

ML PROJECT PREDICTING STUDENTS DROPOUT AND ACADEMIC SUCCESS In this project we are going to learn what aspect of the students life effects more on their studies. To prepare the dataset for analysis, we will initially install specific Python packages including numpy, pandas, seaborn, and matplotlib for data processing and analysis. For machine learning model, we will install Extreme Gradient Boosting (XGB) library and use binary logistics.

Importing necessary libraries

```
import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
import xgboost as xgb
from sklearn.metrics import accuracy_score
```

Reading the dataset

```
df=pd.read_csv("dataset.csv")
```

df

	Marital status	Application mode	Application order	Course \
0	1	8	5	2
1	1	6	1	11
2	1	1	5	5
3	1	8	2	15
4	2	12	1	3
...	...	...	...	...
4419	1	1	6	15
4420	1	1	2	15
4421	1	1	1	12
4422	1	1	1	9
4423	1	5	1	15

\	Daytime/evening attendance	Previous qualification	Nacionality
0	1	1	1
1	1	1	1
2	1	1	1
3	1	1	1

4	0	1	1
...	...	...	...
4419	1	1	1
4420	1	1	19
4421	1	1	1
4422	1	1	1
4423	1	1	9

Mother's qualification occupation \	Father's qualification	Mother's
0	13	10
6		
1	1	3
4		
2	22	27
10		
3	23	27
6		
4	22	28
10		
...	...	...
...		
4419	1	1
6		
4420	1	1
10		
4421	22	27
10		
4422	22	27
8		
4423	23	27
6		

...	Curricular units 2nd sem (credited) \
0	...
1	...
2	...
3	...
4	...
...	...
4419	...

4420	...	0
4421	...	0
4422	...	0
4423	...	0

Curricular units 2nd sem (enrolled) \	
0	0
1	6
2	6
3	6
4	6
...	...
4419	6
4420	6
4421	8
4422	5
4423	6

Curricular units 2nd sem (evaluations) \	
0	0
1	6
2	0
3	10
4	6
...	...
4419	8
4420	6
4421	9
4422	6
4423	6

Curricular units 2nd sem (approved)	Curricular units 2nd sem
(grade) \	
0	0
0.000000	
1	6
13.666667	
2	0
0.000000	
3	5
12.400000	
4	6
13.000000	
...	...
...	
4419	5
12.666667	
4420	2
11.000000	
4421	1

13.500000  
4422  
12.000000  
4423  
13.000000

5  
6

	Curricular units 2nd sem (without evaluations)	Unemployment
rate \		
0		0
10.8		
1		0
13.9		
2		0
10.8		
3		0
9.4		
4		0
13.9		
...	...	..
.		
4419		0
15.5		
4420		0
11.1		
4421		0
13.9		
4422		0
9.4		
4423		0
12.7		

	Inflation rate	GDP	Target
0	1.4	1.74	Dropout
1	-0.3	0.79	Graduate
2	1.4	1.74	Dropout
3	-0.8	-3.12	Graduate
4	-0.3	0.79	Graduate
...	...	...	...
4419	2.8	-4.06	Graduate
4420	0.6	2.02	Dropout
4421	-0.3	0.79	Dropout
4422	-0.8	-3.12	Graduate
4423	3.7	-1.70	Graduate

[4424 rows x 35 columns]

*#shows first five rows of dataset*  
df.head()

	Marital status	Application mode	Application order	Course \
0	1	8	5	2
1	1	6	1	11
2	1	1	5	5
3	1	8	2	15
4	2	12	1	3

	Daytime/evening attendance	Previous qualification	Nacionality \
0	1	1	1
1	1	1	1
2	1	1	1
3	1	1	1
4	0	1	1

	Mother's qualification \	Father's qualification	Mother's occupation
0	13	10	6
1	1	3	4
2	22	27	10
3	23	27	6
4	22	28	10
...			

	Curricular units 2nd sem (enrolled) \	Curricular units 2nd sem (credited)
0	0	
0		
1	0	
6		
2	0	
6		
3	0	
6		
4	0	
6		

	Curricular units 2nd sem (evaluations) \
0	0
1	6
2	0
3	10
4	6

	Curricular units 2nd sem (grade) \	Curricular units 2nd sem (approved)
0	0	

0.000000	
1	6
13.666667	
2	0
0.000000	
3	5
12.400000	
4	6
13.000000	

	Curricular units 2nd sem (without evaluations)	Unemployment rate \
0	0	10.8
1	0	13.9
2	0	10.8
3	0	9.4
4	0	13.9

	Inflation rate	GDP	Target
0	1.4	1.74	Dropout
1	-0.3	0.79	Graduate
2	1.4	1.74	Dropout
3	-0.8	-3.12	Graduate
4	-0.3	0.79	Graduate

[5 rows x 35 columns]

*#shows last five rows of dataset*  
df.tail()

	Marital status	Application mode	Application order	Course \
4419	1	1	6	15
4420	1	1	2	15
4421	1	1	1	12
4422	1	1	1	9
4423	1	5	1	15

	Daytime/evening attendance	Previous qualification	Nacionality
4419	1	1	1
4420	1	1	19
4421	1	1	1

4422	1	1	1
4423	1	1	9

	Mother's qualification occupation \	Father's qualification	Mother's
--	--	------------------------	----------

4419	1	1
6		
4420	1	1
10		
4421	22	27
10		
4422	22	27
8		
4423	23	27
6		

	... Curricular units 2nd sem (credited) \
--	---

4419	...	0
4420	...	0
4421	...	0
4422	...	0
4423	...	0

	Curricular units 2nd sem (enrolled) \
--	---------------------------------------

4419	6
4420	6
4421	8
4422	5
4423	6

	Curricular units 2nd sem (evaluations) \
--	--

4419	8
4420	6
4421	9
4422	6
4423	6

	Curricular units 2nd sem (approved)	Curricular units 2nd sem (grade) \
--	-------------------------------------	---------------------------------------

4419	5
12.666667	
4420	2
11.000000	
4421	1
13.500000	
4422	5

12.000000  
4423  
13.000000

6

	Curricular units 2nd sem (without evaluations)	Unemployment
rate \		
4419		0
15.5		
4420		0
11.1		
4421		0
13.9		
4422		0
9.4		
4423		0
12.7		

	Inflation rate	GDP	Target
4419	2.8	-4.06	Graduate
4420	0.6	2.02	Dropout
4421	-0.3	0.79	Dropout
4422	-0.8	-3.12	Graduate
4423	3.7	-1.70	Graduate

[5 rows x 35 columns]

*#shows sample of dataset*  
df.sample()

	Marital status	Application mode	Application order	Course	\
840	1	1	1	9	

	Daytime/evening attendance	Previous qualification
Nacionality \		
840	1	1
		14

	Mother's qualification	Father's qualification	Mother's
occupation ... \			
840	3	3	
10 ...			

	Curricular units 2nd sem (credited)	Curricular units 2nd sem
(enrolled) \		
840	0	
5		

	Curricular units 2nd sem (evaluations)	\
840	5	



Curricular units 2nd sem (approved)	Curricular units 2nd sem
(grade) \	
840	0
0.0	

Curricular units 2nd sem (without evaluations)	Unemployment rate
\	
840	0 8.9

Inflation rate	GDP	Target
840	1.4 3.51	Dropout

[1 rows x 35 columns]

*#shows the number of rows and columns*

df.shape

(4424, 35)

df.size

154840

*#info shows all the information of the dataset i.e. how many rows and columns are present in the dataset and the datatypes*

*#of the them,if there are any missing or null values present we get to know all of this from df.info()*

df.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 4424 entries, 0 to 4423

Data columns (total 35 columns):

#	Column	Non-Null Count
Dtype		
---	-----	-----
-----		
0	Marital status	4424 non-null
int64		
1	Application mode	4424 non-null
int64		
2	Application order	4424 non-null
int64		
3	Course	4424 non-null
int64		
4	Daytime/evening attendance	4424 non-null
int64		
5	Previous qualification	4424 non-null
int64		
6	Nacionality	4424 non-null
int64		

7	Mother's qualification	4424 non-null
int64		
8	Father's qualification	4424 non-null
int64		
9	Mother's occupation	4424 non-null
int64		
10	Father's occupation	4424 non-null
int64		
11	Displaced	4424 non-null
int64		
12	Educational special needs	4424 non-null
int64		
13	Debtor	4424 non-null
int64		
14	Tuition fees up to date	4424 non-null
int64		
15	Gender	4424 non-null
int64		
16	Scholarship holder	4424 non-null
int64		
17	Age at enrollment	4424 non-null
int64		
18	International	4424 non-null
int64		
19	Curricular units 1st sem (credited)	4424 non-null
int64		
20	Curricular units 1st sem (enrolled)	4424 non-null
int64		
21	Curricular units 1st sem (evaluations)	4424 non-null
int64		
22	Curricular units 1st sem (approved)	4424 non-null
int64		
23	Curricular units 1st sem (grade)	4424 non-null
float64		
24	Curricular units 1st sem (without evaluations)	4424 non-null
int64		
25	Curricular units 2nd sem (credited)	4424 non-null
int64		
26	Curricular units 2nd sem (enrolled)	4424 non-null
int64		
27	Curricular units 2nd sem (evaluations)	4424 non-null
int64		
28	Curricular units 2nd sem (approved)	4424 non-null
int64		
29	Curricular units 2nd sem (grade)	4424 non-null
float64		
30	Curricular units 2nd sem (without evaluations)	4424 non-null
int64		
31	Unemployment rate	4424 non-null
float64		

```

32 Inflation rate          4424 non-null
float64
33 GDP                    4424 non-null
float64
34 Target                4424 non-null
object
dtypes: float64(5), int64(29), object(1)
memory usage: 1.2+ MB

```

*#describe shows the statistical structure of the dataset,we get to see the mean,standard value*  
df.describe()

	Marital status	Application mode	Application order
Course \			
count	4424.000000	4424.000000	4424.000000
4424.000000			
mean	1.178571	6.886980	1.727848
9.899186			
std	0.605747	5.298964	1.313793
4.331792			
min	1.000000	1.000000	0.000000
1.000000			
25%	1.000000	1.000000	1.000000
6.000000			
50%	1.000000	8.000000	1.000000
10.000000			
75%	1.000000	12.000000	2.000000
13.000000			
max	6.000000	18.000000	9.000000
17.000000			

	Daytime/evening attendance	Previous qualification	Nacionality
\			
count	4424.000000	4424.000000	4424.000000
mean	0.890823	2.531420	1.254521
std	0.311897	3.963707	1.748447
min	0.000000	1.000000	1.000000
25%	1.000000	1.000000	1.000000
50%	1.000000	1.000000	1.000000
75%	1.000000	1.000000	1.000000
max	1.000000	17.000000	21.000000

	Mother's qualification	Father's qualification	Mother's
occupation \			
count	4424.000000	4424.000000	
4424.000000			
mean	12.322107	16.455244	
7.317812			
std	9.026251	11.044800	
3.997828			
min	1.000000	1.000000	
1.000000			
25%	2.000000	3.000000	
5.000000			
50%	13.000000	14.000000	
6.000000			
75%	22.000000	27.000000	
10.000000			
max	29.000000	34.000000	
32.000000			

	Curricular units 1st sem (without evaluations) \
count	4424.000000
mean	0.137658
std	0.690880
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	12.000000

	Curricular units 2nd sem (credited) \
count	4424.000000
mean	0.541817
std	1.918546
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	19.000000

	Curricular units 2nd sem (enrolled) \
count	4424.000000
mean	6.232143
std	2.195951
min	0.000000
25%	5.000000
50%	6.000000
75%	7.000000
max	23.000000

	Curricular units 2nd sem (evaluations) \
count	4424.000000
mean	8.063291
std	3.947951
min	0.000000
25%	6.000000
50%	8.000000
75%	10.000000
max	33.000000

	Curricular units 2nd sem (approved) \	Curricular units 2nd sem (grade) \
count	4424.000000	4424.000000
mean	4.435805	10.230206
std	3.014764	5.210808
min	0.000000	0.000000
25%	2.000000	10.750000
50%	5.000000	12.200000
75%	6.000000	13.333333
max	20.000000	18.571429

	Curricular units 2nd sem (without evaluations) \	Unemployment rate \
count	4424.000000	4424.000000
mean	0.150316	11.566139
std	0.753774	2.663850
min	0.000000	7.600000
25%	0.000000	9.400000
50%	0.000000	11.100000
75%	0.000000	13.900000
max	12.000000	16.200000

	Inflation rate	GDP
count	4424.000000	4424.000000

mean	1.228029	0.001969
std	1.382711	2.269935
min	-0.800000	-4.060000
25%	0.300000	-1.700000
50%	1.400000	0.320000
75%	2.600000	1.790000
max	3.700000	3.510000

[8 rows x 34 columns]

*#shows null values in the dataset*

df.isnull().sum()

Marital status	0
Application mode	0
Application order	0
Course	0
Daytime/evening attendance	0
Previous qualification	0
Nacionality	0
Mother's qualification	0
Father's qualification	0
Mother's occupation	0
Father's occupation	0
Displaced	0
Educational special needs	0
Debtor	0
Tuition fees up to date	0
Gender	0
Scholarship holder	0
Age at enrollment	0
International	0
Curricular units 1st sem (credited)	0
Curricular units 1st sem (enrolled)	0
Curricular units 1st sem (evaluations)	0
Curricular units 1st sem (approved)	0
Curricular units 1st sem (grade)	0
Curricular units 1st sem (without evaluations)	0
Curricular units 2nd sem (credited)	0
Curricular units 2nd sem (enrolled)	0
Curricular units 2nd sem (evaluations)	0
Curricular units 2nd sem (approved)	0
Curricular units 2nd sem (grade)	0
Curricular units 2nd sem (without evaluations)	0
Unemployment rate	0
Inflation rate	0
GDP	0
Target	0
dtype: int64	

```
#this will show if there are any duplicate values present in the dataset
```

```
df.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
```

```
...
4419   False
4420   False
4421   False
4422   False
4423   False
```

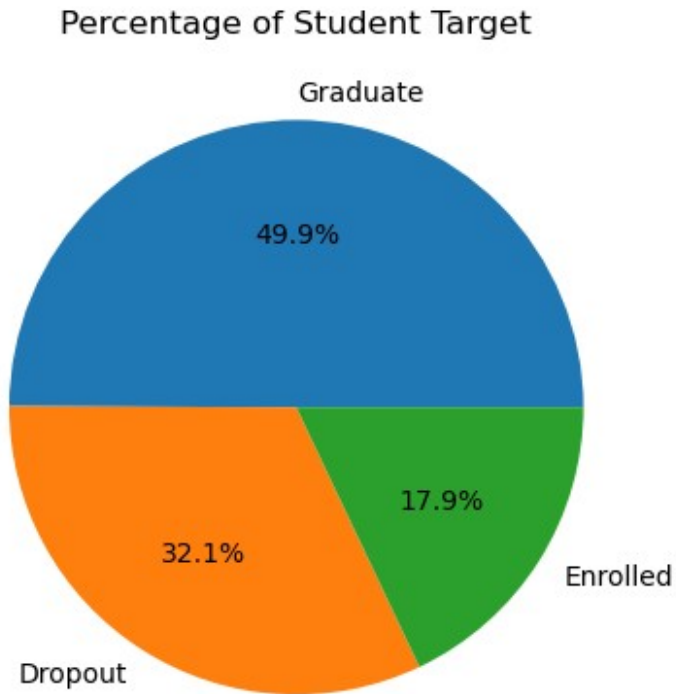
```
Length: 4424, dtype: bool
```

There are no null and duplicated values in the data.

Data Visualisation(EDA)

Since most of the variables in the data set are categorical, we will mainly use bar graphs to visualize them. However, for variables that are discrete or continuous, we will use distribution plots to display their distribution. Additionally, we will utilize correlation heatmaps to examine the relationships between variables in the data.

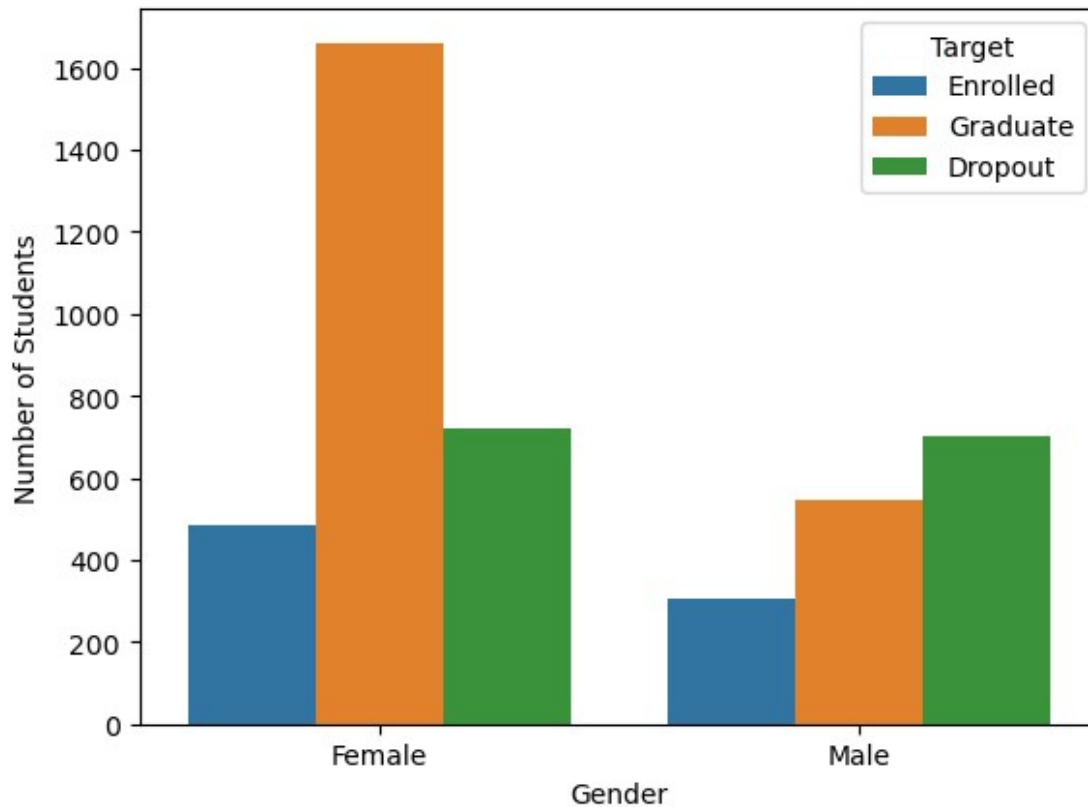
```
student_target=df['Target'].value_counts()
plt.pie(student_target,labels=student_target.index,autopct='%1.1f%%')
plt.title('Percentage of Student Target')
plt.show()
```



Approximately 50% of students in the data have graduated.

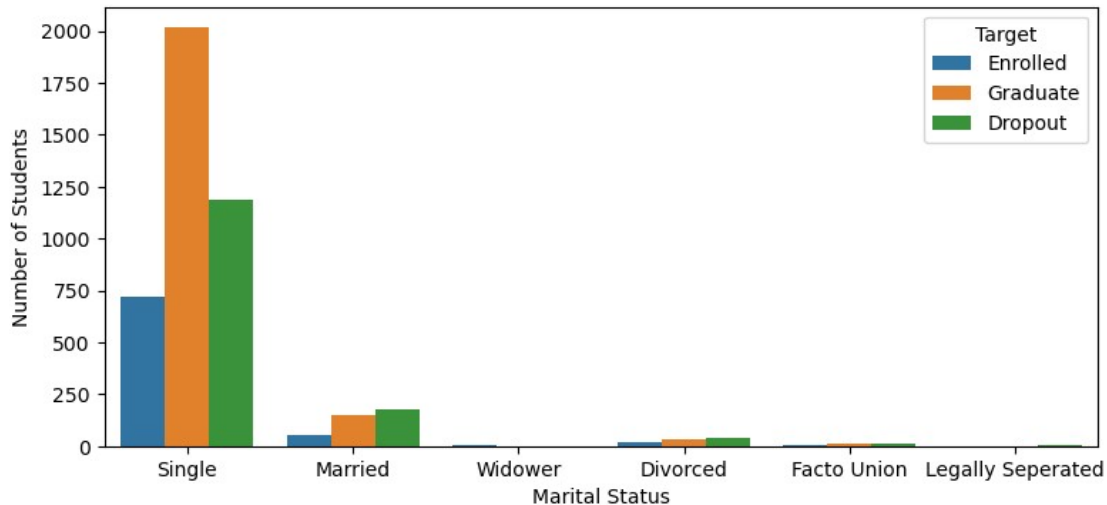
```
sns.countplot(data=df,x='Gender',hue='Target',hue_order=['Enrolled','Graduate','Dropout'])  
plt.xticks(ticks=[0,1],labels=['Female','Male'])  
plt.ylabel('Number of Students')  
plt.show()
```





According to the data, a higher number of graduates are female. However, females also have the highest number of dropouts, although the difference compared to males is small.

```
plt.figure(figsize=(9,4))
sns.countplot(data=df,x='Marital
status',hue='Target',hue_order=['Enrolled','Graduate','Dropout'])
plt.xticks(ticks=[0,1,2,3,4,5],
labels=['Single','Married','Widower','Divorced','Facto Union','Legally
Seperated'])
plt.xlabel('Marital Status')
plt.ylabel('Number of Students')
plt.show()
```

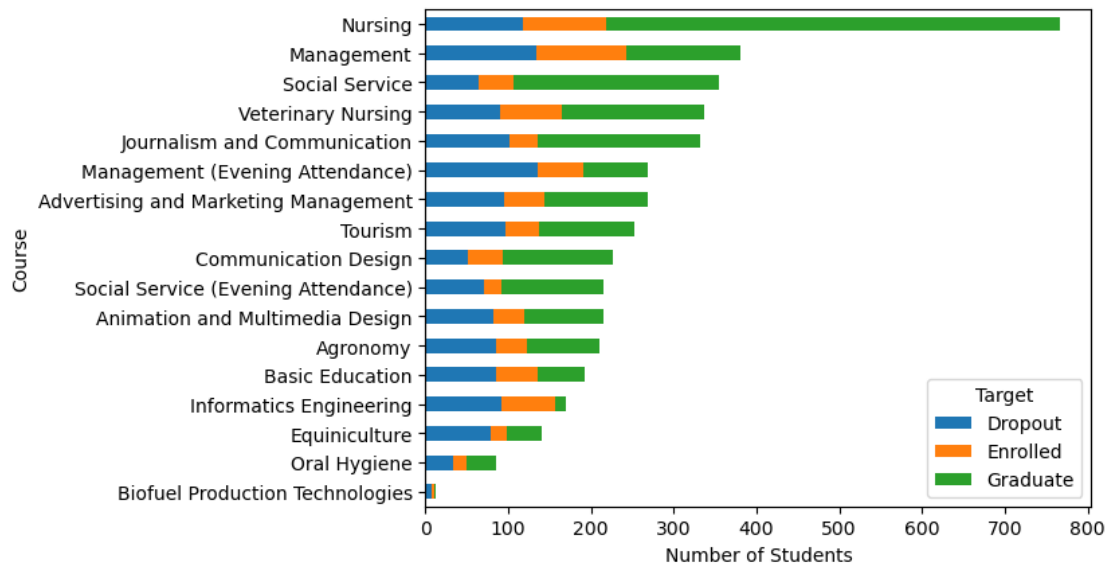


Regarding marital status, the majority of both graduates and dropouts are single.

```
student_course=df.groupby(['Course','Target']).size().reset_index().pivot(
columns='Target',index='Course',values=0)
```

*# Rename the index of the DataFrame*

```
student_course=student_course.rename(index={1:'Biofuel Production
Technologies',2:'Animation and Multimedia Design',3:'Social Service
(Evening Attendance)',4:'Agronomy',5:'Communication
Design',6:'Veterinary Nursing',7:'Informatics
Engineering',8:'Equiniculture',9:'Management',10:'Social
Service',11:'Tourism',12:'Nursing',13:'Oral Hygiene',14:'Advertising
and Marketing Management',15:'Journalism and Communication',16:'Basic
Education',17:'Management (Evening Attendance)'})
student_course_total=student_course.sum(axis=1)
student_course_sorted=student_course_total.sort_values(ascending=True)
student_course.loc[student_course_sorted.index].plot(kind='barh',stack
ed=True)
plt.xlabel('Number of Students')
plt.show()
```



Nursing course produced the highest number of graduates while management course has the highest number of dropouts.

```
nationality=df.groupby(['Nacionality',
'Target']).size().reset_index().pivot(columns='Target',index='Nacional
ity',values=0)
```

*# Rename the index of the DataFrame*

```
nationality=nationality.rename(index={1:'Indian',2:'Chinese',3:'korean',
4:'Japanese',5:'French',6:'Italian',7:'American',8:'English',9:'Germ
an',10:'Mangolian',11:'Spanish',12:'Dutch',13:'Portuguese',14:'Brazili
an',15:'Russian',16:'Mexican',17:'Turkish',18:'Ukrainian',19:'Romanian',
20:'Colombian',21:'Cuban'})
```

```
nationality_total=nationality.sum(axis=1)
```

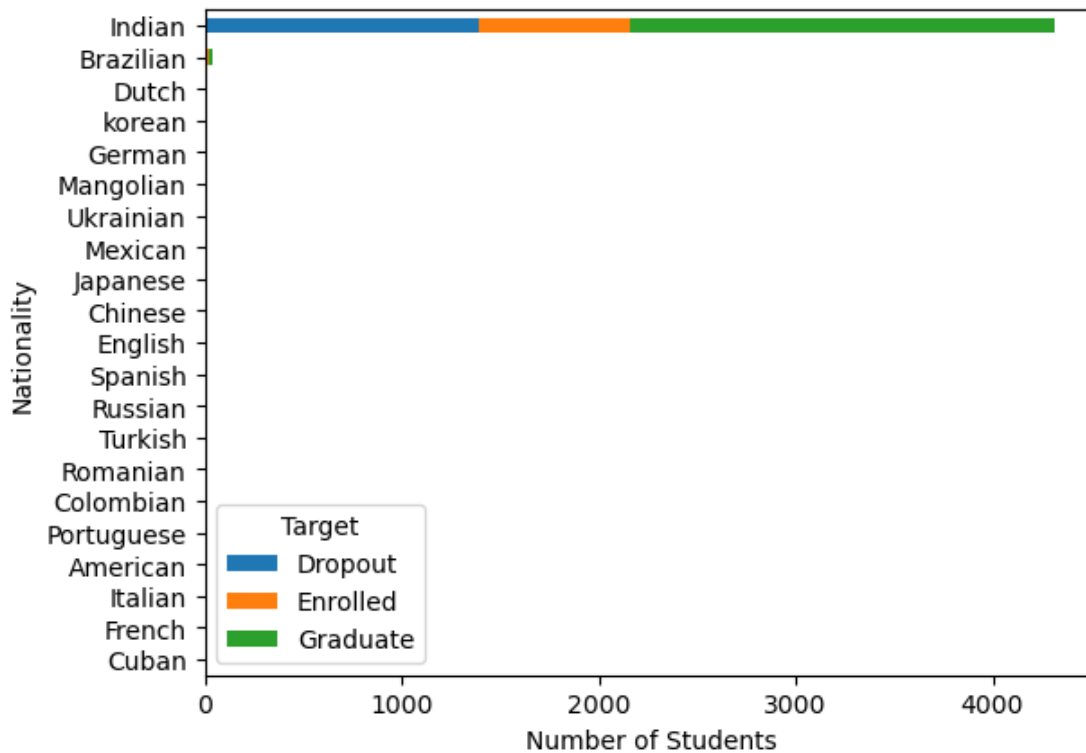
```
nationality_sorted=nationality_total.sort_values(ascending=True)
```

```
nationality.loc[nationality_sorted.index].plot(kind='barh',
stacked=True)
```

```
plt.xlabel('Number of Students')
```

```
plt.ylabel('Nationality')
```

```
plt.show()
```



The plot shows that the majority of the students in the dataset are Indian, which accounts for the highest frequency among all the nationalities.

```
student_prequal=df.groupby(['Previous
qualification','Target']).size().reset_index().pivot(columns='Target',
index='Previous qualification',values=0)
```

```
# Rename the index of the DataFrame
```

```
student_prequal=student_prequal.rename(index={1:'Secondary
Education',2:'Higher Education-Bachelor's Degree',3:'Higher Education-
Degree',4:'Higher Education-Master's Degree',5:'Higher Education-
Doctorate',6:'Frequency of Higher Education',7:'12th Year of Schooling
-Not Completed',8:'11th Year of Schooling-Not Completed',9:'Other-11th
Year of Schooling',10:'10th Year of Schooling',
```

```
11:'10th Year of
Schooling-Not Completed',12:'Basic Education 3rd Cycle (9th/10th/11th
year) or Equivalent',13:'Basic Education 2nd Cycle (6th/7th/8th year)
or Equivalent',14:'Technological Specialization Course',15:'Higher
Education-Degree (1st cycle)',16:'Professional Higher Technical
Course',17:'Higher Education-Master's Degree (2nd Cycle)'}))
```

```
student_prequal_total=student_prequal.sum(axis=1)
```

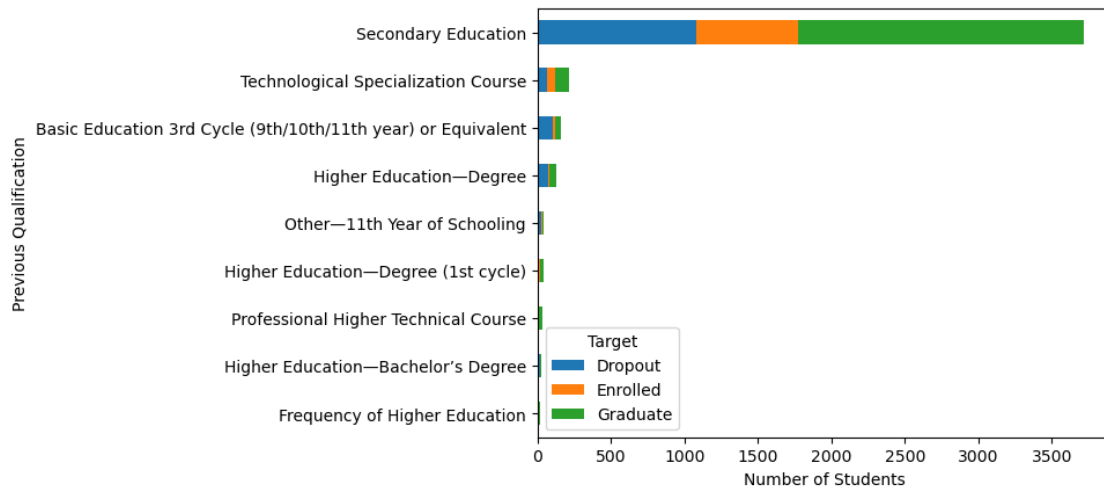
```
student_prequal_sorted=student_prequal_total.sort_values(ascending=True)
```

```
student_prequal_top=student_prequal_sorted[8:]
```

```
student_prequal.loc[student_prequal_top.index].plot(kind='barh',
stacked=True)
```

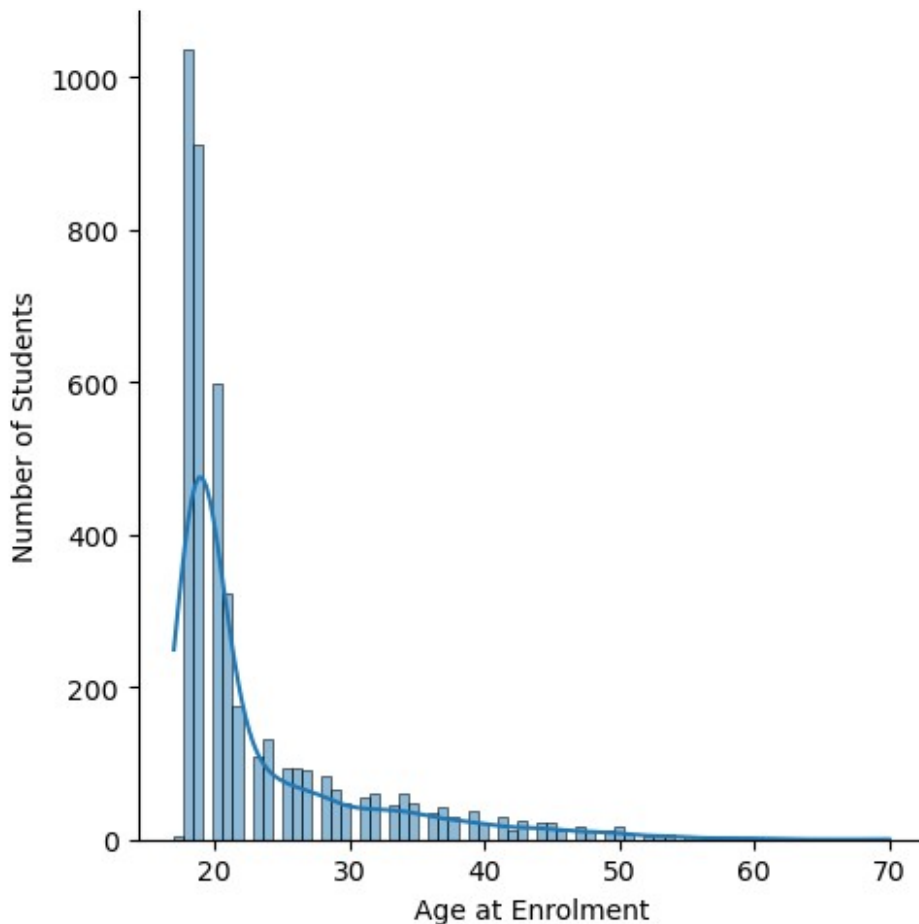
```
plt.xlabel('Count')
```

```
plt.xlabel('Number of Students')
plt.ylabel('Previous Qualification')
plt.show()
```



Most of the students in the data finished secondary education.

```
sns.displot(data=df,x='Age at enrollment',kde=True)
df['Age at enrollment'].describe()
plt.xlabel('Age at Enrolment')
plt.ylabel('Number of Students')
plt.show()
```



The distribution of age at enrolment is positively skewed, indicating that the majority of students enrolled at a relatively young age. The mean age at enrolment is approximately 23 years old, with the most frequent age range falling between 19 to 25 years old.

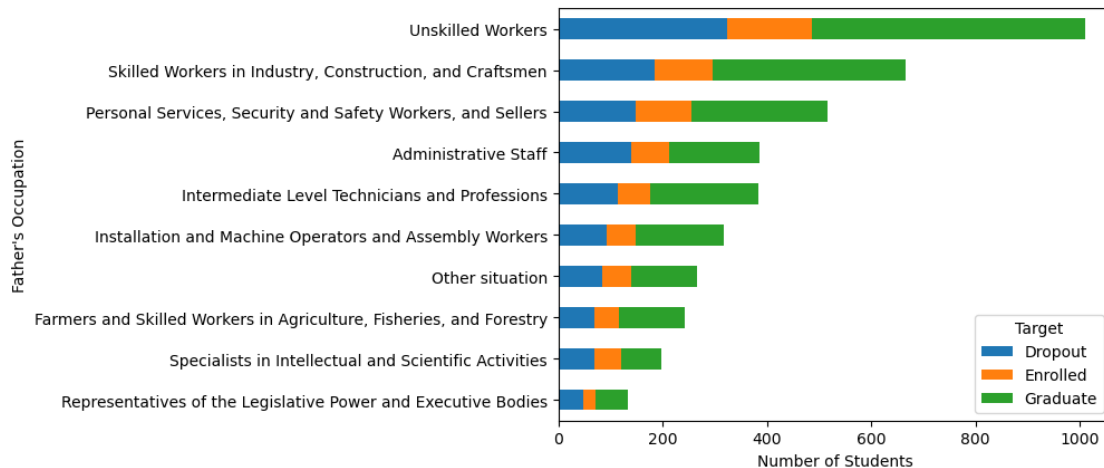
The below graphs are to see the father's and mother's occupation

```
student_foccupation=df.groupby(["Father's occupation",
'Target']).size().reset_index().pivot(columns='Target',index="Father's
occupation",values=0)
student_foccupation=student_foccupation.rename(index={1:'Student',2:'R
epresentatives of the Legislative Power and Executive
Bodies',3:'Specialists in Intellectual and Scientific
Activities',4:'Intermediate Level Technicians and
Professions',5:'Administrative Staff',6:'Personal Services, Security
and Safety Workers, and Sellers',
7:'Farmers and
Skilled Workers in Agriculture, Fisheries, and Forestry',8:'Skilled
Workers in Industry, Construction, and Craftsmen',9:'Installation and
Machine Operators and Assembly Workers',10:'Unskilled
Workers',11:'Other situation'})
student_foccupation_total=student_foccupation.sum(axis=1)
student_foccupation_sorted=student_foccupation_total.sort_values(ascen
```

```

ding=True)
student_foccupation_top10=student_foccupation_sorted[36:]
student_foccupation.loc[student_foccupation_top10.index].plot(kind='barh', stacked=True)
plt.xlabel('Number of Students')
plt.ylabel("Father's Occupation")
plt.show()

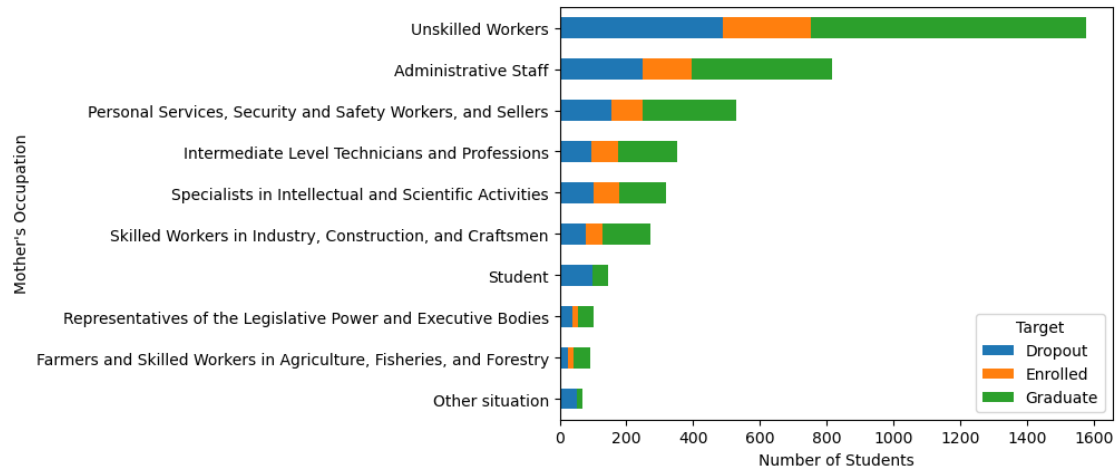
```



```

student_moccupation=df.groupby(["Mother's occupation",
'Target']).size().reset_index().pivot(columns='Target',
index="Mother's occupation", values=0)
student_moccupation=student_moccupation.rename(index={1:'Student',2:'Representatives of the Legislative Power and Executive Bodies',3:'Specialists in Intellectual and Scientific Activities',4:'Intermediate Level Technicians and Professions',5:'Administrative Staff',6:'Personal Services, Security and Safety Workers, and Sellers',7:'Farmers and Skilled Workers in Agriculture, Fisheries, and Forestry',8:'Skilled Workers in Industry, Construction, and Craftsmen',9:'Installation and Machine Operators and Assembly Workers',10:'Unskilled Workers',11:'Armed Forces Professions',12:'Other situation'})
student_moccupation_total = student_moccupation.sum(axis=1)
student_moccupation_sorted =
student_moccupation_total.sort_values(ascending=True)
student_moccupation_top10 = student_moccupation_sorted[22:]
student_moccupation.loc[student_moccupation_top10.index].plot(kind='barh', stacked=True)
plt.xlabel('Number of Students')
plt.ylabel("Mother's Occupation")
plt.show()

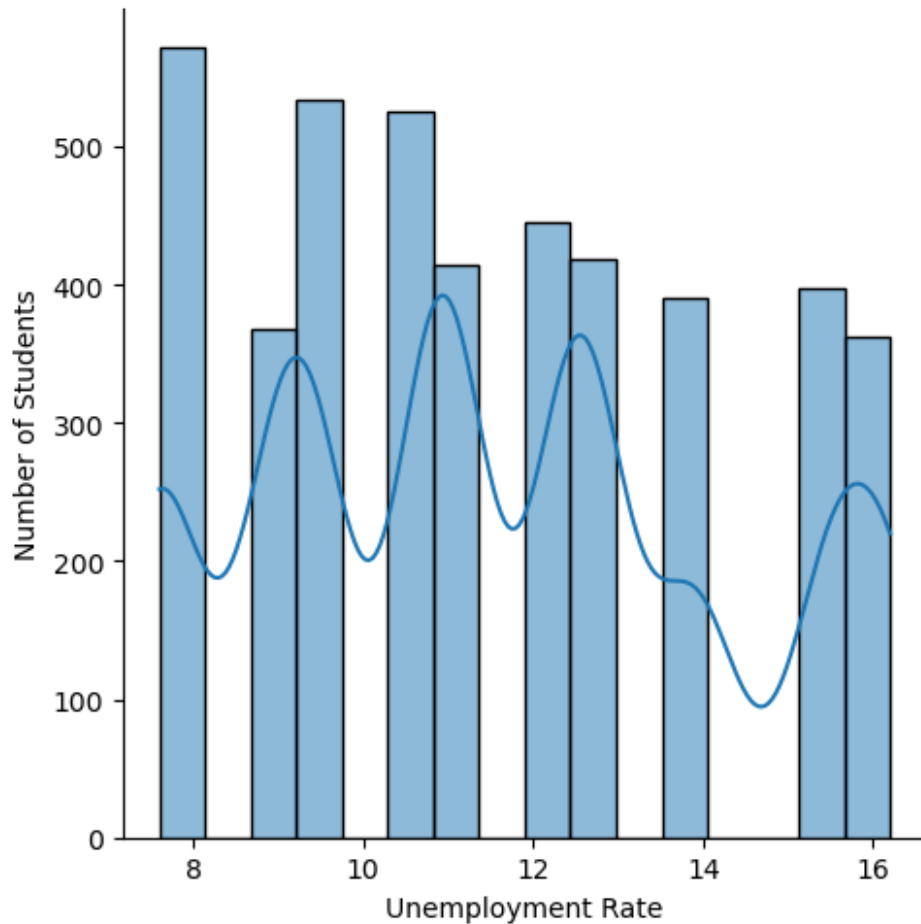
```



Highest number of students who graduated and dropped out have parents who are unskilled workers.

```
sns.displot(data=df,x="Unemployment rate",kde=True)
df['Unemployment rate'].describe()
plt.xlabel('Unemployment Rate')
plt.ylabel('Number of Students')
plt.show()
```





The majority of the data points in the unemployment rate distribution fall within the range of 9 to 13.

#### Correlation and Correlation Heatmap

```
corr=df.corr()
corr
```

	Marital status \
Marital status	1.000000
Application mode	0.224855
Application order	-0.125854
Course	0.018925
Daytime/evening attendance	-0.274939
Previous qualification	0.120925
Nacionality	-0.020722
Mother's qualification	0.185522
Father's qualification	0.128326
Mother's occupation	0.069734
Father's occupation	0.024351
Displaced	-0.234886
Educational special needs	-0.028343

Debtor	0.034304
Tuition fees up to date	-0.087158
Gender	-0.014738
Scholarship holder	-0.053765
Age at enrollment	0.522717
International	-0.027905
Curricular units 1st sem (credited)	0.061209
Curricular units 1st sem (enrolled)	0.052107
Curricular units 1st sem (evaluations)	0.058030
Curricular units 1st sem (approved)	-0.031027
Curricular units 1st sem (grade)	-0.059811
Curricular units 1st sem (without evaluations)	0.034711
Curricular units 2nd sem (credited)	0.062831
Curricular units 2nd sem (enrolled)	0.039026
Curricular units 2nd sem (evaluations)	0.022784
Curricular units 2nd sem (approved)	-0.043739
Curricular units 2nd sem (grade)	-0.071506
Curricular units 2nd sem (without evaluations)	0.020426
Unemployment rate	-0.020338
Inflation rate	0.008761
GDP	-0.027003

	Application mode \
Marital status	0.224855
Application mode	1.000000
Application order	-0.246497
Course	-0.085116
Daytime/evening attendance	-0.268616
Previous qualification	0.433028
Nacionality	-0.001360
Mother's qualification	0.092867
Father's qualification	0.072798
Mother's occupation	0.033489
Father's occupation	0.001253
Displaced	-0.263079
Educational special needs	-0.030868
Debtor	0.114348
Tuition fees up to date	-0.127339
Gender	0.147226
Scholarship holder	-0.152818
Age at enrollment	0.450700
International	0.005050
Curricular units 1st sem (credited)	0.238269
Curricular units 1st sem (enrolled)	0.159547
Curricular units 1st sem (evaluations)	0.219154
Curricular units 1st sem (approved)	-0.023713
Curricular units 1st sem (grade)	-0.106213
Curricular units 1st sem (without evaluations)	0.040255
Curricular units 2nd sem (credited)	0.228973
Curricular units 2nd sem (enrolled)	0.127461

Curricular units 2nd sem (evaluations)	0.164992
Curricular units 2nd sem (approved)	-0.065203
Curricular units 2nd sem (grade)	-0.104424
Curricular units 2nd sem (without evaluations)	0.042009
Unemployment rate	0.091567
Inflation rate	-0.019613
GDP	-0.014563

	Application order
Course \	
Marital status	-0.125854
0.018925	
Application mode	-0.246497 -
0.085116	
Application order	1.000000
0.118928	
Course	0.118928
1.000000	
Daytime/evening attendance	0.158657 -
0.070232	
Previous qualification	-0.199029 -
0.158382	
Nacionality	-0.029385 -
0.004761	
Mother's qualification	-0.061719
0.058909	
Father's qualification	-0.049936
0.045659	
Mother's occupation	-0.046591
0.029672	
Father's occupation	-0.029754
0.016489	
Displaced	0.332362
0.006142	
Educational special needs	0.025597 -
0.001886	
Debtor	-0.072151 -
0.053149	
Tuition fees up to date	0.055891
0.029099	
Gender	-0.089559 -
0.111383	
Scholarship holder	0.073709
0.051668	
Age at enrollment	-0.271154 -
0.036929	
International	-0.028801 -
0.004662	
Curricular units 1st sem (credited)	-0.133354 -
0.140546	

Curricular units 1st sem (enrolled)	-0.016808
0.112285	
Curricular units 1st sem (evaluations)	-0.092156
0.025970	
Curricular units 1st sem (approved)	0.035580
0.077038	
Curricular units 1st sem (grade)	0.058308
0.179482	
Curricular units 1st sem (without evaluations)	-0.031699 -
0.060483	
Curricular units 2nd sem (credited)	-0.125815 -
0.120390	
Curricular units 2nd sem (enrolled)	0.028878
0.185879	
Curricular units 2nd sem (evaluations)	-0.055089
0.049236	
Curricular units 2nd sem (approved)	0.071793
0.120000	
Curricular units 2nd sem (grade)	0.055517
0.178997	
Curricular units 2nd sem (without evaluations)	-0.015757 -
0.013984	
Unemployment rate	-0.098419 -
0.050116	
Inflation rate	-0.011133
0.028775	
GDP	0.030201 -
0.012518	

#### Daytime/evening

attendance \	
Marital status	-
0.274939	
Application mode	-
0.268616	
Application order	
0.158657	
Course	-
0.070232	
Daytime/evening attendance	
1.000000	
Previous qualification	-
0.103022	
Nacionality	
0.024433	
Mother's qualification	-
0.195346	
Father's qualification	-
0.137769	
Mother's occupation	-

0.037986	
Father's occupation	
0.000845	
Displaced	
0.251767	
Educational special needs	
0.031017	
Debtor	
0.006658	
Tuition fees up to date	
0.038799	
Gender	-
0.012326	
Scholarship holder	
0.093912	
Age at enrollment	-
0.462280	
International	
0.027973	
Curricular units 1st sem (credited)	-
0.127466	
Curricular units 1st sem (enrolled)	-
0.043056	
Curricular units 1st sem (evaluations)	-
0.045889	
Curricular units 1st sem (approved)	
0.016935	
Curricular units 1st sem (grade)	
0.063974	
Curricular units 1st sem (without evaluations)	
0.045630	
Curricular units 2nd sem (credited)	-
0.111953	
Curricular units 2nd sem (enrolled)	
0.000371	
Curricular units 2nd sem (evaluations)	
0.014610	
Curricular units 2nd sem (approved)	
0.034022	
Curricular units 2nd sem (grade)	
0.050493	
Curricular units 2nd sem (without evaluations)	-
0.004229	
Unemployment rate	
0.061974	
Inflation rate	-
0.024043	
GDP	
0.022929	

	Previous qualification
\	
Marital status	0.120925
Application mode	0.433028
Application order	-0.199029
Course	-0.158382
Daytime/evening attendance	-0.103022
Previous qualification	1.000000
Nacionality	-0.038997
Mother's qualification	0.018868
Father's qualification	0.013152
Mother's occupation	0.006190
Father's occupation	0.005381
Displaced	-0.149356
Educational special needs	-0.015015
Debtor	0.117447
Tuition fees up to date	-0.095246
Gender	0.089952
Scholarship holder	-0.085668
Age at enrollment	0.249821
International	-0.033498
Curricular units 1st sem (credited)	0.159940
Curricular units 1st sem (enrolled)	0.080860
Curricular units 1st sem (evaluations)	0.129364
Curricular units 1st sem (approved)	-0.005295

Curricular units 1st sem (grade)	-0.034252
Curricular units 1st sem (without evaluations)	0.018276
Curricular units 2nd sem (credited)	0.138463
Curricular units 2nd sem (enrolled)	0.056450
Curricular units 2nd sem (evaluations)	0.101501
Curricular units 2nd sem (approved)	-0.037265
Curricular units 2nd sem (grade)	-0.038765
Curricular units 2nd sem (without evaluations)	0.024186
Unemployment rate	0.096914
Inflation rate	-0.056388
GDP	0.053968

	Nacionality \
Marital status	-0.020722
Application mode	-0.001360
Application order	-0.029385
Course	-0.004761
Daytime/evening attendance	0.024433
Previous qualification	-0.038997
Nacionality	1.000000
Mother's qualification	-0.043847
Father's qualification	-0.088892
Mother's occupation	0.044123
Father's occupation	0.024538
Displaced	-0.010774
Educational special needs	-0.002399
Debtor	0.070860
Tuition fees up to date	-0.041721
Gender	-0.025462
Scholarship holder	-0.018468
Age at enrollment	-0.008241
International	0.911724
Curricular units 1st sem (credited)	0.006604
Curricular units 1st sem (enrolled)	-0.008011
Curricular units 1st sem (evaluations)	0.005640
Curricular units 1st sem (approved)	0.000935
Curricular units 1st sem (grade)	0.002578
Curricular units 1st sem (without evaluations)	0.026203

Curricular units 2nd sem (credited)	-0.000747
Curricular units 2nd sem (enrolled)	-0.020103
Curricular units 2nd sem (evaluations)	-0.018023
Curricular units 2nd sem (approved)	-0.014142
Curricular units 2nd sem (grade)	-0.005409
Curricular units 2nd sem (without evaluations)	-0.012052
Unemployment rate	-0.006013
Inflation rate	-0.012331
GDP	0.044563

	Mother's qualification
\	
Marital status	0.185522
Application mode	0.092867
Application order	-0.061719
Course	0.058909
Daytime/evening attendance	-0.195346
Previous qualification	0.018868
Nacionality	-0.043847
Mother's qualification	1.000000
Father's qualification	0.524529
Mother's occupation	0.295178
Father's occupation	0.115989
Displaced	-0.075864
Educational special needs	-0.019808
Debtor	0.018776
Tuition fees up to date	-0.022861
Gender	-0.062374
Scholarship holder	0.048225
Age at enrollment	0.279921



International	-0.038672
Curricular units 1st sem (credited)	0.041610
Curricular units 1st sem (enrolled)	0.050582
Curricular units 1st sem (evaluations)	0.041967
Curricular units 1st sem (approved)	-0.010555
Curricular units 1st sem (grade)	-0.034105
Curricular units 1st sem (without evaluations)	0.003293
Curricular units 2nd sem (credited)	0.036986
Curricular units 2nd sem (enrolled)	0.033070
Curricular units 2nd sem (evaluations)	0.018874
Curricular units 2nd sem (approved)	-0.013161
Curricular units 2nd sem (grade)	-0.028472
Curricular units 2nd sem (without evaluations)	0.020364
Unemployment rate	-0.106107
Inflation rate	0.056653
GDP	-0.079664

	Father's qualification
\	
Marital status	0.128326
Application mode	0.072798
Application order	-0.049936
Course	0.045659
Daytime/evening attendance	-0.137769
Previous qualification	0.013152
Nacionality	-0.088892

Mother's qualification	0.524529
Father's qualification	1.000000
Mother's occupation	0.207067
Father's occupation	0.184001
Displaced	-0.055007
Educational special needs	0.000917
Debtor	-0.006125
Tuition fees up to date	-0.018033
Gender	-0.073614
Scholarship holder	0.107134
Age at enrollment	0.190410
International	-0.086503
Curricular units 1st sem (credited)	0.039259
Curricular units 1st sem (enrolled)	0.036564
Curricular units 1st sem (evaluations)	0.037225
Curricular units 1st sem (approved)	0.006787
Curricular units 1st sem (grade)	-0.006245
Curricular units 1st sem (without evaluations)	-0.017785
Curricular units 2nd sem (credited)	0.041695
Curricular units 2nd sem (enrolled)	0.023635
Curricular units 2nd sem (evaluations)	0.009471
Curricular units 2nd sem (approved)	0.006052
Curricular units 2nd sem (grade)	-0.006508
Curricular units 2nd sem (without evaluations)	-0.008493

Unemployment rate	-0.075417
Inflation rate	0.056661
GDP	-0.070200

#### Mother's

occupation ... \	
Marital status	
0.069734 ...	
Application mode	
0.033489 ...	
Application order	-
0.046591 ...	
Course	
0.029672 ...	
Daytime/evening attendance	-
0.037986 ...	
Previous qualification	
0.006190 ...	
Nacionality	
0.044123 ...	
Mother's qualification	
0.295178 ...	
Father's qualification	
0.207067 ...	
Mother's occupation	
1.000000 ...	
Father's occupation	
0.724007 ...	
Displaced	-
0.038521 ...	
Educational special needs	-
0.010175 ...	
Debtor	
0.108151 ...	
Tuition fees up to date	-
0.004395 ...	
Gender	-
0.022324 ...	
Scholarship holder	
0.092487 ...	
Age at enrollment	
0.092257 ...	
International	
0.041414 ...	
Curricular units 1st sem (credited)	
0.002390 ...	

Curricular units 1st sem (enrolled)	
0.014607 ...	
Curricular units 1st sem (evaluations)	
0.019332 ...	
Curricular units 1st sem (approved)	
0.015198 ...	
Curricular units 1st sem (grade)	
0.016955 ...	
Curricular units 1st sem (without evaluations)	-
0.012569 ...	
Curricular units 2nd sem (credited)	-
0.002057 ...	
Curricular units 2nd sem (enrolled)	
0.009287 ...	
Curricular units 2nd sem (evaluations)	
0.011546 ...	
Curricular units 2nd sem (approved)	
0.022309 ...	
Curricular units 2nd sem (grade)	
0.035230 ...	
Curricular units 2nd sem (without evaluations)	-
0.004903 ...	
Unemployment rate	-
0.011772 ...	
Inflation rate	
0.015014 ...	
GDP	
0.091880 ...	

Curricular units 1st

sem (without evaluations) \
Marital status
0.034711
Application mode
0.040255
Application order
-0.031699
Course
-0.060483
Daytime/evening attendance
0.045630
Previous qualification
0.018276
Nacionality
0.026203
Mother's qualification
0.003293
Father's qualification
-0.017785
Mother's occupation

-0.012569  
Father's occupation  
-0.035299  
Displaced  
-0.021671  
Educational special needs  
-0.012324  
Debtor  
0.001812  
Tuition fees up to date  
-0.049775  
Gender  
-0.006302  
Scholarship holder  
-0.057770  
Age at enrollment  
0.057470  
International  
0.031222  
Curricular units 1st sem (credited)  
0.116262  
Curricular units 1st sem (enrolled)  
0.129337  
Curricular units 1st sem (evaluations)  
0.241800  
Curricular units 1st sem (approved)  
-0.013360  
Curricular units 1st sem (grade)  
-0.071660  
Curricular units 1st sem (without evaluations)  
1.000000  
Curricular units 2nd sem (credited)  
0.117359  
Curricular units 2nd sem (enrolled)  
0.109924  
Curricular units 2nd sem (evaluations)  
0.144683  
Curricular units 2nd sem (approved)  
-0.013070  
Curricular units 2nd sem (grade)  
-0.061482  
Curricular units 2nd sem (without evaluations)  
0.583261  
Unemployment rate  
-0.045144  
Inflation rate  
-0.052534  
GDP  
-0.144673

## Curricular units 2nd

sem (credited) \  
Marital status  
0.062831  
Application mode  
0.228973  
Application order  
-0.125815  
Course  
-0.120390  
Daytime/evening attendance  
-0.111953  
Previous qualification  
0.138463  
Nacionality  
-0.000747  
Mother's qualification  
0.036986  
Father's qualification  
0.041695  
Mother's occupation  
-0.002057  
Father's occupation  
-0.014596  
Displaced  
-0.091738  
Educational special needs  
-0.021671  
Debtor  
0.025414  
Tuition fees up to date  
0.014204  
Gender  
0.018737  
Scholarship holder  
-0.076480  
Age at enrollment  
0.207561  
International  
0.002573  
Curricular units 1st sem (credited)  
0.944811  
Curricular units 1st sem (enrolled)  
0.753747  
Curricular units 1st sem (evaluations)  
0.522187  
Curricular units 1st sem (approved)  
0.607661  
Curricular units 1st sem (grade)  
0.113937

Curricular units 1st sem (without evaluations)  
0.117359  
Curricular units 2nd sem (credited)  
1.000000  
Curricular units 2nd sem (enrolled)  
0.676258  
Curricular units 2nd sem (evaluations)  
0.430978  
Curricular units 2nd sem (approved)  
0.519081  
Curricular units 2nd sem (grade)  
0.129770  
Curricular units 2nd sem (without evaluations)  
0.070148  
Unemployment rate  
0.010580  
Inflation rate  
0.014490  
GDP  
-0.024491

Curricular units 2nd

sem (enrolled) \  
Marital status  
0.039026  
Application mode  
0.127461  
Application order  
0.028878  
Course  
0.185879  
Daytime/evening attendance  
0.000371  
Previous qualification  
0.056450  
Nacionality  
-0.020103  
Mother's qualification  
0.033070  
Father's qualification  
0.023635  
Mother's occupation  
0.009287  
Father's occupation  
0.005548  
Displaced  
-0.041823  
Educational special needs  
-0.028777  
Debtor

-0.029436  
 Tuition fees up to date  
 0.085918  
 Gender  
 -0.124227  
 Scholarship holder  
 0.026416  
 Age at enrollment  
 0.085914  
 International  
 -0.013577  
 Curricular units 1st sem (credited)  
 0.644826  
 Curricular units 1st sem (enrolled)  
 0.942627  
 Curricular units 1st sem (evaluations)  
 0.611842  
 Curricular units 1st sem (approved)  
 0.733772  
 Curricular units 1st sem (grade)  
 0.406167  
 Curricular units 1st sem (without evaluations)  
 0.109924  
 Curricular units 2nd sem (credited)  
 0.676258  
 Curricular units 2nd sem (enrolled)  
 1.000000  
 Curricular units 2nd sem (evaluations)  
 0.604821  
 Curricular units 2nd sem (approved)  
 0.703258  
 Curricular units 2nd sem (grade)  
 0.395135  
 Curricular units 2nd sem (without evaluations)  
 0.067697  
 Unemployment rate  
 0.064436  
 Inflation rate  
 0.016844  
 GDP  
 -0.007592

Curricular units 2nd

sem (evaluations) \  
 Marital status  
 0.022784  
 Application mode  
 0.164992  
 Application order  
 -0.055089



Course  
0.049236  
Daytime/evening attendance  
0.014610  
Previous qualification  
0.101501  
Nationality  
-0.018023  
Mother's qualification  
0.018874  
Father's qualification  
0.009471  
Mother's occupation  
0.011546  
Father's occupation  
0.000833  
Displaced  
-0.038839  
Educational special needs  
-0.010851  
Debtor  
0.024201  
Tuition fees up to date  
0.063482  
Gender  
-0.041789  
Scholarship holder  
-0.021410  
Age at enrollment  
0.056286  
International  
-0.004399  
Curricular units 1st sem (credited)  
0.427845  
Curricular units 1st sem (enrolled)  
0.599567  
Curricular units 1st sem (evaluations)  
0.778863  
Curricular units 1st sem (approved)  
0.539934  
Curricular units 1st sem (grade)  
0.487236  
Curricular units 1st sem (without evaluations)  
0.144683  
Curricular units 2nd sem (credited)  
0.430978  
Curricular units 2nd sem (enrolled)  
0.604821  
Curricular units 2nd sem (evaluations)  
1.000000

Curricular units 2nd sem (approved)  
0.463535  
Curricular units 2nd sem (grade)  
0.453394  
Curricular units 2nd sem (without evaluations)  
0.144877  
Unemployment rate  
0.045808  
Inflation rate  
-0.012643  
GDP  
-0.004854

Curricular units 2nd

sem (approved) \  
Marital status  
-0.043739  
Application mode  
-0.065203  
Application order  
0.071793  
Course  
0.120000  
Daytime/evening attendance  
0.034022  
Previous qualification  
-0.037265  
Nacionality  
-0.014142  
Mother's qualification  
-0.013161  
Father's qualification  
0.006052  
Mother's occupation  
0.022309  
Father's occupation  
0.023651  
Displaced  
0.063698  
Educational special needs  
-0.016315  
Debtor  
-0.146977  
Tuition fees up to date  
0.291921  
Gender  
-0.224266  
Scholarship holder  
0.202704  
Age at enrollment

-0.112052  
International  
-0.010565  
Curricular units 1st sem (credited)  
0.490478  
Curricular units 1st sem (enrolled)  
0.673341  
Curricular units 1st sem (evaluations)  
0.442265  
Curricular units 1st sem (approved)  
0.904002  
Curricular units 1st sem (grade)  
0.673335  
Curricular units 1st sem (without evaluations)  
-0.013070  
Curricular units 2nd sem (credited)  
0.519081  
Curricular units 2nd sem (enrolled)  
0.703258  
Curricular units 2nd sem (evaluations)  
0.463535  
Curricular units 2nd sem (approved)  
1.000000  
Curricular units 2nd sem (grade)  
0.760804  
Curricular units 2nd sem (without evaluations)  
-0.061567  
Unemployment rate  
0.048805  
Inflation rate  
-0.024566  
GDP  
0.022427

Curricular units 2nd

sem (grade) \  
Marital status  
-0.071506  
Application mode  
-0.104424  
Application order  
0.055517  
Course  
0.178997  
Daytime/evening attendance  
0.050493  
Previous qualification  
-0.038765  
Nacionality  
-0.005409

Mother's qualification  
-0.028472  
Father's qualification  
-0.006508  
Mother's occupation  
0.035230  
Father's occupation  
0.036711  
Displaced  
0.069087  
Educational special needs  
-0.012761  
Debtor  
-0.139424  
Tuition fees up to date  
0.296480  
Gender  
-0.199133  
Scholarship holder  
0.181227  
Age at enrollment  
-0.173419  
International  
0.001460  
Curricular units 1st sem (credited)  
0.132971  
Curricular units 1st sem (enrolled)  
0.361959  
Curricular units 1st sem (evaluations)  
0.355036  
Curricular units 1st sem (approved)  
0.685560  
Curricular units 1st sem (grade)  
0.837170  
Curricular units 1st sem (without evaluations)  
-0.061482  
Curricular units 2nd sem (credited)  
0.129770  
Curricular units 2nd sem (enrolled)  
0.395135  
Curricular units 2nd sem (evaluations)  
0.453394  
Curricular units 2nd sem (approved)  
0.760804  
Curricular units 2nd sem (grade)  
1.000000  
Curricular units 2nd sem (without evaluations)  
-0.079216  
Unemployment rate  
0.001462

Inflation rate  
-0.038166  
GDP  
0.071269

Curricular units 2nd

sem (without evaluations) \  
Marital status  
0.020426  
Application mode  
0.042009  
Application order  
-0.015757  
Course  
-0.013984  
Daytime/evening attendance  
-0.004229  
Previous qualification  
0.024186  
Nacionality  
-0.012052  
Mother's qualification  
0.020364  
Father's qualification  
-0.008493  
Mother's occupation  
-0.004903  
Father's occupation  
-0.044760  
Displaced  
-0.035959  
Educational special needs  
-0.007491  
Debtor  
0.048552  
Tuition fees up to date  
-0.071817  
Gender  
0.057223  
Scholarship holder  
-0.048723  
Age at enrollment  
0.061654  
International  
-0.010660  
Curricular units 1st sem (credited)  
0.055256  
Curricular units 1st sem (enrolled)  
0.069547  
Curricular units 1st sem (evaluations)

0.134296  
 Curricular units 1st sem (approved)  
 -0.053983  
 Curricular units 1st sem (grade)  
 -0.066076  
 Curricular units 1st sem (without evaluations)  
 0.583261  
 Curricular units 2nd sem (credited)  
 0.070148  
 Curricular units 2nd sem (enrolled)  
 0.067697  
 Curricular units 2nd sem (evaluations)  
 0.144877  
 Curricular units 2nd sem (approved)  
 -0.061567  
 Curricular units 2nd sem (grade)  
 -0.079216  
 Curricular units 2nd sem (without evaluations)  
 1.000000  
 Unemployment rate  
 -0.013960  
 Inflation rate  
 -0.034391  
 GDP  
 -0.080292

	Unemployment rate \
Marital status	-0.020338
Application mode	0.091567
Application order	-0.098419
Course	-0.050116
Daytime/evening attendance	0.061974
Previous qualification	0.096914
Nacionality	-0.006013
Mother's qualification	-0.106107
Father's qualification	-0.075417
Mother's occupation	-0.011772
Father's occupation	-0.026094
Displaced	-0.130327
Educational special needs	0.046131
Debtor	0.021128
Tuition fees up to date	0.013460
Gender	0.022195
Scholarship holder	0.055152
Age at enrollment	0.025018
International	-0.010015
Curricular units 1st sem (credited)	0.009778
Curricular units 1st sem (enrolled)	0.038404
Curricular units 1st sem (evaluations)	0.061545
Curricular units 1st sem (approved)	0.051286

Curricular units 1st sem (grade)	0.014821
Curricular units 1st sem (without evaluations)	-0.045144
Curricular units 2nd sem (credited)	0.010580
Curricular units 2nd sem (enrolled)	0.064436
Curricular units 2nd sem (evaluations)	0.045808
Curricular units 2nd sem (approved)	0.048805
Curricular units 2nd sem (grade)	0.001462
Curricular units 2nd sem (without evaluations)	-0.013960
Unemployment rate	1.000000
Inflation rate	-0.028885
GDP	-0.335178

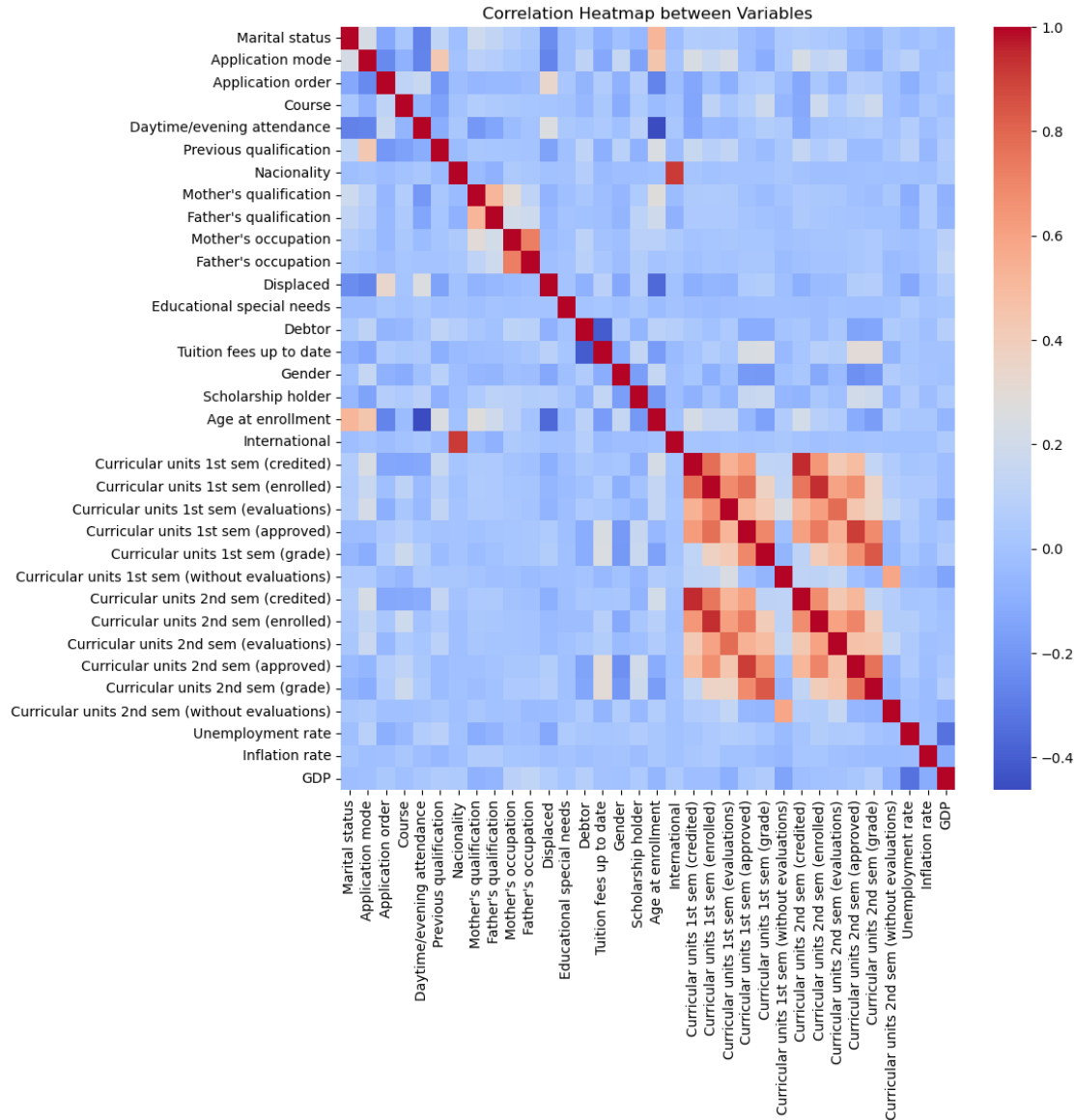
	Inflation rate
GDP	
Marital status	0.008761 -
0.027003	
Application mode	-0.019613 -
0.014563	
Application order	-0.011133
0.030201	
Course	0.028775 -
0.012518	
Daytime/evening attendance	-0.024043
0.022929	
Previous qualification	-0.056388
0.053968	
Nacionality	-0.012331
0.044563	
Mother's qualification	0.056653 -
0.079664	
Father's qualification	0.056661 -
0.070200	
Mother's occupation	0.015014
0.091880	
Father's occupation	0.008047
0.125574	
Displaced	-0.012385
0.062875	
Educational special needs	0.004396
0.012016	
Debtor	-0.021888
0.075050	
Tuition fees up to date	-0.000706 -
0.002768	
Gender	0.003556 -
0.008108	
Scholarship holder	-0.031104
0.035650	
Age at enrollment	0.025377 -
0.064678	

International	-0.009642
0.044389	
Curricular units 1st sem (credited)	0.023348 -
0.026513	
Curricular units 1st sem (enrolled)	0.036758 -
0.026262	
Curricular units 1st sem (evaluations)	-0.006604 -
0.099761	
Curricular units 1st sem (approved)	-0.007114
0.018459	
Curricular units 1st sem (grade)	-0.033904
0.054801	
Curricular units 1st sem (without evaluations)	-0.052534 -
0.144673	
Curricular units 2nd sem (credited)	0.014490 -
0.024491	
Curricular units 2nd sem (enrolled)	0.016844 -
0.007592	
Curricular units 2nd sem (evaluations)	-0.012643 -
0.004854	
Curricular units 2nd sem (approved)	-0.024566
0.022427	
Curricular units 2nd sem (grade)	-0.038166
0.071269	
Curricular units 2nd sem (without evaluations)	-0.034391 -
0.080292	
Unemployment rate	-0.028885 -
0.335178	
Inflation rate	1.000000 -
0.112295	
GDP	-0.112295
1.000000	

[34 rows x 34 columns]

```
plt.figure(figsize=(10,10))
sns.heatmap(corr,cmap='coolwarm')
plt.title('Correlation Heatmap between Variables')
plt.show()
```





Correlation between features are low except for Nationality and International. Hence, we can dropped these features in the regression model for predicting student target.

### Preprocessing the Data

To predict students' academic success and dropout, we will use logistic regression to determine the target variable using the feature variables. Since the target data contains students who are still enrolled, we will drop them from the dataset and use the data for student who dropped out and graduated.

```
df=df.drop(df[df['Target']=='Enrolled'].index)
df.head()
```

	Marital status	Application mode	Application order	Course \
0	1	8	5	2
1	1	6	1	11

2	1	1	5	5
3	1	8	2	15
4	2	12	1	3

	Daytime/evening attendance	Previous qualification	Nacionality	\
0	1		1	1
1	1		1	1
2	1		1	1
3	1		1	1
4	0		1	1

	Mother's qualification	Father's qualification	Mother's occupation
...	\		
0	13	10	6
...			
1	1	3	4
...			
2	22	27	10
...			
3	23	27	6
...			
4	22	28	10
...			

	Curricular units 2nd sem (credited)	Curricular units 2nd sem (enrolled)
0	0	
0		
1	0	
6		
2	0	
6		
3	0	
6		
4	0	
6		

	Curricular units 2nd sem (evaluations)	\
0	0	
1	6	
2	0	
3	10	
4	6	

	Curricular units 2nd sem (approved)	Curricular units 2nd sem (grade)
0	0	
0.000000		
1	6	
13.666667		

2	0
0.000000	
3	5
12.400000	
4	6
13.000000	

	Curricular units 2nd sem (without evaluations)	Unemployment rate \
0	0	10.8
1	0	13.9
2	0	10.8
3	0	9.4
4	0	13.9

	Inflation rate	GDP	Target
0	1.4	1.74	Dropout
1	-0.3	0.79	Graduate
2	1.4	1.74	Dropout
3	-0.8	-3.12	Graduate
4	-0.3	0.79	Graduate

[5 rows x 35 columns]

Converting Target Variable into Numeric Form We will transform the target variable into numeric form using label encoder,a data preprocessing feature from SciKit library.The labels dropout and graduate become 0 and 1, respectively.

```
encoder=LabelEncoder()
df['Target']=encoder.fit_transform(df['Target'])
df.head()
```

	Marital status	Application mode	Application order	Course \
0	1	8	5	2
1	1	6	1	11
2	1	1	5	5
3	1	8	2	15
4	2	12	1	3

	Daytime/evening attendance	Previous qualification	Nacionality \
0	1	1	1
1	1	1	1
2	1	1	1

3	1	1	1
4	0	1	1

	Mother's qualification	Father's qualification	Mother's occupation
...	\		
0	13	10	6
...			
1	1	3	4
...			
2	22	27	10
...			
3	23	27	6
...			
4	22	28	10
...			

Curricular units 2nd sem (enrolled)	Curricular units 2nd sem (credited)
\	
0	0
0	
1	0
6	
2	0
6	
3	0
6	
4	0
6	

Curricular units 2nd sem (evaluations)	\
0	0
1	6
2	0
3	10
4	6

Curricular units 2nd sem (grade)	Curricular units 2nd sem (approved)
\	
0	0
0.000000	
1	6
13.666667	
2	0
0.000000	
3	5
12.400000	
4	6
13.000000	

Curricular units 2nd sem (without evaluations)	Unemployment
--	--------------

rate \		
0	0	10.8
1	0	13.9
2	0	10.8
3	0	9.4
4	0	13.9

	Inflation	rate	GDP	Target
0		1.4	1.74	0
1		-0.3	0.79	1
2		1.4	1.74	0
3		-0.8	-3.12	1
4		-0.3	0.79	1

[5 rows x 35 columns]

Splitting data into x and y We set x and y as the dataframe feature and target variables, respectively. Note that we will drop the Nationality and International columns since they are highly correlated and only one nationality i.e Indian significantly dominates the data. This will prevent bias in the statistical regression.

```
x=df.drop(columns=['Nationality','International','Target'],axis=1)
y=df['Target']
```

```
x.head()
```

	Marital status	Application mode	Application order	Course \
0	1	8	5	2
1	1	6	1	11
2	1	1	5	5
3	1	8	2	15
4	2	12	1	3

	Daytime/evening attendance	Previous qualification	Mother's qualification \
0	1	1	
13			
1	1	1	
1			
2	1	1	
22			
3	1	1	
23			
4	0	1	
22			

Father's qualification occupation ... \	Mother's occupation	Father's
0	10	6
10 ...		
1	3	4
4 ...		
2	27	10
10 ...		
3	27	6
4 ...		
4	28	10
10 ...		

Curricular units 1st sem (without evaluations) \	
0	0
1	0
2	0
3	0
4	0

Curricular units 2nd sem (credited) (enrolled) \	Curricular units 2nd sem
0	0
0	
1	0
6	
2	0
6	
3	0
6	
4	0
6	

Curricular units 2nd sem (evaluations) \	
0	0
1	6
2	0
3	10
4	6

Curricular units 2nd sem (approved) (grade) \	Curricular units 2nd sem
0	0
0.000000	
1	6
13.666667	
2	0
0.000000	
3	5

```
12.400000
4
13.000000
```

6

```
Curricular units 2nd sem (without evaluations)  Unemployment
rate \
0                                                0          10.8
1                                                0          13.9
2                                                0          10.8
3                                                0           9.4
4                                                0          13.9
```

```
Inflation rate  GDP
0              1.4  1.74
1             -0.3  0.79
2              1.4  1.74
3             -0.8 -3.12
4             -0.3  0.79
```

```
[5 rows x 32 columns]
```

```
y.head()
```

```
0    0
1    1
2    0
3    1
4    1
```

```
Name: Target, dtype: int32
```

Splitting Data into Training and Testing Data To begin with the logistic regression as our machine learning model, we split the data into training and testing data. 80% of the data will be our training model and rest 20% will be the testing model. We choose the third state of the random sampling.

```
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.2,random_state=3)
```

```
print(x.shape,xtrain.shape,xtest.shape)
```

```
(3630, 32) (2904, 32) (726, 32)
```

## Model Building

Logistic regression will now be implemented using Extreme Gradient Boosting (XGBoost) which is one of the available open source libraries used for regression models. In this case,

binary logistic is set for our model with 1000 n\_estimators. The n\_estimators serves as the number of decision trees or classification considering the data from feature variables.

```
bin_log=xgb.XGBClassifier(objective='binary:logistic',n_estimators=1000)
bin_log.fit(xtrain,ytrain)
```

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None,
              feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None,
              importance_type=None,
              interaction_constraints=None, learning_rate=None,
              max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan,
              monotone_constraints=None,
              n_estimators=1000, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

Data Prediction and Evaluation of the Model We now set the logistic regression model to the training data.

```
target_prediction=bin_log.predict(xtest)
print(target_prediction)
```

```
[1 1 1 1 1 1 1 1 1 0 1 1 0 0 0 1 1 1 1 0 1 1 0 0 1 1 0 1 1 1 1 1 1 1 1
1 0
1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 0 0 1 0 0 0 0 1 1 0 1 0 0 1 0 1 0 0 0 1
1 1
1 1 1 0 0 1 1 1 0 0 0 1 0 1 0 0 1 0 1 1 1 0 0 0 1 1 0 1 1 1 1 0 1 1 0
1 1
0 0 0 1 0 1 1 1 1 0 0 0 1 1 1 1 1 0 1 1 1 0 1 1 0 0 1 1 1 1 1 1 0 1 0
1 0
1 0 1 1 1 0 1 1 0 1 1 0 0 0 1 0 1 1 1 1 1 1 1 0 1 0 0 1 0 1 1 1 1 0 1
0 1
1 1 0 1 1 1 0 0 1 1 0 1 0 0 0 0 0 1 0 0 1 1 1 1 0 1 1 1 1 1 1 1 0 1 1
0 1
1 0 0 0 0 0 0 1 0 0 1 1 1 1 1 1 0 1 0 1 1 1 1 0 1 1 0 1 1 1 1 1 1 0 1
1 0
1 1 1 0 0 1 0 1 1 1 0 0 1 0 0 1 1 0 0 1 1 1 1 0 0 0 0 1 0 0 1 1 1 1 1
1 0
1 0 0 0 1 0 1 1 0 1 0 0 0 1 1 1 0 1 0 1 0 1 1 0 1 0 0 0 0 1 0 1 1 0 1
1 1
1 1 0 1 1 1 1 0 1 0 1 1 1 0 0 1 1 0 0 1 0 0 0 0 1 0 1 1 1 1 1 1 0 1 0
0 1
1 0 1 1 1 1 1 0 0 0 0 1 0 1 1 1 1 1 0 1 0 1 1 0 0 1 1 1 1 1 0 0 0 1 1
0 1
```



```

0 1 1 1 1 0 0 1 0 1 1 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 1 1 0 0 1 1 1 0
0 0
0 0 1 0 1 1 1 1 1 1 0 1 1 0 0 1 0 1 1 0 1 0 1 0 1 0 0 1 1 1 1 0 1
1 1
1 1 0 1 0 1 0 1 1 1 1 1 1 1 0 0 1 1 0 1 1 1 1 0 1 1 1 0 1 0 0 1 0 1 1
1 1
1 1 1 1 0 1 1 0 0 1 0 1 0 1 1 1 1 1 0 0 1 1 0 1 0 0 1 0 0 0 0 1 1 1 1
1 0
0 0 1 0 1 0 1 1 0 1 1 1 0 1 1 0 0 0 1 1 1 1 1 1 1 1 1 0 0 1 0 1 1 1 1
0 0
0 0 0 1 1 1 0 1 1 1 0 1 1 0 0 0 0 1 1 1 1 1 1 1 1 1 0 0 0 0 0 1 1 1 1
1 0
1 1 1 1 1 1 0 0 1 1 0 1 1 1 1 1 0 1 1 1 1 1 1 1 1 1 0 1 1 0 1 1 0
1 1
1 1 0 1 0 1 1 1 1 1 1 0 1 1 0 0 1 1 1 1 0 1 0 1 1 0 1 1 0 1 1 0 1
1 1
1 1 0 1 0 1 0 0 1 1 0 1 1 1 1 0 0 0 0 0 0 0 1 0]

```

```

data_accuracy=accuracy_score(ytest,target_prediction)
print("Accuracy:",data_accuracy)

```

Accuracy: 0.9008264462809917

Conclusion From the analysis we can conclude,the Extreme Gradient Boosting (XGB) gives the accuracy of 90%.Therefore by using this model we can classify whether the student will graduate or dropout

Crosschecking the value predicted by the model with the value present in data

```
df.iloc[192]
```

Marital status	1.00
Application mode	1.00
Application order	2.00
Course	14.00
Daytime/evening attendance	1.00
Previous qualification	1.00
Nacionality	1.00
Mother's qualification	1.00
Father's qualification	3.00
Mother's occupation	5.00
Father's occupation	4.00
Displaced	0.00
Educational special needs	0.00
Debtor	0.00
Tuition fees up to date	1.00
Gender	0.00
Scholarship holder	0.00
Age at enrollment	19.00
International	0.00
Curricular units 1st sem (credited)	0.00

Curricular units 1st sem (enrolled)	5.00
Curricular units 1st sem (evaluations)	5.00
Curricular units 1st sem (approved)	5.00
Curricular units 1st sem (grade)	13.00
Curricular units 1st sem (without evaluations)	0.00
Curricular units 2nd sem (credited)	0.00
Curricular units 2nd sem (enrolled)	5.00
Curricular units 2nd sem (evaluations)	5.00
Curricular units 2nd sem (approved)	5.00
Curricular units 2nd sem (grade)	13.20
Curricular units 2nd sem (without evaluations)	0.00
Unemployment rate	9.40
Inflation rate	-0.80
GDP	-3.12
Target	1.00

Name: 232, dtype: float64

```
input_data=(1,1,2,14,1,1,1,3,5,4,0,0,0,1,0,0,19,0,5,5,5,13,0,0,5,5,5,1
3.2,0,9.4,-0.8,-3.12)
input_data_as_numpy_array=np.asarray(input_data)
input_data_resaped=input_data_as_numpy_array.reshape(1,-1)
prediction=bin_log.predict(input_data_resaped)
print('Prediction:',prediction)
#print("The initial value is ",prediction[0])
```

Prediction: [1]

As seen above the model has predicted the same value present in the dataset.

Forecasting with unknown data

```
input_data=(1,1,1,9,1,1,22,1,10,11,0,0,0,1,0,0,21,0,5,12,3,12,0,0,5,12
,1,15,3,16,0,-0)
input_data_as_numpy_array=np.asarray(input_data)
input_data_resaped=input_data_as_numpy_array.reshape(1,-1)
prediction=bin_log.predict(input_data_resaped)
print('Prediction:',prediction)
```

Prediction: [0]