



Hybrid Recommender System of university programs for high school students using Deep Learning

Sistema de recomendación de programas universitarios para estudiantes de educación media basado en Deep Learning

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RESUMEN

Palabras clave:
Recommender Systems;
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decision-making;
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university.

Los estudiantes que van a culminar la educación media y se enfrentan a la selección de programas académicos, usualmente usan buscadores web, información de programas y asesorías o pruebas vocacionales. Sin embargo, estas alternativas tienen limitaciones, porque no tienen en cuenta las características sociodemográficas del estudiante ni su desempeño académico o no pueden guiar adecuadamente a todos los estudiantes. Esta propuesta apoya la toma de decisiones de este grupo poblacional con un Sistema de Recomendación que produce recomendaciones basadas en variables sociodemográficas y datos académicos históricos de estudiantes de pregrado. Además, se compara el desempeño de un modelo de Filtrado Colaborativo clásico y Deep Learning.

ABSTRACT

Keywords:
Sistemas de
Recomendación;
Deep Learning;
toma de decisiones;
programas académicos;
universidad.

High school students who are faced with the selection of academic programs decide based on program information available in search engines, websites, vocational counselling by advisors, or tests. However, these alternatives have limitations because they do not take into account important historical and sociodemographic information, or in case of the advisors, they cannot guide all students. This work supports the decision-making of students through a Recommendation System that presents recommendations based on sociodemographic variables and historical academic data. Also, we propose and compare two methods: a classic Collaborative Filtering model and a Deep Learning model.

Introduction

Education, as a process that seeks to direct and guide [1] children and young people, is a matter of general interest throughout the world, since the growth and economic development of a country are directly related to the fact that its inhabitants have access to education and that it is of quality [2]. From this arises the need for many countries, whether developed or not, to focus their efforts to reach more people at different levels of their educational trajectory and in accordance with international standards.

In Colombia, of the nearly 504 thousand grade 11 students reported for 2013, about 174,600 entered higher education in the first and second semester of 2014, suggesting an immediate absorption rate or immediate transit to Higher Education in Colombia of 34.6% [3]. Likewise, 58% of the 2013 high school graduates who entered higher education in 2014 selected programs at the university level, 38% at the technological level and 4% at the professional technical level. In addition, analyses conducted by the Ministry of Education show that a significant number of our high school graduates enter higher education two, three, four and even five years after completing high school.

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In addition, different studies at the national level have shown that the dropout of higher education students is closely linked to the vocational and professional orientation processes [4]. At this point, it is important to talk about the initiative designed by the Center for Studies on Economic Development - CEDE, of the Universidad de los Andes and articulated by the Ministry of National Education called SPADIES (System for the prevention and analysis of dropout in Higher Education Institutions) [5], which monitors and tracks the problem of dropout in higher education, calculates the risk of dropout, supports the evaluation of strategies for each of the situations that influence dropout, such as the situation of the student, the academic program and the institution; Finally, it promotes the consultation, consolidation, interpretation and use of this information. Demonstrating the importance that has taken for the universities of the country, the identification of dropout rates in higher education [6].

With this problem in mind, solutions proposed by other authors are sought to help students in the world to make one of their first decisions: which career or which undergraduate academic program will they study? Some proposals are focused on vocational orientation through psychological methods and student self-discovery. These have their beginnings with the creation of the first vocational and moral guidance program and the first centralized guidance service for all schools, in Michigan, by B. Davis, who was principal of Grand Rapids High School [7]. Others seek to guide decision making through the use of available tools. For example, in Colombia, websites such as Guía Académica [8] of the publishing house El Tiempo, which provides personalized, non-automatic advice and helps students to enroll in the university and program of their choice; or the portal of universities in Colombia [9], created to support students in the eleventh grade of secondary education in the country, is a container of information on universities, academic programs, scholarships, news of interest, vocational tests, among others. Also presenting more complete technological solutions, such as the portal created by the Ministry of National Education [10], which is a system that through online questionnaires captures the preferences of students and then displays results by breaking them down into knowledge cores, main topics of those cores and finally academic programs that contain those topics.

Building systems that support users in their decision making is the main goal of Recommender Systems (RS). In particular, recommender systems seek to provide high quality and easily accessible recommendations for a large community of users [11]. Since the problem of this work is associated with student decision making, it is appropriate to orient the solution to this type of systems, balancing the needs and purposes of students with the implementation of methods, algorithms, equations and technical aspects developed to present an adequate solution [12].

A search is made for academic research papers that support student decision making, mainly in the selection of subjects, programs or universities, and that focus on recommender systems, data mining or machine learning systems or machine learning.

Table I. Work reviewed.

Work reviewed		
RS Objective	RS Type	Documents
Course Selection	Collaborative Filtering	[13]–[16]
	Content Based	[17], [18], [19]
	Knowledge-based	[20]–[23]
	Hybrid	[24]–[32]
Program Selection	Collaborative Filtering	[33], [34], [35]
	Content Based	[36], [37]
	Knowledge-Based	[38]
	Hybrid	[39]
University Selection	Collaborative Filtering	[40]–[43]
	Content Based	[44], [45]
	Hybrid	[26], [46]

In the reviewed works, the algorithmic tasks are focused on recommender system paradigms: Collaborative Filtering (CF) based, its main idea is to exploit information about the past behavior or opinions of an existing user community to predict which items the current user of the system will like or be interested in; to apply it is not necessary to know about the characteristics of the items, but the ratings that users have made. Content-based, based on the description of an item's characteristics and a user profile that somehow describes the user's (past) interests in terms of the preferred item's characteristics, determines the items that best match the user's preferences. Knowledge-based, they operate from requirements set by the user or from an explicit recommendation rule base, no rating data is needed for the calculation of recommendations. Hybrid systems are technical approaches that combine several implementations of recommendation algorithms or components taking the strengths of different paradigms to overcome some of the shortcomings and problems they present [11].

This paper seeks to show a solution that implements a three-component hybrid Recommender System (RS), comparing the performance of a classical Collaborative Filtering model with one based on Deep Learning for the selection of student demographic variables.

Deep Learning offers a set of techniques and algorithms that help parameterize deep neural network structures, i.e., artificial neural networks with many hidden layers and parameters. One of the key ideas behind Deep Learning is to extract high-level features from a given data set. Therefore, it aims to overcome the challenge of the often tedious feature engineering task and helps to parameterize traditional neural networks with many layers [47]. The main advantage of neural networks is that the multi-layered architecture provides the ability to compute complex nonlinear functions that are not easily computable with other classification methods [48]. Hence, the application of these to the model proposed in this paper arises.

The article continues in section 2 with the methods used in the research. Section 3 shows the results obtained and finally, Section 4 concludes this work.

Materials and methods

Data

The data sources obtained for this work are classified into 6 groups: the first is associated with the student and has relevant sociodemographic information obtained in the enrollment process and the Academic Program(s) he/she selected and in which he/she is enrolled in a Colombian University. The second one, the information of state tests that the student has presented as a requirement for secondary education degree, this data set has information of 3 types of exams due to the changes made by the ICFES (Colombian Institute for the Promotion of Higher Education) over the years; for this reason, a standardization is made to define within the same valuation scale the scores obtained by the students in these tests, and thus minimize the inconsistencies and errors that could be presented by this at the time of generating the recommendation models. In addition, the ICFES defines that the comparability of the students' results with the scale used in the second semester of 2014, the moment from which the current test scoring methodology began to be applied and for which the average global score of the students evaluated in each of the five tests is 50 points with a standard deviation of 10 points [49], must be ensured. The third contains information on the student's academic history within the academic program(s). The fourth is the detail of the characteristics of each school where the students studied their high school education, obtained through the Unique Directory of Establishments (DUE) that has the characterization of the country's educational institutions. The fifth corresponds to the information on the academic programs that contains a descriptive text of each one, obtained from various public sources, including the description of the program, the field of action, other names by which it is known, among others. The sixth refers to an open text to be written by the student about his or her interests and tastes, which will be analyzed to refine the results.

Recommendation System

RSs are information filtering systems that actively collect various types of data to elaborate their recommendations [50]. Recommender systems have their roots in various research areas, such as information retrieval, information filtering, and text classification, and apply methods from different fields, such as machine learning, data mining, and knowledge-based systems [11].

There are two types of information used by RSs to predict the relevance of an item to a user: explicit feedback consisting of direct user feedback on an item. Ratings are a common representation of the user's opinion of an item, e.g., a numerical rating (1 to 5), a rating on a likert scale (Strongly Disagree, Disagree, Neither Agree nor Disagree, Agree, Strongly Agree) or Binary ratings (Like, Dislike). Implicit feedback, on the other hand, is the collection of actions that users exert on items, these actions indirectly reflect the user's opinion about the item, e.g., a user may view, click, or purchase an item [51].

The input data are obtained through a web page, in which the user enters his/her sociodemographic and state test information, from it the models included in the RS are run to obtain recommendations for undergraduate academic programs.

Collaborative Filtering

Collaborative Filtering is considered the most popular and highly implemented technique [50]. In this work, its objective is to generate recommendations from information obtained from undergraduate students who have performed well in the academic programs in which they are enrolled. Variables such as personal, socioeconomic and family data, schooling, state exams, academic history and information on the schools or educational institutions where the students included studied high school, classification (between A and D), sector (official or unofficial), area (rural, rural-urban, urban, urban-rural), gender (female, male, mixed), character (academic, technical, technical-academic) and calendar (A or B) are analyzed.

The students are in the set U that contains the information of the system users, and is represented by a vector of C positions thus: $X_u \in \mathbb{R}^C$ where C corresponds to the number of characteristics or independent variables of each user; after applying normalization techniques to the data $C=70$.

Then, the probability that user u has an associated item or class (cat) is calculated [52]:

$$prob_{programa(u,cat)} = \sum_{k \in N(u)} \frac{1}{d(k,u)} * \frac{\mathbb{I}(cat(k)==cat)}{|N(u)|} \quad (1)$$

where $N(u)$ is the neighborhood of the active user u , k is an element within this neighborhood, $d(k,u)$ is the distance in space between the neighborhood element and the active user. The total weight is calculated as follows:

$$total_{peso(u)} = \sum_{k \in N(u)} \frac{1}{d(k,u)} \quad (2)$$

To determine the neighborhood of a user, the Manhattan distance between points is measured. The Manhattan distance, rectilinear distance or L1 distance says that the distance between two points is the sum of the (absolute) differences of their coordinates. That is, the distance d , between two vectors u and v , in an n -dimensional real vector space with a fixed Cartesian coordinate system, is the sum of the lengths of the projections of the line segment projections between the points on the coordinate axis system:

$$d(u, v) = \|u - v\|_1 = \sum_{i=1}^n |u_i - v_i| \quad (3)$$

Where $u = (u_1, u_2, \dots, u_n)$ y $v = (v_1, v_2, \dots, v_n)$ are vectors.

Deep Learning

An Artificial Neural Network (ANN) is a network inspired by biological neural networks that are used to estimate or approximate features that may depend on a large number of inputs that are generally unknown. An ANN is constructed from nodes (neurons) stacked in layers between the feature vector and the target vector. A node in a neural network is constructed from the function Weights and activation. An early version of ANN built from a node was called Perceptron. Perceptron is an algorithm for supervised learning of binary classifiers, functions that can decide whether an input (represented by a vector of numbers) belongs to one class or another. A perceptron network can be designed to have multiple layers, if it has more than one hidden layer it is called (*deep artificial neural network*). [47].

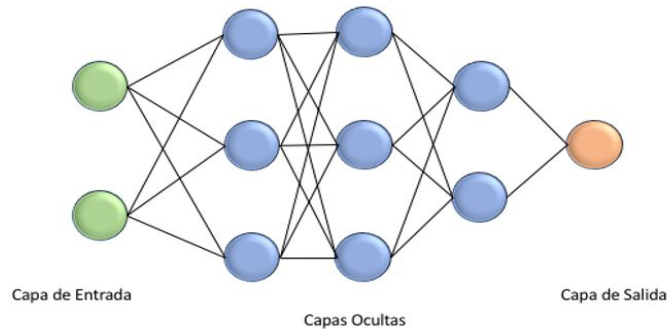


Figure 1. Multilayer neural network.

Source: own elaboration

The stochastic gradient is used as a method for weight optimization. The activation function chosen for the hidden layers is the sigmoid, which allows capturing small changes in the weights w and the bias b . The sigmoid function $\sigma(Z)$ obtains a probability estimate thus:

$$P(Y_i) = P(Y_i = 1 | X, w, b) = \frac{\exp^{\sum_{j=1}^k w_j x_j + b}}{1 + \exp^{\sum_{j=1}^k w_j x_j + b}} = \frac{\exp^z}{1 + \exp^z} = \sigma(Z) \quad (4)$$

Results and Discussion

Model fitting and results obtained

The problem of predicting the student's career is posed as a multiclass classification model, where the objective variable is the program in which the student will perform well.

The sociodemographic characteristics of the students are in different domains, that is, we have 24 categorical and 8 numerical variables. Therefore, before running the models, some strategies are applied to standardize numerical variables by eliminating the mean and scaling to units, as well as coding categorical variables so that they can be used by the algorithms and generate better predictions.

Standardization of a data set is a common requirement for many machine learning estimators: they can misbehave if individual features do not more or less resemble the normally distributed standard data. The standard score of a sample x is calculated as: $z = (x - u)/s$ where u is the mean of the training samples or zero if `with_mean = False`, and s is the standard deviation of the training samples or one if `with_std = False`.

In addition, the historical dataset was divided into 3 subsets, one for training which contains known results, the model learns on this data to then predict on the other subsets, it represents 56% of the total data; the second, is the testing to test the prediction of our model and that in this project corresponds to 25% of the data; and finally the validation, which has 19% of the data that the model has not known and on which all the validations of the metrics are made.

The distribution of the data sets for training, testing and validation was as follows:

Table 2. Distribución del conjunto de datos.

Data set	Number of records	Distribution
Training	10825	56%
Test	4812	25%
Validation	3609	19%
Total	19246	100%

The metric chosen for model optimization is the Accuracy or prediction accuracy of the given labels and test data. In multiclass classification, it returns the accuracy of the subset. If the entire set of labels predicted for a sample strictly matches the actual set of labels, then the subset accuracy is 1.0; otherwise, it is 0.0.

If \hat{y}_i is the predicted value of the i -th sample and y_i is the corresponding true value, then the fraction of correct predictions over $n_{samples}$ is defined as

$$accuracy(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1 - (\hat{y}_i \neq y_i) \quad (5)$$

Modelo KNN

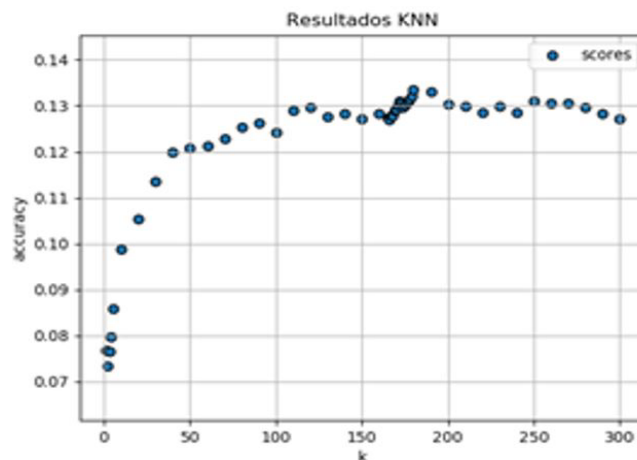


Figure 3. Accuracy CF. Source: own elaboration

Initially a run was made to determine the number of significant neighbors for the data. With this $n_neighbors = 180$ the iterations of parameter variation were executed, however, once the best parameters were defined, the model was varied over all possible $n_neighbors$ to improve the accuracy of the model. The accuracy obtained with this model is 13%.

Parameters such as the distance metric were varied between Euclidean, Manhattan and Minkowski, which are those that determine the distance between the points of an active user against the records that are part of the training; the weight is varied between uniform or distance values, where uniform indicates that all the points of the neighborhood have equal weights and distance indicates that a greater weight is given to those points that have less distance to the active user, i.e., that contribute more to the adjustment. (See Table 3).

Table 3. Better parameters for subsets of data.

Métrica	N_neighbors	Weights	Accuracy test	Accuracy Validación
Euclidean	180	Uniform	0.1334	0.1237
Manhattan	180	Uniform	0.1367	0.1262
Minkowski	180	Uniform	0.1334	0.1237
Euclidean	180	Distance	0.1297	0.1237
Manhattan	180	Distance	0.1340	0.1259
Minkowski	180	Distance	0.1297	0.1237

Source: own elaboration

In this case the best parameters are algorithm = Auto, metric = Mahattan, $n_neighbors = 180$ and weights = Distance.

Neural network model

Parameter exploration is performed for the implemented MLPClassifier model in order to obtain the best ones for the final execution of the neural network. Parameters such as the number of hidden layers and neurons, the activation function for each hidden layer between Relu and Sigmoid (for the implementation called Logistic) were varied; the weight is not varied and is maintained with the stochastic gradient optimizer (adam) and the learning rate is also kept constant (adaptive). (See Table 4).

Table 4. Best parameters for the neural network.

Activation function	Penalization	Hidden layers and neurons	Learning rate	Optimizer	Test score	Validation score	Mean test score	Std test score	
logistic	0.0001	(50, 100, 50)	adaptive	adam	0.564084	0.548232	0.556158	0.007926	1
logistic	0.001	(50, 100, 50)	adaptive	adam	0.558755	0.535849	0.547302	0.011453	2
logistic	0.0001	(50, 50, 50)	adaptive	adam	0.553945	0.536276	0.545111	0.008835	3
logistic	0.001	(50, 50, 50)	adaptive	adam	0.542884	0.536301	0.539593	0.003292	4
logistic	0.05	(50, 50, 50)	adaptive	adam	0.554665	0.523535	0.539101	0.015565	5
logistic	0.05	(50, 100, 50)	adaptive	adam	0.543170	0.534174	0.538672	0.004498	6
logistic	0.05	-100	adaptive	adam	0.541218	0.526874	0.534046	0.007172	7
logistic	0.0001	-100	adaptive	adam	0.533186	0.533301	0.533244	0.000057	8
logistic	0.001	-100	adaptive	adam	0.529470	0.520885	0.525178	0.004292	9
relu	0.05	(50, 100, 50)	adaptive	adam	0.524074	0.510890	0.517482	0.006592	10
relu	0.001	(50, 50, 50)	adaptive	adam	0.515961	0.512135	0.514048	0.001913	11
relu	0.0001	(50, 50, 50)	adaptive	adam	0.515464	0.500225	0.507845	0.007620	12
relu	0.05	(50, 50, 50)	adaptive	adam	0.515912	0.496666	0.506290	0.009623	13
relu	0.0001	(50, 100, 50)	adaptive	adam	0.517945	0.490634	0.504290	0.013655	14
relu	0.001	-100	adaptive	adam	0.510969	0.496585	0.503777	0.007192	15
relu	0.001	(50, 100, 50)	adaptive	adam	0.513140	0.492915	0.503028	0.010113	16
relu	0.05	-100	adaptive	adam	0.505737	0.497436	0.501586	0.004151	17
relu	0.0001	-100	adaptive	adam	0.519327	0.481994	0.500662	0.018666	18

Source: own elaboration

The best results are obtained with the sigmoid activation function and an accuracy of 56%.

Discussion and binary classification model

By applying the multilayer neural network to the data, an accuracy of 56% is obtained, which significantly improves the results obtained in the CF with an accuracy of 13% for 180 nearest neighbors surpassing the baseline of the classical CF model.

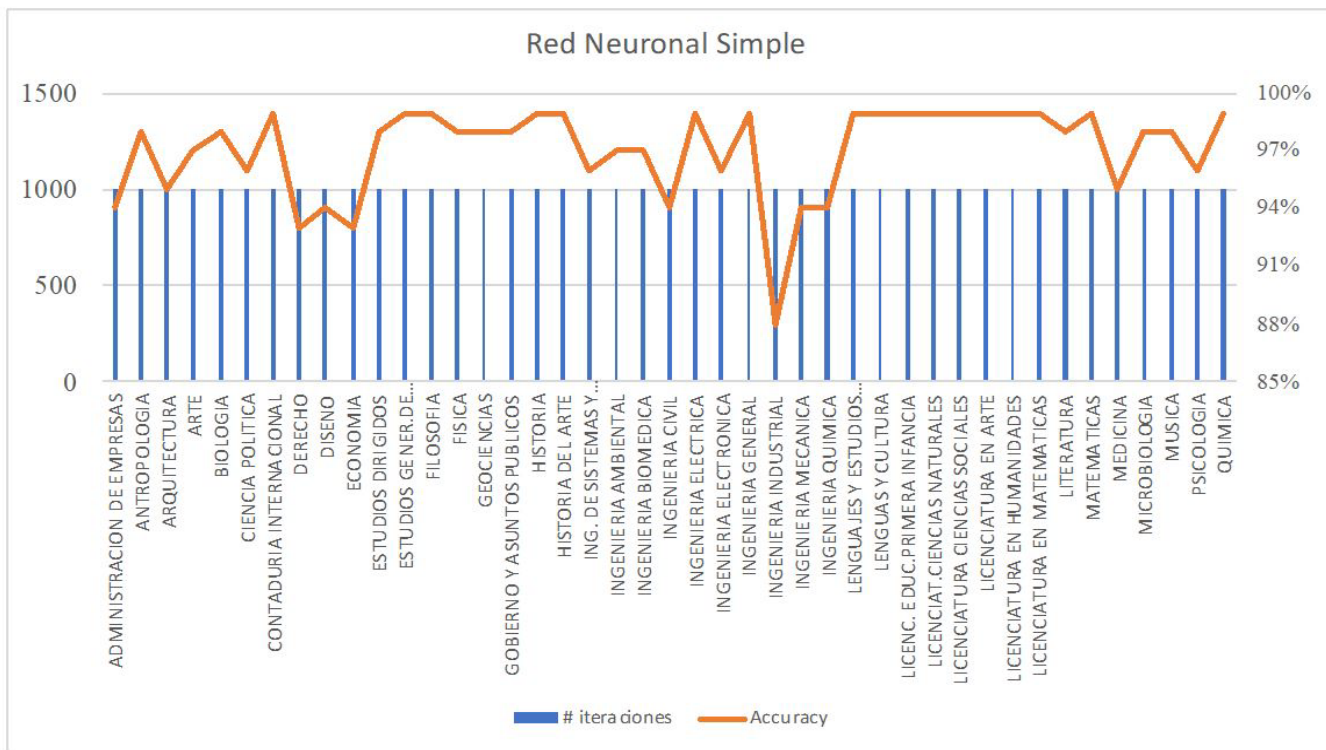


Figure 4. Accuracy Simple neural network. Source: own elaboration.

Likewise, a simple neural network is executed independently for each of the programs found in the output set (see Figure 4). Although this alternative is a little far from the research question, because it analyzes independently each of the outputs, suggesting the user to study or not each program independently, it is important to see the performance obtained.

The accuracy improves significantly if analyzed from this perspective. The program that generates a lower performance is the one mostly represented in the data, i.e., Industrial Engineering. It is important to see this proposal with the data balanced, so that we can analyze how it impacts the results.

Conclusions

Academic recommender systems are a tool for students to make better decisions and set them on the path to a successful professional life. This work results in the feasibility of using data that institutions of higher education have to improve their counseling processes and decrease the burden on advisors. One of the main limitations of this work is that the data set used corresponds to student data from only one private university in the country. This causes the system to have a sampling bias that impacts the results obtained against the general objective.

The Deep Learning approach improves the recommendations generated in the first component due to the optimization process of the error metric and the complexity of the neural network. However, extra work is required to adapt explanation mechanisms for this type of models, since in this context it is important to explain the results of the models to the student.

There are still pending issues associated with having a larger data set of students, including information from students from other regions of the country to eliminate bias in the data. In addition, broadening the profile of academic programs through semantic enrichment systems.

Further work should be done on neural network and Deep Learning strategies, as they are shown to significantly improve the performance of feature-based models.

It is important to include a validation method that allows obtaining feedback from real users of the system, in order to analyze their level of satisfaction with the recommendations generated. Since a recommender system is only as good as its users think it is [24].

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