Decision tree as a method to predict academic success based on the performance of the students at Saber pro

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ABSTRACT

Due to the high's quantity of desertion in universities, several studies have been made to predict the causes of it, but not too much people have concerned about the studies related with the probability of success of the students. Calculating the probability of success of the students may be quite useful for several reasons. For example, it will allow the creation of better circumstances for the students, increasing the success ratio and the results of them. Also, it could improve the education system, allowing it to focus on the student´s problems and needs. In other hand, its necessary to say that the information acquired through this project may help to solve related problems such academic desertion, academic failure, and welfare of the students.

To solve this problem, we designed a decision tree model inspired on the CART algorithm to filter a dataset given by the institution 'ICFES'. The prediction is based on a random forest made of 1000 of these trees and random data from the dataset. For an estimated of 135000 student training students and 45000 test students, we reached an overall (training and testing) time consumption of 8 minutes, while the memory consumption has an average of 700 mb. Despite the long-time execution, we managed to get quite accurate results, those are a 73% of accuracy, 75% of precision and 70% of sensibility, which makes this algorithm totally adequate to the solution of the problematic

Keywords

Decision trees, machine learning, academic success, standardized student scores, test-score prediction

1. INTRODUCTION

Throughout the years, the test Saber Pro in Colombia was the way of check the abilities of the students after finishing their careers. The purpose of this test is to check the abilities of the students and the effectiveness of the different universities around country, and it is also a prerequisite for the student's graduation, allowing the government to make sure that they have nice professionals for the future. Getting an effective way to predict the results in this test is very important to generate a math graph with spoused data, and with these prognostics the government could make an idea about the conditions that allows the students to have a good performance in the test

1.1. Problem

One of the problems in this topic is how the variables affect the students and which changes on them provide more benefits in their performance. We focus in many variables like the students grade, life style and learning process.

1.2 Solution

Due to the fact that black box methods (such as neural networks, support-vector machines and random forests) don't go much into detail and directly tests the functionality of the software, we decided to avoid them. Instead, in this work, we focused on decision trees because they provide better explainability. Specifically, we decided to use the c4.5 algorithm, because it allows us to divide the dataset and select the half that contains the higher gain of information. Also, it allows us to make a complex type code, where, according to Bruno López Takeyas, "the values are assigned to a number of variables of group with its respective possible result for each of them"[9], this due that the scores that an student can get in the "Saber Pro" test are related with different aspects of his life, like the quantity of books that his family possess, the school where he studied the high school, whether or not his school was bilingual, where he is from (either country or state), or others. Separating properly our dataset with these variables will allow us to predict in a more efficient way the probability of success of a student, making the decision tree a quite powerful tool to solve the problematic.

1.3 Article structure

In what follows, in Section 2, we present related work to the problem. Later, in Section 3 we present the datasets and methods used in this research. In Section 4, we present the algorithm design. After, in Section 5, we present the results. Finally, in Section 6, we discuss the results and we propose some future work directions.

2. RELATED WORK

2.1 How Predicting the Academic Success of Students of the ESPAM MFL: A Preliminary Decision Trees Based Study

The topic of this article is how at own project, they use the decision tree's for predict the performance of the students in ESPAM, considering many aspects like at what does a student can do to improve their ratings. For the method used here they pre-processed the data to duplicate the instances and delete the loss data, representing each variable with numeric data, and they assign three categories, "Acceptable", "Good", "Excellent". Finally, they apply this structure in all variables (1086). The accuracy in this investigation have a precision of 55% and 49%. [1]

2.2 Performance Prediction of Engineering Students using Decision Trees

Through the project described in the article, the authors managed to create a model capable of predict the students' performance in the first year of engineering exam. They used the algorithm J48, managing to reach 60.46% and 69.94% of accuracy (they did two models), showing precisely those who were more likely to fail, allowing the university to counsel them so they could improve their results. [2]

2.3 A CHAID based performance prediction model in educational data mining

In this article, the authors developed a prediction model to be able to analyze the relation between the variables and the performance of students at higher secondary school. The features such as medium of instruction, marks obtained in secondary education, location of school, living area and type of secondary education were the most important ones. The algorithm used was CHAID, reaching 44.69% of prediction accuracy. [3]

2.4 Early prediction of student success: Mining student enrollment data

In this investigation Z. J. Kovacic presents an investigation of case of enlistment information mining, which can be used to foreshadow the success of students. The calculations were carried out by the CHAID and CART algorithms on the substitute recruitment information for the ordinary data frames for New Zealand Polytechnic students, thus achieving two trees that classify effective and ineffective substitutes. the precision obtained with CHAD and CART were 59.4% and 60.5% respectively. [4]

3. MATERIALS AND METHODS

In this section, we explain how the data was collected and processed and, after, different solution alternatives considered to choose a decision-tree algorithm.

3.1 Data Collection and Processing

We collected data from the *Colombian Institute for the Promotion of Higher Education* (ICFES), which is available online at ftp.icfes.gov.co. Such data includes anonymized Saber 11 and Saber Pro results. Saber 11 scores of all Colombian high schools graduated from 2008 to 2014 and Saber Pro scores of all Colombian bachelor-degree graduates from 2012 to 2018 were obtained. There were 864,000 records for Saber 11 and records 430,000 for Saber Pro. Both Saber 11 and Saber Pro, included, not only the scores but also socio-economic data from the students, gathered by ICFES, before the test.

In the next step, both datasets were merged using the unique identifier assigned to each student. Therefore, a new dataset that included students that made both standardized tests was created. The size of this new dataset is 212,010 students. After, the binary predictor variable was defined as follows: Does the student score in Saber Pro is higher than the national average of the period?

It was found out that the datasets were not balanced. There were 95,741 students above average and 101,332 students below average. We performed under sampling to balance the dataset to a 50%-50% ratio. After under sampling, the final dataset had 191,412 students.

Finally, to analyze the efficiency and learning rates of our implementation, we randomly created subsets of the main dataset, as shown in Table 1. The dataset was divided into 70% for training and 30% for testing. Datasets are available at https://github.com/mauriciotoro/ST0245-Eafit/tree/master/proyecto/datasets .

	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
Train	15,000	45,000	75,000	105,000	135,000
Test	5,000	15,000	25,000	35,000	45,000

Table 1. Number of students in each dataset used for training and testing.

3.2 Decision-tree algorithm alternatives

3.2.1 ID3

ID3 is an algorithm invented by Ross Quinlan. It uses a greedy approach to build a decision tree from top to down, selecting the best feature at the moment to create a node. ID3 is only used for classification problems with nominal features. Its complexity its $O(M \cdot N^2)$ where m is the size of the training data and n is the number of attributes.

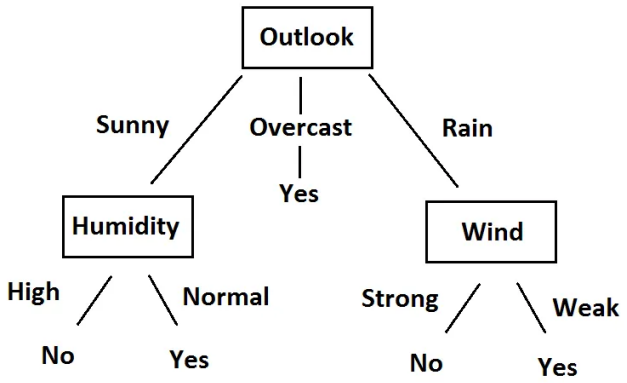


Figure 1 [5]

3.2.2 C4.5

C4.5 is one of the successors of ID3. C4.5 made several improvements in regard to its predecessor, C4.5 uses Gain ratio as an attribute selection measure. Also, C4.5 can handle both discrete and continuous attribute. Its complexity its $O(m \cdot n^2)$ where m is the size of the training data and n is the number of attributes.

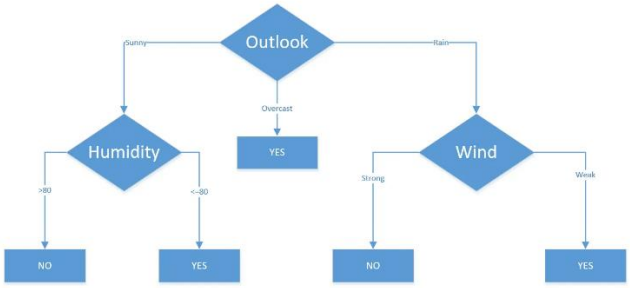


Figure 2 [6]

3.2.3 CART

The CART algorithm is the acronym for Classification and Regression Trees, it was designed by Breiman et al. In this algorithm binary decision trees are generated, so that each node is divided into exactly two branches, true and false. The complexity is $O(v \cdot n \log n)$ the first loop is the v, the second loop is n and the third loop are identical to the second.

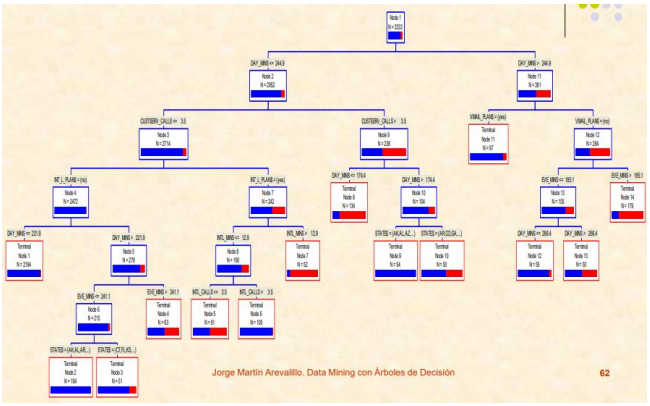


Figure 3 [7]

3.2.4 CHAID

The CHAID algorithm analyzes the values for each variable to predict and through the Chi-square, which was created in 1980 by G. V. Kass and later adapted by Magidson, J. in 1994 and allows us to work with a categorical dependent variable.

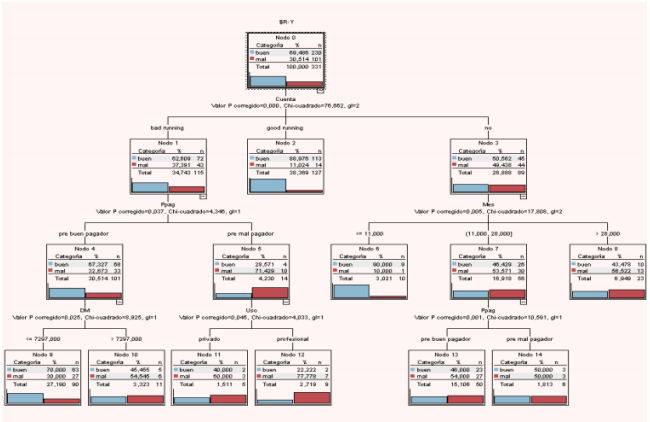
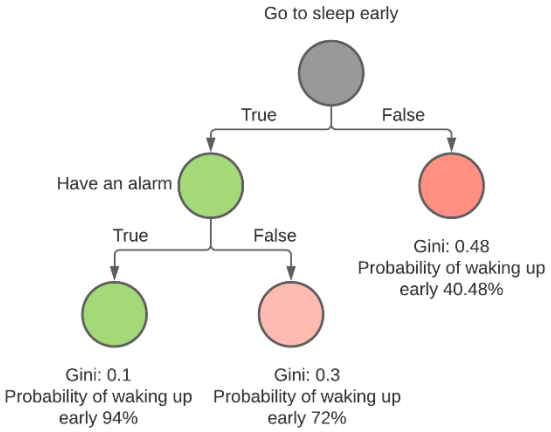


Figure 4 [8]

4. ALGORITHM DESIGN AND IMPLEMENTATION

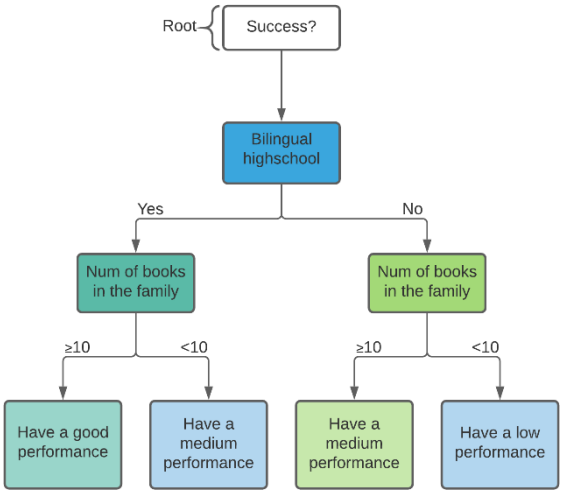
4.1 Data Structure

The data structure that we used to predict the success of the students in the test "Saber pro" was a binary decision tree (see figure 5). It stores the data in nodes, which each node could point to another 2 nodes. The branches on the tree depend of certain conditions that are preselected and it allows the dataset to be filtered over and over. Selecting these conditions properly will filtrate the dataset better, allowing us to know under which conditions the people are more likely to success.



4.2 Algorithms

We used the algorithm CART to solve the problematic, it is designed to filter the datasets according to the conditions that the student matches. It is the responsible to build up the decision tree according to the given parameters, and then we are able to classify new data by calculating with our algorithm the Gini impurity. This calculation allows us to see how efficient works each filter and makes easier to classify new data using the decision tree and therefore giving a more accurate result.



4.2.1 Training the model

The conditions used to train the model, and therefore the conditions that the binary decision tree is built around are: the number of books that the student's family have, the student's antecedents, the student's spectates, the schools calendar, if is a bilingual school, the type of school, the overall student's scores (separated by subjects), the english level of the student, the student's professional score and the student's professional performance.

4.2.2 Testing algorithm

After the decision tree were built up, the other algorithm that we made proceeds to calculate the Gini impurity of the nodes. This calculation basically says how impure is each node. For example, if we tag with 1 the successful students and with 0 the others each student of a given dataset, the node is purer when the tags are more separated. That means that Gini impurity shows how mixed are the tags and how well is working the filter (condition used to build the tree) to separate the data. With that information, classify new information should not be a problem, because we already know which conditions are more likely to filter a successful student, and by that, making the algorithm able to predict with great accuracy the probability of success of the students.n

4.3 Complexity analysis of the algorithms

The time complexity calculated to create the decision tree (training) was based on the time that takes to divide each node (we divide each node in O(N*M) because it takes that time to find the best dividing condition) by the quantity of nodes created (2 raised to m), while the memory consumption is only O(N * M) due to the fact that we only make a copy of the number of reference of the student, not the whole matrix with its values, which means that in each row (with a maximum of m rows) we have x nodes filled with x lists which's sizes will sum in total N. In other words, O (N * M).

On the other hand, the complexity of testing the students is O (n * (M+N)) with n being the quantity of students to test, and M + N because the student has to find the node where he belongs (after a series of questions, that in the worst case will be M). Also, calculating the success probability of the node where the student belongs is O(N) in worst case, which explains the complexity of testing. About memory, is not necessary to worry, because while testing we don't generate new data, making its memory complexity O (1)

Algorithm	Time Complexity
Train the decision tree	$O(N*M*2^M)$
Test the decision tree	O(N*(M+N))

Table 2: Time Complexity of the training and testing algorithms. *In the algorithm N is the number of students in the training dataset, n the students in the test dataset and the M is the number of variables we use to divide the nodes (see 4.2.1)*

Algorithm	Memory Complexity
Train the decision tree	O(N * M)
Test the decision tree	O(1)

Table 3: Memory Complexity of the training and testing algorithms, N being number of training students and M the number of variables used (see 4.2.1)

4.4 Design criteria of the algorithm

The algorithm was designed to prioritize a successful prediction more than time execution. With this objective in mind, we decided to create a random forest of 1000 trees with random data (which keep stable prediction results) that are able to tell each student its prediction accurately. We take in consideration all variables that could affect our results, (the size of the trees, the quantity of data in the trees and the quantity of trees) so we control the range of data that goes inside the random forest, allowing us to train the algorithm real fast, keeping a low memory consumption and an acceptable time consumption, thus maximizing our results.

5. RESULTS

5.1 Model evaluation

In this section, we present some metrics to evaluate the model. Accuracy is the ratio of number of correct predictions to the total number of input samples. Precision is the ratio of successful students identified correctly by the model to successful students identified by the model. Finally, Recall is the ratio of successful students identified correctly by the model to successful students in the dataset.

5.1.1 Evaluation on training datasets

In what follows, we present the evaluation metrics for the training datasets in Table 3.

	15000	***75000***	***135000***
Accuracy	0.75	0.71	0.73
Precision	0.74	0.69	0.81
Recall	0.75	0.80	0.573

Table 3. Model evaluation on the training datasets.

5.1.2 Evaluation on test datasets

In what follows, we present the evaluation metrics for the test datasets in Table 4.

	15000	***75000***	***135000***
Accuracy	0.75	0.74	0.73
Precision	0.76	0.73	0.75
Recall	0.75	0.77	0.70

Table 4. Model evaluation on the test datasets.

5.2 Execution times

Compute execution time for each dataset in GitHub. Measure execution time 100 times for each dataset and report average execution time for each dataset.

	15000	***75000***	***135000***
Training time	4.7 s	5.18 s	6.85 s
Testing time	45.33 s	226.34 s	493.21 s

Table 5: Execution time of the binary decision tree algorithm for different datasets.

5.3 Memory consumption

We present memory consumption of the binary decision tree, for different datasets, in Table 6.

	15000	***75000***	***135000***
Memory consumption	89 MB	460 MB	705 MB

Table 6: Memory consumption of the binary decision tree for different datasets.

6. DISCUSSION OF THE RESULTS

In matters of resources consumption, we saw a considerable quantity of time complexity that makes our algorithm not too efficient by the time of testing the students, while the memory usage was as expected, low an efficient. On other hand, the accuracy obtained (73% in the biggest dataset) is significantly high, so the precision (75%) and the recall are (70%). Due to this high percentages, we consider that recognize students with either low or high probability of success should not be a problem. According to the variables that we used (mostly grades from the Saber 11) it is totally appropriate to give scholarships to the students with the highest percentages of success. Also, given the precision of the program will be possible to accompany more the low success student in their difficult areas and help them to reach better results. Applying this model could allow the education institutions to focus in the welfare and the needs of the students and thus avoiding academic failure or desertion

6.1 Future work

As a team, and after finalizing this project, we consider that is totally necessary for us to learn to reduce the complexity of our programs in order to improve the execution time despite our great prediction (over 70% of accuracy). We also would like to investigate more deeply other machine learning techniques to data prediction with the goal of reach an accuracy of over 90%

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