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A computational modeling of student cognitive processes in science education

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ABSTRACT

The purpose of this paper is to explain and document the creation of a computational model in the form of an Artificial Neural Network (ANN) capable of simulating student cognition. Specifically, the model simulates students' cognition as they complete activities within a science classroom. This study also seeks to examine the effects, as evidenced in the ANN, of an intervention designed to develop increased levels of critical thinking related to science skills. This model is based on the identification of cognitive attributes and integration of two advanced measurement frameworks: cognitive diagnostics and Item Response Theory. Both frameworks examine student response patterns, providing initial inputs for the ANN portion of the model. Once initial task response patterns are identified, they are parameterized and presented to the ANN. The ANN within this study is the foundational component of a computational model based upon the interaction of multiple, connected, adaptive processing elements know as cognitive attributes. These cognitive attributes process student responses to cognitive tasks within science tasks. Using the Student Task and Cognition Model (STAC-M), the study authors simulated a cognitive training intervention using a randomized control trial design of 100,000 students. Results of the simulation suggest that it is possible to increase levels of student success using a targeted cognitive attribute approach and that computational modeling provides a means to test educational theory for future education research. The paper also discusses limitations of the use of this computational model within education and the possible future directions for educators and researchers.

1. Introduction

This study examined the creation and characterization of a computational model in the form of an Artificial Neural Network (ANN) capable of simulating student cognition. Specifically, this paper presents the authors' newly created computational model and a subsequent computational experiment (simulation) using this model. The computational experiment relates student learning and cognition in a science classroom. This model arises from the identification of cognitive attributes and integration of two advanced measurement frameworks: cognitive diagnostics and Item Response Theory (IRT). The integration of these two frameworks acts as a means to identify cognitive attributes from data gathered during the play of Serious Educational Games (SEG). The proposed ANN model, called the Student Task and Cognition Model (STAC-M), represents the convergence of two important goals within education. First, to create levels of understanding related to the complex interactions between the student and science-classroom learning tasks. Second, to develop a computationally powerful model of student cognition that can "learn" to perform complex science based tasks for the purposes of developing computational experiments simulating student learning in the science classroom. This form of modeling addresses a key need to assess effectiveness of interventions prior to implementation in the classroom as districts and teachers have limited time and resources. Computational modeling

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of an intervention is used within the natural sciences, engineering, economics, and other fields to provide initial success or failure data related to the intervention. This success and failure data provides a means to preferentially select those interventions more likely to produce success. In addition, using computational modeling reduces the number of subjects used during experimentation, and provides a means to examine outcomes when ethical considerations provide constraints. Educational interventions often suffer from similar constraints as students are a protected class, and schools and teachers are extremely limited in the time they can dedicate to testing educational interventions *in situ*. Perhaps more importantly, there are several ethical considerations when choosing to withhold an intervention thought to have positive effects in the classroom, which clashes with the continuing push to employ randomized control trials in education (Institute of Education Sciences, 2003). Computational modeling allows researchers to sidestep these concerns through the ability to create an experiment from data collected outside the classroom and with no harmful effects on students.

The modeling of science task learning is complex and requires understanding and development of relationships between the cognitive inputs, cognitive attributes (processing streams), and outputs (behaviors) to be measured. Specifically, each individual task requires the assignment of success and failure probabilities related to student cognitive processing tasks. The STAC-M acts to illustrate the role of cognitive attributes as they interact to solve problems by employing artificial intelligence in the form of flexible analysis systems with adaptive gating of data streams related to cognitive attribute activation. Mechanisms of action provide a means to incorporate new information within the system while using pre-existing information as is the case with Bayesian Models (Clark, 2012). Lamb (2013) trained the initial model STAC-M using a version of pedagogy thought to successfully train students to complete tasks within the science classroom. This pedagogy arises from the use of science based SEGs (Annetta, 2008). A second example of the applications of simulations and SEGs in learning is the HAEMOdynamic SIMulator discussed by Holzinger et al. (Holzinger, Kickmeier-Rust, Wassertheurer, & Hessinger, 2009). The HAEMOdymanic SIMulator is a SEG used to train and teach medical school students around heart arrhythmias. Lamb in two separate studies in 2011 and 2013 further proposed that the use of experiential learning versus rote learning in the form of SEGs has superior outcomes for student. Specifically because the STAC-M was originally developed from data obtained while students played a science based SEG, the STAC-M more generally exemplifies and relates to reinforcement learning mechanisms due to the constant feedback and data received during play (Lamb, 2013). Within the STAC-M model, cognitive channels decrease cognitive load and increase processing power related to task completion (Kalyuga, 2011). The STAC-M was developed in alignment with the connectivist cognitive framework for emergent properties of the mind (Thomas & Laurillard, 2013).

1.1. *Artificial Neural Networks*

An Artificial Neural Network (ANN) such as the STAC-M is a computational model based upon the interaction of multiple, connected, processing elements in a non-linear fashion (Gupta, 2010). The connections of the input to the output though propagation or potentiation weight places ANN computational models in a connectionist framework (Neymotin, Jacobs, Fenton, & Lytton, 2011). A key feature of ANN is the connection between input elements and output elements via hidden non-linear Bayesian computational layers (Hanrahan, 2010). However, the elements dealing with the input–output relationships are not fully known or researchers would model these connections directly via traditional modeling techniques such as regression or other more traditional statistical modeling methods (Zangeneh, Omid, & Akram, 2012). Artificial neural network architecture provides for the analysis of complex cognitive constructs, such as critical reasoning, retrieval, and parity judgment (Lamb, Annetta, Vallett, & Sadler, 2014). The ability to work through non-linear complexity and its interconnections makes an ANN the most appropriate base model for development into models of cognition (Chen, Dey, Muller, Sun, & Ye, 2010). The ANN and derived models approximate the architecture of the parallel, non-linear processing found in biologically based cognitive processing systems (Berger et al., 2012).

ANN are represented statistically in the form of a graphic with parallel architecture that provides an understanding of emergent relationships (patterns such as those found in information processing). ANNs are often used in three modes: (1) as a model of biological nervous systems and processing components, (2) real-time, adaptive, signal processors, and (3) as data analytical methods. This study uses ANNs in all three capacities. The generalization of artificial neural network models reduces to underlying functions and algorithms of pattern recognition in dynamic systems. Within this framework, it is important to remember that the author represents the patterns of the STAC-M in terms of numerical values assigned to hidden nodes within the model (Coppola, Rana, Poulton, Szidarovszky, & Uhl, 2005). The numerical values transmitted along the network use these algorithms of pattern recognition to assign propagation or potentiation weights (Ghosh & Adeli, 2009). It is important to differentiate between the ANN models and ANN algorithms. One of the major differences between ANN models and ANN algorithms is the manner in which data are used. ANN models use data to create dynamic systems while ANN algorithms develop the weighing and potentiation related to information transmission. Thus, ANN algorithms are more appropriate to analyze transient data such as computational aspects of cognition thus making them relatively useless as a statistical test procedure and requiring incorporation of psychological measurement under Item Response Theory (Lamb, 2013; Lamb et al., 2014). While there are considerable similarities between the statistical models and ANN models, there are differences within the terminology and language of ANNs.

Developers of Artificial Neural Networks designate nodes using one of three descriptions. The designations are simply a way of designating the manner in which information processes through the model. The designations are input nodes (from the environment), output nodes (outcomes), and hidden nodes (computational nodes) (Yilmaz, Marschalko, Bednarik, Kaynar, & Fojtova, 2012). The nodes link by using the nodes as a multivariate information processing function (Yilmaz & Kaynar, 2011). This multivariate function provides the means for the propagation and transformation of task processing outcomes related to the students via the ANN hidden nodes. In the case of this study, the ANN accomplished the actual transformation of the parameter estimates using learning algorithms that include the use of only forward-feed propagation. This propagation makes the network more flexible using the ratio differences between the expected and actual output to test fit and reduce error (Bilgehan, 2011). In addition to weighting adjustments, it is possible to standardize the output of the maximum propagation weight to 1.00 creating a more probabilistic interpretation based in Bayesian estimates. This adaptive ability allows for flexibility within this model not seen in other modeling techniques such as regression or structural equation modeling.

The movement from a narrow view of ANNs as an information-transmitting program to a cognitive information processor involves the inclusion of probabilistic assumption developed though psychological and educational measurement techniques. The development of