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Smart Education with artificial intelligence based determination of learning styles

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Abstract

The need of the hour in present day education environment is adaptivity. Adaptive educational systems aim to customize content and learning paths of students. These aid’s in the minimizing disorientation and cognitive overload problems; thus maximizing learning efficiency. Present learning systems are lacking adaptivity; as they offer same resources for all users irrespective of their individual needs and preferences. Students learn according to their learning styles and determining these is a crucial step in making eLearning or traditional education adaptive. To determine learning styles, learning models have been suggested in literature, but there is no readily available software tool that provides the flexibility to select and implement the most suitable learning model. To fulfil this dire need, a framework of a tool is proposed here, which takes into consideration multiple learning models and artificial intelligence techniques for determining students’ learning styles. The tool would provide the facility to compare learning models, to determine the most suitable one for a particular environment. It is suggested that this tool be deployed in a cloud environment to provide a scalable solution that offers easy and rapid determination of learning styles.

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Keywords: Smart education; Artificial intelligence; Learning styles; Felder & Silverman; Kolb; Adaptive learning, Decision trees, Perceptrons

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1. Introduction

Students learn in different ways. Some prefer facts, data and experiments whereas others prefer principles and theories. Some prefer reading written material whereas others prefer problem solving. Learning management systems so far have been developed with the philosophy of "one-size fits all" [15], as a result of which students tend to get disoriented and the information overload results in reduced efficiency. Each student has his or her own learning style. Determining a student’s learning style is a crucial step in making e-learning or traditional education adaptive to students’ needs. There are multiple learning style models described in literature [4,5,6,9]. Some of the prominent learning models are Felder & Silverman’s [4], Kolb’s [9], VARK [5] and Honey & Mumford [6] model. These theories propose that all people can be classified according to their 'style' of learning, and provide differing views on how the styles should be defined and categorized. These have been elaborated in Section 3 of this paper. There are also numerous techniques described in literature that map a student’s behavioral attributes to a particular learning style [3]. Artificial Intelligence (AI) approaches are regarded as valuable tools, as they have the ability to develop and replicate the decision-making process adopted by people. There are various AI techniques that have been used in adaptive educational systems. These include, but are not limited to, Fuzzy Logic, Decision Trees, Neural Networks, Bayesian Networks, Genetic Algorithms and Hidden Markov Models [3]. But there is no standard approach created so far, to find out which is the most suitable learning theory and the most suitable artificial intelligence method to apply for a particular learning environment. Nor is there any software tool developed that facilitates determining the learning style from data of students’ learning behavior. What is required is a tool that is easily configurable, easily accessible and can be used in different learning environments, either traditional or e-learning. Here, an artificial intelligence based system is developed that takes into consideration multiple learning style models and multiple artificial intelligence techniques for determining students’ learning styles. This system can be deployed both in e-learning and traditional educational environments to impart adaptive education.

2. Related work

Various AI methods that have been used earlier for providing adaption in learning are briefly reviewed here. Fuzzy logic is an extension for the traditional set theories statements can be partial truths, lying in between absolute truth and absolute falsity. A multi-agent based student profiling system based on fuzzy logic has been given by [17]. By applying fuzzy logic, the content model, the student model, and the learning plan have been defined formally. Neural networks comprise a large number of interconnected neurons which work together to process information, similar to a biological neural network. These can be used to classify students. Previous studies have shown the application of artificial neural networks in determining learning styles [1,11,14,16,18]. A decision tree is a tree in which each branch node represents a choice between a number of alternatives, and each leaf node represents a decision. In [10], decision trees have been used to provide personalized learning paths. A Bayesian network is a directed acyclic graph in which nodes represent concepts and edges indicate cause-effect dependencies between concepts. In [13], the authors show the use of Bayesian Networks in the modeling of global personalized learning process. In Hidden Markov Model, a set of discrete states are described with the probability matrix being the determining factor of the transition between the states. Hidden Markov Models have been used in [8] to predict student behavior and determine similarity between previous students and the current student. Genetic algorithms use Darwin’s concept of evolution, natural selection and survival of the fittest as their foundation. These have been employed by [7] to construct an optimal learning path for each learner.

3. Existing Learning Theory Models

3.1 Felder & Silverman learning theory model

In the Felder and Silverman learning style model [4] there are four dimensions, each having two learning styles.
There is a total of eight learning styles that can generate sixteen combinations. These four dimensions are active/reflective, sensing/intuitive, visual/verbal and sequential/global. Active learners learn best by working actively, by applying the material, and by trying things out. In contrast, reflective learners prefer to think about and reflect on the learning content. Learners with a sensing learning style use their sensory experiences to learn facts and concrete learning material. In contrast, intuitive learners prefer to learn abstract material, such as theories and their underlying meanings, with general principles. Visual learners remember best what they have seen e.g. pictures, diagrams and flow-charts, whereas verbal learners learn from textual representations, which may be written or spoken. Sequential learners learn in small incremental steps and therefore have a sequential learning progress. In contrast, global learners use a global and a holistic thought process and learn by understanding the larger picture first.

3.2 Kolb’s learning theory model

Kolb’s learning theory [9] has four distinct learning styles, which are based on a four-stage learning cycle. The four-stage learning cycle has: Concrete Experience - (CE), Reflective Observation - (RO), Abstract Conceptualization - (AC) and Active Experimentation - (AE). Each of the four learning styles is a combination of two cycle states. Diverging (CE/RO) learners prefer to watch rather than do, thus tending to gather information and use their imagination to solve problems. Assimilating (RO/AC) learners prefer concise, logical approach. Ideas and concepts are more important than people for them. Converging (AC/AE) learners solve problems and use their learning to find solutions to practical problems. They prefer technical tasks, and are less concerned with people oriented activities. Accommodating (AE/CE) learners are hands-on with tasks, and rely on their intuition rather than logic. They tend to use other’s analysis. They prefer a practical and experience oriented approach in learning.

3.3 Honey and Mumford learning theory model

Honey and Mumford learning styles were developed by Peter Honey and Alan Mumford [6]. Their work is inspired from Kolb’s learning model. The four learning styles are activists, theorists, pragmatists and reflectors. Activists are individuals who learn by doing. The learning activities can be brainstorming, problem solving, group discussion, puzzles, competitions or role-play. Theorists learners require models, ideas and theories to participate in the learning process. Their learning activities include models, statistics, stories and they apply concepts theoretically. Pragmatists have the ability to put their learning into practice in reality. They learn better by applying learning in case studies, in problem solving and in discussions. Reflectors learn by watching, thinking and reflecting on what happened. They like self-analysis and personality questionnaires, observation of activities, feedback from others and interviews.

3.4 VARK learning theory model

VARK stands for Visual, Aural, Read/write, and Kinesthetic styles that are used for learning information. This model was suggested by Fleming and Mills and is based on experiences of students and teachers [5]. Visual learning style includes maps, diagrams, charts, graphs, flow charts and symbols that people use to represent information as a replacement of words. Aural learning style describes a preference for information, which is heard or spoken. Learners who have this learning style learn best from lectures, group discussion, radio, phones, speaking, web-chat and talking about concepts. Those having Read/Write learning style prefer information displayed as words. It emphasizes text-based input and output, reading and writing manuals, reports, essays and assignments. Kinesthetic learning style refers to perceptual preference for experience and practice, which may be simulated or real. It includes demonstrations, simulations, videos, movies and case studies.

4. Comparative Analysis of Models

Comparative analysis of models is done by implementing those models using artificial intelligence techniques. These models have been implemented in Java 1.8 using NetBeans IDE 8.2 on a Windows 7 64-bit machine. Swing
There is a total of eight learning styles that can generate sixteen combinations. These four dimensions are underlying meanings, with general principles. Visual learners remember best what they have seen e.g. pictures, concrete learning material. In contrast, intuitive learners prefer to learn abstract material, such as theories and their actively, by applying the material, and by trying things out. In contrast, reflective learners prefer to think about and active/reflective, sensing/intuitive, visual/verbal and sequential/global. Active learners learn best by working two cycle states. Diverging (CE/RO) learners prefer to watch rather than do, thus tending to gather information and Conceptualization - (AC) and Active Experimentation - (AE). Each of the four learning styles is a combination of four-stage learning cycle has: Concrete Experience - (CE), Reflective Observation - (RO), Abstract

3.2

3.3

3.4

UI components have been used to design the GUI (graphical user interface). A software system for artificial intelligence based adaptive learning has been developed here. Two learning models, Felder & Silverman [4] and Kolb [9] have been simulated using the developed software, using two Artificial Intelligence techniques: Multilayer Perceptron and Decision Trees.

The software system has menu systems for configuring student attributes that are to be considered for determining learning styles. The screenshots for student attributes master for Felder & Silverman and Kolb models are shown in Fig 1 and Fig 2 respectively. These screens show the attribute master, a superset of possible attributes that have been presently built into the system. Either all or a subset of these may be selected for a particular simulation run, depending on the attributes available in a particular learning environment. A typical execution is depicted in Fig 3, showing the generation of model structure and its performance.

Analysis of model structures after carrying out training with sample data has been shown in Table 1. The first column specifies the number of student attributes that were selected for model generation, here six for Felder & Silverman and eight for Kolb’s model.

Student attributes for Felder & Silverman that have been selected for this particular simulation run are:
- Forum visits count (low/high): Number of visits to online forums is low or high
- Content visits count (low/high): Number of visits to online content is low or high
- SAT Factual visits count (low/high): Number of visits to factual type of questions in scholastic aptitude tests is low or high
- SAT Abstract visits count (low/high): Number of visits to abstract type of questions in scholastic aptitude tests is low or high.
- Course figures visits count (low/high): Number of visits to figures within online content is low or high;
- Course text visits count (low/high): Number of visits to text within online content is low or high.

![Attribute master for Kolb's model](image)

Fig. 2: Attribute master for Kolb’s model (all attributes are selected)

The student attributes used for the Kolb’s simulation are:

- Performance in brainstorming sessions (low/high);
- Prefer working in groups (low/high);
- Focus on ideas as compared to people (low/high);
- Attraction to logical theories as compared to practical approaches (low/high);
- Attraction to technical tasks rather than social issues (low/high);
- Finding practical uses for ideas and theories (low/high);
- Hands on approach, sets targets, active field work (low/high);
- Rely on intuition or others analysis rather than logic or own analysis (low/high).

The tool can also be used to specify the number of learning styles, into which the classification is to be carried out. It is six for Felder & Silverman model and all four for Kolb’s model. For Felder & Silverman model, students’ classification is to be carried out into active/reflective, sensing/intuitive or visual/verbal categories. For Kolb’s model, students’ classification is to be carried out into diverging, assimilating, converging and accommodating.

<table>
<thead>
<tr>
<th>Model / AI Method</th>
<th>Number of student attributes</th>
<th>Number of learning styles (classification classes)</th>
<th>Size of student sample data</th>
<th>Number of nodes in model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Felder Silverman/Multilayer Perceptron</td>
<td>6</td>
<td>6</td>
<td>22</td>
<td>12</td>
</tr>
<tr>
<td>Felder Silverman/Decision Tree</td>
<td>6</td>
<td>6</td>
<td>22</td>
<td>11</td>
</tr>
<tr>
<td>Kolb/Multilayer Perceptron</td>
<td>8</td>
<td>4</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Kolb/Decision Tree</td>
<td>8</td>
<td>4</td>
<td>12</td>
<td>7</td>
</tr>
</tbody>
</table>
categories. This is depicted in the second column in Table 1. The third column in Table 1 shows the size of sample data that has been used to generate the model structures. These can also vary based on the learning environment. The tool generates neural network structures and decision trees each for Felder & Silverman and Kolb models. The fourth column in Table 1 shows the number of nodes generated in the model. For the neural network, the multilayer perceptron models have two layers each. The output layer has six neurons for the Felder & Silverman model and four neurons for the Kolb’s model, based on the number of classification categories. Similarly, the decision trees that have been generated have six leaf nodes for Felder & Silverman model; and four leaf nodes for Kolb’s model. Comparisons of model performances have been shown in Table 2. Neural networks have exhibited higher performance as compared to decision trees. This can be seen from the Kappa statistics [2] values. The multilayer perceptron model’s performance is slightly better for Kolb’s as compared to Felder & Silverman’s as it has lower root mean squared error value. Also, the decision tree model’s performance is comparable for both Felder & Silverman and Kolb’s models. Kappa statistics value is higher for Kolb’s model; with a slightly higher root mean squared error value as compared to the decision tree for Felder & Silverman model. The data show here is for a typical execution of the simulation. A simulation first generates a model structure and then measures the model’s performance.

<table>
<thead>
<tr>
<th>Model / AI Method</th>
<th>Number of student attributes</th>
<th>Number of learning styles (classification classes)</th>
<th>Size of student sample data</th>
<th>Number of nodes in model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Felder Silverman/Multilayer Perceptron</td>
<td>6</td>
<td>6</td>
<td>22</td>
<td>12</td>
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<tr>
<td>Felder Silverman/Decision Tree</td>
<td>6</td>
<td>6</td>
<td>22</td>
<td>11</td>
</tr>
<tr>
<td>Kolb/Multilayer Perceptron</td>
<td>8</td>
<td>4</td>
<td>12</td>
<td>10</td>
</tr>
<tr>
<td>Kolb/Decision Tree</td>
<td>8</td>
<td>4</td>
<td>12</td>
<td>7</td>
</tr>
</tbody>
</table>
5. Framework of a Smart Education Model

A framework of a tool for smart education is proposed here. Smart education is about providing personalized learning, anywhere and anytime. To make this realistic and widely available, development of a software system for artificial intelligence based determination of learning styles, is proposed here. The determined learning styles can be used to make learning content adaptive and push different content to different students based on their respective learning styles. As of now we have shown simulations with two artificial intelligence techniques and two learning style theories. The software system is being developed to include more learning theories such as Honey and Mumford [6] and VARK’s [5]; and also more artificial intelligence methods such as Fuzzy Logic, Genetic Algorithms, Bayesian Networks and Hidden Markov Models. A review of various methods that can be applied has been given in [3]. Also, it is expected that wider variations in data set may be taken in future, to include different learning environments. These learning environments could be traditional schools, higher education colleges, institutes in villages or institutes in cities. The variations in data could be due to different courses such as arts, science and engineering; or due to e-learning environments with text, with multimedia, with online aptitude tests or with voice based interfaces. The rich set of student attributes for each learning theory model would facilitate selection of the most appropriate learning theory model for a particular environment.

<table>
<thead>
<tr>
<th>Model / AI Method</th>
<th>Correctly classified instances</th>
<th>Incorrectly classified instances</th>
<th>Kappa statistics</th>
<th>Root mean squared error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Felder Silverman/Multilayer Perceptron</td>
<td>22</td>
<td>0</td>
<td>1</td>
<td>0.0393</td>
</tr>
<tr>
<td>Felder Silverman/Decision Tree</td>
<td>15</td>
<td>7</td>
<td>0.6051</td>
<td>0.2611</td>
</tr>
<tr>
<td>Kolb/Multilayer Perceptron</td>
<td>12</td>
<td>0</td>
<td>1</td>
<td>0.0351</td>
</tr>
<tr>
<td>Kolb/Decision Tree</td>
<td>9</td>
<td>3</td>
<td>0.6667</td>
<td>0.2887</td>
</tr>
</tbody>
</table>

Fig. 4: Framework for smart education showing students interacting with a virtual teacher on a cloud environment. It depicts determination of learning styles using the most suitable learning theory model and artificial intelligence technique.
The framework suggests a multi-step process for delivering personalized smart education. This has been described below and also depicted in Fig 4.

- Identification of student attributes for a particular learning environment where adaptive learning is to be provided
- Based on available student attributes, selection of one or more learning theory models that can be possibly applied. Learning models that do not have sufficient available attributes would get eliminated.
- In case more than one learning theory model is applicable for an educational environment, the tool would help in determination of the most suitable model, based on performance of different models.
- The tool would also facilitate determination of the most suitable artificial intelligence method that should be used to build the final classification model. This would be based on comparison of model performances. The model with highest Kappa statistics value and least mean squared error value would be the most preferred one.
- Once one or more models have been shortlisted and trained for a particular student environment, these may be used to classify students and determine their learning styles. Learning styles can be mapped to learning content and learning paths to deliver personalized education.

Smart education is about taking learning outside the traditional classrooms; and is an activity that can be done anywhere and anytime. Internet enabled tablets to browse personalized learning content that could be text, images or multimedia, internet enabled watches to listen to recorded lectures are some of the devices that can be used. To enable this, use of cloud technologies is suggested here. The software tool being developed can be hosted on a cloud environment for easy access to worldwide audience, without limitations of scalability. Sample learning content would be required to be generated to monitor student behavior and determine the available student attributes. Instead of an actual classroom, a virtual classroom and a virtual teacher may be used. It is suggested that natural language processing [12] APIs, voice to text and text to voice APIs, may be used in future to generate sample learning content; and simulate a student-teacher interaction, with virtual teacher agents. For this, cloud based natural language processing technologies such Microsoft Luis, Amazon Lex or IBM Watson may be used. This would enable students to interact with a virtual teacher by just speaking to the system; as if speaking to a human teacher.

So far, adaptive education has been primarily a research area with scattered implementations of some learning models. With the framework for smart education being suggested here, it is proposed that adaptive education be offered as a cloud based service; so that numerous traditional schools, colleges and e-learning platforms can easily access this service and deliver personalized education to their students.

6. Conclusions

The above framework for smart education, which has been developed here, would help in the future in making adaptive education easily available to a wide audience of students, across different cultural backgrounds, geographies and modes of education, traditional or eLearning. The framework provides a collection of numerous student learning attributes that can be tracked, based on which personalized learning can be provided. This readily available collection, within a single tool, would make it easy to determine which student learning attributes can be selected for a particular learning environment. This would facilitate the implementer to narrow down on possible learning theory models that can be applied to impart adaptive learning. This is the first ever framework that has been developed to compare multiple learning theories; and compare artificial intelligence based classification techniques, based on performance of developed models. These models are developed dynamically, within the same tool; and statistical evaluation helps determine the most suitable model, for implementation in a given learning environment. The selected learning theory and artificial intelligence method can then be used to determine the learning styles of students. The framework suggests for a virtual teacher, to be hosted on a cloud environment; that interacts with learners in a scalable manner using natural language processing APIs, to dynamically determine their learning styles. The determined learning styles of students can be subsequently used by various learning content providers, either traditional schools or e-learning portals, to provide adaptive education.
References