Techniques and Issues in Agent-Based Modeling Validation

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I. Introduction

Validation of simulation models is extremely important. It ensures that the right model has been built and lends confidence to the use of that model to inform critical decisions. Agent-based models (ABM) have been widely deployed in different fields for studying the collective behavior of large numbers of interacting agents. However, researchers have only recently started to consider the issues of validation. Compared to other simulation models, ABM has many differences in model development, usage and validation. An ABM is inherently easier to build than a classical simulation, but more difficult to describe formally since they are closer to human cognition. Using multi-agent models to study complex systems has attracted criticisms because of the challenges involved in their validation [1]. In this report, we describe the challenge of ABM validation and present a novel approach we recently developed for an ABM system.

II. Agent-based models

Agent-based modeling is a new approach that aims to model the complex social macro dynamic behaviors emerging from the interactions of autonomous and interdependent individual actors [6]. ABM builds social structures from the 'bottom-up', by simulating individuals with virtual agents, and creating emergent organizations from the operation of rules that govern interactions among agents. ABM was originally developed in computer science and artificial intelligence as a technology to solve complex information processing problems on the basis of autonomous software units. Each of these units can perform its own computations and have its own local knowledge, but the units exchange information with each other and react to input from other agents. The approach was soon applied to problems involving the complex social dynamics that are of key interest to sociologists; notably, emergent social norms, social structure, and social change. ABM provide true bridging explanations that link two distinct levels of analysis: the properties of individual agents (e.g., their attributes and interactions), and the emergent group-level behavior. ABM can be used for examining how very simple rules of local interaction can generate highly complex emergent behaviors that would be extremely difficult (if not impossible) to model by using traditional methods.

III. Simulation Model Validation Approaches

Sargent [2] defined the recent classical simulations community-standard for validation as: conceptual model validation, computerized model verification, and operational validation. In general, we may classify simulation validation methods into two main groups: a) subjective methods, and b) quantitative methods. *Subjective methods* largely rely on the judgment of domain experts. A particularly useful criterion for the validation of a model is the answer to the question "does the structure of a model make logical and biological sense?" [3]. These subjective methods include, for example, face validation, Turing test, internal validity, tracing, and black-box testing. With *quantitative methods*, often called *statistical methods*, a variety of mainly statistical techniques are used to increase the credibility of the simulation model [4]. *Docking*, or model-to-model comparison or alignment, is also used when another model exists, and it models the same phenomenon. Comparison of several independently developed models may be used to improve the level of confidence in the models tested: general agreement among tested models may lend credibility to conclusions or predictions from model-based studies [5].

IV. ABM V&V Approaches

In general, ABM belong to a class of software sometimes referred to as "non-testable programs" and described by Weyuker [8] as "programs which were written in order to determine the answer in the first place. There would be no need to write such programs if the correct answer were known." Since there are no oracles for these programs, it is generally impossible to know *a priori* what the correct or expected output should be for a given input. There exist many criticisms about using ABM to study complex systems because of the lack of maturate and widely accepted model validation techniques [1].

Recently discussed ABM validation approaches cite several validation frameworks and techniques as the bases to build upon. Depending on access to the actual phenomenon investigated and on model complexity, these techniques include: 1) Compare ABM/system output with real phenomenon. This is a straightforward comparison, with the difficulty being access to complete real data on the relevant aspects of the phenomenon under study. 2) Compare

ABM/system results with mathematical model results. This approach has the disadvantage of requiring construction of the mathematical models which may be difficult to formulate for a complex system. 3) Docking with other simulations of the same phenomenon. This approach aligns two dissimilar models to address the same question or problem, to investigate their similarities and their differences, and to gain new understanding of the issue being investigated [3]. In this paper, we categorize them as historical, predictive and sensitivity validation techniques. *Historical data validation* is a technique applied when historical data exists or can be collected. *Predictive validation* is used to compare a model's prediction with actual system behavior. *Sensitivity analysis* is a method used to evaluate variability in the model's parameters. One recent architectural approach used in building an agent-based simulation validation subsystem is the Virtual Overlay Multi-Agent System (VOMAS) [7]. The VOMAS validation scheme can be considered an extension of companion modeling that involves both subject matter experts as well as simulation specialists in developing an overlay multi-agent system for the purpose of validation.

V. Hybrid ABM validation approach

In our Agent Based Disease Spread Model (ABDSM) validation project, we conducted a novel hybrid model sensitivity analysis based validation approach for ABDSM validation. The validation system integrated several sub-models, including a population model, transportation models and social network model to develop the base validation framework. Testing these various elements is analogous to unit, subsystem, and system testing. Compared to existing ABM validation methods presented in recent literature [2, 3], this technique involves more pre-validated sub-system models as the foundation of the validation framework. The authors provide details on the sensitivity analysis portion of this approach in [9].

By converting the sensitive variation in the model into the variations in the sub-system models, we successfully move the challenges of ABM validation into the solution for validation of the sub-system models, such as the transportation model, social network model and population model. And such challenge transference allows us to use existing validation techniques on sub-system models to validate the ABDSM model. In this research, the aggregate or emergent behavior from the sub-models when individual agents interact can be discovered. If the emergent pattern created by the ABM has the same properties, e.g., statistically similar clustering coefficients and scale-free parameters, to that of the empirical data or validated sub-models, then we claim that our ABM simulation structure is similar to the real world.

VI. Conclusion

The model needs to be validated before it can be accepted and used to support decision making. Because of the heterogeneity of the agents and the possibility of new patterns of macro behavior emerging as a result of agent interactions at the micro level, model validation in agent-based complex social systems is different from the traditional validation. Independent intelligence of agents, the large number of concurrent and non-trivial interactions between those members, varying rates of learning and what is learned, and other factors make the validation of ABM difficult. There are several ways to validate agent-based systems and the choice depends on access to the actual phenomenon investigated and on model complexity. In the next step of our research, we will apply data mining techniques in our validation process. We can perform data mining on the simulation data, and the algorithm will indicate what are considered the most significant factors. Therefore, if data mining produces the same factors and the same clusters for the simulation data as for the empirical data, then we claim that the trends and patterns within the simulation correlate to the same trends and patterns in the real system.

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