Dropout Prediction EDA

In [1]:
```
import pandas as pd
import numpy as np
from hashlib import sha1
import matplotlib.pyplot as plt
import seaborn as sns
import altair as alt
```

1. General Exploration

In [2]:
```
alt.renderers.enable('mimetype')

data_path = '../data/raw/data.csv'
sep = ';'
```

In [3]:
```
df = pd.read_csv(data_path, sep=sep)
df = df.rename(columns={'Nacionality': 'Nationality', 'Daytime/evening attendance\t': 'Daytime_ev
df.shape
```

Out[3]: (4424, 37)

In [4]:
```
df.head()
```

Out[4]:

	Marital status	Application mode	Application order	Course	Daytime_evening_attendance	Previous qualification	Previous qualification (grade)	Nationality
0	1	17	5	171	1	1	122.0	1
1	1	15	1	9254	1	1	160.0	1
2	1	1	5	9070	1	1	122.0	1
3	1	17	2	9773	1	1	122.0	1
4	2	39	1	8014	0	1	100.0	1

5 rows × 37 columns

In [5]:
```
df.tail()
```

Out[5]:

	Marital status	Application mode	Application order	Course	Daytime_evening_attendance	Previous qualification	Previous qualification (grade)	Nationa
4419	1	1	6	9773	1	1	125.0	
4420	1	1	2	9773	1	1	120.0	
4421	1	1	1	9500	1	1	154.0	
4422	1	1	1	9147	1	1	180.0	
4423	1	10	1	9773	1	1	152.0	

5 rows × 37 columns

In [6]:
```
df = df.dropna()
df.shape
```

Out[6]:
```
(4424, 37)
```

The data-set consists of 4424 records with 36 attributes and contains no missing values. The distribution and statistics are above and below.

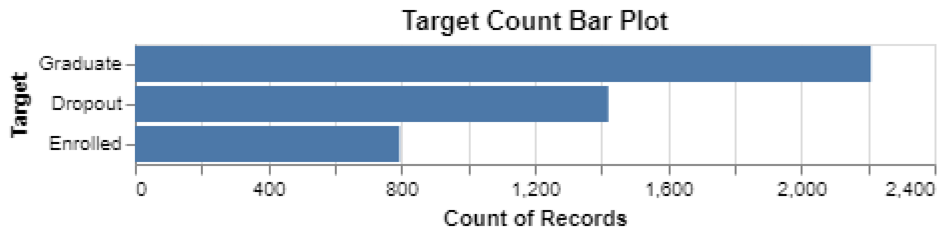
In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4424 entries, 0 to 4423
Data columns (total 37 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   Previous qualification (grade)                  4424 non-null   float64
 7   Nationality                                     4424 non-null   int64  
 8   Mother's qualification                          4424 non-null   int64  
 9   Father's qualification                          4424 non-null   int64  
 10  Mother's occupation                             4424 non-null   int64  
 11  Father's occupation                             4424 non-null   int64  
 12  Admission grade                                 4424 non-null   float64
 13  Displaced                                       4424 non-null   int64  
 14  Educational special needs                       4424 non-null   int64  
 15  Debtor                                          4424 non-null   int64  
 16  Tuition fees up to date                         4424 non-null   int64  
 17  Gender                                          4424 non-null   int64  
 18  Scholarship holder                              4424 non-null   int64  
 19  Age at enrollment                               4424 non-null   int64  
 20  International                                   4424 non-null   int64  
 21  Curricular units 1st sem (credited)             4424 non-null   int64  
 22  Curricular units 1st sem (enrolled)             4424 non-null   int64  
 23  Curricular units 1st sem (evaluations)          4424 non-null   int64  
 24  Curricular units 1st sem (approved)             4424 non-null   int64  
 25  Curricular units 1st sem (grade)                4424 non-null   float64
 26  Curricular units 1st sem (without evaluations)  4424 non-null   int64  
 27  Curricular units 2nd sem (credited)             4424 non-null   int64  
 28  Curricular units 2nd sem (enrolled)             4424 non-null   int64  
 29  Curricular units 2nd sem (evaluations)          4424 non-null   int64  
 30  Curricular units 2nd sem (approved)             4424 non-null   int64  
 31  Curricular units 2nd sem (grade)                4424 non-null   float64
 32  Curricular units 2nd sem (without evaluations)  4424 non-null   int64  
 33  Unemployment rate                               4424 non-null   float64
 34  Inflation rate                                  4424 non-null   float64
 35  GDP                                             4424 non-null   float64
 36  Target                                          4424 non-null   object 
dtypes: float64(7), int64(29), object(1)
memory usage: 1.2+ MB
```

All of our features are either integers or float, and most of the integer variables are categorical features. The class label is also a categorical variable with 3 classes (Graduate, Dropout, Enrolled).

In [8]:
```python
target_bar = alt.Chart(df,
                     title='Target Count Bar Plot'
         ).mark_bar().encode(
                x='count(Target)',
                y=alt.Y('Target', sort='-x'),
)
target_bar
```

Out[8]:



In [9]:
```
df.Target.value_counts(normalize=True)
```

Out[9]:
```
Graduate    0.499322
Dropout     0.321203
Enrolled    0.179476
Name: Target, dtype: float64
```

From the above plot, we can see this problem was a three-category classification task, and there exists a strong imbalance between those three classes. The class Graduate has the majority count which is around 50% of the records and Dropout has 32% of the total records. The Enrolled only has 18% of the total records. Thus, during our training, we need to find a way to fix this imbalance issue, possible solution would be setting the `class_weight` in our model.

1.1 Dropping Enrolled Student

In [10]:
```
df = df.drop(df[df.Target == 'Enrolled'].index)
df.shape
```

Out[10]:
```
(3630, 37)
```

In [11]:
```
df.Target.value_counts(normalize=True)
```

Out[11]:
```
Graduate    0.60854
Dropout     0.39146
Name: Target, dtype: float64
```

After dropping the Enrolled students, we have around 60% graduated students and 40% dropout students.

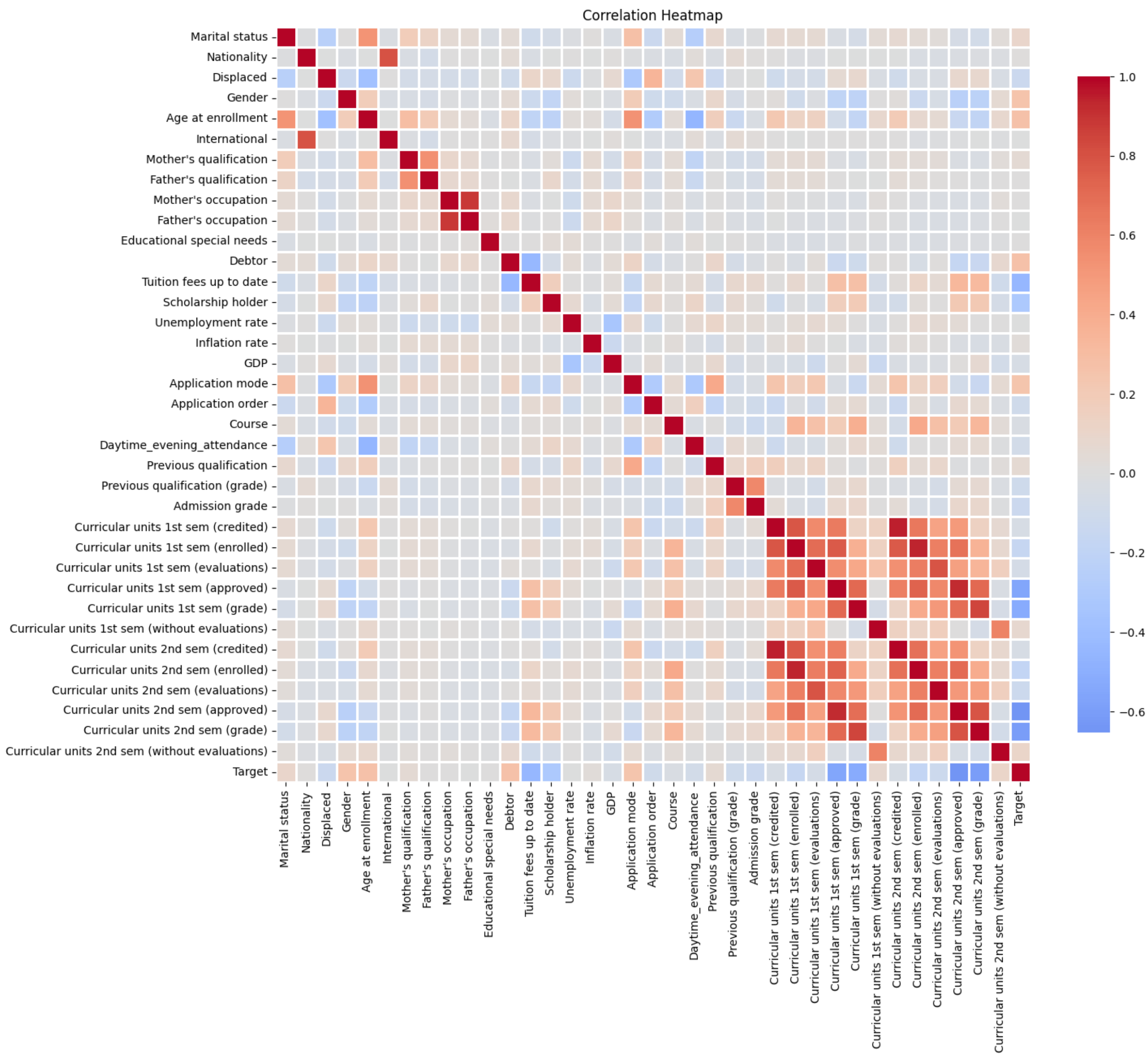
1.2 Rearranging Column Order By Potential Category

In [12]:
```
df = df[['Marital status', 'Nationality','Displaced','Gender',
                'Age at enrollment', 'International',
                "Mother's qualification", "Father's qualification",
       "Mother's occupation", "Father's occupation",

       'Educational special needs', 'Debtor',
       'Tuition fees up to date',  'Scholarship holder',
        'Unemployment rate','Inflation rate', 'GDP',

        'Application mode', 'Application order', 'Course',

       'Daytime_evening_attendance', 'Previous qualification',
       'Previous qualification (grade)',
       'Admission grade',

       '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)', 'Target']]
```

2. Feature Correlation

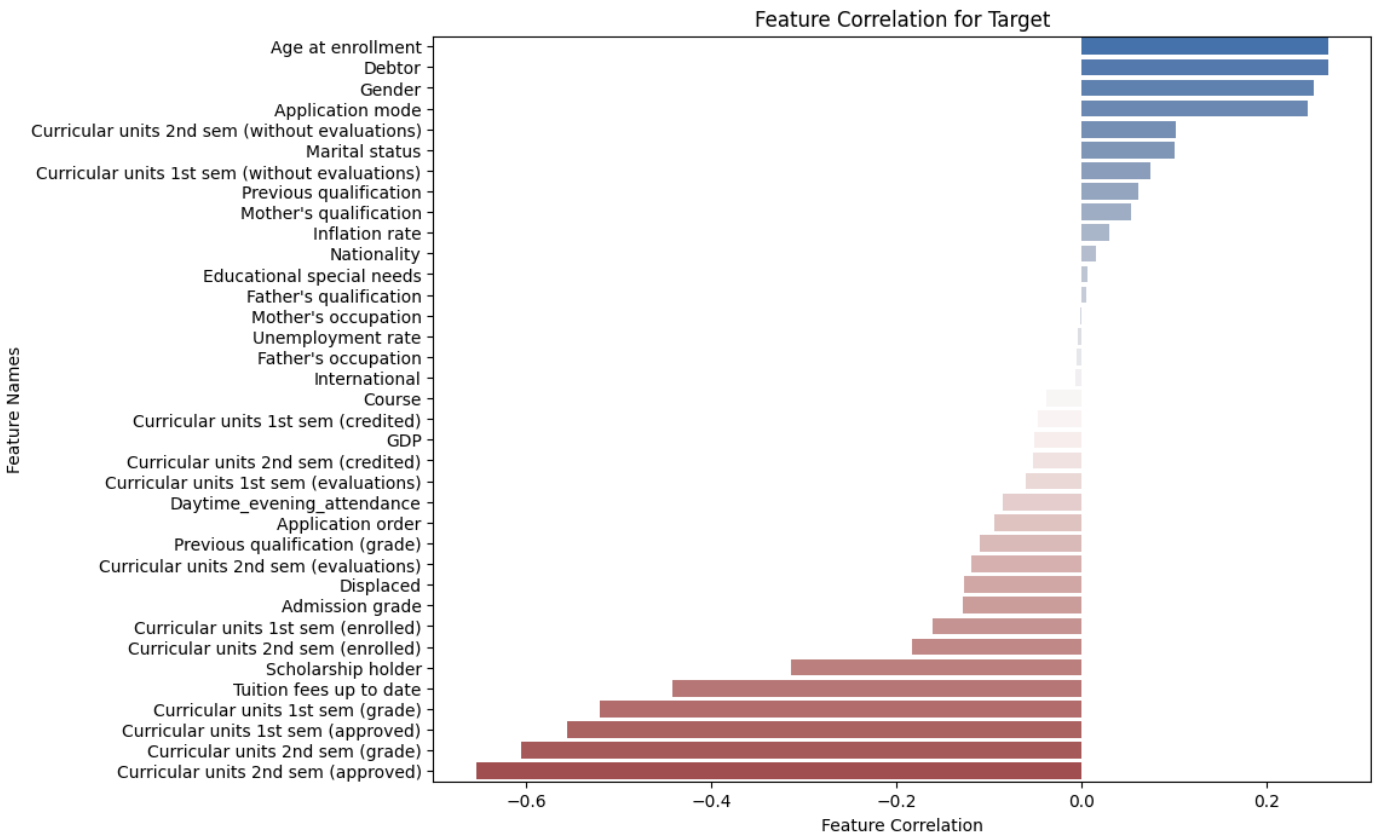
In [13]:
```
df_target = df.replace({'Target': {'Dropout': 1, 'Graduate': 0}})

f = plt.figure(figsize=(15, 15))
sns.heatmap(df_target.corr(),annot=False, cmap='coolwarm',center=0,
            square=True, linewidths=.8, cbar_kws={"shrink": .7})
plt.title('Correlation Heatmap')
plt.show()
```



From the correlation heatmap, we can observe that some features are strongly correlated (the dark red color), for example, Nationality & International, Age at enrollment & Application mode. There are some features with negative correlation, for example, Age at enrollment & Daytime Evening Attendance. In the following sections, we would like to further investigate those positively correlated features, and features in different potential categories (Demographic, Macroeconomic, Academic data at enrollment, etc.).

In [14]:
```
feat_corr = df_target.drop("Target", axis=1).apply(lambda x: x.corr(df_target.Target))
feat_corr = pd.DataFrame(feat_corr, columns=['correlation']).sort_values(['correlation'], ascend:

plt.figure(figsize=(10,8))
sns.barplot(x=feat_corr['correlation'], y=feat_corr.index, palette="vlag")
plt.title('Feature Correlation for Target')
plt.xlabel('Feature Correlation')
plt.ylabel('Feature Names')
```

Out[14]:
```
Text(0, 0.5, 'Feature Names')
```



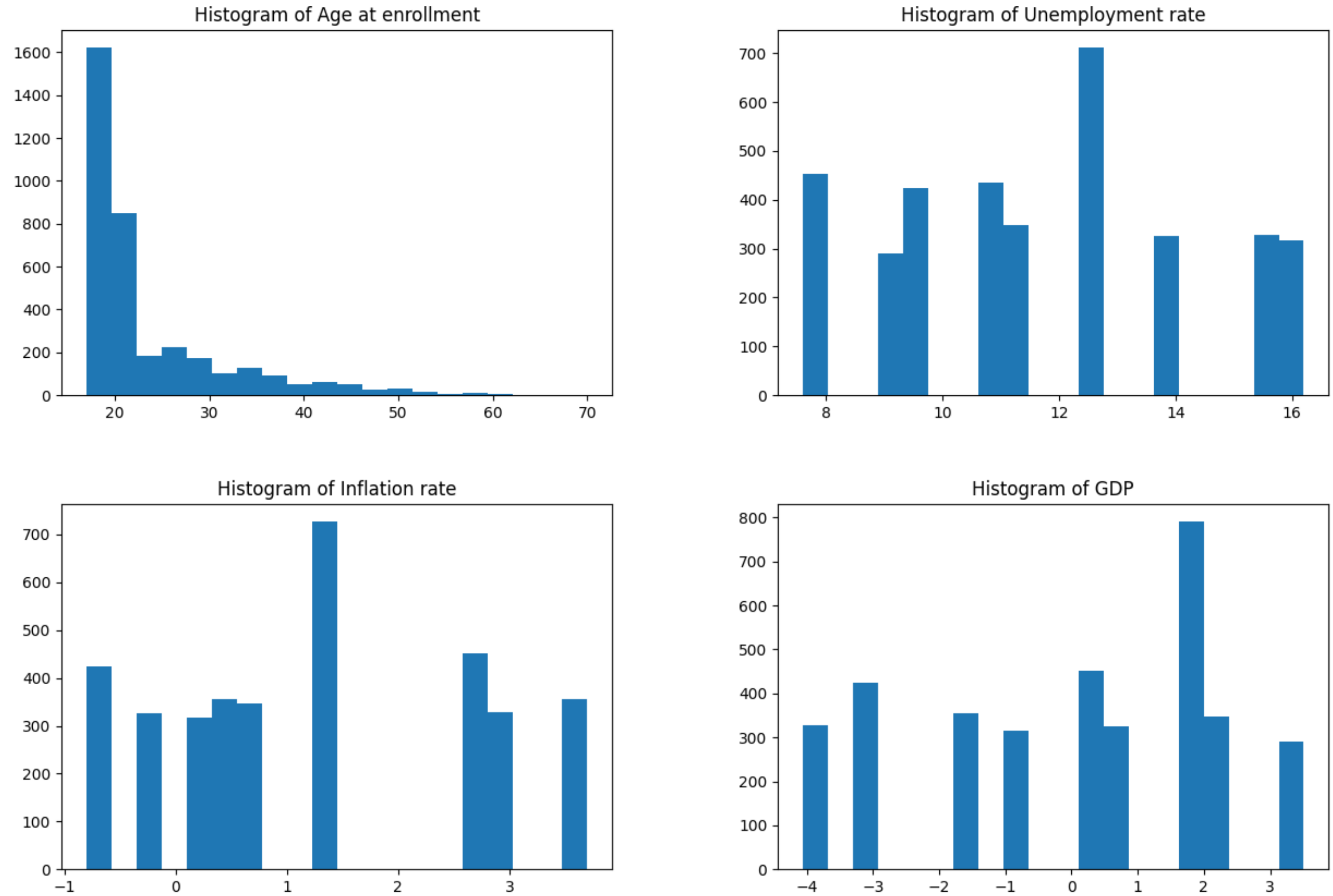
There are more negatively correlated features than positives one. The top 3 positively correlated features are `Age at enrollment`, `Debtor`, and `Gender`. In the below data exploration, we can further investigate their relationship.

3. Numeric / Categorical Feature Overview

3.1 Bar Plot on Continuous Features

In [15]:
```
numeric_cols = ['Age at enrollment',
                'Unemployment rate','Inflation rate', 'GDP'
        ]

fig, axs = plt.subplots(2,2, figsize=(15, 10), facecolor='w', edgecolor='k')
fig.subplots_adjust(hspace = .3, wspace=.3)

axs = axs.ravel()

for i in range(0, len(numeric_cols)):
```

```
    axs[i].hist(df[numeric_cols[i]], bins=20)
    axs[i].set_title("Histogram of " + numeric_cols[i])
```

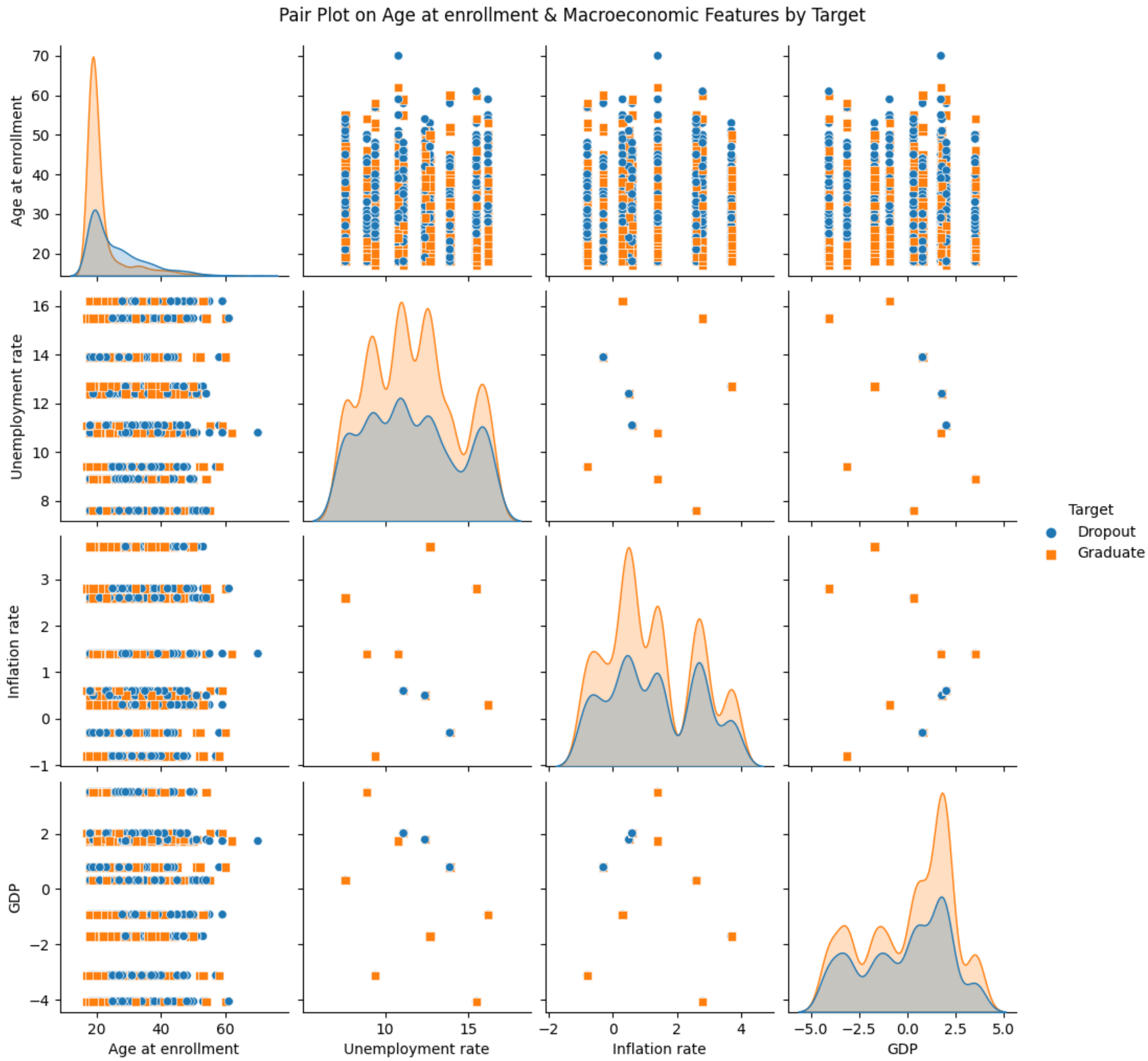


From the above bar plot, most of the students enrolled in the program during their 20s. In terms of macroeconomic features, the unemployment rate, inflation rate, and GDP are distributed among different values.

3.2 Pair Plot on Continuous Features

In [16]:
```
sns_pair = sns.pairplot(df[['Age at enrollment','Unemployment rate',
                 'Inflation rate', 'GDP', 'Target']],
             hue='Target', markers=["o", "s"])
sns_pair.fig.suptitle("Pair Plot on Age at enrollment & Macroeconomic Features by Target", y=1.0
```

Out[16]:
```
Text(0.5, 1.02, 'Pair Plot on Age at enrollment & Macroeconomic Features by Target')
```



In the previous section, we examine the continuous features in the bar plot. We would like to further investigate their relationship with the target. For students in their 20s, there is more student graduating. However, there are more students to drop out in their 30s and older. The possible reason could be a student entering the workforce when they are older. In terms of the macroeconomic features, both dropout & graduate students are distributed similarly. There is no linear relationship between each pair of macroeconomic variables, as both classes are not linearly separated in the scatter plot.

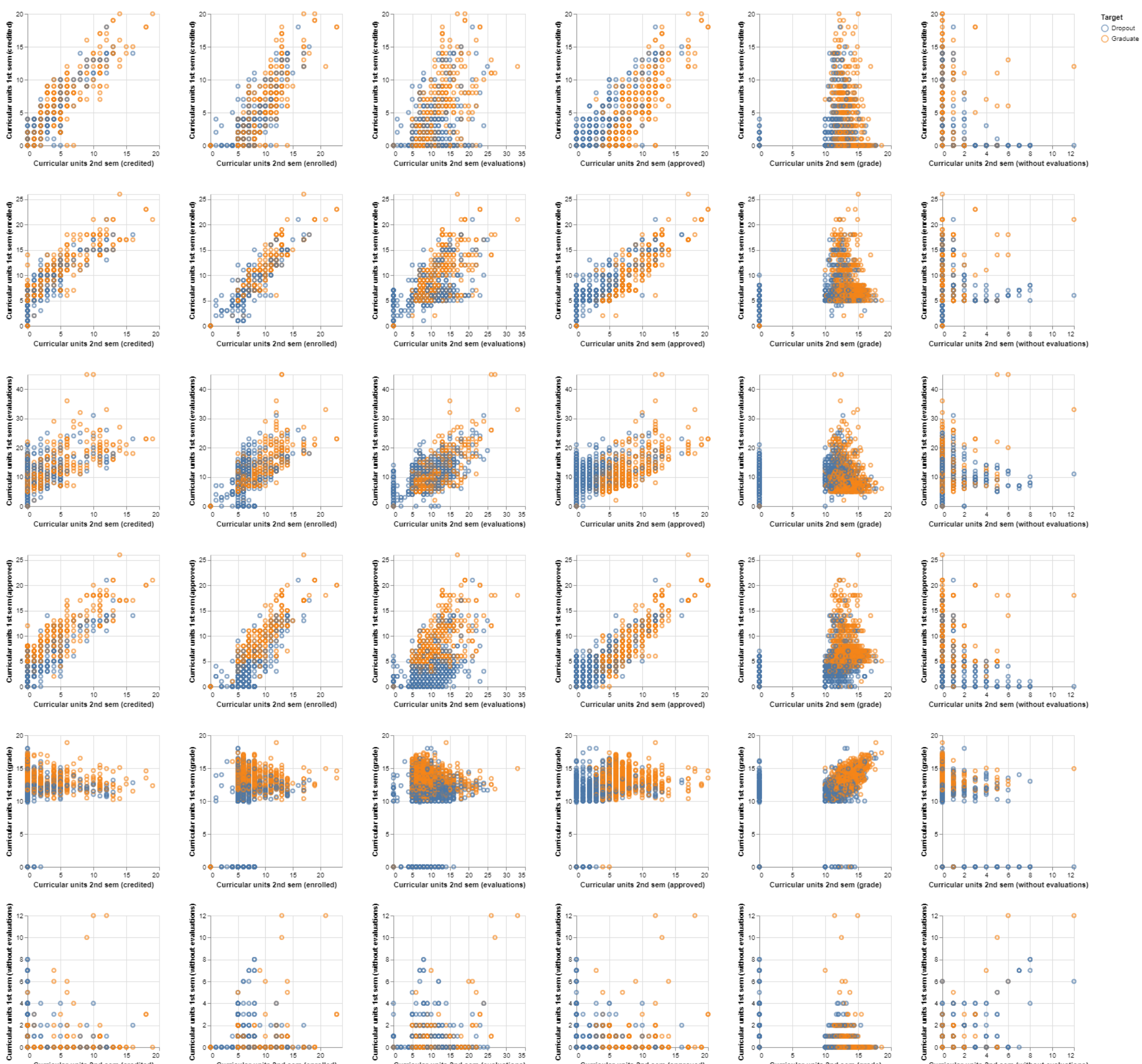
3.3 Scatter Plot on Student Performance by Target

In [17]:

```
numeric_cols = df.select_dtypes('number').columns.tolist()
numeric_cols

# performance of two semester vs Target
df_new = 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)
             '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)
             'Target']]
```

```
first_sem = ['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)

second_sem = ['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

plot = alt.Chart(df_new).mark_point().encode(
     alt.X(alt.repeat('column'), type='quantitative'),
     alt.Y(alt.repeat('row'), type='quantitative'),
     color = 'Target'
).properties(
    width=200,
    height=200
).repeat(
    row = first_sem,
    column = second_sem
)

plot
```

Out[17]:



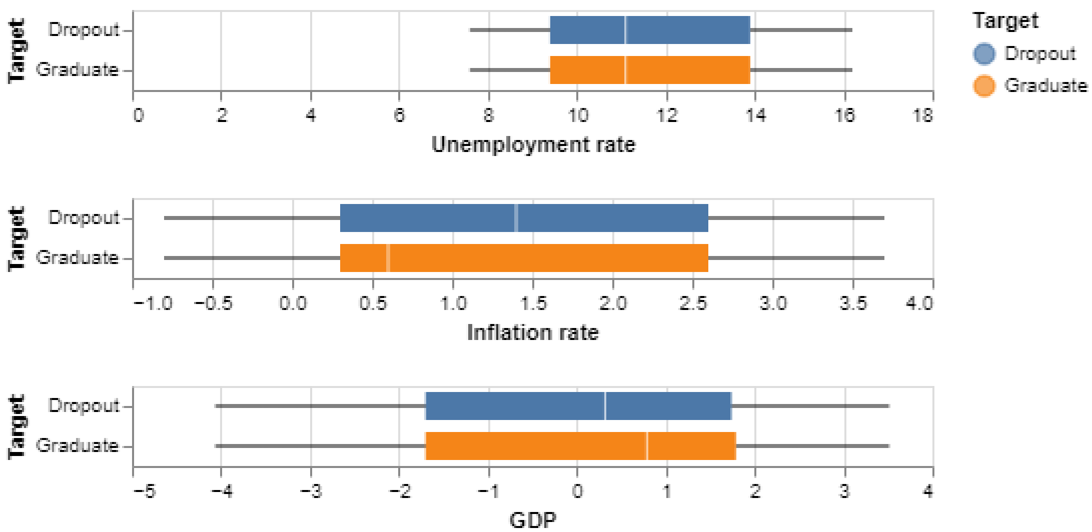
Similarly, in student performance, no linear relationship was found among both classes.

4. Macroeconomic Features

- `Unemployment rate`
- `Inflation rate`
- `GDP`

In [18]:
```
macroeconomic_col = ['Unemployment rate','Inflation rate', 'GDP']

macroeconomic_boxplot = alt.Chart(df).mark_boxplot().encode(
    x=alt.X(alt.repeat(), type='quantitative'),
    y='Target',
    color='Target'
).repeat(repeat=macroeconomic_col, columns=1)


macroeconomic_boxplot
```

Out[18]:



In general, the macroeconomic features show a similar trend for each class in terms of their range and quantile. Both classes tend to have identical distributions as we observed in the pair plot.

In [19]:
```
# sns.scatterplot(x='Unemployment rate', y='Inflation rate', hue="Target", data=df)
# plt.title("Relationship between Unemployment Rate, Inflation Rate and target")
# plt.show()

macroeconomic_scatter = alt.Chart(df,
        ).mark_circle().encode(
    x=alt.X('Unemployment rate', scale=alt.Scale(zero=False)),
    y=alt.Y('Inflation rate', scale=alt.Scale(zero=False)),
    color='Target',
    tooltip=['count()', 'Unemployment rate', 'Inflation rate'],
    size=alt.Size('count()',
                  title='count',  scale=alt.Scale(range=(10, 1000)))
)

macroeconomic_scatter = alt.layer(macroeconomic_scatter).facet(
    facet=alt.Facet('Target', title=None),
    title="Relationship between Unemployment Rate, Inflation Rate and Target"
)
```

```
macroeconomic_scatter
```

Out[19]:

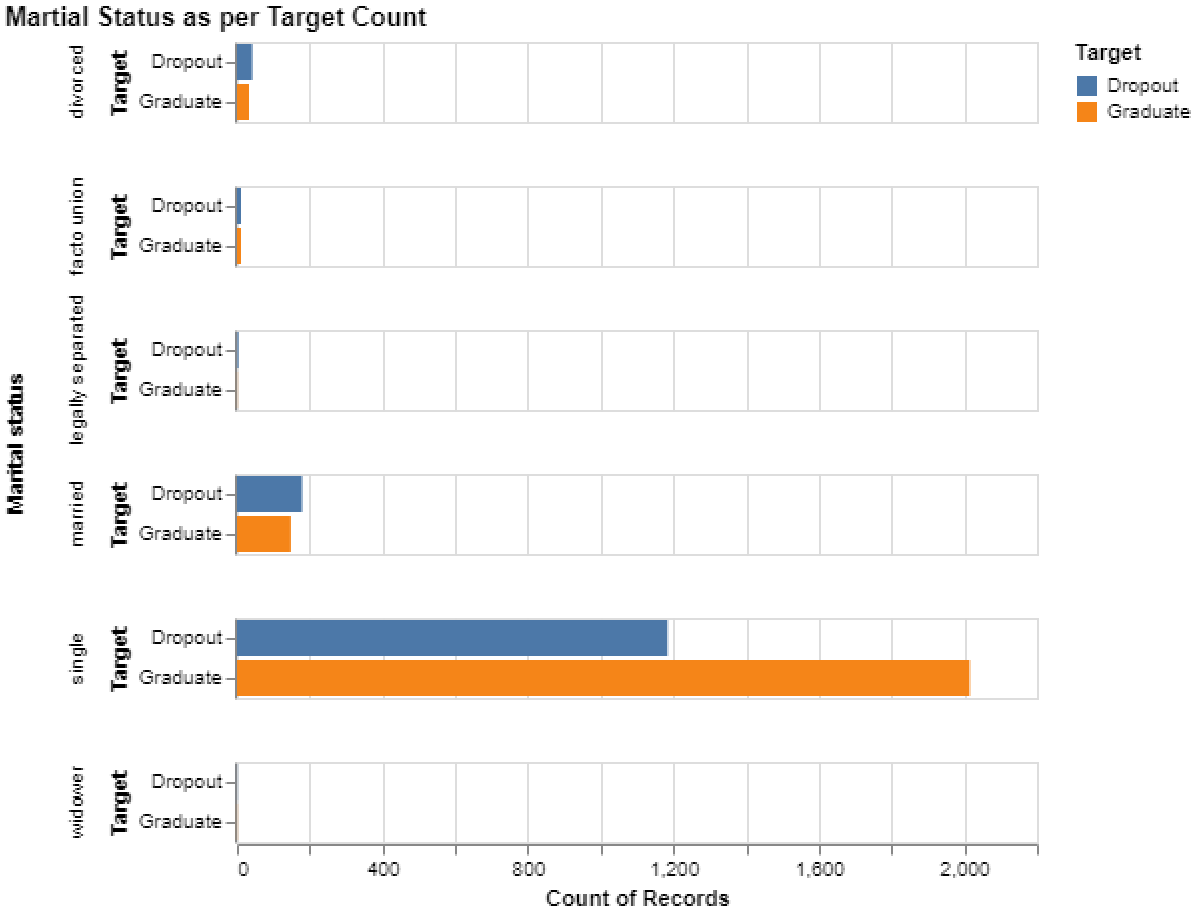
For both the inflation rate and unemployment rate, dropout & graduate students show the same scatter point position. The only difference is the record count in the rating level. Therefore, these features might not be informative in our modeling.

5. Marital Status

In [20]:

```
marital_dict = {1: 'single', 2: 'married', 3 : 'widower', 4 : 'divorced', 5 : 'facto union' , 6
df2=df.replace({"Marital status": marital_dict})

marital_bar = alt.Chart(df2).mark_bar().encode(
    x='count()',
    y='Target',
    color='Target',
    tooltip='count()'
).facet(
    row='Marital status',
    spacing=30,
    title='Martial Status as per Target Count'
)

marital_bar
```

Out[20]:

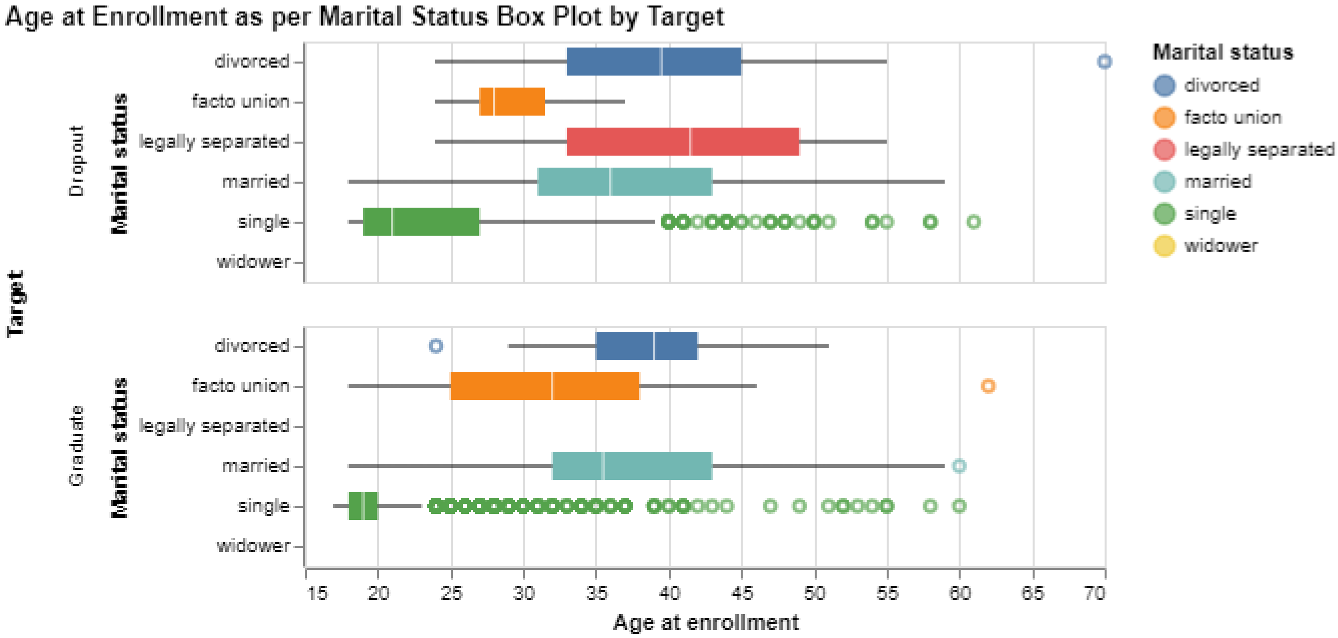


Single student accounts for the majority of the population and tends to graduate from the program. More married or divorced students drop out than graduating, while the other marital status student appears insignificant amount among the group.

In [21]:

```
marital_boxplot = alt.Chart(df2).mark_boxplot().encode(
    x=alt.X('Age at enrollment', scale=alt.Scale(zero=False)),
    y='Marital status:N',
    color='Marital status:N'
).facet(
    row='Target',
    title='Age at Enrollment as per Marital Status Box Plot by Target'
)

marital_boxplot
```

Out[21]:



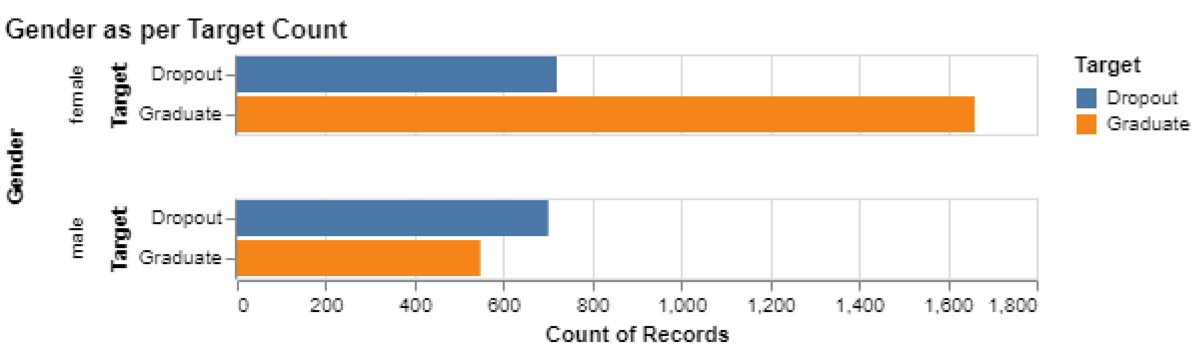
To better understand the marital status, we could examine the student's ages when they enrolled in the program. Most of the single students are in their 20s with outliers observed after their 30s. Students with a marriage history are mainly distributed in their 30s and above. Since there are too few data points for legally separated and widower students, their box plot is omitted. Overall, the age at enrollment and the student's marital status display a logical relationship in modern society.

6. Gender

In [22]:

```
gender_dict = {1: 'male', 0: 'female'}
df2=df2.replace({"Gender": gender_dict})

gender_bar = alt.Chart(df2).mark_bar().encode(
    x='count()',
    y='Target',
    color='Target',
    tooltip='count()'
).facet(
    row='Gender',
    spacing=30,
    title='Gender as per Target Count'
)

gender_bar
```

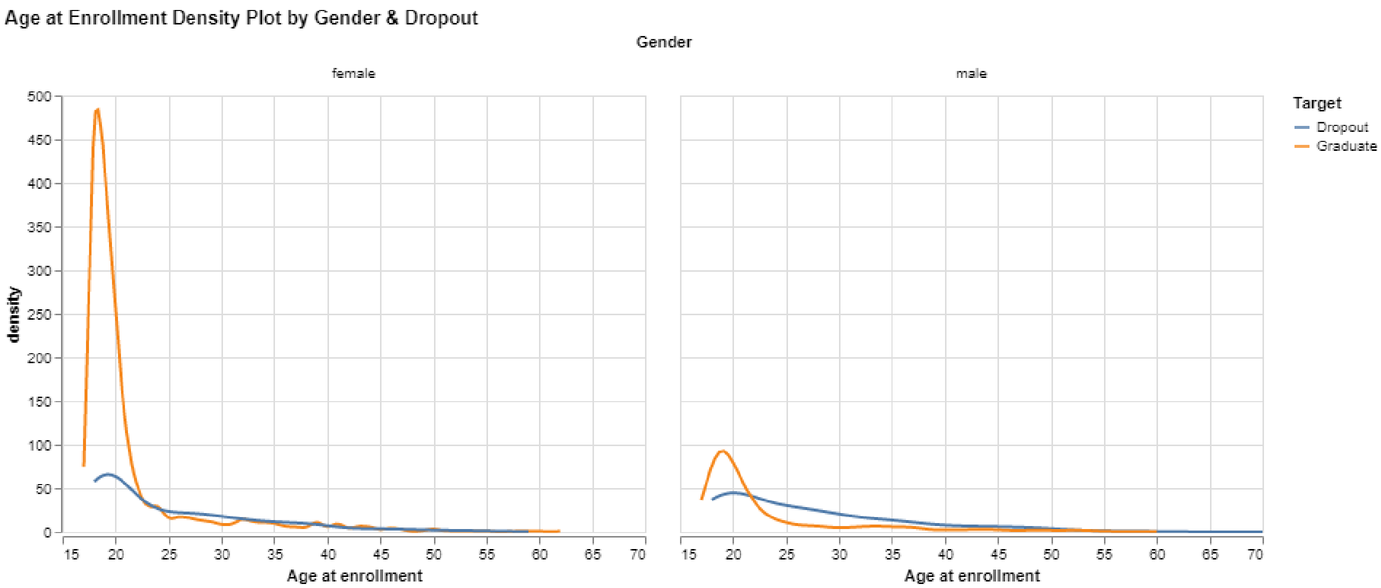
Out[22]:



Apart from marital status, gender is also one of the important demographic features. In this dataset, there is more female sample than males. More female students tend to graduate than drop out of the program, while male students show the opposite behavior.

In [23]:
```
gender_density = (alt.Chart(df2)
 .transform_density(
     'Age at enrollment',
     groupby=['Target','Gender'],
     as_=['Age at enrollment', 'density'],
     counts=True,
 )
 .mark_line().encode(
     x='Age at enrollment',
     y='density:Q',
     color='Target',
 tooltip='Age at enrollment')
 .facet('Gender',
       title="Age at Enrollment Density Plot by Gender & Dropout"
       )
)

gender_density
```

Out[23]:



The density plot reveals the gender imbalance in our dataset with the number of younger female students than males. More male student aged 25 to 30 tends to drop out than females. While the students after their 30s, both gender demonstrate similar patterns.

7. Course & Attendance Mode

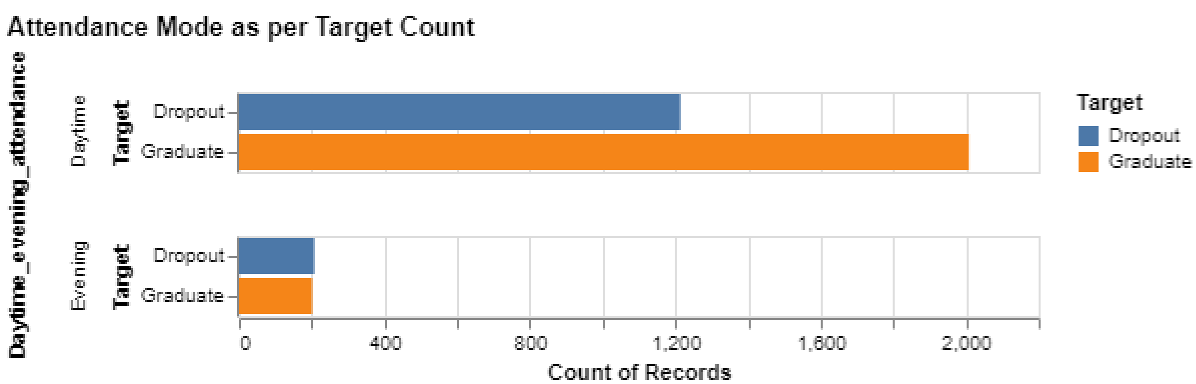
- `Course`:
  - 33 - Biofuel Production Technologies
  - 171 - Animation and Multimedia Design
  - 8014 - Social Service (`evening` attendance)
  - 9003 - Agronomy
  - 9070 - Communication Design
  - 9085 - Veterinary Nursing
  - 9119 - Informatics Engineering
  - 9130 - Equinculture
  - 9147 - Management
  - 9238 - Social Service
  - 9254 - Tourism

- 9500 - Nursing
- 9556 - Oral Hygiene
- 9670 - Advertising and Marketing Management
- 9773 - Journalism and Communication
- 9853 - Basic Education
- 9991 - Management (`evening` attendance)

- `Attendance Mode` : Daytime / Evening (Social Service, Management)

In [24]:
```
day_evening_dict = {1: 'Daytime', 0: 'Evening'}
df2 = df2.replace({'Daytime_evening_attendance': day_evening_dict})
gender_bar = alt.Chart(df2).mark_bar().encode(
    x='count()',
    y='Target',
    color='Target',
    tooltip='count()'
).facet(
    row="Daytime_evening_attendance",
    spacing=30,
    title='Attendance Mode as per Target Count'
)

gender_bar
```

Out[24]:

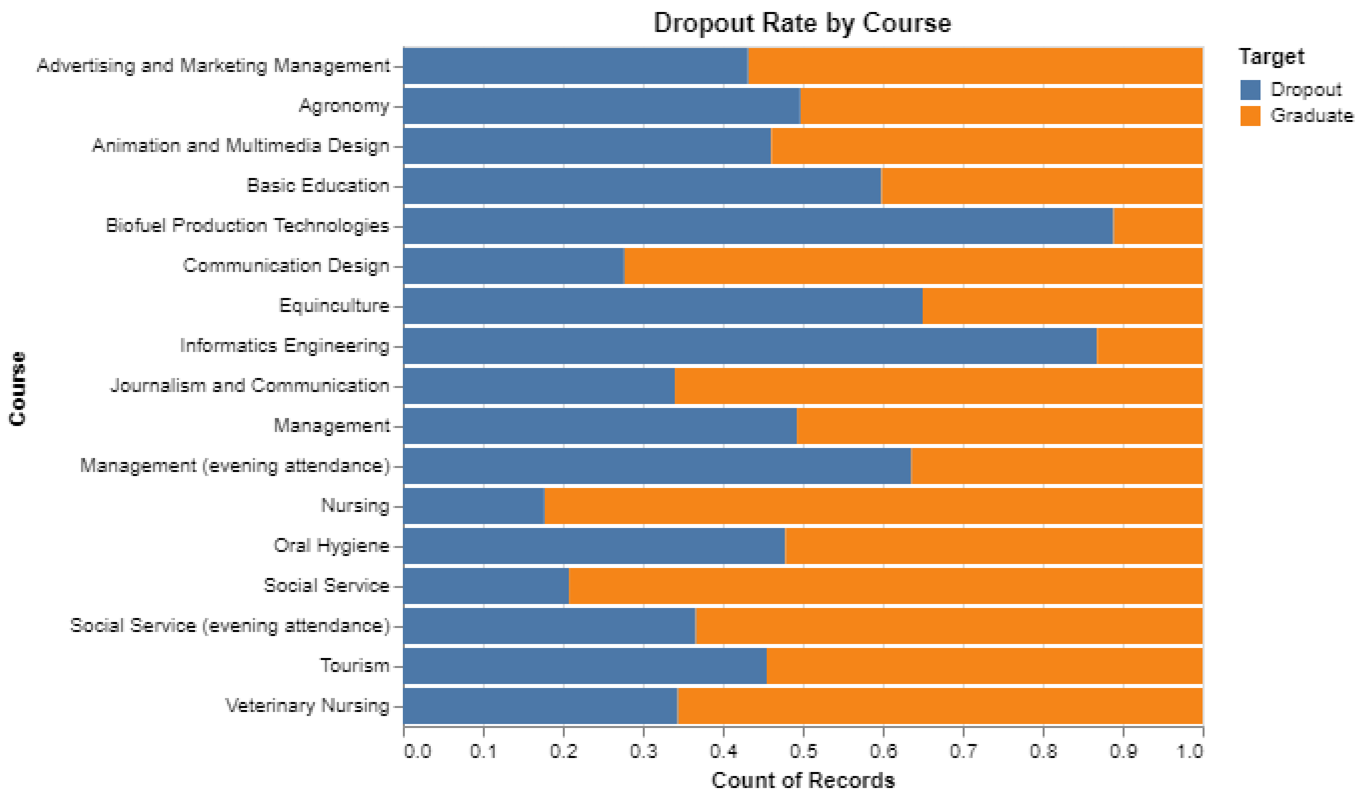


There are only two courses that offer both daytime and evening attendance, which are Social Service and Management. In those daytime courses, more students are graduating than dropping out, while there are an equal amount of students for both classes in the evening class.

In [25]:
```
course_dict = {33:"Biofuel Production Technologies",
171:"Animation and Multimedia Design",
8014:"Social Service (evening attendance)",
9003:"Agronomy",
9070:"Communication Design",
9085:"Veterinary Nursing",
9119:"Informatics Engineering",
9130:"Equinculture",
9147:"Management",
9238:"Social Service",
9254:"Tourism",
9500:"Nursing",
9556:"Oral Hygiene",
9670:"Advertising and Marketing Management",
9773:"Journalism and Communication",
9853:"Basic Education",
9991:"Management (evening attendance)"}
df3 = df2.replace({'Course': course_dict})
```

```
dropout_bars = alt.Chart(df3, title='Dropout Rate by Course').mark_bar().encode(
    x=alt.X('count()' ,stack="normalize"),
    y='Course',
    color='Target',
    tooltip='count()'
)

dropout_bars
```

Out[25]:



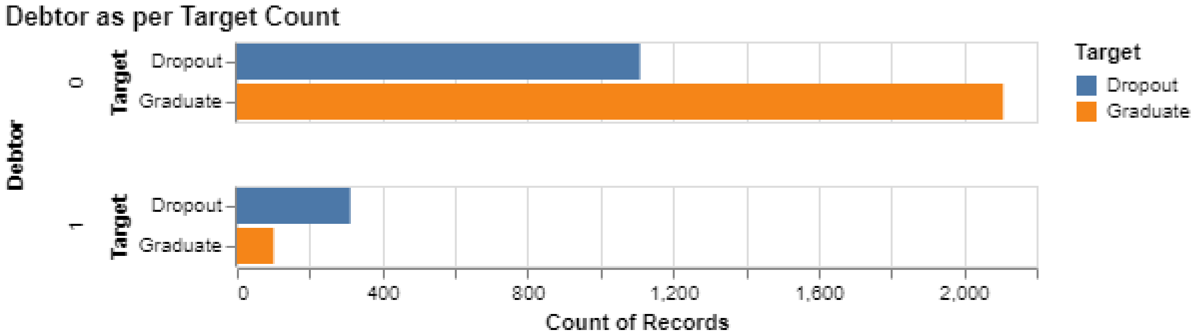
The highest 2 dropout courses are Biofuel Production Technologies and Informatics Engineering with around 85% dropout rate, while Nursing and Social Service (daytime attendance) have the top 2 lowest dropout rate at around 20%. The remaining courses have dropout rate between 30% and 60%.

8. Debtor

In [26]:

```
alt.Chart(df2).mark_bar().encode(
    x='count()',
    y='Target',
    color='Target',
    tooltip='count()'
).facet(
    row='Debtor',
    spacing=30,
    title='Debtor as per Target Count'
)
```

Out[26]:



Most student who owes a debt is likely to drop out of school, while students without debt are likely to graduate with a 66% chance according to the above bar plot.

Key Takeaway from EDA

- We will only consider the `Graduate` (60%) and `Dropout` (40%) students in our dataset.
- The top 3 positively correlated features are `Age at enrollment`, `Debtor`, and `Gender`.
- There is no linear relationship between each pair of macroeconomic and academic performance features.
- Graduate and Dropout student shows a similar trend in the macroeconomic features.
- Most students are single and less likely to drop out.
- Gender imbalance found in the dataset, most female students are likely to graduate.
- The highest 2 dropout courses are Biofuel Production Technologies and Informatics Engineering with around 85% dropout rate.
- Student who owes a debt is likely to drop out of school.

In [ ]: