Chapter 5
The Problem of Knowledge Elicitation from the Expert's Point of View

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5.1 Introduction

The aim of the e-learning environment under study is the implementation of an educational system suitable not only for teaching but also for the evaluation of teaching the English language to deaf individuals. This chapter focuses on the assessment part where an expert system is being used. Expert systems technology is a subfield of artificial intelligence which is based on the idea that knowledge can be transmitted from a human to a computer. The actual aim of expert systems is the implementation of an e-consultant who not only will give advice but also will give explanations if necessary (Turban & Aronson, 2001). The proposed expert system aims at achieving assessment of deaf students in the context of teaching English. The significant components of this expert system are a database centralizing all questions and possible answers, a database including tutorials/lessons, an interface as well as the significant part under study, namely a neural system and/or a neurofuzzy system that allows the system to make trustworthy inferences.

Below we briefly present research conducted so far on the field of student assessment and the wider field of student modeling using artificial intelligence techniques.

Indeed, artificial intelligence has proved to be a fruitful tool when applied to current educational research streams such as student modeling, natural language dialogue (language processing for simulating human dialogues), cognitive modeling (for human thinking simulation), complete systems and evaluation, as well as authoring tools, knowledge acquisition, and development tools (Lane, 2006). Among the fields mentioned above, student modeling seems to be one of the greatest challenges for researchers since it is considered a keyword for personalized interaction between humans and a hypermedia system and consequently for adaptive learning, which has proved to be an efficient way to maximize learning results

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(Frias-Martinez, Magoulas, Chen, & Macredie, 2005). Student modeling consists of the student model and the diagnostic part which performs student diagnosis (Stathakopoulou, Magoulas, Grigoriadou, & Samarakou, 2004).

The student model is one of the components of an Intelligent Tutoring System which provides a description of student-related information such as his knowledge level, skills, or even preferences, while diagnosis is the inference process which in the end updates the student model.

In order for this kind of intelligence to be achieved, researchers have adopted many Artificial Intelligence methods. The most famous among them are neural networks, fuzzy logic, as well as several search methods such as genetic algorithms.

Neural networks are on the top of the researchers' choice since they provide a system with the ability to recognize patterns, to derive meaning from vague data, and to identify matching in similar cases (Frias-Martinez et al., 2005). Fuzzy set theory is widely used since it can deal in a reliable way with human uncertainty and it obtains smooth modeling of human decision making. Genetic algorithms are ideal for optimal expert knowledge representation. Finally, neurofuzzy synergism is getting more and more popular in this area since it seems to overcome obstacles that come up when each of the methods involved is solely applied (Al Hamadi & Milne, 2004). Below we present several typical examples of the application of these methods in student's diagnosis.

A neurofuzzy system has been used in order to obtain maximization of adaptability in business education tutoring. For the training of the network the student's data that come up during interaction are being used (Kinshuk, Nikov, & Patel, 2001).

Grigoriadou et al. incorporated fuzzy logic and multicriteria decision making in INSPIRE (Intelligent System for Personalized Instruction in a Remote Environment), a web-based Adaptive Educational Hypermedia System (Grigoriadou, Kornilakis, Papanikolaou, & Magoulas, 2002).

Mir Sadique and Ashok applied the architecture of the Adaptive Neuro Fuzzy Inference System (ANFIS) in the field of Intelligent Tutoring Systems. The system that came up examined learners' memory, concept understanding, and possible deficiencies and finally obtained reliable classification of their performance (Mir Sadique & Ashok, 2004).

A system implementing a Neural Network Genetic Programming method has also been proposed, aiming at creating a reliable evaluation tool substituting an e-tutor. The system was trained through data extracted from an educational project called DEDALOS and through the assessment given by an expert (Vrettaros, Pavlopoulos, Vouros, & Drigas, 2008).

5.2 Description of the System and Knowledge Elicitation

According to the structural and functional details of the e-learning procedure, the attribution factor of an expert system and therefore, of the e-learning model's synergy, is the codification and the content of the input and output of an expert system

as well as the structure, formulism and content of the questionnaires database which require further attention and adroit handling.

The evaluation procedure of teaching deaf individuals pertains to the accomplishment of ESOL (English for Speakers of Other Languages) models of levels 1 and 2. Those levels consist of five sections which with ascending order of priority are [A], [B], [C], [D], and [E]. Section [A] represents the letter recognition and alphabetical order, section [B] represents spelling and vocabulary, section [C] represents grammar and sentence structure, section [D] represents reading, and section [E] represents writing.

According to the e-learning environment specifications of ESOL, the input and output parameters of an expert system can be specified undoubtedly, while at the same time their translation is simple and direct enough.

About the input, altogether per question there are five couples of parameters, which are: $a = \{a_{val}, a_{rel}\}$, $b = \{b_{val}, b_{rel}\}$, $c = \{c_{val}, c_{rel}\}$, $d = \{d_{val}, d_{rel}\}$, and $e = \{e_{val}, e_{rel}\}$.

That is to say, each couple answers to a section of the language of a specific level. Parameter a describes the letter recognition and alphabetical order of section [A], parameter b correlates with spelling and vocabulary of section [B], parameter c represents grammar and sentence structure of section [C], the respective parameter for reading of section [D] is d, while the ability of writing of section [E] is quantified with parameter e. The index (value) represents the evaluation of the particular section according to a given answer, while the index (relevance) recognizes the grade of relevance/weight of a specific question among the contents of a section.

The evaluation values of the input parameters a_{val}, b_{val}, c_{val}, d_{val}, and e_{val} derive from the universe of discourse $S = \{-1\} \cup [0,1]$. If a section is not examined by a question of the respective parameter, the domain is defined with the value –1. An answer which is incorrect according to a section leads to a respective value zero (0), while the value of the parameter of a section is one (1) if the chosen answer is correct according to that section. Similarly, answers which are partially correct have their values lie in the interval [0,1]

On the other hand, one could claim that the relevance parameters a_{rel}, b_{rel}, c_{rel}, d_{rel}, and e_{rel} characterize the question instead of the probable answers. Although that is true, the negotiation with relative parameters as a part of a given answer is convenient and more governable from evaluation point of view (as further explained below). As a result, the relevance/weight is considered to vary in the interval [0,1], where the value zero (0) or values near zero mean low relevance, value one (1) or values near one mean high relevance and all the other values of weight similarly vary between. However, it should be underlined that the relevance parameters are common and same for all the answers to a given question.

Based on the above, for *single-select questions*, the craftiest method for information supply (records) in the input of an expert system, relative to the five sections, is the sequence in an ordered form by ten values for the parameters of the input pairs:

a_{val}	a_{rel}	b_{val}	b_{rel}	c_{val}	c_{rel}	d_{val}	d_{rel}	e_{val}	e_{rel}

For example, let's consider a question that exhibits low relevance to section A, high relevance to section C, and medium relevance to section B. Let's also suppose that the question under consideration does not contain information about sections D and E. Now, let's also consider an answer to the previous question which is correct according to section A, partially correct according to section C, incorrect according to section B, and obviously does not contain any information about sections D and E. Such an answer results in a sequence set of ten values in the universe of discourse $S = \{-1\} \cup [0,1]$. In addition, it is obvious that the above-mentioned sequence of the ten values can be directly coded as a numerical string similar to the following:

				String of single-select questions					
a_{val}	a_{rel}	b_{val}	b_{rel}	c_{val}	c_{rel}	d_{val}	d_{rel}	e_{val}	e_{rel}
1	0.1	0	1.5	0.7	0.9	−1	0	−1	0

This way, the specific string of single-select questions can be easily imported as input to an expert system.

For *multi-single-select questions*, according to the specifications of e-learning environment by ESOL, the craftiest method for information supply in an expert system, relative to the five sections above, is the sequence of the input parameters in an arranged form, as follows:

String of multi-select questions			
Relevance values of sections	Correct answer	Evaluated learner's answers	Evaluation values of sections for every answer
$a_{rel}b_{rel}c_{rel}d_{rel}e_{rel}$	$c_1c_2c_3c_4...c_n$	$a_1a_2a_3a_4...a_n$	$a_{val}b_{val}c_{val}d_{val}e_{val}$

In the above codification of multi-select questions for information supply (records) as input in an expert system in an e-learning environment, the values in the second column (correct answer) and in the third column (learner's answers) are in binary form, i.e., "0" or "1", where "0" means "FALSE" and "1" means "TRUE". The first bit, c_1 of the correct answer or a_1 of the learner's answer, refers to the first answer of the selected question. The second bit, c_2 or a_2, refers to the second selected answer, etc. The last bit, c_n or a_n, refers to the nth answer of the selected question. It is obvious that for each question with n multi-selections, the above binary codification of the correct answer is just one, but the number of all the learner's possible answers is 2^n. Among those possible answers only several are noticeable while the rest of them are considered as irrelevant, selection that is always handled with caution by an expert pedagogical.

Hence, in multi-select questions for information supply in the input of an expert system in an e-learning environment, there are records which consist of five (5) sections with the five (5) sections relevance values, of the binary codification

domains of the correct answer with n bits, which are as many as the select answers of the questions, of the binary codification domains of the learner's answers with n bits, and of n times the five (5) domains with the five (5) sections evaluation values, which are as many as the select answers of the question.

As an example, for a question with relevance values [4,0,0,1,0] respectively for the five (5) sections a_{rel}, b_{rel}, c_{rel}, d_{rel}, and e_{rel}, with six (6) select answers where the correct ones are 2, 3, and 6, i.e., $c_1c_2c_3c_4c_5c_6 = [011001]$, while the learner's choice as correct answers are 1, 2, and 3, i.e., $a_1a_2a_3a_4a_5a_6 = [111000]$, and with six (6) times the evaluation values $[0, -1, -1, 1, -1]$ respectively for the five (5) sections a_{val}, b_{val}, c_{val}, d_{val}, and e_{val} for each time, the record for information supply in the input of an expert system in an e-learning environment will have 47 domains arranged in the form:

$$[4,0,0,1,0][011001][111000][0, -1, -1, 1, -1][0, -1, -1, 1, -1]$$
$$[0, -1, -1, 1, -1][0, -1, -1, 1, -1][0, -1, -1, 1, -1][0, -1, -1, 1, -1]$$

About the output of both types of questions, single-select questions and multi-select questions, the observation or even the monitoring on the functional and relevant characteristics of an expert system leads to the conclusion that the output parameters of the system are six (6), nominally y_1, y_2, y_3, y_4, y_5, and y_6. The first five parameters are the evaluations/estimation of the language skills per section, while the sixth parameter represents the overall evaluation of the user's overall language skills, as follows:

y_1 = letter recognition and alphabetical order skills
y_2 = spelling/vocabulary skills
y_3 = grammar/sentence structure skills
y_4 = reading skills
y_5 = writing skills
y_6 = overall language skills *(in fact, it is the weighted average of $y_1 - y_5$, representing a general evaluation of the learner's language level, as an expert pedagogical would define it in a real scenario).*

It is obvious that the output parameters are continuous. The evaluation is considered to be normalized in the continuous interval [0,1], because of the fact that the outputs of an expert system represent an estimation which is related to a specific language section. The translation of the final numerical values is simple: zero means no language skills, one means perfect language skills, whereas all other levels of language skills can be evaluated using similar numerical interferences. The output values, which are already numerically encoded, can be inputted to the e-learning environment as an arranged array of six values:

y_1	y_2	y_3	y_4	y_5	y_6

Let us suppose that the next evaluation is real for a student:

0.6 = letter recognition and alphabetical order skills
0.4 = spelling/vocabulary skills
0.2 = grammar/sentence structure skills
0.5 = reading skills
0.3 = writing skills
0.4 = overall language skills

This six-valued sequence, which is ordered and includes continuous elements, could be directly encoded as a numerical string, similar to the following:

y_1	y_2	y_3	y_4	y_5	y_6
0.6	*0.4*	*0.2*	*0.5*	*0.3*	*0.4*

This way, final outputs are directly available to the rest e-learning environment.

It is considered by pedagogical experts that a learner who selects one combination of answers could show more or less understanding than a learner who selects another. Training data values are assigned to specific combinations of answer options.

Evaluation values and training data values are the same for single-select questions as there is only one correct answer option. However, in multi-select questions evaluation values and training data values may differ. In multi-select questions more than one answer is required in order to be completely correct. The learner may still demonstrate partial understanding by selecting say two out of three correct answers.

In this example, "Which three adjectives can you use to describe a car?" the training data values are assigned to five answer option combinations. A, B, C, D, and E refer to the learning areas while OS is an overall skill value and represents the pedagogical expert's view of the learners overall language skills based on the combination of selected answers (Table 5.1).

Which three adjectives can you use to describe a car?

Even though combinations 2, 3, and 4 are not completely correct, the pedagogical expert considered that they demonstrated an understanding of the question and assigned positive values to them. If the learner selects any other combination, data values of 0 are assigned for areas that are relevant to the question and –1 for areas that are not. 0 is assigned as an overall skill value.

The above discussion, which is according to the ESOL specifications, for the adroit codification and the content of the inputs and the outputs, as well as the structure, formulism, and content of the questionnaires database, pertains to the use of neural networks and neurofuzzy technologies for modeling the input–output relation of the e-learning expert system for the automatic prediction of evaluation values of teaching the English language to deaf individuals. Indeed, neural networks and neurofuzzy models are a very fruitful choice when it comes to mining complex patterns in noisy or incomplete data (Frias-Martinez et al., 2005).

Table 5.1 Encoding of students' answers

Answer option combination code	Answer option combination	A	B	C	D	E	OS
1	New (correct) Smart (correct) Small (correct)	−1	1	1	1	−1	1
2	New (correct) Young (incorrect) Smart (correct)	1	0.6	0.6	0.6	−1	0.6
3	New (correct) Smart (correct) Happy (incorrect)	−1	0.6	0.6	0.6	−1	0.6
4	New (correct) Young (incorrect) Small (correct)	−1	0.6	0.6	0.6	−1	0.6
5	All other combinations	0	−1	−1	0	−1	0

Neural networks and neurofuzzy technologies have already been successfully applied to many prediction problems with similar inputs/outputs features (Shavlik & Eliassi, 2001). The present report studies the purpose of applying the neural networks and neurofuzzy technologies on modeling the automatic evaluation of deaf individuals' answers in questions on five sections in an e-learning environment of an expert system.

5.3 Language Skills Database

The e-learning environment's semantic context core is situated around the utilized Language Skills Database. A closer insight reveals the two constituting elements of language skills database, which namely are the Questionnaires Knowledgebase (denoted as QK) and the Tutorials/Lessons Database (denoted as TLDB). During all phases of the proposed e-learning process, questions or questionnaires are interchanged interactively with corresponding lesson/tutorial sessions.

Questionnaires knowledgebase contains the whole series of questions and possible corresponding answers, regarding all three learning phases. Questionnaires knowledgebase is associated directly to the inputs of the expert system, namely, users' answers are applied to the expert system's inputs after a trivial transformation.

Teaching sessions, skill tutorials, and language lessons comprise the tutorials/lessons database. Though the connection between the expert system's outputs and the contents of tutorials/lessons database is not directly visible, it exists and moreover proves determinant. A specific teaching/instructing session or lesson/tutorial sequences of such sessions are controlled by the output values. Suppose a pedagogical expert has defined certain thresholds that determine the basis for

language skills sections. By taking into consideration both factors (the expert system's outputs and the pedagogical expert's thresholds), the language sections whose assessment is not satisfactory need further teaching/tutoring. Consequently, the appropriate elements which are designed so as to enhance the individual's partial language knowledge are being retrieved from tutorials/lessons database and furthermore are being utilized appropriately by the e-learning environment. The structure of language skills database is presented below Fig. 5.1.

Fig. 5.1 Language skills database
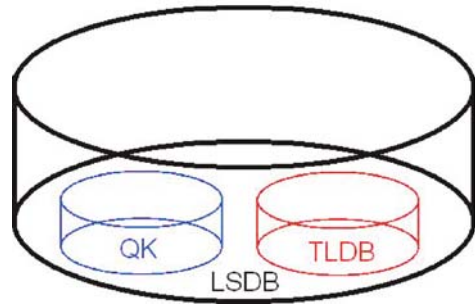
5.4 Adaptive Fuzzy E-Learning Subsystems

The technology of fuzzy inference systems is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if-then rules and fuzzy reasoning. A typical fuzzy inference system for knowledge processing follows three stages: fuzzification of the input data, conduction of fuzzy inference based on fuzzy data, and defuzzification of the output in order for the final outcome to be produced (Frias-Martinez et al., 2005). Fuzzy logic has found successful applications in a wide variety of fields such as control systems (Bugarin & Barro, 1998), medical diagnosis (Meesad & Yen, 2003; Sendelj & Devedzic, 2004), job matching (Drigs, Kouremenos, Vrettos, & Kouremenos, 2004), computer security (Reznik & Dabke, 2004), user modelling (Kuo & Chen, 2004; Vrettos & Stafylopatis, 2002), etc. Because of its multidisciplinary nature the fuzzy inference system is known by numerous other names, such as fuzzy-rule-based system, fuzzy expert system, fuzzy model, fuzzy associative memory, and simply fuzzy system.

The basic structure of a fuzzy inference system consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database (or dictionary), which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion.

A fuzzy inference system implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping. In particular, the antecedent

of a rule defines a fuzzy region in the input space while the consequent specifies the output in the fuzzy region.

In general, the designing of a fuzzy inference system is based on the (possibly partial) known behavior of the target system. The target system under consideration is the language skill evaluation/assessment expert subsystem of the e-learning environment. The fuzzy system is then expected to be able to reproduce the behavior of the target system.

Generally speaking, the standard method for constructing a fuzzy inference system, a process usually called fuzzy modeling, has the following feature: The rule structure of a fuzzy inference system makes it easy to incorporate human expertise on the target system directly into the modeling process, namely, fuzzy modeling takes advantage of domain knowledge that might not be easily or directly employed in other modeling approaches. A key point in designing/defining the proposed system's rule base is presented in the axioms below:

> *Axiom1:* Evaluation of a section using an answer takes place only when information regarding the specific section (possibly among other section(s)) is available.
>
> *Axiom2:* Only meaningful input variables (namely, those with values other than –1) are manipulated by the expert system.

The afore-presented axioms drastically reduce the maximum number of fuzzy if-then rules which can be constructed when taking under consideration the type and amount of input and output variables. Moreover, these axioms delineate the selection of teaching/tutoring sequences, since poor performance in certain language sections is confronted only with teaching sessions (taken from tutorials/lessons database) affecting comprehension of the specific sections.

The proposed rule base which is going to be utilized by the fuzzy system employs fuzzy if-then rules. Note that, in order to accomplish the creation of such a rule base one must rely on preexisting knowledge of the e-learning environment, information provided by pedagogical experts who are familiar with the e-learning environment, or simply trial and error.

After this first stage of fuzzy modeling, the obtained rule base can more or less describe the behavior of the e-learning environment by means of linguistic terms. Further refinement of the rule base is carried out during the second stage, the identification of the deep structure. Specifically, the identification of the deep structure means refining the parameters of the inference system using regression and optimization techniques (adaptation stage).

Literally, the proposed expert system, which is part of the general e-learning environment, demonstrates functionality equivalent to adaptive fuzzy inference systems. Correspondingly, the proposed architecture/model is referred to as Adaptive Fuzzy e-Learning Subsystem (denoted as AFELS). The proposed interconnection and interrelation between the adaptive fuzzy e-learning subsystem architecture (AFELS) and the remaining e-learning environment is illustrated in the next page, mainly for demonstration and clarification purposes. Also, through Fig. 5.2 essential operating issues are presented clearly.
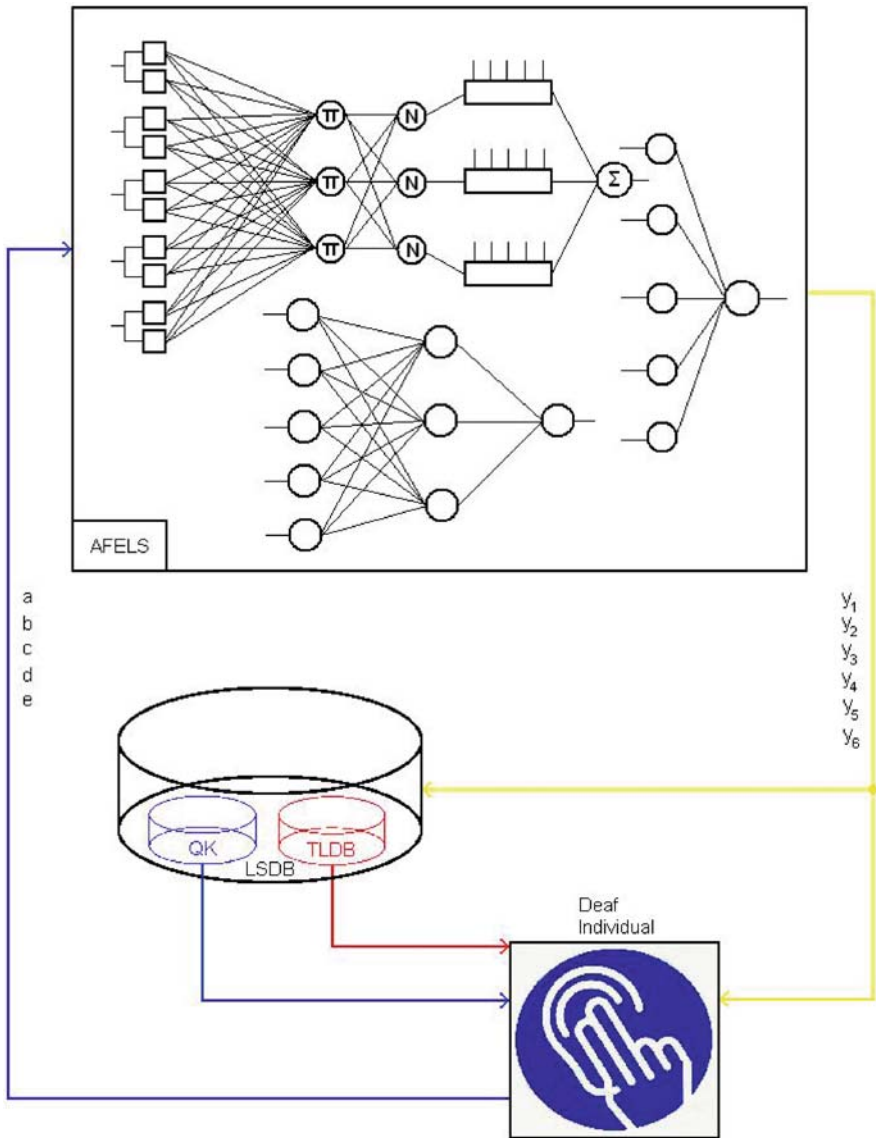
Fig. 5.2 Structure of adaptive fuzzy E-learning subsystems

5.5 Supervised Learning Schema

An adaptive network, like adaptive fuzzy e-learning subsystem, is a network structure consisting of a number of nodes connected through directional links. Each node represents a processing unit and the links between nodes specify

the causal relationship between the connected nodes. Moreover, the outputs of these nodes depend on modifiable parameters pertaining to these nodes. The learning rule specifies how these parameters should be updated to minimize a prescribed error measure, which is a mathematical expression that measures the discrepancy between the network's actual output and desired output.

Conceptually, a feed forward adaptive network is actually a mapping between its input and output spaces. A supervised learning algorithm's aim is to construct a network for achieving a desired nonlinear mapping that is regulated by a data set consisting of desired input–output pairs of the target system to be modeled. This data set is usually called the training data set, and the procedures followed in adjusting the parameters to improve the network's performance are often referred to as the learning rules or adaptation algorithms.

As already mentioned, usually, a network's performance is measured as the discrepancy between the desired output and the network's output under the same input conditions. This discrepancy is called the error measure and it can assume different forms for different applications. Generally speaking, a learning algorithm is derived by applying a specific optimization technique to a given error measure. In the proposed expert system, the scope is confined to modeling problems with desired input–output data sets, so the resulting adaptive fuzzy e-learning subsystem has adjustable parameters that are updated by a supervised learning rule. Such networks are often referred to as supervised learning or mapping networks for obvious reasons.

In order to successfully accomplish the adaptation task, as described briefly in the previous paragraphs, an extensive series of input–output pairs representing the e-learning environment is necessary. Training data could be of any form or format as long as mandatory information is included.

Let $v, v', w, w', x, x', y, y', z, z' \in \{-1\} \cup [0,1]$ and $h, i, j, k, l, n \in [0, 1]$ then each pattern of the training set could be similar to the following template tuple (where ø denotes an empty value):

a	b	c	d	e	
(v, v')	(w, w')	(x, x')	(y, y')	(z, z')	
y_1	y_2	y_3	y_4	y_5	y_6
h if $v \tilde{\neq} 1$	i if $w \tilde{\neq} 1$	j if $x \tilde{\neq} 1$	k if $y \tilde{\neq} 1$	l if $z \tilde{\neq} 1$	n
else ø	else ø	else ø	else ø	else ø	

A sample training set is illustrated in a tabulated form below. It is apparent, that information encapsulated in such a training data set should be collected and preprocessed by a pedagogical expert since such an expert appears as the most suitable person for creating the afore-mentioned content (Table 5.2).

Table 5.2 Sample training set

Pattern (#)		1	2	3	4	5	6	7
a	a_{val}	0.6	0.1	1.0	0.9	0.6	0.1	0.1
	a_{rel}	0.5	0.5	0.5	0.7	0.7	0.7	0.2
b	b_{val}	0.8	0.7	0.1	−1	−1	0.8	−1
	b_{rel}	0.8	0.8	0.8	0	0	0.6	0
c	c_{val}	0.6	0.8	0.2	−1	−1	0.9	0.1
	c_{rel}	0.1	0.1	0.1	0	0	0.5	0.8
d	d_{val}	−1	−1	−1	0.9	0.1	0.6	−1
	d_{rel}	0	0	0	0.5	0.5	0.4	0
e	e_{val}	−1	−1	−1	0.6	0.8	0.2	0.9
	e_{rel}	0	0	0	0.3	0.3	0.1	0.3
	y_1	0.9	0.2	0.3	0.5	0.8	0.4	0.7
	y_2	0.7	0.8	0.2	ø	ø	0.1	ø
	y_3	0.4	0.5	0.2	ø	ø	0.1	0.5
	y_4	ø	ø	ø	0.9	0.0	0.1	ø
	y_5	ø	ø	ø	0.6	0.2	0.6	0.8
	y_6	0.1	0.5	0.7	0.1	0.2	0.9	0.7

5.6 Conclusions

The system proposed in this chapter has been applied in DEDALOS, an EU program in the framework LEONARDO DA VINCI with very encouraging results. Indeed, the use of neural and neurofuzzy technologies proved to be very fruitful when it comes to simulating the knowledge of expert if we succeed in mining the existing knowledge patterns as well as in using appropriate data codification. In the present research, the volume of the available data has been delimited so it is considered as high future priority the enrichment of the input/output data so as to achieve higher success rate and to come to more secure conclusions.

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