countable so that a reality check may be made, and model the basics of social theory, rather than just phenomena that are easy to model but are not representative of social theory. The social model and its use in a study should express intrinsic and epistemic uncertainty and use them to give a measure of confidence in the analysis. A study should represent all applicable schools of social theory and treat the disagreement of social scientists as any other form of uncertainty. Models should generate dynamic structures based on human motivation and agency, that explain how structure and agency interact to cause their behavior, to use for testing CONOPS against. These rules are reflective of good science practices, resulting in models of high confidence. However, additional formal and computational tools are needed to derive objective measures that analysts and scientists need for measurement of confidence, regardless of the model's technique. The main problem in presenting a model data for testing that it has not been trained on, as necessary for validation, is the unavailability of data that exactly corresponds to the data of the model. However, technologies of correspondence and data matching under uncertainty can be used to match models to a great deal of data for the purpose of validation.

The first formalism needed specifically for IW VV&A is that of the social conceptual model. It is the conceptual model which is validated against real world data using patterns as directed by social theory. The conceptual model is also used in verification, the determination that the code accurately implements the conceptual model. The conceptual model is supposed to define the simulation, including all processes that matter to the result. Everything in the simulation that is supposed to have a correspondence in the real world is specified in the conceptual model, and everything that does not have a correspondence is simply implementation. A good conceptual model makes the simulation artifact proof, because if something matters to the result of the process, its description appears in the definition. This is why careful conceptual modeling is difficult: it is often not known what processes matter to the result. For example, computational social scientists advocate docking, the implementation of conceptual models in more than one way, to discover if what was thought of as solely an implementation method was not solely an implementation method because it actually matters to the result. For example, a continuous or discrete time step can make a difference, and if it does, then which to use and what it reflects of the real world should be part of the conceptual model. If a conceptual model is weak, as in a social theory in qualitative form and not specifically an implementation on a computer, then the same amount of work must be put into verification, to ensure that computer technologies that model human behavioral phenomena adequately are used. Note that verification in social simulation is very difficult or impossible without precise specifications because we do not have the advanced technology to faithfully model the human behavior in a typical qualitative social theory.

Additionally, a conceptual model is important to computational social science itself, because it is the actual theory that is being tested, to be replicated and tested by the science community. For example, if one scientist claims that his model of segregation shows that prejudice is not a necessary condition for segregation of housing to occur, another scientist could refute his claim by saying that the segregation result of the model depends on the existence of a precise geometry of neighbors, something that does not exist in the real world, and therefore the model is not valid. It is only by such formal statements and refutations that scientific knowledge can accumulate. If the precise geometry of neighbors is not in the model, the community can invalidate the conceptual model by showing that precise geometry should be described in the conceptual model because it matters to the result. If the precise geometry is in the model, the community can invalidate it by saying it is a poor abstraction because its lack of fidelity to the world matters to the result, and a good abstraction's lack of fidelity does not matter to the result. Thus, a conceptual model draws the line between what is the functional specification, and what is the implementation. The same computational technique could conceivably be functional specification in one model and implementation in another, depending on whether it was a part that is supposed to corresponded to the real world or not. For example, a genetic algorithm may be an implementation of a general method of induction in one simulation, because it meets a functional specification in a conceptual model for agents that need to induce the meaning of signs. In that case, the genetic algorithm would not be mentioned in the conceptual model specification. However, if the conceptual model was about the memetic reproduction of culture, then many details of the genetic algorithm may appear in the conceptual model, because many of the processes of the genetic algorithm have a correspondence with the theory of memetic reproduction of culture.

An excellent standard for the representation of a conceptual model for the scientific community is the representation in an ontology, such as the Web Ontology Language (OWL). Ontologies represent concepts and the relations between them precisely, in a hierarchy so that different levels of abstraction may be represented. Ontologies are also made to interact with inference engines, so that their consistency may be checked. Levels of abstraction and the ability to check consistency facilitate drawing correspondences between the computer simulation data and the real world data, which is precisely what needs to be compared for conceptual model validation. The precise formalism of ontologies is needed for the accumulation of scientific knowledge, and the ability to abstract is needed for the specification of a correspondence, even a probabilistic correspondence.

The correspondence property of ontologies is particularly important to the validation of social simulation. In the social sciences we have a lot of uncertain data. However, a lot of uncertain data can be made use of as soft constraints in computational optimization methods, as long as there is a way to draw a correspondence. We can use the technology of ontologies to draw correspondence, and optimization techniques to find a numerical match between simulation data and many social correlative studies, none of which may correspond perfectly, but many of which can draw a picture of a general degree of match to the data. The ontology describes the theory-based patterns that are supposed to correspond, and the optimization technique gives an overall match based on the correlations from the correlative social studies. Thus, using ontologies for the conceptual model facilitates large scale, automated, validation testing against many datasets, none of which fit perfectly.

8. Conclusion

Differences in the validation of physics-based simulations and of social simulations is derived from the basic differences between physics and the social sciences. While physicists seek universal laws of physics, social science truths exist somewhere between "universal" and "case specific." Rather, social truths fall into types, and social theories point us to the relevant indicators to identify types with, in order to gain insight into types of interventions and their effects. For example, there are types of personality disorders recognized by the psychological community, for which psychological theory has helped in establishing indicators known as diagnostic criteria. Although the psychologist is unable to predict a patient's exact behaviors, and although each patient is different and each treatment is individually tailored,, knowledge of types of illness informs the relevant types of treatments. Similarly, in social simulation, we cannot predict exact events, and our interventions will be tailored to the situation, but mappings of possible future states can help us to navigate the social environment to desirable solutions. Validation and analysis are the numerical expression of type matches under uncertainty, and the formalization of this measure is a problem whose solution is on the horizon of our present technologies.

9. References

[1] Box. George, and George Tiao. *Bayesian Inference in Statistical Analysis.* New York: Wiley, 1992.

[2] Smith, Adam. *The Wealth of Nations*. New York: The Modern Library, 1994.

[3] Smith, Daniel Jordan. *A Culture of Corruption*. Princeton: Princeton University Press, 2007.

[4] Epstein, Joshua and Robert Axtell. *Growing Artificial Societies: Social Science from the Bottom up.* Boston: MIT Press 1996.

[5] North, Douglass. *Understanding the Process of Economic Change.* Princeton: Princeton University Press, 2005.

[6] Holland, John. *Adaptation in Natural and Artificial Systems*, Boston: MIT Press, 1992.

[7] Axelrod, Robert. *The Evolution of Cooperation*, New York: Basic Books, 1984.

Acknowledgements

Opinions expressed in this paper are those of the author and do not necessarily represent the position of Augustine Consulting, Inc., TRAC-Monterey, or SISO.

Author's Biography

DEBORAH DUONG is a Senior OR Analyst at Augustine Consulting, Inc. on contract at US Army TRAC-Monterey. Dr. Duong has nearly twenty years experience in Computational Social Science, including invention of the first agent based cognitive social model in 1991. Her experience includes OSD HBR modeling on the Joint Warfare Simulation (JWARS) project and for the IW team, and US Army INSCOM work on data representation. She authored the Nexus, Oz and Indra programs, and is now working on US Army TRAC's Cultural Geography model.