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Classifier Model For Personalizing Exercises Given To Students Using Artificial Neural Networks

Modelo clasificador para personalizar ejercicios propuestos a estudiantes utilizando redes neuronales artificiales

使用人工神经网络向学生提供的个性化练习的分类器模型

Классификационная модель для индивидуализации упражнений, предлагаемых студентам, с применением искусственных нейронных сетей

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Resumen

El artículo tiene como objetivo el desarrollo de un modelo que permite predecir en forma personalizada los ejercicios que puede resolver un estudiante, y por otro lado los que no puede resolver. El modelo está basado en una serie de factores que influye en los ritmos de aprendizaje de los estudiantes. El curso que se utilizó como experimento en el proyecto es el manejo de funciones en hojas de cálculo. Para el desarrollo del proceso se ha utilizado la metodología de minería de datos KDD (Knowledge Discovery in Databases) y para el modelo se ha utilizado redes neuronales artificiales con aprendizaje hacia atrás (Backpropagation), el cual es un algoritmo de aprendizaje supervisado. El modelo se alimenta con datos como sexo, edad, grado académico, nivel de instrucción de los padres, tipo de colegio, calificaciones previas de los temas que el estudiante obtiene mientras avanza en el curso. El enfoque de la investigación es de corte cuantitativo, experimental, de tipo aplicada y la población estuvo representada por 85 estudiantes. El resultado muestra que el modelo logra una probabilidad del 72% de precisión al predecir la asignación de ejercicios a los estudiantes según sus características. Los ejercicios que no pueden ser resueltos se les anexa una ayuda para su mejor comprensión y resolución.

Palabras clave: redes neuronales artificiales, aprendizaje supervisado, minería de datos, validación cruzada.

Abstract

The objective of the article is to develop a model that allows to predict in a personalized way the exercises that a student can solve, and on the other hand the exercises that a student cannot solve. The model is based on a series of factors that influence students' learning rates. The course that was used as an experiment in the project is the handling of functions in spreadsheets. For the development of the process, the KDD (Knowledge Discovery in Databases) data mining methodology has been used and artificial neural networks with backward learning (Backpropagation), which is a supervised learning algorithm, have been used for the model. The model is fed with data such as gender, age, academic grade, parents' level of education, type of school, previous grades of the subjects that the student obtains while advancing in the course. The research approach is quantitative, experimental, applied and the population was represented by eighty five students. The result shows that the model achieves a 72% probability of accuracy in predicting the assignment of exercises to students according to their characteristics. Exercises that cannot be solved are given a help for their better understanding and resolution.

Keywords: artificial neural networks, supervised learning, data mining, cross validation.

Аннотация

Цель статьи - разработать модель, позволяющую индивидуализированно прогнозировать те упражнения, которые студент может решить, и, с другой стороны, те, которые он/она не может решить. Модель основана на ряде факторов, влияющих на скорость обучения студентов. Предмет, используемый в качестве эксперимента в проекте, - работа с функциями в электронных таблицах. Для разработки процесса использовалась методология поиска данных KDD (Knowledge Discovery in Databases), а для модели - искусственные нейронные сети с обратным распространением, которые являются алгоритмом контролируемого обучения. В модель вводятся такие данные, как пол, возраст, академический курс, уровень образования родителей, тип школы, предыдущие оценки по предметам, полученные студентом при прохождении курса.

Исследовательский подход является количественным, экспериментальным, прикладным, а выборка была представлена 85 студентами. Результат показывает, что модель достигает 72% вероятности точности в предсказании назначения упражнений студентам в соответствии с их характеристиками. Упражнения, которые не удается решить, снабжены подсказкой для их лучшего понимания и решения.

Ключевые слова: контролируемое обучение, добыча данных, искусственные нейронные сети, кросс-валидация.

概要

本文的目标是开发一个允许以个性化的方式预测学可以解决的练习以及无法解决的练习的模型。该模型基于一系列影响学生学习率的因素。在项目中用作实验的课程是电子表格中函数的处理。对于流程的开发，使用了KDD （数据库中的知识发现）数据挖掘方法，并使用了具有反向学习（反向传播）的模型人工神经网络，这一监督学习算法。该模型输入的数据包括性别、年龄、学业成绩、父母的教育水平、学校类型、学生在课程中取得的先前科目资格。研究方法是定量的、实验性的、应用型的，研究对象为85 名学生。结果表明，该模型在预测根据学生的特征分配给学生的练习时，准确率达到了72%。无法解决的练习附有帮助，以便更好地理解和解决。

关键词：监督学习，数据挖掘，人工神经网络，交叉验证。

Introduction

The teaching-learning process is comprehensive according to Anijovich and Cappelletti (2017), they point out that, if the conditions of students are always different, such as the rates, ways of learning and starting points of each student, then, what is learned and what is assessed cannot be standardized, but must be differentiated according to the individual characterization. Méndez (2007) indicates that students process information according to their capacity, motivation, environment and the guidance provided by the teacher in their learning. Learning rates are linked to academic performance, which is determined by personal, family, social and educational factors, as pointed out by Medina et al. (2018) and Saucedo et al. (2014). A learning session in the classroom is represented by several moments, one of them represents the practice, which mostly aims to have students solve exercises regarding the topic developed. It has been noted that many students have doubts and certain fears when interacting with new learning topics; they are students who find it difficult to adapt to the pace of progress imposed by the majority of students and even by the teacher. This reality has been reflected in the evaluation results of the course of functions, which have shown students with low averages, course dropouts and failing students. Anaya-Durand and Anaya-Huertas (2010) propose that teachers should work at a moderate level of demand, which does not cause discouragement and low grades. According to Tourón et al. (2014), he indicates that it is a mistake to use the same contents, rates and evaluation to students, this is a problem because it can cause frustrations and it influences the relationship with other students. The problems described above are very common in the classroom, and many research studies have used predictions to find the best ways to know the student profile based on certain factors and this way be able to collaborate in proposing solutions that help.

Related works

Related and prior works are characterized by the fact that they use one or more classification algorithms. Some research uses those traces or interactions that students leave on virtual platforms such as Moodle as input data; other research uses data that are collected through instruments as input and that are custom designed for the research and finally, there is also the research that uses data that are collected over the years in systems of registration and enrollment systems. The literature has been reviewed and scenarios are observed to make predictions with data that arise from the teaching-learning process and are crucial in the prediction of students' academic performance. In Table 1 we can see a summary of works related to the research.

Table 1

Summary of previous works

Authors	Title	Contribution	Opportunities for improvement
(Otero et al., 2019)	ICT for education: adaptive system based on automatic learning mechanisms for the appropriation of technologies in students	A system was built that enables the initial recommendations of educational content appropriate to the individual characteristics of students, administered according to their performance and the characteristics of the territory	The system was fed with data collected from virtual courses, both from students and educators. Data analytics and machine learning to make initial predictions and recommendations is limited when the teaching-learning process is in-person, as there is not as much data available as in the virtual process. An alternative way to improve data collection is to analyze the recordings of in-person classes and extract behavioral patterns.
(Salgado Reyes et al., 2019)	Model to predict academic performance based on neural networks and learning analytics	A predictive model of academic performance was proposed using data provided by a virtual interaction system with students, using learning analytics through artificial neural networks; patterns were found that were crucial in the academic performance of students.	The data collected and used to make the predictions are from the virtual course system they have; however, there is still an opportunity for improvement if personal, social and other data of interest to the research are included.

Authors	Title	Contribution	Opportunities for improvement
(Menacho Chiok, 2017)	Prediction of academic performance applying data mining techniques	It shows a range of predictions to classify (pass, fail) prospective students enrolled in a course. Data mining techniques were used and results were compared using logistic regression, decision trees, neural networks and Bayesian networks. A predictive effectiveness of 70% was achieved.	In order to achieve the classification, the academic data of the students enrolled in the General Statistics course at UNALM were used; however, the factors or predictor variables were selected based on the data they already had, without taking into account, according to research, that there are very influential variables in academic performance, which was not taken into account in their research.
(Gutiérrez Cárdenas & Casafranca Aguilar, 2015)	Implementation of a Computerized Assessment System by using Backpropagation Neural Networks with R and Shiny	Through the use of artificial neural networks, an environment of attention to the needs of each student was created with the use of correct materials through exercises in their evaluation. This allows to reduce the feeling of dissatisfaction and to avoid, in many cases, the dropout of the courses.	Data generated by the same project have been used. The results obtained were different levels of difficulty for the students in the exercises; however, there is still room to analyze other determining factors and to take into account the levels achieved by students in the previous topic, since this process is changing.

Research problems

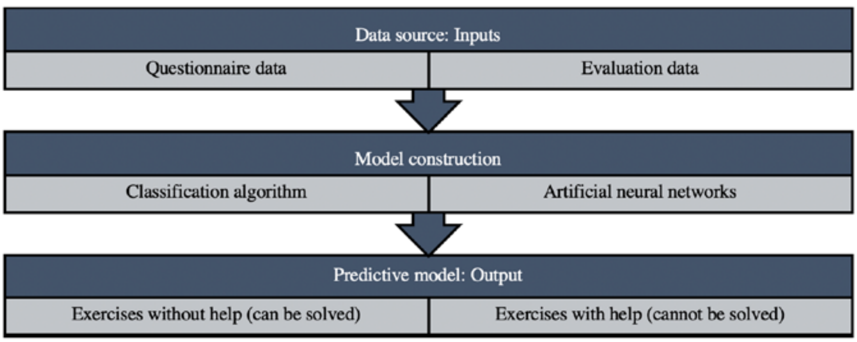
At schools, students are characterized by being unique, singular and belonging to heterogeneous groups. In each learning session, the teachers try to improve their work with the students, especially when developing the part of the practice, where it is common for teachers to propose a set of exercises during the class, in which they present cases where the students must solve them individually and in a certain amount of time. Taurón and Santiago (2015) indicate that a school model where teachers teach the same contents, with the same level of complexity and at one speed for the whole class, this school is not attending to the differential needs of the students. It has been noted during the classes that students when solving the set of exercises need support, tutoring, help in formulas, in their application and syntax of the functions to be used. The teacher is regularly confronted with two situations: first, when a student asks the teacher for help or tutoring, time is always short and it is not possible to attend to everyone or to give adequate time to each student, and second, many students need help, but do not ask for it. Diversity can be understood as the variety of students that exist within our classrooms. Each student is different in gender, culture, learning rates, ways of thinking, physical limitations or possibilities, disabilities (Méndez, 2017).

Proposal

In order to address the problem raised, a model has been implemented that allows predicting the assignment of exercises to students on an individualized basis, providing textual help in the exercises that the student is unable to solve. A predictive model based on artificial neural networks was implemented in the proposal. This artificial neural network system manages to establish a connection or relationship between inputs and outputs, which has a behavior similar to the human brain, where information is processed in parallel, in order to learn and generalize results (Singhal & Swarup, 2011). The proposed Model has personal factors, social factors and students' academic performance grades as input, which were collected over several months. Data mining allows obtaining analytical models that uncover interesting patterns and trends in the information used by the student (Romero et al., 2008). Figure 1 shows the outline of the proposal.

Figure 1

Model Structure



Population

The students who participated in the research took the course of functions in spreadsheets to a basic level, this type of course has a duration of one month with one-hour-and-a-half sessions from Monday to Friday. The topics developed in the course are mathematical operators, mathematical functions, statistical functions, among others. There are 8 topics that were addressed in the course and they are 100% practical topics, that is to say, the computer is used at all times. The study groups are heterogeneous and there are no prerequisites to take the course. The group can be made up of students from 15 to 70 years old, with levels of education ranging from high school to graduate school, and many may be working or unemployed. In total we worked with 85 students as the population, which also represents the sample.

Questionnaire data

An instrument based on the survey technique was created. For the preparation of the questionnaire instrument, the literature on those factors that influence students in the handling of function topics was reviewed, in addition to including other factors contextualized to the problem being addressed. Academic performance, being multicausal, can be grouped into social, personal and institutional determinants as indicated by Garbanzo Vargas (2007). One of the determining aspects for success in the spreadsheet course was to determine whether the student had a preference for mathematics or had numerical skills, due to the time constraints and having zero data, a question was posed based on the Likert scale, asking: to what extent do you consider yourself a person with numerical skills? The alternatives for this question were always, often, sometimes and never. This question was recommended by the pedagogue and psychologist with whom I supported the research. Table 2 shows the factors that were taken into account for the questionnaire.

Table 2

Attribute classification

Type	Attribute
Individual	Age, sex, marital status
Academic	Person with numerical skills
	You were taught computing in school
	Experience with Excel
	Academic degree
	How many hours a day do you study?
Institutional	Type of school
Socioeconomic	Current occupation
	How many hours per day do you work?
	Father’s level of education
	Mother’s level of education
	Reason for studying Excel

The instrument was validated with a psychologist in Education and a professional in Educational Sciences, the reliability of the instrument was calculated by applying Cronbach’s alpha, where the result was .733, which represents a value with a good reliability score. With the validity and reliability obtained, the questionnaire was applied to 85 students who took the course.

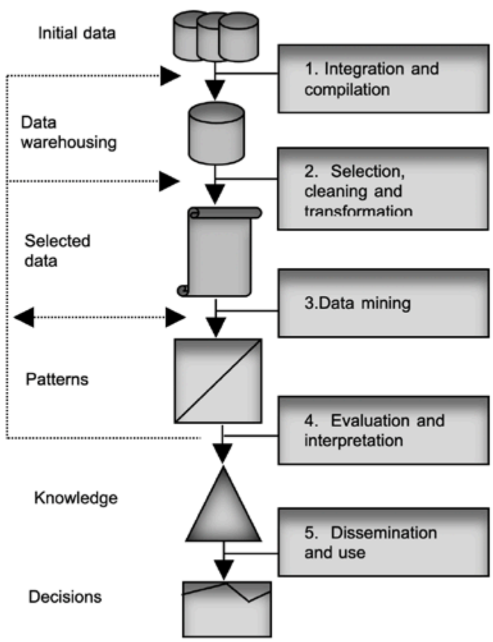
Evaluation data

The data collection regarding the evaluation represents data from 85 students. The evaluation grades are an indicator that determines the academic performance of students, as stated by Cueto (2006), which indicates that academic performance is the level of knowledge that a student has and is reflected in a numerical grade, which measures the result of the teaching-learning process, in which the student participates. For each of the 8 topics of the course, suitable exercises were prepared covering the fundamentals of the topics and the objectives to be met. For each topic, 10 types of exercises were designed. A total of 80 types of exercises were prepared. The data collection was done during several months, since each group was normally formed by an average of 10 students. We worked with 9 groups and applied the types of exercises designed in each topic, and we made a list of the types of exercises that can be solved and those that cannot be solved by each student in the group.

Methodology

In order to develop the proposal, the KDD (Knowledge Discovery in Databases) data mining process was followed, as stated by Hernández et al. (2004), which is represented by five stages. The KDD process is defined as a process of extracting useful information, patterns or trends within large volumes of data, including those related to big data (Londhe et al., 2013). In the data mining stage, we worked with the classification algorithm called neural networks. It is true that in order to develop machine learning, a greater amount of data is needed; however, the school where the research took place did not have any data on its students regarding their profile and academic evaluations as required for this research. Part of the work began by applying the questionnaire to the nine groups, the 80 types of exercises were designed and the types of exercises were applied to each group for several months. This entire data collection process disarticulated the traditional evaluation process that existed in the school. Figure 2 shows the stages of the data mining process.

Figure 2
KDD process



Integration and Compilation Phase

Two sources of data were merged and collected. The first source of data was obtained by applying the questionnaire to the students who enrolled in the course. Figure 3 shows part of the data collected.

Figure 3

Student data

Code	Age	Sex	Marital status	Number of siblings	You are a person with numerical skills	Type of school	You were taught computing
1	19	Female	Single	1	Often	Private	Often
2	29	Female	Single	1	Often	Public	Sometimes
3	25	Female	Single	4	Often	Public	Sometimes
4	17	Female	Single	5	Often	Private	Often
5	23	Female	Single	3	Often	Public	Sometimes
6	25	Female	Single	3	Often	Public	Never
7	21	Male	Single	1	Often	Public	Sometimes
8	22	Female	Single	1	Always	Private	Often

The second source of data collected consisted of the evaluation data (for each topic and type of exercise, we recorded whether or not the student was able to solve the exercise). In Figure 4, we can see part of the evaluations recorded. A value of 1 indicates that a student was able to solve a type of exercise and a value of 0 indicates that the student was not able to solve that type of exercise. As mentioned for each topic, 10 types of exercises were designed, which were labeled with the letters A, B, C, D, E, F, F, G, H, I. J.

Figure 4

Recorded evaluations

	Topic 01											Topic 02										
Code	A	B	C	D	E	F	G	H	I	J	Grade 1	A	B	C	D	E	F	G	H	I	J	Grade 2
1	1	0	1	1	1	1	1	1	1	0	16	1	1	1	1	1	1	0	1	1	1	18
2	1	1	1	1	0	1	1	1	1	1	18	1	1	1	0	1	0	1	1	1	1	16
3	1	0	1	1	0	1	1	1	1	0	14	1	1	0	1	1	1	1	0	0	0	12
4	0	1	1	1	0	1	0	0	0	0	8	1	1	0	1	1	0	1	1	1	1	16
5	1	1	1	1	1	1	1	1	1	1	20	1	1	1	1	0	1	1	1	1	1	18

	Topic 03											Topic 04										
Code	A	B	C	D	E	F	G	H	I	J	Grade 3	A	B	C	D	E	F	G	H	I	J	Grade 4
1	1	0	1	1	1	1	1	1	1	0	16	1	1	1	1	1	1	1	1	1	1	20
2	1	1	1	1	1	1	1	1	1	1	20	1	1	1	1	1	1	1	1	1	1	20
3	0	1	1	1	1	1	0	1	1	0	14	1	1	1	1	0	0	1	0	0	0	10
4	1	0	1	1	0	1	1	1	1	1	16	1	1	1	1	1	1	1	1	1	1	20
5	0	1	1	1	1	1	1	1	1	1	18	1	1	1	1	1	1	1	1	1	1	20

Selection, cleaning and transformation phase

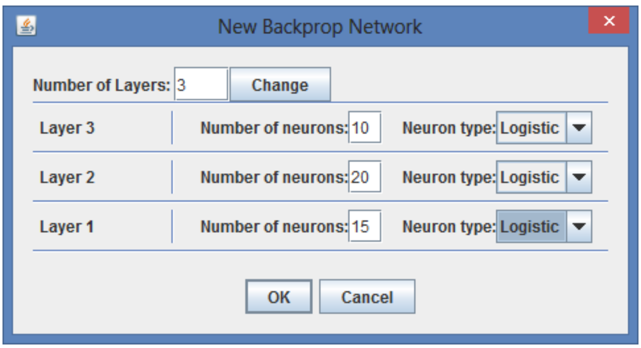
The selection phase involved the use of all the data from the questionnaire with the totality of the records collected. The cleaning phase was applied in the evaluations with students who did not have evaluation grades, due to missing one or more evaluation days. Finally, in the transformation phase, all the questionnaire data were numerically coded in order to process the data, in some cases using binary dummy variables. The only field calculated was the final grade for each topic, since each type of exercise received 2 points and there were 10 types, the value of the grade ranged between 0 and 20. The two data sources were integrated and related. Finally, the data were scaled, since there were values that showed biases.

Data mining phase

The data mining technique applied to the proposed project is classification. The collected data were separated, where 92% were assigned for training and 8% for model validation. The Artificial Neural Networks algorithm with supervised learning (backpropagation) was used. Initially the weights assigned to the input variables (input layer) were at random, which were determined by the Backpropagation Neural Network. This algorithm achieves that the error outputs are back-propagated, starting from the input layer replicating to all the neurons of the hidden layer and contributing directly to the output, at the end all the neurons receive an error signal which contributes to the total error and the weights are updated (García et al., 2003). In order to obtain the predictive model, a free tool based on Artificial Neural Networks, called "Simbrain", was used. Figure 5 shows the network topology for the first topic.

Figure 5

Topology of the first topic



Layer 1 represents the input layer (15 attributes of the questionnaire), Layer 2 represents the hidden layer with 20 neurons and finally, Layer 3 represents the output layer with 10 answers. In order to train the model for the second topic (mathematical functions), the topology must now have 16 inputs, which represents the 15 data from the questionnaire regarding the student and the grade obtained for the academic performance of the previous topic (first topic) and so on will increase the inputs for the other topics. The same will happen if we train the model for the last topic (search functions), where the inputs were 15 data from the questionnaire plus the 6 grades of each of the previous topics. In each topic the grade of the previous topic is accumulated and so on, because the grade obtained by a student in the previous topic has a decisive influence on the evaluation grade of the next topic. Numerous research studies such as Betts and Morell (1999), Porto and Gresia (2001) and Naylor and Smith (2004) have found evidence that prior academic performance may condition future outcomes. Figure 6 shows the network diagram proposed for the first topic.

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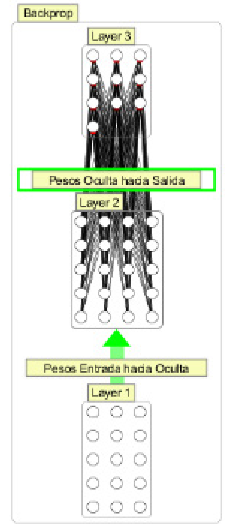
Figure 6

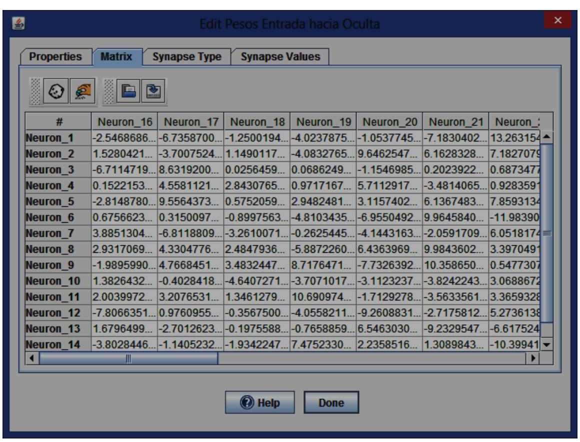
Proposed diagram. Source: Chart generated with the Simbrain tool



The weights are randomly initialized and the learning or training process of the neural network begins. At all times we tried to keep the error to a minimum and began to search for the best topology, performing many tests and modifying its adjustment parameters. The final weights were obtained based on tests, as shown in Figure 7, using the Simbrain tool.

Figure 7

Weights of model neurons



#	Neuron_16	Neuron_17	Neuron_18	Neuron_19	Neuron_20	Neuron_21	Neuron_:
Neuron_1	-2.5468686...	-6.7358700...	-1.2500194...	-4.0237875...	-1.0537745...	-7.1830402...	13.263154
Neuron_2	1.5280421...	-3.7007524...	1.1490117...	-4.0832765...	9.6462547...	6.1628328...	7.1827079
Neuron_3	-6.7114719...	8.6319200...	0.0256459...	0.0686249...	-1.1546985...	0.2023922...	0.6873477
Neuron_4	0.1522153...	4.5581121...	2.8430765...	0.9717167...	5.7112917...	-3.4814065...	0.9283591
Neuron_5	-2.8148780...	9.5564373...	0.5752059...	2.9482481...	3.1157402...	6.1367483...	7.8593134
Neuron_6	0.6756623...	0.3150097...	-0.8997563...	-4.8103435...	-6.9550492...	9.9645840...	-11.98390
Neuron_7	3.8851304...	-6.8118809...	-3.2610071...	-0.2625445...	-4.1443163...	-2.0591709...	6.0518174
Neuron_8	2.9317069...	4.3304776...	2.4847936...	-5.8872260...	6.4363969...	9.9843602...	3.3970491
Neuron_9	-1.9895990...	4.7668451...	3.4832447...	8.7176471...	-7.7326392...	10.358650...	0.5477307
Neuron_10	1.3826432...	-0.4028418...	-4.6407271...	-3.7071017...	-3.1123237...	-3.8242243...	3.0688672
Neuron_11	2.0039972...	3.2076531...	1.3461279...	10.690974...	-1.7129278...	-3.5633561...	3.3659328
Neuron_12	-7.8066351...	0.9760955...	-0.3567500...	-4.0558211...	-9.2608831...	-2.7175812...	5.2736138
Neuron_13	1.6796499...	-2.7012623...	-0.1975588...	-0.7658859...	6.5463030...	-9.2329547...	-6.617524
Neuron_14	-3.8028446...	-1.1405232...	-1.9342247...	7.4752330...	2.2358516...	1.3089843...	-10.39941

With the weights determined, the model was already able to make predictions regarding the first topic, where a new student providing his data through the questionnaire, it can be seen what kind of exercises he can solve and what kind of exercise he cannot solve. Table 3 shows the number of inputs, neurons and outputs for each layer of the model for the first five topics.

Table 3

Final topology of the proposed model

Topic	Input layer	Hidden layer	Output layer
Topic 01	15	20	10
Topic 02	16	30	10
Topic 03	17	20	10
Topic 04	18	20	10
Topic 05	19	20	10

Evaluation and Interpretation Phase

The 8% of the records that were initially separated were validated by entering data that had never been seen before into the model. The results are shown in Table 4 for the first topic. Recall that the value 1 represents that the student was able to solve the exercise and the value 0 represents that the student was not able to solve the exercise. The prediction based on the 8% of students had an accuracy of approximately 72%.

Table 4

Model prediction for students

Student	Model result	Expected result	Accurate prediction
1	1111111111	1111011100	70%
2	1111111111	1111011101	80%
3	1110000100	1010000111	70%
4	1011011110	1111111101	60%
5	1111011110	1011011111	80%

Dissemination and use phase

At the end of the evaluation, both teachers and students were satisfied with the results, since an assertiveness of 72% was achieved. The strength of the model is to identify those types of exercises where students show difficulty, and it is in this gap where the student will be supported.

Results

Based on the predictive model obtained, its effectiveness was tested by selecting experimental groups (group of students new to the course), to which the predictive model was applied for the first two topics. In addition, control groups were selected (groups of students new to the course) where the first two topics were also developed, but applying the traditional model. A total of 3 experimental groups and 3 control groups were used for testing.

The type of course used to collect the academic data and the type of course where the final model was tested are courses related to spreadsheets, and the 80 types of exercises designed are also related to the handling of functions in spreadsheets, such as mathematical, statistical, text, date-time, logical, etc. functions. In Table 5 we can see the averages obtained by the experimental group, as well as the number of exercises that could and could not be solved.

Table 5

Experimental group results

Results of Topic 01 applying the predictive model - Group 1			
Code	was able to solve	was unable to solve	Grade
1	7 de 8	1 de 2	16
2	6 de 8	0 de 2	12
3	8 de 8	2 de 2	20
4	7 de 8	1 de 2	16
5	8 de 8	2 de 2	20
6	7de 8	0 de 2	14
7	7 de 10	0 de 0	14
8	7 de 8	0 de 2	14
9	8 de 9	0 de 1	16
10	8 de 8	2 de 2	20
11	9 de10	0 de 0	18
		Average	16.3

Table 6 shows the results obtained from the control group.

Table 6

Control group results

Results of the First Topic - Group 1	
Student code	Grade
12	16
13	18
14	20
15	08
16	08
17	14
18	02
19	16
20	14
21	18
22	18
Average	13.8

In Table 7 we can see the averages obtained by the experimental and control groups where the average increased from 13.4 to 17.2.

Table 7

Group results

Group No.	Topic No.	Experimental	Control
Group 1	Topic 01	16.3	13.8
	Topic 02	17.4	12.0
Group 2	Topic 01	18.3	15.4
	Topic 02	16.8	12.0
Group 3	Topic 01	17.9	15.2
	Topic 02	16.8	12.5
Averages		17.2	13.4

For the results in Table 7, an ANOVA statistical analysis was developed, as shown in Table 8.

Table 8

Analysis of Variance for table 7

Source	DF	Adj SS	Adj MS	F-value	p-value
Groups	1	42.563	42.5633z	81.72	.000
Topics	1	7.363	7.3633	14.14	.006
Groups*topics	1	3.413	3.4133	6.55	.034
Error	8	4.167	.5208		
Total	11	57.507			

There is a significant difference in the students' grades, with the results of the experimental group in relation to the control group, as well as the topics proposed in the study. In order to give more reliability support to the predictive model obtained, the averages of the current results of the predictive model were compared with the averages of students from previous years, the grades of 3 groups were taken and it was found that the model proposed in this research improves the averages from 13.3 to 16.4. Table 9 shows the comparison results.

Table 9

Group results

No.	Experimental	Historical
Group 1	16.2	12.8
Group 2	17.0	14.0
Group 3	16.1	13.1
Average	16.4	13.3

Table 10 shows the ANOVA results of Table 9.

Table 10

ANOVA results of table 9

Source	DF	Adj SS	Adj MS	F-value	p-value
Groups	1	14.7267	14.7267	552.25	.002
Topics	2	1.2133	.6067	22.75	.042
Error	2	.0533	.0267		
Total	5	15.9933			

When performing ANOVA analysis of the results we can see a significant difference between the experimental values over the historical ones.

Discussion and conclusions

In this section we indicate that the predictive model obtained, not only the accuracy was verified with the test data, but also an application based on the model has been implemented, this application has been used in new groups of students taking the spreadsheet course, and it was possible to verify the accuracy of the model with an approximation of 72%. In other research studies related to this project, the accuracy check of their final model is done with test validation data (initially separated), which is part of the research sample. Nevertheless, in this work, new students (outside the sample) were sought to verify the accuracy of the model. The results were robust in terms of testing their accuracy.

According to Menacho Chiok (2017) in his work of prediction of academic performance, he obtained an average prediction of 70% with the Naïve Bayes network among other algorithms he tested. The number of students was crucial in his results, since he had 914 students, which were collected in two years; on the other hand, it is important to mention that the quality of the data has a lot of influence against the amount of data. The data often collected by schools over the years is not managed in such a way that it can be used for predictive research on academic performance. In many cases the data are only recorded for statistical or backup purposes. Another related comparison is the prediction of Salgado et al. (2019) where they used neural networks and made a prediction on the data found in the Moodle virtual platform of 300 students with 75% accuracy. Variation, quality and quantity of data are a determining alternative to extend and give another approach to research.

Based on the experience gained in this research, we point out that, in order to obtain more efficient predictive models, it is necessary to work not only with a larger number of observations or student data, but also the predictor variables must be of high quality and must have a significant impact on the dependent variable. In order to select the quality of the predictor variables, the criteria of an expert in this discipline should be taken into account. Another important criterion for selecting the most significant variables is to take other experiences and research on related topics as a reference and endorsement. Many schools have data in their virtual systems as indicated by Timarán-Pereira (2019) and Zarate-Valderrama (2019), which are collected over many years; however, there is a gap between the quantity of these data versus the quality of data, this reflection is related to the fact that schools must record data that have a strong impact and in a constant manner, in order to use these records and have more complete research. The fact that schools do not record such data over the years, we are forced to search and collect the data, and due to the short time available very little data is collected, and it is very likely that research based on little data will need more evidence.

Based on the experience obtained in this research, it is recommended to expand the model to work with exercises based on levels of complexity such as basic, intermediate and advanced, where the exercises will be assigned gradually according to the capabilities shown by the student throughout the development of the course.

It has been shown that the proposed model can be successfully used to predict the types of exercises that a student can solve and the types of exercises where he or she shows difficulties. The model was exposed to a cross-validation to demonstrate its robustness, which resulted in an average prediction of 72% with respect to the expected results. An increase in the student's average from 13.49 to 17.29 was evident when using the predictive model, the grades of the evaluations of the new groups of students using the model increased. In this research the model was not only applied to new students, but also comparisons were made of historical averages with traditional method groups from months prior to the research, where the result also showed evidence of the increase in the average of their grades. The model obtained can be improved by working with more students and predictor variables related to academic performance.

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