HYBRID INTELLIGENT TUTORING SYSTEMS BASED ON PSYCHOLOGICAL PROFILES AND LEARNING STYLES – DESIGN, IMPLEMENTATION AND EVALUATION

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Abstract

This paper presents a novel Hybrid Intelligent Tutoring System based on traditional and connectionist Artificial Intelligence. It is adaptive and reactive and has the ability to offer customized and dynamic tuition. Features of apprentice's psychological profile or learning style are employed as basic elements for customization, and they are complemented by (human) expert rules. These rules are represented by probability distributions. The proposed system is implemented on web environment to take advantages such as wide reach and portability. Three types of navigation (on course contents) are compared based on user performances: free (user has full control), random (user is controlled by chance) and intelligent (navigation is controlled by the proposed system: neural network combined with expert rules). Descriptive and inferential analysis of data indicate that the application of proposed techniques is adequate, based on (significant at 5%) results. The main aspects that have been studied are retention ("learning improvement") normalized gain, navigation total user interaction time and number of steps (length of visited content). Both customizations (by psychological profiles and learning styles) have shown good results and no significant difference has been found between them.

1. Introduction

Since long time ago, the knowledge — its acquisition and transmission — has been an instrument used to promote and to guarantee the human survival, the personal and social evolution and the sovereignty of the nations [1]. As a consequence, the acquisition (learning) and transmission (instruction) of knowledge have are the target of many thoughts and investigations, as well as they have been inducing technological progresses along the human evolutionary history [2]-[7].

The use of computers in the Education [8] began in the fifties with the creation of tutoring systems. Such programs are considered simple "electronic books." In order to contextualize the proposal of tutors, using intelligent tutoring systems (ITS) based on artificial neural networks, it is important to present the main structures used at the moment [9]. Usually, an introduction marks the beginning of the lesson and, as a final step, a summary is presented for revision of the concepts, following by test or other activity to measure the acquired knowledge.

In classical tutorial, users access the content in basic, intermediary and advanced levels progressively. In the tutorial focused in activities, another activity with some information or additional motivations precedes the accomplishment of the goal activity. In the tutorial customized by the apprentice, between the introduction and the summary, there are cycles of pages of options (navigation) and content pages. The page of options presents a list of alternatives for the apprentice or a test in the sense of defining the next step. In the progress by knowledge tutorial, the apprentice can omit contents dominated already, being submitted to tests of progressive difficulty to determine the entrance point in the sequence of contents. In exploratory tutorial, the initial page of exploration has access links to documents, databases or other information sources. In lesson generating tutorial, the result of the test defines the personalized sequence of topics to be exposed the apprentice.

Other recent structure proposes connectionist tutoring systems [10] and [11]. The content is partitioned in several topics (contexts). Each context is subdivided in five levels: easy, intermediary, advanced, examples and frequent answered questions (faq). The entrance in each context is accomplished through the intermediary level. After each level, there is a test. After this test, the apprentice can choose (free navigation) or to be driven (guided navigation) for any one of the other levels or for the next context. In this structure, a neural network is used for each level of each context (five nets are used for each context), in other words, for a course of 15 contexts and 5 levels, we would have 75 different neural networks. The results were promising, but the dependence of the formatting of the content impedes the fast development of new tutorials. In other words, any alteration in that formatting implicates in the need of new free navigations and training of all involved neural networks.

We have noticed a great progress with the introduction of the structure and the idea of connectionist models. However, there is room for improvements. The first point is the need of retraining neural networks (usually a non-trivial task). The second point, is the occurrence of serious mistakes (incoherencies), for instance, when students have incorrect answers in intermediary levels and are sent to advanced levels instead of easy ones.

2. Psychological Spaces

According to Jung, psychological typologies describe and explain the human personality. Jung observed that the human behavior is not random, but can be conceived as corresponding to the structure of the human mind, and are present from birth. From this general conception, Jung developed a theory of psychological types based in four factors and in two attitudes. The four factors are a) feeling (F), b) thinking (T), c) intuition (N), and d) sensing (S); and the two attitudes are extraversion (E) and the introversion (I) [12]-[14].

The psychological types are revealed or they act as different demands impose differential driving of the individual's energies for each end of the pairs of factors and of attitudes opposed: sensibility-intuition, reasoning-feeling, and extraversion-introversion. For each individual, this dynamics result in a factor (a dominant mental disposition) that constitutes the core of the individual's personality, his/her basic psychological identity. The definition and the classification of the types in Jung's typology are based in dichotomies and lead to eight basic types of personality (see Table 1).

Table 1 – Categorization of Jungian Psychological Typology

		Extroversion	Introversion
Rational	Feeling	FE	FI
	Reasoning	TE	TI
Irrational	Intuition	NE	NI
	sensibility	SE	SI

The main subsequent development of the Jungian typology happened with Myers & Briggs [15]. They have added another group of structures (for judging and perceiving) and. they defend that mind dynamics is more complex. In the typology Myers-Briggs, there are 16 psychological types.

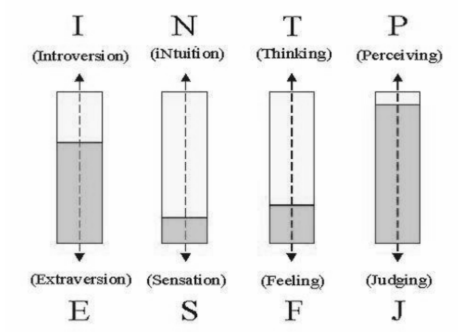

Figure 1 – Model of Myers-Briggs.

Keirsey, other follower of the Jungian thought, proposed another model [16] and [17]. In this model, in spite of the different labels of the types, the theoretical proposal is parallel to the one of the work of Myers & Briggs. The typology of Keirsey is not related with what is in the mind, but with what people does, the patterns of long term behavior or temperament. Their descriptions, a little different from the form of Myers-Briggs, they are more integrated. He looks at the personality notion as entirely. The model proposed by Keirsey considers the influence of the factors as a group, which implicates in a nonlinear relation, where there is higher variation.

3. Learning Styles

The process of learning is considered by a lot of people as a natural process, independent of attendance and ended in the adult age. For Skinner [18], learning would be, basically, a change of behavior. Learning happens when a person demonstrates to know something that didn't know before. Learning is the way people acquire, store and use knowledge.

With effective learning in focus, scientists in Education have been identifying the different ways people notice and process new information; as well as how certain learning strategies work the information and how mind is influenced by each person's perceptions. This perception combination and processing is the individual form of the learning style. The learning style is the way in which each individual begins to ponder, to process and to retain new information [19], expressing differences in the processing of information. Essentially, the learning style possesses three components: i) the way information is processed ii) dynamic selection of learning strategies; and iii) the person's own perception with regard to his learning.

According to Dunn [20], the orientation of a person's learning is, perhaps, the most important determinant of his/her educational accomplishment. Logically, the more consistent with the used pedagogic method, the larger the success chance [21]. Therefore, there are instruments to measure learning styles. In the last years, many authors researched the concept of learning styles resulting in many models.

David Kolb [22] created a model, see Figure 2, to classify the styles based, mainly, on the work in theoretical and experimental learning (John Dewey, Kurt Lewin and Jean Piaget) and has been influenced by therapeutic psychologists (Carl Jung [23]).

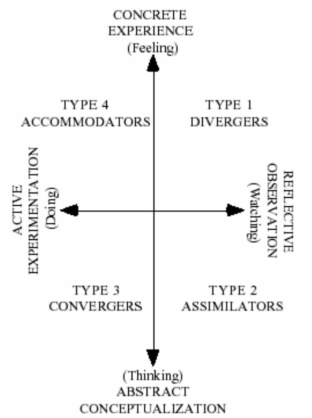

Figure 2 – Learning Styles

Kolb's model presents basic structural dimensions of the process of experimental learning and the resulting basic forms of knowledge. Kolb used four extreme points to define the phases of the learning cycle: reflexive observation (attending), active experimentation (doing), concrete experience (feeling) and abstract conceptualization (thinking). Four different types of students (learning styles) were identified: diversifier, assimilator, solver and adapter, they are defined from the combination of the opposite dimensions of the two learning activities.

Felder and Silverman [24] define different learning styles, where they consider the learning with five dimensions: input (visual or aural), perception (sensorial or intuitive), organization (inductive or deductive), processing (active or reflexive) and understanding (sequential or global). The dimensions of learning style proposed are originated from other models. It is important to point out that the models of Kolb, Felder and Silverman are not the only models of learning style found in the literature.

4. Artificial Neural Networks

The human brain, a neural network, is composed of neurons. The biological neurons are divided in three interrelated sections: i) the body of the cell, ii) dendrites and iii) the axon. The dendrites receive the nervous pulses (information) of other neurons, transmitting them to the body of the cell. Soon afterwards, the information is transformed in new pulses that are transmitted through the axon. The connection done between the axon of a neuron and the dendrite of another neuron is called "synapse." The synapses work as valves, being capable to control the transmission of pulses (flow of information) among the neurons in the neural network. The effect of the synapses is variable and their plasticity implements the adaptation capacity of the neuron [25]. Inputs are sensed by dendrites and affected by synapses (each one with its specific weight, gain value). The output is defined based on the sum of received stimuli and on the activation function that converts such information on the neuron activation level.

Typically, an Artificial Neural Networks (ANN) has the following operation: after the specification of the structure (number of neurons, topology, neuron dynamics, training algorithm), a series of examples (training set) is presented to adjust ANN for their recognition and, more important, the generalization for unseen situations. The present work is based on multilayer perceptrons (MLP). They are the most employed and studied neural model [26].

5. Probability Distributions as Representations of Expert Knowledge

It is not an easy task to combine traditional (symbolic) and connectionist Artificial Intelligence approaches. On the other hand, they complement each other in many aspects. By considering the task of teaching, even teachers are not sure when directions should be pointed to the student.

When best (or optimal) actions are unknown, one possibility of expert knowledge representation is the employment of a consensual probability distribution. If the set of possible results is not too large, situations can be raised to experts and their answers can be recorded in the format of probability distributions. The integration of expert advice can be realized by the sum of answers and posterior scaling (see Figure 3). In our case, based on the specific instructional design (mostly supported by classroom experience), a group of teachers were invited to express their knowledge by filling forms. The subject of our enquiry is the proper next contents students should encounter based on their own histories. On other words, what is the best destination inside the structure of the proposed system?

expert 1

	choices		
situation	1	2	3
A	30%	40%	30%
B	60%	20%	20%

expert 2

	choices		
situation	1	2	3
A	50%	30%	20%
B	40%	10%	50%

sum

	choices		
situation	1	2	3
A	80	70	50
B	100	30	70

normalization

	choices		
situation	1	2	3
A	40%	35%	25%
B	50%	15%	35%

Figure 3 – Scheme of Expert Knowledge Representation By Using Probability Distributions.

6. Proposed System

The presented work is based on the capacity of artificial neural networks to extract useful patterns in the aid of content navigation in intelligent tutor systems. This proposal improves the student's use through the consideration of personal characteristics (and technological ability of interface usage) in the generation of the navigation patterns [27]-[30]. A navigation pattern establishes global distributions of probabilities of visitations of the five levels in each context in the structure of the connectionist tutoring system. To treat the local situation, expert (human) rules are introduced by means of probability distributions. By integrating the global and local strategies, we have composed a hybrid intelligent tutoring system. In the proposed structure (presented in Figure 3), there is a single and generic net for the whole tutor. The decision of proposed ITS is based on the navigation pattern (defined by ANN) and on the apprentice's local acting (current level and the score at the test).

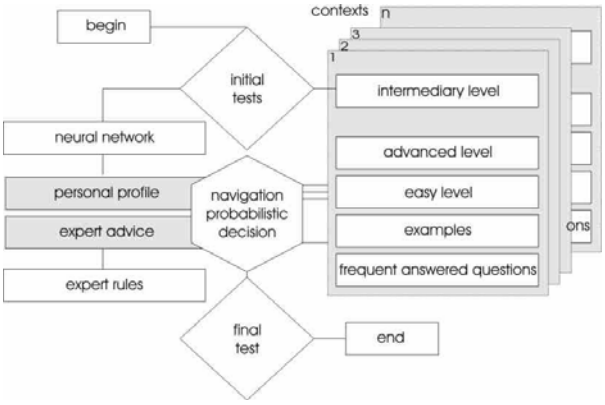

Figure 3 – Proposed System

The use of individual psychological and learning styles characteristics in the tutor's guidance through the course contents allows the system to decide what should be presented based on the student's individual preferences. The dimensions that characterize the psychological characteristics and learning styles are used in the determination of the navigation patterns. Such patterns can be extracted for the neural networks starting from individual preferences (dimensions that characterize the type) of the best students. The apprentice's preferences are collected through questionnaire of psychological and learning styles characteristics and the answers are used as ANN inputs in the sense of making possible the connection between personal characteristics and an appropriate guidance in the learning process.

The employed neural network does not depend on the formatting of the content once the structure is maintained (number of levels in each context). The increment of new contexts or alteration of the content, for instance, does not implicate in changes in the tutoring system. Such fact allows the reuse of the structure in new subjects.

To complement the generic decision of the intelligent navigation and to use the apprentice's local acting better, a set of symbolic rules [31]-[32] is added to the system. The definition of the symbolic rules is made by specialists in teaching. The rules treat existing situations in agreement with the tutor's structure (composed of context levels and tests), guiding the chances of choice of levels (or next context) faced with the acting at the level just executed. Those rules nearly exclude the possibility of incoherencies in the user navigation since the probability of reaching “wrong” levels is reduced highly.

The efficiency of the proposed system is measured by results of guided navigations. The main objective is to drive the apprentice to reach good learning result based on paths that discard unnecessary resources (context levels) to the apprentice's profile. In the Equation 1, it can be observed that efficiency (E) is directly related to the student's productivity (P) and is inversely proportional to the used resources (R) (visited levels, used nets, etc.) [33]-[34].

$$E = \frac{P}{R} \tag{1}$$

7. Experiments and Results

The composition of the (neural) training set has lead to the implementation of a tutoring system for the data collection, called Free Tutor, and a guided tutor (without intelligence) denominated Random Tutor for evaluation of the decisions of navigation of the intelligent tutor. The Free Tutor and the Random Tutor possess the same structure of the Intelligent Tutor. However, they are not endowed with advice of the ANN and the set of expert rules. Students from under graduation in Administration course have composed our samples. After the training of the neural networks, a new data collection was made, with the Intelligent Tutor and the Random Tutor for a comparative study. The Intelligent Tutor has been built by using two approaches for individual characterization: psychological profiles (PP) and learning styles (LE).

In the Tables 2, 3 and 4 we presented the data of the descriptive analysis. In the four situations, initial test marks are close and inferior to the traditional average of approval, 5.0. The global average of the final marks was higher than 5.0, which indicates improvement. The highest average was reached by intelligent navigations (7.21 and 7.29), followed for the free (6.87) and, last, the random navigation (5.93). In the observation of such averages, the most interesting fact is related to the average of the normalized improvement. The intelligent navigations (proposed system) reached a mean normalized improvements of 58,02% and 57.76% (the most expressive results). For the sake of clarity, a student that reaches the maximum mark in the final test has normalized improvement equals to 100% and so on.

Table 2 – Descriptive Analysis of the Initial Mark

Tutor - *statistics*	**Free**	**Random**	**Intelligent PP**	**Intelligent LE**
# cases	148	31	31	31
mean	4.56	3.99	3.92	3.72
standard deviation	1.78	2.17	2.21	2.35

Table 3 – Descriptive Analysis of Final Mark

Tutor - *statistics*	**Free**	**Random**	**Intelligent PP**	**Intelligent LE**
# cases	148	31	31	31
mean	6.87	5.93	7.21	7.29
standard deviation	1.66	2.16	1.83	1.81

Table 4 – Descriptive Analysis of the Normalized Gain

Tutor - *statistics*	Free	Random	Intelligent PP	Intelligent LE
# cases	148	31	31	31
mean	39.59	32.59	58,02	57.76
standard deviation	32.87	27.42	25.79	26.63

The Table 5 summarizes the description of average results in the comparative analysis of the data from free, random and intelligent navigations. The intelligent navigations present, without incoherencies, the highest final marks and normalized gains with the lowest execution times and amounts of visitations. Therefore, it is verified that the averages of the proposed system are better and with the use of less resources (visited levels and time). In other works, the Intelligent Tutor (in its two approaches) is the most efficient of all three tutors.

Table 5 – Comparison among Navigations

Navigation	Duration (min)	Visited levels	Incohe-rencies	Final Mark	Gain (%)
Free	37.88	35.34	0.63	6.87	39.6
Random	35.97	45	1.06	5.93	32.6
Intelligent PP	26.80	26.71	0	7.21	58.0
Intelligent LE	36.99	25.70	0	7.29	57.8

In order to generalize our results, the t-Student test with 5% significance level was employed. The Table 6 presents the application of the test t in the comparison of the initial marks. The objective of the comparison of the initial marks of the samples is to be sure they are similar. For the psychological profile approach, as the probability of casual sample differences is greater than 5% (the level of significance), one should not reject the null hypothesis with states that groups (samples) come from the same population (more precisely, from populations that have identical mean). For the learning styles approach, notice that a significant difference has occurred between intelligent and free navigations but it should be reminded that this difference favors the free navigation. In other words, the free tutor has been initiated with a group that knows more. In practical sense, on the other hand, such difference is not so high.

Table 6 – T Tests on Initial Marks

Navigation	Free X Random	Intelligent PP X Free	Intelligent LE X Free	Intelligent PP X Random	Intelligent LE X Random
Averages	4.56 X 3.99	3.92 X 4.56	3.72 X 4.56	3.92 X 3.99	3.72 X 3.99
Probability (%)	11.9	8.2	2.4	90.2	63.8

The Table 7 presents the application of the t-Student test in the comparison of the final marks. First, the poor performance of random guidance has to be emphasized. On the other hand, in spite of the differences between free and intelligent navigations are not significant, the proposed system has used fewer resources (visited levels and time) of the student. The result is an indicative that the intelligent guidance is capable to conduct navigations where the results are at least equivalent to free navigations.

Table 7 – T Tests on Final Marks

Navigation	Free X Random	Intelligent PP X Free	Intelligent LE X Free	Intelligent PP X Random	Intelligent LE X Random
Averages	6.87 X 5,93	7.21 X 6.87	7.29 X 6.87	7.21 X 5.93	7.29 X 5.93
Probability (%)	0.7	15.2	10.6	0.7	0.4

In order to generalize our results, the t-Student test with 5% significance level was employed. The Table 8 presents the application of the test t in the comparison of the initial marks. The objective of the comparison of the initial marks of the samples is to be sure they are similar. For the psychological profile approach, as the probability of casual sample differences is greater than 5% (the level of significance), one should not reject the null hypothesis with states that groups (samples) come from the same population (more precisely, from populations that have identical mean). For the learning styles approach, notice that a significant difference has occurred between intelligent and free navigations but it should be reminded that this difference favors the free navigation. In other words, the free tutor has been initiated with a group that knows more. In practical sense, on the other hand, such difference is not so high.

Table 8 – T Tests on Normalized Gain ("Learning Improvement")

Navigation	Free X Random	Intelligent PP X Free	Intelligent LE X Free	Intelligent PP X Random	Intelligent LE X Random
Averages	39.59 X 32.59	58.02 X 39.59	57.76 X 39.59	58.02 X 32.59	57.76 X 32.59
Probability (%)	27	0.2	0.2	0.02	0.02

8. Conclusion

In this work, we proposed and developed a hybrid intelligent tutoring system based on neural networks and expert (human) rules. Answers of questionnaire were used to characterize the psychological profile and learning styles of users. The proposed system has clear advantages when comparing to similar models. In particular, one should notice the addition of prior knowledge (explicit on expert rules) and the use of only one MLP neural network of generic use. The reuse of the proposed system to other contents is straightforward: no change is required unless additional levels are introduced.

Moreover, we conducted an empirical investigation by comparing the proposed system with two other versions that use the same content: free tutor (where users have full control of their navigations) and random tutor (where destinations are chosen at random). Statistical procedures have shown that the proposed system is the most efficient of all three types of navigation (5% significance level). Similar results were achieved with psychological and learning styles characterizations and no significant difference has been found between them.

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