ADAPTIVE PERSONALIZED E – LEARNING USING WEIGHTED FUZZY & RECOMMENDATION

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Abstract:

Fuzzy logic has a number of properties that make it suitable for describing e learning events: (i) it can tolerate the unreliable and imprecise datasets; (ii) it is much closer to the way of thinking than crisp logic. (iii) Compared to other classification algorithms based on probability theory, fuzzy logic is much more intuitive and easier to use. A disadvantage of using fuzzy logic is that storing the rule base might require a significant amount of storage. The number of rules grows exponentially to the number of variables. With n variables each of which can take m values, the number of rules in the rule-base is mn.

Introduction

In this chapter, it is proposed to mine e learning data using personalization techniques to extract useful patterns and support to the learners. Fuzzy logic is used with knowledge definer system for effective personalization of rules from quantitative datasets. The proposed method uses synthetic dataset showed in chapter 4 consisting of 10 numbers of domains and learner details.

- **Weighted Fuzzy Intelligent Computing in Knowledge Learning System** (WFR_IEM_MCF) phase of a web-based educational application is created for individualized instruction on the computer science domains.
- The proposed system effectively identifies the individual students skills based on their objective questions, practical results, and the time based evaluations.
- The time analysis is one of the factor included to define the students proficiency in each domain.
- WFR_IEM_MCFis the basis for providing personalized tutoring, which identifies and updates the student's knowledge level.
- The WFR_IEM_MCFhave the ability to recognize the alterations of the student's learning states and dynamically adapt the presentation of the learning material accordingly.

Advantages of the proposed system:

1. This approach improves the efficiency of the adaptively of the instructional process.
2. WFR_IEM_MCFmodule, which identifies the alterations on the state of students' knowledge level.
3. Student can read the learning material more times, until they have learned the domain knowledge Fully The goal of this proposal was to personalize the e-learning procedure using rule based fuzzy sets. In order to enhance individual proficiency and adaptive learning process, WFR_IEM_MCFhas been proposed.

It combined the user skill state and the domain concepts to promote personalization in educational applications. It sequentially verifies the student's knowledge and concept depth from various events with their personal choices. The process has divided into three steps known as domain knowledge; proficiency evaluation and course prediction based on the skill state and concept matching. Initially the chapter discusses about fuzzy logic implementation in e learning.

Weighted Fuzzy Rule Implementation:

Weighted Fuzzy Rule(FL) is a multi valued paradigm which allows intermediate values to be defined between conventional evaluations like true/false, yes/no, pass/fail, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers. The Fuzzy systems are an alternative to traditional notions of set membership and logic on e learning.

The simplest fuzzy model consists of a set of rules with an "if – then" structure:

If < condition 1 > and … and > condition n > then < conclusion >

Where, condition i is a statement of type "Ziis Yij". In this statement *Zi*represents the actual value of some i-th real world variable meanwhile Yijis a flexible predicate naming the j-th linguistic term of the corresponding i-th Linguistic Variable. Yijis given by a fuzzy set which represents the use of the flexible predicate on the domain of Zi. Statements of this kind are called "premises". The conclusion is also a fuzzy set, which represents the linguistic term expressing a flexible predicate, which characterizes the output behaviour of the system if all conditions are satisfied. Notice that "if – then" rules may be used both to model the state of a system (see Rule 1 and ambiguous. Hence, membership of an element from the universe in this set is measured by a function that attempts to describe vagueness and ambiguity.

A fuzzy set, then, is a set containing elements that have varying degrees of membership in the set. This idea is in contrast with classical, or crisp, sets because members of a crisp set would not be members unless their membership was full, or complete, in that set (i.e., their membership is assigned a value of 1. Elements in a fuzzy set, because their membership need not be complete, can also be members of other fuzzy sets on the same universe. Elements of a fuzzy set are mapped to a universe of *membership values* using a function-theoretic form. This function maps elements of a fuzzy set A~ to a real numbered value on the interval 0 to 1.

When a simple database T with two attributes (X1 and X2 as level 1 and level 2 respectively) and (three below) and to take a decision to control the system (see Rule 2).

Rule 1 : *If* knowledge level (KL) of (level1) is high *and* the KL(level2) is high *and* KL(level 3) is low *then* the user need to concentrate on level3.

Rule 2 : *If* knowledge level (KL) of (level1) is medium *and* KL(level2) is low. Fuzzy control is then closely related to fuzzy decision making. Take as example the following set of "if – then" rules constituting a fuzzy control-model for an extreme simple e learning system for a particular learner:

R1 : *If* knowledge level (KL) of (level1) is low *and* the KL (level2) is low *and* KL (level 3) is low *then* the user need to concentrate on level1.

R2 : *If* knowledge level (KL) of (level1) is medium *and* the KL (level2) is high *and* KL (level 3) is low *then* the user need to concentrate on level1.

R3 : *If* knowledge level (KL) of (level1) is high *and* the KL (level2) is high *and* KL (level 3) is high *then* the user need to go on level4.

In classical or crisp, sets the transition for an element in the universe between membership and non-membership in a given set is abrupt and well-defined. For an element in a universe that contains fuzzy sets, this transition can be gradual. This transition among various degrees of membership can be thought of as conforming to the fact that the boundaries of the fuzzy sets are vague linguistic terms and associated MFs (see Figure 3.1) is considered.

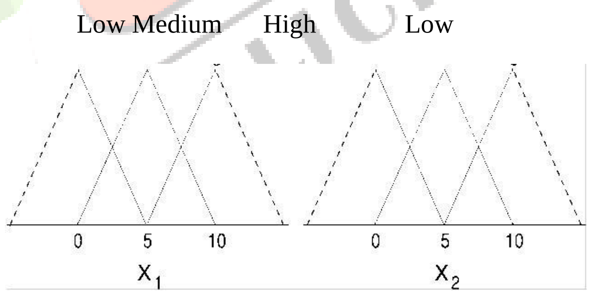


Figure 3.1 Attributes and linguistic terms for the attributes X1 and X2

As per the E-leaning dataset, the above attributes and linguistic terms are defines as the value of individual scores. If the value for X1 is defined as 5, then the score will be modified into the linguistic terms (High, medium, Low). This is calculated from the total questions and time taken for every question.

If total question is 10 → the score is 8 → the time take for each question is 2 ms approximately ➔ then the linguistic score will be converted as "High".

3.3 WFR_IEM_MCFProcess:

A. Domain Knowledge Representation using Fuzzy

Domain concepts are the learning material, and directed arcs, which represent relations between the concepts of the learning material. The relations that exist between the concepts of the learning material depict so the order in which the domain concepts have to be delivered and the structure of the learning material, as the knowledge dependencies. In particular, there are three types of relations between the concepts: "precedes" that declares the order in which each domain concept of the learning material has to be taught. A domain concept is affected regarding the knowledge level of its related domain concepts. In other words, they depict the "strength of impact" of a domain concept on a related concept.
The particular numbers are only positive [14].

Dotnet	datatypes	java	0.89
Dotnet	Introduciton	java	0
Dotnet	control statements	java	0.79
Dotnet	Array	java	0.59
C	datatypes	C++	1
Dotnet	conditional	Dotnet	0.59

Fig 3.2 concept similarity score calculation in every domain

The above Figure 3.2 represents the concept similarities between different programming languages. Using this, the learner can choose the language for further study. This is happened due to the fact that the increase of the knowledge level of a domain concept leads to the increase of the knowledge level of a depended domain concept, and the decrease of the knowledge level of a domain concept leads to the decrease of the knowledge level of a depended domain concept. Therefore, the numbers of the directed arcs that depict the knowledge dependencies belong to the interval (0, 1).

One important module of the WFR_IEM_MCFis the domain module, which contains a description of the knowledge or behaviors that represent expertise in the subject-matter domain of the system. To enable communication between system and learner at a content level, the domain model of the system has to be adequate with respect to inferences and relations of domain entities and compatible.

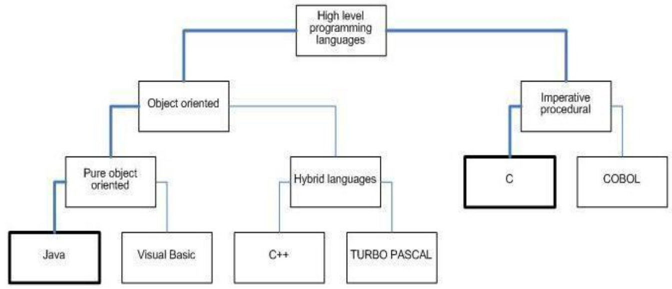


Fig. 3.3. Concept Hierarchy

The hierarchy of the domain concepts, as well as the dependence relations among them must be represented. Therefore, the domain knowledge of the presented system is organized into a hierarchical structure in combination with FCMs.

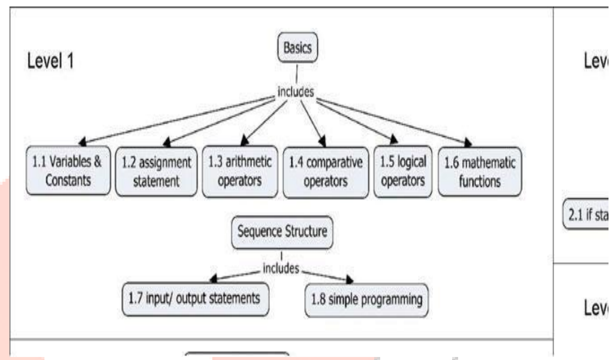


Fig. 3.3.1 domain for level 1 Hierarch

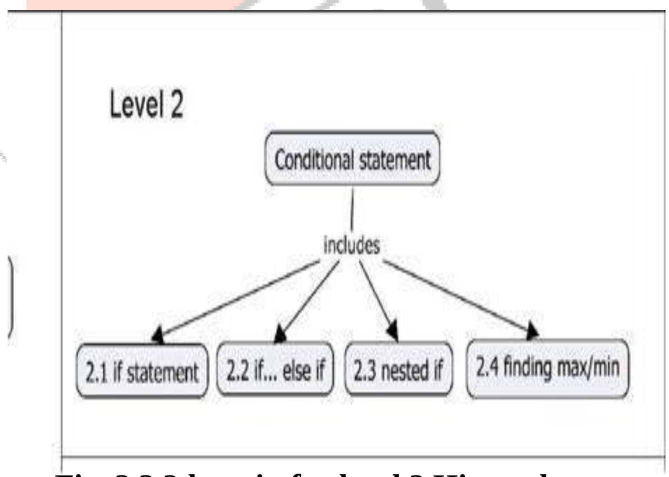


Fig. 3.3.2domain for level 2 Hierarchy

The hierarchical structure shown in Fig 3.3 and 3.3.1 depicts the difficulty level of the domain topics and the order in which each topic must be taught.

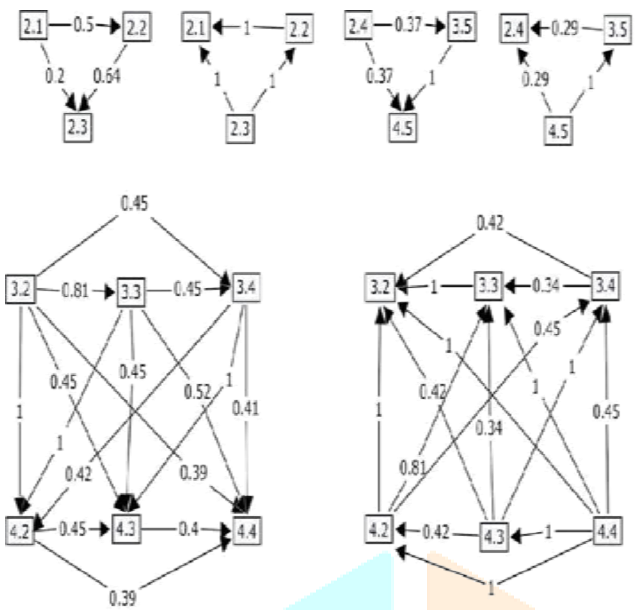


Fig 3.4 cognitive maps

The Fuzzy Cognitive Maps shown in Fig. 3.4, which represent the dependence relations between the domain concepts of the learning material concerning the influences of the knowledge level of a concept to that of another related concept. The creation of the hierarchy is based on the knowledge domain, on the logic of programming languages, and on the dependencies that exist among the components of a programming language. The set of the domain concepts that have to be taught to a student each time depends on the knowledge level of the student. The domain concepts that belong to an upper level should be taught only when all the domain concepts of all the lower levels have been learned by the student (the nodes "Basics" and "Sequence structures" are in level 1 and the node "Sub programming" is in level 7).

Weighted Fuzzy Rule for Knowledge Representation

The knowledge domain module is one of the most major modules of an Intelligent Tutoring System (ITS). The knowledge domain representation is the base for the representation of the learner's knowledge, which is usually performed as a subset of the knowledge domain. It contains a description of the knowledge or behaviors that represent expertise in the subject-matter domain the ITS is teaching.

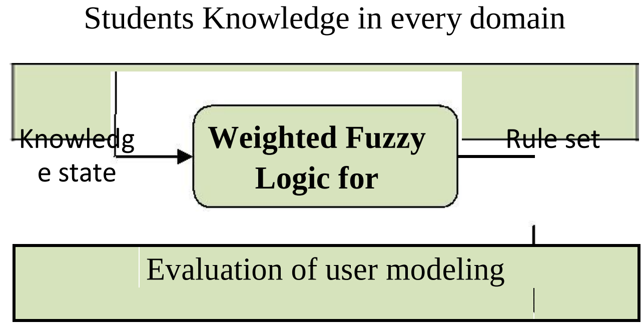


Fig 3.5Knowledge representation in E-learning

In other words, the knowledge domain module is responsible for the representation of the subject matter taking into account. the course modules, which absorb domain concepts. The meticulous module has been introduced in ITS but its use has been extended to most current educational software applications that aim to be adaptive and/or personalized [13]. To enable communication between system and learner at content level, the domain model of the system has to be adequate with respect to inferences and relations of domain entities with the mental domain of a human expert. This technique makes easier the assortment of the appropriate educational material satisfying the student's learning needs.

Domain of the Programming Language

This model is used for Learners of programming languages have different backgrounds and their knowledge of a concept of the programming language, which they are taught, is subject to change. A new concept may be completely unknown to the learner but in other circumstances it may be partly or completely known due to previous related knowledge of the learner. For example, if a learner already knows an algorithm (e.g., calculating the sum of integers in a 'for' loop), there is no need to learn another similar algorithm (e.g., counting in a 'for' loop). Similarly, if a learner knows programming structure (e.g., one-dimensional arrays), it is easier to understand another programming structure (e.g., multidimensional arrays). so this new structure should not be considered as being completely unknown to the learner.

Weighted Fuzzy intelligence computing for automatically learning Process of a Student

The Weighted Fuzzy intelligence computing system is used to model the cognitive states of learners of the programming language. This system for modeling automatically the learning or forgetting process of a student is presented. Fuzzy sets are finding very wide applicability in Weighted Fuzzy intelligence computing systems (WFICs). The operation of WFICs is based on rules. The rules are expressed as a collection of IF-THEN statements. The Weighted Fuzzy intelligence computing module is responsible for identifying and updating the student's knowledge level of all the concepts of the knowledge domain.

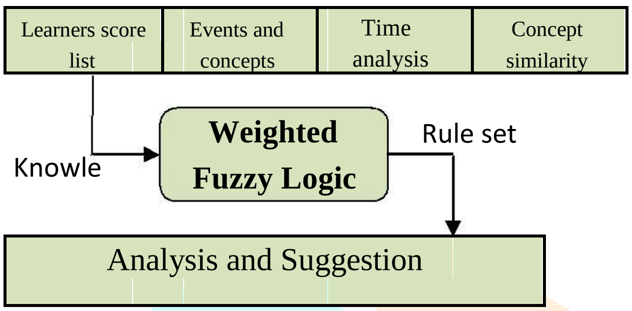


Fig 3.6 Rule based WFR_IEM_MCFprocess

Its operation is based on the Fuzzy Related-Concepts Network that is used to represent the structure of the learning material and the dependencies that exist between the domain concepts. It uses fuzzy sets to represent the student's knowledge level and a mechanism of rules over the fuzzy sets, which is triggered after a change, has occurred on the student's knowledge level of a domain concept.

S1: If KL(C1.1 ..C1.8)<100% Known, then select course1.

S2: If KL[C1.1 ..C1.8]≥ 100% Known and KL(C2.1 ..C2.4)<
100% Known, then select course2.

S3: If KL[C1.1 ..C2.4]≥ 100% Known and KL(C3.1 ..C3.5)<
100% Known, then select course3.

S4: If KL[C1.1 ..C3.5]≥ 100% Known and KL(C4.1 ..C4.6)<
100% Known, then select course4.

S5: If KL[C1.1 ..C4.6]≥ 100% Known and KL(C5.1 ..C5.3)<
100% Known, then select course5.

This mechanism updates the student's knowledge level of all related with this concept, concepts. With this approach the alterations on the state of student's knowledge level, such as forgetting or learning are represented. Finally, a brief discussion and the conclusions drawn from this work are presented [17].

Fuzzy Logic (FL) is a multi-valued logic that allows intermediate values to be defined between conventional evaluations like low/high, yes/no, pass/fail. Fuzzy systems are an alternative to traditional notions of set membership and logic. The training and testing fuzzy logic is to map the input pattern with target output data. For this, the inbuilt function has to prepare membership table and finally a set of number is stored. During testing, the membership function is used to test the pattern.

Initial process

Step 1: Read the pattern and its target value.
Step 2: Create Fuzzy membership function.
Step 3: Create clustering of domain levels using scores.
Step 4: Process with target values.
Step 5: Obtain final weights.

Proposed Algorithm :

Initial process

Step 1: Read the data D

Step 2: For each attribute Ai do linguistic function L and make fuzzy set Fs.

Step 3: Create Weighted Fuzzy membership function. $M_{F(Score)}$={High, Medium, Low}

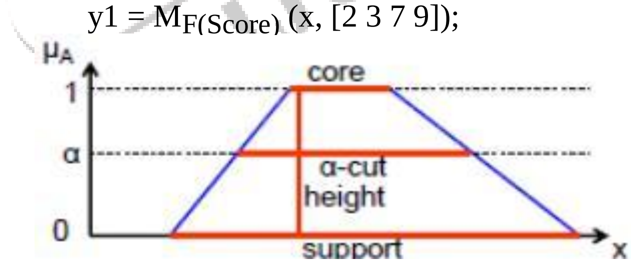
Support: elements having non-zero degree of membership.

Core: set with elements having degree of 1

-Cut: set of elements with degree >= α.

Height: maximum degree of membership.

y1 = $M_{F(Score)}$ (x, [2 3 7 9]);



Step 4: Create clustering of domain levels using scores.

i. Let n is the total number of clusters; n1 is the length of D.

ii. Define Centroid C from lowest and highest set

a. C=(d_{min}(i), d_{max}(j))

iii. Calculate distance y1=dist(D, C.get());

iv. D.cluster(cluster);

v. Return cluster

Step 5: formulate rules

Select rules according to the WFM

Step 6: de-fuzzificaiton

Step 7: Testing process and return KL

Testing process

Step 1: Input a pattern.

Step 2: Process with Fuzzy membership function.

Step 5: Find the cluster to which the pattern belongs.

Dataset information's	values
Total number of programming Languages selected	**4**
Total number of learners	**100**
Total number of domains used	**28**
Stereo types	**8**
Types of knowledge level	**4**

Step 4: Obtain estimated target values.

Step 5: Classify the status (KL)

The proposed algorithm takes less number of iterations to reach a stable state. The time taken by this algorithm is in between the time taken by the existing fuzKSD and time taken by ITS.

Dynamic adaptability of the WFR_IEM_MCFmodel depends on predicting learner‘s expected results and comparing those results with learner's achieved results. The results are analyzed to infer the weak points in the plan that needs adaptation. In doing so, the tree of topics included in the plan is traced to calculate the expected learner's results according to his background knowledge mastering levels. The topics are weighted by the instructional designer to determine their relevance importance during the course intake. This is similar to the process of calculating the score of a learner in which the weight is an integer value (usually 2 or 3) that represents the importance of the topic. First, the set of prerequisite topics that must be mastered before learning the current topic is determined along with their relevance importance value and the mastering level value. The sigma of multiplying each topic mastering level by e-learning weight is then calculated. Finally, the calculated result is multiplied by a special factor that determines the difficulty level of the current topic. This factor can be calculated by referring to the results achieved by all the learners that studied this topic before. The better the achieved results the higher the difficulty factor value is. This process is illustrated through the following formula:

$$E_T = \frac{\sum_{p \in P_T} (W_p * R_p)}{\sum_{p \in P_T} W_p} * D_T$$

Where E_T is the expected result of topic T, P_T is the set of all the prerequisites of topic T, W_P is the relevance importance value of topic P, R_P is the mastering level of topic P and D_T is the difficulty factor of topic T. The skill analyzer module has to compare the expected result E_T to the achieved result Rand modify the plan accordingly.

IMPLEMENTATION AND RESULT

This section describes the implementation process. Implementation is the realization of an application, or execution of plan, idea, model, design of a research. This section explains the software, datasets and modules which are used to develop the research.

DATASETS

The system used a synthetic dataset, which can be any number of e learners created by the proposed website. Data collection is the first step of our proposed system, the data authenticity and integrality will directly affect the following works smoothly carrying on and the final recommendation of characteristic service's quality. Therefore it must use scientific, reasonable and advanced technology to gather various data.

At present, towards e learning technology, the main data origin has three kinds: server data, client data and middle data. The first step in the Web usage mining process consists of collecting the relevant learning data, which will be analyzed to provide useful information about the learners' proficiency.

Table 4.2dataset descriptions

The above table describes the dataset description used for the experiments. Where the dataset contains

8 number of stereo type learners which are described below.

Stereotype name	Description
Stereotype 1	Novice learners;
Stereotype 2	learners that know about the foundations of programming (like variables and constants, operands, expressions);
Stereotype 3	learners that know about the selection statement (if, if-else if, nested if);
Stereotype 4	learners that know about how to built programs using the “for” statement;
Stereotype 5	learners that know about the iteration statements “while” and “do..while;”
Stereotype 6	learners that know about 1-D arrays;
Stereotype 7	learners that know about multidimensional arrays;
Stereotype 8	Expert learners (they know, also, about the process of sub programming).

Table 4.3 stereo type

The following four fuzzy sets for representing students’ knowledge level of a domain concept are defined.

Knowledge Levels	Description
Unknown (Un)	the degree of success is from 0–60%;
Insufficiently Known (InK)	the degree of success is from 55–75%;
Known (K)	the degree of success is from 70–90%;
Learned (L)	the degree of success is from 85–100%.

Table 4.4 knowledge levels

From the above set of learners, 12 learners are based on stereo type1, 15 are stereo type2, 23 are stereo type3, 23, 27 are stereo type4 respectively. The details are shown in the following table. The table has been generated from the above dataset D.

Type	Learners
Stereo1	12
Stereo2	15
Stereo3	23
Stereo4	4
Stereo5	6
Stereo6	20
Stereo7	18
Stereo8	2
Total	100

Table 4.5 Students count in different stereo type

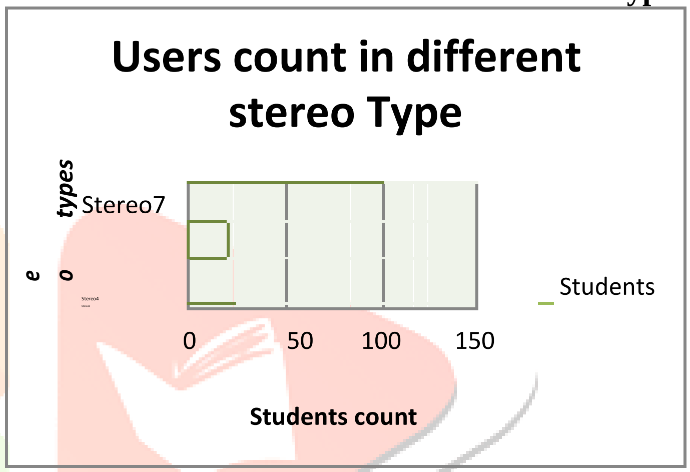


Fig 4.1 chart for learner type

The above chart shows, the stereo type 3 has more number of learners that others, finally the stereo type ie S8 has only 4 learners in the domain.

The next process is analyzing the learner knowledge type, From the 100 learners, 31% learners are under knowledge level 1, 38% are under knowledge level 2, 29% under level3,2 % are level 4 respectively. The details are shown in the following table. The table has been generated from the above dataset D.

Type	Students (%)
Unknown(UK)	31
Insufficiently Known (InK)	38
Known(K)	29
Learned (L)	2

Table 4.5.1 Students count in different knowledge level

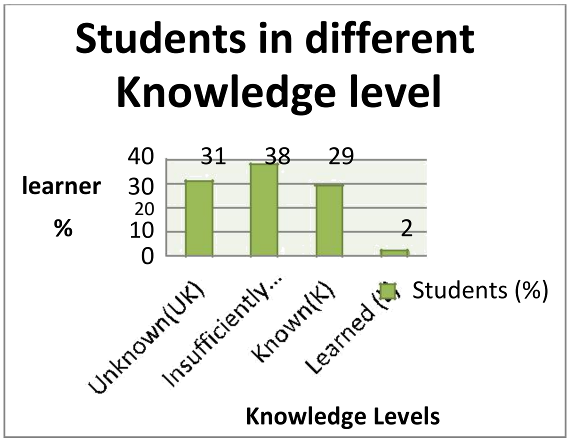


Fig 4.2 chart for total learners percentage in different knowledge levels

The above chart shows, the level 2 has more number of learners that others, finally the level4 ie K4 has only 2% learners in the domain.

Step1: Learner Level

Researchers in the e-learning community have always considered it important to develop a model of the novice learner. The adaptive and collaborative capabilities of the system are mainly based on this model. Along with many characteristics that define the learner model there are characteristics that have a great influence on the learning process such are:

- Prior knowledge of the learner that determines the concepts that he can learn.
- Learner's skills and learning styles that determines the teaching approach that best suits the learner.
- Learner's emotions and motivations is another important characteristic that is usually forgotten in learner modelling research.

Thus, the system proposes a multi-level comprehensive learner model that is based on the Novice learner Information Package (NIP). The proposed novice learner model consists of three levels as follows.

- *Personality level*: This level consists of information related to the learner type and any extensions to it, along with information about the learning style and skills of the novice learner.
- *Behaviour Level*: This level is responsible for recording information about learner activities in the system. For example test and time taken for each test has been analyzed.
- *Knowledge Level*: This level includes information about novice learner current knowledge as opposed to a Knowledge sharing systems.

Step 2: Domain *Knowledge Model*

Knowledge of the domain can be seen as interconnection of two networks which are the network of concepts known as knowledge space and the network of educational material. Knowledge space is a structured representation of the domain knowledge, in our proposal the score has been used for knowledge representation. It consists of interconnected nodes where each node represents a small piece of knowledge (i.e. a concept).

Course Model

The adaptation capability of the proposed system highly depends on the past successful course plans stored in the database along with the scores. The course model is a structured case-based model, where each case represents an experience of course delivery.

Every learner can view their domain knowledge on each domain. Finally the proposed system will provide appropriate tutorials and notes to improve their knowledge.

Step 3: Evaluation model

Each training state was designed with specific issues in mind. The evaluation of past training cases includes calculating the similarity measures between the state of current learner and the previous training cases. This process should consider all the issues that affect the construction of the previous training state. These issues include the training objectives, learner's knowledge mastering levels, his skills appraisal levels, his learning style along with any possible effective environmental issues. Moreover, looking at past learners' achieved results may be helpful in choosing the best previous training experience.

It is worth noting that each of the above issues has e-learning own relative impact on the training experience. The relative importance of each issue can be set by the system administrator.

The problem is how to evaluate previous training cases in order to choose the training state that has the highest degree of similarity to novice learner*l*. First, let us suppose that$E = \{e_1, e_2, \ldots, e_n\}$ is a set of n-effective issues. Second, assume that$L = \{l_1, l_2, \ldots, l_k\}$is a set of k-previous learning cases, while l by e-learningelf will be used to indicate the current learning state. Moreover, the similarity between the effect of e_i on the current learning state and e-learning effect on previous learning state l_p is $S_i(l, l_p)$.

$R=\{r_1, r_2, \ldots, r_n\}$ is a set of relative importance values corresponding to different effective issues in E;

$$\sum_{j=1}^{n} r_j = 1$$

so that r_j is the relative importance of issue e_j; where (r_j< 1) and.

Based on the above assumptions, the following formula can be used to evaluate the similarity between the current learning state l and previous learning state l_p.

$$S(l, l_p) = \sum_{i=1}^{n} r_i * S_i(l, l_p) \quad \ldots \textbf{[1]}$$

Definition 1: N(A)represents the number elements of the set A.

Next, we will shed lights on some practical ways to calculate $S_i(l, l_p)$.Putting in mind that $S_j(l, l_p) \leq 1$ which implies that $S(l, l_p) \leq 1$. First, recall that the cornerstone in building a course is the course objectives. So, we will start by proposing a way to calculate $S_o(l, l_p)$ which is the similarity between objectives of novice learner l and objectives in the learning state l_p. To do so, assume that the set of objectives required by the current learning state is

$O=\{o_1, o_2, \ldots, o_m\}$ and the set of objectives in the learning state l_p is $O_p=\{o_{p1}, o_{p2}, \ldots, o_{pf}\}$ then:

$$S_O(l, l_p) = \frac{N(O \cap O_p)}{N(O)} \quad \ldots \textbf{[2]}$$

Assuming that every novice learner has at least one learning objective, then we can derive that $S_o(l, l_p) \leq 1$. Next, $S_o(l, l_p)$ can be substituted in formula 1 for $S_h(l, l_p)$ where $h \in \{1, .., n\}$ and e_h is the label for the objectives issue which is a element in E.

$$S_t(l, l_p) = \begin{cases} 1 & \textbf{if } N(T) = N(T_p) = 0 \\ \frac{1}{N(T_p)} & \textbf{if } N(T) = 0 \ \& \ N(T_p) \neq 0 \\ \frac{N(T \cap T_p)}{N(T)} & \textbf{otherwise} \end{cases}$$

Note that if the current learner needs no topics to be added to his training plan (i.e. N(T)= 0) then the most suitable previous plan could be the least tough (i.e. with the least number of added topics); meaning that $1/N(T_p)$ will yield smaller values if $N(T_p)$ is large. In the same way, $S_t(l, l_p)$ can be substituted in formula 1.

Third step is, referring to the four dimensions of Felder's learning styles model, we can define $f_d \in \{-1, 0, +1\}$; Where F_{ld} is the learning style of novice learner l in dimension d which can take one of three values. Similarly, $f_{pd} \in \{-1, 0, +1\}$ is the learning of style of novice learner l_p in dimension d.

Second steps is, let us suppose that the set of topics needed to be added to the course plan due to lack in learner l background knowledge or skills is $T = \{t_1, t_2, \ldots, t_m\}$ and the set of topics in the learning state l_p that has no direct links to the objectives of that course (rather, it was added to compensate a lack of learner's background knowledge or skills) is $T_p = \{t_{p1}, t_{p2}, \ldots, t_{pf}\}$. Then:

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