Human Machine Learning Symbiosis

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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 that 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 whereby the explicit structure of the problem is not coded by the programmer, but rather is discovered by the machine by 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 individualistically to learner's unique characteristics than traditional structured learning tools. 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 new learning systems that may 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 learner's motivation to put forth effort to change to improve those states. A number of paradigms on learning research have emerged historically and have been focused through scientific methods, particularly in the last century and a half. Each new family of research was able to ask new questions and put the human learner in new light showing another characteristic of the complex way in which humans learn. What is interesting is that each new wave tended to add new knowledge by creating new methods and perspectives that added depth to our understanding of learning. However, applying multiple perspective to activities has been a challenge since so many factors need to be considered in real time. In fact, the complex decision making of the human teacher is still one of the most important learning tools. A machine learning approach is a step toward systematically considering a wide range of learning characteristics, content, and environments and to apply multiple learning theoretical perspectives.

The behaviorists helped our understanding of the effect of reward systems on behavior and on how contingencies, or partial results, could be used to develop the learner to the desired behavioral level (Skinner, 1968). Although later theorist criticized the early behaviorist work, much was still informed by the basic principles of motivation, learning, and rewards, the sophistication of these constructs has grown considerably over time. Skinner (1968) noted that although some aspects of human learning appear to have simple stimulus and response relationship that may be amendable to straight forward curriculum programming, 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 understand it before moving on; but programming is much more than this" (Chapter 4, page 3). These observations lead to the need for learning systems to address learners at multiple levels and from multiple theoretical perspectives.

Cognitive Learning

The spacing between learning activities has been shown to change the effectiveness of learning activities. For example, students "cramming" for a test may show a short term effectiveness, but the memory level may decay quickly thereafter. In general, dividing study time over multiple session increases its effectiveness (Carpenter et al., 2012). The implication for a machine learning system is that using only the learning activities and outcomes as input would 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 (Rohrer, 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 alternating learning 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 experimental design where concepts within a subject area have been interleaved. For example, Kornell and Bjork (2008) found interleaving helped students learn how to differentiate painting from artists with similar styles. Little has been done asking 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 interleaving. 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, culture, 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. The degree to which the learners affective state effect learning also 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 dishearten the learner and reduce their confidence in successfully mastering such material. On the other hand successfully completing a learning exercise can boost confidence for future activities.

During deep learning experiences, that is when learning about something novel and difficult, learners are put in a state of disequilibrium whereby what they understand does not match well with the new material being presented. The state of disequilibrium leads to the negative affective states of "confusion, frustration, boredom, curiosity, and anxiety" (p. 14) and may be a necessary part of learning (Graesser and D'Mello 2011). Positive affect is usually 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 cycles of disequilibrium and equilibrium follow together. A consequence of this interpretation of flow is that the right level of disequilibrium needs to be introduced so that the learner can have the positive experience of returning to the equilibrium state. With too difficult a task, the learner will never come back to equilibrium to reach the positive state and will become frustrated and may disengage. With too simple a task, the learner will not need to leave the equilibrium state to begin with and will have a minimal feeling of accomplishment. Making the application of gaging learning activities difficult is that the appropriate level of difficulty varies widely by the learner.

The balancing of equilibrium through learning activity and difficulty is mediated by feedback mechanism. To the extent that feedback is given, it can encourage the learner to exert more effort to complete a more difficult exercise. Feedback can also reinforce the success so that the learner experiences the expected positive affect. Some researcher such a Graesser et al. (2008) found confusion to be a similar construct to disequilibrium as a prerequisite for learning. For example, Graesser et al. (2008) found that an automated tutoring system could engender confusion in the learner when giving hints designed to make the learner think further and would reduce confusion when the tutor gave specific facts. Graesser et al. also found that positive feedback from the automated tutor when a learner grasped a concept increased the students eureka emotion. 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 breakthrough and, therefore, the study may have been more accurately measuring delight, rather than eureka. Nevertheless, strong correlation between comments from the automated tutoring system and the learners affect were measured.

Bosch and D'Mello (in press) studied an automatic tutoring system for teaching computer programming and found the affective states of confusion and frustration following learner errors and those states were lessoned when the system gave them guidance. Shute et al (2015) studied the video game Physics Playground, designed to support physics education and found frustration lead to higher performance in the game and ultimately to higher post test scores in the subject matter. DiMello et al. (2014) suggest 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 Academic Diligence Task as a measure of self-control in an academic setting. They found it "demonstrated incremental predictive validity for objectively measured GPA, standardized math and reading achievement test scores, high school graduation, and college enrollment, over and beyond demographics and intelligence" (p. 2).

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 understand the feedback 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 room activities, including attending classes, submitting required work, and participating in classroom discussions (Natriello 1984). Students who are engaged show sustained behavioral involvement in learning activities accompanied by a positive emotional tone. They select tasks which cognitively challenge them, initiate action when given the opportunity, and make concerted efforts as they participate in learning tasks (Skinner and Belmont 1993; Chapman 2003).

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 a;. 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 aforementioned, 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 are essential components to successful gamification initiatives. Further, it proposes that gamification tools can not only be affective at engaging consumers in the business environment, but such tools can also be effective at creating student engagement in the classroom. The study that follows investigates the efficacy of two instructional methods in creating student engagement, one in which gamification techniques were employed and the other in which a traditional lecture format was enlisted. The details regarding the design of the study, along with its findings, are discussed next.

Online Learning

Bowen et al. (2012) found that machine-guided instruction used in a hybrid course could be used with one hour of weekly face-to-face instruction and achieve equal learning outcomes to a traditional course employing three hours of weekly face-to-face instruction. Bowen's example shows an increase in learning efficiency within the context of students having complete certain prerequisites in a relative homogenous educational environment and still replies on the support of the human teacher, although at a reduced level. These results beg the question how can such learning opportunities become more effective and less costly.

Toward a Symbiotic Model of Human and Machine Learning

Proposed Machine Learning based Learning Tools

Our proposed Interactive and Intelligent Education Delivery System (IIEDS) is a software-tool, through which a full course can be delivered to a student in an interactive and intelligent manner.

Teachers' Perspective

A teacher or an instructor will be able to transfer his/her teaching material in IIEDS's required format. Once the input is given, then in the absence of the teacher, IIEDS will guide and engage a student learn and help solve an exercise effectively.

Modules of IIEDS

The IIEDS 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 jargon to check the related information for further details, as needed – which could be supplied beforehand or, can be supplied from Internet (links and readouts) to be explored by the interested students.

The module will record the behavior of the student, suggest further reading and information and will ask questions to raise intuition of the student. Student may skip or answer. For correct answers, student will be encouraged 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; Kaelbling and Littman, 1996) (Sutton and Barto 2016), (Szepesvari 2013) implemented via machine learning techniques (Rashid et al., 2015; Iqbal and Hoque, 2015) for both IIEDS and the students.

Exercise Module (EM)

This EM module will be invoked or, independently started 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 recoded. Necessary steps will to 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 IIEDS: The engine of the IIEDS will be built based on Machine Learning (ML) techniques and will incorporate the following features:

- 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: interleaved or non-interleaved delivery of the similar topics (as discussed in the Cognitive Learning section of this article), and success and failure rate per questions per level etc. will be recorded and use as features in the proposed ML approach.
- Based on the computed (using Extra-Tree classifier (Geurts and Wehenkel, 2006) and/or TensonFlow (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.
- 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 TensonFlow could be applied for multi-class classification to rank the performing students appropriately.
- The IIEDS 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-theoretic approach (Tomlin, Lygeros, and Sastry, 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 IIEDS

To train IIEDS, 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 need-based-variable 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.

Expectation from IIEDS

IIEDS is a learner, and being a learner IIEDS will capture effective and intelligent moves by the users – thus, IIEDS will be an excellent tool to store the collective efforts which can keep growing richer by the usage – and in return, IIEDS can deliver most suitable pathways for a student based on the student's need determined by the performance and feature-parameter values. Eventually, IIEDS can be regarded as a personal teacher, standing by the student to provide encouragement as well as assistance as needed.

Enhancement of the Intelligence of IIEDS

The IIEDS can be made more powerful by enhancing its intelligent and capacity to scale. Primarily, IIDES 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, Chetty 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 hGRGA (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 effectiveness 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, faculty 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 time 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 of application of refined design processes.

Measures that can contribute to efficiency calculation include:

- Faculty design hours in a traditional course (FDH_{tc})
- Faculty design hours in Connect Thinking Lab course (FDHctl)
- Course designer design hours in Connected Thinking Lab course (DDHctl)
- Course (C)
- Faculty cost (FC)
- Course designer cost (DC)

Equation 1
Course Design Time Efficiency

$$Design\ efficency = \frac{FDH_{tc}}{C}\ vs\ \frac{FDH_{ctl} + DDH_{ctl}}{C}$$

Equation 2
Course Design Cost Efficiency

$$Design\ efficency = \frac{FC \times FDH_{tc}}{C}\ vs\ \frac{FC \times FDH_{ctl} + DC \times DDH_{ctl}}{C}$$

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 base on the early discussion as:

Classroom modules then will be redesigned to either in-

Equation 3
Relative Costs of Student Time

$$STA < STSD < STSF$$

crease the efficiency of a student time or shift the activity to a lower cost time period.

Other efficiency measures in the assessment include course delivery time efficiency, course delivery cost efficiency, which can be measured from both the university and student perspective, as well as design and delivery efficiency normalized on a per student basis.

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 the 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 interactions between factors leading to richer learning environments.

Furthering 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. For the whole system to work in concert, theories from the cognitive sciences, education, and computer sciences need to be integrated and evaluated concurrently.

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