

ADAPTIVE COMPUTER-AIDED QUESTION SETTING SYSTEM

FIELD OF INVENTION

The present disclosure relates to an adaptive computer-aided system and method for selecting
5 a question for a user based on their similarity to past users who have used the system.

BACKGROUND

Multiple choice and open ended questions are frequently employed methods of objective
assessment for testing a range of well-defined or combination of lower-order and higher-order
10 skills. Computer-aided assessment systems can enhance the assessment process by
providing users with convenient access to a database of questions while providing records of
their progress for monitoring purposes. However, computer-aided learning systems are
typically unable to provide targeted assessment that focuses on questions of subject matter
that a user is relatively weak at answering correctly.

15 Further, the reliance on a fixed set of questions reduces the effectiveness of the assessment
once the student has exhausted the pool of questions since repeat questions that are
answered by a user may not be reflective of their actual ability but rather their ability to recall
the correct answer.

WO/2016/080907 discloses a data processing apparatus for teaching, the device configured
20 to keep a data record of questions and a data record of student answers to those questions.
A new user who answers a first question incorrectly is subsequently presented with a new
question that was answered incorrectly by a statistically significant number of other students
who also answered the first question incorrectly.

Accordingly, there exists a need for a computer-aided assessment system that assesses a
25 user's weaknesses holistically based on the user's performance to date are not simply based
on the last incorrectly answered question while taking into account the similarity of the user's
profile to that of other existing users along with similarities in behavioural patterns.

SUMMARY OF THE INVENTION

30 In one aspect of the invention, there is provided an adaptive computer-aided system for setting
a question for a user comprising a user dataset of past users, a templates dataset of question
templates, an answers dataset of answers of the past users to each question template in the

templates dataset, a processor configured to determine for each past user of the user dataset in comparison with the user, a user similarity score, determine from each answer, an answer adjustment derived from a corresponding answer result, wherein each answer adjustment incorporates the past user's user similarity score, obtain for each question template, a
 5 template similarity score incorporating each answer adjustment associated with each specific question template and select the question based on the question template having the highest template similarity score.

Preferably, the user dataset comprises a user profile data subset and a user answer metadata subset. Preferably, a contribution of the user profile data subset and the user answer metadata
 10 subset to the user similarity score is modified by a weight factor. Preferably, the weight factor is determined by the use of a machine learning algorithm. Preferably, the machine learning algorithm uses a stochastic gradient descent optimization algorithm. Preferably, the answer adjustment is weighted higher for correct answers and weighted lower for incorrect answers. Preferably, the question dynamically generated. Preferably, the question is pre-constructed.
 15 Preferably, the processor is further configured to update the user answer dataset and user answer metadata based on a user's response to the question. Preferably, the question is generated based on the question template having the highest template similarity score.

In another aspect of the invention, there is provided a method for setting a question for a user comprising the steps of determining for each past user of a user dataset in comparison with
 20 the user, a user similarity score, determining for each answer in a answers dataset, an answer adjustment derived from a result, wherein each answer adjustment incorporates the past user's user similarity score, obtaining for each question template, a template similarity score incorporating each answer adjustment associated with each question template and selecting the question template having the highest template similarity score.

25 In one embodiment the method further comprises the step of generating the question based on the question template having the highest template similarity score. In one embodiment the method further comprises the step of updating a user answer dataset and a user answer metadata based on the user's response to the question.

BRIEF DESCRIPTION OF DRAWINGS

30 Fig. 1 depicts a simplified block diagram of the adaptive computer-aided system.

Fig. 2 depicts a method of selecting a question for a current user based on his/her similarity to existing users.

DETAILED DESCRIPTION OF THE INVENTION

In the following detailed description, reference is made to the accompanying drawings, which form a part hereof. The illustrative embodiments described in the detailed description, drawings and claims are not meant to be limiting. Other embodiments can be utilized, and other changes can be made, without departing from the spirit or scope of the subject matter presented herein.

Fig. 1 is a simple block diagram of a computer-aided system **100** according to an embodiment of the present invention comprising a non-transitory computer readable storage medium **101** storing datasets including a user dataset **102** of past users, a templates dataset **103** of question templates, an answers dataset **104** of answers of the past users made in relation to each template in the templates dataset **103** and instructions **105** to be executed by a processor **106**, a main memory **107** for holding datasets and instructions **105** and a transmitting and receiving unit **108** for communication with a client device.

The datasets may be organised in a database which may be unstructured such as in a flat file or in a more structured format such as in a relational database. The user dataset **102** contains a plurality of attributes associated with each user. Any attribute that is relevant in distinguishing a user from other users from an academic standpoint can be included in the user dataset. Non-limiting examples of relevant attributes that can be employed include age, gender, school, grade and class ranking as depicted in Table 1. Attributes relating to a user's behaviour patterns while answering a question from a specific question template in other words, behavioural attributes may also be included. Non-limiting examples of suitable behavioural attributes include whether a user answered a question from a specific question template correctly the first time the question was presented to him, the time taken to answer the question, the type of wrong answer selected and whether the user changed his/her answer selection/input before submitting his response. The inventors have found behavioural attributes to be particularly relevant in determining similarity amongst users.

User ID	Age	Gender	School	Grade	Class Ranking
0	10	M	ACS	P5	0.05
1	11	F	MGS	P6	0.30
2	10	M	FFS	P5	0.60
3	8	M	NYP	P3	0.10
4	6	F	NYP	P1	0.50

5	9	F	STJ	P3	0.20
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Table 1

The templates dataset **103** contains data relating to a plurality of questions templates. Each question template in turn contains the necessary data that can be used in the presentation of a question to the current user. Non-limiting examples of attributes that may be assigned to a question template for the purposes of categorization include cognitive levels, assessment objectives, topics and sub-topics. Any attribute that can be used to differentiate a question from another question may be used.

In some embodiments, the question is dynamically generated each time a question template with the highest template similarity score is selected. Each question template would further comprise variables, domains, constraints and formulas for the answer and distractors (incorrect answers). The manner in which a template similarity score can be obtained is described in greater detail below.

The answers dataset **104** records the last answer made by a user to a question derived from a specific question template, and may also record whether the result of the last answer was correct or incorrect. It is expected that there will be gaps in the data in instances where a user has yet to answer his/her first question from a particular question template. In some embodiments, the specific response selected or inputted by the user may be included in the answers dataset **104**.

Referring to Fig. 2, the instructions **105** are such that they are operative by the processor **106** to determine for each past user of the user dataset **102** in comparison with the user, a user similarity score **201**, determine from each answer, an answer adjustment derived from a corresponding answer result, wherein each answer adjustment incorporates the past user's user similarity score **202**, obtain for each question template, a template similarity score incorporating each answer adjustment associated with the question template **203** and select the question based on the question template having the highest template similarity score **204**.

The user similarity score is a quantitative measure of similarity between the user dataset of a current user who is actively using the system and that of past users. The higher the similarity score, the more similar a past user is to the current user. Specifically, the user similarity score is obtained by comparing the attributes recorded in the user dataset of a current user with the corresponding attributes of each of the past users that exist in the user dataset **102** using a similarity measure. A non-limiting example of a similarity measure that may be employed is cosine similarity and is depicted by the formula below:

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}},$$

where A and B are vectors representing the current user and a past user. Other non-limiting examples of similarity measures that may be employed include Euclidean distance, Manhattan distance, Minkowski distance, Jaccard similarity, Mahalanobis Distance and Jaccard Similarity may be used. Any similarity measure may be employed.

The first step in determining the similar score would be to convert the categorical values present in the user dataset **102** into numeric values. Known methods of categorical variable handling include but are not limited to label encoding and dummies method. The conversion of Table 1 from categorical values into numerical values is depicted in Table 2:

User ID	Age	Gender	School	Level	Class Ranking
0	10	1	0	2	0.05
1	11	0	2	3	0.30
2	10	1	1	2	0.60
3	8	1	3	1	0.10
4	6	0	3	0	0.50
5	9	0	4	3	0.20

10 *Table 2*

Once converted, and assuming User ID 5 is the current user, cosine similarity or any other suitable similarity measure can then be applied to Table 2 to compare User IDs 0 through 4 to the current user yield the following result as depicted below in Table 3.

User ID	User Similarity Score
0	0.909875
1	0.973306
2	0.942751
3	0.975719
4	0.954239

Table 3

15 Based on the result obtained, User ID 3 is the most similar to our current user, User ID 5.

In some embodiments the user dataset **102** is categorised into subsets comprising a user profile data subset and a user answer metadata subset, the user profile data subset and the user answer metadata subset both providing a separate contribution to the user similarity score where the separate contributions of the user profile data subset and the user answer metadata subset. In some embodiments, their contributions are modified by a weight factor.

A similarity measure such as cosine similarity is then applied to each subset separately to obtain two user subset similarity scores for each user as depicted in Table 4.

User ID	User Profile Data Subset Similarity Score	User Answer Metadata Subset Similarity Score
0	0.948205	0.978442
1	0.946194	0.900714
2	0.980743	0.990320
3	0.923466	0.964224
4	0.975436	0.936237

Table 4

These subsets are groups of attributes that are related to each other, for example, the user profile data subset contains attributes that relate to user demographics while the user answer metadata subset as explained previously, relates to the user's behaviour while answering questions. More importantly, the subset classification is premised on the understanding that certain groups of attributes are stronger determinants of user similarity and should be given increased weight when determining the user similarity score. This is reflected in some embodiments by assigning a weight factor, specifically a higher weight factor to subsets that are stronger determinants of user similarity as depicted in Table 5 relative to attributes that are weaker determinants of user similarity. The sum of the weight factors assigned to each subset is a value should not exceed 1. Further subsets with attributes that are relevant in determining similarity amongst users can also be added.

Subset	Weight Factor
User Profile Data	0.1
User Answer Metadata	0.9

Table 5

The weight factor is then applied to each subset similarity score to obtain a weighted subset similarity score for each of the subsets:

Weighted subset similarity score = subset similarity score * weight factor

The combined similarity score can then be obtained by adding the subset similarity scores as seen in table 6.

User ID	Combined Similarity Score
0	0.9754183
1	0.905262
2	0.9893623
3	0.9601482
4	0.9401569

Table 6

- 5 In some embodiments, the weight factor is a predetermined value. In some embodiments, the weight factor is determined by a machine learning optimization algorithm such as stochastic gradient descent where the target function is an exponential function $f(s^{\rightarrow}) = a \cdot e^{-w^{\rightarrow} \cdot s^{\rightarrow}}$, in which $s^{\rightarrow}$ is the vector of user profile data subset similarity score and user answer metadata subset similarity score, and $w^{\rightarrow}$ is the vector of corresponding weights. Optimization techniques such as Stochastic Gradient Descent are hence used in regression to find the weights for student user profile data subset similarity score and user answer metadata subset similarity score such that it is the closest to the target function. It will be apparent to the skilled addressee that other machine learning optimization algorithms may be employed. Other suitable optimization techniques that may be used include, but are not limited to, Root Mean Square Propagation (RMSProp) and Adaptive Moment Optimization (Adam).

In order to select a question template which will form the basis for presenting a question to the current user, a template similarity score for each question template is obtained with the aim of selecting the question template that best fits the desired outcome. Let's assume that the objective is to select a question template the present user is most likely to get wrong. For each question template, each past user's last response and result (if any) is retrieved from the answers dataset **104** with an answer adjustment determined for each last response. Starting with a base value, the template similarity score for a question template is modified as follows: a correct result leads to a negative answer adjustment of the base value, while an incorrect result leads to a positive answer adjustment of the base value. Prior to modification of the base value, each answer adjustment (positive or negative) first incorporates the corresponding past user's user similarity score as obtained previously by for example, multiplication with the corresponding user's user similarity score. In some embodiments, the positive adjustment may

vary depending on the specific incorrect answer made by the past user. For example, the positive adjustment may be higher if the past user selected/inputted the same incorrect answer as the current user. The process is repeated for each question template. In this manner, the results from users who are more similar to the current user are weighted higher than less similar users. The template similarity score for a question template is thus obtained by incorporating all corresponding answer adjustments into the base value. The question template with the highest template similarity score is the selected question template and will serve as the basis for selecting and presenting a question to the current user. Once the question presented is answered by the current user, the response to the question may be used to update the corresponding entry in the answers dataset **104** and the user dataset **102**, specifically the user answer metadata subset.

In some embodiments, a pre-constructed question with the same categorisation as the selected question template is selected to be presented to the current user. In some embodiments, a question with the same categorisation as the selected question template can be dynamically generated using data from the selected question template. This is advantageous as it avoids presenting a repeated question to the student who may know the answer from memory rather than solving the problem using his or her own ability. A combination of pre-constructed and dynamically generated questions may also be used.

In a non-limiting example, the dynamic generation of a question can be modelled as a Constraint Satisfaction Problem (CSP) where the question template comprises a variable set, a domain set, and constraint set and formulas for the answer and distractors (incorrect answers). The variables store the solution while the domain set consists of discrete values from which a solution is selected. The variables are necessarily in congruence with the categorization of its respective question template. Consider the question below:

Mr. Tan has 5 apples, 3 of them are red, how many are green?

The question can first be tokenized as follows:

<person> has <x> <fruit>, <a> of them are <color_1>, how many are <color_2>

Working backwards, the tokenized question can be mapped to a CSP as follows:

Variables:

person, fruit, color_1, color_2, x, a, and b (hidden variable, namely the answer)

Domain of values:

person: Last names

fruit: fruit names

color_1: color names

5 color_2: color names

x: positive integer

a: positive integer

b: positive integer

Constraints:

10 color_1 != color_2

$2 < x < 50$

$1 < a < x$

Answer:

$b = x - a$

15 **Distractors (wrong answers):**

x, a, $x + a$

The domain subsets for example integers a and x can be randomly generated and a solution i.e. one that includes all the variables and does not violate the constraints can be generated and selected at random to ensure a large number of permutations of questions based on a question template can be generated at random. In the context of the present application, an optimal solution is not required. Non-limiting examples of suitable known techniques for obtaining a solution include backtracking, constraint propagation and heuristics which may be implemented as processor executable instructions stored on a non-transitory computer readable data medium. While the above example concerns the dynamic generation of a multiple-choice mathematics problem, the inventors envisage the use of the system and

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methods described herein in any application that requires the dynamic generation of a question and an answer(s) thereto regardless of topic/subject matter and/or delivery type, for example multiple choice, open-ended questions.

- 5 It will be readily understood by a skilled person that the manner in which the datasets are organised is arbitrary and is intended to facilitate explanation and understanding of the necessary attributes that need to be recorded and accessed by the system and is not intended to be limiting. For example, the results may be part of the user answer metadata subset instead of the answers dataset.

CLAIMS

1. A computer-aided system for setting a question for a user comprising:
a user dataset of past users;
5 a templates dataset of question templates;
an answers dataset of answers of the past users made in response to each question template in the templates dataset;
a processor configured to:
determine for each past user of the user dataset in comparison with the user, a user similarity
10 score;
determine from each answer, an answer adjustment derived from a corresponding answer result, wherein each answer adjustment incorporates the past user's user similarity score;
obtain for each question template, a template similarity score incorporating each answer adjustment associated with the question template;
15 select the question template having the highest template similarity score.
2. The computer-aided system according to claim 1, wherein the user dataset is categorised into subsets comprising a user profile data subset and a user answer metadata subset, the user profile data subset and the user answer metadata subset each providing a separate contribution to the user similarity score.
- 20 3. The computer-aided system according to claim 2, wherein the separate contribution of the user profile data subset and the user answer metadata subset are modified by a weight factor.
4. The computer-aided system according to claim 3, wherein the weight factor is determined by use of a machine learning algorithm.
- 25 5. The computer-aided system according to claim 4, wherein the machine learning algorithm uses a stochastic gradient descent optimization algorithm.
6. The computer-aided system according to any of claims 1-5, wherein the answer adjustment is weighted higher for correct answers and weighted lower for incorrect answers.
7. The computer-aided system according to any of claims 1-6, wherein the question is
30 dynamically generated.

8. The computer-aided system according to any of claims 1-6, wherein the question is pre-constructed.
9. The computer-aided system according to any of claims 1-8, wherein the processor is further configured to update the answers data set and user dataset based on a user's response to the question.
10. A computer-implemented method for setting a question for a user comprising the steps of:
- determining for each past user of a user dataset in comparison with the user, a user similarity score;
- 10 determining from each answer, an answer adjustment derived from the result, wherein each answer adjustment incorporates the past user's user similarity score;
- obtaining for each question template, a template similarity score incorporating each answer adjustment associated the question template; and
- selecting the question based on the question template having the highest template similarity score.
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11. The method according to claim 10, further comprising the step of:
- generating the question based on the question template having the highest template similarity score.
12. The method according to claim 10, further comprising the step of:
- 20 updating a user answer dataset and a user answer metadata based on the user's response to the question.