Analyzing the determinant characteristics for a good performance at ENADE Brazilian exam stratified by teaching modality: face-to-face versus online

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Keywords: ENADE, Feature Selection, Educational Data Mining, Data Science.

Abstract: The National Student Performance Exam (ENADE) annually evaluates different Brazilian higher education courses. This exam considers both face-to-face and distance learning courses. Distance learning is growing increasingly, especially during the coronavirus (COVID-19) pandemic. This study applies different techniques for selecting ENADE 2018 database characteristics, like information gain, gain rate, symmetric uncertainty, Pearson correlation, and relief F. The objective of the work is to discover which personal and socioeconomic characteristics are decisive for the student's performance at ENADE, whether the student is in the context of Distance Education or face-to-face. It can be concluded, among other results, that: the father's level of education directly influences performance; the higher the income, the better the performance; and white students have better performance than black and brown-skinned ones. Thus, the results obtained in this study may initiate analyzes of public policies towards improving performance at ENADE.

1 INTRODUCTION

Higher education is booming in Brazil, and according to CES (acronym in Portuguese for Higher Education Census) (Inep, 2019), from 2009 to 2019, enrollment in higher education increased by 43,7%. CES constitutes an essential instrument for obtaining data to generate information that subsidizes public policies' feeding, monitoring, and evaluation. In 2019, students enrolled in higher education reached 8,6 million, a growth of 5,4% compared to 2018. This increase is due to distance learning (DL) (Barreto and Amaral, 2019) which, from 2009 to 2019, increased 378,9 %. DL is a form of education in which learning occurs at a distance (physical and temporal), mediated by a technology tool that allows communication and interaction between participants.

Directly linked to teaching, we have the National Student Performance Exam (ENADE), an assessment that annually analyzes the different Brazilian higher education courses. This exam considers both on-site and distance learning courses. The National Institute of Educational Studies and Research Anísio Teixeira (Inep), a federal agency linked to the Ministry of Education (MEC), currently applies and elaborates this exam. ENADE microdata is generated through the examination, the minor level of granularity of collected data. They meet the demand for specific information by providing tests, templates, information about items (manual and dictionary), grades, and the student questionnaire, which contains different information regarding the candidate.

Considering the microdata from ENADE, this work aims to find which personal and socioeconomic characteristics are decisive for the student's performance, whether he/she is a DL or a face-to-face (F2F) student. To achieve our objective, this work employs a well-established methodology called Knowledge Discovery in Database (KDD) (Tan et al., 2016). Applying data mining techniques in the field of education has shown promising results, giving rise to a new area of scientific investigation called Educational Data Mining (EDM) (Baker et al., 2011).

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This article is organized as follows. In Section 2, we find the related works. In Sect. 3, feature selection techniques are presented. In Sect. 4, the adopted methodology is described. The results are presented in Sect. 5, and we have the conclusions in Sect. 6.

2 RELATED WORK

The possibilities for applying EDM techniques in Brazil are presented by (Baker et al., 2011). The study demonstrates how this area of research can contribute to a better understanding of teaching and learning processes and student motivation. (Gottardo et al., 2012) proposes the definition of a broad and generalizable set of attributes used to make inferences regarding student performance. Experiments performed showed indexes of 76% accuracy in predicting performance. (Romero et al., 2008) highlights the possibilities of using data mining to extract relevant information about students in the educational context.

Specifically, at ENADE, (Araújo et al., 2019) proposed the use of knowledge discovery techniques to develop a tool for exploring the exam data. In addition to evaluating the structure and distribution of test data, they also proposed a model based on the CART (Breiman et al., 1984) algorithm capable of predicting student performance. (Faria, 2017) work has as its primary objective the identification of the determining factors in the performance of students in Business Administration courses. They used microdata from ENADE 2012 of the Federal District. The research has predominantly quantitative analysis characteristics based on descriptive and multivariate statistical techniques. The multiple regression method was used to verify whether the student's characteristics, such as personal and socioeconomic aspects, the institution, and the didactic-pedagogical organization, would be significant variables in explaining the test result. The results showed that the student relevant factors that aided in predicting performance were: family income, male gender, mother's and father's education level.

Unlike the works exposed above, our proposal aims to apply different techniques for feature selection, to point out which personal and socio-economic aspects are significant characteristics in explaining the result of ENADE 2018.

3 FEATURE SELECTION

Feature Selection (FS) is the process of identifying and removing irrelevant attributes and redundant information as much as possible (Miao and Niu, 2016). FS reduces the dimensionality of the data. It improves the performance of the classifiers, as it eliminates attributes that do not add value to the classification or deteriorate the results. It contributes to a better understanding and analysis of the results obtained and allows learning algorithms to operate more quickly and effectively. FS main objective is to identify the set of attributes best representing the useful information in the data (Tasca, 2015), within a context.

3.1 Entropy

Entropy (Shannon, 1948) is defined as a form of measurement or average degree of uncertainty regarding sources of information, which consequently allows a quantification of the information present that flows in the system. In simple terms, the concept of entropy is associated with the idea that the more certain the outcome of a random experiment, the more information you get from observing its occurrence.

It can also be defined as the amount of uncertainty in a message, which decreases as the symbols are transmitted, that is, as the message becomes known, then information is obtained, which can be seen as uncertainty reduction. Entropy is calculated by: $E(A) = -\sum_{a \in A} P(a) \log_2 P(a)$, where A is the attribute to be calculated, a is the value of this attribute and P is the relative frequency of values.

3.2 Information Gain

The information gain (IG) (Hall and Smith, 1998) is defined as the amount of information obtained about a random variable or signal from the observation of another random variable. It measures the significance of the attribute with the target class; i.e., it measures the reduction of uncertainty (entropy) as a division function. As a disadvantage, it tends to prefer divisions that result in numerous partitions, each one being small but neat. Information Gain is calculated by: $IG(A) = E(C) - \sum_{a \in A} \frac{n_a}{n} E(a)$, where E denotes the entropy function, C is the class, A is the attribute to be evaluated, n_a is the number of instances of the category belonging to the attribute, n is the total number of instances and a is the attribute value.

3.3 Gain Ratio

The gain ratio (GR) (Karegowda et al., 2010) was developed to solve the IG problem. It is the ratio of IG and the attribute entropy, which is nothing more than the relative IG as an evaluation criterion. It adjusts the IG by partitioning entropy, causing high entropy partitioning (a large number of small partitions) to be penalized. GR is defined by: $GR(A) = \frac{IG(A)}{E(A)}$, where $IG(A)$ is information gain and E is the entropy.

3.4 Symmetric Uncertainty

Symmetric uncertainty (SU) (Yu and Liu, 2003) is a nonlinear correlation measure developed with the same purpose of GR, that is, an attempt to normalize the IG of an attribute A with the class C. SU is defined by: $SU(A) = 2 \cdot \frac{IG(A)}{E(A)+E(C)}$, where $IG(A)$ is Information Gain and E is the entropy.

3.5 Pearson Correlation

Pearson Correlation (PC) (Hall, 1998), also known as a linear coefficient, measures the degree of correlation between two metric scale variables. It is a relationship degree between two quantitative attributes, and it expresses the correlation degree through values between -1 (negative or inverse correlation) and 1 (positive linear relationship). A correlation coefficient near zero indicates no relationship between the attributes. The PC is given by: $PC(A) = \frac{Cov(X,Y)}{\sqrt{Var(X)*Var(Y)}}$, where Cov is the covariance between the two attributes and Var is the variance of each attribute. To calculate the qualitative attributes correlation, data are adapted by turning them into binary data.

3.6 Relief F

Over the years, a Relief extension called Relief F (Kononenko, 1994; Kira and Rendell, 1992; Urbanowicz et al., 2018) has been developed, aiming to improve the original algorithm by estimating probabilities more reliably. It handles multiclass and incomplete datasets, while the complexity remains the same. It is calculated using a function W defined by: $W(A) = W(A) - \frac{diff(A,R_i,H)}{m} + \frac{diff(A,R_i,M)}{m}$, where A is the attribute, W(A) is a vector with each attribute score, R_i is the target instance, H is the closest instance of the same class, M is the closest instance to the other class, m is the number of random instances selected to be part of the calculation, and the function $diff$ calculates the difference between attributes.

4 METHODOLOGY

In this section, we present the methodology used for this study. We emphasize that the work is supported by the KDD process, which comprises five stages.

1. **Selection** This work takes into account ENADE 2018 microdata. They have 548,127 instances and 137 attributes of the numeric or character type. The attributes are divided, among others, into the institution and course information, student information, the number of items in the objective part, types of presence (participant present, absent or canceled test), test perception questionnaire, and student questionnaire. The original database was divided into online students (96,927 instances) and F2F students (451,200 instances). After analyzing all database attributes, we focus on the personal, socioeconomic aspects and participant's course. We emphasize that at this point, 23 attributes were kept in each database[1].

2. **Preprocessing** The first preprocessing operation was the application of a filter to select only those participants who had actually taken the test. We removed 32,285 participants from the online modality and 115,765 F2F students. The criteria for removing attributes include absent candidates, candidates with a blank test in the objective and discursive part of general education, candidates with a blank test in the objective and discursive part of the specific component, participation with a result disregarded by the Applicator. The second step verified null or incomplete data, including blank test notes and the blank part of the questionnaire. We excluded 15 online cases and 103 F2F. Online databases had 64,627 instances, and F2F had 335,332.

3. **Transformation** The first operation was to rename the attributes. At this stage, 23 attributes had names referring to the student's questionnaire number (QE_I01 to QE_In). The nominal values of the attributes (A, B, etc.) were also renamed, for example, the father's level of schooling was renamed to (None, Elementary 1, Elementary 2, High school, Undergraduate, Graduate).

   The courses were also grouped according to their primary areas, according to the tables provided by CNPq and CAPES, Brazilian funding agencies. ENADE's exam occurs every three years in a specific set of courses. Not all courses took the test in 2018. The scores obtained by the candidates were also categorized, with their values discretized into three frequency categories (low, medium, and high performance), keeping the original distribution. Discretized online student grades performance: Low ($\leq$ 30), Medium (30 $<$ grade $\leq$ 60) and High ($>$ 60). Discretized grades of face-to-face students: Low ($\leq$ 31), Medium (31 $<$ grade $\leq$ 62) and High ($>$ 62).

4. **Data Mining** In this step, we apply the five distinct methods for FS. We consider the database (online and F2F), taking into account 23 pre-selected attributes. In Sect. 3 we present the ap-

[1]The original database and the complete list of attributes are available at – https://www.gov.br/inep/pt-br/acesso-a-informacao/dados-abertos/microdados/enade

plied FS algorithms in detail. For each algorithm, the most relevant characteristics are selected according to the ranking generated by the algorithms. We also perform an exploratory analysis of the most frequent attributes in all methods.

5. **Interpretation and Evaluation** After applying the five FS methods and analyzing the ranking generated by the algorithms, the top-10 most frequent attributes are considered in at least four of the FS algorithms, both for the students in online and F2F modality. After choosing the best attributes, we perform an exploratory analysis of each attribute. We generate graphics for each modality and compare online and face-to-face modality profiles. In Sect. 5, we present and discuss the results of the exploratory analysis.

5 RESULTS

This section presents the results of applying the different FS algorithms.

5.1 Online modality results

This subsection presents the results obtained for the FS techniques in the online modality data. Such results are available in Table 1, where the lines are the 22 attributes considered and the columns are the different FS methods. Each cell values refer to the result of the operation and the *ranking* obtained by the attribute. The top ten values for each method are underlined. In addition, we highlight in **bold** the attributes selected in the first ten positions in at least four of the algorithms used. At the end of the table, the column *Rank* contains the sum of the four best positions obtained by the different SA methods. To define the most relevant characteristics to explain the online students' performance at ENADE 2018, we considered the top-10 most frequent attributes in at least four of the feature selection algorithms.

Analyzing the gender (Figure 1), most (60.8%) of the participants are female, and however, they obtained inferior results compared to the males. Analyzing the skin color (Fig. 2), white people are predominant, with 33,845 participants (52.4% of them) having the most outstanding high-performance rates (9%) and the least low-performance rates (25%). Brown-skinned people is the second-highest rate of participants (35.5%), having the worst high-performance (5%) and one of the highest low-performance indices (32%). Similarly, we find low-performance indices for black, yellow, and indigenous people. Finally, the best overall performance came from those who did not declare their skin color.

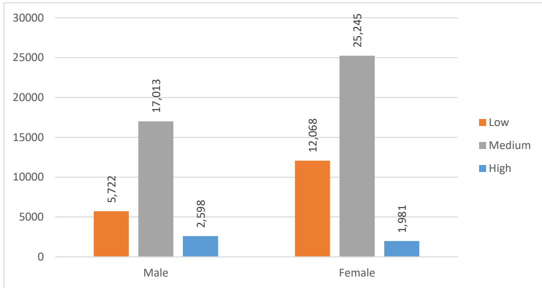


Figure 1: Relationship between gender and participant performance in the online modality.

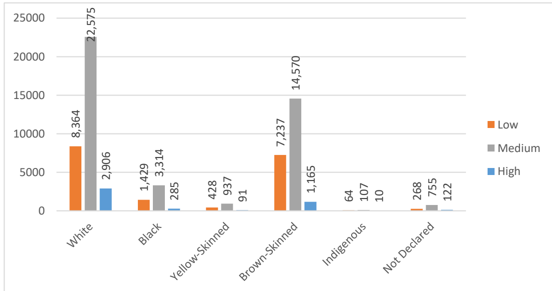


Figure 2: Relationship between skin color and participant performance in the online modality

5.2 Face-to-face modality results

This subsection presents the results obtained when the FS techniques are applied in the base that considers the F2F modality. Such results are available in Table 2, using the same approach seen in Table 1.

The same criterion used in online education was used to define the most important characteristics. Most participants (289,580/86.4%) did not receive any academic scholarship; 10% and 20% of them presented high and low performances, respectively. Those with a scholarship (Fig. 3) show a notable superior performance compared to the ones without it. We highlight that scientific research and PET (acronym in Portuguese for Tutorial Education Program) participants have the most elevated high-performance (32% and 35%) and the least low-performance (7% and 8%). Analyzing the weekly study time (Fig. 4), the majority (46.3%) studies from 1 to 3 hours a week, with a high performance of 8% and a low performance of 22%. Clearly, when the number of weekly study hours increases, high-performance increases and low-performance decreases. Considering the mother's education level (Fig. 5), those whose mothers have no education or have completed just elementary school 1 and 2 have the worst high-performance rates and the highest low-performance rates. Mothers with undergraduate and graduate degree studies imply better performance on student rates.

Table 1: Online modality results obtained with different feature selection methods.

#	characteristics	PC		IG		GR		SU		RF		Rank
1	**Knowledge Area**	1	0.1255	2	0.0404	1	0.0377	1	0.0358	1	0.0415	4
2	**Family Income**	3	0.0445	1	0.0424	2	0.0177	2	0.0237	2	0.0412	7
3	**Gender**	2	0.0510	5	0.0108	4	0.0112	4	0.0100	13	0.0102	15
4	**High School Education**	6	0.0390	3	0.0139	3	0.0131	3	0.0124	11	0.0120	15
5	**Scholarship/Funding**	4	0.0436	7	0.0099	6	0.0050	6	0.0063	3	0.0229	20
6	**Father's Level of Education**	17	0.0163	4	0.0113	5	0.0051	5	0.0067	6	0.0190	20
7	**Chosen Course**	13	0.0229	6	0.0102	7	0.0042	7	0.0057	4	0.0228	24
8	**Skin Color**	7	0.0373	10	0.0063	10	0.0040	8	0.0046	10	0.0128	35
9	Mother's Level of Education	18	0.0128	8	0.0070	13	0.0031	9	0.0041	9	0.0173	39
10	Weekly Study Time	9	0.0333	11	0.0058	14	0.0031	12	0.0038	7	0.0189	39
11	Age	8	0.0369	12	0.0057	12	0.0034	10	0.0040	20	0.0029	42
12	Financial Status	15	0.0197	9	0.0069	16	0.0029	11	0.0039	8	0.0189	44
13	High School Modality	12	0.0244	13	0.0046	11	0.0037	13	0.0038	12	0.0111	48
14	Family's Undergraduate Degree	14	0.0197	15	0.0040	8	0.0042	14	0.0037	14	0.0101	50
15	Work Status	10	0.0314	14	0.0046	15	0.0029	16	0.0033	16	0.0083	55
16	Marital Status	5	0.0402	18	0.0029	17	0.0019	17	0.0021	17	0.0081	56
17	People Living in your Household	19	0.0123	16	0.0039	20	0.0015	18	0.0021	5	0.0211	58
18	Social Inclusion Program	16	0.0163	17	0.0038	9	0.0041	15	0.0036	15	0.0083	60
19	Household Location and People in it	11	0.0310	19	0.0024	19	0.0017	19	0.0019	19	0.0065	68
20	Chosen Education Institution	21	0.0058	20	0.0016	22	0.0008	20	0.0010	18	0.0079	79
21	Academic Scholarship	20	0.0074	21	0.0004	21	0.0012	21	0.0005	21	0.0021	83
22	Student financial aid	22	0.0020	22	0.0001	18	0.0017	22	0.0002	22	0.0001	84

Table 2: Face-to-face modality results obtained with different feature selection methods.

#	characteristics	PC		IG		GR		SU		RF		rank
1	**Scholarship/Funding**	5	0.0272	1	0.0337	2	0.0124	1	0.0173	1	0.0482	5
2	**Academic scholarship**	2	0.0431	3	0.0166	1	0.0206	2	0.0168	18	0.0080	8
3	**High School Education**	3	0.0360	4	0.0150	3	0.0111	3	0.0119	13	0.0130	13
4	**Family Income**	11	0.0196	2	0.0168	5	0.0065	5	0.0090	2	0.0360	14
5	**Knowledge Area**	1	0.0561	6	0.0124	4	0.0106	4	0.0106	6	0.0246	15
6	**Chosen Course**	10	0.0205	5	0.0130	6	0.0056	6	0.0075	3	0.0327	20
7	**Weekly Study Time**	8	0.0218	9	0.0104	7	0.0053	9	0.0066	5	0.0254	29
8	**Father's Level of Education**	15	0.0149	7	0.0123	8	0.0052	7	0.0069	8	0.0229	30
9	**Mother's Level of Education**	14	0.0155	8	0.0121	9	0.0051	8	0.0068	7	0.0231	32
10	Social Inclusion Program	9	0.0215	11	0.0063	11	0.0050	10	0.0051	11	0.0173	41
11	Family's Undergraduate Degree	6	0.0229	14	0.0045	10	0.0050	11	0.0043	16	0.0090	41
12	Age	4	0.0297	10	0.0080	16	0.0030	12	0.0041	21	0.0017	42
13	Work Status	7	0.0219	12	0.0058	15	0.0030	14	0.0038	10	0.0174	43
14	Household Location and People in it	16	0.0138	13	0.0053	13	0.0035	13	0.0039	15	0.0093	54
15	Skin Color	17	0.0136	15	0.0040	18	0.0025	15	0.0029	12	0.0158	59
16	Financial Status	20	0.0108	16	0.0037	20	0.0015	19	0.0021	9	0.0229	64
17	Marital Status	13	0.0161	18	0.0030	17	0.0029	16	0.0027	20	0.0054	64
18	Chosen Education Institution	12	0.0182	17	0.0037	19	0.0018	18	0.0023	17	0.0088	64
19	People Living in your household	21	0.0077	19	0.0030	22	0.0011	21	0.0016	4	0.0269	65
20	High School Modality	22	0.0064	20	0.0026	14	0.0031	17	0.0026	19	0.0067	70
21	Student financial aid	19	0.0124	21	0.0015	12	0.0044	20	0.0019	22	0.0014	72
22	Gender	18	0.0135	22	0.0014	21	0.0015	22	0.0013	14	0.0112	75

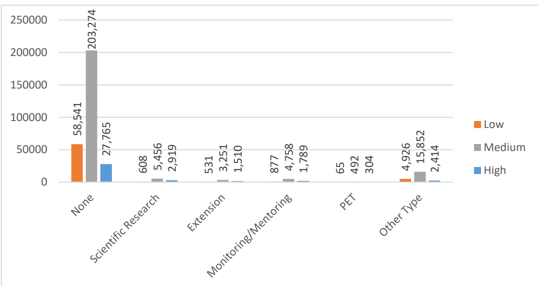


Figure 3: Relation of the type of academic scholarship and the participant performance in the face-to-face modality

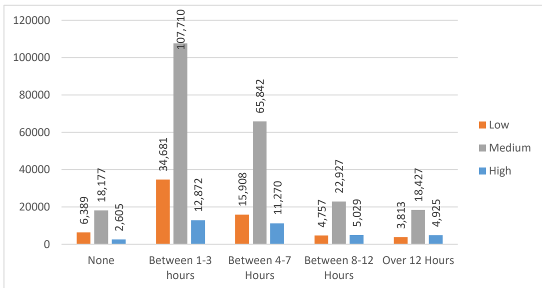


Figure 4: Relation of weekly study hours and participant performance in the face-to-face modality

5.3 Comparing results between online and face-to-face modalities

In this section, we sought to compare the characteristics in common between online and F2F participants, in which we seek to understand the difference between these two profiles. Comparisons are shown in Figures 6 to 11. For each figure (attribute), we will

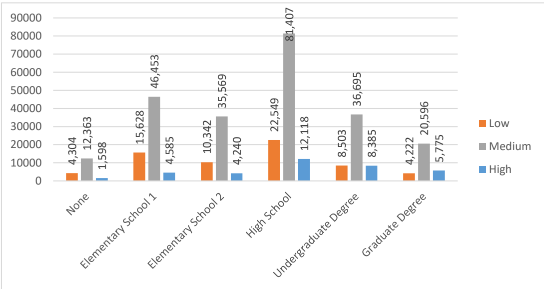
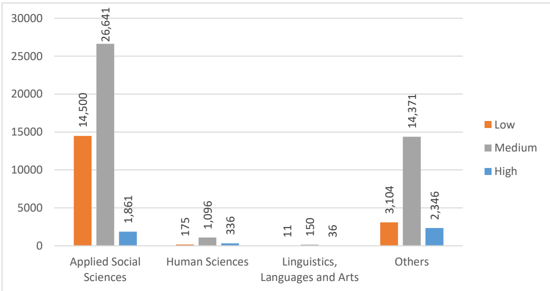
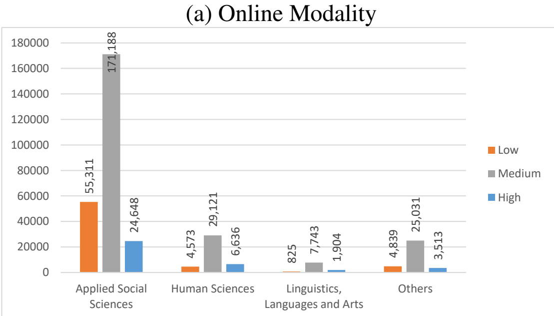


Figure 5: Relationship of mother's level of education and participant's performance in the face-to-face modality

perform an exploratory analysis.



(a) Online Modality

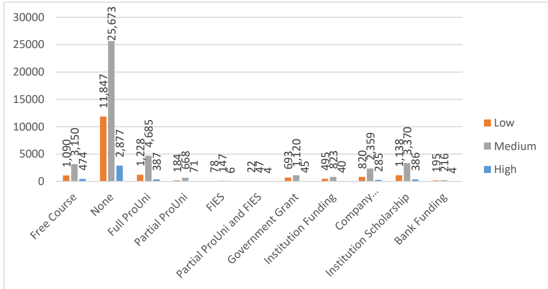


(b) Face-To-Face Modality

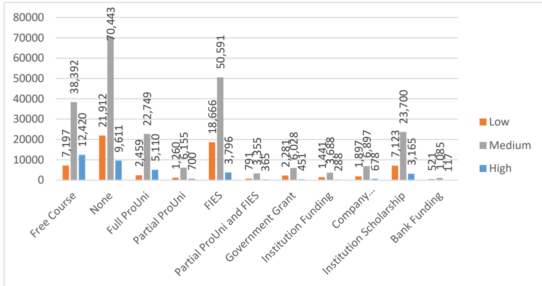
Figure 6: Relation between knowledge area and participant's online and face-to-face modality performance.

Analyzing Fig. 6, we can see a slight growth of applied social sciences, going from 66.5% in online modality to 74.9% in F2F. There is a better distribution in the F2F data in the other categories. Regarding performance, there is an improvement in the F2F students in applied social sciences. Among all categories in the online modality, human sciences have the best overall performance with rates of 21% (high) and 11% (low). In the F2F modality, the highlight is Linguistics, Languages, and Arts with an efficiency of 18% (high) and 8% (low).

Observing the students who receive scholarships or funding grants (Fig. 7), there is an increase in the number of students in free courses and FIES (acronym



(a) Online Modality



(b) Face-To-Face Modality

Figure 7: Relation between scholarship/funding type and participant's online and face-to-face modality performance.

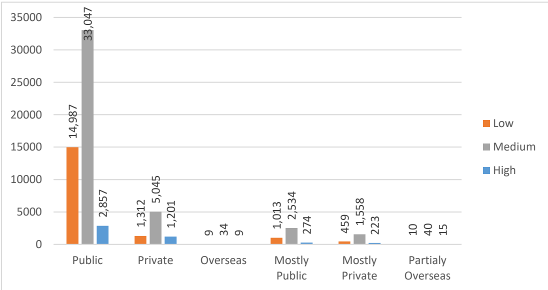
in Portuguese for Finance Fund for Higher Education Students), in F2F modality. Better overall performance can be seen in all on-site students, highlighting free courses and fully funded ProUni students, who rose from 10%, 6% to 21%, 17% respectively. Sadly, those with some scholarship or funding grants are the worst performers in both modalities.

Considering the school type attended in high school (Fig. 8), we see most students are from public schools. It is also noticeable that the proportion of face-to-face students from private schools (26.8%) is twice as much compared to online students, 11.7%. Students' performance from private schools presents the best results for high and low performance.

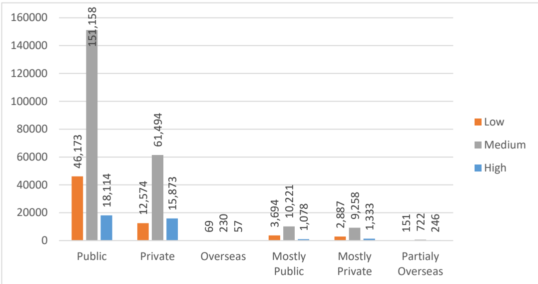
Regarding the parents' level of education (Fig. 9), in online modality, elementary school 1 is the majority with 39.4%, whereas, in F2F modality, high school predominates with 32.6%. There is an increase in the F2F modality for those with a father having an undergraduate and graduate degree education. It is seen that as the level of education increases, the high-performance index also increases.

The course choice by job market inclusion is mostly seen in online and F2F modalities, as seen in Fig. 10. Focusing on F2F participants' performance, we notice an increase in performance compared to online students. We note that those who opt for an online course have the best results in this same modality.

Analyzing the family income (Fig. 11), most stu-

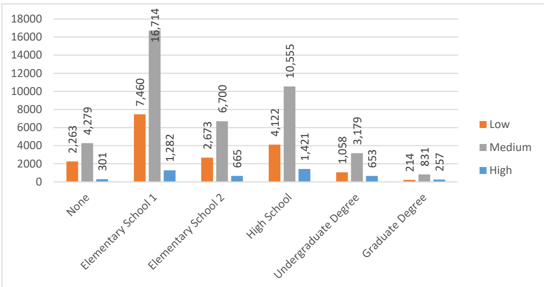


(a) Online Modality

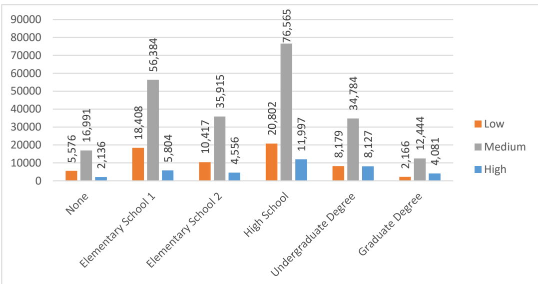


(b) Face-To-Face Modality

Figure 8: Relation between participants' high school type and their performance in online and F2F modalities.

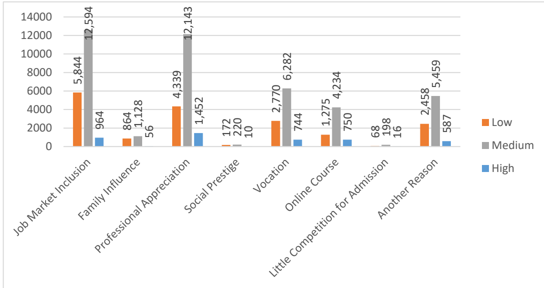


(a) Online Modality

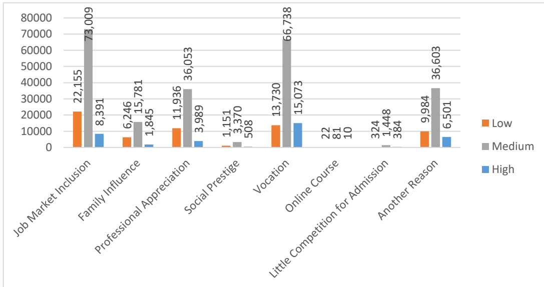


(b) Face-To-Face Modality

Figure 9: Relation between parents' level of education and participant's online and face-to-face modality performance.

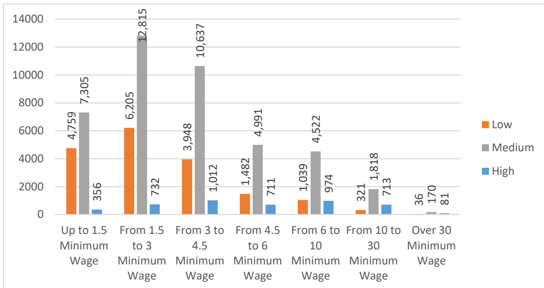


(a) Online Modality

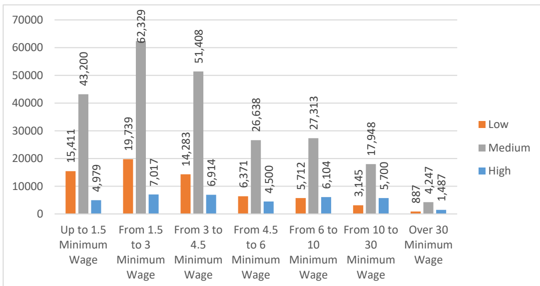


(b) Face-To-Face Modality

Figure 10: Relation between reason for choosing the course and participant's online and F2F modality performance.



(a) Online Modality



(b) Face-To-Face Modality

Figure 11: Relation between family income and participant's online and F2F modality performance.

dents have an income lower than 4.5 minimum wages (mw). There is an increase in F2F students with a family income above 10 mw. In performance, we observe F2F students with an income less than 6 mw increase high performance. In both modalities, as income increases, the high performance also increases.

6 CONCLUSIONS

In this paper, we applied educational data mining in ENADE 2018 data set to find the main characteristics related to performance, both in distance learning and F2F modality. We used five different algorithms for selecting attributes to 23 pre-selected personal and socioeconomic characteristics. The essential characteristics selected in both modalities were: knowledge area, family income, public or private high school, scholarships and funding, father's level of education, and reason for choosing the course. Gender and skin color were also important for online modality. And for the F2F modality, the type of academic scholarship, weekly study time, and the mother's schooling.

Parents' education directly influenced the results, and the higher the level of education, the better the performance. Public universities were protagonists, as students who paid no fees performed better than those in private institutions, even if financed by government programs or scholarships from the institutions. We see a direct and proportional relationship between family income and student performance. The higher the income, the better the high-performance index and the lower the low-performance index. Participants who attended (fully or partially) private high schools have an advantage over those who attended public schools. Finally, we conclude that analyzing the factors that influence the performance of undergraduate students significantly contributes to a better understanding of the national education panorama. Besides, this study can help authorities make decisions and propose new public policies concerning Higher Education.

ACKNOWLEDGEMENTS

This study was supported by CNPq (305805/2021-5) and PNPD/CAPES (464880/2019-00).

REFERENCES

Araújo, R. A. et al. (2019). Análise dos microdados do enade: Proposta de uma ferramenta de exploração utilizando mineração de dados. Master's thesis, Universidade Federal de Goiás.

Baker, R., Isotani, S., and Carvalho, A. (2011). Mineração de dados educacionais: Oportunidades para o brasil. *Revista Brasileira de Informática na Educação*, 19(02):03.

Barreto, L. S. and Amaral, S. C. S. (2019). Análise da expansão do ensino superior a distância no contexto brasileiro a partir do censo da educação superior de 2016. *InterSciencePlace*, 13(3).

Breiman, L., Friedman, J., Olshen, R., and Stone, C. (1984). *Classification and Regression Trees*. Chapman and Hall (Wadsworth and Inc.).

Faria, E. d. O. (2017). Uma análise dos fatores determinantes do desempenho dos alunos dos cursos superiores em administração do distrito federal. Master's thesis, Universidade de Basília.

Gottardo, E., Kaestner, C., and Noronha, R. V. (2012). Avaliação de desempenho de estudantes em cursos de educação a distância utilizando mineração de dados. In *Workshop de Desafios da Computação Aplicada à Educação*, pages 30–39.

Hall, M. A. (1998). *Correlation-based Feature Subset Selection for Machine Learning*. PhD thesis, University of Waikato, Hamilton, New Zealand.

Hall, M. A. and Smith, L. A. (1998). Practical feature subset selection for machine learning. In *Australasian Computer Science Conference ACSC'98*, volume 20, pages 181–191, Berlin. Springer.

Inep (2019). Censo da educação superior. Access on: October, 2020.

Karegowda, A. G., Manjunath, A., and Jayaram, M. (2010). Comparative study of attribute selection using gain ratio and correlation based feature selection. *Int. J. Information Technology and Knowledge Management*, 2(2):271–277.

Kira, K. and Rendell, L. A. (1992). A practical approach to feature selection. In Sleeman, D. H. and Edwards, P., editors, *9th Int. Workshop on Machine Learning*, pages 249–256. Morgan Kaufmann.

Kononenko, I. (1994). Estimating attributes: Analysis and extensions of relief. In *Machine Learning: ECML-94*, pages 171–182, Berlin, Heidelberg. Springer Berlin Heidelberg.

Miao, J. and Niu, L. (2016). A survey on feature selection. *Procedia Computer Science*, 91:919–926.

Romero, C., Ventura, S., and García, E. (2008). Data mining in course management systems: Moodle case study and tutorial. *Computers & Education*, 51(1):368–384.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, 27(3):379–423.

Tan, P.-N., Steinbach, M., and Kumar, V. (2016). *Introduction to data mining*. Pearson Education India.

Tasca, M. (2015). *Contribuições ao Problema de Seleção de Atributos*. PhD thesis, Universidade Federal Fluminense, Niterói, Rio de Janeiro.

Urbanowicz, R. J., Meeker, M., La Cava, W., Olson, R. S., and Moore, J. H. (2018). Relief-based feature selection: Introduction and review. *Journal of biomedical informatics*, 85:189–203.

Yu, L. and Liu, H. (2003). Feature selection for high-dimensional data: A fast correlation-based filter solution. In *Proc. Twentieth Int. Conference on Machine Learning*, pages 856–863. AAAI Press.