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AN INTELLIGENT AND EFFECTIVE E-LEARNING SYSTEM (IELS)

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***Abstract*-The intelligence of E-learning system has become one of regarded topic to public. Using adoptive E-learning system to supplement or replace the classroom is becoming more common in education. to develop, implement and evaluate learning An Intelligent and Effective E-learning System (IELS) is to provide tailored lessons to every student based on their levels of comprehension, progress and weakness. By analyzing the student's statistic data on his/her background and intellectual ability, and dynamic data collected during a lecture session in real time, IELS is able to provide personalized lessons with different levels of difficulty for students with diverse backgrounds.**

Keywords— **E-learning, Adaptive learning, Knowledge Acquisition, intelligent Tutoring System**

I. INTRODUCTION

The traditional teaching environment is usually thought to be that of a classroom: a single teacher giving lectures to a group of students who are expected to use their notes and textbook to prepare for periodic examinations and demonstrate that they have learned. An obvious problem with this approach is that everyone receives the same lecture within a fixed time frame. With so many students with different levels of understanding, it is impossible for the teacher to provide tailored lessons to every student.

Most of the E-learning systems lack artificial intelligence and merely present the content materials without evaluating the students' comprehension and competence. The lecture materials in traditional e-learning systems are presented in a predefined order and within a certain timeframe regardless the students' understanding of the topic being discussed. If some students did not understand the materials, all they can do is to repeat the same materials all over again. these E-learning systems cannot handle a large and potentially diverse student population.

In responses to these challenges and difficulties, this Research proposes designs, implements, and tests An Intelligent and Effective E-learning System (IELS) that provides individualized lessons to students based on their levels of comprehension, progress and weakness. IELS combines expert knowledge, analogical reasoning and fuzzy reasoning to provide tailored lessons to students. By analyzing the student's statistic data on his/her background and intellectual ability, and dynamic data collected during a lecture session in real time, IELS is able to provide personalized lessons with different levels of difficulty for students with diverse backgrounds. IELS evaluates the student's real time learning activity, determines their competency level, analyzes their progress, and selects appropriate teaching mafterials. Good students can finish a lecture unit much faster than others, while the students at the introductory level may take longer. All students, hopefully, can meet the lecture objective at the end of a lecture. A variety of students with different backgrounds and abilities can benefit from this effective, efficient and individualized pedagogical strategy. The knowledge base in IELS captures the expertise of domain subject experts and uses it to dynamically construct a lecture content based on the student's competency. The case base in IELS enables it to recognize similar situations and recall and adapt its past course content for students with similar characteristics. The fuzzy reasoning component allows IELS to conduct approximate reason and handle vague and imprecise terms. By combing expert's knowledge, analogical reasoning and fuzzy reasoning, IELS demonstrates its adaptive ability to deliver personalized courses to students. To show its benefits and feasibility, IELS has been tested in the domain of computer science courses, but its design and structure promise to be domain-independent. Without any structure changes, any domain subject expert, such as in the fields of SAT, GRE, MCAT or any college courses, can input their lectures with ease. The potential applications of IELS are promising and unlimited.

II. SYSTEM ORGANIZATION AND MAJOR COMPONENTS

In terms of the system architecture, IELS consists of the following major components: an answer vector, a student model consisting of a background profile and real time profile, a lecture material depository, a knowledge base, a case base, a conflict resolution component, a fuzzy reasoning mechanism, a lecture organizer, and teachers/students GUI interfaces. The student GUI allows the student to see the lectures and receives the feedback, providing an interactive way to communicate with the system. The performance vector collects and records the answers from the student to be analyzed further. The student model allows the system assesses the student's

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intellectual and comprehension level. The lecture material depository stores and organizes lecture materials in a tree-shape data structure which makes it easy for the system to retrieve and organize lectures. The knowledge base provides guidance under which a set of appropriate lecture units can be accessed and retrieved. The case base stores pass experiences and make it possible for the system to select lecture materials for students with similar characteristics. The conflict resolution mechanism decides the most relevant set of lecture materials for the student. The fuzzy inference component employs fuzzy logic and reasoning to measure partial truth values of matched rules and data. It makes reasoning processes more robust and accurate. The lecture organizer with the guidance from knowledge base and case base compose a new lecture unit for students. The teacher GUI helps the domain subject expert to design lecture materials and enable the expert to enter and modify them easily.

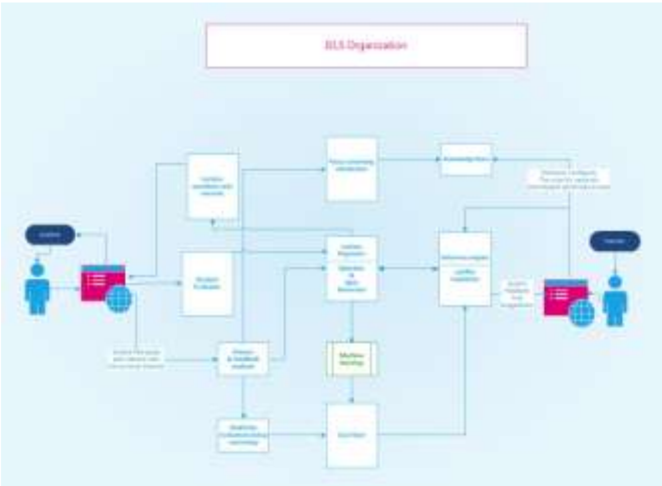

Fig. 1. IELS Business Flow

A. Student Profiles-

To approach individualization in e-learning environments and to describe students' characteristics and performance, IELS builds two profiles for each student: a background profile and an active profile. The background profile contains the student's name, GPA, age, year_at_school, major, learning style preference in terms of text, video or animation, a self-assessment knowledge level in terms of advanced, intermediate or introduction of the topic being discussed. When reading course materials or studying, some students prefer to have complete silence, while others like to play music or have some other sort of background noise to stimulate their brain. IELS lets students choose the lecture format they feel comfortable with and prefer to. The age data may tell the system how mature a student is. A GPA is a good measurement on a student's aptitude and intellectual ability. It could show how well a student may master the topic and how fast a student may understand the lectures. The learning style preference helps the system to present the teaching material in a preferable format for a student. The year_at_school data shows the maturity of a student and how familiar s/he is to the learning environment. The historical data stored in the background profile enables IELS to have an initial assessment on the student and therefore provide a course content appropriate to his/her level of knowledge and aptitude at the beginning of the lecture delivery. The active profile records the actual performance of a student during the tutorial session. It captures the student's activities when s/he views tutorial materials. It includes the following data and information: the length of time viewing a segment of the tutorial, the number of examples requested for the same topic, how many rewinds if the lecture is presented in a video format, how many times of scrolling and browsing, how many clicks on a particular segment, the number of correct answers of exercises/quizzes, and the length of time spent on an exercise. Thus, a student's learning performance and pattern are then quantifiable, observable and digitalized.

B. Performance measurement Vector and Data Collection-

The feedbacks from students are extremely important data for IELS to determine the student's level of comprehension and intellectual capability in order to dynamically construct a lecture unit to satisfy his/her need. For good students, the lecture content may be abstract, concise, and not too many simple examples. For students at the introductory level, the lecture content may contain detailed discussions and simple examples and exercises. To make such an assessment of a student's level of knowledge, IELS has a vector placed between the student's GUI and other components of the IELS. It collects records and measures the student's learning activity and performance during a lecture session as well as the student's statistic data. The vector consists of 14 slots, see the diagram below.

Fig. 2. Performence measurement Vector

The first 5 slots are allocated to store a student's statistic data after the student has login into the system. See below:

V1	GPA
V2	age
V3	year-at-school
V4	major
V5	self-assessment

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The data collected from these slots enables IELS to make an initial assessment on the student's level of the knowledge and then accordingly prepares a set of lecture units appropriate to his/her level. IELS may, however, change its assessment and the lecture content as more real time data comes in during a lecture session. The next segment of the performance vector from V6 to V14 contains dynamic data produced by a student during his/her lecture session. It contains the following data:

V6 the length of time a student views a lecture segment

V7 the number of times a student clicks and scrolls on a page

V8 the number of times a student requests additional examples

V9 the number of correct answers to given examples/answers

V10 the number of correct answers to given exercises

V11 the number of times going between tutorial and examples

V12 the number of times going between tutorial and exercises

V13 the length of time a student views an example

V14 the number of correct answers given a set of quizzes at the end of lecture

Before, during and after each session, IELS poses questions, exercises, and quizzes to the student, and collects the feedback from the student. IELS also monitors and records the student's real time learning activity such as the number of clicks and the length of time viewing a lecture unit. These data define the level of the student, advanced, intermediate, or introduction. It helps IELS select the lecture units appropriate to the student's knowledge and comprehension relevant to the topic to be discussed in the session. The data collected during the session is used to build a student model for future reference and to construct a lecture unit for similar students that may be encountered in the future. The data collected after the session determines whether or not the student has understood the topic and decides if the student can go to a new topic. Part of the diagnostic data collected is used to match the rules in the knowledge base to dynamically select suitable lecture materials appropriate to the student's level. Part of the data is used to recall prior lesson materials recorded in the case base so that a proven and effective lecture can be provided to students with similar characteristics. Unlike most e-learning systems, IELS interacts with students and collects data to classify students into different categories based on their performance and feedbacks. With these data, IELS is able to provide personalized learning experience and to facilitate students to learn better by using different ways of selecting examples, exercises and lecture materials. The idea is to adapt both the content and presentation of the course based on a student's learning style, background, progress, and comprehension. The purpose of gathering this data is to accurately model the student, to more effectively assist the student during the lecture session and to predict how to organize the lectures for future students with similar characteristics.

C. Lecture Material Repository-

The ability to effectively organize educational resources in terms of accessibility, reusability and interoperability lies in the construction of a repository. A lecture material repository plays crucial role in an intelligent tutoring system. It digitally stores, processes and retrieves teaching materials prepared by domain subject experts (teachers). Large amounts of content are placed in a hierarchically organized and aggregating structure on several levels. A group of lecture notes related to a particular subject resides in a tree-like data structure where the general topic is at the top and more specific sub topics are stored below. IELS employs a hierarchical structure where each node represents a concept to be learned, a set of examples associated with the concept, a set of exercises for students to self-evaluate how much they understood the concept, and a set of quizzes to test the student's comprehension of the concept being discussed. A lecture material repository is designed with four goals in mind. First, it should help teachers enter and modify teaching materials in an easy and user-friendly way. Second, it should facilitate the retrieval of relevant materials efficiently and accurately. Third, it should make the process of reorganizing a lecture unit possible and straightforward. Fourth, it should allow the system to form a new lecture with ease, flexibility and continuation. There are three kinds of nodes in this hierarchy: topics node, lecture note and module node. A topic node specifies the topic being discussed. A lecture unit node contains any number of lecture modules decided by the domain subject expert. A module node consists of tutorial, examples and exercises with different level of difficulty. See the following diagram which contains the topic nodes and lecture unit nodes.

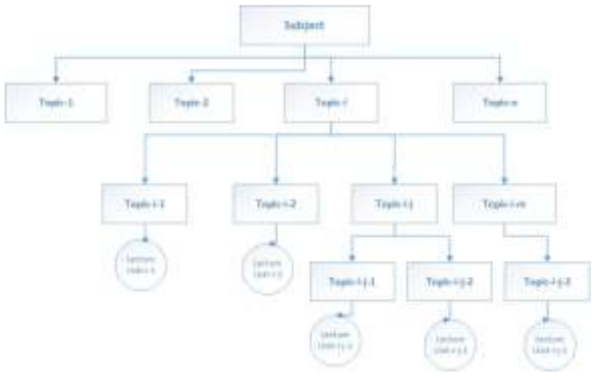

Fig. 3. Lectural Material Repository

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III. THEORETICAL FRAMEWORK AND FEATURE

A. Knowledge Base-

The knowledge base captures the knowledge of domain subject experts in the form of If-Then rules. It gets its power from domain subject experts that have been coded into facts, rules, heuristics and procedures. This knowledge of a teacher is stored in the knowledge base separate from other control and inference components in IELS. It is possible to add new educational strategies and methods in the system easily. It is also easy to modify the existing knowledge already in the knowledge base. Researchers believe that a single rule corresponds to a unit of human knowledge. In the design of an intelligent tutoring system, a knowledge representation for human problem solving expertise is a critical and complex task. The main purpose of the rules in the knowledge base is to determine a student's comprehension and intellectual level so that appropriate teaching materials can be retrieved from the Lecture Depository. In what follows, the knowledge representation in IELS is described along with actual rules as examples.

RULE <ID>

IF {(<condition_1 RO value_1 >)

LO (<condition_2 RO value_2>) …..

LO (<condition_n RO value_n>)}

THEN (Recommendation)

UNLESS (statement)

REASONS (statement_1, statement_2… statement_m)

WITH (CERTAINTY FACTOR = <real number>)

Where the term LO represents a logical operator, such as AND, OR and NOT. The term RO represents one of the following relational operators: equal to (==), less than and equal to(<=), not equal(!=) to and greater than and equal to(>=). These operators together with the conditions in the Condition clause express a certain requirement that must be satisfied before the rule can make a recommendation listed in the THEN clause. The UNLESS specifies an exception that prohibits the rule to be triggered and fired. The REASONS clause lists the reasons in order to explain and justify why a conclusion is reached. The WITH clause contains a real number in the range of (0...1) measuring the strength of evidence in support of the rule's hypothesis. It expresses how much confidence we should trust this rule and its recommendation. There are two kinds of knowledge captured in the form of IF-Then in IELS: an initial assessment on students' levels before a lecture and a final assessment on students' performance in the lecture. The assessment data for diagnostics comes from the student's background profile. It provides an initial assessment on the level of a student's knowledge, intellectual ability and comprehension so that IELS can provide individualized teaching materials appropriate to students to begin a lecture session. If this decision is not accurate, IELS is capable of making adjustments during the lecture session.

B. Case Base and Analogical Reasoning-

Analogical

The case base in IELS maintains a rich set of cases (scenario) of student's learning patterns, their performance and backgrounds along with a set of examples, exercises and quizzes appropriate to their comprehension. A case consists of an attribute part and a recommendation part. When comparing a new case to the cases in the case base, the values in the attribute part are calculated. A similar score indicates how similar they are. Once a case is considered similar enough, the content in its recommendation part is retrieved and applied to the new case. The content in the recommendation part usually contains a combination of modules along with a set of examples and exercises. Its components are shown below:

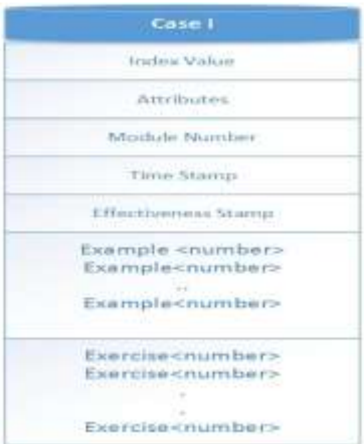

Fig. 4. Case and its Components

Each case in the case base has a time stamp attached to it. Every time a case is retrieved, the value in the time stamp is increased to indicate its appropriateness. It also has an effectiveness slot. If the retrieved case can be applied to the current student successful, the value in the effectiveness slot is increased to indicate its examples and exercise are very helpful in the process of learning. If some cases are stored there for a long time without being retrieved and applied, it will be deleted eventually. This process demonstrates a form of machine learning in the design of IELS. Each case in the case base of IELS is a unique teaching strategy: given a topic and a particular group of students with common characteristics, what are the best set of examples and exercises to explain the concept most effectively? The index value in a case represents a path and a module number where the case should be attached to the Lecture Repository Hierarchy. It begins with the subject, followed by a topic path and a module number. The recommendation part consists of a list of examples and

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exercises. Each example or exercise has a number corresponding to the location where is should be inserted into the tutorial segment. The attributes in each case are used to measure a student's dynamic activity in a session of lecture: the time viewing a lecture segment, the number of clicks on a page of lecture content, the number of examples requested, the number of correct answers to a set of exercises, the number of correct numbers to a set of quizzes, the number of times going back-and-forth between a tutorial segment and an example, the number of times going back-and-forth between an exercise and a tutorial segment. The abbreviations and their meanings are presented in the following table.

TMS	The time length viewing a segment
NC	The numbers of times clicking and scrolling
NE	The number of times requesting additional examples
CEXA	The number of correct answers to examples
CEXE	The number of correct answers to exercises
BTE	The number of times between Tutorial and Examples
BTX	The number of times between Tutorial and Exercises
TME	The time length viewing an example

Table of attributes of a case

The attribute part of a case is also known as features. In the following formula the 8 features represent the 8 abbreviations listed in the above table.

Let N be a case with 8 features:

N = {n1 n2. n8}

And O is an old case with 8 features:

O = {o1 o2 ... o8}

CF denotes a common feature set

CF = {c1 c2 ... ck} where 1 <= k <= 8

Where { C1 and O1 = TMS
C2 and O2 = NC
C3 and O3 = NE
C4 and O4 = CEXA
C5 and O5 = CEXE
C6 and O6 = BTE
C7 and O7 = BTX
C8 and O8 = TME }

Since some attributes may be missing, the number of common features k may be fewer than 8.

Thus, a similarity score, S (N, O), of a new case N with respect to an old case O is given as:

$$S(N, O) = \frac{\left[\sum_{i=1}^{k} \lambda i \times c\, i\right] \times k}{8} \qquad 1 \le i \le 8$$

Where λi is a weight assigned to the ith feature of a case.

A high similarity score indicates the current student is similar to some past students in terms of real time learning activity and performance. By providing a set of examples and exercises proved to be effective in the past, the current student can shorten the learning curve and master the new concepts quickly.

IV. CONCLUSION

The purpose of the research was to develop, implement and evaluate learning An Intelligent and Effective E-learning System (IELS) is to provide tailored lessons to every student based on their levels of comprehension, progress and weakness. By analyzing the student's statistic data on his/her background and intellectual ability, and dynamic data collected during a lecture session in real time, IELS is able to provide personalized lessons with different levels of difficulty for students with diverse backgrounds. IELS evaluates the student's real time learning activity, determines their competency level, analyzes their progress, and selects appropriate teaching materials. IELS not only apply on E-learning, But also can be applied on entrance examinations to colleges (SAT and ACT), Business schools (GMAT), Law schools (LSAT), medical schools (MCAT) and graduate schools (GRE).

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