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Neural network-based data analysis for medical-surgical nursing learning*

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Abstract— **This paper presents the results of a project on neural network-based data analysis for knowledge clustering in a second-year course on medical-surgical nursing. Data was collected from 208 nursing students which performed one Multiple Choice Question (MCQ) test at the end of the first term. A total of 23 pattern groups were created using snap-drift. Data obtained can be integrated with an on-line MCQ system for training purposes. Findings about how students are classified suggest that the level of knowledge of the individuals can be addressed by customized feedback to guide them towards a greater understanding of particular concepts.**

I. INTRODUCTION

Multiple Choice Questions (MCQs) are an effective way to assess students. When students attempt such questions, they generate data that is invaluable for understanding their learning process. That data, which provides a simple depiction of their knowledge concerning a defined topic, is generally lost. In this project, the data is captured and automatically analyzed by a neural network. Then, lecturers receive groups of answers generated by the neural network, thus procuring a picture of how their students are progressing in their learning. The tutors can see which concepts have been mastered and which ones have not. This information can be employed to address any issues that students did not understand and provide them with customized feedback. The feedback is created according to a set of common responses from the students to a set of questions on the given topic, and is not tied to any particular question. Thus, the learner is encouraged to think through the questions and resolve errors or misconceptions independently.

The virtual learning system presented in this paper provides a generic method for intelligent analysis and grouping of student responses that is applicable to any medical area of study. This paper is structured as follows: after this introduction, Section II justifies the importance of this research by reviewing the related literature. Section III presents the Snap-Drift Neural Network (SDNN), a neural network that supports the learning process to present diagnostic feedback. Section IV describes the case study in which the data collected from 208 nursing students is presented, and discusses the results obtained. Finally, Section V draws some conclusions and outlines future work.

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II. LITERATURE REVIEW

A number of advantages can be found in the use of MCQs [1], [2], [3]: rapid feedback, automatic evaluation, perceived objectivity, easily-computed statistical analysis of test results, and the re-use of questions from databases as required, thus saving time for instructors. MCQs have nonetheless been criticized [4], [5], [6]: significant effort is required to construct MCQs, they only assess knowledge and recall, and are unable to test literacy and creativity. However, some nurse-educators [7] [8] suggest that higher cognitive domains such as critical thinking skills can also be assessed with MCQs.

Some studies [9] are found in the nursing literature claiming that MCQs can fulfill the criteria for effective assessment suggested by Quinn [10]: practicality, reliability, validity, and discrimination. However, significant effort is required in preparation to produce reliable and valid examination tools. MCQs should be short, understandable and discriminating. Moreover, both in the realm of the theory and in that of the practice, the use of MCQ testing can cause individuals to learn incorrect information, false knowledge that persists over time [11]. Feedback processes which address both inaccurate knowledge and metacognitive errors [12] are proposed to neutralize these potential negative MCQ consequences.

Educational data mining is a newer sub-field of data mining which can provide insight into the behavior of lecturers, students, managers, and other educational staff and can be used to take better decisions about their educational activities [13]. There is recent research [14] that describes an Intelligent Information Access system which automatically detects significant concepts available within a given clinical case and allows students to gain understanding of the concepts by providing direct access to enriched related information from Medlineplus, Freebase, and PubMed. In our proposal, the students groups (states of knowledge) produced by a neural network can be used to prepare specific feedback which addresses misconceptions and guides students towards a greater understanding of particular concepts. To the best of the authors' knowledge, no other studies related to MCQs and formative assessments have employed any similar form of intelligent analysis of the students' responses in the health field.

III. E-LEARNING SYSTEM

To interpret the students' answers and to gain insights into the students' learning needs, a SDNN approach is proposed. SDNN provides an efficient means of discovering a relatively small and therefore manageable number of groups of similar answers [15]. In the following sections, the e-learning system based on SDNN is briefly described.

A. Snap-Drift Neural Networks (SDNN)

The snap-drift neural network algorithm (SDNN) is an unsupervised learning algorithm used for high speed data categorization. The method has been successfully applied to many real data sets [16], [17]. The snap-drift algorithm employs a modal learning approach [18], [19] that switches between the two different modes of learning snap and drift. Snap is based on logical intersection or fuzzy AND; and drift is based on learning vector quantization (LVQ) [20]. Using these two modes of learning improves the speed of the learning process and takes advantage of the strength of each mode. The learning process is different from the error minimization and maximum likelihood methods in Multilayer Perceptrons (MLPs) [21]. Such methods have no requirement for the features to be statistically significant within the input data while the snap-drift algorithm discovers common features in the data to form different categories. The SDNN architecture consists of an input layer, a feature extraction or distributed layer and a feature grouping or selection layer [18]. On presentation of data patterns at the input layer, the feature extraction layer of the SDNN learns to group them according to their features using snap-drift [16], [19]. The weights corresponding to the neurons with the highest activations are adapted. Weights are also normalized to ensure that only the angle of the weight vector is adapted. This guarantees that a recognized feature is based on a particular ratio of values, rather than absolute values. The output winning neurons from the feature extraction layer act as input data to the selection layer of the SDNN. Snap-drift learning is applied to this layer as well. Through this learning process the output groupings of the data are formed via self-organization. A more detailed description of the SDNN algorithm can be found in [17], [19].

B. Training the Neural Network

The SDNN is trained with the students' responses to questions on a particular topic in a course. Before training, each of the responses from the students is encoded into binary form, in preparation for presentation as input patterns for SDNN. Table I shows examples of a possible format of questions for five possible answers, and some encoded responses. During training, on presentation of each input pattern, the SDNN will learn to group the input patterns according to their general features. The groups are recorded, and represent different states of knowledge regarding a given topic, inasmuch as they contain the same incorrect and/or correct answers to the questions. The instructors receive the groups in the form of templates of student responses.

TABLE I
EXAMPLE OF INPUT PATTERNS FOR SDNN.

Codification	**a - 00001; b - 00010 ; c - 00100; d - 01000 ; e - 10000**
Response	**Encoded response**
[a, d, c, b, a]	[0,0,0,0,1,0,1,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,0,0,1]
[d, a, b]	[0,1,0,0,0,0,0,0,0,1,0,0,0,1,0]

The training relies upon having representative training data. The number of responses required to train the system so that it can generate the states of knowledge varies from one domain to another. When new responses are still creating new groups, more training data is required. Once new responses are not creating new groups, it is because those new responses are similar to previous responses, and enough responses to train the system reliably are already available. The number of groups formed and the training of the system depend on the variation in student responses.

IV. PROCEDURE AND RESULTS

A. Participants

SDNN has been used in an medical-surgical nursing course at the Catholic University of San Antonio. *Clinical Nursing I* (CN) is a second-year course which focuses on the processes to be the cause of illness, the pathophysiology of diverse health disorders and the nursing care to individuals with medical-surgical problems. Students attend 2 h/week of lectures in the first term and 14 hours of clinical skills practice. This term takes place during a 15-week period. The assignments proposed in this course cover different learning objectives in the cognitive domain of Bloom's Taxonomy which involves knowledge and development of intellectual skills. There are six categories, each holding a different degree of difficulty: knowledge, comprehension, application, analysis, synthesis and evaluation. The subjects were the following: different routes of medication administration, basic life support, wound care, drains, fluid balance, surgical instruments, central venous pressure measurement, surgical area behaviour, oxygen therapy and arterial blood gas, intravenous catheter insertion and care, urethral catheterization, enteral nutrition, breath sounds, and other related subjects.

B. Experiment

To investigate the effectiveness of SDNN, one experiment was designed and conducted during the first term of the academic year 2011/12. In the experiment, data was collected from 208 nursing students which performed one MCQ test at the end of the term. Most participants (82.2%) were female, with a mean age of 25.7 (SD: 7.36) years. A test consisting of ten MCQs related to surgical-medical nursing, with five options each, was prepared. All of the MCQs were composed taking into consideration a range of quality factors presented in [22] [23]. Students were asked to complete the test in a maximum of 35 minutes. The experiment was completed in a written exam session. Table II shows an English translation of one of the 10 questions used.

TABLE II

EXAMPLE OF A MCQ.

For lung auscultation, normal breath sounds are:
- a. Rhonchi
- b. Wheezing sound
- c. Vesicular breath sounds
- d. Rales
- e. No noise is to be heard in a normal auscultation

The students' answers were used for training the SDNN. The neural network created a total of 23 pattern groups with five outlier groups (of size 1). The average group size is 9. Two groups (68 and 32) are particularly large, representing very common responses. These large groups include four or more questions which are given the same answer by the members of the group. Table III shows all the groups obtained by the SDNN. Let us take, for instance, group 1. All of its members chose the answer *c* to question 1, *b* to question 7, *d* to question 8, and *e* to question 9. The answers to the remaining questions vary within the group. All the students of this group answered *d* or *no answer* to question 2, *b* or *e* or *no answer* to question 3, *c* or *no answer* to question 4, *d* or *no answer* to question 6, and disparate answers to questions 5 and 10 (symbol *). Hence, the educator can easily spot the common mistakes in the groups of the student answers highlighted by the tool. Notice that each group is produced by the neural network on grounds of the commonality between the answers to some of the questions (to four of them in our example). In this experiment, with a 10-question test, the groups had 3 to 10 answers in common.

TABLE III

STUDENTS' STATES OF KNOWLEDGE. G: GROUP IDENTIFIER; S: SIZE.

G	S	q1	q2	q3	q4	q5	q6	q7	q8	q9	q10
1	32	c	d/n	b/e/n	c/n	*	d/n	b	d	e	*
3	7	c/d	d/n	*	c	*	d	b	n	*	*
4	6	c	n	n	c	n	n/d	b	n	n	d
5	1	n	a	b	e	n	b	b	n	e	b
6	1	d	d/n	c	b	n	e	n	n	d	d
7	1	a	d	b	d	d	b	n	n	d	d
8	68	c	e	*	c	*	d	b	d	e	d/n
9	6	c	e	*	c	*	n	b/e	*	e	n
12	14	c	*	*	b	*	*	b	d	e	*
13	3	c	*	*	b	*	*	b	*	*	*
16	1	b	n	e	c	a	d	e	d	e	d
17	6	c	e	*	*	*	n	e	d	e	d
18	2	*	e	*	d	n	*	b	d	e	*
19	3	c	e	b	n	e	n	b	e	*	d/n
20	1	c	d	c	n	b	d	b	d	c	d
22	9	c	d/n	b	c	*	*	*	d	*	*
23	2	c	*	n	*	e	*	b	*	e	*
25	13	c	e	*	*	*	d	*	d/n	e	*
26	14	c/n	d	*	*	e	d/n	*	*	e	d/n
27	5	d	e	b	c	*	d	b	d	*	n
28	2	*	e	*	*	*	d	*	*	e	n
29	9	d	e	*	c	*	d/n	b	d	e	*
30	2	c	e	*	c	*	*	e	n	*	n

Figure 1 illustrates the behavior of students in terms of the states of knowledge produced by SDNN in the test carried out, and shows some knowledge state transitions. A justification for calling the states "states of knowledge" is to be found in their self-organization in the layers. For example, a student who receives feedback on state 23 (three correct answers), should progress via one of the states in the next layer, such as state 1 (four correct answers), then state 8 (six correct answers), before reaching the "state of perfect knowledge" (state 31) which represents correct answers to all questions. In this example, students in state 1 do not understand concepts such as anamnesis or procedures such as pulmonary angiography, and are not able to raise key questions to obtain information useful in formulating a diagnosis and providing medical care to a patient with cough. Moreover, these students have difficulties in identifying breath sounds. In contrast, students in state 8 do know and understand how to perform a pulmonary angiography.

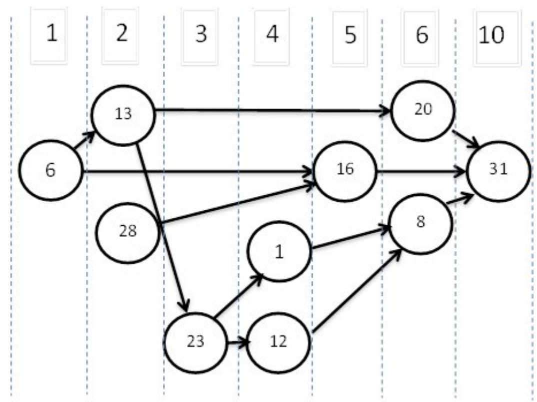

Fig. 1. Ten knowledge states and transitions layered by number of correct answers.

Finally, clustering was also applied to form groups of questions which were answered similarly (correctly or incorrectly) by all the students. Only clusters of one question were obtained, which shows that the questions were well formulated inasmuch as they did not measure the same or similar knowledge.

C. Discussion

The student response groups can help to understand the progress of the students and to identify misunderstood concepts that can be addressed in subsequent face-to-face sessions. Instructors can prepare feedback giving hints as to what the student has not understood and providing explanation of a concept or a reference to material that the student needs to read. It should be relatively short, with reference to certain concepts that the student needs to revise. Then, the students have the opportunity to reflect on their answers and do some further reading. Notice that the student should not be told exactly which answer(s) is/are wrong because that would not encourage reflection and cognition. An example of feedback is provided in Table IV and Figure 2.

Although the results obtained can be considered satisfactory from a formative point of view, there is still room for improvement. The number of outliers is high (21.73% of the groups). Students of three outliers answered correctly one (minimum recorded) to three questions. This leads to the speculation that some students did not take their time

TABLE IV

EXAMPLE OF FEEDBACK.

Auscultation of a patient with breath problems is performed by listening through a stethoscope. To achieve optimum results the following is to be considered: - Position: sitting, head and shoulders slightly leaning forward for auscultation of the back; arms raised above the head for auscultation of the sides of the chest; and shoulders and spine straight, for auscultation of the front part of the chest. - Breathing: slow, deep breathing through the mouth. Auscultation must be short to prevent hyperventilation.

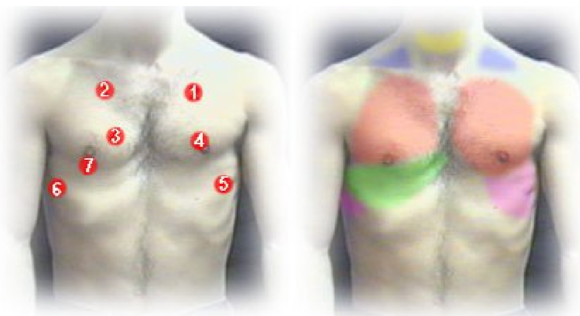

Fig. 2. Image illustrating auscultation points.

to read and reflect on the questions, and even chose the answers randomly. Thus, some of these groups might not be considered significant. In contrast, students of two outliers responded correctly to five and six questions, which is the maximum number of questions answered correctly in a group.

V. CONCLUSIONS AND FUTURE WORK

In this paper, a novel method for using snap-drift in nursing education has been presented. The most innovative aspect of the proposal is the use of a neural network to discover groups of similar answers which represent different states of knowledge of nursing students. Feedback texts targeting the level of knowledge of individuals can be associated with each of the pattern groupings, and can be composed to address misconceptions that may have caused the incorrect answers common to that pattern group. These data might be recorded in a database, and a tool might be used for monitoring the progress of the students and guiding them towards a greater understanding of particular concepts. New student responses can be used to retrain the neural network and see whether refined groupings are created which can be used by the educator to improve the feedback. Once designed, MCQs and feedback can be reused for subsequent cohorts of students.

In future work, it is intended to apply the SDNN to a cohort of students using a diagnostic tool to provide automatic feedback. This tool will support the construction of knowledge state transition diagrams and statistical data collection, which could help instructors to analyze the difficulty of the MCQs and the evolution of the students during their learning process. Currently, the system is under further development and a GUI is being used for uploading data, training, optimization of the neural network and generating groups. Therefore, the tutor will soon be equipped with a supportive interface for creating feedback and personalized assignments according to the level of knowledge of the individuals.

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