Human Machine Learning Symbiosis

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Abstract

Human Machine Learning Symbiosis is a cooperative system where both the human leaner 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 learners learning state both in terms of knowledge and motivation. This paper describes the benefits of such a system and a proposed design that integrates making learning and learning gamification.

Human Machine Learning Symbiosis

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 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 of 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 who have mastered certain level and present remedial material to learns 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 design can be applied to many learners, they can be used a lower cost per learner that the human teacher alone. However, the coarse grained adaptability may make learning less efficient to the individual learns when compared to direct teacher interaction. Further, such systems are usually weak at motivating the student.

Machine learning is 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 spend 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 economic more and more favor letting the computer solve the problem.

Embedding machine learning in online learning modules has the potential for modules to adapt to greater degrees and more individualistically to learners unique characteristics than tradition structured learning tools. Further, their lower cost can increase the availability of such techniques to a wider audience. The popularity and addictiveness of video game suggests potential for the gamification of online learning as a source of leaner motivation.

Developing a learning machine that is symbiotic with the human leaner 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.

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 equally 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 who can such learning opportunities become more effective and less costly.

Gamification of Learning

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.

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).

Thus, the purpose of this research is to examine how applying gamification techniques and customer engagement principles in the classroom facilitate student engagement and learning. A study is conducted which investigates how using game-like features in the class room enhances student engagement similar to how such techniques engage the customer in an industry context. First, a conceptualization of customer engagement, along with its applicability to gamification is discussed. Next, a study which involved using gamification techniques in the classroom setting is presented. Finally, the findings from the study, along with implications for promoting student learning and engagement in the classroom are discussed.

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.

Toward a Symbiotic Model of Human and Machine Learning

A Build and Learn Methodology

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.

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 students learn and help solve exercise effectively.

Modules of IIEDS: The IIEDS will have two (02) modules:

(a) Lecture Delivery Module (LDM) and

(b) Exercise Module (EM).

<u>LDM</u>: 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, 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) implemented via machine learning techniques (Rashid et al., 2015; Iqbal and Hoque, 2015) for both IIEDS and the students.

<u>EM</u>: This (Exercise 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 instruction to place additional information to bridge the gap if connecting steps are missing for a students to go to the next level of challenging questions. EM will also include test and quiz.

- **<u>Architecture of IIEDS</u>**: The engine of the IIEDS will be built based on Machine Learning (ML) techniques.
    - 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, and success and failure rate per questions per level etc. will be utilized in ML.
    - 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 grades of performances, for example. An efficient classifier such as support-vector-machine (SVM) 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 tools**: 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 tools 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.

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 has 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 measure 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 (FDH_{ctl})
- Course designer design hours in Connected Thinking Lab course (DDH_{ctl})
- Course (C)
- Faculty cost (FC)
- Course designer cost (DC)

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

Equation 1: Course Design Time Efficiency

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

Equation 2: Course Design Cost Efficiency

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 the 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:

$$STA < STSD < STSF$$

Equation 3: Relative Costs of Student Time

Classroom modules then will be redesigned to either increase to 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.

Furthering science in human computer symbiosis will require multi-disciplinary approaches in 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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