Human Machine Learning Symbiosis

Kenneth R. Walsh
Associate Professor
Department of Management and Marketing
College of Business, University of New Orleans
New Orleans, Louisiana

Md Tamjidul Hoque
Assistant Professor
Department of Computer Science
College of Sciences, University of New Orleans
New Orleans, Louisiana

Kim H. Williams
Director and Associate Professor
Lester E. Kabacoff School of Hotel, Restaurant and Tourism Administration
College of Business, University of New Orleans
New Orleans, Louisiana

ABSTRACT

Human Machine Learning Symbiosis is a cooperative system where both the human learner and the machine learner learn from each other to create an effective and efficient learning environment adapted to the needs of the human learner. Such a system can be used in online learning modules so that the modules adapt to each learner’s learning state both in terms of knowledge and motivation. This paper describes the benefits of such a system and a proposed design that integrates human learning in both the cognitive and affective domains with machine learning which adapts to both.

Introduction

Learning can be viewed as the transformation from a current state of knowledge and abilities to an improved state of knowledge and abilities. Humans learn through a wide variety of artifacts such as computers, books, real-world interaction and teachers taking them from a given state to another. Effective learning artifacts help take the learner from where they are to a new state, however, each human exists at a unique state of knowledge and abilities.

Human teachers are exceptional tools for learners because of their ability to adapt to the state of the learner. A tutor helping a single learner can be effective often because they can take the time to understand the individual learner and what would help them progress. The teacher in a classroom of similar learners can engage the learners in a learning exercise that helps them all. However, learners in the same class may be similar, but are not the same and the teacher adapts adjusting the experience or addressing learners individually. In larger classes, the teacher has more of a challenge adapting to individual learners. Complicating the process is the human learner must expend effort to learn which requires motivation. The human teacher is adept at providing motivational input to learners along with the content itself. However, teachers come at a cost of the teacher themselves and their infrastructure. In a society with many potential learners, the potential for teaching costs can be extraordinary.

In many online learning environments, computer learning tools are used to augment or replace the teacher in order to increase the availability or decrease the cost of the learning experience. However, as the tool becomes available to more learners, its design assumptions about the current state of the learner may become further off the mark making the tool less effective. Further, as the learner learns he or she may outgrow the tool or fall behind the tool. Attempts to make adaptive tool, where based on learner responses, the tool can present more advanced information to those who have mastered certain levels and present remedial material to learners who are not progressing widens the range of learners that can be served. The cost now shifts to the teacher’s ability to redesign tools with the many paths that learners may need. Since these designs can be applied to many learners, they can be used...
at a lower cost per learner than the human teacher alone. However, the coarse grained adaptability may make learning less efficient to the individual learners when compared to direct teacher interaction. Further, such systems are usually weak at motivating the student.

Machine learning is a method of computer problem solving where the explicit structure of the problem is not coded by the programmer, but rather is discovered by the machine through analyzing data over time. In complex problem solving, machine learning can be more cost effective than traditional computer algorithm design because the human programmer spends less time with the details of the problem structure and allows the computer to discover that structure. This can be a computer intensive process, but with falling computer prices the economics more and more justify letting the computer explore the solution space over a human programmer explicitly testing the combinations.

Embedding machine learning in online learning modules has the potential for modules to adapt to greater degrees and more individually to learner’s unique characteristics than traditional structured teaching modules. Further, their lower cost can increase the availability of such techniques to a wider audience. Developing a learning machine that is symbiotic with the human learner is at the heart of the new generation of greatly accelerate learning while increasing availability and decreasing costs.

Previous Research

Human Learning

Human learning involves the acquisition of new knowledge and skills through effort put forth by the learner. The effectiveness of learning activities is effected by both the current state of knowledge and skills of the learner and the learner's motivation to put forth effort to change to a more advanced state. A number of paradigms on learning have been considered over time. Skinner (1968) noted that although some aspects of human learning appear to have simple stimulus and response relationship that may be amenable to straightforward conditioning, those stimuli alone would not constitute effective teaching. He observed “A good program does lead the student step by step, each step within his range, and he usually succeeds in the end if he wishes to succeed.” However, the coarse grained adaptability may make learning less efficient, but the memory level may decay quickly thereafter. In general, dividing study time over multiple sessions increases its effectiveness (Carpenter et al., 2012). The implication for a machine learning system is that using only the learning activities and outcomes as inputs to the learning system may be insufficient. When and in what order the learner participates in the activities effects outcomes and needs to be included as inputs to a machine learning model so that the machine learning system can find the best timing and combination of activities.

How learning activities are interleaved can dramatically change their impact on the learner (Roehrer, 2012). For example, most learning environments will have more than one activity around a learning objective. A learning design where several learning activities around one concept are completed sequentially, before moving on to another concept may not be as effective as interleaving activities between the two concepts. Concepts that are similar can easily be confused and can be difficult to differentiate between and such an interleaved learning approach can help the learner understand the differences. The implication for a machine learning system is that input on past student performance should be known temporally so that ordering effects can be learned by the system. The interleaving that has been studied has focused on experi-mental design where concepts within a subject area have been interleaved. For example, Kornell and Bjork (2008) found interleaving helped students learn how to differen-tiate painting from artists with similar styles. Little has been said about the broader question of how different subjects should be interleaved and how the timing of learning activities across subjects should be conducted. A machine learning approach that uses input across subjects or academic classes could yield useful information on the broader question of interleaving activities. Rohrer (2012) notes that the research on interleaving has been limited to short term learning activities and simple patterns of inter-leafing. A machine learning approach has the ability to consider a wider range of data and may be able to find larger time scale patterns of interleaving. Further, in a real world setting, patterns of interleaving may be at the whim of student habits and, therefore, data available to machine learning systems may be biased based on social norms, cul-ture, and current practice.

Effect of Affect

The affective state of the learner changes their ability to use, focus upon, and learn from learning systems. Affective state at any one time may be more or less conducive to learning and may change dramatically for one over time. How the affective states of a learner affect their learning activity varies by individual. Alternatively, the use of a learning system can change the affective state of the learner. For example, particularly challenging learning task that the learner is not prepared for may disheart-en the learner and reduce their confidence in successfully mastering the material. On the other hand successfully completing a challenging exercise can boost confidence for future activities. During deep learning experiences, that is when learning about something novel and difficult, the learner is put in a state of disequilibrium whereby what they understand does not match well with the new material being present-ed. The state of disequilibrium leads to the negative affec-tive states of “confusion, frustration, boredom, curiosity, and anxiety” (p. 14) and may be a necessary part of learning (Roehrer and Bjork, 2012). Positive feelings are not felt by learners until they have moved back into a state of equilibrium relative to the learning material and have overcome a hurdle or succeeded in an objective (Graesser and D’Mello 2011). Graesser and D’Mello interpret the Csikzentmihalyi concept of flow as situation where many positive feedback from the automated tutor when a learn-er grasped a concept increased the students eureka emo-tion. Their research was exploratory but the results seem promising and worthy of further research. They also note the eureka concept is intended to be a major breakthrough in learning although it was measured here as a relatively small break through and, therefore, the study may have missed an opportunity to provide large gains in learning outcomes. Nevertheless, strong correlation between comments from the automated tutoring system and the learners af-fect were measured. Bosh and D’Mello (in press) studied an automated tu-toring system to how they supported computer programming and found the affective states of confusion and frustration fol-lowing learner errors and those states were lessened when the system gave them guidance. Shute et al (2015) studied the video game Prince of Persia, designed to support physics education and found frustration lead to higher performance in the game and ultimately to higher post test scores in the classroom. D’Mello et al (2014) stud-ied that confusion, when introduced properly and when resolved properly, can have a beneficial effect on learning. A learner’s level of disequilibrium or frustration in the moment of an education experience influences outcome; however, general student traits that are more persistent over time also influence a learner’s ability to engage in a learning activity. Galla et al (2014) developed the Aca-demic Diligence Test as a measure of self-control in an academic setting. They found that a pre-test measure of academic predictive validity for objectively measured GPA, standardized math and reading achievement test scores,
Gamification is the process of using game-like elements such as points, badges, challenges, and levels of difficulty to encourage people to act and boost customer participation. Its significance has become increasingly important in the corporate sector, and it is forecasted to be a substantial portion of social media marketing budgets in the future (Findlay and Alberts 2011). Gamification has come to involve studying and identifying natural human tendencies and employing game-like mechanisms to give customers a sense that they are having fun while working toward a rewards-based goal. An example of gamification would include Nike Plus, an online community that motivates individuals to exercise more by enabling players to earn points and set goals. Gamification lessons are another way to use mechanisms that could be used by a machine learning system as a feedback tool. In a business context, the potential value of gamification is an increased level of customer engagement. Customer engagement facilitates repeated interactions that strengthen the emotional, psychological and physical investment a customer has in a product offering or brand (Brodie et al. 2011). This research proposes that the same principles of gamification and customer engagement used in industry can be applied to the classroom setting, particularly with respect to student engagement. Student engagement has been used to depict students’ willingness to participate in classroom activities, including attending classes, submitting required work, and participating in classroom discussions (Natriollo 1994). Students who are engaged show sustained behavioral involvement in learning activities and have a participative role in classroom discussions (Sandhu and Sams, 2009). Customer engagement (CE) has been defined as the “intensity of customer participation with both representatives of the organization and with other customers in a collaborative knowledge exchange process” (Wagner and Majchrzak 2007, p. 20). CE manifests in an individual’s participation in and connection with an organization’s offerings and activities (Van Doorn et al. 2010; Vivek et al. 2012). Bowden (2009) viewed customer engagement as a psychological process comprising cognitive and emotional aspects. Further, Bowden proposed that CE is an iterative process, beginning with customer satisfaction and culminating in customer loyalty. CE may be manifested cognitively, affectively, behaviorally, or socially. The cognitive and affective elements of CE incorporate the experiences and feelings of customers, and the behavioral and social elements include participation by current and potential customers, both within and outside of exchange situations (Vivek et al. 2012). Potential or current customers build experience-based relationships through intense participation with the brand by way of unique experiences they have with the offerings and activities of the organization (Vivek et al. 2012).

As aforesaid, gamification is a tool that organizations may use to promote customer engagement. Because CE involves eliciting cognitive, affective, social and behavioral responses from consumers, effective gamification efforts must be successful at engendering these same reactions. Vivek et al. (2012) suggested that participation and involvement are key requisites to CE. Implicit in participation and involvement are cognitive, affective, social and behavioral components. Thus, this research suggests that both participation and involvement mechanisms could be created and used as a feedback tool to guide and engage a student learn and help solve an exercise effectively.

The HEIDS will have two (02) modules: (a) Lecture Delivery Module (LDM) and (b) Exercise Module (EM). These methods are described below.

**Lecture Delivery Module (LDM)**

To deliver, lecture-slides will be readout by the software for the students. Student should be able to pause, repeat, and fast-forward as well as will be able to click the highlighted terms and check the related information for further details, as needed – which could be supplied beforehand or, can be supplied from Internet (links and readings) to be explored by the interested students. The module will record the behavior of the student, suggest and will be asked next (deeper) questions. For wrong answers, the theory behind the question will be readout again. If it is still wrong, the link of related information from Internet could be provided. For having repeated wrong answers, the instructor should be notified by the system. All these behaviors will be recorded including the solution provided by the instructor to overcome the failing situation. This will form the foundation of reinforcement learning (Dogan and Olmez, 2015; Kasibing and Littman, 1996) (Sutton and Barto 2016). (Szepesvari 2013) implemented via machine learning techniques (Rashid et al., 2015; Iqbal and Hoque, 2015) for both HEDS and the students.

**Exercise Module (EM)**

This EM module will be invoked or, independently start at the end of each section of the lecture. Here, questions and solutions will be delivered in the order from easy to hard or, as predicted by the software based on the experience (generated from the Machine Learning technique ran in the background) – the behavior of the students such as how fast he is answering what level of questions, correctness and how he is slowing down, etc. will be recorded. Necessary steps will be taken by the instructor to place additional information to bridge the gap if connecting steps are missing for a student to go to the next level of challenging questions. EM will also include tests and quizzes.

**Architecture of the HEIDS:**

The engine of the HEIDS will be built based on Machine learning (ML) techniques and will incorporate the following features:

1. Based on the collection of the behavioral entries and response-features such as various mouse-clicks and responses, amount of time to get to a particular level, lesson delivery pattern and timing; inter-leaved or non-interleaved delivery of the similar topics (as discussed in the Cognitive Learning section of this article), and success and failure rate per question per level etc. will be recorded and use as features in the proposed ML approach.

2. Based on the computed (using Extra-tree classifier (Geurs and Welchen, 2006)) and/or TensorFlow (Abadi et al., 2015) effective feature-sets will be determined. The feature-selection step will not only help the next steps of ML but also will help us identify the key features involved in the student’s learning.

3. Based on the (effective) feature-set, a classifier will be built which will classify student’s current performance level per lesson – we may define 10 different levels of performance score or grades, for example. An efficient classifier such as support-vector-machine (SVM) (Hsu, Chang et al. 2010) or, deep artificial-neural-net (ANN) based TensorFlow could be applied for multi-class classification to rank the performing student(s) accurately.

4. The HEIDS itself will be a reinforced learner with a goal: what information needs to provide and when, how to provide better pathways to a student to help the student become the top ranker based on game-theoretical approach (Tomin, Lygyeres, and Sany, 2000) as well as reinforcement learning based approaches. Top-ranking target can be defined by setting the goal to score ≥ 90%, for example.

**Training of HEIDS:**

To train HEIDS, it will simply need to be used by students – the more it is used, the more it will obtain the experiences and will be able to provide effective as well as needed-based-variables pathways or suggestions to the students based on their individual feature-parameter values.
Utilization of the IIEDS Tool

IIEDS can be used in both synchronous and asynchronous modes. It will be interesting to see what different experience IIEDS can get from the synchronous versus asynchronous users—which can also help justify better mode. Train IIEDS using synchronous users to generate and capture intelligent moves and then allow asynchronous user to use the mature IIEDS, for example, and this can turn into an effective learning approach.

Enhancement of the Intelligence of IIEDS

The IIEDS can be made more powerful by enhancing its intelligent and capacity to scale. Primarily, IIEDS will collect several optimal sequences of actions via reinforcement learning that helped students achieve higher score. The dataset will be invaluable in generating more creative pathways from the samples. Utilizing short schema (Hoque, Cherry et al. 2007) or, short action-steps from the collected successful action-sequences, novel and interesting pathways can be generated fast and intelligently using our effective evolutionary algorithm (Hoque and Iqbal 2015). These pathways can then be cross-validated using IIEDS again.

As the feature-space of IIEDS is expected to be very high, naturally scalability can be a concern while enhancing the intelligence of IIEDS. Fortunately, we have already developed novel approach, named FDGCA (Iqbal and Hoque 2016), to handle such scalability issues within our evolutionary approach. The idea will be transformed for this IIEDS application. Thus, this overall recurrent approach can make the IIEDS grow its intelligence effectively.

A Build and Learn Methodology

Understanding levels of affect in real time and adapting appropriately has the potential to greatly improve the efficiency of learning environments. The build and learn; evaluate and learn methodology integrates systems development with the scientific method allowing for both proof of concept to test feasibility of technology and behavior measures to measure efficacy of system on outcomes (Nunamaker, 1991). The methodology is important to this study both because we will be creating new never tried environments and because the fast pace of technology change can be taken advantage of in iterations of the test cycle.

Efficiency Outcome Measures

One measure of efficiency is course design efficiency which is the cost of course design with the value. A number of related measures can be developed as a comparison between traditional course design approaches, facility intensive online course design, and Connected Thinking Lab design approaches. The Connected Thinking Lab design approach pairs a course designer with a faculty member in the design of multimedia content, student assessment, and collaborative exercises. If done well, faculty will make better use of their time contributing as subject matter experts as course designers efficiently craft artifacts. The hope would be that time and cost saved of the faculty member is greater than that of the course designer.

Equation 1 shows the efficiency of course design using traditional methods vs Connected Think Lab methods. Equation 2 shows the cost efficiency of course design using traditional methods vs Connected Think Lab methods. This model measures the efficiency of methods in two ways. First, the study will compare design times of new methods to traditional methods. Secondly, it will compare how new methods design efficiency changes over time to capture the likely learning curve effective application of refined design processes.

Measures that can contribute to efficiency calculation include:

- Faculty design hours in a traditional course (FDH)
- Faculty design hours in Connect Thinking Lab course (FDHct)
- Course designer design hours in Connected Thinking Lab course (DDHct)
- Course (C)
- Faculty cost (FC)
- Course designer cost (DC)

On the other hand, the efficiency of the student balancing school, work, and family is important as well. A challenge with traditional teaching formats for students is the time commitment of meeting at a particular time and place for class. Students must therefore consider both cost of tuition ad time. Time can be divided into the two categories, time spent on synchronous activities and time spent on asynchronous activities. Time spent on synchronous activities can be divided into time spent on same place synchronous activities and different place synchronous activities. Synchronous same place time is often the most expensive time for students because they must forgo time at work or with family and must travel to the location. Synchronous distance classes reduce travel cost, but still have opportunity costs while asynchronous activities allow students to schedule learning activities around work and family commitments.

Student Costs:

- Tuition (T)
- Student time in asynchronous learning activities (STA)
- Student time in synchronous distant learning activities (STSD)
- Student time in synchronous face-to-face learning activities (STSF)

Where the magnitude of the costs can be ordered based on the early discussion as:

Equation 3

Relative Costs of Student Time

STA < STSD < STSF

Equation 2

Course Design Cost Efficiency

Design efficiency = \( \frac{FDH_{ct}}{FDH} + \frac{DDH_{ct}}{DC} \)

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Classroom modules then will be redesigned to either include:

- Faculty design hours in a traditional course (FDH)
- Faculty design hours in Connect Thinking Lab course (FDHct)
- Course designer design hours in Connected Thinking Lab course (DDHct)
- Course (C)
- Faculty cost (FC)
- Course designer cost (DC)

Conclusion

"New ideas about ways to facilitate learning—and about who is most capable of learning—can powerfully affect the quality of people’s lives" (NRC, 2000, p. 5). Achieving human computer symbiosis has the potential to drastically change availability and efficiency of advanced education. The machine learning approach allows for the consideration of many more variables simultaneously in both the design of learning systems and the design of research on such systems. Since human learning is influenced by a wide range of competing factors, this approach may find new intersections between factors leading to richer learning environments.

Furtheing science in human computer symbiosis will require multi-disciplinary approaches to better understand the human learning process and how artifacts such as machine learning impact the human learner. The whole system to work in concert, theories from the cognitive sciences, education, and computer sciences need to be integrated and evaluated concurrently.

References


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