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Supporting Adaptive Learning Environment through Cognitive Skill based Learner Classification

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Abstract

Background/Objectives: Adaptive learning has become a key accelerator to provide personalized content based on the learners' preferences, as existing Learning management system support to manage the content and learner data analysis. **Methods**: To provide suitable content for the learner, Learning Style (LS) of the learner plays an important role. The limitation in existing learning environment is identifying the individual's learning skill based on the mental processing capability of the learners. In this paper, a model is proposed to incorporate an effective learner model for adaptive learning environment through cognitive skill based learner classification. **Findings:** A Multiple Choice Questionaries' was conducted to test the cognitive capability. Around 107 learners participated. The questionnaire was prepared based on the four cognitive skills such as Memory, Concentration, Perception and Logical Thinking. Each of the students is evaluated and the scores earned by them are normalized to assess them uniformly. Based on the mean score earned by each of the student under each cognitive skill category, the skill level is set as low, medium and high. The skill set categorization helps in classifying the learners into three broad categories which would facilitate the suitable learning object to be followed and hence the knowledge competency level can be improved. Most of the existing methodology permits no classification of learners and it permitted the direct approach on improving the memory based skills alone. Thus the attempted approach is observed to be helpful as the learners are classified based on their cognitive skill. **Application/Improvements**: The results obtained by the proposed architecture are promising in assessing the learner's ability. The approach can be applied in any education system starting from high school to higher education.

Keywords: Adaptive Learning, Cognitive Skill, Learner Classification, Learning Management System

1. Introduction

Adaptive Learning includes three core elements such as content or Learning Object (LO) model, Learner Model and Instructional (LO delivery) Model. The content model refers to presentation style of a topic or domain content with learning outcome. It includes a learning sequence to be carried out in achieving the learning outcome. Cognitive skills, a psychological concept are the vital tools that facilitate one to successfully think, prioritize, design, understand, visualize, remember, create suitable associations and solve problems. In order to characterise the learning style, it is desired to understand the dominant cognitive skill of individual so as to decide on the learning style and its associated LOs. Thus, this paper focuses on classifying the learners according to their cognitive capability.

The major objective of 'education' is to nurturing one's development. Research is being conducted to identify the factors affecting teaching learning process so as to find a mechanism to improve it. Recently, many researchers are investigating the mentioned process and are trying to devise different methodologies to design an improving strategy. One of the promising methodologies identified is the learning style. For considering learning styles in education, the students learning styles need to be known first. According to Honey, Mumford and others[1] Learning Style (LS) is defined as "Specified patterns of behavior and/or performance according to which the individual approaches a learning experience[1]; a way in which the individual takes

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in new information and develops new skills; the process by which an individual retains new information or skills". Cassidy states that a LS as "The manner in which individuals choose, or are inclined to approach, a learning situation"[2] and Beebe, Mottet and Roach[3] viewed LS as "The way an individual perceives, organizes, processes and remembers information". Several learning style models have been proposed for defining and measuring learning styles[4–7]. Numerous research works had been proposed to detect and identify learning styles[8,9,24]. Some attempted towards the automation of the same[10–13]. The automation process mostly focused on the behavior of the learners[10,14]. Another perspective took forward for the learning style detection which considered cognitive skill of learner[15–19]. Recently, the issue is being approached using soft computing techniques, Riding and Rayner[21] designed a case based reasoning model[20], combined neural network with fuzzy logic[8], applied Bayesian Model[21], developed an automated rule based system, Chang et al. used genetic algorithm[23], Sanders and Bergasa-Suso approached the problem using K-NN[22], while Deborah et al. addressed the learning style detection using fuzzy logic[9]. The results of these attempts supported the existence of a relationship between cognitive traits and the learning style model especially with respect to the sensing/intuitive and the verbal/visual dimensions. However no significant correlation with other cognitive traits was established. Hence, an attempt is made to relate cognitive skills with the learning style. As a first step, to characterize the learners for learning style detection, a classification of learners based on cognitive skill is performed. The classified users thus form a part of the environment that is required for adaptive learning.

2. Learner Model of Adaptive Learning Environment

As a first step in expediting adaptive learning to support reinforcement model, an environment is to be modelled. An environment in Artificial Intelligence defines a surroundings or conditions on which an agent or living things perform. In the case of an education system, an environment involves learners, their capability, course and course materials and finally the level of competency attained. Therefore, the entire decision making process involves the factors such as: Learner's capability, Type of Course Material, Level of Competency. The environment for this domain appears to be episodic and dynamic to enclose the mentioned factors.

In order to build up the environment, initially learners are to be classified based on the learner's capability to form a learner model. The learner model is generated as depicted in Figure 1.

The Learner Model is intended to identify the type of the individual based on the cognitive skills possessed by them. Past Research has shown that cognitive skill in human being is classified as memory, concentration, perception and logical thinking and its composition as 15%, 20%, 25% and 40% respectively. In order to pursue engineering education and to improve the learning ability all these four skills are highly essential. However, each individual tend to possess various proportion of these skills. In order to impart the minimum competency of subject knowledge, it is desired to provide the learners with the materials that they can easily follow to assimilate the knowledge. Hence to provide the suitable materials, initially the users are categorised into four groups based on their cognitive skill. For performing the categorization, the responses received from them on undertaking the MCQs are considered.

Earlier, the questionnaires required for this assessment is stored in a Learning Environment Repository. With the help of a Learning Management System (LMS), the performance of each individual is recorded and results are retrieved in a structure format for further analysis. The following procedure is adopted to carry out the analysis.

```
Begin
  For each S_i
      For each CS_j
          Assess student's performance and grade S_Score
      End for
Rescale the score based on cognitive skill weightage
Normalize the Scores of all students as S_NScore
Compute the Average_score for each CS_j
For each S_i
 Check if (S_Nscore <= ("Average_score-0.1"))
              then assign S_i to Class = 1
  Elseif (S_Nscore > "Average_score – 0.1") and (S_Nscore
<= "Average_score +0.1")
              then assign S_i to Class = 2
Else assign S_i to Class = 3
```

Initially, MCQs on the chosen course is segregated based on the required cognitive skill. The questionnaire was prepared based on the opinion survey of bloom's taxonomy verb actions and a possible cognitive skill. Each student of the class is allowed to take up the initial screening test and

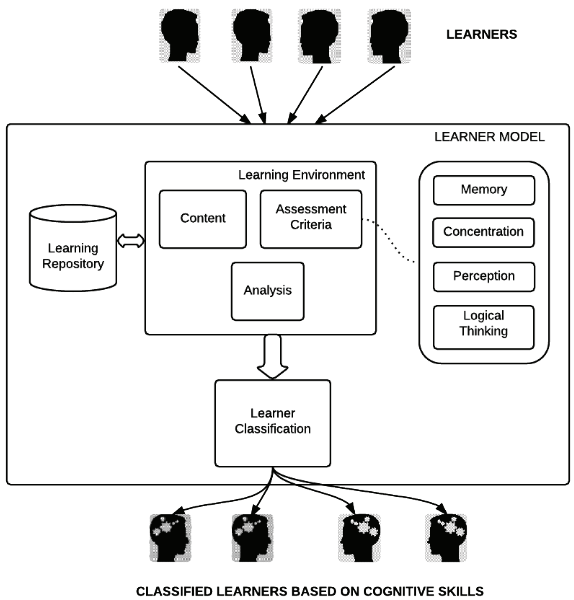


Figure 1. Learner model for adaptive learning environment.

an absolute grading is awarded. Assuming the normal human's cognitive skill composition the scores of each student under the different cognitive skill is scaled. To analyse the factors uniformly, the scores are normalised. The following Table 1 shows data collected by conducting initial assessment process to predict the learner's class.

2.1 Score Normalization

The scaled scores of each student are normalized using the one technique called Min-Max Normalization. Min-Max Normalization transforms a value A to B which fits in the range [M,N]. It is given by the formula below

$$B = \left(\frac{(A - minimum\ value\ of\ A)}{(maximum\ value\ of\ A - minimum\ value\ of\ A)} \right) * (N - M) + M$$

The normalization performs a linear transformation of original scores and fits the scores in the range of 0 to 1. Hence, for the further processing, data range uniformity is obtained. After having the data normalization, the mean score for each cognitive skill CS_j is computed.

Further the user classification is performed based on the following conditions:

if (S_Nscore < Average_score) and (S_Nscore <= "Average_score – 0.1") then S_i *= Class 1*
if (S_Nscore > "Average_score – 0.1" and S_NScore <= "Average_score +0.1") then S_i *= Class 2*
Else assign S_i *to Class 3.*

Where Class 1 is S_{low}, Class 2 is S_{med} and Class 3 is S_{high}.

Class 1 represents the users with low level of competency in the corresponding cognitive skill. Similarly Class 2 and Class 3 represent average level of competency and high level of competency in the cognitive skill. Considering the above mentioned conditions, the users are classified. According to the class, the materials are designed to improve one's competency level.

3. Results and Discussion

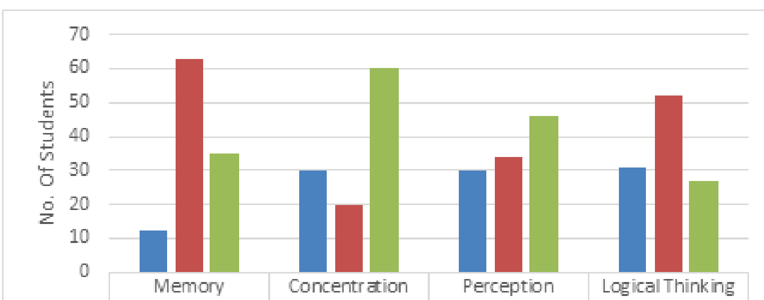
According to the sample data collected, it was observed the mean score of cognitive skill Memory as [0.75] and Concentration as [0.63], perception as [0.54] and Logical Thinking as [0.43]. Using these measures, it was found that 107 students categorised for each cognitive skill as low, average and high is as shown in Figure 2. The classified learners form the learner model of an environment that could be employed in an adaptive learning.

It was noted from the performance that, around 11% of learners ended up with poor memory skills while 57% learners of same level possessed moderate level of memory. 32% showed good memory skill. As far as concentration is concerned, in the chosen group, 27% had

Table 1. Initial assessment process for learner classification

	Observed Values				Normalized Values				Classified Values			
RegNo	**Mem**	**Con**	**Per**	**LT**	**Mem**	**Con**	**Per**	**LT**	**Mem**	**Con**	**Per**	**LT**
xxx1	8	8	7	6	0.6	0.71	0.58	0.5	s_{low}	s_{high}	s_{med}	s_{med}
xxx2	10	8	6	3	1	0.71	0.29	0.13	s_{high}	s_{high}	s_{low}	s_{low}
xxx3	10	8	8	7	1	0.71	0.67	0.63	s_{high}	s_{high}	s_{med}	s_{high}
xxx4	10	8	8	7	1	0.71	0.67	0.63	s_{high}	s_{high}	s_{med}	s_{high}
xxx5	9	8	7	6	0.8	0.71	0.58	0.5	s_{med}	s_{high}	s_{med}	s_{med}
xxx6	9	8	8	7	0.8	0.71	0.67	0.63	s_{med}	s_{high}	s_{med}	s_{high}
xxx7	9	7	7	6	0.8	0.57	0.48	0.5	s_{med}	s_{low}	s_{low}	s_{med}
xxx8	10	7	8	8	1	0.57	0.67	0.75	s_{high}	s_{low}	s_{med}	s_{high}
xxx9	10	7	8	9	1	0.57	0.77	0.88	s_{high}	s_{low}	s_{high}	s_{high}
xxx10	10	9	8	7	1	0.86	0.77	0.63	s_{high}	s_{high}	s_{high}	s_{high}
xxx11	9	6	8	9	0.8	0.43	0.67	0.88	s_{med}	s_{low}	s_{med}	s_{high}
xxx12	10	7	6	4	1	0.57	0.29	0.25	s_{high}	s_{low}	s_{low}	s_{low}
xxx13	10	9	8	6	1	0.86	0.67	0.5	s_{high}	s_{high}	s_{med}	s_{med}
xxx14	10	7	7	7	1	0.57	0.58	0.63	s_{high}	s_{low}	s_{med}	s_{high}
xxx15	9	6	7	7	0.8	0.43	0.48	0.63	s_{med}	s_{low}	s_{low}	s_{high}

Mem - Memory, Con - Concentration, Per - Perception, LT - Logical Thinking



	Memory	Concentration	Perception	Logical Thinking
Low	12	30	30	31
Med	63	20	34	52
High	35	60	46	27

Figure 2. Learner classification based on cognitive skills.

low level of concentration and 54% reported high level of concentration. For perception only 41% demonstrated high level. In case of logical thinking, a highly essential Cognitive Skill (CSs) for engineering education, majority of learners (75%) possessed only medium level and low level. Hence, from the obtained data it is inferred that the learners need to be strengthened in memory and concentration skill so as to see a significant rise in the other two CSs. Thus the environment is created with learners classified accordingly for each of the CSs.

4. Conclusion

A learner model to form a part of an adaptive learning environment is created. For each cognitive skill, the learners are classified according to the low, medium and high level of acquaintances of CSs. Indeed the learner model helps to create an environment with different classes where each class can be provided with suitable course materials for a significant improvement at that level or to the next level and thereby improving the level of knowledge attainment.

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