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Article

Computational Modeling of Teaching and Learning through Application of Evolutionary Algorithms

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Abstract: Within the mind, there are a myriad of ideas that make sense within the bounds of everyday experience, but are not reflective of how the world actually exists; this is particularly true in the domain of science. Classroom learning with teacher explanation are a bridge through which these naive understandings can be brought in line with scientific reality. The purpose of this paper is to examine how the application of a Multiobjective Evolutionary Algorithm (MOEA) can work in concert with an existing computational-model to effectively model critical-thinking in the science classroom. An evolutionary algorithm is an algorithm that iteratively optimizes machine learning based computational models. The research question is, does the application of an evolutionary algorithm provide a means to optimize the Student Task and Cognition Model (STAC-M) and does the optimized model sufficiently represent and predict teaching and learning outcomes in the science classroom? Within this computational study, the authors outline and simulate the effect of teaching on the ability of a “virtual” student to solve a Piagetian task. Using the Student Task and Cognition Model (STAC-M) a computational model of student cognitive processing in science class developed in 2013, the authors complete a computational experiment which examines the role of cognitive retraining on student learning. Comparison of the STAC-M and the STAC-M with inclusion of the Multiobjective Evolutionary Algorithm shows greater success in solving the Piagetian science-tasks post cognitive retraining with the Multiobjective Evolutionary Algorithm. This illustrates the potential uses of cognitive and neuropsychological computational modeling in educational research. The authors also outline the limitations and assumptions of computational modeling.

Keywords: cognition; computational model; teaching and learning; science education

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1. Introduction

Computational modeling of human critical thinking expands the ability of researchers to examine complex human actions, such as teaching and learning in the classroom, with greater control and clarity than is possible in traditional classroom research. One of the major area of difficultly in educational research is the interaction of teachers and students. The difficultly in the research arises in the capture of and analysis of the complexity of teachers interact with students. During student-teacher interactions, the teacher intentionally shapes the classroom environment through application of selective pressures arising from classroom management techniques. A particularly rich area in which computational modeling can be informative is in elucidating the complex interactions between teachers and their students in such a scenario. Within the computational model in this study teacher responses can be seen as a selective pressure which shape student cognitive experience.

A second property of the brain that is difficult in educational research is the need to model the presence of the mind that emerges from the brain. However, the mind is uniquely complex and difficult to model [1]. Part of the complexity of the mind arises from its ability to hold multiple conceptions, which can be either mutually supporting or in opposition to one another. These types of naive understandings have been shown to conflict with classroom science instruction [2]. Naïve understandings serve an important purpose in shaping everyday experience, but are not reflective of reality as seen through a scientific lens. This conflict is particularly apparent when students begin to learn of new scientific phenomena that contrasts these naive understandings and must use critical thinking to reconcile the differences. During this conflicting period students often require explanation and teaching in order to reconcile the differences between both understandings and ultimately adopt the scientifically validated version that best reflects reality [3]. In such a conflicting scenario naive understandings or misconceptions are pathways that are not optimized to resolve incoming environmental stimuli and create usable outcomes for students in classrooms [4].

This lack of pathway optimization occurs in part, because the rate of biological evolutionary change of instinctual information processing and the rate of change in modern society are on vastly different time scales. This leads to students with non-optimized pathways that cannot correctly reconcile environmental inputs and their scientific mechanism of action [5]. This is a disconnect which has left humans with pathways which are not optimized to detect and reject information that contrast scientific understanding. Instead of recognizing differences in scientifically accurate and inaccurate environmental inputs, humans make use of each equally as long as they lead to beneficial results during everyday experience. These outcomes, which result from instinctual information processing developed as a part of a psychology arising in past evolutionary environments and result incorrect information processing outcomes and casual beliefs [6]. For example, it makes extremely good sense to interpret the sun as rising in the East and setting in the West because it offers both a way to track time and direction. Yet in reality, the Earth is the celestial body and is just rotating. The lack of situational awareness leads to wrong assumptions because of selective pressure on our critical reasoning abilities resulting in underlying psychological heuristics that are potentially misapplied [7]. A second example of this misapplication of heuristics is related to medical doctor's reliance on the use of cognitive heuristics during diagnosis of medical conditions. The heuristics themselves evolved long before human understanding of disease, this can result in the misapplication of the cognitive heuristics to the medical problem evidenced by symptoms and result in faulty diagnosis [8].

Ultimately, untenable psychological heuristics are purged from the evolutionary system through attrition from a population over generations [9]. This type of systemic instinctual change will not occur in the short term such as an individual's lifespan because evolution requires substantial differences in survival and reproduction over generations for change to occur. Even with this period of generations being met, sufficient variations in cognitive systems would have to be present and be directly selected for. Given these restraints, only through education can naive understandings be disregarded in favor of scientific reality.

Teacher's assist in the transition of naïve understanding to truer understanding through selectively exerting pressures on specific cognitive pathways for example through dialogic interactions that are reflective of scientific reality [10]. This can lead to an optimization of student cognitive pathways where they are more likely to recognize information which is reflective of a scientific reality and make use of this over the naïve understandings. Teaching acts on cognitive pathways in much the same way evolution acts upon biological systems. This process leads to students approaching problems differently and ultimately results in the optimization of a cognitive pathways for reasoning around a specific task or related tasks that functions more quickly than trial and error approaches [11]. This type of optimization in critical thinking, as well as other cognitive systems, builds required cognitive heuristics in a mechanism akin to cognitive retraining.

The balance of the teacher-student relationship is similar to the characterization of command balance suggested by Gabris, and Artman (1998) [12]. Command balance creates the casual component in optimization problems for students solving science tasks. The number of variables within the interactions alone creates difficulty for educational researcher attempting to examine, model, and isolate systems used in the learning of science such as critical thinking. The ability to successfully isolate cognitive systems is critical in creating realistic models of interactions [13]. One approach to isolation and modeling these complex systems is to choose one system and related cognitive pathway for modeling. A cognitive pathway is the sequential activation of particular brain systems processing specific data streams form internal and external antecedents [14]. The characteristics and complexity of cognitive pathways lend themselves to modeling via artificial neural networks (ANN) [15].This level of complexity is incredibly difficult to model even when using systems which are best suited for models of this complexity. Part of this difficulty arises from there being multiple objectives occurring non-sequentially in a dynamic system during teaching and learning. Teaching and learning when contextualized in this manner has striking similarities and parallels to a class of algorithms known as Multiobjective Evolutionary Algorithms (MOEA) for optimization of Artificial Neural Networks (ANN). All of the conflicting explanations and attempts to overcome instinctual information processing increases cognitive load and decrease efficiency in thinking ultimately limiting the system's ability (student's ability) to solve problems [16]. The increase in cognitive load on the part of the student forces greater interactions with the teacher ultimately increasing cognitive load for the teacher. The increased cognitive load reduces the ability of the teacher and student to assess perceptions, comprehension, projection, and prediction within the mind of the student and teacher and reduces learning.

The purpose of this paper is to examine how the application of a Multiobjective Evolutionary Algorithm (MOEA) can work in concert with a cognitive computational model to solve critical thinking problems in the science classroom. A secondary purpose is to model intentional human critical thinking without a using a trial and error approach to model optimization. An important assumption of this model is that appropriate selective pressures on the processing element, the ANN, as a part of the computational model would optimize outputs from the artificial system and resemble student cognition in the science classroom. The optimization would also confer an additional advantage of occurring in a far shorter period than in natural biological systems. In this way, researchers may characterize and experiment in compressed timeframes with models of human cognition and teaching and learning in the framework of a Multiobjective Evolutionary Algorithm (MOEA). The ability to compress time creates some of the value of evolutionary algorithm use in educational research. The research questions are (1) does the application of MOEA provide a means to optimize the Student Task and Cognition Model (STAC-M) computational model? (2) Do the optimized model result in adjustments that mimic teaching and learning in an educational environment? Consideration of this research question suggests the following hypothesis. The STAC-M optimized using a MOEA will result in fewer iterations to successfully solve the presented Piagetian task. Substantiation of this hypothesis would lend evidence to the view that the inclusion of a MOEA within a cognitive model replicates teaching and learning. Substantiation would also provide support for teaching as a means by which classroom selective pressures can be leveraged to encourage cognitive growth.

1.1. Intention

The STAC-M makes use of educational and psychological measurement models describing the student's cognitive state at any given time as they complete tasks in a virtual environment. The change in state over time as the student completes the tasks is translated into intention within the data. The modeled data set has the effect of bypassing the problem of composite actions. The problem of composite actions is the seeming disconnection between two actions link only through situation but not necessarily dependent on one another for completion, in this way composite actions do not require intention. Composite actions are accounted for in educational and psychological measurement models through the a (task discrimination), b (task difficulty), and c (guessing) parameters under item response theory (IRT). Item response theory is a psychometric theory and paradigm for the design, analysis, and scoring of mental measures of ability, attitudes, and other constructs [17]. Under IRT, composite tasks are assigned probabilities in relation to each of the parameters a, b, and c. The combination of probabilities is combined with second measurement method known as cognitive diagnostics. Cognitive diagnostics is a psychometric modeling techniques used to develop profiles of cognitive systems used in task and skill mastery [15,18]. The combination of IRT and Cognitive Diagnostics converts all composite actions toward task completion into patterns of probabilities that are fed into the input nodes for the artificial neural network. This is in effect similar to a decision tree where the nodes represent cognitive tools or attributes and outcomes are predicated on the activation of the correct patterns of the tool. Conceptualization of the STAC-M under IRT and Cognitive Diagnostics places it into a class of computational model operating under the Beliefs, Desires, and Intentions Model (BDI) as the STAC-M inherently desires an outcome state of success independent of the environment in which it is set.

1.2. Multiobjective Evolutionary Algorithms

Many real world critical reasoning problems including the Piagetian conservation tasks involve multiple inputs and assessments of information from the external environment and internal memory [19]. Research using other types of computational models do not focus on the system of cognition as a whole, instead they focus on one aspect of the system and then relate all other aspects to the one [20]. The multiple inputs associated with the teacher-student learning interactions often require simultaneous cognitive optimization of the teacher and the student for processing and successful task completion. With the requirement of simultaneous optimization, task completion is not serial but parallel in nature. Critical thinking in the biological sense is a cognitive attribute and supporting cognitive architecture responsible for the analysis, evaluation, and conclusions drawn from incoming data streams via the senses, internal memory, and psychological affect [9,21]. Modeling of the nonlinear dynamics associated with critical thinking is difficult requiring the use of complex measurement methods and applications of theories of nonlinear dynamics such as Chaos Theory [21,22]. With this level of complexity, conventional modeling optimization techniques are often difficult to extend to even simple models of human cognitive functioning. Evolutionary algorithms and specifically MOEA are well suited to this purpose due to their ability to handle this complexity. A MOEA's ability to handle these complex problems rests with its ability to search for multiple solutions in parallel. One example of a MOEA that provides a means to optimize STAC-M is NeuroEvolution of Augmented Topologies. Source code is available for download [23]. Some additional examples of evolutionary algorithms are the multiobjective firefly algorithm and the multiobjective flower pollination algorithm. Each of these algorithms works to optimize the multiple, conflicting criteria associated with a complex problem.

Within the MOEA framework for optimization of a computational model, a real-world critical thinking problem involves multiple objectives and solutions. In this understanding, critical thinking represents the cognitive pathway requiring optimization and teaching in the model is represented by the MOEA optimizing the computational model's cognitive pathways. Within the process of optimization, the intent is to minimize the theoretical decision space associated with potential outcomes for successful solutions [24]. This is very similar to the ways teachers attempt to work with students to minimize the number and distance associated with proper choice selection around topics. Minimization of the solution space occurred using the function,

$$F(x) = (f1(x) \ldots fm(x))^T \text{ s.x. } x \in \Omega$$

where Ω is the theoretical decision space, s.x. is the standard error of x, and $x \in \Omega$ represents the vector of choices consisting of m objective functions within the objective space for decision processing. The minimization of theoretical decision space is difficult requiring significant computational resources [25]. Though the minimization of decision space does not seem difficult for biological systems, there is little understanding of the actual mechanisms of action that biological systems use to achieve this minimization and create agency. Thus, proposed computational models using algorithms such as MOEA would be incredibly useful for testing prospective mechanisms for teaching and learning.

Using artificial neural networks (ANN) as a model of human cognitive function allows researchers to use the resultant probability to develop new cognitive models and theorems related to student learning and processing of science tasks. Artificial neural networks combine both a graphical and statistical outcomes to solve cognitive psychology, educational, and teaching problems and more specifically allow one to develop a deeper understanding of learning and the impact of teaching. One specific model developed by the author, the *Student Task and Cognition Model* (STAC-M), models critical thinking and lateral thinking [26]. The STAC-M is a useful tool and has the potential to be improved through the integration of evolutionary algorithms to solve optimization problems associated with teaching. The MOEA acts as a representation for teaching with the optimized STAC-M representing the learning outcome. While this model (STAC-M) of human reasoning without the addition of the MOEA has some of the underlying principals and characteristics of biological-information processing, it lacks the ability to optimize, this is a critical characteristic that readily occurs within biological systems through learning, pruning, and other neurological mechanisms.

The dynamic and complex problems associated with student information processing and reasoning in the real world effectively outstrips even the most sophisticated artificial intelligences. As such, the development of overarching algorithms that achieve reasonable approximations of simple human reasoning, teaching, and learning when applied to problems of human information processing is an intensely active area of research in several domains of computational education and computational cognitive psychology. One area of significant promise is evolutionary (genetic) computational algorithms. Through the application of these algorithms to computational models such as the STAC-M one would expect an increase in the effectiveness of solution success and effective mimicry of learning for simulation purposes.

1.3. Student Task and Cognition Model (STAC-M)

The STAC-M is an attempt to model the biological mechanisms of action associated with lateral thinking and critical reasoning [27]. The model was developed within the framework of connectivism. Identification of the attributes occurred using a modified cognitive diagnostics approach (CDA) [28]. The modification of the CDA is the use of video game server data based on student choices and actions as opposed to talk aloud protocols [29]. The number of neurons (seven) within the STAC-M clearly illustrates the level of comparative sophistication of the STAC-M in comparison to humans and even the simplest biological system. For example *Caenorhabditis elegans*, contains 302 neurons allowing for far greater cognitive flexibility than current computational models of cognition.

The use of an artificial neural network as the underlying computational aspect of the STAC-M allows for the examination of the model using Bayesian assumptions and networks. In order to model science task learning one must first understand the complexity of the relationships between the cognitive inputs, cognitive attributes, and outputs measured by educators such as science task completion. Specifically, each individual science task requires the assignment of success and failure probabilities using item response theory. Practically this process of assigning probabilities must be related to student cognitive processing of tasks using Cognitive Diagnosis, a second powerful educational measurement technique. The STAC-M acts to illustrate the role of cognitive attributes as they interact as a dynamic non-linear system to solve problems. This is accomplished by employing machine learning in the form of flexible networks based in Bayesian approaches specifically artificial neural networks. These systems make use adaptive gating of data streams related to cognitive attribute activation to provide the processing power necessary to solve science based critical reasoning tasks such as Piagetian conservation tasks.

In educational research, computational models represent possible mechanisms of action associated with teaching and learning. Multiple types of models exist examine various aspects of human cognition and leaning, Two examples of models are the ACT-R model from Carnegie Mellon University and the SimStudent Model also from Carnegie Mellon University. While an artificial neural network is the processing element in the model STAC-M uses of Item Response Theory Models and CDA to provide a means to incorporate new information within the modeled system of interacting neurons while using pre-existing information. The inclusion of prior knowledge leads to the identification of the STAC-M as a Bayesian Model [30].

1.4. Bayesian Networks

A generalized Bayesian Network in this case an ANN consists of two interdependent aspects. The first aspect is a directional tree diagram or directional acyclic graph illustrating set conditional independencies. In the case of STAC-M these conditional interdependencies are parameterized using an Item Response Theory (IRT) model combined with Cognitive Diagnostic Assessment (CDA) [8,9,27]. The parameterization of the variables using IRT and CDA creates the second structure within Bayesian network consisting of a set of local parameters A_i representing the conditional probability distribution for the cognitive information processing given different value combinations of their parent values in the structural form of a Q-Matrix. By combining neural network propagation weighting with the two Parameter Logistic IRT model probabilities of item completion, one can merge the two models and create a means to measure the contribution each attribute makes to the overall task completion as either a 1 or 0 for success or failure. Specific parameters such D are a scaling factor equal to 1.70, (this approximates a normal ogive curve), a_i is the item discrimination, Θ is the subjects ability for success on the particular task item. Through manipulation of these variables, one can calculate P_i, the probability of correctly completing a task. This mode of use allows the STAC-M to make use of a Markov Chain related to probability distributions of the variables. When combined with the neural network model, φ is the non-linear activation function for the artificial neural network, $w\hat{}_i l(n)$ represents the gradient decent along the training function, and $x^{\wedge l} n-1$ represents the input to the hidden layers via the cognitive attributes.

There are a number of ways to relate Bayesian networks to machine learning and specifically artificial neural networks. In particular, one can use such methods as supervised learning, unsupervised learning, and inferential Bayesian networks. The STAC-M falls into a specific type of network identified as learning Bayesian network. These networks derive their structure and conditional probabilities either necessarily from an external expert acting as a referential point, or through automatic learning from databases. In the case of STAC-M the learning data derives from students playing a science based Serious Educational Game with embedded critical reasoning tasks. Thus, the model of cognition within the STAC-M is used as identification of the topology of the network occurs by examination of biological models of critical reasoning (students) and in particular the topology of the biological neural network as a mesh network.

The two methods IRT and CDA allow STAC-M to make use of and act as a hybrid between a score and search method algorithm and a detection of conditional probabilities algorithm. This hybridization occurs through a combination of the constrained-based method and score and search methods. The constrained-based method of occurs during the use of Cognitive Diagnostic Assessment applications with the estimations occurring though a maximum likelihood method. The score and search method is integrated into the model via applications of IRT. The application of IRT allows the development of a scoring metric to evaluate the quality of each Bayesian network with respect to completion of the cognitive task and search through the network to examine the probabilities showing successful outcomes.

1.5. Evolutionary Algorithm Characteristics

There has been a rapid increase in the number and types of research into evolutionary algorithms as a means to optimize real-world problem solving. As a class of algorithms, evolutionary algorithms represent an important advance in approaches for solving real world problems such as the optimization of cognitive models used to solve critical reasoning problems in science. Evolutionary algorithms are defined as a form of artificial intelligence meant to mimic biological evolutionary selective pressures working to approximate solutions to novel problems through model optimization [31]. In this approach, the evolutionary algorithms acts to optimize solutions under the uncertain and dynamic outcomes associated with critical thinking in the sciences such as the Piagetian conservation tasks. The overall objective of the evolutionary algorithm in relation to models such as STAC-M is to obtain a desired level of functionality that more closely mimicking that of biological critical thinking. In a broader sense, the addition of the evolutionary algorithms can be used to generate new optimized node values for critical thinking increasing odds of success in solving a science-based problem and identifying critical threshold levels of the critical reasoning system.

The combination of IRT and CDA helps to identify the algorithm as a probabilistic model for optimization. A critical advantage of this method of algorithm generation is that individual processing pathways and node values are sampled from the distribution and retained for future use as a successful solution or removed as non-viable from the solution space. In this way, the inclusion of the evolutionary algorithms allows the model to deal with problems around the interactions of cognitive variables not initially introduces into the system until post artificial neural network training. This combined with the models ability to solve novel problems creates a means to more closely mimic and thus model biological cognition in science students.

In many real-world uses of computational models, such as teaching and learning, the optimization values of nodes, the fitness function of the model in conjunction with the derived parameters, and optimal decision space are fluid creating increased complexity. These non-linear dynamic systems create increased challenges for models initially developed under static assumptions such as those found in traditional educational measurement and psychometrics. However, the educational process is not static or linear, creating an incredibly difficult problem for researchers to model and optimize. Thus, the main challenge is ability to dynamically model the change in student cognition over time and in real time. This difficulty is due to the sensitivity of starting conditions and often leads educational researcher to engage in qualitative assessments of learning. For this reason, an algorithm that adjusts the model based upon cognitive attribute gating and necessary task or environmental learning details are required. Essentially an algorithm with multiple inputs can accomplish this through real-time examination of key environmental characteristics associated with student cognition in learning.

A second potentially more important characteristic of the proposed evolutionary algorithms within cognitive models is the ability to optimize with noise. Noise in this context is defined as non-optimal solution space reducing the efficiency of successful cognitive pathway model development. Within this type of modeling, there are relatively few methods for mitigating noise. Most commonly, a resampling method resulting in a rank ordering of solutions provides a means to reduce noise. Using resampling in conjunction with adaptive machine learning, cognitive model makes use of past node weights and variations in vector direction allowing a quicker model convergence. In this way, the cognitive optimization model can divide the solution space into an n-dimensional hypersphere with solution vectors equidistant to the optimal solution. The average performance of the vector through the sphere is used to classify noise resulting in greater ability to optimize pathways to the appropriate cognitive solution and science task completion.

2. Experimental Section

Experiments with the STAC-M with and without the addition of MOEA occurred using the JMP 11.0 statistical package with and Artificial Neural Network featuring a graphical user interface. Within the simulation, there is a modified Piagetian conservation task to solve. The agent's ability to process within the simulation is controlled via an artificial neural network representing the human critical thinking system. The controlling neural network is organized using three layers with one neuron in the first layer, five neurons in the second layer, and two neurons in the final layer. Each neuron represents a specific system in the biological network. Each evolution of the weightings contains a different cumulative probability function. Function f_i randomly generates weights constrained via Ω between 0 and 2 between the inputs and the first processing layer of the neurons representing the critical reasoning system in the biological system. The subsequent function f_a computes the bias of the second layer neurons representing additional cognitive attributes recruited to solve the task post data parsing by critical thinking. Finally, f_b represents the final integration function representing lateral thinking systems and the ultimate connection weights among neurons in the final stages of the input information integration in the biological system. The implementation of the MOEA as an optimizing agent for the STAC-M cognitive pathways is akin to a teacher working and teaching students through complex science problems in a classroom. Table 1 summarizes the parameter setting of the constants determining the genotypic distance between two of the modeled variants of STAC-M.

Table 1. Multiobjective Evolutionary Algorithms (MOEA) parameters.

Parameter	Value
Population Size	100
CPPN Weights Amplitude	2.00
CPPN Output Amplitude	1.00
Distance Threshold	10.0
Distance 1	2.00
Distance 2	2.00
Distance 3	0.50
Mating Probability	0.80
Add Link Mutation Probability	0.40
Add Node Mutation Probability	0.01
Elitism Per Species	5%

Table 2 illustrates the experimental design and variables tested. The experimental condition consisted of the addition of the evolutionary algorithm to optimize the Student Task and Cognition Model (STAC-M).

Table 2. Study design.

Treatment Condition	Group Label	Pretest	Treatment	Posttest
Experimental	E	O_1	X (Addition of Evolutionary Algorithm)	O_2
Control	C	O_1		O_2

3. Results and Discussion

Lamb (2013) trained the initial model, STAC-M using a Serious Educational Game to collect data as students completed tasks within the virtual science classroom in the game [32]. This method of collecting data about teaching and learning arises from the use of science based Serious Educational Games as conceptualized by Annetta (2010) to generate sufficient data for model development in this case n = 450,000 [29,33,34].

Data for the development of the initial STAC-M was garnered from 645 high school students located in the mid-Atlantic region of the United States. Subjects consist of student enrolled in full-time high school classes and specifically, those enrolled in science classes at the grade 9–12 level. Subject ages ranged from 14 to 18. Over the course of 15 hours of play, the subjects generated approximately 450,000 data points for training, analysis, and development of parameters around critical reasoning tasks using IRT and CDA. Upon completion of the presentation of training data to the STAC-M researchers presented the STAC-M with modification of the Piagetian conservations tasks for analysis [17,35].

MOEA parameters were setup as illustrated in Table 1. The algorithm was executed a total of 100 times allowing randomization of sampling populations and convergence of the rival models generated by the optimization algorithm. The iterations represent places where the teacher taught a specific concept around the conservation task in the science classroom. Convergence of STAC-M with the algorithm and without the algorithm is illustrated in Figure 1 The target fitness of 85% success or mastery was reached at the median generation of 63 by STAC-M using the evolutionary algorithm.

STAC-M without the evolutionary algorithm did not reach the 85% mastery level within the 100 iterations tested. The number of iterations was extended to 180 with STAC-M converging at iteration 162. In this way we can observed that the STAC-M using the evolutionary algorithm outperformed STAC-M in the speed of convergence, which is indicative of solving the problem science critical reasoning problem. Thus, the model demonstrates that teaching out performs self-taught or trial and error methods of learning. This also provided some evidence of validation of this computational model of teaching and learning. Figure 2 provides a visual representation of the evolved neural network and the original STAC-M for comparison. It is critical to note that the intent was not to add nodes (addition cognitive systems) as the STAC-M is a previously validated model of human cognition and it is highly unlikely that the human brain would spontaneously recruit new systems to solve a particular set of problems. It is far more likely from a biological standpoint that data channels within the biological system would be retrained to handle differing amounts of information through the process cognitive retraining. This is because evolution builds off existing variation already present in systems, making the immergence new systems being an extremely rare event in the history of life.

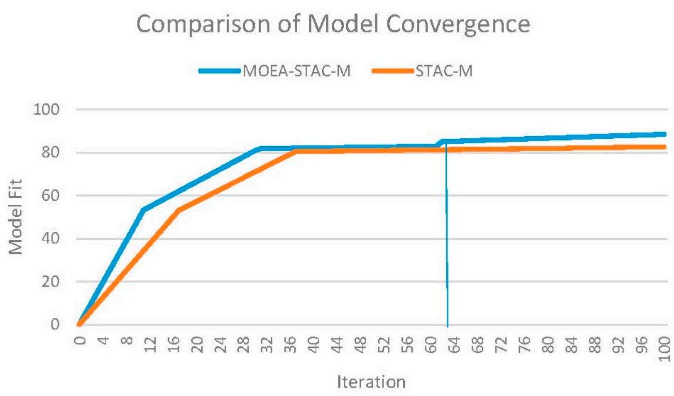

Figure 1. Comparison of model convergence between Multiobjective Evolutionary Algorithm-Student Task and Cognition Model (MOEA-STAC-M) and Student Task and Cognition Model (STAC-M).

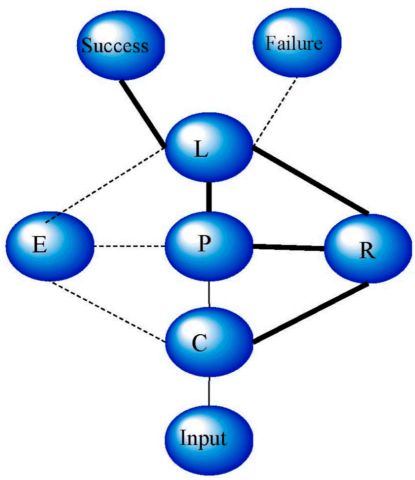

Figure 2. Resultant MOEA-STAC-M. Bold lines indicate weightings increased by the addition of MOEA, dashed lines indicate weightings decreased by the addition of MOEA, and thin solid lines are lines unchanged by the addition of MOEA.

3.1. Application of Educational Research

The primary purpose of this paper is to examine how evolutionary algorithms can be applied in concert with cognitive computational models such as the STAC-M to solve critical thinking problems and model human critical reasoning in the science classroom. In order to answer the research questions the primary author generated two models one with the application of an MOEA and one without. Model comparison occurred in an effort to find optimal cognitive attribute weights for solutions to Piagetian conservation tasks found in a Serious Educational Game (SEG). A SEG is a simulation of real-world events and processes designed to teach using embedded pedagogical approaches [35]. Fields in the natural sciences, computer science, and engineering have used evolutionary algorithms and computational modeling to address complex questions and find solutions to complex optimization problems with great success. These fields often make use of computational models to examine non-liner dynamic systems such as traffic flow and neuronal activations. However, the field of education has been slow to approach and apply this powerful tool while sister fields such as sociology, psychology, and anthropology have embraced these tools with great success. As computing power increases and computational modeling becomes more prevalent educational researchers should make use of these models for the examination of mechanisms of action related to teaching and learning. Making use of a combination of computational modeling experiments and educational experimental in conjunction with one another, it would be possible to develop theoretical assumptions, modes of action, and hypothesizes for examination often absent in educational research.

Much of the cognitive research in science education, and critical thinking specifically, is seen at the level of the student as a simple linear serial input-output system, as evidenced with the prominent use of simple pretest post-test examinations without control. This situation arises because researchers view the processes between input and output as too complex for empirical study [28]. This linear system out of necessity often becomes focused on external environmental systems such as culture without consideration of internal cognitive processing. Even when science education researchers address cognitive processing, it is often addressed at a surface level with little consideration of testable models, mechanisms of action, and hypotheses. The use of a linear research approaches without testable underlying mechanisms of action and attempts to reconcile across frameworks fragments science education, isolates researchers, and advocates for a singular approach to the study of constructs. A study by Lamb, Cavagnetto, and Akmal (2014) provides direct evidence for the systemic non-linear nature of learning and more importantly provides a testable mechanism of action related to cognition around student learning [28]. Furthermore, several recent computational experiments using cognitive computational model have suggested the power of the computational model approach as means to test and understand cognition related to learning in science. More to this point neuroimaging studies and computational modeling studies in science education provide further evidence that current research on student learning in science education is underdeveloped in the area of cognition.

In this paper, the authors present the results of a two-fold computational experiment. The first part applies a MOEA as a means to simulate teaching a lesson on an artificially intelligent model of cognition and second illustrates the potential power of simulations in educational research using computational models. Within the simulation using the MOEA, the results illustrate greater generation of complex functions earlier in the evolution of the simulated cognitive pathway. This runs akin to the experiences of students as they gain exposure to ideas throughout a class. Further, the simulated lesson illustrates the value cognitive retraining in the optimization of the cognitive system node weightings in the model as a pedagogical approach. Using cognitive retraining prior to the teaching of concepts and skills in a virtual environment such as an SEG may allow greater success with applications in the classroom. In this way, cognitive retraining can be central to the learning process and tied to the model accordingly. Researchers using these types of models can examine the strengths and weakness of pedagogical approaches and interventions through manipulation of the MOEA algorithm and STAC-M weightings. By doing so, educational researchers can examine and simulate many types of interventions, teaching models, and learning models prior to implementation in the classroom. Being able to do so would not only result in more efficient use of resources, but also allow researchers to begin optimizing their intervention prior to entering a classroom and potentially bolstering its effectiveness.

This paper provides the theoretical framework for future education researchers to apply evolutionary algorithms and computational modeling using machine learning to student learning in the science classroom. This becomes possible using data collected in an immersive three dimensional serious education game environment. Thus, student play through the game provides a window into student cognition relating to science learning. Using mixed measurement approach of IRT and CDA the researchers are able to develop the necessary probabilistic inputs allowing cognitive modeling of learning. Ultimately, this results in usable simulation data for educators. The STAC-M in conjunction with a Multiobjective Evolutionary Algorithm provides a view of the complex processes of learning and sets the conditions to develop further computational models in science education. Emergent factors developed from the psychometric analysis and solution vector provide educators a means to identify critical computational components of human cognition using these models. Educational interventions designed to optimize human cognitive attributes via attributional retraining and learning would provide for the greatest student increases in task completion. From a substantive point of view, this allows educators to assess and optimize interventions prior to use in the classroom. Modulation of attributes, related psychological affect and behavior might allow one to manipulate variables to understand individual differences in education at a deeper level governed by psychological mechanisms. One important aspect of this research is that individual neurons within the STAC-M are representative of regions of the brain associated with the various cognitive attributes and not the individual neurons themselves. Hence, while there is one individual neuron within the hidden layer identified as critical thinking it is actually representative of the regions and systems of the brain associated with the striatum regulated (gated) via the frontal cortex. Recruitment of additional processing centers, via this gated mechanism, allows for an increase in the number of data channels and increasing processing power when presented with difficult problems. This can lead to an assumption within computational modeling that simply adding neurons to the hidden layer will create more outcomes that are successful solutions to the science task problems. The addition of the MOEA would allow one to find the optimal weighting of nodes to solve the science task problems. In this way, teachers can target and assess student learning as a function of task completion. However, though it is tempting to simply add nodes and computational power, this assumption becomes problematic because as one increases computational components associated with STAC-M this can lead to overfit errors from a statistical view and the addition of biological nodes (systems) is unlikely. The additions of the correct number of computational neurons related to processing also supports the link between affect, cognition, and behavior as portions of the striatum (represented in the STAC-M as a critical thinking neuron) are associated with motivation and behavior in addition to critical thinking and related attributes.

3.2. Study Limitations

This study is limited in that it focuses solely on the role of cognition in solving critical thinking tasks and does not account for behavior or psychological affect. The authors agree that these are critical components to learning. Given the novelty of these methods and the nascent nature of the field of computational education, significant research is still necessary to account for these components and link them within these mechanisms of action within the models. The study is also conducted from the computational view of cognition taking into account the internal activities of the learning and assumes that intelligence belongs to the individual alone. Another limitation of this approach is the understanding that despite the sophistication of the artificial intelligence and its ability to account for the non-linear dynamics of the classroom, the model is still relatively unsophisticated in relation to biological systems despite its ability to evolve and solve novel problems. The authors would also like to note that this level of sophistication places educational computational modeling at the level of weather forecast modeling in the late 1950s. The authors also acknowledges that this form of modeling of nonlinear dynamic systems such as student learning is in its nascent form as requires more research to bring its full potential to fruition.

4. Conclusions

The addition of a Mulitobjective Evolutionary Algorithm in the broader context of a cognitive computational model provides a means to create intention, more rapid model convergence, greater success outcomes, and model teacher-student interactions in a more realistic way. Regarding the methodological approach, the use of these types of algorithms is of increasing interest across fields such education not traditionally using these approaches. The proposed addition should exhibit improved performance when compared to the computational model algorithms lacking Multiobjective Evolutionary Algorithms. The author does not claim that scheme will work for all problems in the study of student learning as it has only been applied to one particular aspect of this process. Further testing of a Multiobjective Evolutionary Algorithm under multiple conditions is needed. Future research efforts should include the implementation of the proposed scheme in other forms of cognitive problem solving optimization. Computer code and algorithm coding are available upon request to the author.

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Author Contributions

The authors were responsible for all aspects of this study, including collecting data from video game systems, measurement of cognitive state, and analysis of computation outcomes.

Conflicts of Interest

The authors declare no conflict of interest.

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