Enhancing the Intelligence of the Adaptive Learning Software through an AI assisted Data Analytics on Students Learning Attributes with Unequal Weight

Yanzhen Qu
School of Computer Science
Colorado Technical University
Colorado Springs, CO, USA
yqu@coloradotech.edu

Olanrewaju Ogunkunle
Oyster Learning Network, Inc
2600 South Shore Blvd #300
League City, TX 77573. USA
lanre@pleysmart.org

***Abstract*— Along with the growing popularity of the adaptive learning platform software in STEM education programs, further enhancing the ability of the adaptive learning platform to support learning effectiveness has become a priority. A common goal of all the adaptive learning platform software is to identify gaps in a student's knowledge, and provide relevant learning materials based on the result of the assessment of the student's exiting knowledge towards to the targeted subject, to increase the learning effectiveness. However, the student's existing knowledge is only one learning attribute, and it cannot reflect all the aspects that have an impact to the student's learning effectiveness. A natural solution to overcome this weakness is to make the adaptive learning decision making algorithm capable to process the dataset of multiple learning attributes of the student efficiently. This paper presents a machine learning algorithm to efficiently process the dataset of a student's multiple learning attributes. The main enabling foundation for this new algorithm is a data structure called "student learning attributes index" which represents every learning attribute as a tuple of three elements: the "learning-attribute-ID", the "weight" of the learning attribute among all the learning attributes, and the "efficiency" of the contribution to the student's learning effectiveness made by the learning attribute. This study has applied unequal weight to each of the learning attributes, more accurately reflecting that different learning attributes will have different impacts on a student's learning effectiveness. This new algorithm enables various learning support applications to become more practical and accurate in supporting student learning.**

Keywords*— STEM education program, machine learning, knowledge discovery, intelligent tutoring system Adaptive Learning, learning effectiveness, learning attributes

I. INTRODUCTION

Over the last ten years, supported by many adaptive learning platform software, the adaptive learning as a pedagogy which is more suited online education is getting popular in the higher education especially in the online STEM degree programs [1]. The most attractive feature of the adaptive learning model and associated platform software is to have the ability to make the pre-defined learning materials to be customized based on the result of a pre-assessment to the learners existing knowledge on a targeted learning subject [2]. For example, let's assume that a student is scheduled to take a course named "Advanced Computer Algorithms" through an Online Learning Environment (OLE) based on an adaptive learning platform software. Before displaying any learning material to the student, the software performs a "determine knowledge" assessment of the student in which the student is presented with a set of questions which are selected from the questions associated with various lessons of the course. If the student answers questions correctly, then the lessons related to those questions are removed from the learning materials originally scheduled for the student since they have demonstrated the fluency and accuracy on the subjects of those lessons through answering the questions related to those lessons correctly. This type of knowledge assessment approach used by the adaptive learning platform software can be called the single learning attribute based adaptive learning method as it makes the adaptive learning decision purely based on one learning attribute: the learner's prior knowledge or experience with the targeted learning subject.

However, a person's learning ability and learning effectiveness are a combination of many aspects of the person. For example, a person may be a visual learner who learns a new subject easier by watching videos. However if the adaptive learning software does not include this learning attribute into the assessment formula used to determine a person's existing knowledge and competence, it will never be able to customize the learning materials for this student with many videos. As another example, consider two students enrolled in the same class. One student prefers participating in a topical discussion as preparation before working on an assignment, while the other student prefers to prepare for the assignment by watching video tutorials they found on the web. That is learning is often a coordinated behavior, and most learners need some stimulates from a learning environment which consists of some other people, such as instructor and classmates. Unfortunately, these learning styles and learning enabling conditions are currently not addressed by existing adaptive learning software. Let's assume that if we use an adaptive learning software used as the tool to build up an e-tutor for this class, and it knows these learning attributes of these two students, and it will offer a set of people's contact information to the first student, and provide a set of web links of relevant tutorials to the second student, that would be much effective helps to these two students.

All the examples above have shown how customized learning delivery of adaptive learning software can be improved by incorporating multiple learning attributes into its decision-making algorithm. However, as adding more learning attributes added to the algorithm will make the algorithm more complicated and subsequently more difficult to integrate into software implementations, it is desirable to design an approach that provides a reasonable balance between delivering a more precise adaptive learning decision for individual students while avoiding overcomplicated algorithms. This is the main purpose of this paper.

II. RELATED WORK

The three areas are closely related to our research project which are adaptive learning, education data mining, and e-tutoring system.

A. Adaptive Learning

Although the adaptive learning model and its associated software platform have only just become popular within the recent decade, the early history of the adaptive learning can actually be traced back to the 1970's [3]. Many attractive features of adaptive learning software are enabled through applying basic artificial intelligence technologies such as auto-grading, continuous assessment, and customized learning materials, etc., and have made this classic learning method a popular online education platform [4][5].

Among several dozen adaptive learning platforms, Realizeit [6] is an adaptive learning platform capable of incorporating multiple learning resources such as video, audio, testing, objective test questions, exercises, and case studies into the curriculum. It incorporates probabilistic reasoning using Bayesian estimation procedures within an instructor-created learning network [7]. Cerego is another adaptive learning platform based on principles of neuroscience and cognitive science [8]. It has instructional design support with Open Educational Resources (OER), real-time media, standards-aligned content, lesson plans, and learner-generated materials. Preliminary results from a study conducted at Excelsior College in 2014 indicated that using Cerego can help students increase grades when studying math and biology online [8]. Smart Sparrow, now owned by Pearson, is an adaptive learning platform with an impressive intelligent tutoring system famous on its ability to provide students personalized feedback [9][10].

In contrast to all current adaptive learning platforms which use only the single learning attribute as the base to offer students the learning advices, our new algorithm based on multiple learning attributes is a direct enrichment to the ability of adaptive learning platform.

B. Education Data Mining

Education Data Mining (EDM) as a technical tool to facilitate the process of extracting meaningful information from the captured data about the learning activities of learners in educational settings [11]. It utilizes techniques of data mining, machine learning, and statistics to extract information via processing and analysing varous types of raw data coming from educational environments like universities, colleges, and tutorial systems [11] [12]. The ultimate goal of EDM is be able to extract enough information from various raw data related to a student's learning process to predict student learning behavior, analyze the result of the provided educational support, discover improvements made by a new teaching model over existing models, and measure the advancement of scientific knowledge among the students [13].

The scope, format, and resources of education data are very broad and includes not only student demographic data or captured data reflecting navigation behavior within a learning environment, but also data on students' learning activities such as quizzes, interactive class exercises, and activities as well as the data from multi-student collaboration and text chat forums [14][15]. The most important data resources for an EDM are the learning management system (LMS) logs, database queries, and analytics reports [16]. There are five methods commonly utilized by EDM: prediction, clustering, relationship mining, discovery models, and distillation of data used in human judgment. Among these, prediction, clustering, and relationship mining are standard in traditional data mining while EDM utilizes discovery models and distillation of data for human judgment more often[17].

Lacking a practical way to measure students' learning effectiveness has always been a weakness of the existing EDM systems. Our work will enable EDM systems to build a practical learning effectiveness metrices so that it can enter a new application area: assessing students' learning effectiveness.

C. E-Tutoring System

The E-Tutoring System is also called the Intelligent Tutoring System (ITS). The initial concept and pilot system was proposed in late of 1980's and was used as a critical component of an adaptive learning platform which can monitor and interpret students' activities, explain students' needs and preferences based on activities, and make changes to the learning process [9][18]. An ITS is a good fit for delivering customized instruction due to its ability to measure and diagnose knowledge, use the information to determine variances in actual and anticipated level of knowledge, and provide learning tasks that fit appropriately to the observed difference[18]. Customized instruction to individual students is a critical advantage of ITS, but research results pointed to the fact that using computers to enhance learning has fallen short of the initial expectations due to the limitation of the artificial intelligence technology used by ITS [19].

As early as 1999, Nancy Dewald conducted an analysis of online tutorials for library instruction practices and found library instruction on the Web can supplement and complement classroom instruction by expanding the librarian's teaching options and by expanding the student's options of time and place for instruction [20]. More recently, Priscila Valdiviezo-Díaz, et al. implemented business intelligence strategies in the online tutoring process [21]. Ada Kim and Andrew Ko analyzed 30 online coding tutorials and indicated the needs for educational games and interactive tutorials [22]. Mastaneh Davis, et al. developed an online intelligent tutorial system for Mathematics students to provide meaningful and informative feedback while they used online resources [23].

As our work is directly improve the effectiveness of the learning advice offered to students, if the ITS systems use our new approach, the capability of ITS systems will be further improved, so is the usage of ITS systems.

III. PROBLEM STATEMENT, HYPOTHESIS STATEMENT, AND RESEARCH QUESTION

A. Problem Statement

Currently, the adaptive learning platform software lacks the ability to accurately customize learning materials based on a comprehensive understanding about the learning style and background of the student because it does not have a machine learning algorithm to efficiently process the dataset of students' multiple learning attributes.

B. Hypothesis Statement

If a machine learning algorithm can efficiently process the dataset of students' multiple learning attributes, then the learning platform's recommendation of customized learning materials can be more accurately matched with students' learning style and background to make learning more effective.

C. Research Question

What type of data structure lends itself well for representing multiple learning attributes and how can it be leveraged by a machine learning algorithm that is not only efficient enough to process the dataset of students' multiple learning attributes but simple enough to easily serve as a base for or integrate into an existing adaptive learning platform?

IV. METHODOLOGY

A. A Simple Data Structure for Capturing Multiple Learning Attributes

Generally speaking, the solution space encapsulates all the possible combinations of all learning attributes' possible data values on the surface will be a very difficult task due to the complexity. Therefore, the key to developing a simple and efficient machine learning algorithm for processing the dataset of multiple learning attributes is to find a simple but meaningful data structure to capture the nature of multiple learning attributes. Based on such consideration, a very simple data structure has been proposed to capture multiple learning attributes consistently.

This data structure is called "the Learning Attributes Indexing Vector", and it is a list of tuples as shown below:

{ learning-attribute-ID, Index = weight **x** efficiency} (1)

where the "learning-attribute-ID" represents a specific given learning attribute; the "weight" is a number between 0 and 1, represents the importance level of the given learning attribute among all the learning attributes, and for all learning attributes, and the Summation of the weights of all learning attributes will always be 1; and the" efficiency" is a number of percentage, represents how much contribution to the student's learning effectiveness made by the given learning attribute; the notation "x" represents the "multiplication sign".

To demonstrated the suitability of the proposed data structure, in this study, for each student, we have chosen three learning attributes to consider: the prior knowledge (PK), the self-efficacy perception (SEP) and the peer-collaboration (PC). Among these three learning attributes, the most important also most well-known attribute is the PK of the student, which is also the only learning attribute used by almost all existing adaptive learning platform software to make adaptive learning decision so far. The SEP represents student's ability on both self-motivation and self-initiative towards learning, while the PC represents student's ability of social engagement with other people and collaboration in a team setting. For example, if a student's SEP score is higher, that implies that student is highly self-motivated and very capable in conducting self-studies on the given learning material. If a student's PC score is higher, that implies that student is doing well in a group learning environment. TABLE I has summarized both definitions of three learning attributes, and the possible educational data sources from which the students' three learning attributes can be derived

TABLE I. LEARNING ATTRIBUTES' DEFINITION & DATA SOURCE

Attribute Definition	**Data Can Be Derived From**
PK: Prior Knowledge. Represents knowledge accumulated on a subject.	Prior learning and working experience: courses have already taken, trainings and conferences have attended, books have been read, projects have participated/completed, and jobs have been doing, etc.
SEP: Self-efficacy perception. Represents ability of self-motivating and self-studies.	Existing assessments: academic honors, course grade, exam score, class rank, competition result, peer comments, and performance review, etc.
PC: Peer-collaboration. Represents ability of social engagement and team working.	Class discussion participation rate, brainstorm behavior, feedbacks to others' works, student club participation, student club leadership, and community service participation, etc.

Some research work have found that PK, SEP and PC have some correlations [24][25][26]. In this study, for the simplicity, we have omitted such correlations among PK, SEP and PC. Under such assumption, we can define some mapping functions for each type of learning attribute such that each individual source data will contribute to weight and efficiency factor, so that having the impact to the final value of the index. That is we have

$$I\_pk = e\{\text{weight (source data), efficiency(source data)}\} \quad (2)$$
$$I\_sep = f\{\text{weight (source data), efficiency(source data)}\} \quad (3)$$
$$I\_pc = g\{\text{weight (source data), efficiency(source data)}\} \quad (4)$$

where *I_pk, I_sep,* and *I_pc* are the indices of PK, SEP and PC; *e,f* and *g* are the mapping functions which translate each type of activities data into the index value of the corresponding learning attribute.

Both SEP and PC are two new learning attributes not only reflect the student's personal behavioral habit which may have some impact to student's learning effectiveness, but also represent two new dimensions that the adaptive learning platform software need to consider when make an adaptive learning decision for a student. Because these three learning attributes do not have an equal impact to student's learning effectiveness, we will use assign each of them two parameters: a weight and an efficiency factor of the learning attribute. Each student's learning attribute has an associated "index" which is calculated by multiplying the weight of the learning attribute with the efficiency factor of the learning attribute. The weight represents the individual student's learning attribute ability while efficiency factor is a percentage number used to measure the contribution of the weighted learning attribute to the learning effectiveness of a student. TABLE II below has shown a set of examples of the four students' three learning attributes' weight and efficiency factors.

TABLE II. STUDENTS' THREE LEARNING ATTRIBUTES' EXAMPLES

Student	S1	S2	S3
PK: Weight x Efficiency	0.8x0.9	0.1x0.5	0.1x0.3
SEP: Weight x Efficiency	0.1x0.5	0.8x0.9	0.1x0.5
PC: Weight x Efficiency	0.1x0.3	0.1x0.3	0.8x0.9

From TABLE II we can see that, the summation of the weight indexes of three learning attributes of each student is equal to 1. For example, for Student S1, the Sum (weights of three learning attributes) = 0.8+0.1 +0.1 = 1. The efficiency factor represents what percentage of the weight of a leaning attribute will contribute to student's learning effectiveness. For Student S1, 90% of PE's weight has contributed to the S1's learning effectiveness, 50% of SEP's weight has contributed to S1's learning effectiveness, and 30% of PC's weight has contributed to the S1's learning effectiveness.

The data values of three learning attributes of three students shown in TABLE II represent three typical situations. For student S1, the learning effectiveness is mainly driven by the PK. For student S2, the learning effectiveness is mainly driven by SEP. And the student S3, the learning effectiveness is mainly driven from PC. Therefore the learning advice offered to S1 will be most likely based on the assessment of PK, and will be learning content related. The learning advice offered to S2 will be most likely be a few tutorials or videos or audios files about the subject for S2 to conduct some self-studies on the subject. The learning advice to S3 can be very different from those provided to S1 and S2: a few people's communication information so that S3 can contact those people to conduct some discussions.

B. Develop a Simple but Efficient Machine Learing Algorithm

In order to develop a simple but efficient machine learning algorithm, the three indices of three learning attributes can be considered as the coordinate of an individual point P in the three dimensional space of the entire learning effectiveness. Students who have similar indices of their three learning attributes are close to each other in the space of the learning effectiveness; meaning, they are in the same "cluster". For example, the TABLE III has shown that the four students have very similar indices data values for their weights and efficiency factors. For those students, we consider them to be in the same "cluster". Therefore, the entire learning effectiveness space can be split into a set of clusters, and each cluster has one center.

TABLE III. STUDENTS' THREE LEARNING ATTRIBUTES' EXAMPLES

Student	S1	S2	S3	S4
PK: Weight x Efficiency	0.8x0.9	0.85x0.9	0.86x0.9	0.82x0.9
SEP: Weight x Efficiency	0.1x0.5	0.1x0.5	0.1x0.5	0.1x0.5
PC: Weight x Efficiency	0.1x0.3	0.05x0.3	0.04x0.3	0.08x0.3

To construct the clusters, the algorithm used is similar to the one described in [27], which is an improved classic Lloyd's algorithm [28], the most famous K-Means Clustering algorithm with many variances for performance improvement [29][30][31][32]. Then, each of the "the center of clusters" can be associated with a decision of learning advice offered to the students whose points fall within the cluster. In this way, a cost effective way to implement an adaptive learning decision making algorithm based on three learning attributes can be materialized. TABLE IV has shown some of clusters examples used in our experiments

TABLE IV. DATASET AND PREDICTION RATE EXPERIMENT

Experiment 1:	(Cluster11, 0.8227), (Cluster21, 0.7783), (Cluster31, 0.7313), (Cluster41, 0.6755), (Cluster51, 0.633)
Experiment 2:	(Cluster21, 0.7383), (Cluster22, 0.70395), (Cluster23, 0.66655), (Cluster24, 0.6206), (Cluster25, 0.5881)
Experiment 3:	(Cluster31, 0.6539), (Cluster32, 0.6296), (Cluster33, 0.6018, (Cluster34, 0.5657), (Cluster35, 0.5432)
Experiment 4:	(Cluster41, 0.5695), (Cluster42, 0.55525), (Cluster43, 0.53705, (Cluster44, 0.5108), (Cluster45, 0.4983)
Experiment 5:	(Cluster51, 0.4851, (Cluster52, 0.4809), (Cluster53, 0.4723, (Cluster54, 0.4559, (Cluster55, 0.4539)

In real-world applications, along with the increasing number of students in each cluster, the center of each cluster may be shifting from its original coordinate. However, a simple variation of K-Means Clustering algorithm, named the Mean Shift Clustering algorithm, can be applied to address this issue and be used as the final base for our new three learning attributes based adaptive learning decision making algorithm [33][34].

The details of the design and testing of the Mean Shift Clustering algorithm used in this application has been presented in [34]. This algorithm has a runtime complexity of $O(n(\log m + \log p))$, where n is the total number of data points, m is the total number of the clusters, p is the maximum number of data points in a cluster, and one binary tree is used as the data structure to hold all the centers of m clusters, and for each cluster, a binary tree is used to hold all the data points in that cluster. This algorithm is very efficient for large datasets [35].

V. Application Examples

In this section we will discuss how this new algorithm, in addition to enhance the adaptive learning platform software, can be utilized by some other software relevant to education also.

The first application is the Knowledge Discovery from Database (KDD) which provides a mechanism that accurately identifies students learning gap using weighted learning attributes [36]. The main objective of KDD is to extract high-level knowledge from low-level data in a massive data sets context with a focus on the overall knowledge discovery process that includes scaling of algorithms to massive data sets while retaining the ability for efficient result interpretation and visualization. Most educational software solutions rely on generalized scripts with broad categorization of student learning ability. Some previous research works have demonstrated how data analytics can be leveraged to improve selection of educational resources based on student learning attributes. The limitation of our approach was the fundamental assumption of given equal weight to the attributes to determine the result [37]. Whereas, in the real-world, students learn differently and even though there might be a weakness in one attribute and strength in another, these attributes can vary widely. Applying unequal weight to different learning attributes will more accurately reflect the reality. One benefit in building a KDD system that is that it is capable of being reused by different system. A third-party software system may plug in to the KDD system and use it to adapt learning for students appropriately. Also, educators can use the KDD system to make informed education decisions that affect student classification and grouping and in selecting resources for students that best address the needs of the students.

The second application is the Intelligent Tutoring System (ITS). This application can be either used in almost any type of learning platform software or used as an independent student service software for any level of education. Incorporating a machine learning algorithm based on multiple learning attributes will certainly enrich the ability of the ITS to offer the students more personalized recommendations. For example, for a student whose SEP weight and efficiency factor are relatively high, the ITS can provide some web content rich with tutorials and short videos matched student's learning style. For a student whose PC weight and efficiency factor are relatively high, the ITS should offer the students the names and contact information of a few people who can share good conversation with the student on the subjects with which the student might be having some difficulties. In summary, the more learning attributes examined by the algorithm used by the ITS will result in a more accurate recommendation offered by the ITS to the students.

VI. Conclusion

In this study, a design and implementation of a simple but efficient machine learning algorithm has been presented. This new algorithm allows the adaptive learning platform software to make the adaptive learning decision for a student's learning needs based on three learning attributes. The potential applications of this new algorithm in KDD and ITS have also been discussed. That is this new algorithm can be used in many advanced learning platforms as the core of a critical system component to collect and process students learning behavior reflected by students' learning attributes. It can also be used to translate the results of such data processing into a meaningful service back to students. This is the main contribution of this research.

Restricted by the time and space, this paper does not provide any detail on how to map various real-world students' educational data and the results of the analytics of the related educational data to the corresponding learning attributes of the students. This type of work will be reported in another research paper of ours. Several possible future works include integrating this algorithm with a real-world KDD or ITS software, validating the learning material and tutoring recommendations presented according to this new algorithm with various groups of students and faculty, and integrating the student service component based on this new algorithm with a natural language processing component so that more advanced student service can be implemented.

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