Adaptive MCQ Test Generation Based on Affective State Feedback

Kavita Kelkar[1] and Dr Jagdish Bakal[2]

[1] Sardar Patel Institute of Technolgy,Mumbai, India
kavitakelkar@somaiya.edu
[2] S S Jondhale College of Engineering, Dombivali, India
bakaljw@gmail.com

Abstract. There is a great requirement that online learning should become personalized and adaptive. The paper proposes an adaptive MCQ test system which dynamically adapts to feedback of learner's affective state during learning process. Cognitive levels are associated with questions in the test. The affective states can be emotions like confidence or confusion.. The system identifies the affective state of the learner, adapts the further questions in the test series in accordance with this affective state. The confused learner will get easier questions and confident learner will get more difficult questions. This process will continue for the learning activity. Thus test system becomes adaptive.

Keywords: Adaptive MCQ, Affective state, Fuzzy logic, Linear regression, Affective Learning system.

1 Introduction

Virtual learning is the need of current times. There are many existing virtual learning systems which deliver learning contents. [1] The learners follow these virtual learning systems for their learning requirements.

Such systems have a traditional feedback mechanism of learner's understanding through tests. Mostly such tests are of the type MCQ (Multiple choice questions). [2] After a learning activity, the learner is supposed to attempt the MCQ test to gauge his learning. The system calculates correctly answered questions solved by the learner. The learning activity completes here. There could be a case that the learner has not understood many concepts and is not able to solve questions. There is also possibility that the learner has solved most or all questions correctly. In other words learner may be exhibiting affective state of confusion or confidence [3].

We propose the design of adaptive test series in accordance to affective state exhibited by the learner. When confidence is displayed by the learner, more difficult questions are posed. When confusion is showed by the performance in the MCQ test, easier questions are posed. The adaptive test logic is based on affective state.

The correct answer score is indicative of learner's understanding level. When correct answer score is low, it would be expected of an ideal training system to repose the learning material and questions. With more confusion shown by the learner the system will pose easy questions. With lowered difficulty level questions learners can learn again, improve correct answer score and can then attempt more difficult level questions. This adaptive nature of virtual learning will ensure that learner's confusion is removed and learner has understood the topic.

When correct answer score is high, the ideal learning system should be able to adapt to the confidence shown by the learner. The next test should pose more difficult level questions. This test can recalculate the confidence level of the learner after a series of difficult level tests and confirm the learner's confidence in the topic. Adaptive tests in series can affirm the understanding of the topic by the learner.

The authors have designed the questions in the MCQ test based on well-known education technology standard Bloom's taxonomy. The questions are associated with difficulty level according to cognitive domain of Bloom's taxonomy [4]. Cognitive levels are various levels of understanding, namely knowledge, comprehension, application, analysis, synthesis and evaluation [5]. When a learner is able to answer a question of a particular level, it means that learner has exhibited respective level of cognition.

In the design of MCQ test, the system captures behavioral parameters of the learner along with correctness of the answer. The additional behavioral parameters are

1. Option changes (number of times learner changes the options before finalizing answer)
2. Time taken to solve a question (different cognitive level questions)
3. Time taken to solve whole test (time taken to solve the test where questions are from various levels of cognitive levels)

The adaptive test design proposed by authors in this paper has following steps;

1. Initial MCQ test generation logic on the basis of Cognitive level of Bloom's taxonomy
2. Identifying the affective state of the learner from the performance of the given MCQ test on a fuzzy scale.
3. If affective state is confidence, generate next test with more questions of higher cognitive level
4. If affective state is confusion, generate next test with more questions of lower cognitive level
5. Repeat the steps 2 to 4 till learner becomes confident in the topic.

Further sections comprise of explanation of adaptive test generation logic in detail. Section 2 explains cognitive level of Bloom's taxonomy and mapping different levels to MCQ test questions. Section 3 explains identification of confusion and confidence affective state. Section 4 elaborates exclusive algorithm for adaptive MCQ generation. Section 5 shows the implementation details and experimental results. Section 6 is Conclusion.

2 Cognitive Levels

Bloom's taxonomy is a classification of learning behaviors [4]. It has three domains namely cognitive, affective and psychomotor. Cognitive domain caters to knowledge

and understanding of the learning contents. As cognitive domain is about understanding, we associate cognitive domain levels to the questions in the MCQ test.
Cognitive domain: These levels show knowledge acquiring and intellectual skill development of learner. It indicates the thinking and expression pattern of the learner based on level of knowledge learned [5]. There are six levels in cognitive domain. The ordering from simple to complex level is: knowledge, comprehension, application, analysis, synthesis and evaluation [4], [5]. Each level's meaning is described in Table 1.

Table 1: Cognitive Levels

Level Number	Cognitive Level	Ability Description
1	Knowledge	remember previously learned material
2	Comprehension	understand and comprehend the learned material
3	Application	apply the learned material in various situations
4	Analysis	decode the learned material for better understanding of its constituent parts
5	Synthesis	construct the parts so as to formulate a new structure
6	Evaluate	judge the constructed structure so that a quantitative value is associated

In our MCQ system design, cognitive levels are mapped to all questions in the question set of a topic as per the Table 1.

3 Identifying Affective State

3.1 Affective state confusion and confidence

Confusion and confidence are learning attributes displayed by a learner. We define confusion and confidence of the learner.
Confusion is defined as lack of understanding and a state of uncertainty where learner is unable to decide how to act or what to do next. Confidence is learner attribute observed through six factors studying, understanding, verbalizing, clarifying, attendance and grades [6], [7].

3.2 Learner Test performance parameters for deriving affective state

Performance in the test is only one of the major indications of such affective state. Our system captures following behavioral parameters.

1) Correctness of the question (P1)
2) No. of times a user changes the options (P2)
3) Time taken per question (P3)

Using these parameters, we compute 'A' value, a fuzzy value, and affective state value. 'A' value lies between 0 to 1 which represents the affective state of confusion and confidence of a learner in a topic. 1 means the user knows the topic very well

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indicating affective state of confidence and, 0 means the user does not know the topic indicating affective state of confusion.

3.3 Linear regression for affective state

In order to derive ‘A’ value from P1, P2, P3 we establish linear regression equation

$$A= a*P1 + b*P2 + c*P3 \quad (1)$$

where a,b,c are coefficients of regression.

The explanation of deriving linear regression coefficients is as follows

1. P1 (Correctness) can have two values, 0 for wrong answer or 1 for correct answer.
2. P2 (Option changes) can have any integral value, where 0 is the best case where as anything greater than 2 is treated as bad. When learner is confident he will not keep on changing the answer. A confused learner unsure of answer will incline more to keep changing the options.

Table 2: Number of option changes per question to performance class

Option Changes	0	1	>=2
Class Value	0 (Best)	1 (Medium)	2 (Worst)

3. P3 (time per question) is divided into ranges, in accordance to Cognitive level of that question.

Table 3: Ideal time in seconds for level-wise questions

Time per question for Level 1,2	10 - 20s	20 - 40s	>= 40s
Time per question for Level 3,4	30 - 40s	40 - 80s	>=80s
Time per question for Level 5,6	120s	120 - 210s	>=210s
Class value	1	2	3

We then pass the above mentioned P1, P2, P3 class values, to our linear regression model, which returns a ‘A’ value for each question which will be between 0 to 1. The values of a,b and c (regression coefficients) are found in the training phase, each MCQ test attempted by the user becomes the test phase for the model. After getting a ‘A’ value for each question, we take average of all ‘A’ value for questions of a particular topic, generating a cumulative fuzzy value ‘A’ topic wise.

Thus ‘A’ value is generated which is the Affective state of the learner on basis of performance in the first MCQ test. ‘A’ value near to 0 indicates confusion and ‘A’ value nearing 1 indicate Confidence.

4 Adaptive MCQ test generation

Affective state value ‘A’ value acts as input to the adaptive test generation logic. From database of questions which are mapped to six Cognitive levels of Bloom’s taxonomy [4] , we decide the ratio of number of questions of respective level to be present in the next test in the series of adaptive tests. Low ‘A’ value indicates Confusion affective state. Here we will need more easy questions (level1, level2) to be put together in the test. High ‘A’ value indicates Confidence. So it will call for more difficult level questions to be bundled in the next test. Thus the test becomes adaptive to the affective state of the learner.

We pass ‘A’ value to the Inference Engine wherein we have divided the ‘A’ value into 10 ranges between 0 and 1. Each range corresponds to a class which has a ratio of the difficulty levels. We have mapped questions of knowledge and comprehension at level as 1, application and analysis at level 2 and synthesis and evaluation at level 3. They are as shown in Table 4.

Table 4: Mapping of Affective state value to ratio of level-wise questions in test

Range Of ‘A’ Value	Number of Questions in MCQ test of each level Level 1: Level 2: Level 3
0.00 - 0.09	15:0:0
0.10 - 0.19	13:2:0
0.20 - 0.29	10:5:0
0.30 - 0.39	7:7:1
0.40 - 0.49	5:8:2
0.50 - 0.59	3:10:2
0.60 - 0.69	2:8:5
0.70 - 0.79	2:5:8
0.80 - 0.89	1:3:11
0.90 - 1.00	0:0:15

Using this ratio we determine the number of questions to be asked from each level of a particular topic. Thus, using learner's affective state and obtained ‘A’ value, we determine how many questions of each level per topic are needed to generate next test. Next time the user gives the test, this ratio is accessed from the database, and the 15 questions of the test are generated according to the ratios, making the test adaptive. The following system model diagram depicts the described process.

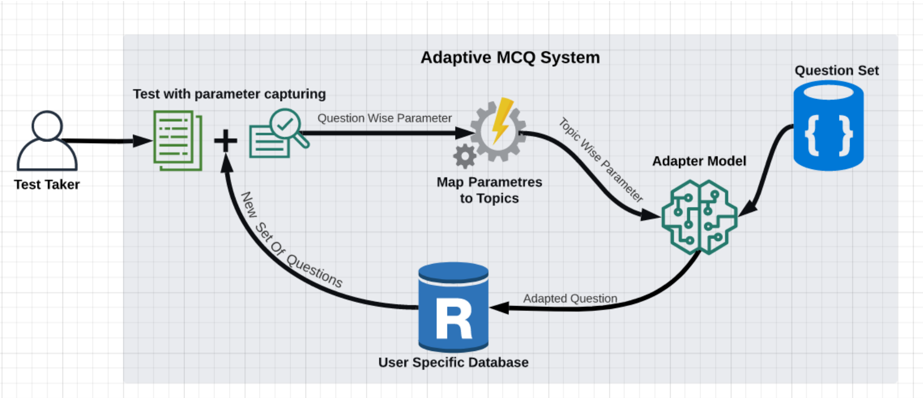

Fig.1 System Model Diagram

5 Experimental Results

5.1 Implementation details

The system is implemented as a web based system using Python, My-sql for back-end and HTML, javascript for front end with flask framework. Snapshots of the system are shown below.

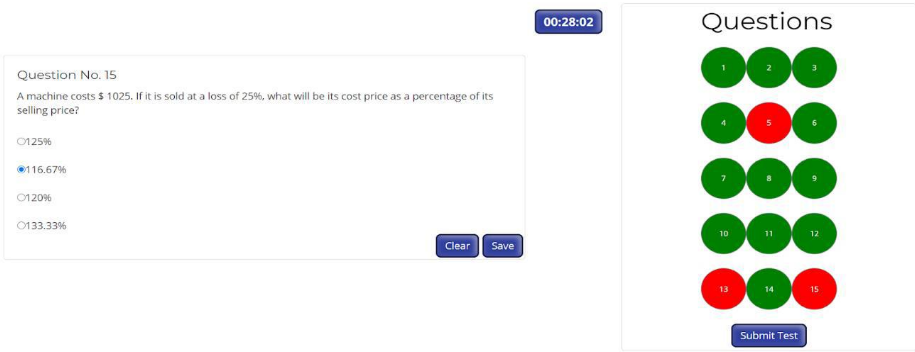

Figure2: Ongoing Test (Green signifies question attempted and Red signifies Question visited but unattempted)

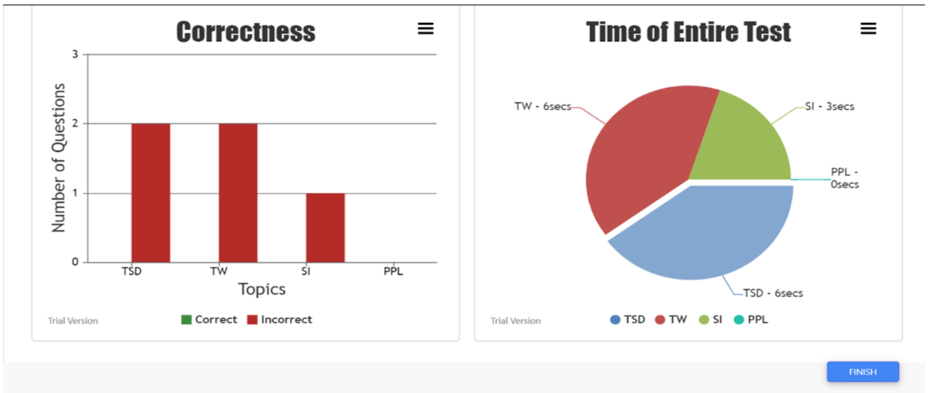

Figure 3: Bar Chart & Donut Chart showing captured performance parameters

5.2 Experiment description and Results

Experimental test scenario is depicted in the following steps

1. A learner undertook adaptive MCQ test for the first time.
2. The initial level-wise question assignment to learner was 15:0:0 considering Affective state 'A' value in the range 0.0 to 0.09 from Table 4.
3. The test was attempted and the parameters P1, P2, P2 (correctness of answer, option changes class, time for solving class) per question were captured, class values of which were 1, 1, 2.
4. P1, P2 and P3 parameters of 15 questions were captured by linear regression model the value of 'A' for this test was derived. Here 'A' = 0.34
5. From Table 4, the next test in series was generated with level-wise questions 7:7:1 from Table 4.
6. Learner kept attempting the test showing improvement in Affective state value. After fifth test 'A' value was derived to 'A' =0.75.
7. Thus through adaptive test generation based on affective state, the learner progressed from confusion to confidence affective state.

The system was used by 20 learners from Final year Computer Engineering. The author has maintained the log of every student's affective state per test and progression through test series. The learners could appreciate adaptiveness of the test system and moving towards confident affective state.

6 Conclusion

Adaptive MCQ test generation based on affective state of the learner gives the learner personalized experience. The system identifies the affective state of the learner not only through performance in the test but other behavioral parameters as option changes and time spent per question. The learner is identified as confused or confident on a

fuzzy scale. The adaptive test dynamically adapts to the affective state of the learner in series of MCQ tests.
Thus adaptive test generation is designed on the basis of affective computing, cognition level, linear regression model and fuzzy logic. The experimental results validate the proof of concept.

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