

Decision trees to predict a student's performance on Saber Pro

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ABSTRACT

Soon, technology will play a big role in the digital transition for education to achieve the so called Education 4.0, often mentioned as the fourth industrial revolution which will be dependent of new technologies. The main problem that we are facing is student dropouts since it's a concern for our country's because of the waste of resources from the institutions as they lose students. Not only that, but it also affects the country's amount of professional/capable people for jobs.

Keywords

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

1. INTRODUCTION

Student dropouts have reasons to do what they did, the reasons are usually a combination of factors that are generated from within the system in a social context, familiar, individual and the setting. Student dropouts involve some problems for educational institutions, because of students deciding to leave the institution, the institution will face a waste of resources.

1.1. Problem

The main problem is how student dropouts affects the economy of our country by negatively affecting the development of human capital, thus generating high social costs because the human capital is less qualified. Its important to resolve this problem because of the reasons previously mentioned.

1.2 Solution

In this work, we focused on decision trees because they provide great explainability (Orea, S. V., Vargas, A. S., & Alonso, M. G. (2005). *Minería de datos: predicción de la deserción escolar mediante el algoritmo de árboles de decisión y el algoritmo de los k vecinos más cercanos*. Ene, 779(73), 33). We avoid black-box methods such as neural networks, support-vector machines, and random forests because they lack explainability.

The main solution to the problem is to anticipate future outcomes and identify potential student populations that have a high percentage of missing tests. The algorithm that makes this possible is decision trees CART, which are used primarily for their ability to separate data into groups of data and determine the probability of such an event occurring.

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 Decision trees for predicting the academic success of students

the algorithm predicts, based on information from grades in elementary and high school, whether a student will attend college successfully or not. Mesarić, J. (2016, 30 December). Decision trees for predicting the academic success of students. hrcak. https://hrcak.srce.hr/index.php?id_clanak_jezik=257113&show=clanak

2.2 Predicting Students Final GPA Using Decision Trees

an educational data mining is used to predict students' final GPA based on their grades in previous courses. After pre-processing the data, they applied the J48 decision tree algorithm to discover classification rules. Al-Barrak, M. A., & Al-Razgan, M. (2016). Predicting student's final GPA using decision trees: a case study. International journal of information and education technology, 6(7), 528.

2.3 Australia-wide predictions of soil properties using decision trees

An algorithm predicts from data taken from the soil the properties of the soil throughout Australia. Properties considered include pH, organic carbon, total phosphorus, total nitrogen, thickness, texture and clay content. Henderson, B. L., Bui, E. N., Moran, C. J., & Simon, D. A. P. (2005). Australia-wide predictions of soil properties using decision trees. Geoderma, 124(3-4), 383-398.

2.4 Predicting Students' Performance Using ID3 And C4.5 Classification Algorithms

the algorithm predicts whether a student will drop out of a college based on his or her previous semester's grades and the college entrance exam Adhatrio, K., Gaykar, A., Dhawan, A., Jha, R., & Honrao, V. (2013). Predicting students' performance using ID3 and C4. 5 classification algorithms. *arXiv preprint arXiv:1310.2071*.

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 undersampling to balance the dataset to a 50%-50% ratio. After undersampling, 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>.

Train	15,000	45,000	75,000	105,000	135,000
Test	5,000	15,000	25,000	35,000	45,000

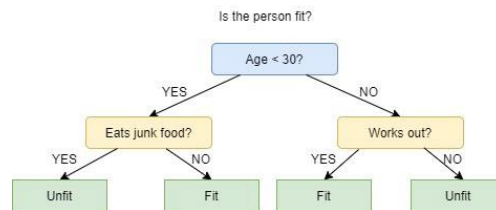
Table 1. Number of students in each dataset used for training and testing.

3.2 Decision-tree algorithm alternatives

In what follows, we present different algorithms to solve to automatically build a binary decision tree. (*In this semester, examples of such algorithms are ID3, C4.5 and CART*).

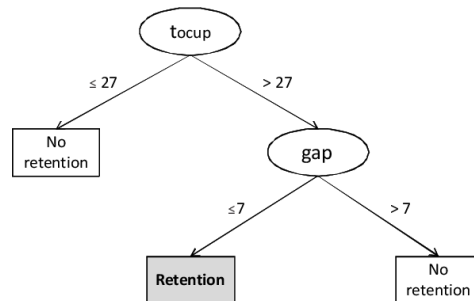
3.2.1 ID3

ID3, also known as Iterative Dichotomiser 3. ID3 uses a top-down greedy approach to build a decision tree. This means that we start building the tree from the top and “greedy” means that at each iteration we select the better feature to create a node.



3.2.2 C4.5

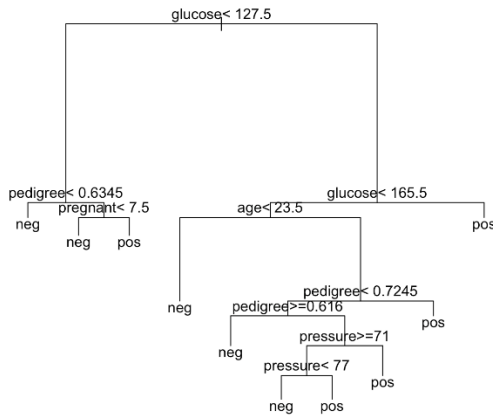
The C4.5 algorithm is used in Data Mining as a decision tree classifier and can later on be employed to generate a decision, all based on data. This algorithm can work with discrete and continuous data, and also it inherently employs a process named single pass pruning process which mitigates overfitting.



3.2.3 CART

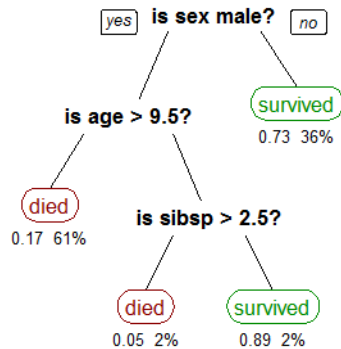
CART algorithm is based on classification and regression trees by Breiman. CART consists of a tree that is constructed by splitting a node in two child nodes repeatedly.

	Dataset 1	Dataset 2	Dataset 3	Dataset 4	Dataset 5
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3.2.4 CHAID

CHAID makes predictions similar to regression analysis (XAID) and can also be used in detecting and identifying the interaction of variables.



4. ALGORITHM DESIGN AND IMPLEMENTATION

The decision trees are algorithms that use data to simulate the specimens contemplated in it, these data must describe with one or more parameters the variables that are desired to predict, for it the algorithm separates in sets the variables depending on the parameters that define it and defining a percentage of probability in which this one happens (purity of Gini), this way there can be events that are defined by certain parameters and his probability of success of 100 %.

4.1 Data Structure

The data must follow a specific structure, for example, in the rows there are several examples of the data you want to train with and in the columns, you must have the variables that define that example. Thus, our decision tree has the necessary information to predict each specimen contemplated in the data.

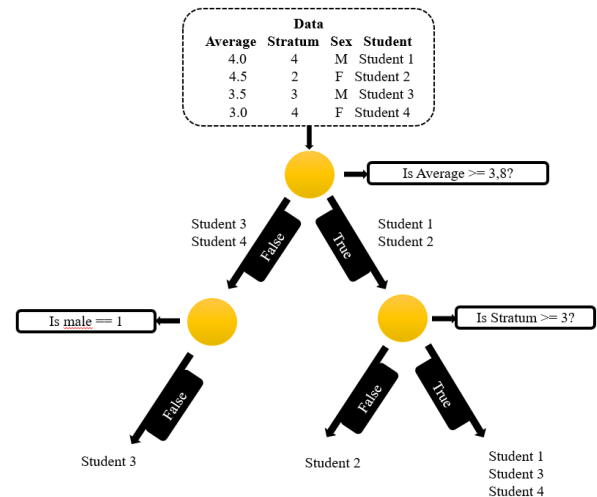


Figure 1: A binary decision tree to predict Saber Pro based on the results of Saber 11. Violet nodes represent those with a high probability of success, green medium probability and red a low probability of success.

4.2 Algorithms

The algorithm divides the information into branches depending on the variables that describe the data (see Figure 1). The more parameters are taken into account, the more the tree branches, this is called depth and differs mainly in the precision with which the tree will predict an event and the purity of Gini indicates how mixed the specimens are, that is to say that when you have a purity of Gini equal to zero, it is because the specimen is described in 100%.

4.2.1 Training the model

In the training the algorithm separates the information depending on the parameters given a specific depth and a given purity of Gini.

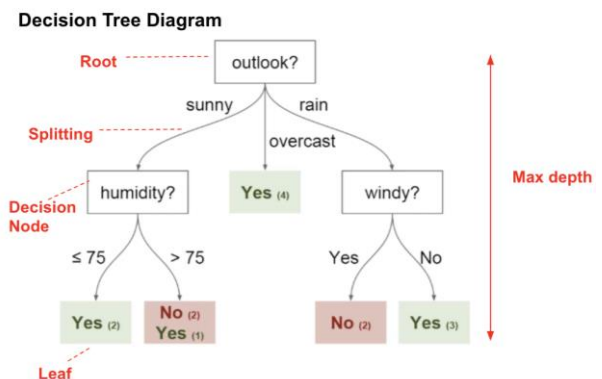


Figure 2: Training a binary decision tree using (In this semester, one could be CART, ID3, C4.5... please choose).

In this example, we show a model to predict whether or not to play Golf, according to weather.

4.2.2 Testing algorithm

The CART algorithm separates the variables thanks to two indicators called information gain and Gini purity; these two indicators are calculated in each call recursive to detect which of the variables separates more effectively information.

4.3 Complexity analysis of the algorithms

In the case of the training code, the tree is built in a recursive way, so it is logical to say that it has an $O(n)$ complexity. Similarly, the test code is a binary search, so it has a complexity of $O(\log n)$.

Algorithm	Time Complexity
Train the decision tree	$O(N \times M)$
Test the decision tree	$O(\log N \times M)$

Table 2: Time Complexity of the training and testing algorithms. (*n* is the number of variables entered by the user.)

Algorithm	Memory Complexity
Train the decision tree	$O(N \times M)$
Test the decision tree	$O(1)$

Table 3: Memory Complexity of the training and testing algorithms.

4.4 Design criteria of the algorithm

The clear advantages of the CART algorithm is that it allows the best possible separation of variables with the minimum use of memory. The algorithm also achieves the highest accuracy with little data, so fewer resources and less processing time can be used.

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.

	Dataset 1	Dataset 2	...Dataset n
Accuracy	96.29%	108.40%	106.97%
Precision	92.6%	92.8%	93.87%
Recall	100%	100%	0.9%

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.

	Dataset 1	Dataset 2	...Dataset n
Accuracy	97.56%	98.83%	98.91%
Precision	95.13%	97.67%	97.82%
Recall	100%	100%	100%

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.

	Dataset 1	Dataset 2	...Dataset n
Training time	7.12 s	21.69 s	72.0423 s
Testing time	0.0438 s	0.0498 s	0.09471 s

Table 5: Execution time of the (Please write the name of the algorithm, C4.5, ID3) algorithm for different datasets.

5.3 Memory consumption

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

	Dataset 1	Dataset 2	...Dataset n
Memory consumption	10 MB	20 MB	5 MB

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

To measure memory consumption, you should use a profiler. An very good one for Java is VisualVM, developed by Oracle, <http://docs.oracle.com/javase/7/docs/technotes/guides/visualvm/profiler.html> For Python, use C Profiler.

6. DISCUSSION OF THE RESULTS

The results we had are very precise: with the algorithm we had implemented, the precision is very high when we're speaking of 100+ results (around 98% precision), we made the best possible model that would very accurately predict the outcome of a student's performance in Pruebas Saber Pro with their results from Pruebas Saber 11.

6.1 Future work

We would like to implement our coding in a more efficient way making it a little easier and more organized to achieve a very clean code.

ACKNOWLEDGEMENTS

Identify the kind of acknowledgment you want to write: for a person or for an institution. Consider the following guidelines: 1. Name of teacher is not mentioned because he is an author. 2. You should not mention websites of authors of articles that you have not contacted. 3. You should mention students, teachers from other courses that helped you.

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REFERENCES

As an example, consider these two references:

1. Adobe Acrobat Reader 7, Be sure that the references sections text is Ragged Right, Not Justified. <http://www.adobe.com/products/acrobat/>.
2. Fischer, G. and Nakakoji, K. Amplifying designers' creativity with domainoriented design environments. in Dartnall, T. ed. Artificial Intelligence and Creativity: An Interdisciplinary Approach, Kluwer Academic Publishers, Dordrecht, 1994, 343-364.
3. Sakkaf, Y. (2020, April 17). Decision Trees: ID3 Algorithm Explained | Towards Data Science. Medium. <https://towardsdatascience.com/decision-trees-for-classification-id3-algorithm-explained-89df76e72df1>
4. Saha, S. (2018, November 16). What is the C4.5 algorithm and how does it work? - Towards Data Science. Medium. <https://towardsdatascience.com/what-is-the-c4-5-algorithm-and-how-does-it-work-2b971a9e7db0>

5. Data Mining for Predicting Traffic Congestion and Its Application to Spanish Data - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Tree-generated-by-the-C45-algorithm-for-the-case-of-60-minutes-of-anticipation_fig1_274700559 [accessed 16 Aug, 2020]

6. (2018, March 11). CART Model: Decision Tree Essentials. Articles - STHDA. <http://www.sthda.com/english/articles/35-statistical-machine-learning-essentials/141-cart-model-decision-tree-essentials/>

7. Wikipedia contributors. (2019, 5 enero). Chi-square automatic interaction detection. Wikipedia. https://en.wikipedia.org/wiki/Chi-square_automatic_interaction_detection