Student dropout analysis based on previously acquired educational achievements: A case of the University of Portalegre

Business Analysis, Business Informatics Ms, Fall 2023.

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2023-12-11

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Abstract

In the world of education, the path to success is often visualized as a linear progression, where students follow a predefined journey from kindergarten to graduation. However, the reality is far more complex. Various reasons lead students to choose to deviate from this path. These students have encountered different challenges, circumstances, or a lack of proper resources that have led them to drop out of university.

In this dataset provided to us, we will delve deeper into understanding the reasons why students have dropped out of the university, based on the data at our disposal. We will leverage our social knowledge to comprehend the factors that influenced their decision to drop out and work to prevent such occurrences if the issues are within the university's purview. Our goal is to offer solutions, support, and the necessary resources to facilitate students' educational journeys. We will also use the analysis we've conducted on the dropout students to learn from their experiences and chart a unique educational pathway with fewer dropouts.

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Introduction

Starting from preliminary school we are told that having an education is very important for your future or that without higher education your job possibilities are going to be very limited. While primary education is mandatory, having higher education is not. But why do people actually take their time and resources to pursue it? Well, according to studies the most important factor for pursuing higher education is job acquisition. (Knutsen 2011) Some other factors may include increased income in the existing job, improved work conditions or increased ability for retirement. All in all they do all tie up to materialistic benefits in the end. Of course, other, more intrisic factors include seeking for additional knowledge or self-fulfillment (Cortes et al. 2023). There are also factors like meeting new friends, improving social interaction skills or just wanting to make a difference in the world. Of course factors that cannot be ignored are social pressure (Temple 2009), meaning that having friends that want to pursue higher education can influence ones own decision or influence of family members. Pursuing higher edication is good, but what about people who prematurely end their studies and drop out? What could be the factors that lead to such a decision? Based on the study and datasets that we used for our research there are multiple factors that influence dropping out.

Nevertheless, pursuing higher education and actually getting the degree has some tangible benefits. According to an OECD – Education at a Glance 2019 research paper (OECD 2019), "On average across OECD countries, adults with a short-cycle tertiary degree earn 20% more than adults with upper secondary education. The earnings advantage increases to 44% for those with a bachelor's degree and to 91% for those with a master's or doctorPal degree." With this in mind, it is important for government and educational institutions to ensure high level of graduates in society to ensure economic growth and overall increase in well-being. To measure the success of this goal, it is important to set KPI's, track them and make educated conclusions on what needs to be done or is being done right to reach the goal of higher educated society.

Target Metrics and KPI

In this particular case, KPI's will be chosen based on datasets of Portugese High Schools but most likely data can be generalised, atleast for Europe, as the region and sociodemographics are not so different. Even though there are many factors that influence the success of graduation, only factors that can be proven by government and educational institutions will be chosen. After rigorous analysis, we propose the following grades.

1. Academic support. Based on the dataset students who had support had 3x lower dropout rates than students that didn't have. This means that governments should be incentivised to allocate a higher amount of budget towards education to give financial aid and motivate students to complete their studies.

2. Institutional improvements. Again, based on datasets, schools with improvements have 40% less dropout rate than schools without. This is something that can be improved by incentivizing teachers with higher salaries or giving schools more budget to improve their workstations.

3. Student grades. Datasets tell us that the higher the average grade, the lower the dropout rate. Usually students that have low grades are uninterested in the subjects which could be due to having chosen not the right program for them or that the way lectures and information is presented is uninteresting or outdated. Either way this can be improved. Increasing the possibility that the student has chosen the right program for him can be done by introducing more "open days" in higher education institutions and having more upfront information about what can be expected from programs. The overall lecture performance can be improved by taking more time to have up-to-date information presented and teachers having decent motivation of teaching students. This can be achieved by increasing teacher salaries and institutions having more control over teachers and information they present to students.

Exploratory Data Analysis

Descriptive Statistics

	Data Type
Marital status	int64
Application mode	int64
Application order	int64
Course	int64
Daytime/evening attendance	int64
Previous qualification	int64
Previous qualification (grade)	float64
Nacionality	int64
Mother's qualification	int64
Father's qualification	int64
Mother's occupation	int64
Father's occupation	int64
Admission grade	float64
Displaced	int64
Educational special needs	int64
Debtor	int64
Tuition fees up to date	int64
Gender	int64
Scholarship holder	int64

	Data Type
Age at enrollment	int64
International	int64
Curricular units 1st sem (credited)	int64
Curricular units 1st sem (enrolled)	int64
Curricular units 1st sem (evaluations)	int64
Curricular units 1st sem (approved)	int64
Curricular units 1st sem (grade)	float64
Curricular units 1st sem (without evaluations)	int64
Curricular units 2nd sem (credited)	int64
Curricular units 2nd sem (enrolled)	int64
Curricular units 2nd sem (evaluations)	int64
Curricular units 2nd sem (approved)	int64
Curricular units 2nd sem (grade)	float64
Curricular units 2nd sem (without evaluations)	int64
Unemployment rate	float64
Inflation rate	float64
GDP	float64
Target	object

Table 1: The data types of the datast columns

As we have checked, the dataset does not have zero values, so there is nothing to purge inside it. Later on, we get the basic descriptive statistics, shown below.

	Marital status	Application mode	Application order	Course	Daytime/evening attendance
count	4424.00	4424.00	4424.00	4424.00	4424.00
mean	1.18	18.67	1.73	8856.64	0.89
std	0.61	17.48	1.31	2063.57	0.31
min	1.00	1.00	0.00	33.00	0.00
25%	1.00	1.00	1.00	9085.00	1.00
50%	1.00	17.00	1.00	9238.00	1.00
75%	1.00	39.00	2.00	9556.00	1.00
max	6.00	57.00	9.00	9991.00	1.00

Table 2: Descriptive statistics

	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	Father's
count	4424.00	4424.00	4424.00	4424.00	4424.00

	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	Father's
mean	4.58	132.61	1.87	19.56	22.28
std	10.22	13.19	6.91	15.60	15.34
min	1.00	95.00	1.00	1.00	1.00
25%	1.00	125.00	1.00	2.00	3.00
50%	1.00	133.10	1.00	19.00	19.00
75%	1.00	140.00	1.00	37.00	37.00
max	43.00	190.00	109.00	44.00	44.00

Table 3: Descriptive statistics (cont'd)

	Mother's occupation	Father's occupation	Admission grade	Displaced	Educational special needs
count	4424.00	4424.00	4424.00	4424.00	4424.00
mean	10.96	11.03	126.98	0.55	0.01
std	26.42	25.26	14.48	0.50	0.11
min	0.00	0.00	95.00	0.00	0.00
25%	4.00	4.00	117.90	0.00	0.00
50%	5.00	7.00	126.10	1.00	0.00
75%	9.00	9.00	134.80	1.00	0.00
max	194.00	195.00	190.00	1.00	1.00

Table 4: Descriptive statistics (cont'd)

	Debtor	Tuition fees up to date	Gender	Scholarship holder	Age at enrollment
count	4424.00	4424.00	4424.00	4424.00	4424.00
mean	0.11	0.88	0.35	0.25	23.27
std	0.32	0.32	0.48	0.43	7.59
min	0.00	0.00	0.00	0.00	17.00
25%	0.00	1.00	0.00	0.00	19.00
50%	0.00	1.00	0.00	0.00	20.00
75%	0.00	1.00	1.00	0.00	25.00
max	1.00	1.00	1.00	1.00	70.00

Table 5: Descriptive statistics (cont'd)

	International	Curricular units 1st sem (credited)	Curricular units 1st sem (enrolled)	Curricular u
count	4424.00	4424.00	4424.00	4424.00
mean	0.02	0.71	6.27	8.30

	International	Curricular units 1st sem (credited)	Curricular units 1st sem (enrolled)	Curricular u...
std	0.16	2.36	2.48	4.18
min	0.00	0.00	0.00	0.00
25%	0.00	0.00	5.00	6.00
50%	0.00	0.00	6.00	8.00
75%	0.00	0.00	7.00	10.00
max	1.00	20.00	26.00	45.00

Table 6: Descriptive statistics (cont'd)

	Curricular units 1st sem (approved)	Curricular units 1st sem (grade)	Curricular units 1st sem (with...
count	4424.00	4424.00	4424.00
mean	4.71	10.64	0.14
std	3.09	4.84	0.69
min	0.00	0.00	0.00
25%	3.00	11.00	0.00
50%	5.00	12.29	0.00
75%	6.00	13.40	0.00
max	26.00	18.88	12.00

Table 7: Descriptive statistics (cont'd)

	Curricular units 2nd sem (enrolled)	Curricular units 2nd sem (evaluations)	Curricular units 2nd se...
count	4424.00	4424.00	4424.00
mean	6.23	8.06	4.44
std	2.20	3.95	3.01
min	0.00	0.00	0.00
25%	5.00	6.00	2.00
50%	6.00	8.00	5.00
75%	7.00	10.00	6.00
max	23.00	33.00	20.00

Table 8: Descriptive statistics (cont'd)

The students are from multiple countries, but the overwhelming majority of the students are from Portugal. It would be interesting to see how the students' admission grade depends on their previous qualification in their home countries, but the samples are scarce. Many students from abroad are from the Ultramarine Territories where it's more challenging to get

comparable education. However, they and inland Portugal students were naturally given some exemptions, as the dataset states [1]

. For example, the students admitted per Ordance no. 854 [2] were not required to demonstrate the proof of their validity since their received a diploma in secondary education administered in Portuguese (Angola, East Timor, Mozambique, Guinea Equatorial). Students admitted per Ordnance no. 533 [3] were from another university in Portugal with overlapping courses covered recently enough so they were not required to repeat them. Finally, those admitted per Ord. no. 612 [4] came from other countries but had comparable material in their studies and so their points were recalculated with some amortization.
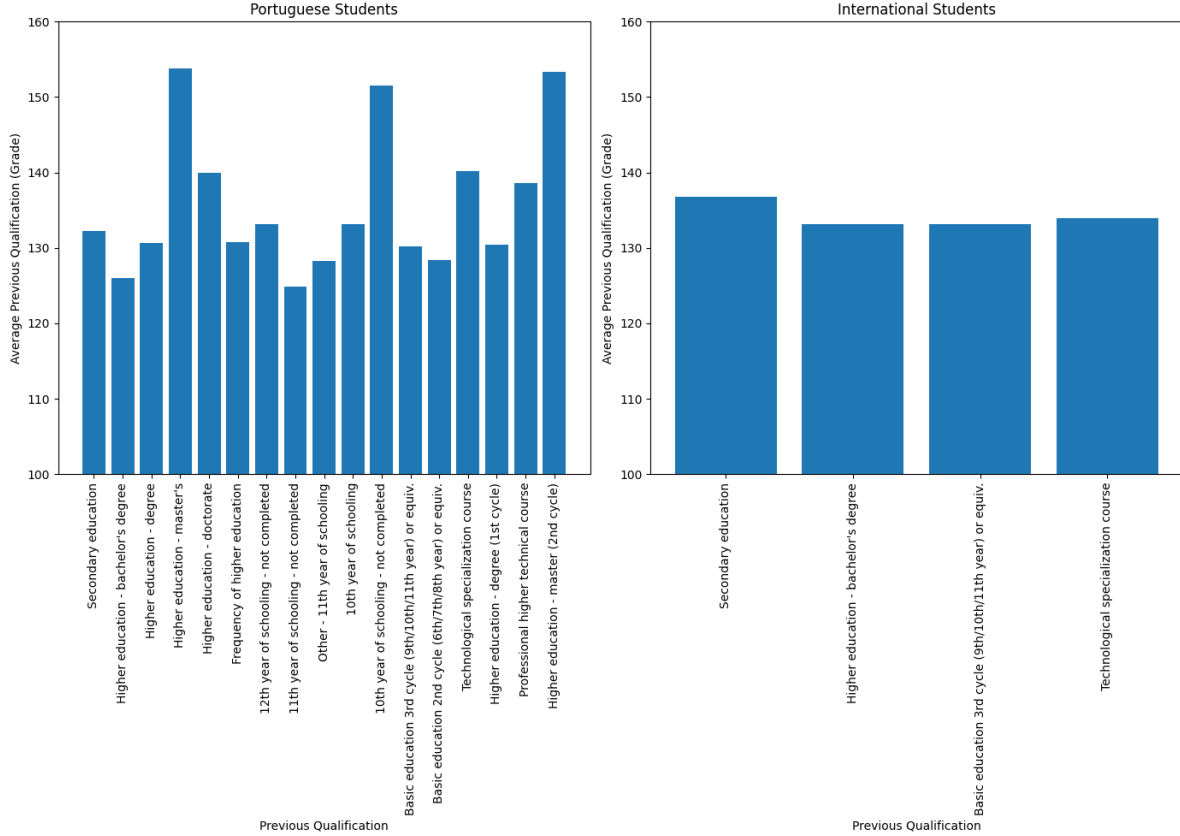
Figure 1: Relative graduation points for students with different education backgrounds

Due to class imbalance , the variability for the Portuguese is much higher, and while the 3 categories with highest grades are natural, i. e. doctors, masters as higher education, the 3rd

1. Link to the dataset description: https://archive.ics.uci.edu/dataset/697/predict+students+dropout+and+academic+success

2. Link to the source document: https://dre.tretas.org/dre/106607/portaria-854-B-99-de-4-de-outubro

3. Link to the source document: https://dre.tretas.org/dre/104726/portaria-533-A-99-de-22-de-julho

4. Link to the source document: https://dre.tretas.org/dre/51542/portaria-612-93-de-29-de-junho

is unintuitive (the 10 classes) and we tend to explain it as self-selection and high correlation with other indicators (those entering the university in the 10th grade are more motivated then dwelling in schools in 11th and 12th grades).

Also, there is a drastic imbalance over yet another crucial factor: age. As it was mentioned previously, students of age are far less ubiquitous, can have far more incentives to abandon studies and with smaller potential to apprehension of material. Indeed, this is eloquently manifested on the next graph.
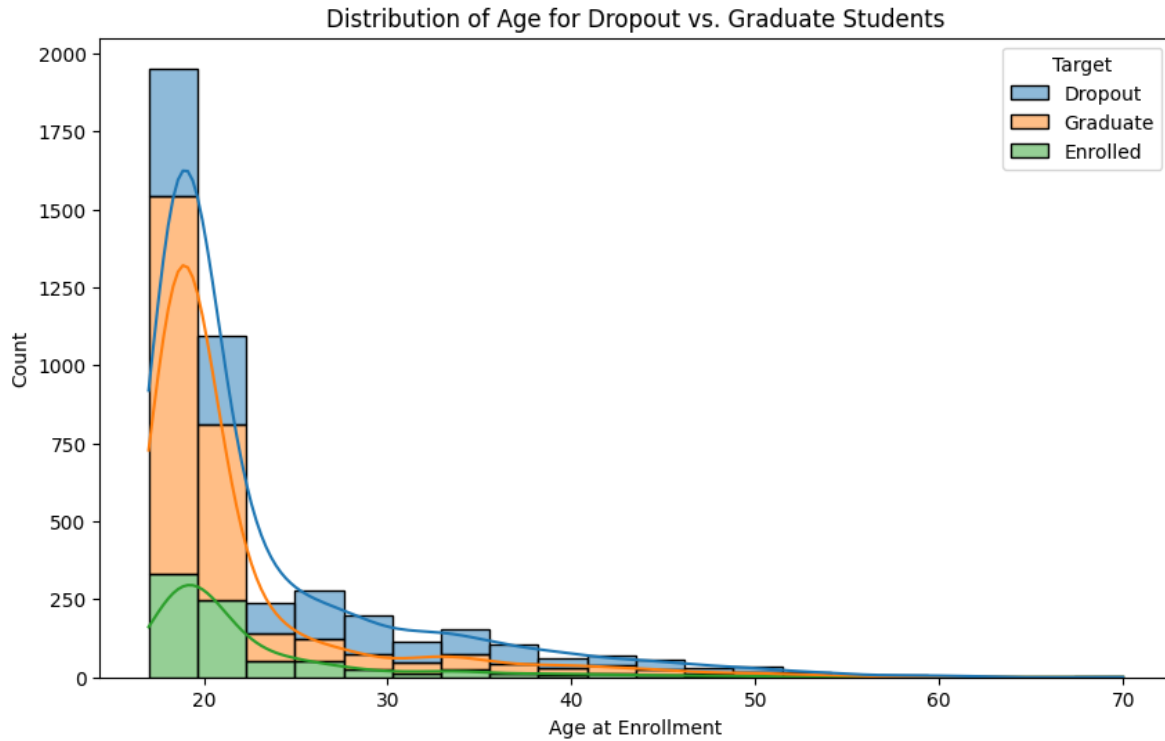
Figure 2: Distribution of age for dropout and graduate student

Q. v. the sizes of the bins for dropout students differ far less than the total size for the name of the student.

If the hypothesis about some external factors, The target variable should be much dependent on previous grades,
The datapoint cloud, however, shows that this rule has a lot of exceptions.
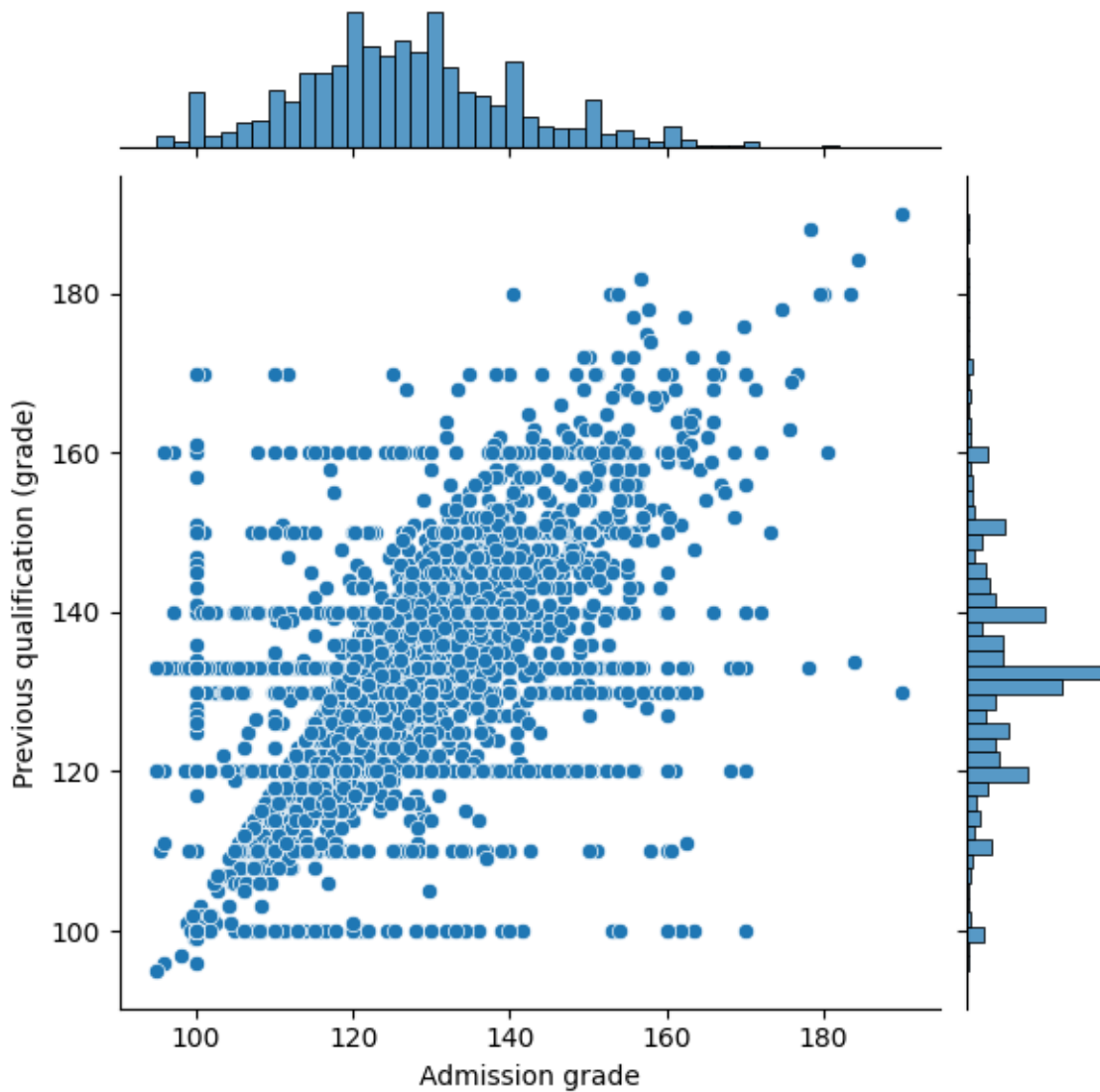
We can draw the following observations:

- The **distribution of admission grades** is roughly normal with most students scoring between **60 to 80 marks**.

- The **distribution of previous qualifications** (grades) is also the same with most of them having grades in between **12 and 16**.

- There is seen a **positive correlation** between admission grade and previous qualification grade indicating students with higher previous qualifications tend to have higher admission grades.

This was the visualization for the few quantitative columns, which shows the natural interconnection between the curricularly accrued units in the 1st and the 2nd year, which are in turn mostly unrelated to the admission grade. This is understandable since the grades are commonly based on the successfulness of the local program and student's toil, while the students' backgrounds are commonly different and this puts them into inequitable positions when passing the admission exams.

In these previous graphs, we considered quantitative columns that are more or less exogenous to the dataset (e. g. age and the previous qualification grade are not influenced by the the current grade of the students).

However, the majority of columns of this dataset are qualitative and they are at least partially endogenous as stulk from the decisions during the study. For this, we need to propose a mechanism of influence, then formulate and test a hypothesis via an analysis of discriminate groups.

We also consider the impact of scholarships and other compensations in academic support, which should alleviate the complications associated with adaptations in new environment.

We see that having debt is always a serious impediment against studies because it gives wrong incentives towards directly making money in the short run instead of mastering knowledge that could aid to make altogether greater money in the long run.

In different studies, it is quite common to compare the academic success of a student with the academic successes of ttheir parents as this has both direct and indirect effects , s. a. i. e. both are connected to welfare, but also it can be that there is another channel of knowledge transmission to the younger generation.

Observations : * The bar chart shows that mother's occupation is quite influential. This influence is greater the pa's due to traditional effect, and we distinctly see that students whose mothers are 'white collars' dropout significantly more rarely than those whose mothers are more engaged in physical labor.

- This also may suggest the mother's occupation can influence student retention, emphasizing the need for financial support and family engagement.

Data correlation table (quantitative columns only)

In this matrix for correlations, we already see high correlations between many values. Hence, if we (certainly) consider qualitative variables in our data mining analysis, we must reduce the number of variables because the true dimensionality of the initial space is too high and virtually all ways of embedding are too costly and prohibitive given a relatively small amount of datapoints in this dataset. First our common step would be to dispose of multicollinear columns.
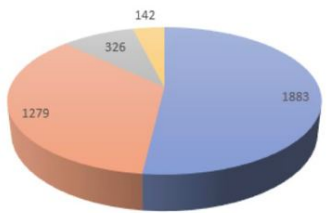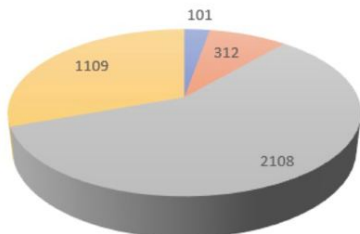
N o	Reason	Based on data explanation example	Visual representation
1	Student doesn't like what they study	If the student is learning their first choice (TOP3), they might have bigger motivation to graduate	**Application order - 0 first choice, 9- last** Application choice based on order 142 326 1279 1883 ■ TOP3 graduates ■ TOP3 dropouts ■ 4-9 graduates ■ 4-9 dropouts
2	Has a debt, that doesn't allow student to focus on studies because of money issues (small income, already big debt, stress about credit)	People with debt have 3 times more dropouts than graduates. People who don't have debt have the biggest number of graduates	Students and their debt 101 312 1109 2108 ■ Have debt- Graduates ■ Have debt- Dropouts ■ No debt- Graduates ■ No debt- Dropouts

Figure 3: Student mobility and financial burden as indicators and drivers of their motivation and impediments

3	Being displaced can help finish the studies because then you actually like what you study	Can see with red and yellow, that people who stayed have more dropouts than who displaced and with blue can see that displaced students have the highest count of graduates.	
4	Pregnancy- If gender is female, she is around age when could possibly have child and in cases married it is possible reason for drop out	The data denied this reason, in fact dropout males that are married are more than females.	

Figure 4: Student inter-university mobility and health conditions proxies as indicators and drivers of their motivation towards learning and impediments (Part 2)

7	More single people graduate than married. Maybe marriage gives some stability and additional responsibility, and graduating is not priority anymore		
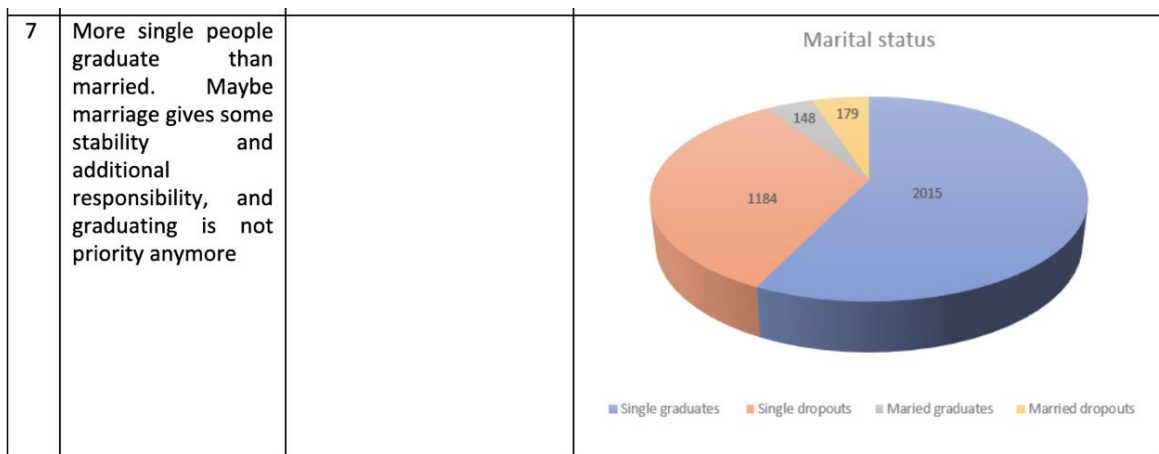
Figure 5: Marital status as distractor from studying
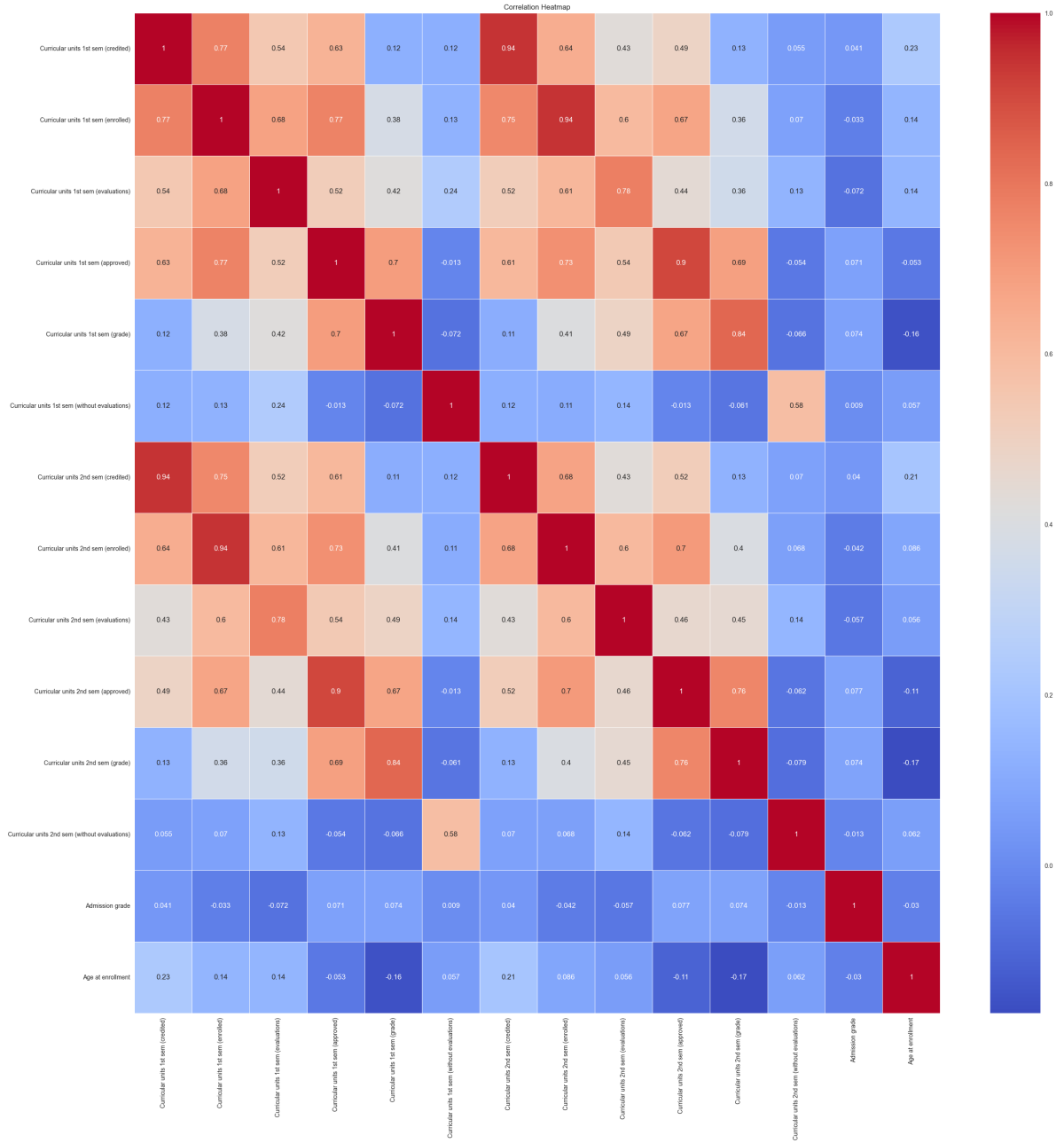
Figure 6: Data correlation table (quantitative columns are represented only since there to compute true correlations between quantitative columns it is necessary to OHE-encode them, which would burst no. of columns to many thousands, but the values of the correlations will be statistically insignificant due to low cardinality of 90% of classes)

High dimensionality prevents intuitive DBSCAN threshold setting and some inferior algorithms as TSNE.

Index(['Marital status', 'Application mode', 'Application order', 'Course',
       'Daytime/evening attendance', 'Previous qualification',
       'Previous qualification (grade)', 'Nacionality',
       'Mother's qualification', 'Father's qualification',
       'Mother's occupation', 'Father's occupation', 'Admission grade',
       'Displaced', 'Educational special needs', 'Debtor',
       'Tuition fees up to date', 'Gender', 'Scholarship holder',
       'Age at enrollment', 'International',
       'Curricular units 1st sem (credited)',
       'Curricular units 1st sem (enrolled)',
       'Curricular units 1st sem (evaluations)',
       'Curricular units 1st sem (approved)',
       'Curricular units 1st sem (grade)',
       'Curricular units 1st sem (without evaluations)',
       'Curricular units 2nd sem (credited)',
       'Curricular units 2nd sem (enrolled)',
       'Curricular units 2nd sem (evaluations)',
       'Curricular units 2nd sem (approved)',
       'Curricular units 2nd sem (grade)',
       'Curricular units 2nd sem (without evaluations)', 'Unemployment rate',
       'Inflation rate', 'GDP', 'Target'],
      dtype='object')

Found existing installation: pycaret 3.2.0
Uninstalling pycaret-3.2.0:
  Successfully uninstalled pycaret-3.2.0

Collecting mlflow
  Using cached mlflow-2.9.1-py3-none-any.whl (19.1 MB)
Requirement already satisfied: click<9,>=7.0 in /opt/homebrew/Caskroom/miniconda/base/lib/python3.11/si
Requirement already satisfied: cloudpickle<4 in /opt/homebrew/Caskroom/miniconda/base/lib/python3.11/si
Requirement already satisfied: databricks-cli<1,>=0.8.7 in /opt/homebrew/Caskroom/miniconda/base/lib/py
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Requirement already satisfied: gitpython<4,>=2.1.0 in /opt/homebrew/Caskroom/miniconda/base/lib/python
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Installing collected packages: mlflow
Successfully installed mlflow-2.9.1

ImportError: MlflowLogger requires mlflow. Install using `pip install mlflow`

In the remaining part, we examine the correlations of purely endogenous temporal variables. This does not give a scoop about the source of causation and is not a good predictor, but exhibits an analysis of autocorrelation inside the quasi-temporal data.
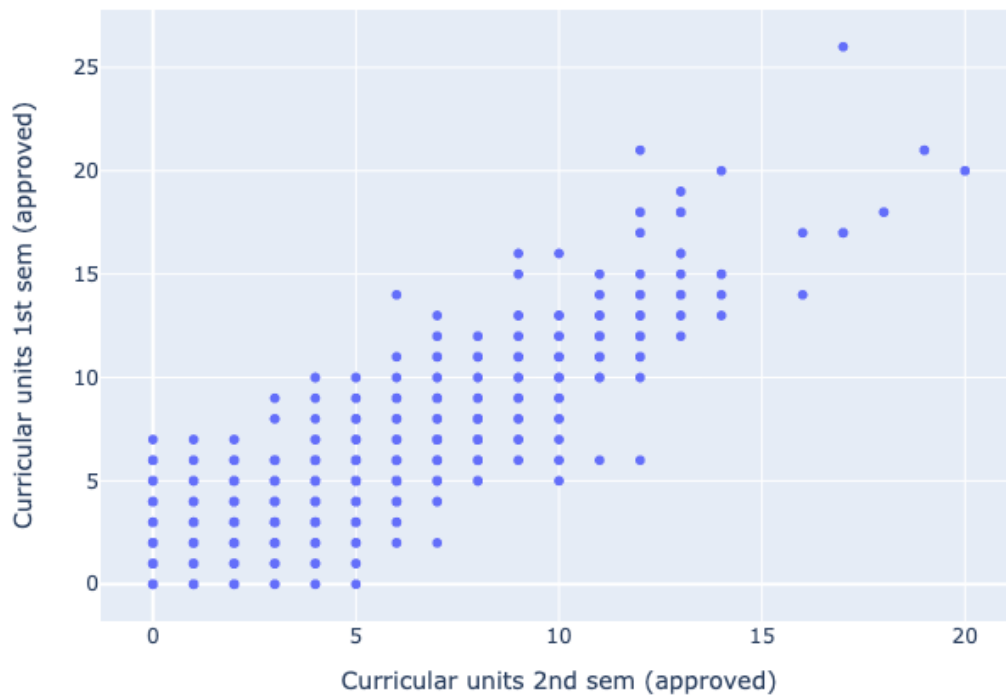
We can see that the points for the 1st semester and 2nd semester are correlated which shows that are one's marks are primary drivers of success and exhibit sizeable correlations
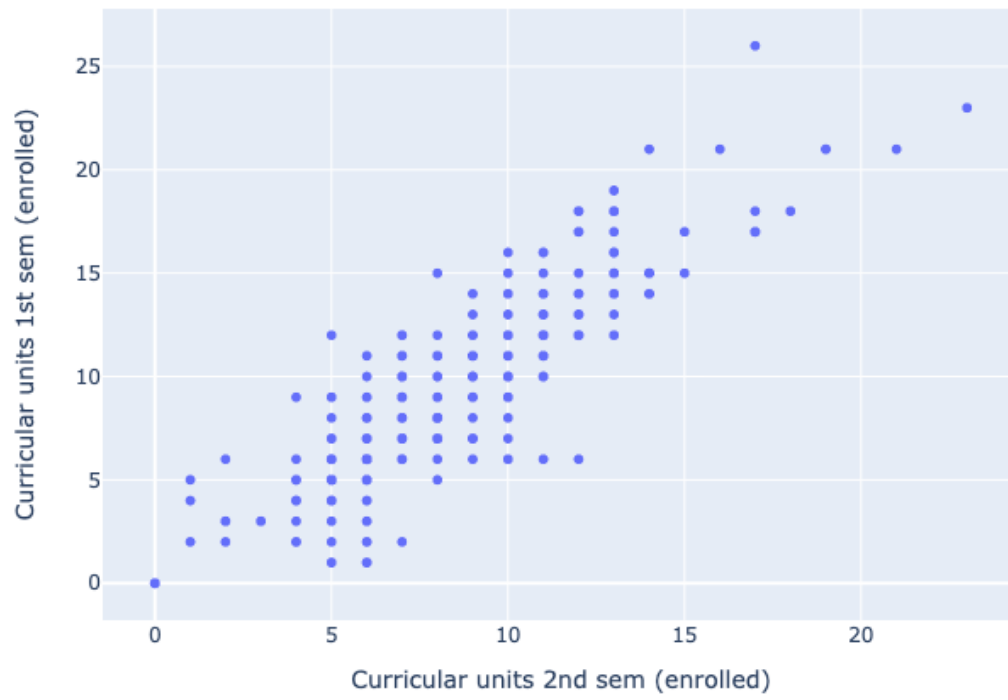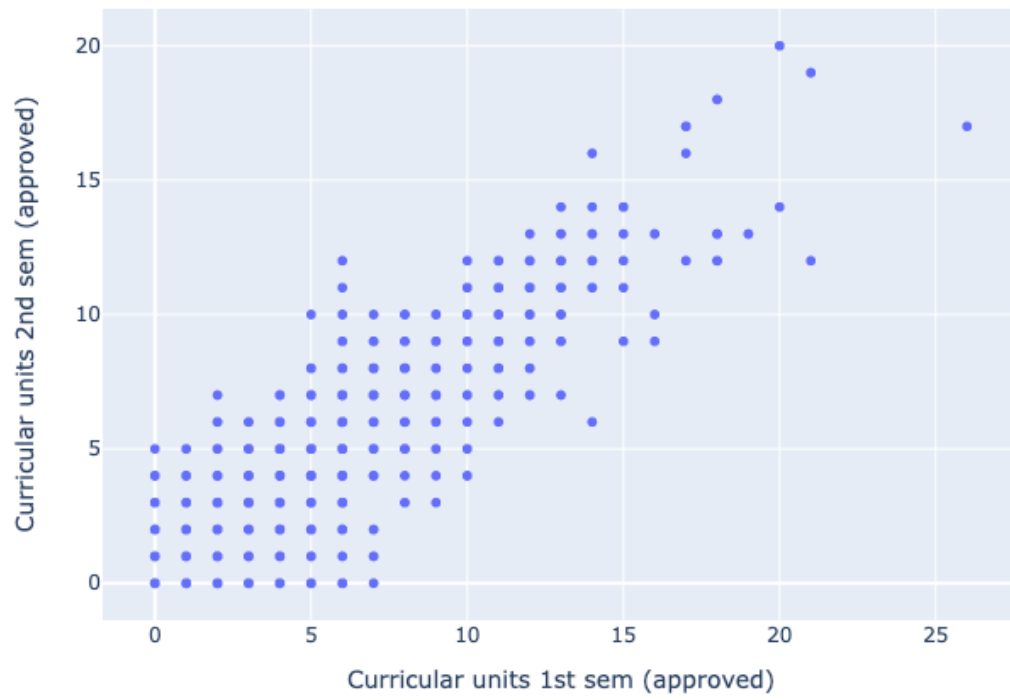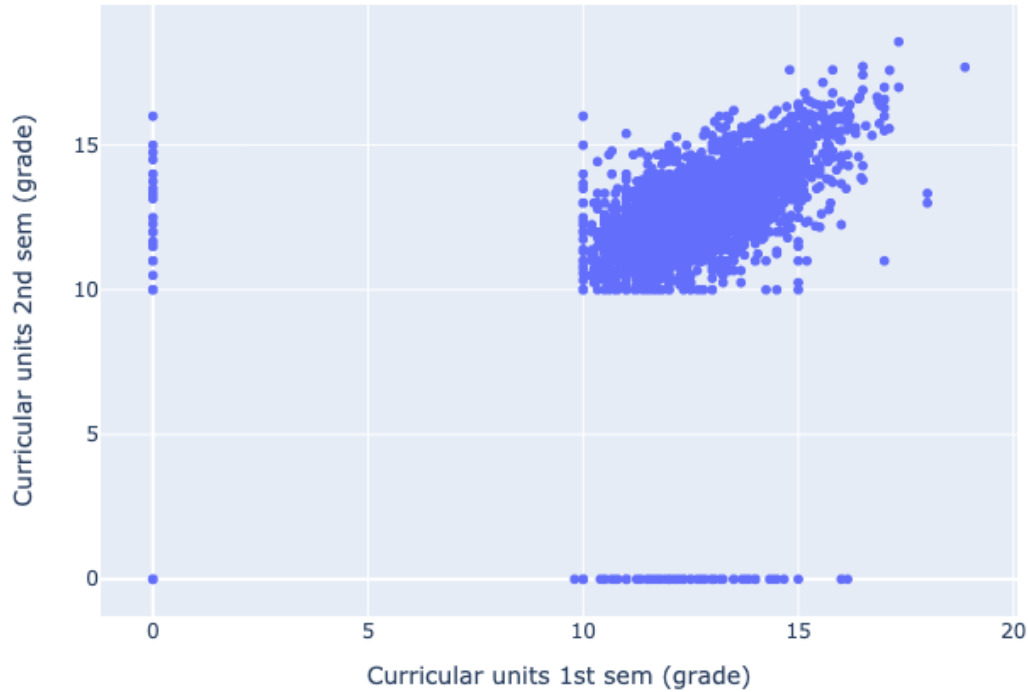
Data Mining

Conclusion

With this analysis, we have some valuable insights some crucial factors like Academic support, socioeconomic factors, previous qualifications, and others play a significant role in student retention.

The observed patterns imply a lot to stress in the lives of students and their associates. First, we strive to insentivize parents to improve their labour efficiency and pursue greater carreer so that ultimately they could dedicate more time to their children's education, and proactively stir their self-propelled interest. Additionally, we could provide financial assistance to those who are struggling to pay with if this is contemporaneous with a significant degradation in their university marks, as this subrogates the stimuli for a person in an age where they are most perceptive to knowledge and is a good predictor of a dropout. Also importantly, we could teach the students, especially going on their second studies, that it is quite unlikely

that they are going to get high grades or exit the university without proper time management and confirmation that they assign top priority to their studies. They are also advised to make that clear to all their relatives and stakeholders who might underestimate the effects of such a change. Although this could result in a reduction of enthusiastic entrants, this would increase at least the KPI of retention and arguably also increase the KPI on number of diplomas issued, because with fewer but more motivated students the university would have more time to dedicate to most obstinate pending alumni.

Addressing these factors carefully can effectively lead to dropout rates reduction and improve overall student outcomes

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