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COGNITIVE ENERGY FLOW MODEL CONCEPT FOR VIRTUAL STUDENT

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ABSTRACT

Complex mathematical approaches exist in biological, social, and educational sciences, creating models to understand and explain cognition processes in human brain. Yet, the logged raw data is just an initial learners' behavior footprint in Virtual Learning Environments. Exploratory Data analysis would help to deepen the understanding of cognition processes in students' brain. The challenge is: the evaluation of usability of e-learning courses before the large-scale implementation. With this aim, we combine knowledge elements explored from logged learners behavior data and cognitive theories to formulate a computer model for Virtual Student's evolution. We assume that some of the brains energetic expenses in learning and memorization are due to energy-extraction skills from cognitive abilities, knowledge, information, etc. We also assume that the Virtual Student model can perform energy flow modeling by extracting energy from the environmental learning objects and losing the power in a tedious learning process. The research shows that on a Virtual Student's cognitive energy flow model based approach can potentially improve the model compliance with real student's behavior model and can be applied to predictive analytics classification problems in both inexpensive small and large-scale applications.

KEYWORDS

Cognitive Energy, E-leaning, Agent, Virtual Student

1. INTRODUCTION

A Since 1950th, intelligent agents used to use almost in all of the computer systems with the aim to get the system objects information, to rethink and provide local feedback or public actions. Usually, intelligent agents follow some road-map: (1) Perception, (2) Cognition, and (3) Actuation. These are functional properties of almost all the independent autonomous agents. Among the number of different agents categories, Learning Agents are more advanced because they have a similar to human ability to learn from experienced interaction with the host learning system.

The goal of this paper is to reflect the improved Learning Agent Model with additional specific properties: (1) emotional states, (2) ability to forget the learned facts, (3) need for rest, and (4) agent's energy flow. Concerning that, we propose the improved model based on the agent's energy flow assumption, that is the crucial point of interest. For instance: no energy - no action in learning process.

The new approach goal is to create the preliminary model that would further help to simplify real learners' classification problems using traditional predictive analytics methods in Virtual Learning Environments (VLEs) where (1) usage of Machine Learning Methods is not cost-efficient or (2) the environment has a new learning course and learners have not produced any data yet.

We expect that proposed Learning Agent namely Virtual Student (VS) cognitive energy flow model based approach improves agent model to be applicable for Predictive Analytics (PA) applied on real learners without non cost-efficient Machine Learning (ML) operations. This is the current research question.

The research organized as follows: Section 2 - the reflexion of related theories, methods, and approaches. In Section 3, that is the most important in the research we propose the concept of the Virtual Student's Cognitive Energy Flow Model. In Section 4 we provide a discussion of results and conclude the paper.

2. RELATED WORK

The full theory of intelligence is not yet in existence, although we assume that Master Theory of Cognitive Development should exist in the future [Domingos, 2015], and is applicable in a Human or Artificial World. Overall, Artificial Intelligence (AI) are held on a couple of key concepts: Sensing, Perception, Cognition, and Semantic [Sheth et al., 2015]. Assuming that Computer-Agent have Senses to receive various data from the digital learning environment host, the next conscious process in a computational sequence is the Perception: a cyclic process of interpreting data. Perception involves both interpretation and exploration with a strong reliance on background knowledge patterns of the domain of application [Gregory, 1997].

Cognition utilizes all the data received from a Perception act. Similarly like in a perception process, cognitive computing context is provided by existing knowledge base [Modha et al., 2011]. Finally, Semantics layer involves mapping observations from various stimuli on Computer-Agent input staying out of current research scope.

Of full value, cognitive process implementation serves goals to complete matching microarchitectures: (1) Senses (Intensity of Sensation), (2) Affection (Weber's Law - quantifying the perception of change in a given stimulus), (3) Attention (Rate, Duration, Degree, Inertia), (4) Perception (Temporal, Qualitative, Quantitative(Simple, Complex)), (5) Association (Law of Association), (6) Memory & Imagination (Cache Operative(a couple of seconds), Middle, Long Term Storage Network), and (7) Action (Emotions & Thoughts). Individual cognitive system requirements can cause simplification of the whole architecture or more detailed research and design of the specific item.

Levels of Cognitive Learning. We find an applicable reduced version of Bloom's taxonomy: (1) Memorization, (2) Understanding, and (3) Application.

Cognitive Cycles. Research results in psychology [Franklin and Graesser, 1997,Anderson et al., 2004] show that cognition in autonomous agents, whether artificial, animal or human, can be thought of as consisting of repeated perception-understanding-action cycles.

On Cognitive Cycles Timing. Results from studies in neurosciences determine the length of time taken by each of the phases of the cognitive cycle and are well known. Some results successfully adopted for specific architectures, for instance: LIDA (Learning Intelligent Distribution Agent) [Madl et al., 2011].

Mental Energy in Learning Process. Formulation of Mental Energy (a hard mental effort) in scientific magazines belong to Julian Huxley [Huxley, 1944]. It is a generally recognized truth that physical events can be looked at in two ways: from the mechanistic and from the energic standpoint [JUNG, 1969]. Time and Energy. The fundamental principle of causality and a proportional connection between

Intelligent Agents. Overall, exist more than one Intelligent Agents classification schemes proposed by Russell [Russell and Norvig, 2003] and Weiss [Weiss, 2013]. We follow Russel classification, where group agents divided into five classes based on their degree of perception and capability. Russell evolves five agent groups: (1) simple reflex agents,(2) model-based reflex agents, (3) goal-based agents, (4) utility-based agents, and (5) learning agents. Intelligent Agents can act either as a single instance or in groups: multi-agent systems. In the current paper, we discuss a single instance model.

3. DISCUSSION AND OUTCOMES

We specify some crucial principles we follow creating Agent's named Virtual Student's model: (1) Reliable Mental Energy Flow Model for Virtual Student is the primary interest of our research, (2) Virtual Student's Learning Process is a Mental Energy Flow expressed as a consuming of Internal Energy or growing from inherited Learning Objects, (3) Every single mental activity is a transition along the learning path rewarded with a specified but finite Energy Portion - Energy Token if the change has a direction to the comfortable emotional condition, (4) If the transition has a direction to the uncomfortable emotional condition, Virtual Student becomes fined by Energy Token Decreasing, (5) Virtual Student initially has enough Energy Tokens to overcome threshold level to join the Learning Course, or to start to explore specific Learning Object, and (6) Virtual Student runs based on the principle of causality and a proportional (linearity is not the obligation) relation between time and energy.

On research roadmap, firstly we draft the digital Ecosystem boundaries for Virtual Student's evolution. Then, we specify Virtual Student's properties. Finally, we propose the Virtual Student Learning Model implementation ready concept.

3.1 Virtual Student Ecosystem

Learning Energy Network. Here, we invent the isolated learning network with boundaries for Virtual Student operations when sensing, and declare rules for reasoning (perception, cognition) and acting. Learning network bounds energy consumption or production. We specify three top class energy-related objects for the ecosystem and their properties: (1) System Energy Depot - D, (2) Virtual Student's Energy Buffer - VS, and (3) Learning Object Energy Storage - LO.

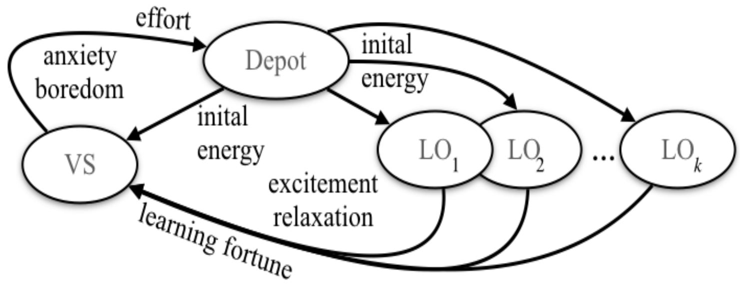

Figure 1. Energy Flow Model for Virtual Student's Ecosystem: System Energy Depot (Depot), Virtual Student's Energy Buffer (VS), and k Energy Storages for Learning Objects (LO1 . . . LOk)

3.2 Virtual Student Properties

We invent following groups of static and dynamic properties: (1) need the rest in daily workout process, (2) ability to forget the learned facts, (3) emotional states, and (3) cycling through motivational sequences. Newly invented and research specific properties we discuss in this paper.

Emotional States. With the Emotional States, we understand real learners' emotional conditions playing a specific role in the learning modeling confidence. We specify following emotional states: very pessimistic, skeptical, confident, and very confident. Considering correlation to Virtual Student's energy model, we elaborated the Emotional States factors.

Virtual Student's Motivational Sequences Model. To form Virtual Student emotionally motivated interactions with ecosystem layers and components required for cognitive learning process modeling, we adopt a commonly occurring Motivational Sequence model [Van der Molen, 1984)]. Virtual Student's attempts to catch and hold certain pleasant states like excitement or relaxation are alternating with unpleasant ones like flat, tiresome states. Four alternating model states (see Figure 2) represent cycling through comfort levels: excitement, anxiety, relaxation, boredom mapped to the timeline. We argue that a tendency to begin to learn at the emotional excitement phase correlates with the real learners' motivation keen to learn.

Alternating Emotional states represent stochastic emotional cycling process leading to Energy Fluctuation in the proposed Virtual Student Learning Model.

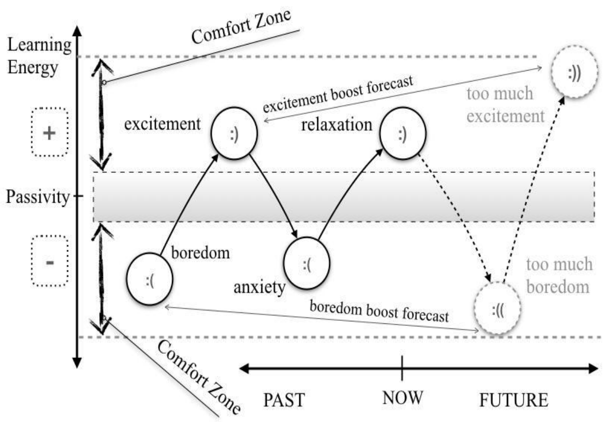

Figure 2. Energy Fluctuation model. Scenario: Suspicious Energy boosting in both directions leaving a Comfort Zone moving towards extreme threshold levels

3.3 Virtual Student Learning Model

From Franklin's results [Franklin and Graesser, 1997], we take into consideration the existence of universal cognitive cycling paradigm: cognition in autonomous agents is subject independent - whether artificial, animal or human. This is the crucial concept point to follow.

We find that Stringer's Action Spiral model [Nasrollahi, 2015,Stringer, 2013] stated existence of look-think-act cycles in cognitive learning correlate with similar results proposed by Anderson [Anderson et al., 2004]. By adding operation control logic we combine both motivational cycling and cognition cycles approaches in to one coherent system presenting Virtual Student Learning Model concept. Figure 3 depicts the Virtual Student Learning model in dynamics. Each transition on the scheme denoted as a colored circle object with a sequence number inside.

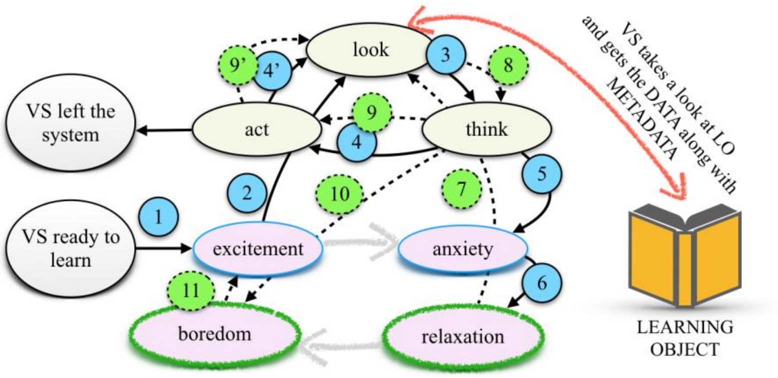

Figure 3. Interaction of Virtual Student Learning model States in a Spatial Design

The main algorithm controls the learning process interacting with every module with the aim to supervise ecosystem energy flow. On a condition of insufficient enough energy, what is the worst scenario, Virtual Student is dropped out of the course. In the case of acceptable quality of interaction with learning objects, the mission completed.

4. CONCLUSION AND FUTURE DIRECTIONS

Summarizing research results regarding energy aspects of the discussed model, **we conclude**: (1) proposed Ecosystem for Virtual Student evolution has clear operating conditions to simulate the learning process based on the energy balance principles, (2) Learning Energy redistribution flow among the system objects can be observed and controlled by the main system algorithm, (3) Ecosystem model's Energy Quantity is constant for every simulation run. For **future works** we consider to follow the crucial concept point: cognition for every autonomous agent is subject independent: (1) to study Virtual Student model computer implementation depending on model Verification results on the model validation stages, (2) to translate conceptual model to operational one and verify it by implementation ir real VLE. Further research by applying validation to the proposed model with an implementation in the Virtual Learning Environment might clarify the aspect of Virtual Student's potential.

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