Stats 504 Assignment 6: Graduation Rates

Introduction

Admission grade cutoffs are used to determine if a student is admitted into a university or not. These cutoffs are important because they greatly impact both the university and the student. If the cutoffs are too low, students who will potentially struggle with the coursework and fail to graduate are admitted and this is unfavorable for both the student (who pays for tuition, and does not get a degree) and the university (whose graduation rates go down). The aim of this report is to investigate and shed light on the effect of admission grade cutoffs on the chances of a student graduating, given other details about the student. It is found that admission grade is indeed an influential factor (and specifically has a causal relationship) with the graduation rate, and more concrete findings are presented in the results section.

Methods

The goal of the analysis is to help depict and understand the relationship between the admission grade and chances of graduation of a student. Other information about the student such as age, gender, parents' grades and occupations, previous qualification and corresponding grades are also used in determining this outcome.

Since this analysis involves identifying whether changes in admission grade cutoffs affect the chances of a student graduating, causal inference methodologies were adapted as this is more informative as compared to linear regression modeling for example, which only provides information about associations which are not necessarily the same as a causal relationship. To put it another way, the client wants to determine not just how a change in admission grade changes the chances of graduation, but also if that change is directly accounted for by the change in admission grade (causally). This is precisely what causal inference methods provide.

The primary idea in causal inference is to capture the effect of "confounding variables" so that the true causal parameter estimate can be computed. A confounding variable is one which affects both the treatment and outcome variables (which in this analysis are admission grade and graduation). If confounding variables are not controlled for, the association between the treatment and outcome will include the effect of the confounding variables. Thus, including the confounding variables in the model will capture their effects thereby isolating the effect of the treatment which is the true causal estimate. Another aspect of causal inference is the usage of "propensity scores" or weights for each observation. These weights are used to reduce selection bias and make the treatment and control group comparable to each other. In this analysis, the treatment variable is numerical (admission grade) so it is possible to split it into two categories based on the median value and use those as two treatment groups (this is presented in the baseline table of the results section). However, this results in loss of information so the decision was made to treat the admission grade as a continuous treatment variable, and use an adapted method to calculate propensity scores for weighting each observation of the data, which is later used in the weighted linear model to compute the causal effect of admission grade on graduation status.

More specific to this analysis, thought was put into selecting confounding variables from the dataset and controlling for them in the analysis so that the true causal effect of admission grade on graduation is isolated. This variable selection is subjective, and based on intuition rather than quantitative tests, although t-tests and chi-square tests are used as ways of validating the intuitive reasoning for including or excluding a variable. The reasoning for dropping a few important variables that may look seemingly important to the client, are presented in the following paragraphs.

Application Mode and Application Order indicate how the student applied to the university, and since these occur after they take the admissions test (and assigned an admission grade), these variables are "downstream" variables, meaning they cannot affect admission grade. For this reason, they cannot be confounders, and hence were excluded from the analysis. Similar reasoning follows for the Course the student applied to study. It is likely that they decide the course based on their scores and a self-evaluation of how likely they are to be admitted to the program for a given course. However, their course selection cannot affect their admission grade, and thus was also excluded from the model. Tuition and Scholarships are also similar in that they are applicable only once the student is admitted to the university (and thus already has an admission grade). Also, all the information about the curricular units the student is enrolled in is excluded for the same reason that this is after they start school.

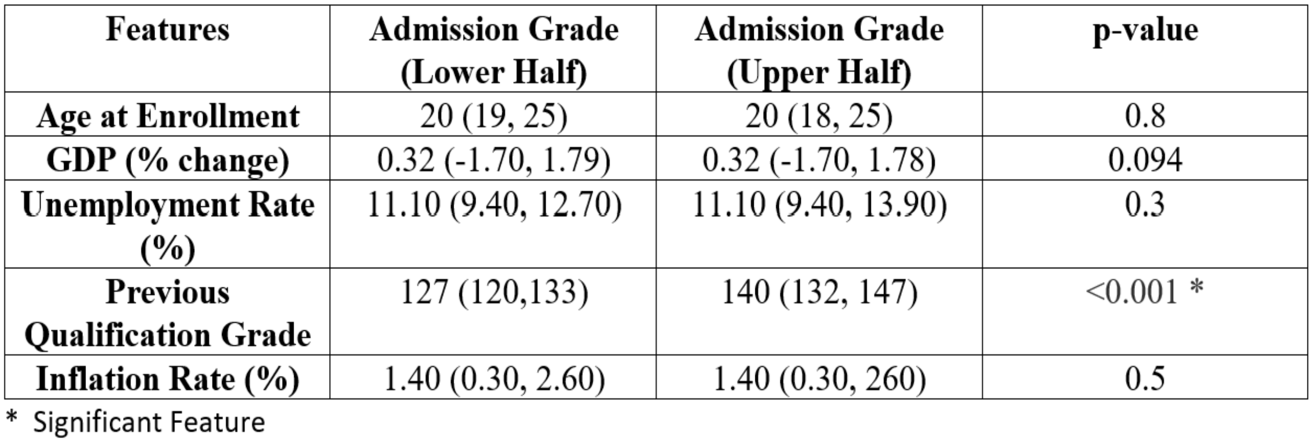
The data dictionary does not provide any information about the Displaced variable, and without more information it seemed reasonable to exclude the variable from the analysis to avoid any unwanted effects from including it.

Finally, the nationality variable was excluded and perhaps this is the most subjective assumption of all, but it seemed fairly reasonable to assume that a student would perform the same on an admissions test and in college regardless of their nationality. GDP, Inflation Rate, Unemployment Rate, and Age were excluded based on a t-test which showed that they had no significant effect on the admission grade, and it seemed reasonable to assume that these factors do not necessarily affect a student's performance on an admissions test.

The causal inference model is fairly complex and has its share of limitations. It assumes that there are no latent confounders i.e variables which are unobserved but ones which are not captured by the dataset. This is a reasonable assumption but it is likely that the dataset does not have all the variables that affect both admission grades and graduation rates. However, with enough variables the model should be sufficient to provide a good enough estimate of the coefficients. Another assumption is that the variables have a linear relationship in the data. This is also unlikely to be completely true, as we don't expect these variables to change linearly, but this assumption can be relaxed and the model will still be interpretable if the variables are not entirely linearly dependent.

Results

The client provided the dataset required for this analysis as a CSV file which was acquired from several disjoint databases related to student enrollment in undergraduate courses between 2008 to 2019. This data represented various student information along with the status of whether they graduated, dropped out, or were still enrolled at the end of the stipulated time to degree. Each row of the data represents a single student, and there are 4424 such records. This data was already preprocessed by the client, so there was no necessity for cleaning or handling missing values. For each student, there was a multitude of information most of which proved fairly unusable for this specific type of analysis. If the variable was not a confounder it was discarded from the analysis, as described in the methods section. The causal inference analysis was finally performed with each observation having 16 different features. The numerical features are further described in Table 1, while the categorical features are presented in the appendix due to there being a large number of categories for each variable.

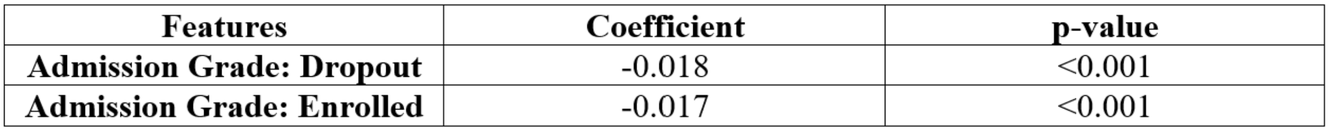


Features	Admission Grade (Lower Half)	Admission Grade (Upper Half)	p-value
Age at Enrollment	20 (19, 25)	20 (18, 25)	0.8
GDP (% change)	0.32 (-1.70, 1.79)	0.32 (-1.70, 1.78)	0.094
Unemployment Rate (%)	11.10 (9.40, 12.70)	11.10 (9.40, 13.90)	0.3
Previous Qualification Grade	127 (120,133)	140 (132, 147)	<0.001 *
Inflation Rate (%)	1.40 (0.30, 2.60)	1.40 (0.30, 260)	0.5

* Significant Feature

Table 1: Baseline table indicating summary statistics of data of numerical features

The regression model was fitted, and the results are presented in Table 2. More insights which may be useful to the client are presented in Table 3.



Features	Coefficient	p-value
Admission Grade: Dropout	-0.018	<0.001
Admission Grade: Enrolled	-0.017	<0.001

Table 2: Regression Coefficients. The two features are interaction terms between graduation status and admission grade (with graduate as reference group.)

With a one point increase in admission grade, chance of dropout (Admission Grade: Dropout) goes down by 1.8% and chance of still being enrolled (failed to graduate in stipulated time) goes down by 1.7%. These values are in comparison with graduating, if all other variables are held constant.

In order to shed additional light for the client, the model can be used to compute the expected probability change of the graduation status given different admission grade cutoffs for which the client is contemplating a change. The following table presents some realistic scenarios for the client to consider.

Change in Admission Grade	**Decrease in Dropout (%)**	**Decrease in Enrolled (%)**
+5	8.75	8.35
+10	17.5	16.7
+20	35	33.4

Table 3: Changes in graduation status with different levels of admission grades.

Additionally, Figure 1 below provides information on how admission grades are distributed amongst the different graduation status. For example, the admission grade of a majority of students who graduated is higher (blue peak) than that of those who are still enrolled and those who dropped out of university (green and red peaks). In reference to the client's question about where to set the admission grade cutoff, a reasonable level seems to be 125 points, relative probabilities of graduating are higher than dropping out or staying enrolled as is depicted in Figure 1. If the client desires a more lax cutoff, they may refer to the figure to make their decision.

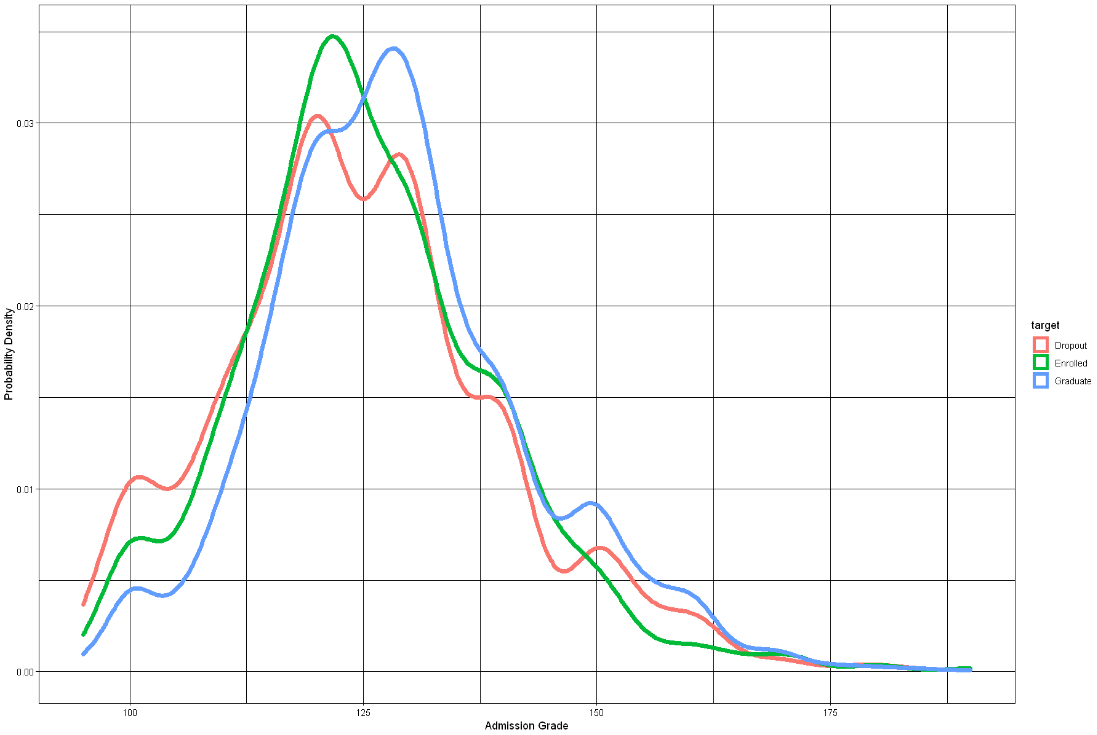


Figure 1: Density Plot for Admission Grade across Graduation Status

Conclusion

This report presents the results of a causal inference analysis performed on student information, with the objective of trying to understand the effect of admission grade on the graduation status of the student. Admission grade is deemed a significant variable by the model and impacts the graduation rate in a causal fashion. An increase in one point of admission grade, lowers the probability of dropping out or staying enrolled at the end of the stipulated time to graduation by 1.8% and 1.7% respectively, as compared to the probability of graduating. While these results are expected to be useful, it must be noted that the model comes with a fair share of limitations; It assumes that all confounding variables are included in the model, and that there are no latent (i.e unobserved) confounders. It also assumes linear relationships in the data, and the propensity score weights are accurate. While there may be limitations in the methods, it is expected that these results will still guide the client in tinkering with their admission grade cutoffs in order to enhance both their reputation with respect to graduation rates, as well as providing students a fair opportunity to earn a degree.

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
X	2,194 (1,086, 3,296)	2,224 (1,129, 3,341)
previous_qualification		
1	2,100 (89%)	1,617 (78%)
2	12 (0.5%)	11 (0.5%)
3	27 (1.1%)	99 (4.8%)
4	4 (0.2%)	4 (0.2%)
5	0 (0%)	1 (<0.1%)
6	11 (0.5%)	5 (0.2%)
9	10 (0.4%)	1 (<0.1%)
10	2 (<0.1%)	2 (<0.1%)
12	24 (1.0%)	21 (1.0%)
14	1 (<0.1%)	0 (0%)
15	2 (<0.1%)	0 (0%)
19	110 (4.7%)	52 (2.5%)
38	4 (0.2%)	3 (0.1%)
39	36 (1.5%)	183 (8.9%)
40	12 (0.5%)	28 (1.4%)
42	3 (0.1%)	33 (1.6%)
43	0 (0%)	6 (0.3%)
previous_qualification_grade_	127 (120, 133)	140 (132, 147)
mother_s_qualification		
1	563 (24%)	506 (24%)
2	39 (1.7%)	44 (2.1%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
3	211 (8.9%)	227 (11%)
4	27 (1.1%)	22 (1.1%)
5	5 (0.2%)	16 (0.8%)
6	2 (<0.1%)	2 (<0.1%)
9	3 (0.1%)	5 (0.2%)
10	1 (<0.1%)	2 (<0.1%)
11	2 (<0.1%)	1 (<0.1%)
12	29 (1.2%)	13 (0.6%)
14	1 (<0.1%)	1 (<0.1%)
18	0 (0%)	1 (<0.1%)
19	525 (22%)	428 (21%)
22	0 (0%)	1 (<0.1%)
26	0 (0%)	1 (<0.1%)
27	1 (<0.1%)	0 (0%)
29	1 (<0.1%)	2 (<0.1%)
30	2 (<0.1%)	1 (<0.1%)
34	75 (3.2%)	55 (2.7%)
35	1 (<0.1%)	2 (<0.1%)
36	1 (<0.1%)	2 (<0.1%)
37	545 (23%)	464 (22%)
38	311 (13%)	251 (12%)
39	1 (<0.1%)	7 (0.3%)
40	1 (<0.1%)	8 (0.4%)
41	5 (0.2%)	1 (<0.1%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
42	2 (<0.1%)	2 (<0.1%)
43	3 (0.1%)	1 (<0.1%)
44	1 (<0.1%)	0 (0%)
father_s_qualification		
1	464 (20%)	440 (21%)
2	34 (1.4%)	34 (1.6%)
3	120 (5.1%)	162 (7.8%)
4	15 (0.6%)	24 (1.2%)
5	12 (0.5%)	6 (0.3%)
6	2 (<0.1%)	0 (0%)
9	2 (<0.1%)	3 (0.1%)
10	0 (0%)	2 (<0.1%)
11	4 (0.2%)	6 (0.3%)
12	22 (0.9%)	16 (0.8%)
13	1 (<0.1%)	0 (0%)
14	2 (<0.1%)	2 (<0.1%)
18	0 (0%)	1 (<0.1%)
19	552 (23%)	416 (20%)
20	0 (0%)	1 (<0.1%)
22	3 (0.1%)	1 (<0.1%)
25	0 (0%)	1 (<0.1%)
26	0 (0%)	2 (<0.1%)
27	0 (0%)	1 (<0.1%)
29	3 (0.1%)	0 (0%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
30	2 (<0.1%)	2 (<0.1%)
31	1 (<0.1%)	0 (0%)
33	0 (0%)	1 (<0.1%)
34	69 (2.9%)	43 (2.1%)
35	0 (0%)	2 (<0.1%)
36	3 (0.1%)	5 (0.2%)
37	660 (28%)	549 (27%)
38	377 (16%)	325 (16%)
39	6 (0.3%)	14 (0.7%)
40	2 (<0.1%)	3 (0.1%)
41	0 (0%)	2 (<0.1%)
42	1 (<0.1%)	0 (0%)
43	0 (0%)	2 (<0.1%)
44	1 (<0.1%)	0 (0%)
mother_s_occupation		
0	82 (3.5%)	62 (3.0%)
1	42 (1.8%)	60 (2.9%)
2	152 (6.4%)	166 (8.0%)
3	199 (8.4%)	152 (7.4%)
4	415 (18%)	402 (19%)
5	300 (13%)	230 (11%)
6	42 (1.8%)	49 (2.4%)
7	163 (6.9%)	109 (5.3%)
8	20 (0.8%)	16 (0.8%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
9	835 (35%)	742 (36%)
10	2 (<0.1%)	2 (<0.1%)
90	42 (1.8%)	28 (1.4%)
99	11 (0.5%)	6 (0.3%)
122	1 (<0.1%)	1 (<0.1%)
123	4 (0.2%)	3 (0.1%)
125	0 (0%)	1 (<0.1%)
131	1 (<0.1%)	0 (0%)
132	2 (<0.1%)	1 (<0.1%)
134	1 (<0.1%)	3 (0.1%)
141	4 (0.2%)	4 (0.2%)
143	0 (0%)	3 (0.1%)
144	5 (0.2%)	1 (<0.1%)
151	0 (0%)	3 (0.1%)
152	1 (<0.1%)	1 (<0.1%)
153	1 (<0.1%)	1 (<0.1%)
171	1 (<0.1%)	0 (0%)
173	1 (<0.1%)	0 (0%)
175	3 (0.1%)	2 (<0.1%)
191	18 (0.8%)	8 (0.4%)
192	2 (<0.1%)	3 (0.1%)
193	3 (0.1%)	1 (<0.1%)
194	5 (0.2%)	6 (0.3%)
father_s_occupation		

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
0	71 (3.0%)	57 (2.8%)
1	65 (2.8%)	69 (3.3%)
2	82 (3.5%)	115 (5.6%)
3	204 (8.7%)	180 (8.7%)
4	190 (8.1%)	196 (9.5%)
5	279 (12%)	237 (11%)
6	114 (4.8%)	128 (6.2%)
7	385 (16%)	281 (14%)
8	162 (6.9%)	156 (7.6%)
9	551 (23%)	459 (22%)
10	149 (6.3%)	117 (5.7%)
90	40 (1.7%)	25 (1.2%)
99	14 (0.6%)	5 (0.2%)
101	1 (<0.1%)	0 (0%)
102	0 (0%)	2 (<0.1%)
103	3 (0.1%)	1 (<0.1%)
112	0 (0%)	2 (<0.1%)
114	0 (0%)	1 (<0.1%)
121	1 (<0.1%)	0 (0%)
122	1 (<0.1%)	1 (<0.1%)
123	3 (0.1%)	0 (0%)
124	0 (0%)	1 (<0.1%)
131	0 (0%)	1 (<0.1%)
132	1 (<0.1%)	0 (0%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
134	0 (0%)	1 (<0.1%)
135	1 (<0.1%)	2 (<0.1%)
141	0 (0%)	1 (<0.1%)
143	1 (<0.1%)	0 (0%)
144	5 (0.2%)	3 (0.1%)
151	0 (0%)	2 (<0.1%)
152	1 (<0.1%)	2 (<0.1%)
153	1 (<0.1%)	0 (0%)
154	1 (<0.1%)	0 (0%)
161	0 (0%)	1 (<0.1%)
163	3 (0.1%)	2 (<0.1%)
171	6 (0.3%)	2 (<0.1%)
172	1 (<0.1%)	1 (<0.1%)
174	1 (<0.1%)	0 (0%)
175	3 (0.1%)	1 (<0.1%)
181	3 (0.1%)	0 (0%)
182	2 (<0.1%)	0 (0%)
183	2 (<0.1%)	1 (<0.1%)
192	3 (0.1%)	3 (0.1%)
193	6 (0.3%)	9 (0.4%)
194	1 (<0.1%)	1 (<0.1%)
195	1 (<0.1%)	0 (0%)
admission_grade	118 (112, 122)	136 (130, 144)
educational_special_needs		

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
0	2,324 (99%)	2,049 (99%)
1	34 (1.4%)	17 (0.8%)
gender		
0	1,539 (65%)	1,329 (64%)
1	819 (35%)	737 (36%)
age_at_enrollment	20 (19, 25)	20 (18, 25)
international		
0	2,308 (98%)	2,006 (97%)
1	50 (2.1%)	60 (2.9%)
unemployment_rate	11.10 (9.40, 12.70)	11.10 (9.40, 13.90)
inflation_rate		
-0.8	272 (12%)	261 (13%)
-0.3	186 (7.9%)	204 (9.9%)
0.3	183 (7.8%)	179 (8.7%)
0.5	241 (10%)	204 (9.9%)
0.6	259 (11%)	155 (7.5%)
1.4	478 (20%)	415 (20%)
2.6	306 (13%)	265 (13%)
2.8	220 (9.3%)	177 (8.6%)
3.7	213 (9.0%)	206 (10.0%)
gdp	0.32 (-1.70, 1.79)	0.32 (-1.70, 1.78)
target		
Dropout	809 (34%)	612 (30%)
Enrolled	471 (20%)	323 (16%)

[1] Median (IQR); n (%)

Characteristic	**Lower**, N = 2,358[1]	**Upper**, N = 2,066[1]
Graduate	1,078 (46%)	1,131 (55%)

[1] Median (IQR); n (%)

In [1]:

```
import pandas as pd
```

In [5]:

```
df = pd.read_csv("graduation.csv", index_col=0)
```

In [3]:

```
df.describe()
```

Out[3]:

	Unnamed: 0	Marital.status	Application.mode	Application.order	Course	Daytime.evening.attendance.
count	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000
mean	2212.500000	1.178571	18.669078	1.727848	8856.642631	0.890823
std	1277.243125	0.605747	17.484682	1.313793	2063.566416	0.311897
min	1.000000	1.000000	1.000000	0.000000	33.000000	0.000000
25%	1106.750000	1.000000	1.000000	1.000000	9085.000000	1.000000
50%	2212.500000	1.000000	17.000000	1.000000	9238.000000	1.000000
75%	3318.250000	1.000000	39.000000	2.000000	9556.000000	1.000000
max	4424.000000	6.000000	57.000000	9.000000	9991.000000	1.000000

8 rows × 37 columns

In [4]:

```
df.columns
```

Out[4]:

```
Index(['Unnamed: 0', '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')
```

Run t-tests against admission grade to check if these are confounders

Marital Status Daytime Evening Attendance GDP Inflation Rate Unemployment Rate Debtor

Drop:

Appl Mode Appl Order Course Nationality Displaced Tuition Scholarship

In [17]:

```
df_confounders = df[
    [
        "Previous.qualification",
        "Previous.qualification..grade.",
        "Mother.s.qualification",
        "Father.s.qualification",
        "Mother.s.occupation",
        "Father.s.occupation",
        "Admission.grade",
        "Educational.special.needs",
        "Gender",
        "Age.at.enrollment",
        "International",
        "Unemployment.rate",
        "Inflation.rate",
        "GDP",
        "Target"
    ]
]
```

In [18]:

```
df_confounders.columns = list(map(lambda c: c.lower().replace(".", "_").replace("__", "_
df_confounders
```

Out[18]:

	previous_qualification	previous_qualification_grade_	mother_s_qualification	father_s_qualification	mother_s_
1	1	122.0	19	12	
2	1	160.0	1	3	
3	1	122.0	37	37	
4	1	122.0	38	37	
5	1	100.0	37	38	
...	...	...	...	...	
4420	1	125.0	1	1	
4421	1	120.0	1	1	
4422	1	154.0	37	37	
4423	1	180.0	37	37	
4424	1	152.0	38	37	

4424 rows × 15 columns

In [19]:

```
df_confounders.to_csv("dat.csv")
```

In [10]:

```
df["GDP"].describe()
```

Out[10]:

```
count    4424.000000
mean        0.001969
std         2.269935
min        -4.060000
25%        -1.700000
50%         0.320000
75%         1.790000
max         3.510000
Name: GDP, dtype: float64
```

In [12]:

```
df["Debtor"].value_counts()
```

Out[12]:

```
0    3921
1     503
Name: Debtor, dtype: int64
```

In [11]:

```
df["Nacionality"].value_counts()
```

Out[11]:

```
1      4314
41       38
26       14
22       13
6        13
24        5
100       3
11        3
103       3
21        2
101       2
62        2
25        2
2         2
105       2
32        1
13        1
109       1
108       1
14        1
17        1
Name: Nacionality, dtype: int64
```

In [8]:

```
len(df.columns)
```

Out[8]:

```
38
```

In [9]:

```
df.shape
```

Out[9]:

```
(4424, 38)
```

In [21]:

```
df[['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.', 'Target']]
```

Out[21]:

	Curricular.units.1st.sem..credited.	Curricular.units.1st.sem..enrolled.	Curricular.units.1st.sem..evaluations.	Curri
0	0	0	0	
1	0	6	6	
2	0	6	0	
3	0	6	8	
4	0	6	9	
...	...	...	...	
4419	0	6	7	
4420	0	6	6	
4421	0	7	8	
4422	0	5	5	
4423	0	6	8	

4424 rows × 7 columns

In [5]:

```
df["Nacionality"].value_counts()
```

Out[5]:

```
1      4314
41       38
26       14
22       13
6        13
24        5
100       3
11        3
103       3
21        2
101       2
62        2
25        2
2         2
105       2
32        1
13        1
109       1
108       1
14        1
17        1
Name: Nacionality, dtype: int64
```

In [25]:

```
df["Course"].value_counts()
```

Out[25]:

```
12    766
9     380
10    355
6     337
15    331
14    268
17    268
11    252
5     226
2     215
3     215
4     210
16    192
7     170
8     141
13     86
1      12
Name: Course, dtype: int64
```

In [19]:

```
df.groupby("Target")["Curricular.units.1st.sem..credited."].mean()
```

Out[19]:

```
Target
Dropout     0.609430
Enrolled    0.507557
Graduate    0.847442
Name: Curricular.units.1st.sem..credited., dtype: float64
```

In [13]:

```
df["Target"].value_counts()
```

Out[13]:

```
Graduate    2209
Dropout     1421
Enrolled     794
Name: Target, dtype: int64
```

In [22]:

```
g = df.groupby("Target")
gg = g.get_group("Graduate")
gd = g.get_group("Dropout")
ge = g.get_group("Enrolled")
```

In [23]:

```
import scipy.stats as stats
# stats f_oneway functions takes the groups as input and returns ANOVA F and p value
fvalue, pvalue = stats.f_oneway(gg['Admission.grade'], gd['Admission.grade'], ge['Admiss
print(fvalue, pvalue)
```

```
35.64860425750162 4.380466113389808e-16
```

In [ ]:

In [2]:

```
# Loading the dataset and changing categorical variables to factors
df = read.csv("dat.csv")
df["previous_qualification"] = as.factor(df$previous_qualification)
df["mother_s_qualification"] = as.factor(df$mother_s_qualification)
df["father_s_qualification"] = as.factor(df$father_s_qualification)
df["mother_s_occupation"] = as.factor(df$mother_s_occupation)
df["father_s_occupation"] = as.factor(df$father_s_occupation)
df["educational_special_needs"] = as.factor(df$educational_special_needs)
df["gender"] = as.factor(df$gender)
df["international"] = as.factor(df$international)
df["target"] = as.factor(df$target)
head(df)
```

	X	previous_qualification	previous_qualification_grade_	mother_s_qualification	father_s_qualification	mothe
	<int>	<fct>	<dbl>	<fct>	<fct>	
1	1	1	122.0	19	12	
2	2	1	160.0	1	3	
3	3	1	122.0	37	37	
4	4	1	122.0	38	37	
5	5	1	100.0	37	38	
6	6	19	133.1	37	37	

In [19]:

```
# Loading libraries
library(twangContinuous)
library(cobalt)
library(survey)
library(gtsummary)
library(dplyr)
```

In [4]:

```
# Summary of the dataset
summary(df)
```

```
       X        previous_qualification previous_qualification_grade_
 Min.   :   1   1      :3717           Min.   : 95.0
 1st Qu.:1107   39     : 219           1st Qu.:125.0
 Median :2212   19     : 162           Median :133.1
 Mean   :2212   3      : 126           Mean   :132.6
 3rd Qu.:3318   12     :  45           3rd Qu.:140.0
 Max.   :4424   40     :  40           Max.   :190.0
                (Other): 115
 mother_s_qualification father_s_qualification mother_s_occupation
 1      :1069           37     :1209           9      :1577
 37     :1009           19     : 968           4      : 817
 19     : 953           1      : 904           5      : 530
 38     : 562           38     : 702           3      : 351
 3      : 438           3      : 282           2      : 318
 34     : 130           34     : 112           7      : 272
 (Other): 263           (Other): 247           (Other): 559
 father_s_occupation admission_grade educational_special_needs gender
 9      :1010        Min.   : 95.0   0:4373                    0:2868
 7      : 666        1st Qu.:117.9   1:   51                   1:1556
 5      : 516        Median :126.1
 4      : 386        Mean   :127.0
 3      : 384        3rd Qu.:134.8
 8      : 318        Max.   :190.0
 (Other):1144
 age_at_enrollment international unemployment_rate inflation_rate
 Min.   :17.00     0:4314        Min.   : 7.60     Min.   :-0.800
 1st Qu.:19.00     1: 110        1st Qu.: 9.40     1st Qu.: 0.300
 Median :20.00                   Median :11.10     Median : 1.400
 Mean   :23.27                   Mean   :11.57     Mean   : 1.228
 3rd Qu.:25.00                   3rd Qu.:13.90     3rd Qu.: 2.600
 Max.   :70.00                   Max.   :16.20     Max.   : 3.700

      gdp                   target
 Min.   :-4.060000   Dropout :1421
 1st Qu.:-1.700000   Enrolled: 794
 Median : 0.320000   Graduate:2209
 Mean   : 0.001969
 3rd Qu.: 1.790000
 Max.   : 3.510000
```

In [8]:

```
# Column names
colnames(df)
```

'X' · 'previous_qualification' · 'previous_qualification_grade_' · 'mother_s_qualification' · 'father_s_qualification' · 'mother_s_occupation' · 'father_s_occupation' · 'admission_grade' · 'educational_special_needs' · 'gender' · 'age_at_enrollment' · 'international' · 'unemployment_rate' · 'inflation_rate' · 'gdp' · 'target'

ps.cont is a way of getting propensity scores for a continuous treatment variables (admission_grade in our case). Propensity scores are a probability of how likely a particular observation is to have that value of the treatment (check this definition)

In [9]:

```
# Calculation of Propensity Scores to use as weights for our regression model
psc.out <- ps.cont(admission_grade ~ previous_qualification +
                   previous_qualification_grade_ +
                   mother_s_qualification +
                   father_s_qualification +
                   mother_s_occupation +
                   father_s_occupation +
                   educational_special_needs +
                   gender +
                   international
                   , data = df)
summary(psc.out)
```

A matrix: 2 × 6 of type dbl

	n	ess	max.wcor	mean.wcor	rms.wcor	iter
unw	4424	4424.000	0.5804442	0.02516172	0.05686047	NA
AAC	4424	3556.534	0.2525825	0.02312257	0.03952497	45

In [10]:

```
head(df$admission_grade)
```

127.3 · 142.5 · 124.8 · 119.6 · 141.5 · 114.8

`w` are the weights, and there is one for each observation of the data. We use this to perform the survey weighted glm.

In [11]:

```
head(psc.out$w)
```

1: 0.905988619974881 **2:** 0.638202184695573 **3:** 0.881982325873705 **4:** 0.854787073872639 **5:** 1.4351401335233 **6:** 0.891158171133763

In [18]:

```
# Running the model
library(svyVGAM)
design <- svydesign(ids=~1, weights=psc.out$w, data=df)
mmodel <- svy_vglm(target ~ admission_grade, family=multinomial, design=design)
```

In [13]:

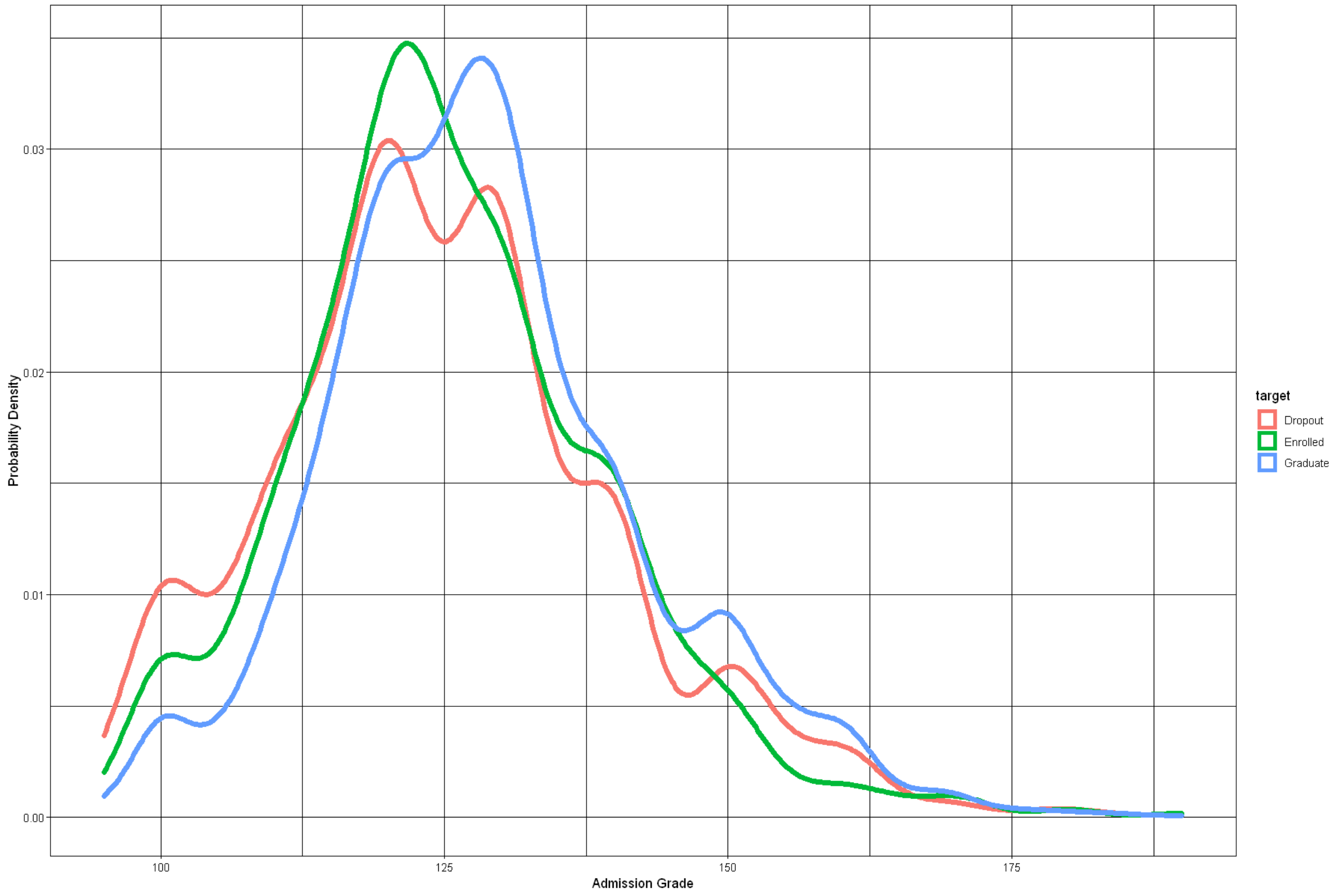
```
Z# Summary of the model
summary(mmodel)
```

```
svy_vglm.survey.design(target ~ admission_grade, family = multinomial,
    design = design)
Independent Sampling design (with replacement)
svydesign(ids = ~1, weights = psc.out$w, data = df)
                        Coef          SE         z           p
(Intercept):1      1.8325499  0.4079344  4.4923 7.047e-06
(Intercept):2      1.1172709  0.4504119  2.4806   0.01312
admission_grade:1 -0.0175567  0.0032498 -5.4024 6.574e-08
admission_grade:2 -0.0167687  0.0035593 -4.7113 2.462e-06
```

Interpretation: With 1 point increase in admission_grade, chance of dropout (`admission_grade:1`) goes down by 1.8% and chance of still being enrolled (failed to graduate in stipulated time) goes down by 1.7%

In [15]:

```
# Plotting the figure
library(ggplot2)
options(repr.plot.width = 15, repr.plot.height =10)
ggplot(df, aes(x = admission_grade)) +
  geom_density(aes(color = target), size=2) +
  xlab("Admission Grade") +
  ylab("Probability Density") + theme_linedraw() +
  labs("Density Plot for Admission Grade across Graduation Status")
```



In [16]:

```
# Descriptive statistics for our dataset using admission grade as two groups
data = df
data$group = with(df, ifelse(admission_grade > 127, 'Upper', 'Lower'))
glimpse(data)
```

```
Rows: 4,424
Columns: 17
$ X                               <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 1…
$ previous_qualification          <fct> 1, 1, 1, 1, 1, 19, 1, 1, 1, 1, 1, 1, 1, …
$ previous_qualification_grade_   <dbl> 122.0, 160.0, 122.0, 122.0, 100.0, 133.1…
$ mother_s_qualification          <fct> 19, 1, 37, 38, 37, 37, 19, 37, 1, 1, 38,…
$ father_s_qualification          <fct> 12, 3, 37, 37, 38, 37, 38, 37, 1, 19, 19…
$ mother_s_occupation             <fct> 5, 3, 9, 5, 9, 9, 7, 9, 9, 4, 5, 9, 4, 4…
$ father_s_occupation             <fct> 9, 3, 9, 3, 9, 7, 10, 9, 9, 7, 7, 9, 9, …
$ admission_grade                 <dbl> 127.3, 142.5, 124.8, 119.6, 141.5, 114.8…
$ educational_special_needs       <fct> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
$ gender                          <fct> 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0…
$ age_at_enrollment               <int> 20, 19, 19, 20, 45, 50, 18, 22, 21, 18, …
$ international                   <fct> 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0…
$ unemployment_rate               <dbl> 10.8, 13.9, 10.8, 9.4, 13.9, 16.2, 15.5,…
$ inflation_rate                  <dbl> 1.4, -0.3, 1.4, -0.8, -0.3, 0.3, 2.8, 2.…
$ gdp                             <dbl> 1.74, 0.79, 1.74, -3.12, 0.79, -0.92, -4…
$ target                          <fct> Dropout, Graduate, Dropout, Graduate, Gr…
$ group                           <chr> "Upper", "Upper", "Lower", "Lower", "Upp…
```

In [17]:

```
t = tbl_summary(data, by = group)
dat1 = data[c(3,11,13,14,15,17)]
t2 = dat1 %>%
  tbl_summary(by = group, type = list(where(is.numeric) ~ "continuous2")) %>%
  add_p(all_continuous() ~ "t.test")
```