Modelling an Adaptive Learning System Using Artificial Intelligence

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Abstract

The goal of this paper is to use artificial intelligence to build and evaluate an adaptive learning system where we adopt the basic approaches of spiking neural networks as well as artificial neural networks. Spiking neural networks receive increasing attention due to their advantages over traditional artificial neural networks. They have proven to be energy efficient, biological plausible, and up to 105 times faster if they are simulated on analogue traditional learning systems. Artificial neural network libraries use computational graphs as a pervasive representation, however, spiking models remain heterogeneous and difficult to train. Using the artificial intelligence deductive method, the paper posits two hypotheses that examines whether 1) there exists a common representation for both neural networks paradigms for tutorial mentoring, and whether 2) spiking and non-spiking models can learn a simple recognition task for learning activities for adaptive learning. The first hypothesis is confirmed by specifying and implementing a domain-specific language that generates semantically similar spiking and non-spiking neural networks for tutorial mentoring. Through three classification experiments, the second hypothesis is shown to hold for non-spiking models, but cannot be proven for the spiking models. The paper contributes three findings: 1) a domain-specific language for modelling neural network topologies in adaptive tutorial mentoring for students, 2) a preliminary model for generalizable learning through back-propagation in spiking neural networks for learning activities for students also represented in results section, and 3) a method for transferring optimised non-spiking parameters to spiking neural networks has also been developed for adaptive learning system. The latter contribution is promising because the vast machine learning literature can spill-over to the emerging field of spiking neural networks and adaptive learning computing. Future work includes improving the back-propagation model, exploring time-dependent models for learning, and adding support for adaptive learning systems.

Keywords

Adaptive Learning, Neural Network, Spiking Neurons.

Introduction

In this paper, an artificial intelligence based digital image processing system for face recognition on multicore platform has been introduced that could identify the faces of people in less time with more accuracy. The field of machine learning is evolving rapidly, and has in some recognition tasks surpassed human-level precision. This acceleration is propelled by the advances in artificial neural networks, which recently defeated a human in the advanced real-time strategy game StarCraft II (Brains, 2013). ANNs second generation neural networks (NNs), because they supersede the first generation networks based on the perceptron. We believes they themselves will be superseded by a third generation of neuron models that closely resemble biology. Unlike neurons in ANNs that follow well-behaved continuous functions, biological neurons communicate by spikes of electricity over time.

Because of their biological similarities, third generation NNs are of great interest to (cognitive) neuroscientists. Compared to experimental studies involving living neural substrate, it is significantly cheaper and faster to build neural models either as pure simulations or as analogue circuits that resemble the physical structure of neural networks. Further-more, researchers have complete control over virtual models to pause, lesion, or even disassemble at will.

Learning computation is a paradigm that aims to exploit this new generation of network models, by constructing circuits that encode information in spikes over time instead of digital signals (Dayan & Abbott, 2003). The artificial neuron model can be built in silicon and have shown to accelerate the performance of NNs by a factor of up to 105.

A challenge for third generation networks is the relatively poor under- standing of learning processes within spiking neurons. This topic is subject to intense research, and there is a growing body of work that attempts to validate the theories through simulated experiments. Within the field of machine learning is a well-researched topic, and in the absence of clear neurophysiological learning models, it is a common approach to explore learning algorithms from machine learning in the simulated neural systems. The landscape for neural simulations are, how- ever, heterogeneous and the simulated models typically imply a number of assumptions (such as neuron parameters and model topology), that renders the experiments near-incommensurable. The outcome is that the experimental findings are difficult to validate and re-integrate with theoretical models (Morrison, Mehring, Geisel, Aertsen, & Diesmann, 2005).

This paper sets out to explore spiking neural networks (SNNs) and their potential for the field of machine learning, focusing on two major challenges for the third generation models: homogeneous modelling and learning. The paper is built around the artificial intelligence based deductive learning model, in which falsifiable hypotheses are formulated, tested and evaluated.

1) Problem Statement

This paper examines and solve two problem to some extent given by:

- The artificial intelligence based adaptive learning can translate into spiking and non-spiking neural networks such that the network topologies are retained.
- Using training it is possible for spiking and non-spiking models to solve tutorial mentoring and adaptive learning activities recognition task.

The problems are driven by two inquiries around modelling and learning of adaptive system using artificial intelligence.

Background

The adaptive learning systems (ALSs) are developed to combine the adaptive system and learning technology. ALSs are separated the two different forms basing on adaptive method. The first one focuses on the adaptive presentation. Information content providers to each user, that information can be represented differently in detail, complex level, and the use of hypermedia depend on the needs, backgrounds or individual cognitive characteristics. The last one approaches the adaptive navigation support base on user profile with different types such as: direct guidance, adaptive link hiding, adaptive link sorting, adaptive link annotation, and map adaptation.

A special style of ALS is the adaptive educational learning system (AELS) applying in education which consists of document space, user model, historical record component keeps interactive process between user and system to update user model, and adaptation component included the adaptive rules (e.g. proposes to read a document) and adaptive treatment (e.g. arranges the links to supporting documents) depend on user model (Davison et al., 2009).

User model in ALS/AELS can be organized for knowledge, interests, goals, backgrounds, and individual traits.

- Knowledge is the understanding of learning subject. This is the most important component of user model, and can be changed (increase or decrease) when transfers from this subject to the other subject in the same section.
- Interests are the preferred subjects of user (relate or not relate to the course).
- Goals present purposes of the user's task. These can be the need of instant information or learning targets. This component can be the most changeable, it happens when user transfers from this session to the other session and even can be change many times in the same session.
- Backgrounds include the former knowledge, skills, and experiences, outside the field of the subject (or course). This is a fairly stable component, which rarely change in processing and can be defined explicitly by user.

Individual Traits are the personal characteristics which form the behavior of the user such as personality, cognitive factors, and learning styles. The recent researches usually aim in two groups: cognitive style and learning style. Until now, no work has been given a clear model and also evaluated specifically the effectiveness of this part in systems.

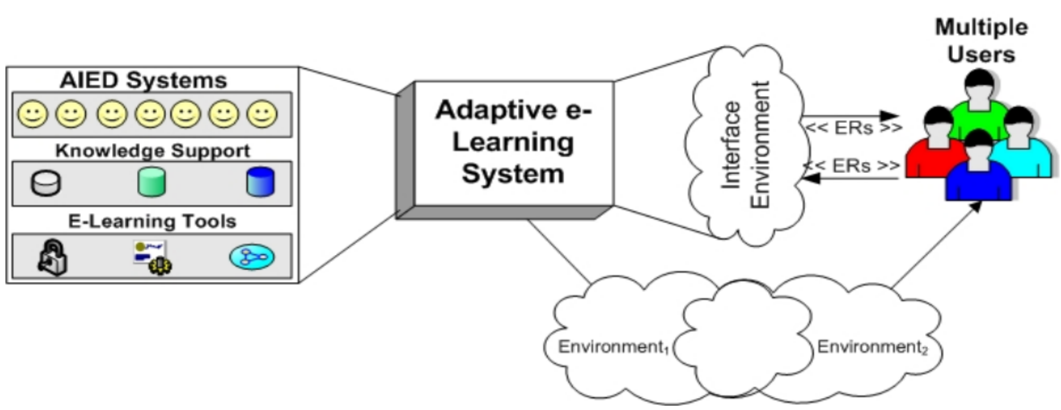

Figure 1 User and system to update user model and adaptation component using interface environment. Source (Davison et al., 2009)

Adaptive e-Learning system, the frame architecture that we propose in this paper it has a purpose to apply e-Learning environment and combine the approach between intelligent tutoring system (ITS) and adaptive educational learning system (AELS) (Nguyen et al., 2019). The main goal reinforces the support to self-study activities and promotes the learning motivations base on the interactions of the participants, especially between the learners who work together. Main topic of the paper is learner profile and will be presented in detail.

- Standard knowledge is very popular in the e-Learning system, it is often called domain space (or hypermedia space), which is included standard knowledge of the curriculum contents in system (Vinyals et al., 2019).
- Expert-based Knowledge includes the knowledge that can be varied lively depend on each instructor/teacher, mainly his/her experiences and pedagogical capacity.
- Collaborative Learning is the combination of various co-operative activities among participants in learning process such as interchanging and sharing information, discussion and exchange of knowledge through forum.

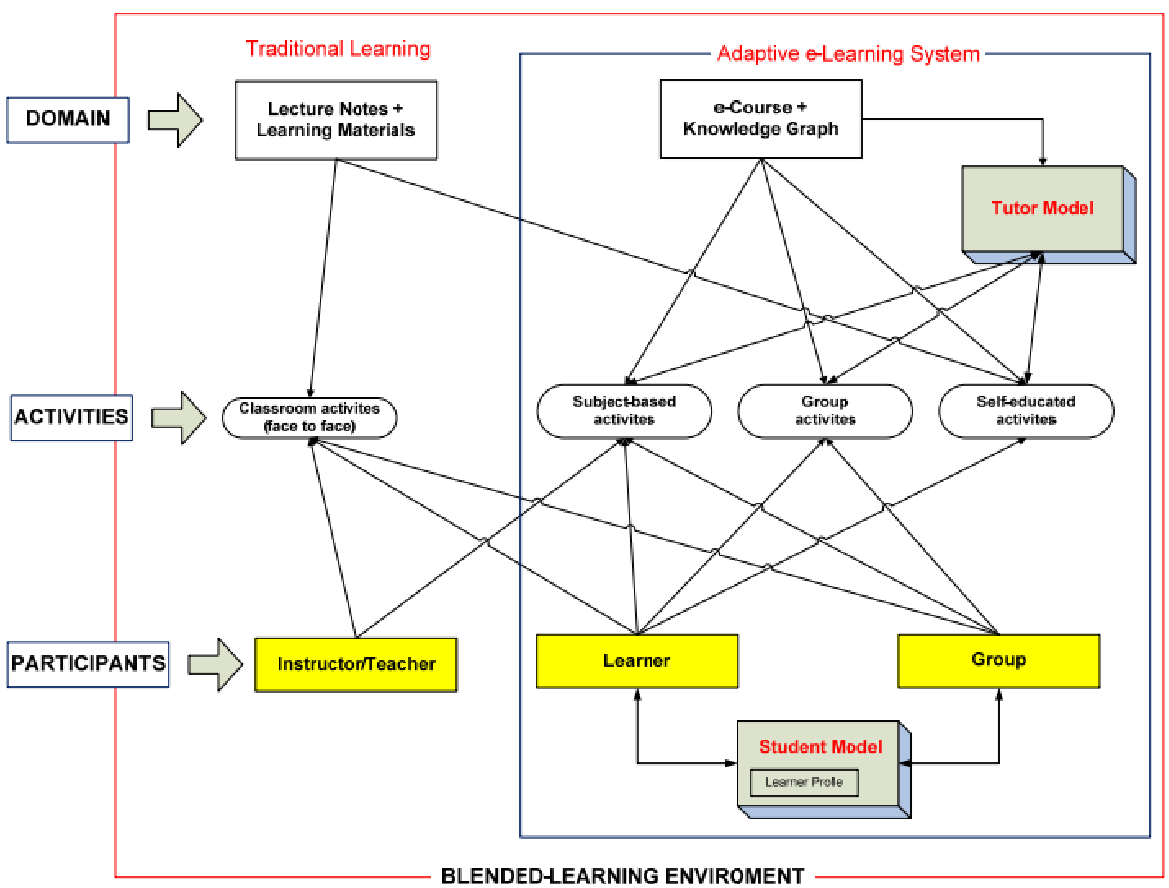

Figure 2 Blended-learning environment combines traditional learning and AeLS

An example about the generation of an adaptive learning script to learner in self-study activity basing on learner profile is shown in Figure 2. At first, depending on course subject, the instructor/teacher will select the teaching script and prepare the sub-knowledge graph from topics and the built knowledge graph (Diehl et al., 2015). Then, the system bases on each learner's profile to define the adaptive learning script for individual learner by generating the dynamic knowledge graph to perform his/her own self-study. Finally, through the evaluated results and feedbacks at the end of course, the system can continue to support and instruct the following topic, at the same time the system uses the information above to update learner profile and also readjust DKG to suit the learner (Elsman, Henriksen, Annenkov, & Oancea, 2018).

Methodology

1). Neural Networks

NN is a broad term that originates in the neuronal models from the biological brain. The general architecture of neural systems can be explained as circuits of neurons connected through weighted edges.

In this abstract sense, a neuron is a computational unit that takes a number of signals (inputs) and processes them through a function that outputs a single value. Composed in a network, neurons can compute complex non- linear functions.

In a more concrete sense, NNs compute over either continuous (e.g., volt- age and numbers) or discrete signals (Elsman, Henriksen, & Oancea, 2018). Discrete models served as the foundation for the first generation of neural networks. They are based on the perceptron model as seen in Equation 1, also known as the McCulluch-Pitts neuron model.

$$\sigma(x) = \frac{1\ if\ x>0}{0\ otherwise} \qquad (1)$$

- **Neural Networks as Directed Graphs**

These first NNs collect neurons in groups that connect to other groups in a sequence. Figure 2 shows an example of such a network.

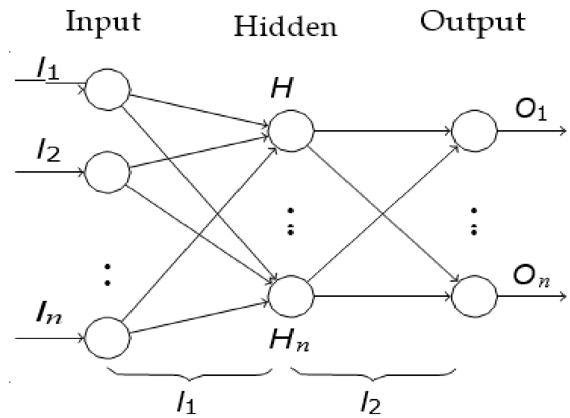

Figure 3 An example neural network of depth 3 with two layers (l1, l2) and a single hidden neuron group (H)

The number of groups determines the depth of a network graph. Each group applies a non-linear transformation to the input that is forwarded to the next layer, and so on. From a computational point of view, a neuron group is simply a computational unit, which allows NNs to be abstracted as circuits of units connected in a directed graph. This view can be simplified as shown in Figure 2, such that each neuron group (node) is considered a function. Here the output is generated by the sequential composition of activation functions over the input x. Neuron groups are sometimes referred to as layers in the literature, but from a computational perspective it is simpler to view layers as functions, such that they include the output activations for the next neuron group. In this paper, a layer is defined as computational units that transform input with a non-linear function to produce some output. Thus the network consists of two layers.

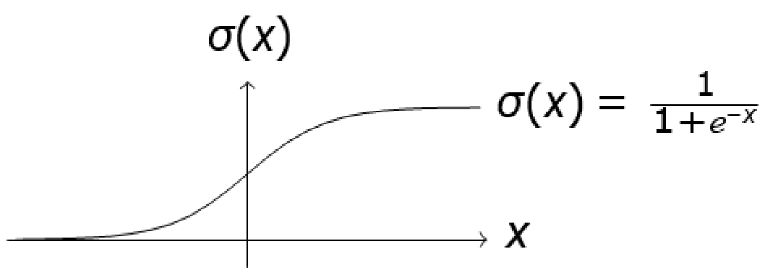

Figure 4 A sigmoidal (soft step) function

Where σ is the neuron function. For a single neuron x, the output signal is calculated through a weight (w) and a bias (b). Weights and biases allow the model to adapt the relative importance of each input neuron, thus allowing the model to train to a given domain (Pelayo Valle & Morillas Gutiérrez, 2018).

- **Second Generation Neural Networks**

Second generation neural networks augment the perceptron model by a) allowing continuous output values of a neuron and b) parameterizing the computation of the neuron by adding an activation function that determines the output of the neuron. Sigmoidal functions are commonly used for activation functions because they resemble the perceptron step function while retaining continuity.

A number of variations for sigmoidal activation functions exist such as the hyperbolic tangent and the rectified linear unit (ReLU, see Equation 2).

$$f(x) = \frac{0\ if\ x>0}{x\ otherwise} \qquad (2)$$

They are applied either in a feed-forward or recurrent (cyclic) manner, where the recurrent variant performs temporal transformations.

- **Third Generation Neural Networks**

Constructing a network of neuron models essentially creates a non-linear response to a given numerical vector. This transformative view can be adopted to biological (third generation) SNNs, where the data being transferred are no longer vectors, but spikes of electrical signals over time. In biological networks there is a temporal dimension, in that neurons produce and fire spikes asynchronously to other neurons in the same group. We worked on a conductance model that could describe this process dubbed the integrate-and-fire model. The model essentially integrates received current over time, and if the integrated current reaches a certain voltage threshold, the neuron fires. In biological neurons this also implies a spatial dimension, because the current is sent through neurons that extend in space. The biological cell body (soma) separates the neuron cell from the exterior with a membrane. The soma receives impulses from a number of dendrites, and emits spikes through an axon, when the currents across the cell membrane exceeds the voltage threshold. The geometry of the components influence the time as well as the amount of current it requires to send impulses through the neuron. This has been modelled to a high degree of precision. While it is more precise than models below, it is more complex, and rarely used in simulations (Montavon, Orr, & Müller, 2012).

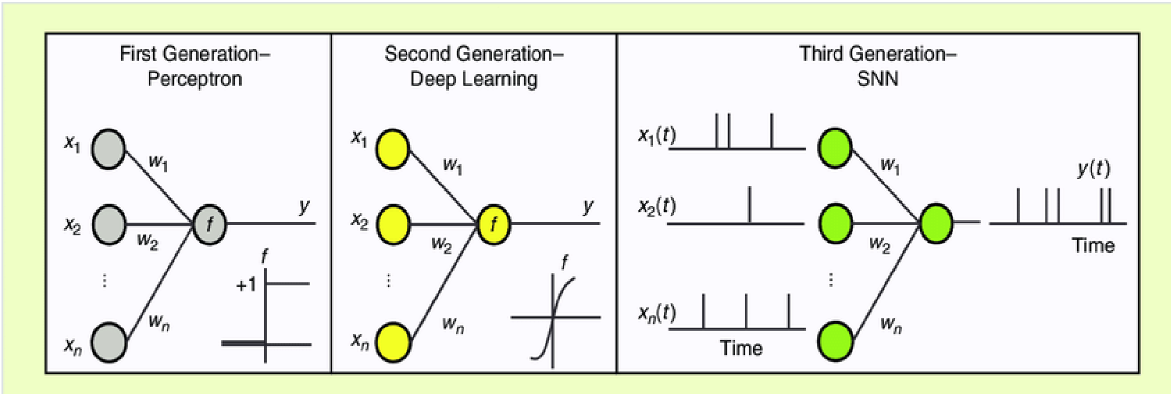

Figure 5 Graphical representation of first, second and third generation neural network.
Source (Montavon et al., 2012)

The spiking model is based on a neuron that builds voltage over time, until it reaches a threshold voltage and emits a spike. The spike carries a charge, and is received by a post-synaptic neuron as input current, which, in turn, decides whether to fire.

2). Learning

Defining an agent as a system that can act on previous knowledge, learning in the context of an agent refers to "the process of gaining information through observation".

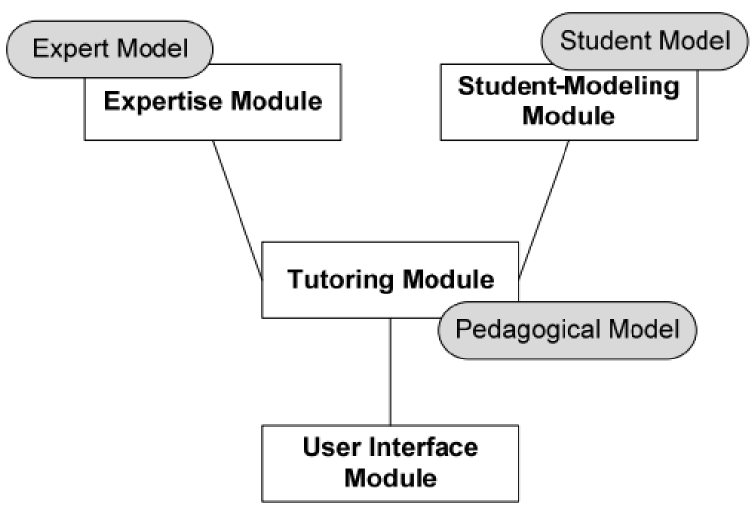

Figure 6 Architecture of Intelligent Tutoring System (ITS)

Following the above abstraction of neural networks as computations over vectors, "learning" can be understood as the development of consistent patterns, given the same input. Within the machine learning literature, this is commonly referred to as prediction. In practice this is expressed in terms of general functions or rules in a network.

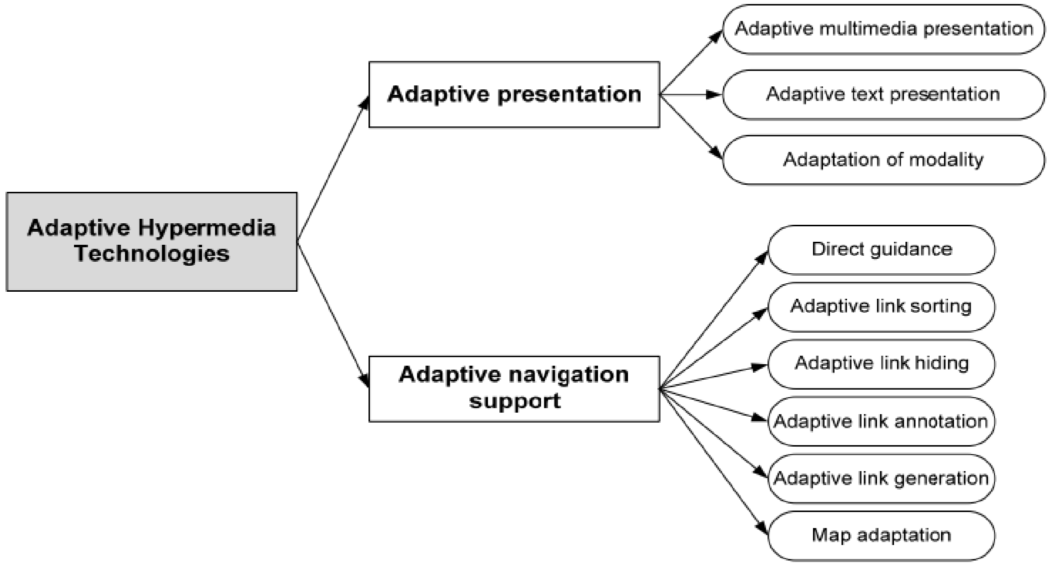

Figure 7 Adaptive Hypermedia Systems (AHS)

Within machine learning, systems are typically classified into supervised, unsupervised, and reinforced learning systems.

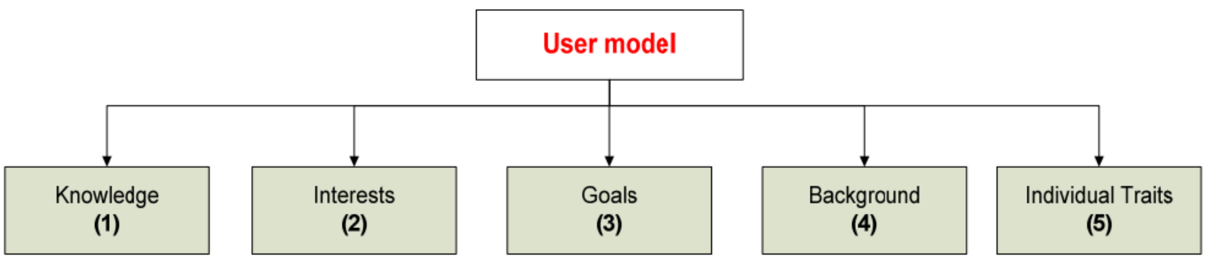

Figure 8 The framework developed for the user model learning using spiking neural network and artificial neural network

- **Supervised Learning**

It relies on a set of expected outputs which the learning agent must predict, given some input. The agent is told how 'wrong' it was, so it can adapt accordingly. Learning typically happens in a training phase, where the agent is allowed to build its internal representation. This representation is later tested in the testing phase, where the model is asked to infer based on previously unseen data.

- **Unsupervised Learning**

It asks the agent to learn without having any idea of error margin. Rather, the agent is asked to explore a domain in search of patterns, which then form the basis for future predictions or classifications.

- **Reinforced Learning**

It reinforces the agent through rewards, and discourages it through punishments. Contrary to supervised learning the rewards and punishments are not instructing the agent on what the output should be, but rather how well it performed the task, leaving the agent to infer rules or behaviors by itself (Doets, 2012).

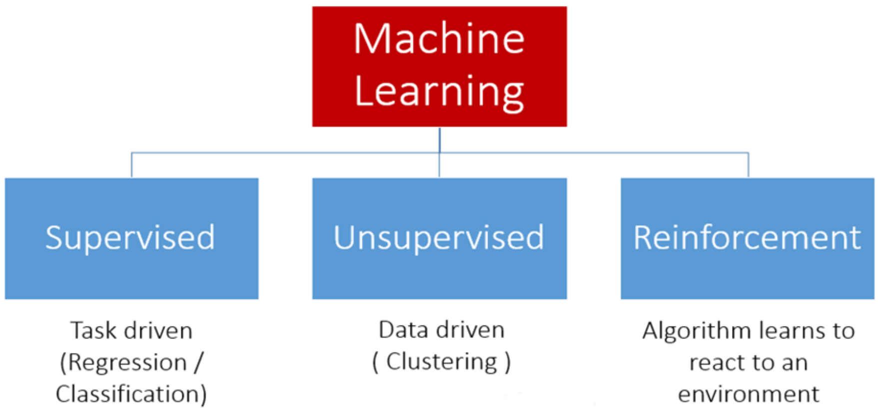

Figure 9 Brief on types of machine learning being used to train the models in artificial intelligence (Doets, 2012)

The process of learning can either be inductive or deductive. The latter requires a basis in rule-based systems from which new knowledge can be deduced, while the former requires a measurement of success.

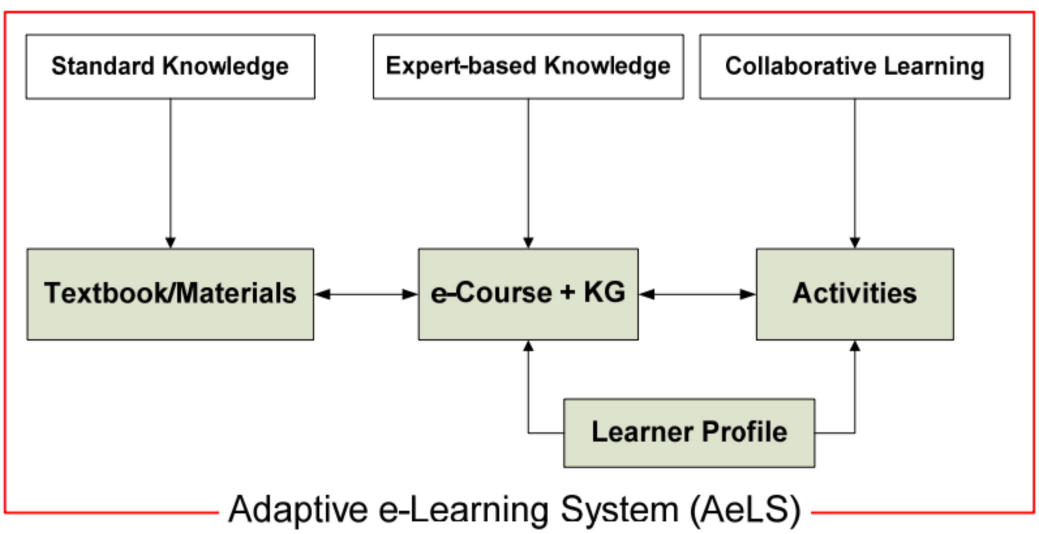

Figure 10 The architecture of Adaptive e-Learning System

Such a measurement is typically referred to as the error or loss function, because it shows how much the prediction deviated from the expectation (goal).

- **Intelligent Computing**

Intelligent computing is based on the idea of NNs where the activation units are modelled outside the classical von Neumann architecture, either in integrated circuits or in simulated environments. This approach permits the simulators to work several hundred of magnitudes faster than regular ANNs, but at the cost of precision and noise. The precision problems occur because of hardware limitations where the typical weight is restricted to a few bits, compared to larger ANNs. The noise problems are caused by noise in the integrated circuit components.

The technology is still relatively young and suffers from a number of practical problems. For instance, networks above a couple of thousand neurons remain problematic with the current technology. Training is also challenging because of the embedded components. Both memory and processing power is limited, which makes is practically difficult to store enough data to recall the spike trains and calculate the, sometimes complex, weight update rules.

One practical approach to combat this problem is to model and simulate the adaptive learning system outside the hardware, in a system with sufficient resources. Because the simulated systems have the same topology, the optimized model parameters can be directly transferred to the hardware. This paradigm is dubbed 'learning-to-learn', and have already been shown to produce decent results. However it has still not been generalized to support arbitrary machine learning models.

- **Dataset Acquisition**

The dataset was obtained from an open-source repository for adaptive learning known as Adaptive Learning Achieves. We performed tests which demonstrated similar (scalability) results by processing this dataset. A heuristic solution had been proposed such that we divided the total number of scales by half. The first half containing the heavy sized scales data of learning purpose would be parallelized using a row wise parallel for, while the second half containing the light sized scales would be parallelized computing in parallel each scale. That's how the dataset was processed using the multi-cross folds.

Results

1. Data Analysis

Based on theoretical review and research of developments in the growth of modern artificial intelligence-based education, the convenience of applying the teaching methods based on the students building expert training system information database has been demonstrated. Students of the Master's degree and those attending refresher courses for teachers.

Detailed findings obtained through experimental data processing validate its efficient implementation in the educational process. Survey findings by year are shown in Table 1.

Table 1 Sampling of adaptive learning programs using the SNN and ANN approach as indicated

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018
Number of answers	31	28	32	34	45	52	34	45	58

The time series obtained meets the requirements that are imposed by the method indicated on the initial sampling information. Namely: the period grades are equidistant from each other; period grades are exactly equivalent; time series has a reasonable length; no measurements in the time series are missing; time series levels do not contain irregular values.

The measurements and evaluation of the growth dynamics metrics were carried out after reviewing the initial information for compliance with the requirements. A model was developed to forecast interest in learning and applying the construction methods in order to enhance potential students' technical training. is the serial number of the year in the coordinate system $Y_t 0_t$, where Y_t is the number of students who replied positively to the study of AI. Figure 1 shows the dynamics of positive responses to the students' question about the feasibility of ETS KB construction.

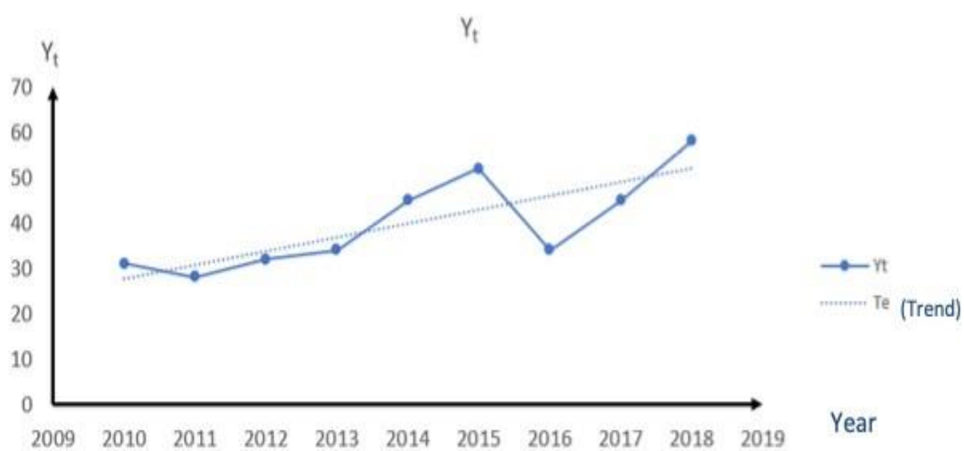

Figure 11 Dynamics of positive responses

Average values were obtained in the experiment group of Master's students and refresher students for each form of new educational activities during the study. Then the ranking was made, where one rank was the unit of measurement and 18 ranks was the maximum value. The results of this ranking are shown in Table 2.

Table 2 Masters, refresher, and post-doctoral students use artificial intelligence to test adaptive learning practices

Types of Learning Activities using AI	Evaluation of master's students	Evaluation of refresher students	Post-Doctorate
Study of the multivariance and the alternatives of expert decisions	1	2	1
Stressing the Information Key	2	8.5	42.25
The development of expert and technical knowledge using different methods	3	13.5	110.25
Education preparation cycle	4	12	64
Ability to arrange the subject-matter of the students	5	5	0
Learning the principles of knowledge-building for students	6	3	9
Studying how interdisciplinary knowledge synthesis is implemented in practice	7	8.5	2.25
Research adaptive technologies for teaching educational content	8	6	4
Ability to learn various technical approaches and working types	9	7	4
Modeling complex scenarios	10	10	0
Create interpersonal and commercial relationships, engage with the work environment	11	1	100
Independent acquisition of knowledge by the use of traditional and modern information sources	12.5	15	6.25
Teaching knowledge	12.5	11	2.25
Plan and execute research activities	14	16	4
Forming of a information network on the topic under review	15	4	121
Identification of the key elements, their systematic study and synthesis in the subject matter under consideration	16	18	4
Mastering the methods of handling school planning;	17	13.5	12.25
Consideration of the psychological strengths of students in the structure of the learning process	18	17	1

Accepted theory. The link between Master's students' opinion and refresher students is statistically relevant and positive at the level of sense of 5% significance level.

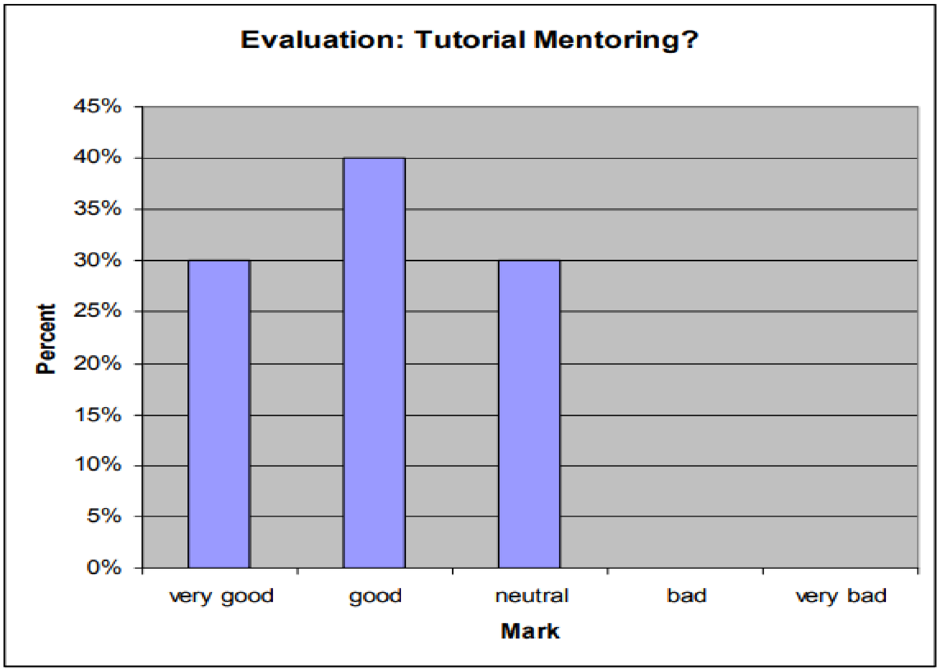

Figure 12 Evaluation of tutorial mentoring with the percentage of traits of adaptive learning

The most notable findings include: 1) The creation of radically new information technology material in the discipline of professional activities for students of the Pedagogical Education master's degree and the refresher program for teachers of information technology and e-learning in teaching school subjects; 2) Introduction and effective implementation of teaching strategies focused on student participation in the educational process through the resolution of teaching goals using approaches used in the growth of students' learning.

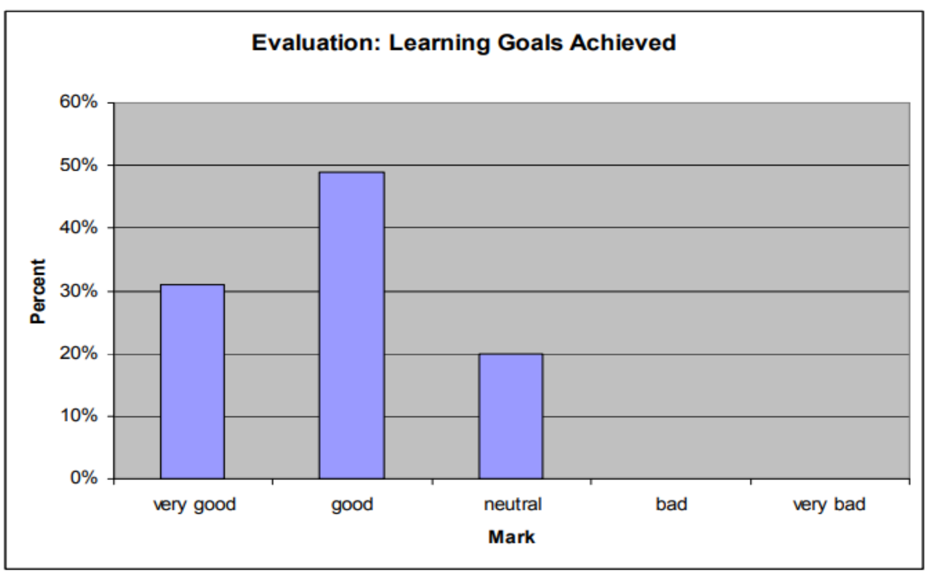

Figure 13 Evaluation of learning goals achieved with the percentage of traits of adaptive learning

In the evolving conditions of teaching and learning in analytical, educational settings, the material is adapted to the professional activity of the teacher; packed with theoretical and practical problems of using AI technologies, techniques, and tools related to education.

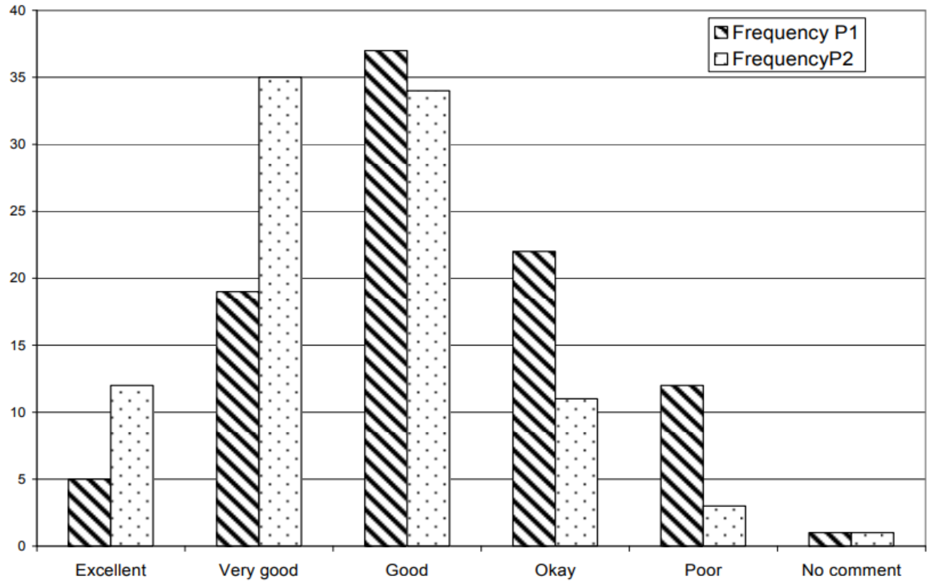

Figure 14 Frequency of traits of for adaptive learning represented by P1 and traditional learning represented by P2

An action plan will be drawn up to meet the needs of a training program for vocational teachers. A plan like that should have access to the following:

- Dissemination of knowledge relating to e-learning and seminar organization in classrooms.
- Teacher help in the development and teaching of subjects for e-course.
- Administration and management of e-learning vocational programs at the respective institutions;
- Foster collaboration in the area of technical e-learning.
- Creation of website for vocational e-learning.

2. Discussion

This paper sat out to explore SNNs and their future relevance to the field of for neural models was presented, along with two libraries for the training of second and third generation for adaptive learning system using artificial intelligence.

Table 3 A summary of the findings

Assumption 1	Translation to ANN	Confirmed
Assumption 1	Translation to SNN	Confirmed
Assumption 2	Learning an MNIST task in Single User	Confirmed
Assumption 2	Learning an MNIST task in Multi User	Unconfirmed

It models various ways of organizing knowledge on a knowledge base, designing different learning situations, taking into account their adaptation to the user system, modeling the behaviors of the students and teachers through their study and synthesis. An earlier understanding of the subject is the basis for its creation. Through this regard, the writers will address the student's evolution from his current knowledge to the information arising from the creation of a knowledge base. (Hunsberger & Eliasmith, 2015). The variety and multivariance of educational tasks are achieved by the study of different alternative approaches to the organization and conduct of the education process. For this reason, undergraduates and refresher students researched the work experience of experts in subject areas and got to know alternative approaches to the same educational or methodological problem, and examined different ways of applying expert thoughts and their decision-making multiplicity. That is, the students studied the variants of nonlinearity when solving tasks of one kind. Synergetic school representatives stress that it is not linearity that offers excellent adaptation opportunities. The researchers should conclude that the students' experiences in the course of collaborating with experts conform them to the teaching profession, developing divergent thinking; that is, the ability to find different methods to solve the problem, refine them and recognize the original.

Conclusion

This paper sat out to explore artificial intelligence in education and their future relevance to the field of for neural models was presented used to develop an adaptive learning system for tutorial mentoring and learning activity goals, along with two libraries for the training of second and third generation. To validate that adaptive learning system, two hypotheses were put forward and experiments were designed to attempt to falsify these hypotheses. Finally, a theory for the translation of model parameters for artificial intelligence was developed and tested empirically. Three experiments, each executed on two different back ends, were conducted to prove two things: that the adaptive learning using artificial intelligence can translate into second and third generation neural networks and adapt to a well-known recognition task, using back-propagation learning. The experimental results prove that the adaptive learning concepts are translatable between the NN paradigms, and that the adaptive learning using artificial intelligence can generate executable programs that retain the abstract network topologies. The results further show, that some form of learning was taking place in the experiments with SNNs. However, flaws in the gradient approximation model and the spike rate coding scheme, suggests that the model learns consistently wrong patterns and produces a large quantity of dead neurons. The experimental results do not disprove that training within SNNs is possible, but further adaptations to the gradient and coding models are required.

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