A Soft Computing Approach to Quality Evaluation of General Chemistry Learning in Higher Education

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Abstract. In contemporary societies higher education must shape individuals able to solve problems in a workable and simpler manner and, therefore, a multidisciplinary view of the problems, with insights in disciplines like psychology, mathematics or computer science becomes mandatory. Undeniably, the great challenge for teachers is to provide a comprehensive training in General Chemistry with high standards of quality, and aiming not only at the promotion of the student's academic success, but also at the understanding of the competences/skills required to their future doings. Thus, this work will be focused on the development of an intelligent system to assess the Quality-of-General-Chemistry-Learning, based on factors related with subject, teachers and students.

Keywords: General Chemistry · Higher Education · Logic Programming · Knowledge Representation and Reasoning · Artificial Neural Networks.

1 Introduction

In recent decades technological courses in different areas become increasingly essential in modern societies. Many of these areas are related with basic sciences like chemistry, physics or biology, making it necessary to include such curricula in the study plans of these courses. Indeed, only a solid background in these areas will give students a multidisciplinary vision of the problems. However, frequently these disciplines are not properly framed in the curricula or adjusted to the student's previous knowledge. In particular, in General Chemistry (GC), some studies show that it is seen as a difficult and boring discipline, and thus jeopardize the role that it should play in the student`s training [1, 2]. Therefore, the main challenge is to highlight the

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relationships between academic syllabus and daily life, aiming to avoid the indifference of some students when attending GC. Therefore, teachers must create stimulant-learning environments that may awake students' interest [2]. However, success in studies is a complex phenomenon that involves a large number of factors, some of which depend on the student, others on the teachers, and even on the institutions [3]. Thus, the assessment of university education should be focused not only on the student`s progress but also on the development of abilities and skills necessary for access to employment, lifelong education and personal success [4]. Consequently, it is difficult to assess the Quality Evaluation of General Chemistry Learning (QEGQL) since it needs to consider different conditions with complex relations among them, where the available data may be incomplete/unknown (e.g., absence of answers to some questions presented in the questionnaire), and/or contradictory (e.g., questions relating to the same issue with incongruous answers). In order to overcome these difficulties, the present work reports the founding of an intelligent computational framework that uses knowledge representation and reasoning techniques to set the structure of the information and the associate inference mechanisms, i.e., it will be centered on a Proof Theoretical approach to Logic Programming (LP) [5], complemented with a computational framework based on Artificial Neural Networks (ANNs), selected due to their dynamics like adaptability, robustness, and flexibility [6].

2 Knowledge Representation and Reasoning

Knowledge and belief are generally incomplete, contradictory, or even error sensitive, being desirable to use formal tools to deal with the problems that arise from the use of partial, contradictory, ambiguous, imperfect, nebulous, or missing information [5, 6]. The LP paradigm has been used in knowledge representation and reasoning in different areas, such as Model Theory [7], and Proof Theory [5, 6]. In this work the proof theoretical approach is followed in terms of an extension to LP. An Extended Logic Program may be seen as a finite set of clauses given in the form:

$$
\begin{array}{l}
\{ \;\; p \leftarrow p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m \\
\quad ?\,(p_1, \cdots, p_n, not\ q_1, \cdots, not\ q_m) \;\; (n, m \geq 0) \\
\quad exception_{p_1} \quad \ldots \quad exception_{p_j} \;\; (0 \leq j \leq k),\;\; being\ k\ an\ integer \\
\} :: scoring_{value}
\end{array}
$$

where "*?*" is a domain atom denoting falsity, the p_i, q_j, and p are classical ground literals, i.e., either positive atoms or atoms preceded by the classical negation sign ¬ [5]. Under this formalism, every program is associated with a set of abducibles [7], given here in the form of exceptions to the extensions of the predicates that make the program. The term $scoring_{value}$ stands for the relative weight of the extension of a specific predicate with respect to the extensions of the peer ones that make the overall program.

In order to evaluate the knowledge that can be associated to a logic program, an assessment of the Quality-of-Information (QoI), given by a truth-value in the interval 0…1, that stems from the extensions of the predicates that make a program, inclusive in dynamic environments, is set [8]. Thus, $QoI_i = 1$ when the information is known (positive) or false (negative) and $QoI_i = 0$ if the information is unknown. Finally for situations where the extension of $predicate_i$ is unknown but can be taken from a set of terms, $QoI_i \in]0 \ldots 1[$. Thus, for those situations, the QoI is given by:

$$QoI_i = 1/Card \tag{1}$$

where Card denotes the cardinality of the abducible or exception set for i, if the abducible or exception set is disjoint. If the abducible or exception set is not disjoint, the clause's set is given by $C_1^{Card} + \cdots + C_{Card}^{Card}$, under which the QoI evaluation takes the form:

$$QoI_{i_{1 \le i \le Card}} = 1/C_1^{Card}, \cdots, 1/C_{Card}^{Card} \tag{2}$$

where C_{Card}^{Card} is a card-combination subset, with Card elements. The objective is to build a quantification process of QoI and measure one's Degree of Confidence (DoC) on the argument values or attributes of the terms that make a predicate's extension, taking into consideration their domains [9]. Thus, the universe of discourse is engendered according to the information presented in the extensions of such predicates, according to productions of the type:

$$predicate_i - \bigcup_{1 \le j \le m} clause_j\left(\left(QoI_{x_1}, DoC_{x_1}\right), \cdots, \left(QoI_{x_n}, DoC_{x_n}\right)\right) :: QoI_i :: DoC_i \tag{3}$$

where ∪ and m stand, respectively, for set union and the cardinality of the extension of $predicate_i$.

3 Methods

Aiming to develop a predictive model to assess the QEGQL a questionnaire was designed specifically for this study and applied to a cohort of 127 General Chemistry students. This section describes briefly the data collection tool and how the information is pre-processed.

3.1 Questionnaire

The questions included in the questionnaire were organized into three sections, where the former one includes the questions related with student attendance in different types of GC classes and the number of study hours (Table *Student Related Factors* in Fig. 2). The second one comprises the questions related with the student's opinions about the subject GC (Table *Subject Related Factors* in Fig. 2). The last one includes questions related with the opinion of students about the GC trainer (Table *Teacher Related Factors* in Fig. 2).

3.2 Data Pre-processing

Aiming at the quantification of the qualitative information obtained via the questionnaire, and in order to make easy the understanding of the process, it was decided to put it in a graphical form. Taking as an example a set of 3 (three) questions regarding a particular subject (where the possible answers are *low*, *moderate*, *high* and *very high*) a unitary radius circle split into 3 (three) slices is itemized (Fig. 1). The marks in the axis correspond to each of the possible answers. If the answer to question 1 is *high* the area correspondent is $\pi \times 0.75^2/3$, i.e., $0.19\,\pi$ (Fig. 1(a)). Assuming that in the question 2 are marked the answers *high* and *very high*, the correspondent area ranges in the interval $\pi \times 0.75^2/3\ \cdots\ \pi \times 1^2/3$, i.e., $0.19\,\pi\ \cdots\ 0.33\pi$ (Fig. 1(b)). Finally, in question 3 if no answer is ticked, all the hypotheses should be considered and the area varies in the interval $\pi \times 0.25^2/3\ \cdots\ \pi \times 1^2/3$, i.e., $0.08\,\pi\ \cdots\ 0.33\pi$ (Fig. 1(c)). The total area is the sum of the partial ones and is set in the interval $0.46\,\pi\ \cdots\ 0.85\pi$ (Fig. 1(d)). The normalized area is the ratio between the area of the figure and the area of the unitary radius circle. Thus, the quantitative value regarding the subject in analysis is set to the interval $0.46\ \cdots\ 0.85$.

4 Results and Discussion

It is now possible to build up a knowledge database given in terms of the extensions of the relations (or tables) depicted in Fig. 2, which denote a situation where one has to manage information in order to evaluate the Quality-of-Learning of the GC students. Indeed, the *Subject*, *Student*, and *Teacher Related Factors* tables are populated with the responses to the issues presented in the questionnaire, where some incomplete, default and/or unknown data is present. For instance, in the former case the response to the question related with the *coherence syllabus/objectives* is unknown (depicted by the symbol $\perp$), while the response to the question associated to the *coherence teaching methodologies/objectives* is not conclusive (*High/Moderate*).

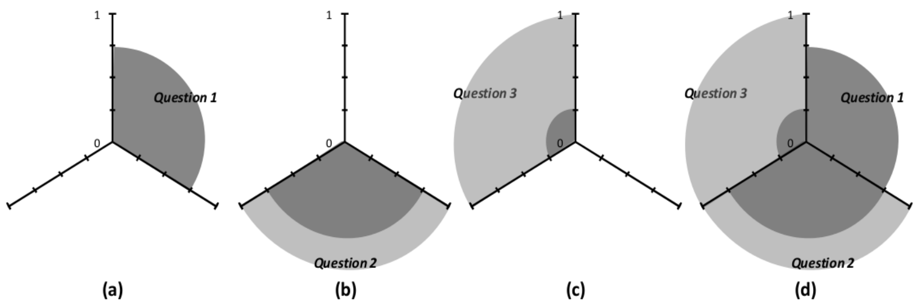
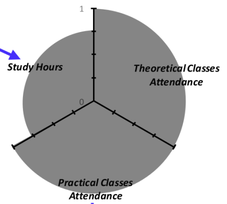
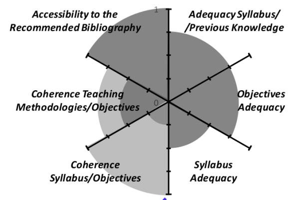


Fig. 1. A view of the questions qualitative evaluation process.

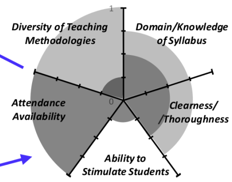
Subject Related Factors						
#	*Adequacy Syllabus/ /Previous Knowledge*	*Objectives Adequacy*	*Syllabus Adequacy*	*Coherence Syllabus/Objectives*	*Coherence Teaching Methodologies/Objectives*	*Accessibility to the Recommended Bibliography*
1	High	High	Moderate	⊥	High/Moderate	Very High
2	Low	Moderate	Moderate	Moderate	Moderate	High
…	…	…	…	…	…	…
127	Very High	Very High	High	High	Very High	Very High

Student Related Factors			
#	*Theoretical Classes Attendance*	*Practical Classes Attendance*	*Study Hours*
1	Very High	Very High	High
2	High	High	High
…	…	…	…
127	Very High	Very High	Very High





General Chemistry Learning Quality			
#	*Student Issues*	*Teacher Issues*	*Subject Issues*
1	0.85	[0.33, 0.64]	[0.48, 0.66]
2	0.56	0.31	0.27
…	…	…	…
127	1	[0.53, 1]	0.85



Teacher Related Factors					
#	*Domain/Knowledge of Syllabus*	*Clearness/Thoroughness*	*Ability to Stimulate Students*	*Attendance Availability*	*Diversity of Teaching Methodologies*
1	High/Moderate	High/Moderate	Low	Very High	⊥
2	Moderate	Moderate	Moderate	High	Moderate
…	…	…	…	…	…
127	Very High/High	Very High	⊥	Very High	⊥

Fig. 2. A knowledge base fragment.

In order to quantify the information present in the *Subject*, *Student*, and *Teacher Related Factors* tables the procedures already described above were followed. Applying the algorithm presented in [9] to the table or relation`s fields that make the knowledge base for QEGQL (Fig. 2), and looking to the DoC_s values obtained as described in [9], it is possible to set the arguments of the predicate *quality_evaluation_of_g(eneral)_c(hemistry)_l(earning)* ($quality_{gcl}$) referred to below, that also denotes the objective function with respect to the problem under analyze.

$$quality_{gcl}: Stud_{ent\ Issues}, Teacher_{Issues}, Subj_{ect\ Issues} \rightarrow \{0,1\}$$

where 0 (zero) and 1 (one) denote, respectively, the truth values *false* and *true*. Exemplifying the application of the algorithm presented in [9] to a term (clause) that presents feature vector ($Stud_{ents\,Issues} = 0.71$, $Teacher_{Issues} = 0.25 \ldots 0.56$, $Subj_{ect\,Issues} = \perp$), one may have:

$$\{ \quad \neg\, quality_{gcl} \left((QoI_{Stud}, DoC_{Stud}), (QoI_{Teacher}, DoC_{Teacher}), (QoI_{Subj}, DoC_{Subj}) \right)$$

$$\leftarrow not\; quality_{gcl} \left((QoI_{Stud}, DoC_{Stud}), (QoI_{Teacher}, DoC_{Teacher}), (QoI_{Subj}, DoC_{Subj}) \right)$$

$$quality_{gcl} \underbrace{\left((1,\ 1), \quad (1,\ 0.95), \quad (1,\ 0) \right)}_{\substack{attribute`s\ quality-of-information \\ and\ respective\ confidence\ values}} :: 1 :: 0.65$$

$$\underbrace{[0.71,\ 0.71]\ [0.25,\ 0.56]\ [0,\ 1]}_{attribute`s\ values\ ranges}$$

$$\underbrace{[0, 1] \qquad [0, 1] \qquad [0,\ 1]}_{attribute`s\ domains}$$

$$\} :: 1$$

4.1 Artificial Neural Networks

The model presented previously shows how the information comes together and how it is processed. In this section, a data mining approach to deal with the processed information is considered. A hybrid computing approach was set to model the universe of discourse, where the computational part is based on ANNs, which are used not only to structure data but also to capture the objective function's nature (i.e., the relationships between inputs and outputs) [10].

Now, looking at Fig. 3, we shall see a case being submitted to a QEGQL's assessment (its QoI's and DoC's values stand for the inputs to the ANN). The output is given in terms of a QEGQL's value and the degree of confidence that one has on such a happening. In this study 127 responses to the questionnaire were considered (i.e., one hundred and twenty seven terms or clauses of the extension of predicate $quality_{gcl}$ were considered). To ensure statistical significance of the attained results, 30 (thirty) experiments were applied in all tests. In each simulation, the available data was randomly divided into two mutually exclusive partitions, i.e., the training set with 67% of the available data, used during the modeling phase, and the test set with the remaining data (i.e., 33%), used after training in order to evaluate the model performance and to validate it. The back propagation algorithm was used in the learning process of the ANN. As the output function in the pre-processing layer it was used the identity one, while in the other layers it was used the sigmoid one.

Table 1 presents the coincidence matrix of the ANN model, where the values presented denote the average of 30 experiments. A glance at Table 1 shows that the model accuracy was 94.2% for the training set (82 correctly classified in 87) and 92.5% for test set (37 correctly classified in 40). Thus, the predictions made by the ANN model are satisfactory, attaining accuracies higher than 90%.

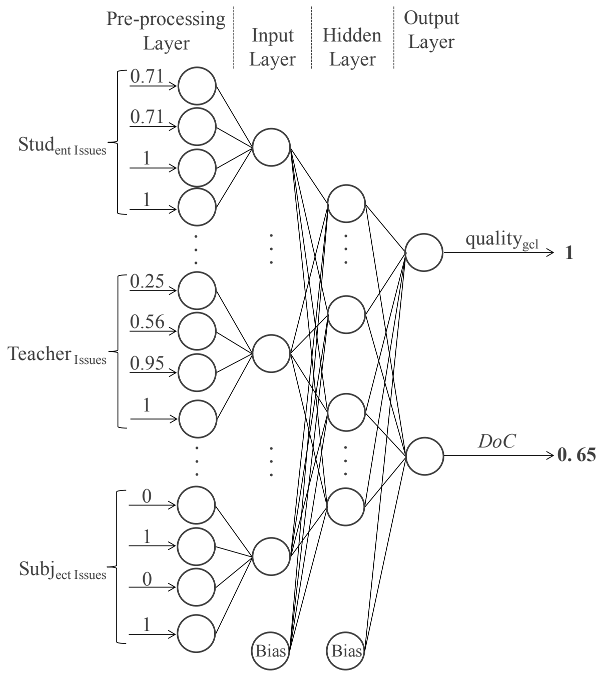


Fig. 3. The Artificial Neural Network Topology.

Table 1. The coincidence matrix for ANN model.

Target	**Predictive**			
	Training set		Test set	
	True (1)	False (0)	True (1)	False (0)
True (1)	62	2	29	1
False (0)	3	20	2	8

5 Conclusions

A QEGQL performance measurement is not only an inestimable practice, but something of utmost importance in a Higher Education context. The problems faced by contemporary society require from the Higher Educational Institutions the highest standards of quality in training future professionals. To meet this challenge it is necessary that the educational practice and the simultaneous evaluation of its impact on the students' learning process be intertwined. However, it is difficult to assess the QEGQL since it is necessary to consider different variables and/or conditions with complex relations entwined them, where the data may be incomplete, contradictory, and even unknown. This approach not only allows for the assessment of QEGQL but it also permits the estimation of a measure of confidence associated with such an evaluation. In fact, this is one of the added values of this method that arises from the complementarity between Logic Programming (for knowledge representation and reasoning) and the computing process based on ANNs (selected due to their dynamics like adaptability, robustness, and flexibility). Furthermore, this new methodology for problem solving may be used to assess the quality of learning in other subjects since the analyzed data do not refer explicitly to the contents taught, but how the learning process is organized.

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