

Behavioral Modeling

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INTRODUCTION

Behavioral modeling is a term that is used in multiple contexts, such as modeling used to describe agents interacting or possibly software accomplishing some tasks. Behavioral modeling is a means of modeling processes that represent some real-world phenomenon. This article emphasizes an information systems perspective on behavioral modeling as a means of making explicit relevant representations that can be manipulated, often through computer programs, to replicate (generate) some form of observed behavior. The article addresses the following topics: levels of representation and the importance of abstraction for creating tractable models, behavioral models as a form of theory for both explanation and prediction, processes used to create behavioral models (such as task analyses), and ways to test and validate behavioral models.

There are several definitions of a behavioral model: (1) a specification for how an agent chooses actions based on a given set of rules to be used within a specified environment (Arifovic & Ledyard, 2011); (2) a mapping between what a system *is* and what a system *does* for a some set of circumstances (Malak & Paredis, 2007); (3) a high-level representation that captures terminal characteristics of a system without having to rely on a particular implementation (Casinovi & Jeen-Mo, 1994). Common to each of these definitions is the concept of an abstract representation of some real phenomenon that is subject to constraints which are specific to a given context, and the representation provides a correspondence between inputs and outputs within a circumscribed context or environment.

Behavioral models are used to explain and predict phenomena associated with systems, these models serve as stand-ins for actual systems of interest. Behavioral models have utility when it is not practical or possible to observe and measure attributes associated with a real system. Such models can take several forms and are typically examined via computer simulation. Behavioral

models in computational form, that is, models which constitute processes that can be computed to generate behavior of interest, are the focus of this article.

The article is organized in the following manner. First, a literature review is presented on prior work that addresses behavioral modeling. Second, some issues that are relevant to behavioral modeling are discussed. Third, some recommendations for the principled development of behavioral models are provided. Finally, a discussion of possible future directions in research on behavioral modeling and conclusions are provided.

BACKGROUND

Behavioral modeling has been influenced by several fields, such as engineering, computer science, psychology, organizational science, economics, and cognitive science. Each of these fields has made contributions which have helped to advance the state of behavioral modeling. A brief review of some contributions made by early pioneers follows, along with comments regarding how their efforts have helped to shape the field. After a historical perspective is presented, recent advances in research are described.

Historical Perspective

Edwards (1962) was one of the first to characterize behavior associated with making decisions in dynamic environments. The notion of *dynamic environments* established a means for modeling environments that changed over time where a sequence of decisions was needed to achieve an objective or goal. Rosenblueth et al. (1943) emphasized the importance of feedback from the decision environment to attain goals. Wiener (1967) further defined feedback as a way to reintroduce results from past actions as a method for achieving control of a system. It is through the reinsertion of this past information that a goal can exert control over the

behavior of a system (Richardson, 1991). These streams of research all helped to specify an environment in which behavioral models would have to operate and be able to explain system behavior with respect to a goal or an objective.

Ashby (1957) under the subject of cybernetics introduced the three concepts of mechanism, variety, and regulation. Mechanism is a means of specifying transformations from inputs to outputs to define what a system is doing at a given point in time. Variety is a statement of constraints, information, and the richness of communication that passes through a system. Regulation is a specification for how regulation and control of a system are constrained by the quantity and richness of information within that system. Conant and Ashby (1970) extended Ashby's original work and defined the model principle, which states that a regulator of a system needs a model of the system that it is attempting to control. These modeling developments set forth principles used to represent dynamic environments (i.e., environments which change as a function of time and actions taken) (Edwards, 1962).

Rounding out the stream of work by Ashby was research performed by von Bertalanffy (1950), who introduced the concept of equifinality. Equifinality is defined as a final state or goal of a system that can be reached under different initial conditions using different processes. Equifinality bears on behavioral modeling by allowing for more than one plausible formulation of a model that can achieve a system goal accounting for varying sets of initial conditions.

Simon (1959) introduced the concepts of bounded rationality and satisficing. Bounded rationality states that decision agents are rationale decision makers for a bounded decision space, thus making computations and searches for possible solutions to problems more tractable (Simon, 1959). Satisficing is the idea that a decision agent will search for a decision that sufficiently satisfies requirements for making a decision without requiring that the decision be optimal (Simon, 1959). These concepts enabled the economics community to model behavior that more closely resembled human agents' decision making processes.

Newell and Simon (1972) performed studies on human information processing systems which characterized task environments, performed task analyses, and developed computable representations. A task environment is a specification of an environment and

a goal to be achieved (Newell & Simon, 1972). Task analyses are investigations of a problem environment, goals, and processes that can be used to achieve goals (Newell & Simon, 1972). Computable representations are symbols an information processing system uses to stand-in for the problem being solved and can be manipulated by the system, subject to constraints, to achieve the goal (Newell & Simon, 1972).

Marr (1982) theorized that computable representations in the form of computational models are specified at three levels, which from highest to lowest levels are: (1) the computational level, which is a specification of what is computed and why, (2) the representation/algorithm level, which is a specification of the algorithm used to transform inputs (subject to constraints) into system goals, and (3) the implementation level, which is a specification of how the algorithm is performed to achieve system goals.

Recent Developments

An agent-based approach is a dominant paradigm for developing behavioral models. This modeling approach is computational in nature because the models incorporate "process details using algorithmic descriptions" (Sun, 2008, p. 4) which are computed to generate modeled behavior. Agent-based models, which are autonomous decision-making entities (Bonabeau, 2002), are useful for examining global effects of locally interacting agents within a given environment (Scholl, 2001). These agents are a generative source of emergent behavior (Holland & Miller, 1999), which means behavior produced by interacting agents is not deducible by analyzing the behavior of individual agents (Scholl, 2001). However, explanations derived from agent-based models start with analyses of individual agents.

Agent-based modeling uses a bottom-up approach for characterizing systems. Agents are characterized as being (Smith & Conrey, 2007): (1) discrete – self-contained with discernible boundaries, (2) situated – existing and functioning within environments typically interacting with other agents, (3) active – affected by and affecting their environment, (4) goal-oriented – engaging in purposeful actions to achieve internal goals, (5) adaptable – adapting their behavior as the environment changes, and (6) bounded by rationality – gathering sufficient information and using relatively simple rules for making decisions to satisfy goals without striving

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