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Combining human and machine intelligence to derive agents' behavioral rules for groundwater irrigation

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ABSTRACT

For agent-based modeling, the major challenges in deriving agents' behavioral rules arise from agents' bounded rationality and data scarcity. This study proposes a "gray box" approach to address the challenge by incorporating expert domain knowledge (i.e., human intelligence) with machine learning techniques (i.e., machine intelligence). Specifically, we propose using directed information graph (DIG), boosted regression trees (BRT), and domain knowledge to infer causal factors and identify behavioral rules from data. A case study is conducted to investigate farmers' pumping behavior in the Midwest, U.S.A. Results show that four factors identified by the DIG algorithm- corn price, underlying groundwater level, monthly mean temperature and precipitation- have main causal influences on agents' decisions on monthly groundwater irrigation depth. The agent-based model is then developed based on the behavioral rules represented by three DIGs and modeled by BRTs, and coupled with a physically-based groundwater model to investigate the impacts of agents' pumping behavior on the underlying groundwater system in the context of coupled human and environmental systems.

1. Introduction

In the new era of water resources management, a good understanding of physical systems alone cannot guarantee the effectiveness of the policies that are drawn upon. Policy makers need to understand stakeholders' behavior to make appropriate policies that can mitigate water conflicts and promote the sustainable use of water resources. As a result, modeling stakeholders' behavior, in particular their interactions with their biophysical systems, has never been so important in the history of water resource management. Over the last decade, agents have gained in importance for the modeling of human behaviors, and agent-based models (ABMs) have been used to study the dynamics of complex systems consisting of distributed agents, gaining its popularity in both social science and economics (Arthur, 1999; Bonabeau, 2002; Tesfatsion, 2006).

The design of an agent-based model follows a bottom-up, distributed approach. It starts from the definition of the attributes and behaviors of individual agents, and their interactions with the surrounding environments (Ng et al., 2011; Hu et al., 2015a). Employing ABMs allows modelers to focus on the attributes and behaviors of individuals which otherwise may not be possible using other modeling methodologies (Crooks and Heppenstall, 2012; Urban and Schmidt, 2001). Modelers can test a variety of theoretical assumptions and concepts about human behavior within the safe environment of a computer simulation (Stanilov, 2012). Thus, for coupled human and environmental systems, ABMs outweigh conventional simulation models, built based on the top-down centralized approach, in studying the system dynamics. ABMs are more likely to capture emergent phenomena arising from the interactions between human and environmental systems.

Modeling human behavior is complex. Human behavior is not random but based on our diverse knowledge and abilities, and modeling such behavior would not be particularly challenging if it were always rational (Kennedy, 2012). The rationality of human behavior is affected by emotional, intuitive, or unconscious decision-making processes. These processes can distort agents' perceptions of the environment and the likelihood of future evaluations (Loewenstein and Lerner, 2003). Furthermore, limited information, varying cognitive abilities and insufficient time all contribute to limit the rationality of human decision making (Simon, 1996). Regardless of its origin, agents' bounded rationality makes it difficult, if not impossible, to derive "perfect" rules for an ABM.

For coupled human-environment systems, the behavioral rules of agents are usually the result of combining effects of environmental, socio-economic, and institutional factors. For example,

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rule-based ABMs usually assume the availability of explicit behavior rules from domain knowledge and empirical observations. Commonly used representations of expert knowledge consist of two basic forms, declarative knowledge of facts and procedural knowledge, and the latter is typically represented in IF-THEN rules (Newell, 1972; Anderson, 2007). Other ABM studies assume that all agents are rational and follow the general utility optimization principles (e.g., Yang et al., 2009; Ng et al., 2011). However, neither the rule-based approach nor the optimization-based approach is sufficient to capture the behavioral uncertainty arising from the bounded rationality of agents' decision-making processes. Models developed under these approaches usually do not fully reflect observed facts and phenomena, which can raise concerns when validating modeling of agents' behaviors within ABM (Elsawah et al., 2015).

However, it would be prohibitive to pinpoint the origin of agents' bounded rationality case by case and simulate them explicitly. Instead, this paper proposes an alternative approach, which presents a “gray box” to simulate agents' behaviors under the influence of bounded rationality. We will later discuss how to identify the major factors relevant to the decision variables, and obtain the gray box (i.e. agents' behavioral rules) from the data sets of these factors that hold memories of agents' behavior with the data-driven approach. The gray box can then be fed by the data of the decision variable and its major factors to predict agents' decisions given these factors.

This paper is organized with the goal of deriving agents' behavioral rules under the impact of bounded rationality using a combined data-driven approach and domain expertise. In the next section, we first present general concepts and models necessary to introduce our methodology. Following that, we propose a methodological framework to derive agents' behavioral rules, use a case study to demonstrate the proposed framework, and present results. Finally, we conclude with our findings on the methodology and results.

2. Background: concepts and models

Agents' behavior reflects their cognitive processes of decision-making. They may be modeled either by how decisions should be ideally made (i.e., optimization-based) or by describing how they are actually made (i.e., rule-based) (Elsawah et al., 2015). Both the optimization-based and rule-based approaches require modelers to have a thorough understanding of the underlying mechanism that drives agents' decision-making and then model the mechanism with behavioral parameters. However, these two approaches are designed to describe agents' behavioral rules without accounting for behavioral uncertainty arising from agents' bounded rationality. Separate techniques are usually needed for the quantification of the impacts of agents' behavioral uncertainty, such as global sensitivity analysis (Hu et al., 2015b). A holistic method from the data-driven approach perspective (e.g., statistical modeling) can be used to derive behavioral rules using both the available data and the expert knowledge to accommodate behavioral uncertainty.

Some limitations are noticed regarding the application of data-driven approaches to derive agents' behavioral rules. The first is with data availability. Although significant progress has been made in recent years to gather data for the definition of agents and the representation of their behavioral rules (Janssen and Ostrom, 2006; Robinson et al., 2007; Smajgl et al., 2011), ways to measure human behaviors directly, unlike measuring physical quantities, are limited. Some aspects, for instance emotion and social behaviors, are very difficult to measure, if not unmeasurable. Conventionally, researchers use social surveys such as interviews to gather human behavioral data indirectly. Lack of sufficient data, in particular good quality behavioral data, makes derivation, validation and verification of agents' behavioral rules difficult for ABM development (Kennedy, 2012). Furthermore, the relationships derived by a data-driven approach can be spurious due to the neglect of a confounding variable, which is an extraneous variable that correlates with other variables in a statistical model. For example, considering the DNA of two non-twin brothers, their DNA would be highly correlated, even when the DNA of non-relatives is known. However, once the DNA of the parents is known, then conditioned on the parents' DNA, the DNA of the brothers would be statistically independent. Thus, the DNA of the parents would be a confounding variable in that case. If it is not known, then a spurious causal relationship between the brothers could have been inferred. To rule out spurious relationships, this study incorporates expert domain knowledge.

In the following section, we will firstly introduce basic concepts and applications of a particular type of statistical models, namely probabilistic graphical models (PGMs). Then, we will delve into a specific PGM, directed information graph (DIG), and explain how it can be used to derive the causal relationships between agents' decisions and the factors. Based on the DIGs for different agents, a machine learning technique called boosted regression trees (BRT) is applied to converting the DIGs to the behavioral rules for different agents.

2.1. Probabilistic graphical models

Probabilistic graphical models (PGMs) emerge as an innovative approach to organically connect different parts used to build up the complex system while ensuring the consistency of the system. PGMs are considered as the marriage between probability theory and graph theory. The probability theory side provides ways to interface models to data and the graph theory side enables humans to vividly model highly interacting sets of variables (Jordan, 1998; Koller and Friedman, 2009). PGMs are the representations of the probabilistic relationships between variables in a complex system (Buntine, 1996). In recent decades, there has been a large body of work on PGMs, including but not limited to, Markov networks, Bayesian networks, and factor graphs (Pearl, 1988; Koller and Friedman, 2009).

PGMs are widely used in various fields including, but not limited to, medical diagnosis, navigation, image processing and communication. Recently, a few case studies have been conducted in land and watershed management in the context of adaptive natural resource management using PGMs (Alexandridis, 2006; Carmona et al., 2011). For example, Aalders (2008) tries to incorporate the characteristics of land managers with Belief Networks (BNs) to explore the impacts of their behaviors in decision-making processes. However, they usually obtain the structure of the graphical models purely based on the domain expertise.

One major research thrust in the PGM literature is inferring the network topology – who is influencing or interacting with whom. For example, given the joint distribution and a specified variable ordering, the structure of Bayesian networks (i.e. directed and acyclic graph) can be found using Markov blanket properties (Pearl, 1988). However, if the variable ordering is not known, learning and optimally approximating the structure becomes NP-hard (Chickering et al., 1994). In addition, some researches are focused on identifying causal relationships using Bayesian networks (Koller and Friedman, 2009, Ch. 21), which requires the use of expert domain knowledge to label the variables. Thus, the resulting Bayesian network depends on the variable labeling; without expert labeling the Bayesian network is not unique and the identified relationships are only correlative. For the setting of time-series variables, dynamic Bayesian networks can be applied to finding a Bayesian network to characterize their relationships over time. Each variable corresponds to multiple nodes in the graph, one for