# Math 189 Group 41 Final Project 3

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## 1 Math 189 - Prediction on College Student Dropouts

### 1.1 Link to Video:

### 1.2 Names


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### 1.3 Abstract


Studying students' dropout and success can help us to conduct early intervention which can help students who are underperforming to be helped on time. Also, knowing the key features of success and failure, universities can allocate their resources more effectively to help students. Lastly, knowing these facts, the government and education institutes can develop policies to address educational disparities.

Our dataset is pulled from the UC Irvine Machine Learning Repository. This website can be considered a reliable source, and is known for staging a wide variety of datasets for use in machine learning. This suits the needs of this project, because datasets used in ML are ideally large and generally suitable for statistical analysis. About

This specific dataset was created by the contributors of "Early Prediction of student's Performance in Higher Education: A Case Study".


### 1.4 Introduction

Dropout rate has always been a problem that's worth noticing for education institutions since it's considered to be having a significant impact on the development, as well as reputations of educational institutions. To investigate the reasons that students dropout of college, UCI built a dataset on student's dropout and included variables that might contribute to the dropout of students in the dataset. The goal of our project is to build a reliable model that predicts the dropout of students based on information provided in the dataset. This research has meaningful implications as it helps colleges to better predict the dropout of students so that accurate adjustments can be made to efficiently decrease the dropout rate. Improvement on dropout rates also has social and economic benefits based on research, as college graduates are more likely to earn higher wages based on the result. In our project, we used EDA to evaluate influences on dropout rates of different variables, and built models to make predictions based on these variables.

### 1.5 Import Packages

[28]:
```
import pandas as pd
import numpy as np
import math
import matplotlib.pyplot as plt
```

[29]:
```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn import preprocessing
from sklearn import metrics
from sklearn.preprocessing import FunctionTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.metrics import f1_score
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score
import seaborn as sns
from sklearn.metrics import confusion_matrix
import statsmodels.formula.api as smf
```

### 1.6 Data Overview

**Column descriptions at https://archive.ics.uci.edu/dataset/697/predict+students+dropout+and+a**

[30]:
```
df = pd.read_csv('data.csv', sep=';')
```

[31]:
```
df.head()
```

[31]:
```
   Marital status  Application mode  Application order  Course  \
0               1                17                  5     171
1               1                15                  1    9254
2               1                 1                  5    9070
3               1                17                  2    9773
4               2                39                  1    8014

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

```
   Previous qualification (grade)  Nacionality  Mother's qualification  \
0                           122.0            1                      19   
1                           160.0            1                       1   
2                           122.0            1                      37   
3                           122.0            1                      38   
4                           100.0            1                      37   

   Father's qualification  …  Curricular units 2nd sem (credited)  \
0                      12  …                                    0   
1                       3  …                                    0   
2                      37  …                                    0   
3                      37  …                                    0   
4                      38  …                                    0   

   Curricular units 2nd sem (enrolled)  \
0                                    0   
1                                    6   
2                                    6   
3                                    6   
4                                    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 37 columns]
```

[32]:

```python
# select only Graduates and Dropouts
df = df[df['Target'] != 'Enrolled']
```

[33]:

```python
for i in range(len(df.columns)):
    print('Column ' + str(i) + ': ' + df.columns[i])
```

```
Column 0: Marital status
Column 1: Application mode
Column 2: Application order
Column 3: Course
Column 4: Daytime/evening attendance
Column 5: Previous qualification
Column 6: Previous qualification (grade)
Column 7: Nacionality
Column 8: Mother's qualification
Column 9: Father's qualification
Column 10: Mother's occupation
Column 11: Father's occupation
Column 12: Admission grade
Column 13: Displaced
Column 14: Educational special needs
Column 15: Debtor
Column 16: Tuition fees up to date
Column 17: Gender
Column 18: Scholarship holder
Column 19: Age at enrollment
Column 20: International
Column 21: Curricular units 1st sem (credited)
Column 22: Curricular units 1st sem (enrolled)
Column 23: Curricular units 1st sem (evaluations)
Column 24: Curricular units 1st sem (approved)
Column 25: Curricular units 1st sem (grade)
Column 26: Curricular units 1st sem (without evaluations)
Column 27: Curricular units 2nd sem (credited)
Column 28: Curricular units 2nd sem (enrolled)
Column 29: Curricular units 2nd sem (evaluations)
Column 30: Curricular units 2nd sem (approved)
Column 31: Curricular units 2nd sem (grade)
Column 32: Curricular units 2nd sem (without evaluations)
Column 33: Unemployment rate
Column 34: Inflation rate
Column 35: GDP
Column 36: Target
```

## 1.7 Data Cleaning

[7]:
```
# find null values
df.isnull().sum().sum()
# no nulls found; the dataset's creators did all necessary cleaning
```

[7]:
```
0
```

Dataset creators' comment on cleaning: 'We performed a rigorous data preprocessing to handle data from anomalies, unexplainable outliers, and missing values.'

## 1.8 Exploratory Data Analysis

**Columns 1 -> 18; run prior to preprocessing**

[9]:
```
# color dictionary
colors = {'Graduate': 'darkgreen', 'Dropout': 'darkred'}
```

[10]:
```
# print #uniqe values per column
for i in range(16):
    print('Columns #' + str(i) + '; ' + df.columns[i] + ' has ' + str(len(df[df.
 ↪columns[i]].unique())) + ' unique values')
```

```
Columns #0; Marital status has 6 unique values
Columns #1; Application mode has 18 unique values
Columns #2; Application order has 7 unique values
Columns #3; Course has 17 unique values
Columns #4; Daytime/evening attendance	has 2 unique values
Columns #5; Previous qualification has 17 unique values
Columns #6; Previous qualification (grade) has 101 unique values
Columns #7; Nacionality has 19 unique values
Columns #8; Mother's qualification has 29 unique values
Columns #9; Father's qualification has 34 unique values
Columns #10; Mother's occupation has 29 unique values
Columns #11; Father's occupation has 42 unique values
Columns #12; Admission grade has 602 unique values
Columns #13; Displaced has 2 unique values
Columns #14; Educational special needs has 2 unique values
Columns #15; Debtor has 2 unique values
```

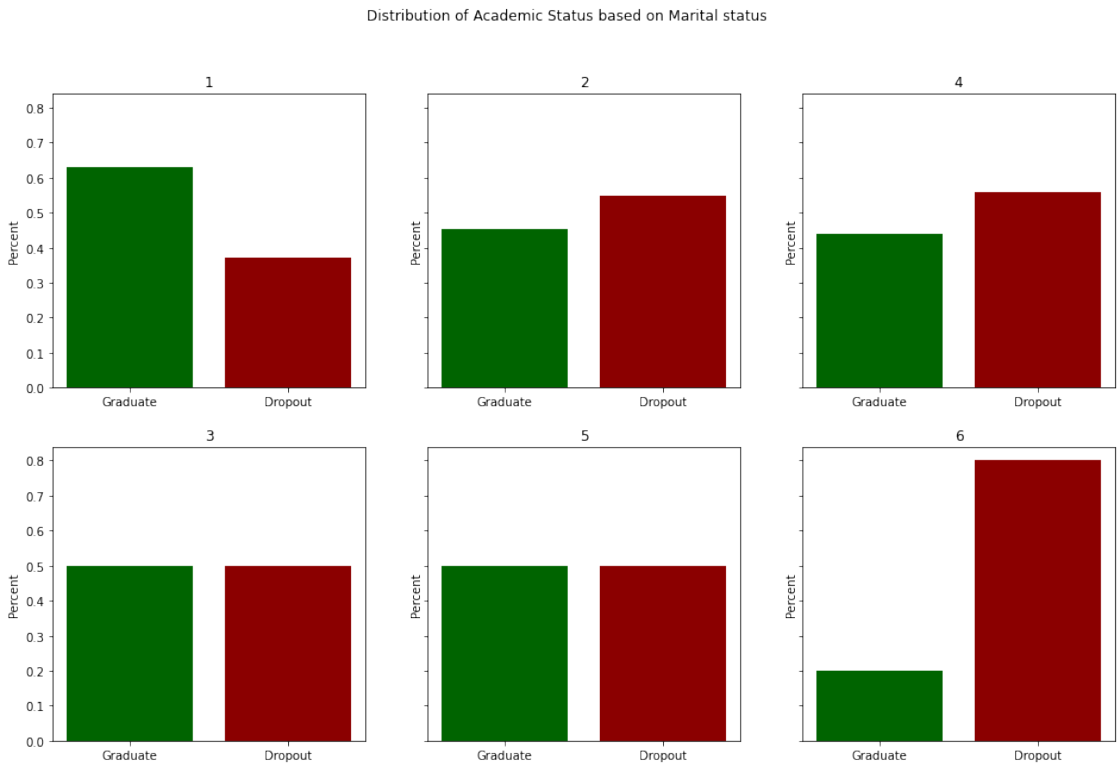
[10]:
```
# categorical columns are num 0, 1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 13, 14; use␣
 ↪bar charts
# continuous columns are num 6, 12; use histogram
```

### 1.8.1 Column 0: Marital Status

[11]:
```
# select subset of dataset
col = df.columns[0]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 2
subplots_width = 3
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 10),␣
↪sharey=True)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: significantly less graduates in status 6, significantly more enrolled in status 3**

Likely an influential feature

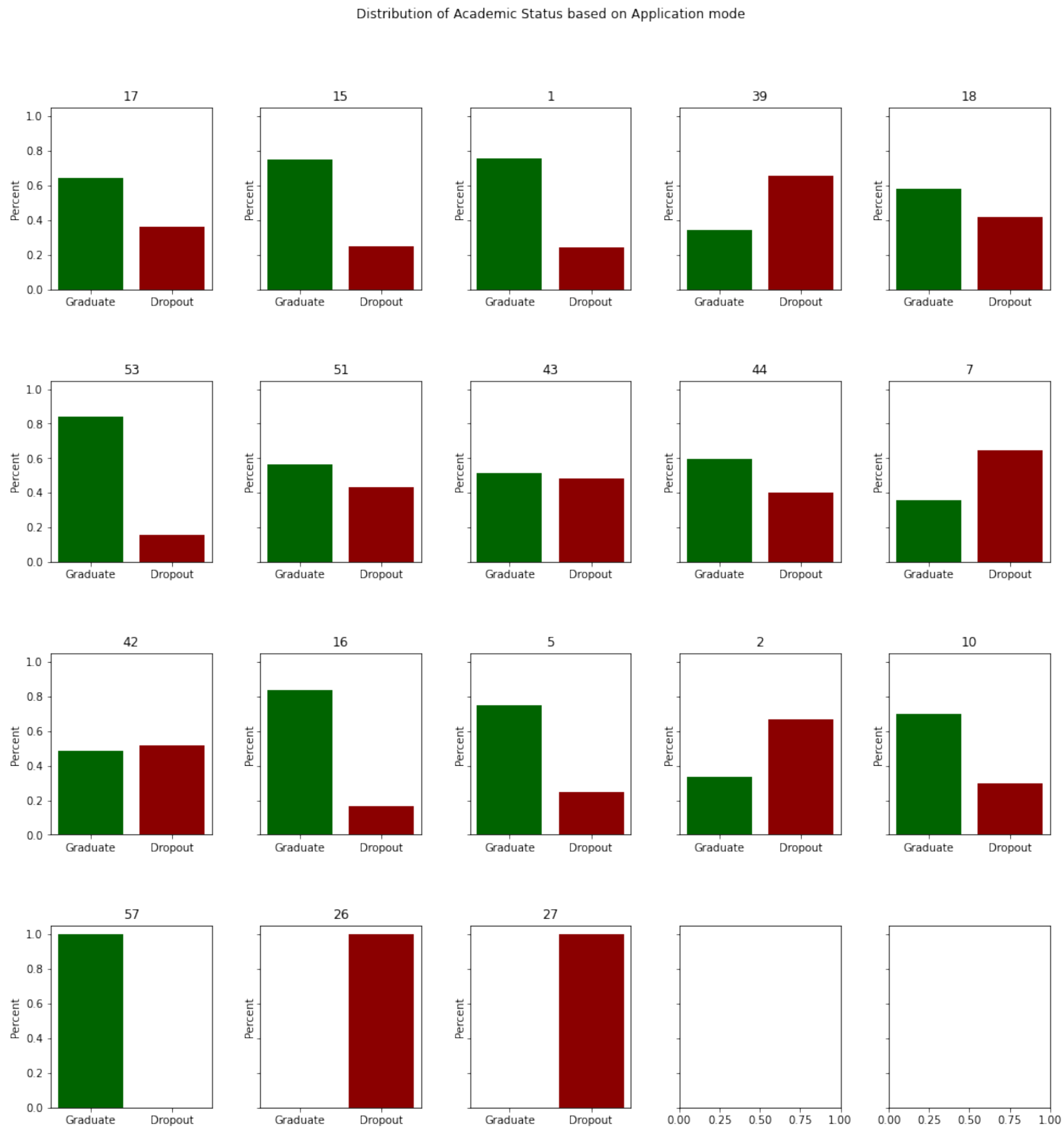
### 1.8.2 Column 1: Application Mode

[12]:
```
# select subset of dataset
col = df.columns[1]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 4
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
```

```
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




### Observation: Significant fluctuations within this feature

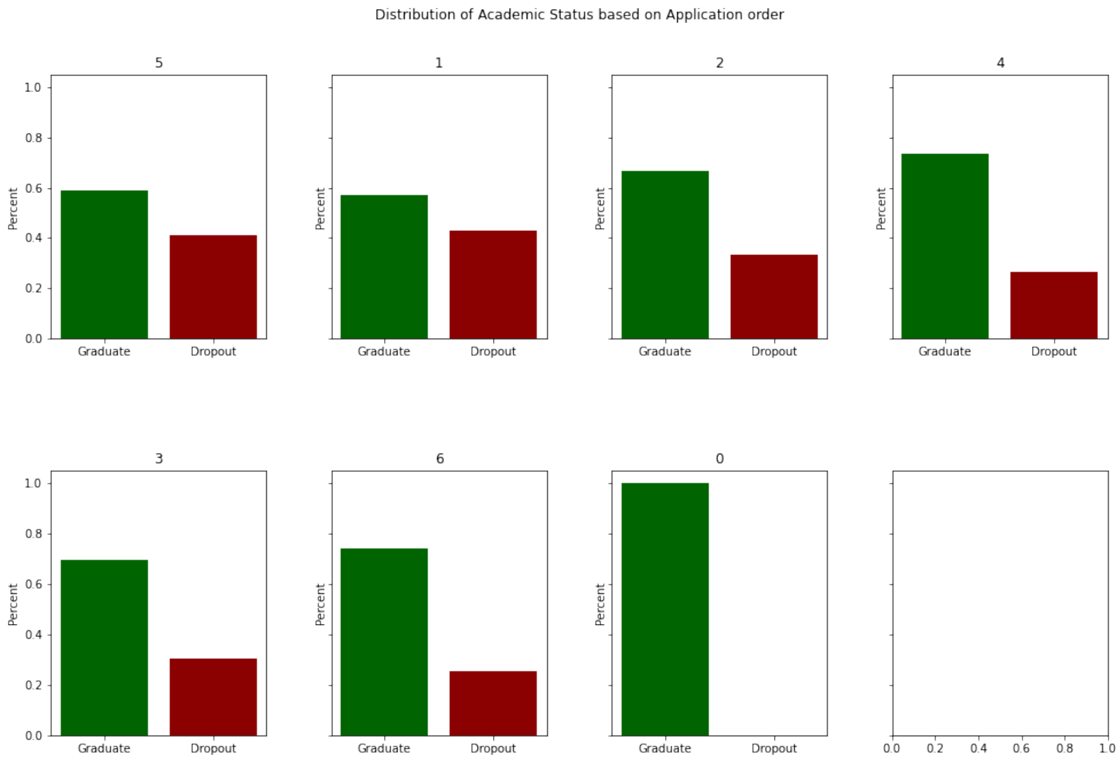
Likely an influential feature

### 1.8.3 Column 2: Application Order

[13]:
```
# select subset of dataset
col = df.columns[2]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 2
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 10),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




### Observation: Not much fluctuation within this feature

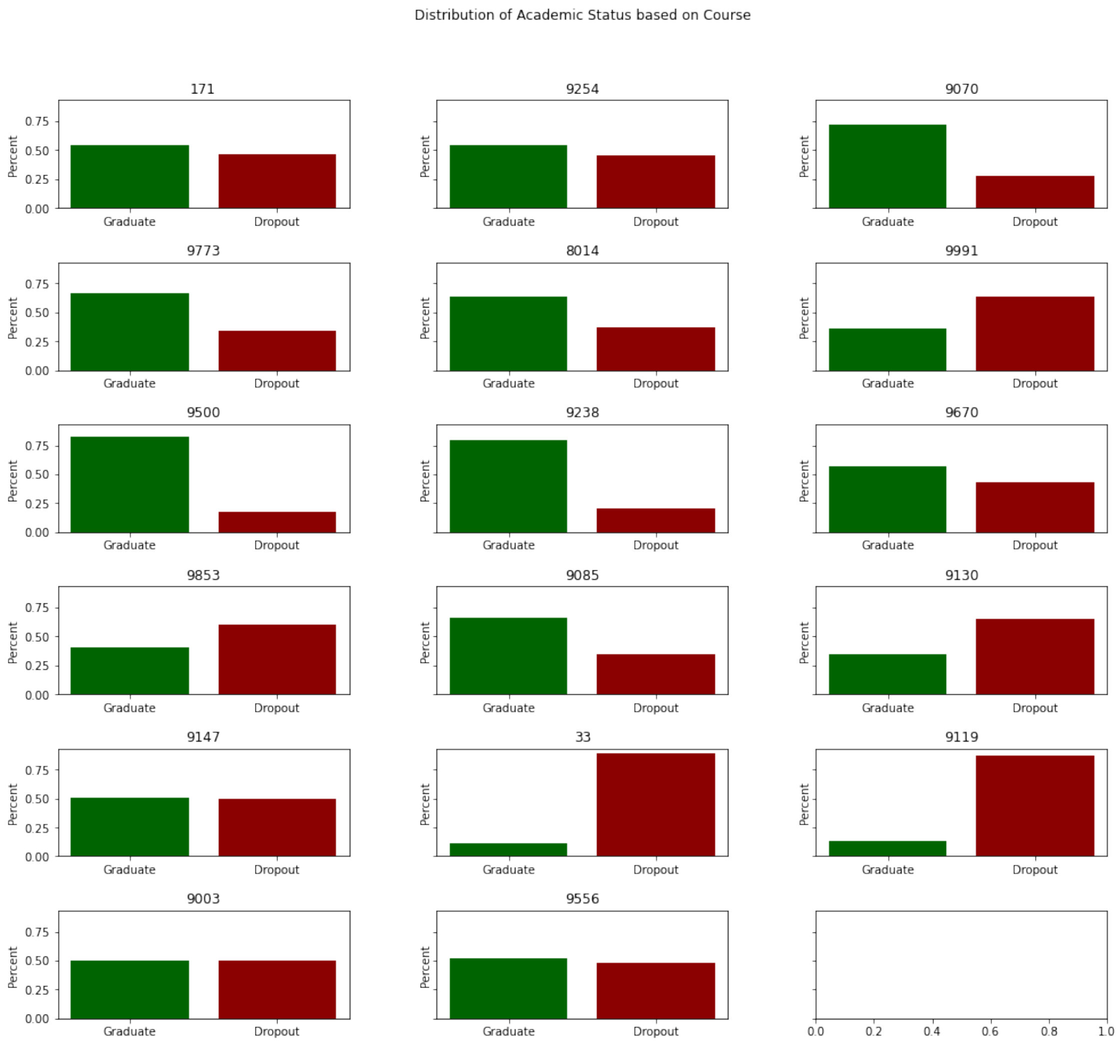
Probably not an influential feature

### 1.8.4 Column 3: Course

[14]:
```
# select subset of dataset
col = df.columns[3]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 6
subplots_width = 3
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 14),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)
```

```
# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

Likely an influential feature

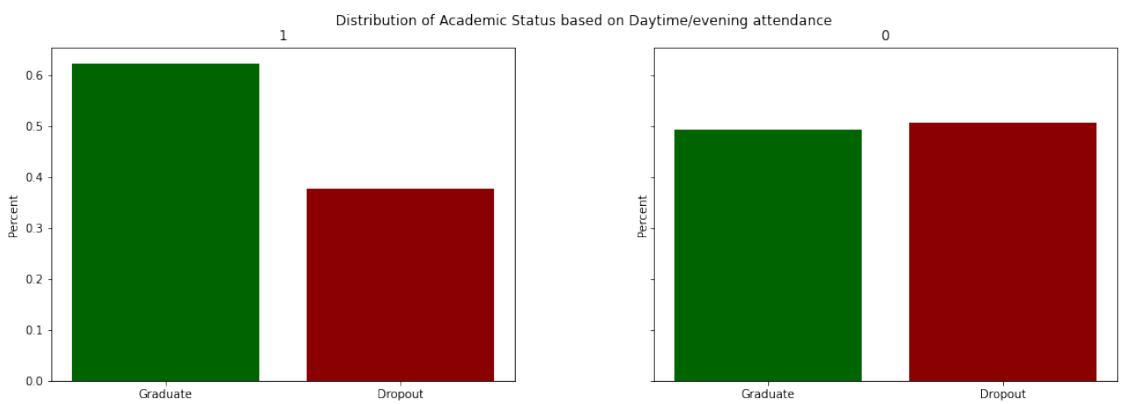
### 1.8.5 Column 4: Daytime/Evening attendance

[15]:
```
# select subset of dataset
col = df.columns[4]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
```

```
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col[:-1])
plt.show()
```




### Observation: Not much fluctuation within this feature

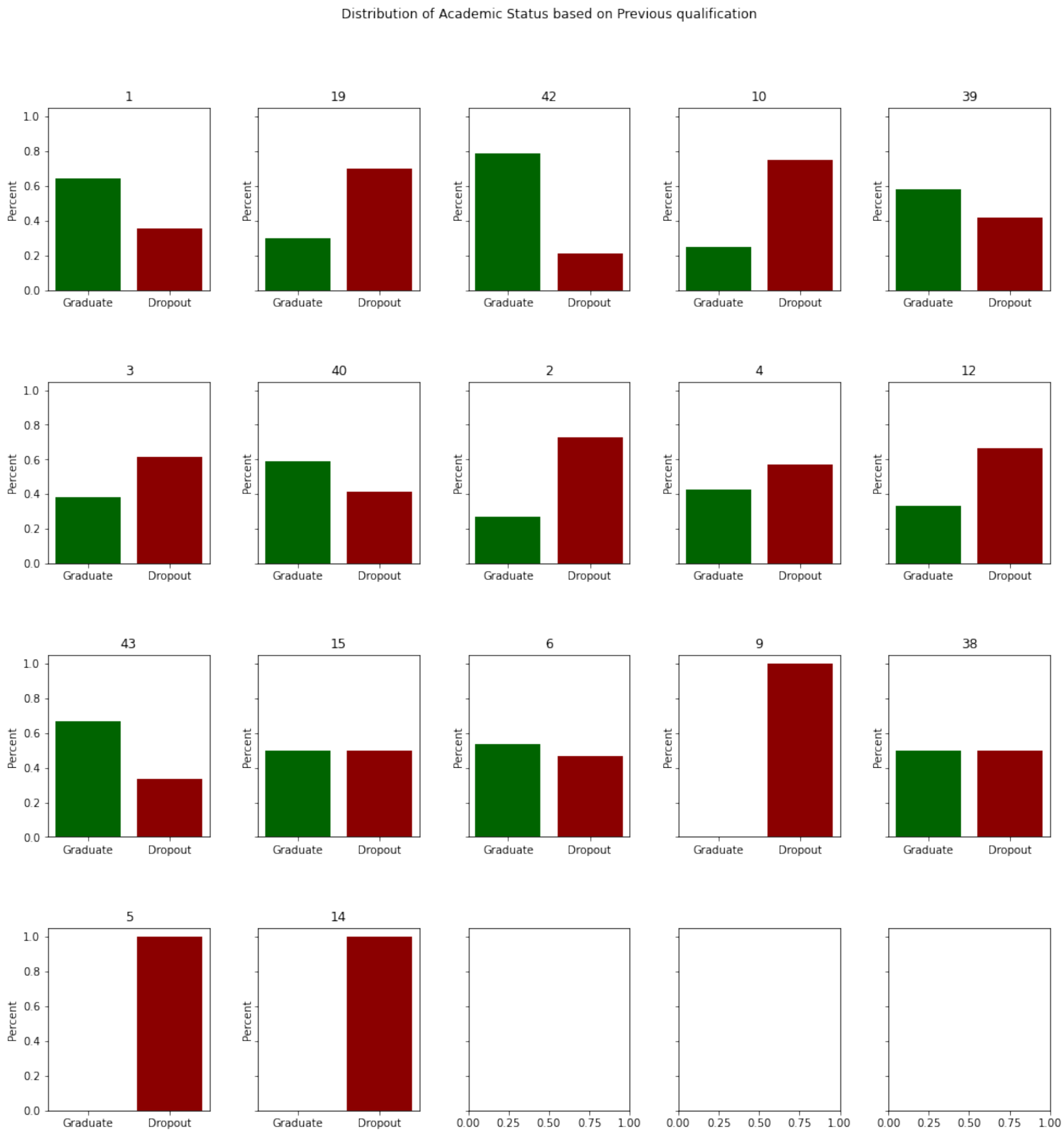
Probably not an influential feature

### 1.8.6 Column 5: Previous Qualification

[16]:
```
# select subset of dataset
col = df.columns[5]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 4
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




#### Observation: Significant fluctuation within this feature

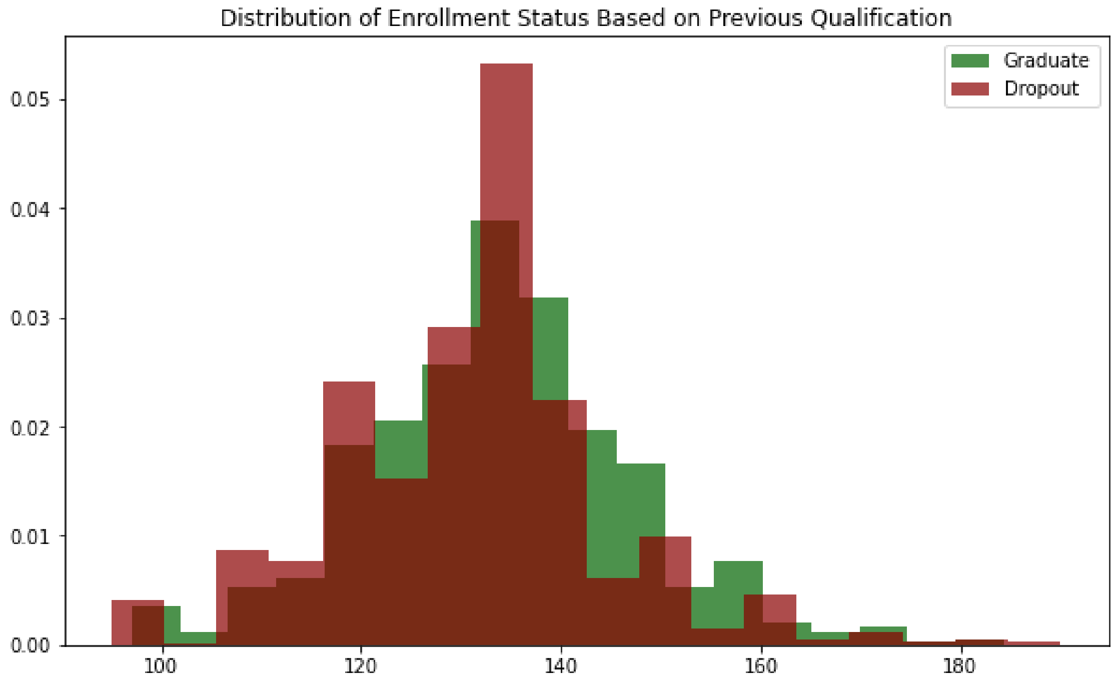
Probably an influential feature

### 1.8.7 Column 6: Previous Qualification (grade)

[17]:
```
col = df.columns[6]

plt.figure(figsize=(10,6))
feature_ser = df[col]
for target_val in ['Graduate', 'Dropout']:
```

```
    plt.hist(feature_ser[df['Target'] == target_val], color=colors[target_val],␣
 ↪alpha=.7, bins=18, label=target_val, density=True)
plt.title('Distribution of Enrollment Status Based on Previous Qualification')
plt.legend()
plt.show()
```




**Observation: Not much fluctuation within this feature (distributions are nearly the same)**

Probably not an influential feature

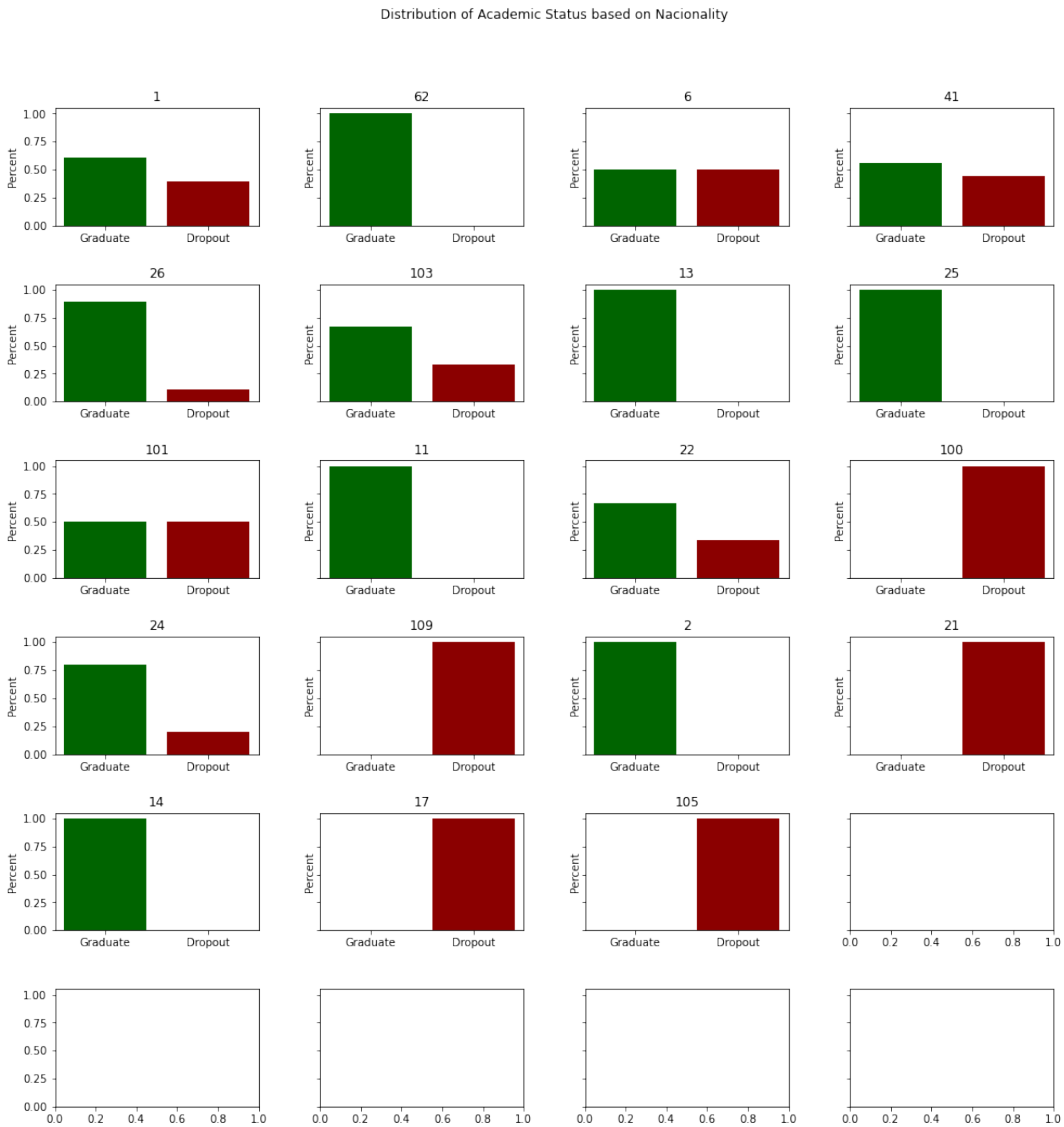
### 1.8.8 Column 7: Nationality

[18]:
```
# select subset of dataset
col = df.columns[7]
# group by feature column values, find %makeup for each target val (Graduate,␣
 ↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 6
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
```

```
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant differences within this feature (but also unequal representation of each type of nationality)**

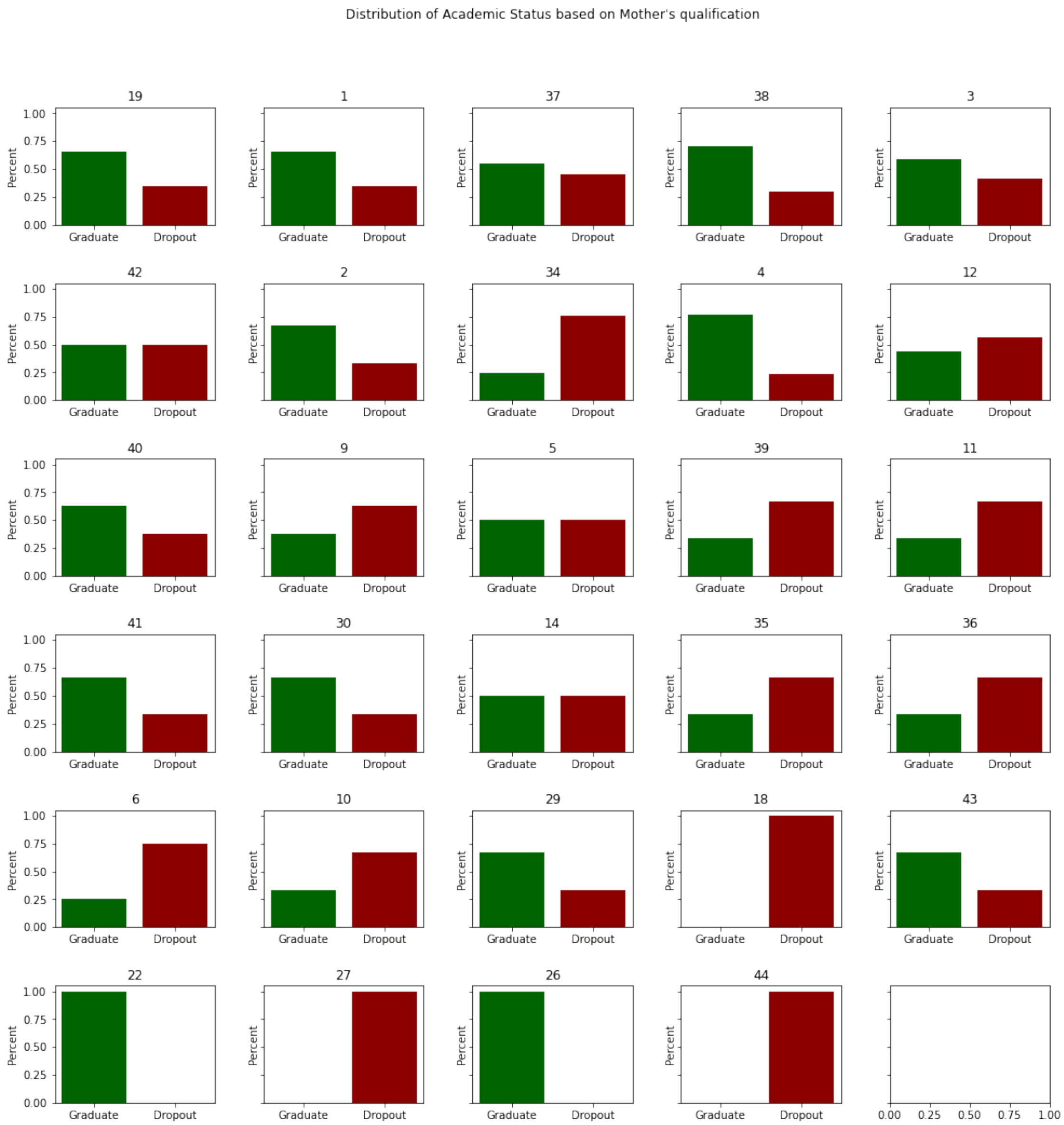
Maybe an influential feature

### 1.8.9 Column 8: Mother's Qualification

[19]:
```
# select subset of dataset
col = df.columns[8]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 6
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Generally few fluctuations; large variety draws concern to representation of each type of feature (mother's qualification) within whole dataset**

Probably not an influential feature

### 1.8.10 Column 9: Father's Qualification

[20]:
```
# select subset of dataset
col = df.columns[9]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 9
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
  ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
  ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
  ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
  ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```


**Observation: Lots of fluctuations; large variety draws concern to representation of each type of feature (father's qualification) within whole dataset. Lots of 100% dropout rates within types of features**

Likely an influential feature

### 1.8.11 Column 10: Mother's Occupation

[21]:
```
# select subset of dataset
col = df.columns[10]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
```

```
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 7
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```


**Observation: Lots of fluctuations; large variety draws concern to representation of each type of feature (mother's occupation) within whole dataset**

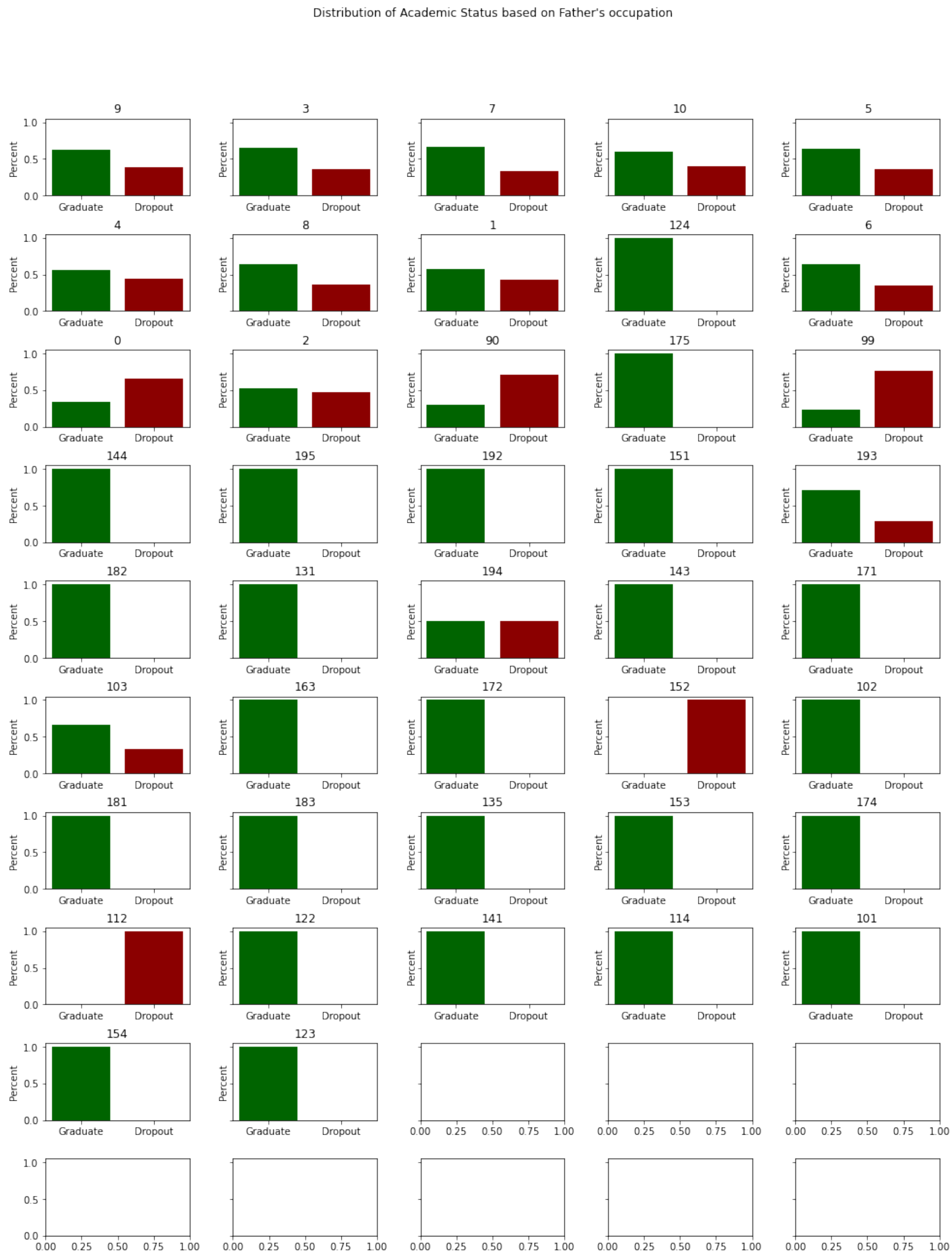
Likely an influential feature

### 1.8.12 Column 11: Father's Occupation

[22]:
```
# select subset of dataset
col = df.columns[11]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 10
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 20),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```



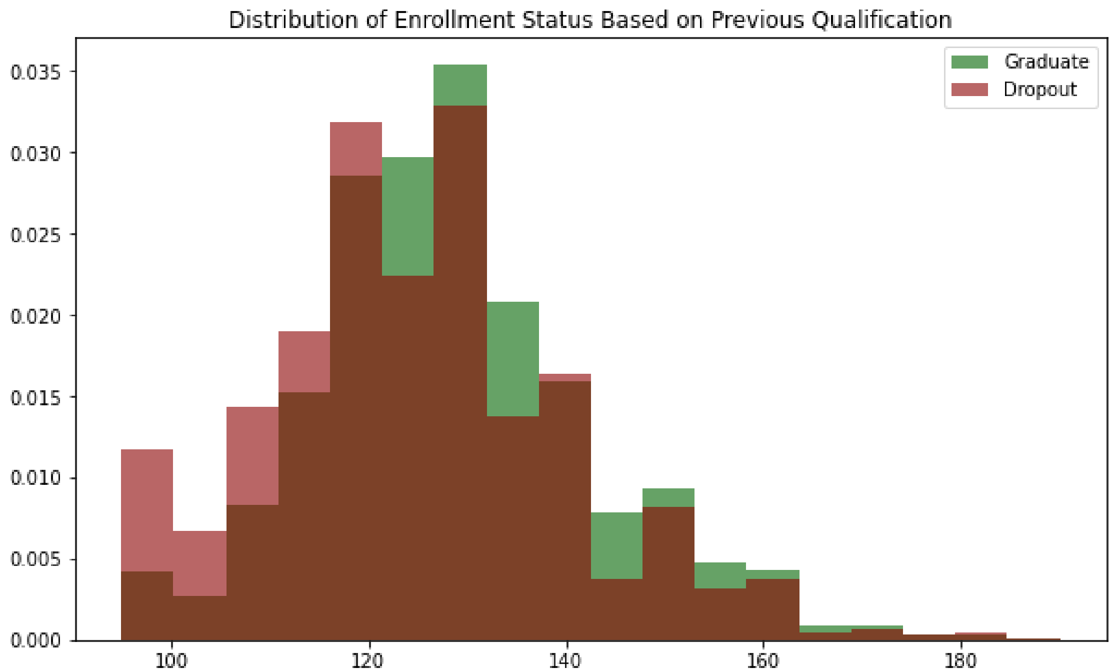

**Observation: Lots of fluctuations; large variety draws concern to representation of each type of feature (mother's occupation) within whole dataset. Lots of 100% graduation rates based on types of feature.**

Likely an influential feature

### 1.8.13 Column 12: Admission Grade

[23]:
```
col = df.columns[12]

plt.figure(figsize=(10,6))
feature_ser = df[col]
for target_val in ['Graduate', 'Dropout']:
    plt.hist(feature_ser[df['Target'] == target_val], color=colors[target_val],␣
 ↪alpha=.6, bins=18, label=target_val, density=True)
plt.title('Distribution of Enrollment Status Based on Previous Qualification')
plt.legend()
plt.show()
```




**Observation: Very similar distribution within each enrollment status**

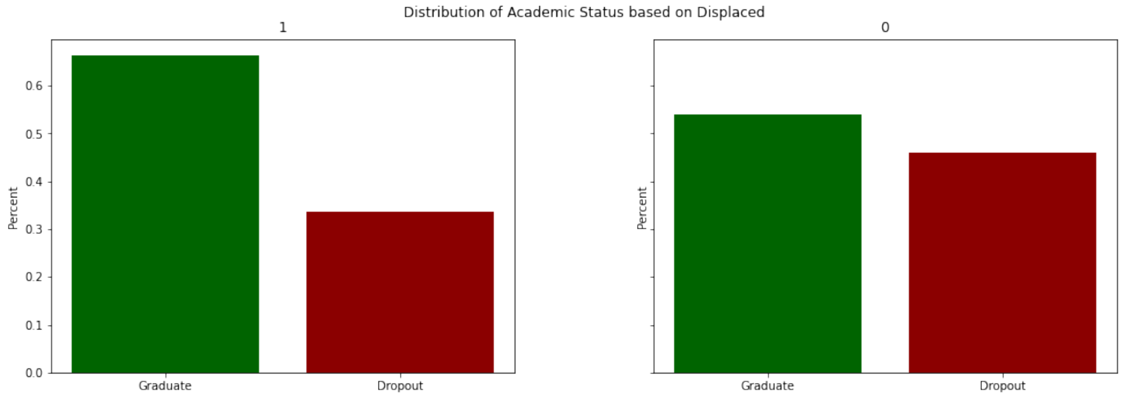
Probably not an influential feature

### 1.8.14 Column 13: Displaced

[24]:
```
# select subset of dataset
col = df.columns[13]
# group by feature column values, find %makeup for each target val (Graduate,␣
 ↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```



**Observation: Very similar distributions**

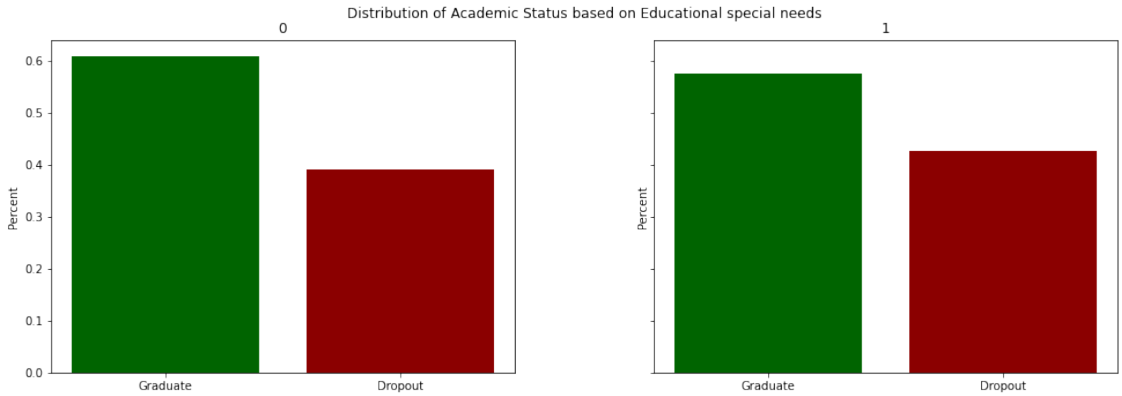
Probably not an influential feature

#### 1.8.15 Column 14: Education Special Needs

[25]:
```
# select subset of dataset
col = df.columns[14]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Very similar distributions.**

Probably not an influential feature

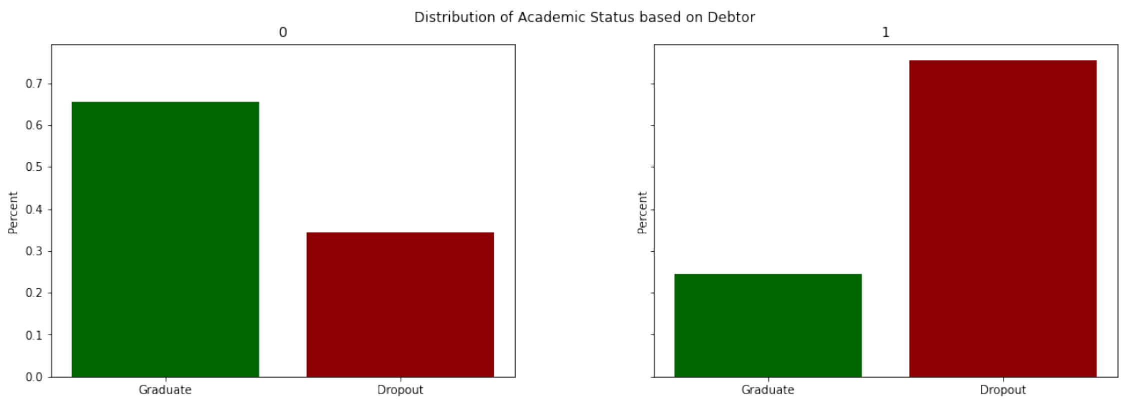
### 1.8.16 Column 15: Debtor

[26]:
```
# select subset of dataset
col = df.columns[15]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
```

```
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Very different distributions.**

Very likely to be an influential feature

## 2 Summary on EDA for Columns 0-15:

- Columns #0; Marital status : likely
- Columns #1; Application mode : Likely
- Columns #2; Application order : Unlikely
- Columns #3; Course : Likely
- Columns #4; Daytime/evening attendance : Unlikely
- Columns #5; Previous qualification : Likely
- Columns #6; Previous qualification (grade) : Unlikely
- Columns #7; Nationality : Likely
- Columns #8; Mother's qualification : Unlikely
- Columns #9; Father's qualification : Likely
- Columns #10; Mother's occupation : Likely
- Columns #11; Father's occupation : Likely
- Columns #12; Admission grade : Unlikely
- Columns #13; Displaced : Unlikely
- Columns #14; Educational special needs : Unlikely
- Columns #15; Debtor : Likely

[27]:
```
# print #uniqe values per column
for i in range(16,36):
    print('Columns #' + str(i) + '; ' + df.columns[i] + ' has ' + str(len(df[df.
↪columns[i]].unique())) + ' unique values')
```

```
Columns #16; Tuition fees up to date has 2 unique values
Columns #17; Gender has 2 unique values
Columns #18; Scholarship holder has 2 unique values
Columns #19; Age at enrollment has 46 unique values
Columns #20; International has 2 unique values
Columns #21; Curricular units 1st sem (credited) has 21 unique values
Columns #22; Curricular units 1st sem (enrolled) has 23 unique values
Columns #23; Curricular units 1st sem (evaluations) has 35 unique values
Columns #24; Curricular units 1st sem (approved) has 23 unique values
Columns #25; Curricular units 1st sem (grade) has 752 unique values
Columns #26; Curricular units 1st sem (without evaluations) has 11 unique values
Columns #27; Curricular units 2nd sem (credited) has 19 unique values
Columns #28; Curricular units 2nd sem (enrolled) has 22 unique values
Columns #29; Curricular units 2nd sem (evaluations) has 29 unique values
Columns #30; Curricular units 2nd sem (approved) has 20 unique values
Columns #31; Curricular units 2nd sem (grade) has 724 unique values
Columns #32; Curricular units 2nd sem (without evaluations) has 10 unique values
Columns #33; Unemployment rate has 10 unique values
Columns #34; Inflation rate has 9 unique values
Columns #35; GDP has 10 unique values
```

[28]:
```
# categorical columns are num␣
↪16,17,18,20,21,22,23,24,26,27,28,29,30,32,33,34,35; use bar charts
# continuous columns are num 19,25,31; use histogram
```

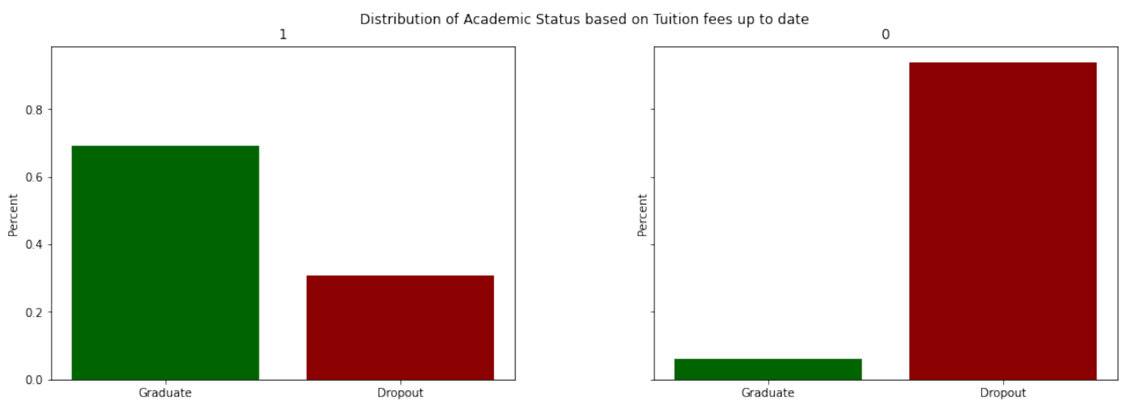
### 2.0.1 Column 16: Tuition fees up to date

[29]:
```
# select subset of dataset
col = df.columns[16]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
```

```
                     top=0.9,
                     wspace=0.3,
                     hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




### observation: significant difference with features

Likely an influential feature

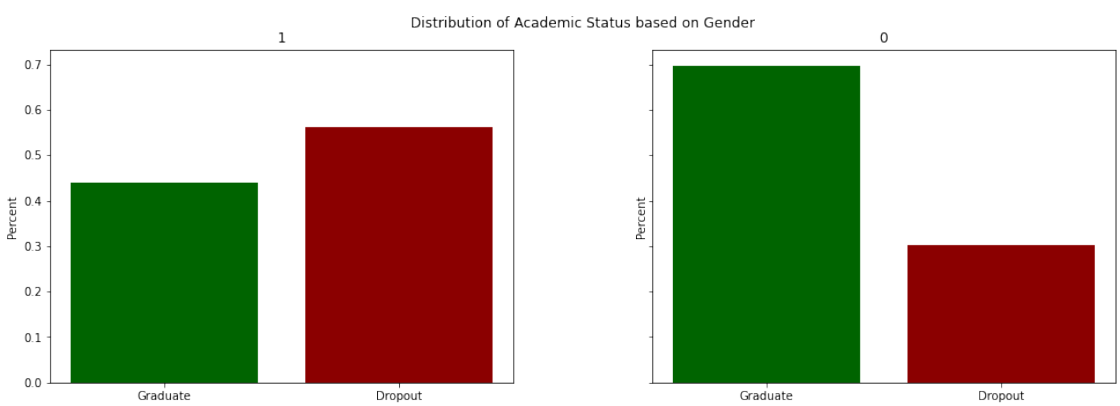
### 2.0.2 Columns 17; Gender

[30]:
```
# select subset of dataset
col = df.columns[17]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
```

```python
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5), sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```



**observation: Not much fluctuation within this feature**

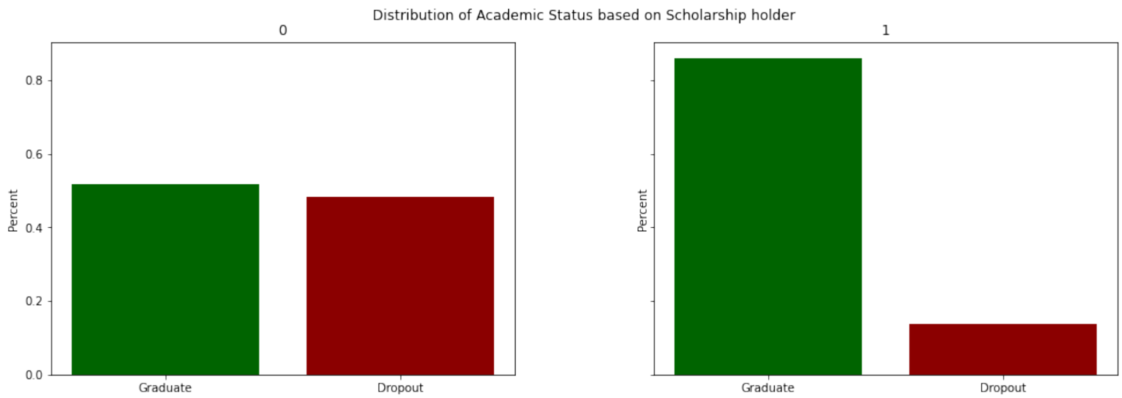
Probably not an influential feature

### 2.0.3 Columns 18: Scholarship holder

[31]:
```
# select subset of dataset
col = df.columns[18]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```



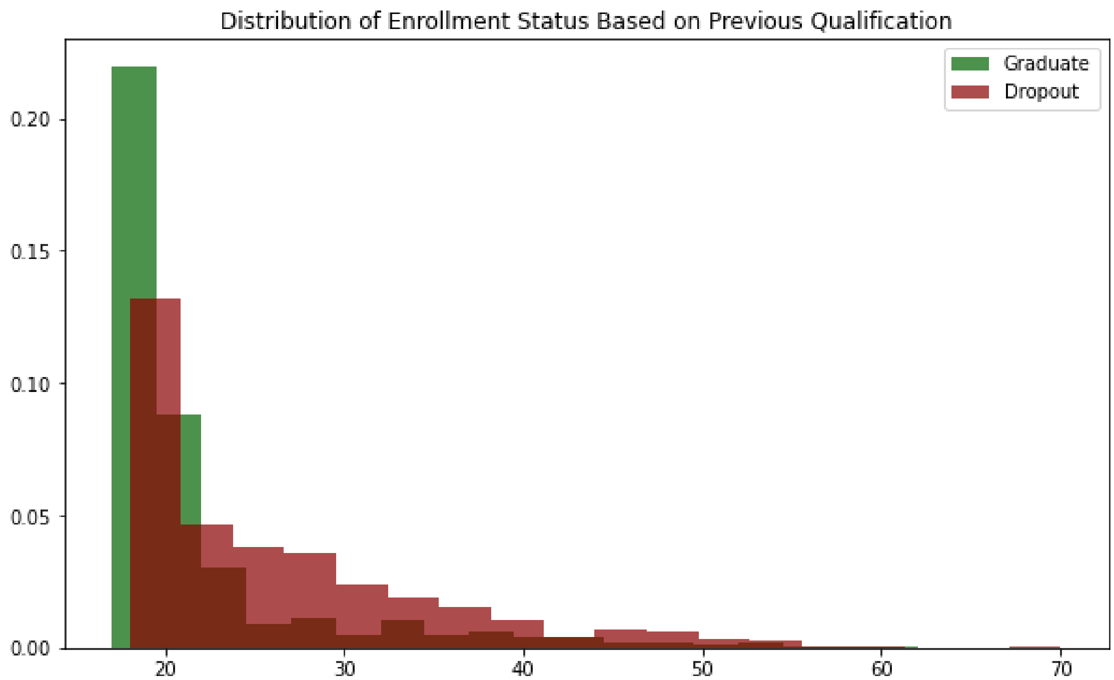

**observation: significant difference with features**

Likely an influential feature

### 2.0.4 Columns 19: Age at enrollment

[32]:
```
col = df.columns[19]

plt.figure(figsize=(10,6))
feature_ser = df[col]
for target_val in ['Graduate', 'Dropout']:
    plt.hist(feature_ser[df['Target'] == target_val], color=colors[target_val],␣
 ↪alpha=.7, bins=18, label=target_val, density=True)
plt.title('Distribution of Enrollment Status Based on Previous Qualification')
plt.legend()
plt.show()
```




**Observation: Not much fluctuation within this feature (distributions are nearly the same)**

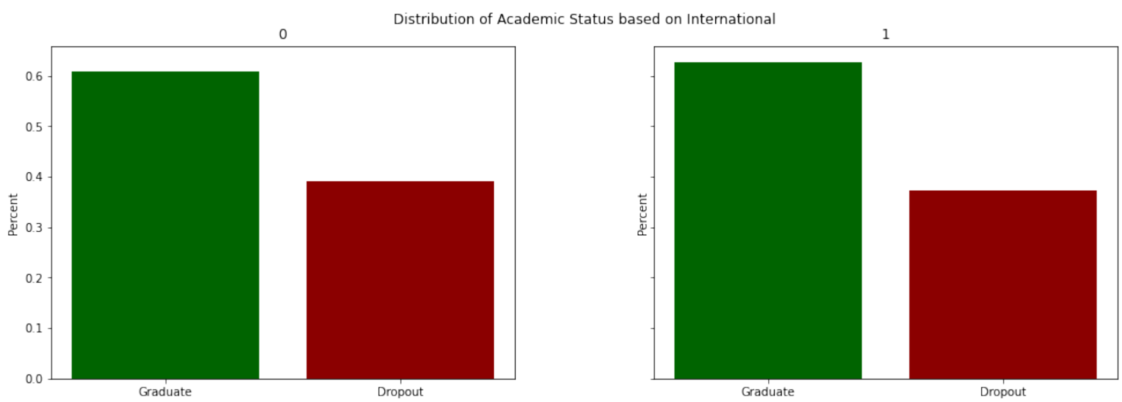
Probably not an influential feature

### 2.0.5 Columns 20: International

[33]:
```
# select subset of dataset
col = df.columns[20]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 1
subplots_width = 2
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 5),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)
```

```
# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[i].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[i].set_title(feature_vals[i])
    # set y-axis title
    axs[i].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**observation: Not much fluctuation within this feature**

Probably not an influential feature

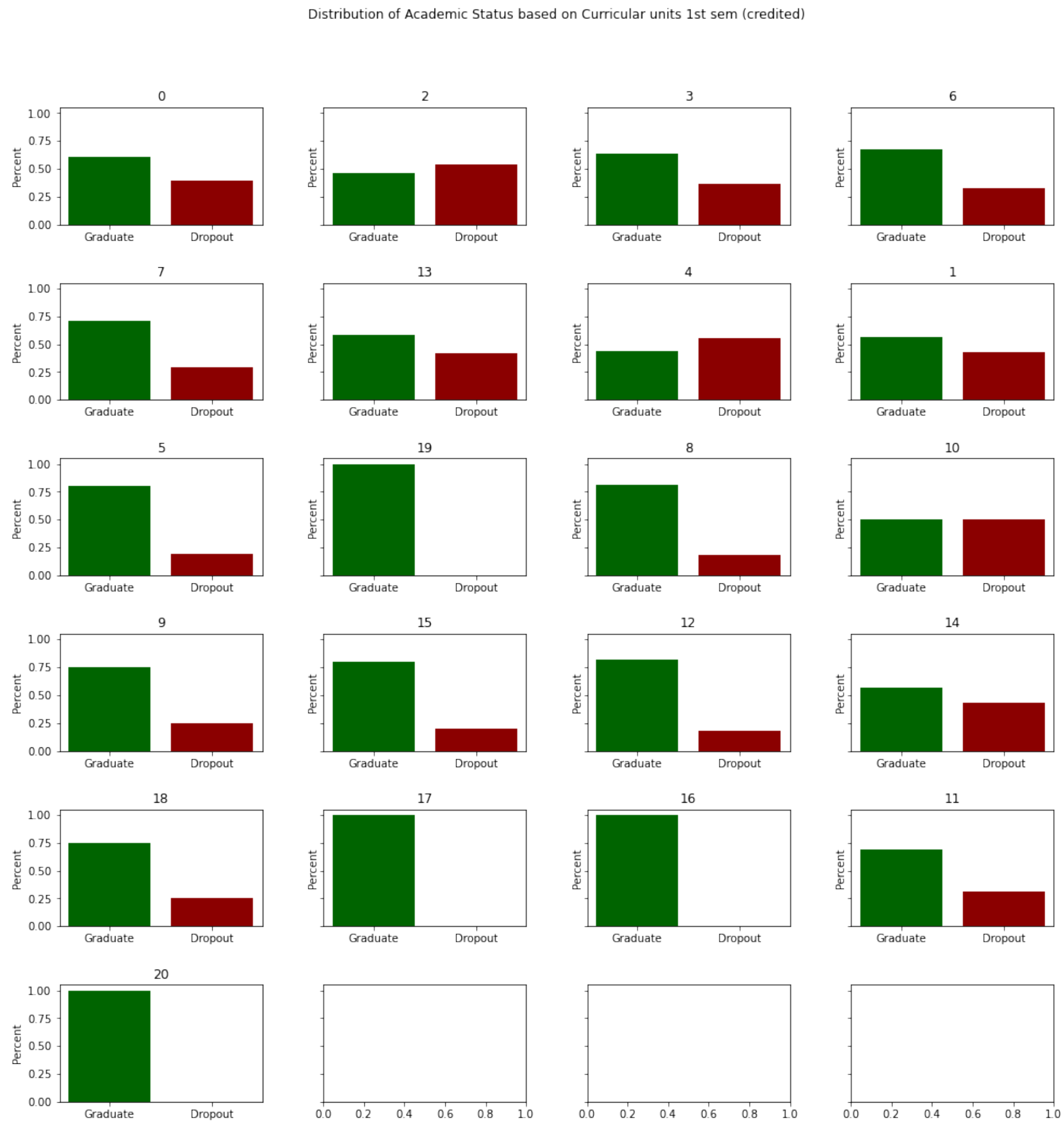
### 2.0.6 Columns 21: Curricular units 1st sem (credited)

[34]:
```
# select subset of dataset
col = df.columns[21]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 6
```

```python
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**observation: Not much fluctuation within this feature**

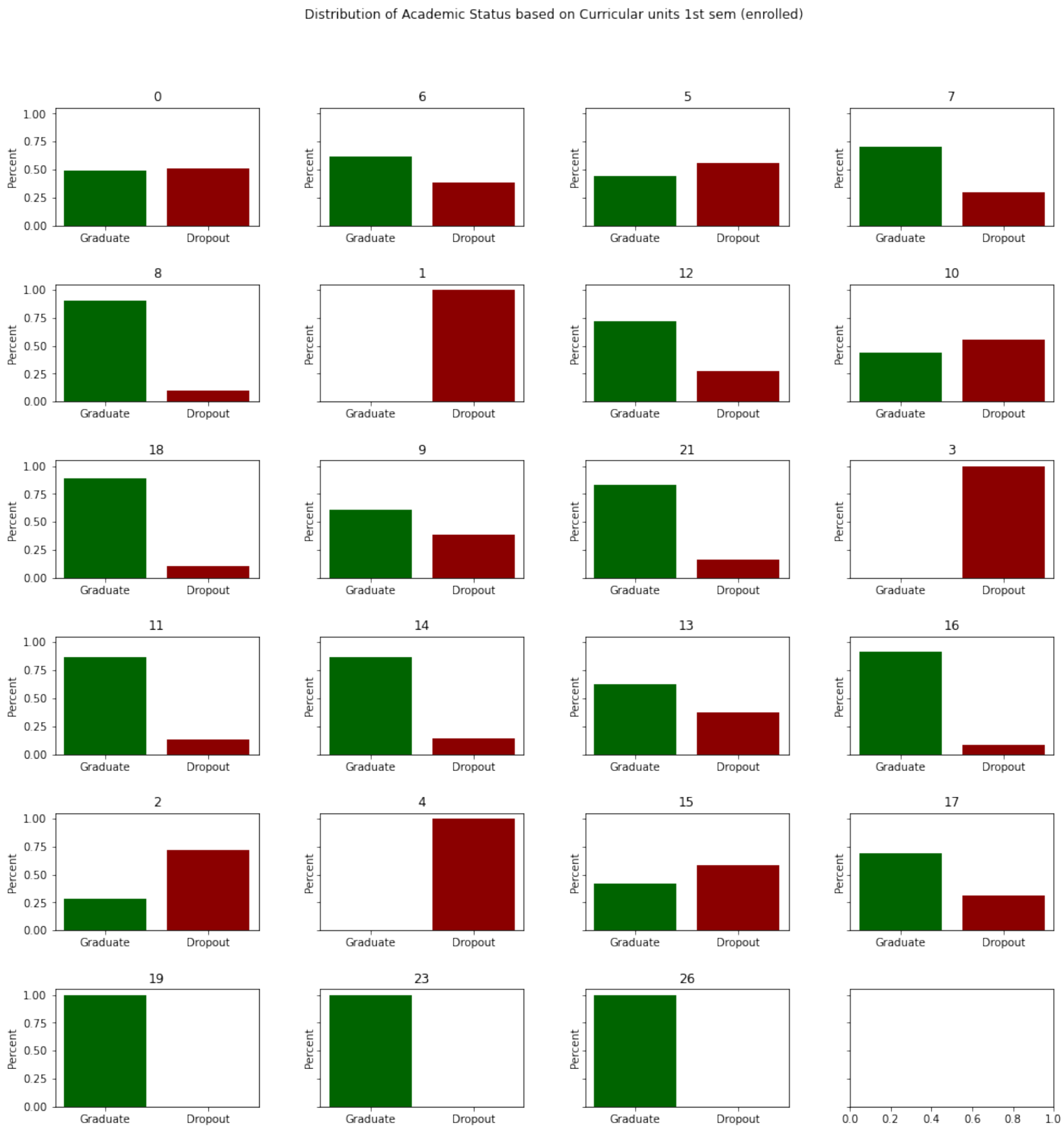
Probably not an influential feature

### 2.0.7 Columns 22: Curricular units 1st sem (enrolled)

[35]:
```
# select subset of dataset
col = df.columns[22]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 6
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




#### Observation: Significant difference within some feature types

Likely an influential feature

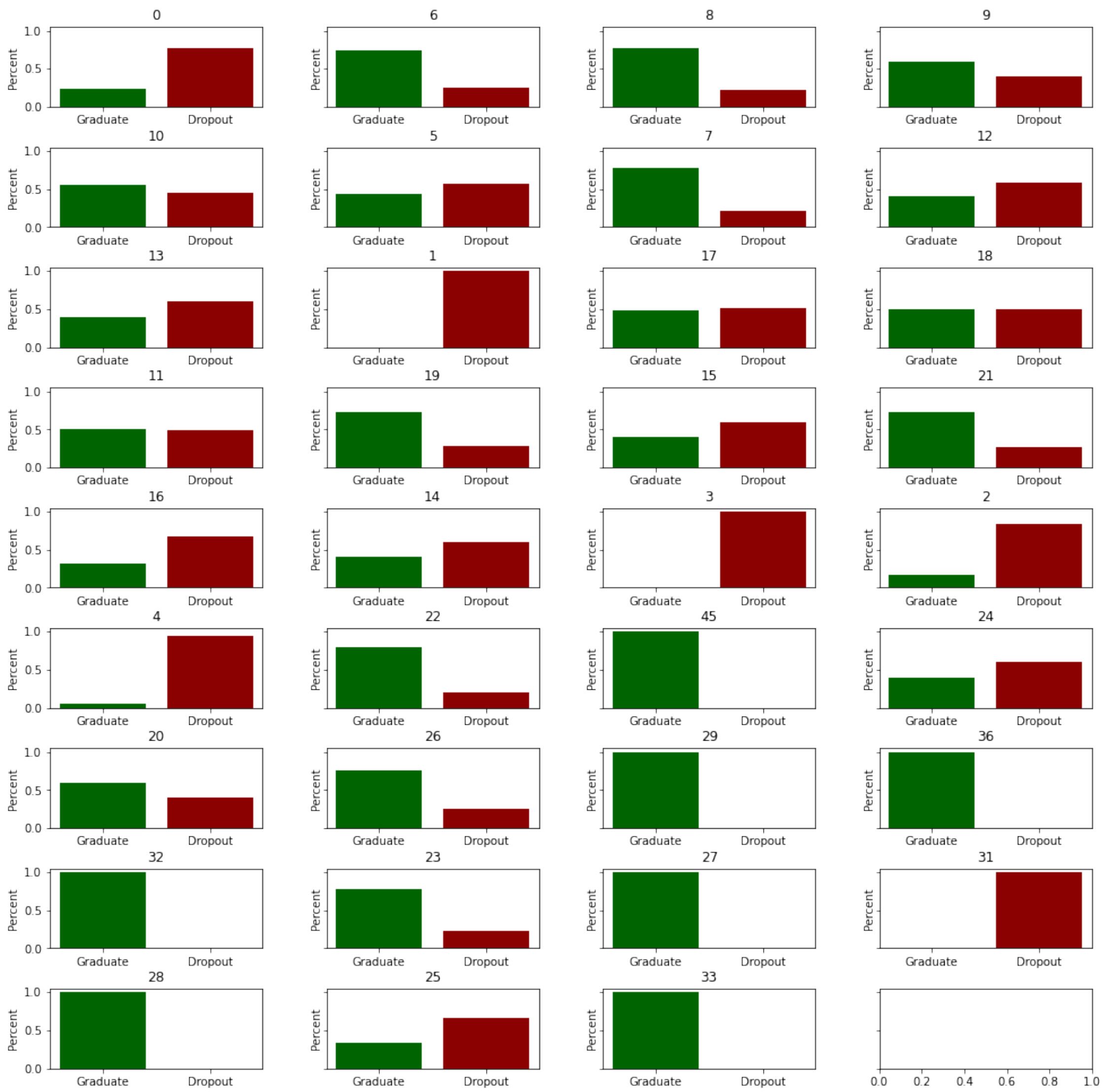
### 2.0.8 Columns 23: Curricular units 1st sem (evaluations)

[36]:
```
# select subset of dataset
col = df.columns[23]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 9
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```

Distribution of Academic Status based on Curricular units 1st sem (evaluations)




**Observation: Significant difference within some feature types**

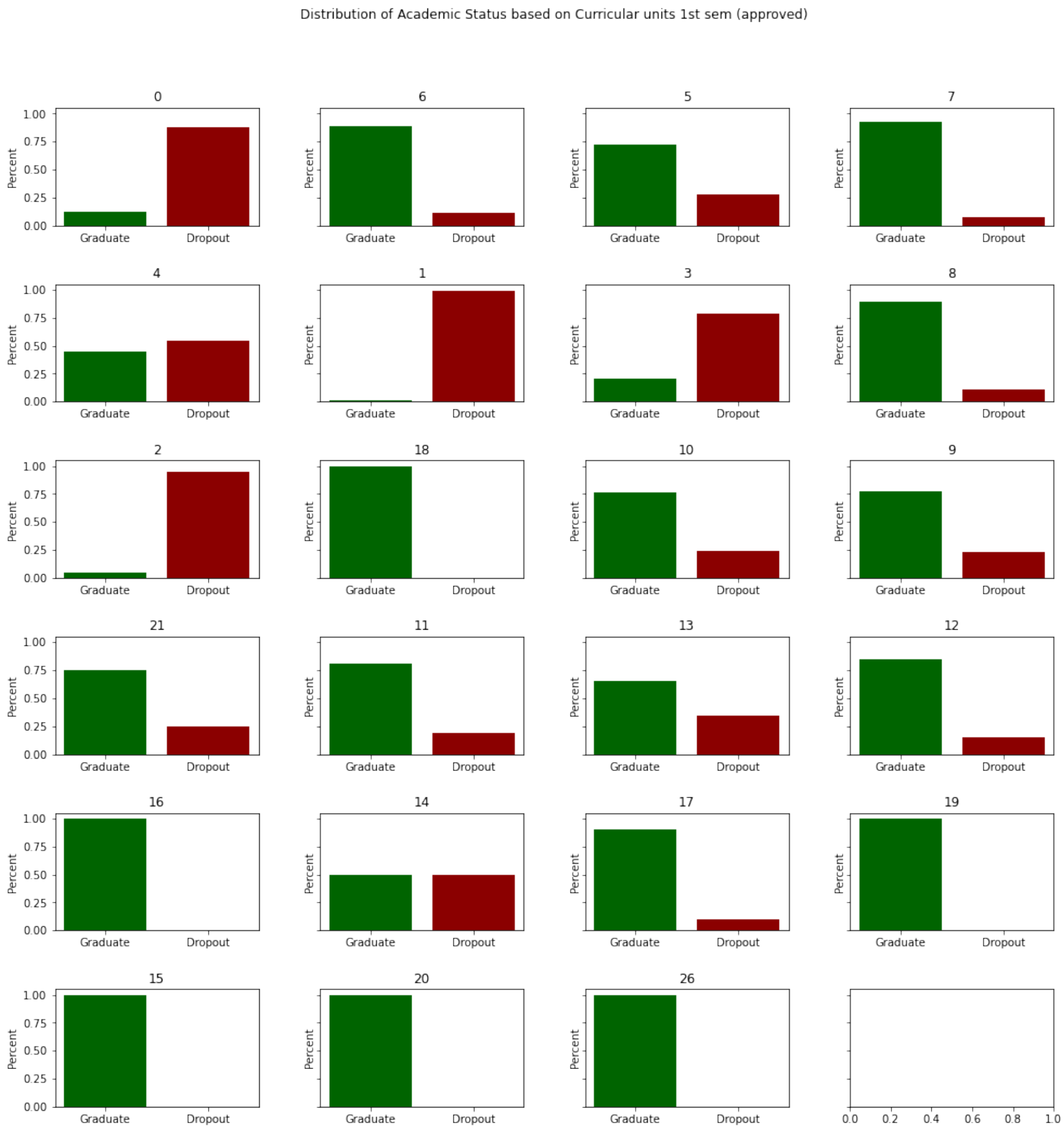
Likely an influential feature

### 2.0.9 Columns 24: Curricular units 1st sem (approved)

[37]:
```
# select subset of dataset
col = df.columns[24]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 6
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

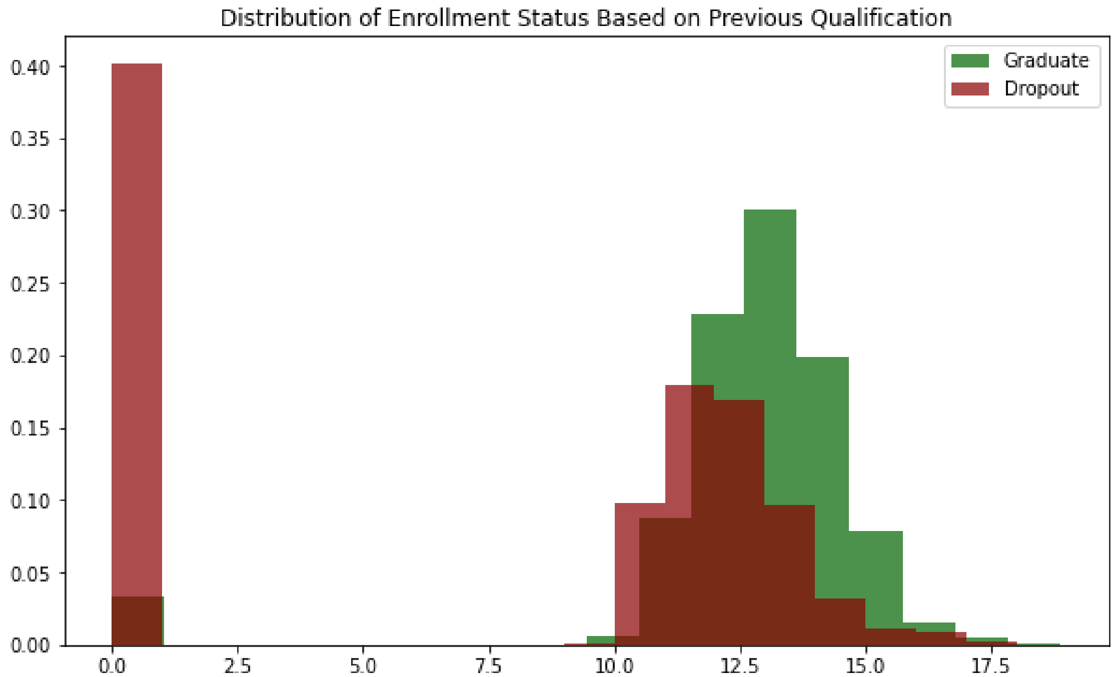
Likely an influential feature

### 2.0.10 Columns 25: Curricular units 1st sem (grade)

[38]:
```python
col = df.columns[25]

plt.figure(figsize=(10,6))
feature_ser = df[col]
for target_val in ['Graduate', 'Dropout']:
```

```
    plt.hist(feature_ser[df['Target'] == target_val], color=colors[target_val],␣
↪alpha=.7, bins=18, label=target_val, density=True)
plt.title('Distribution of Enrollment Status Based on Previous Qualification')
plt.legend()
plt.show()
```




**Observation: Not much fluctuation within this feature (distributions are nearly the same)**

Probably not an influential feature

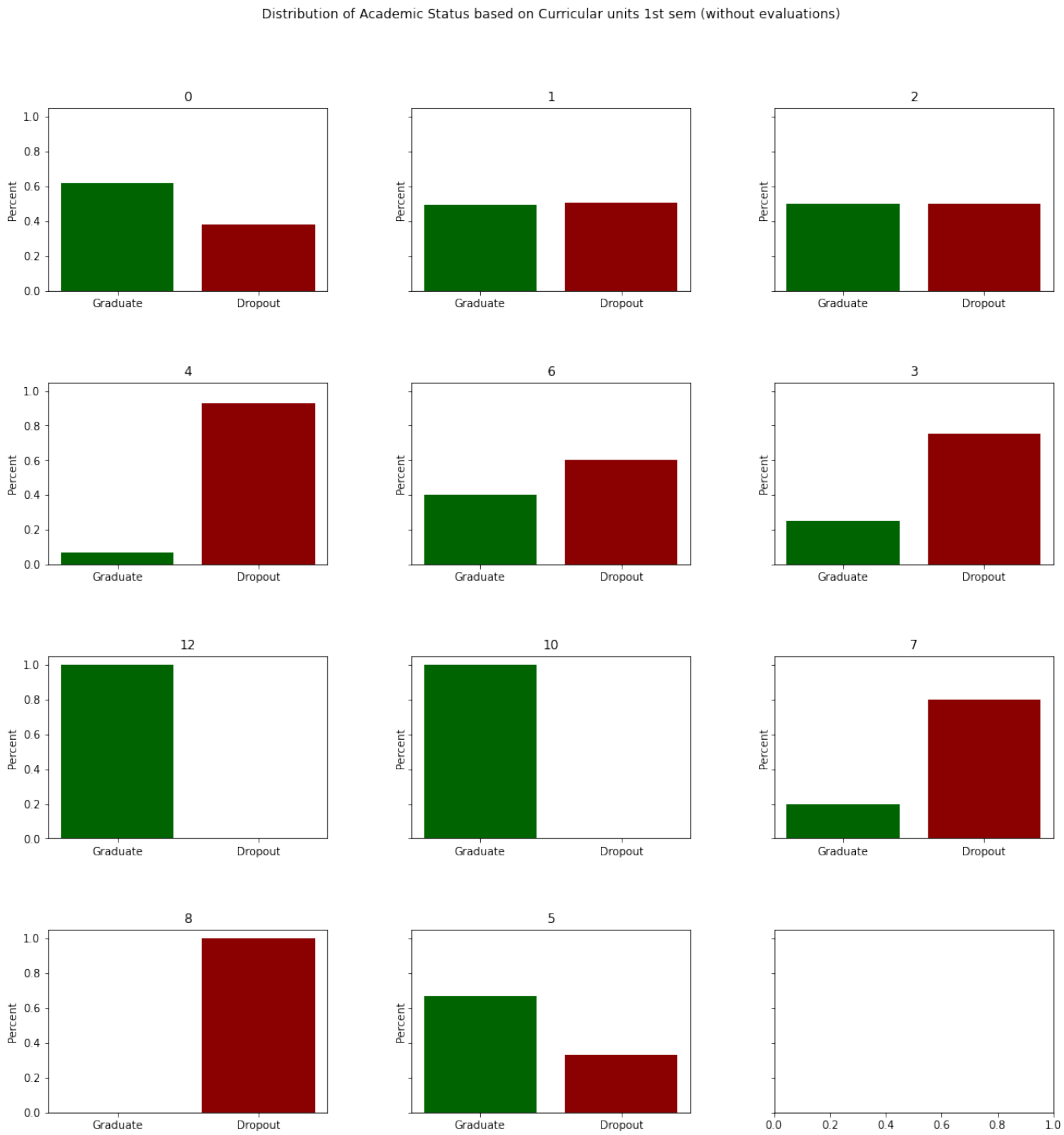
### 2.0.11 Columns 26: Curricular units 1st sem (without evaluations)

[39]:
```
# select subset of dataset
col = df.columns[26]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 4
subplots_width = 3
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
```

```
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

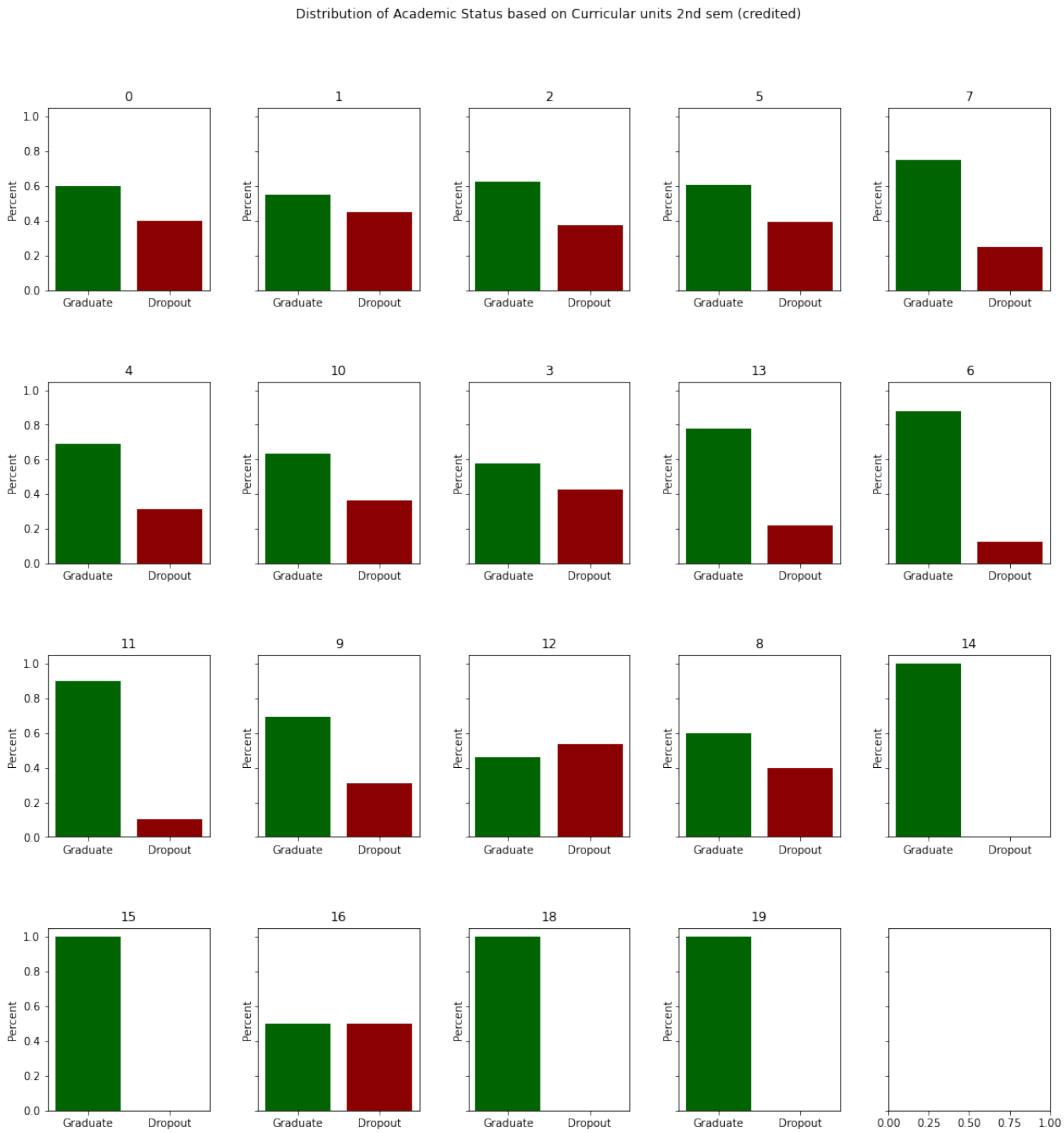
Likely an influential feature

### 2.0.12 Columns 27: Curricular units 2nd sem (credited)

[40]:
```
# select subset of dataset
col = df.columns[27]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 4
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16), sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




### Observation: Significant difference within some feature types

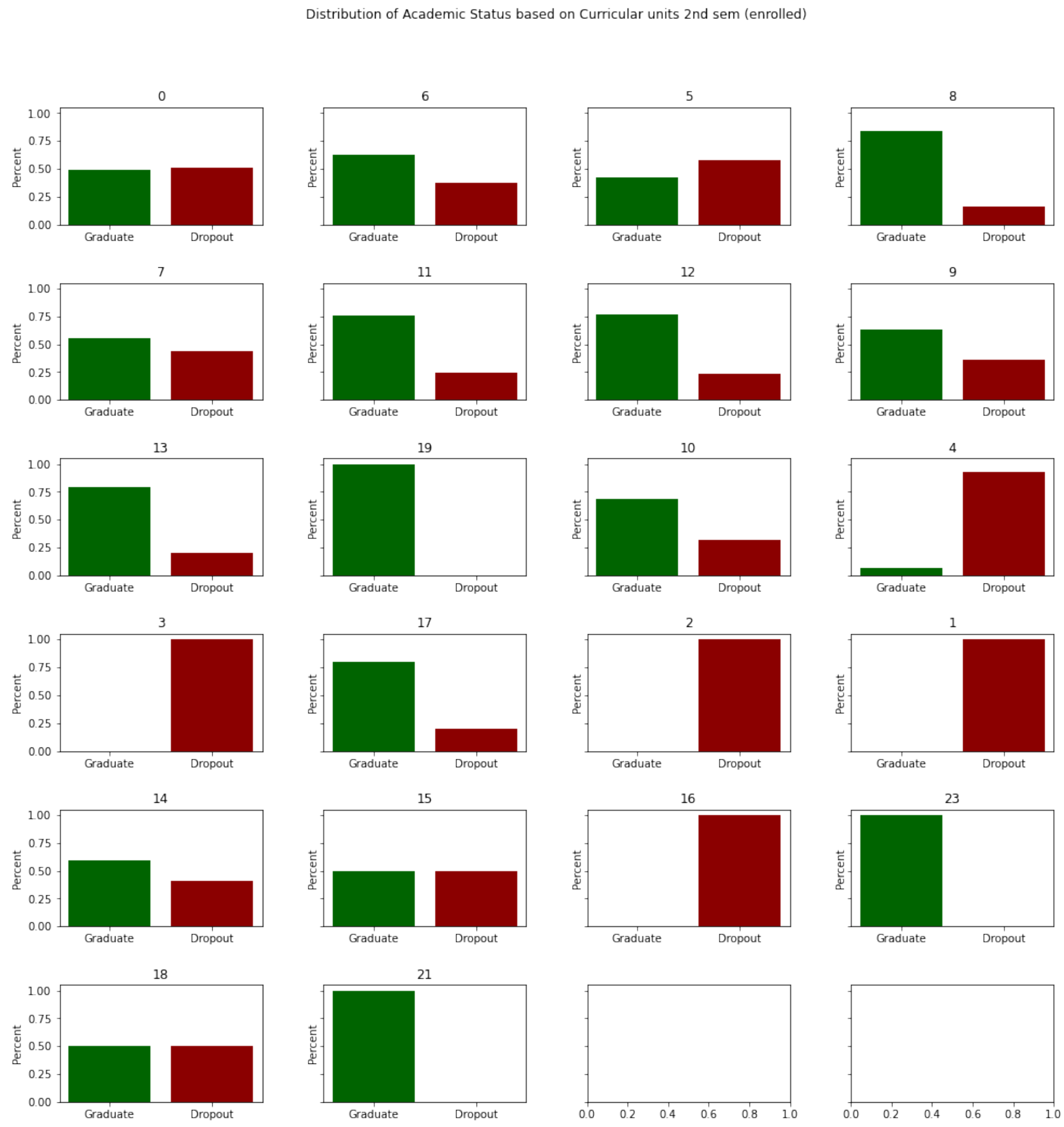
Likely an influential feature

### 2.0.13 Columns 28: Curricular units 2nd sem (enrolled)

[41]:
```
# select subset of dataset
col = df.columns[28]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 6
subplots_width = 4
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




### Observation: Significant difference within some feature types

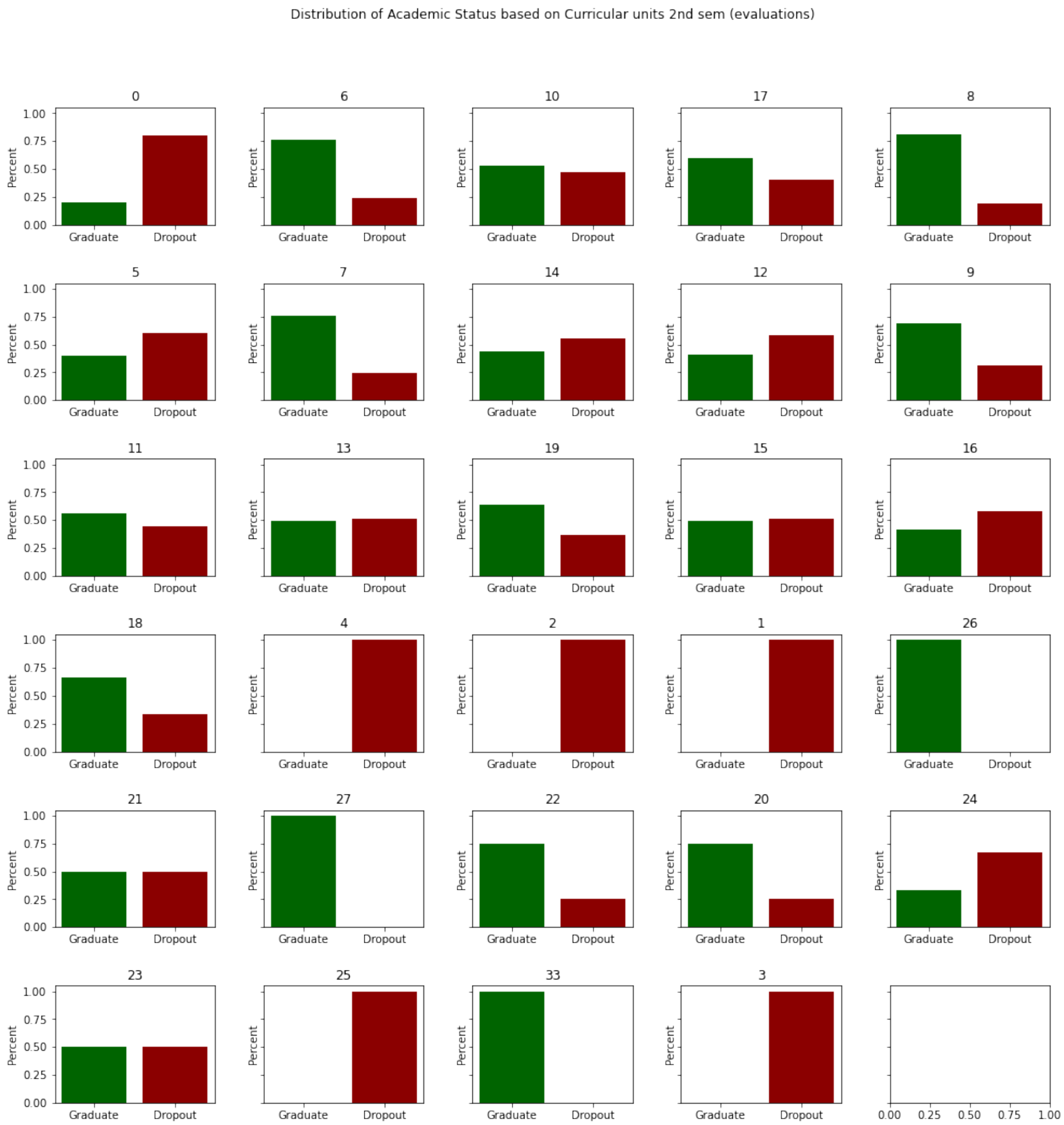
Likely an influential feature

### 2.0.14 Columns 29: Curricular units 2nd sem (evaluations)

[42]:
```
# select subset of dataset
col = df.columns[29]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 6
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

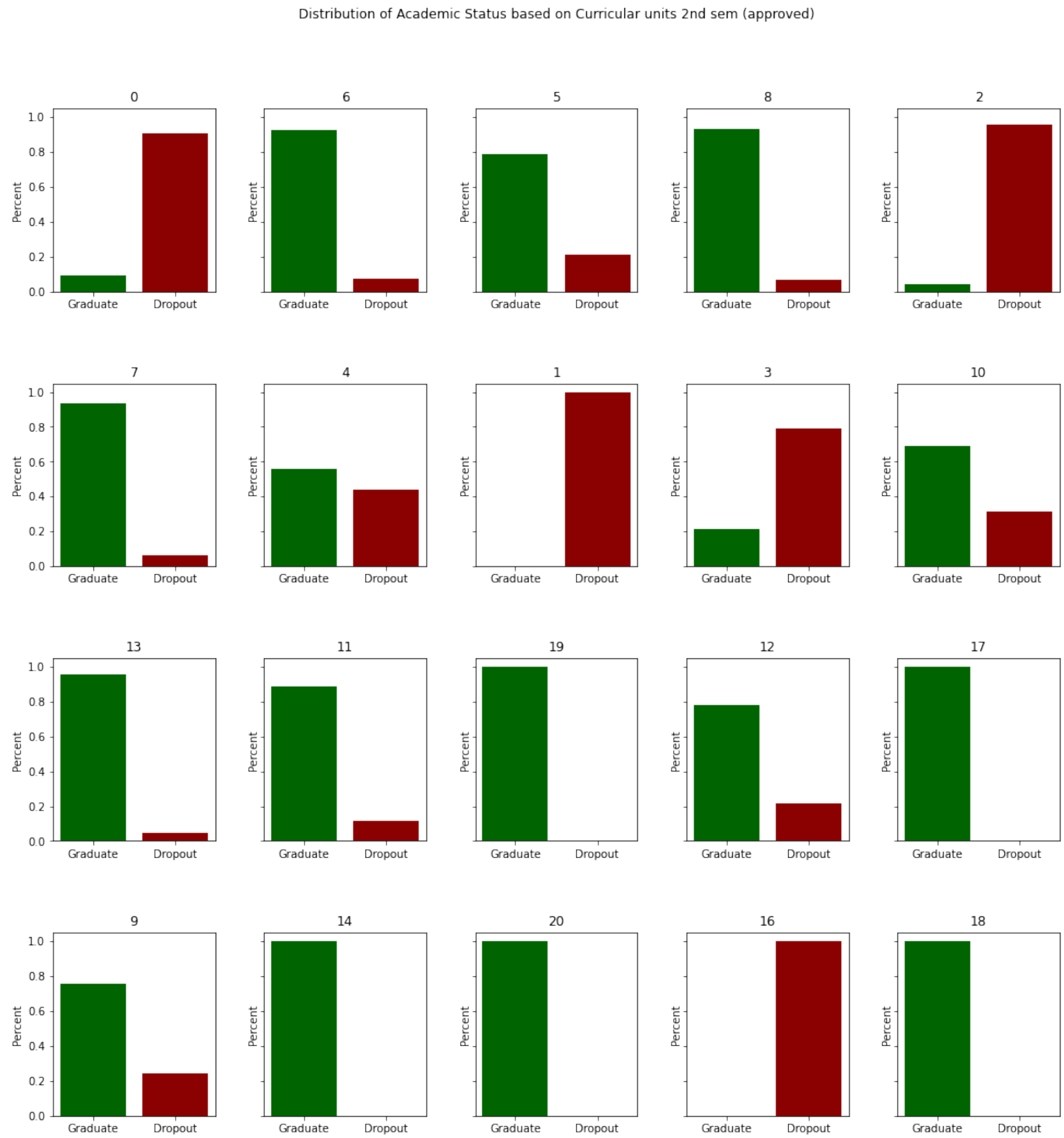
Likely an influential feature

### 2.0.15 Columns 30: Curricular units 2nd sem (approved)

[43]:
```
# select subset of dataset
col = df.columns[30]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 4
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

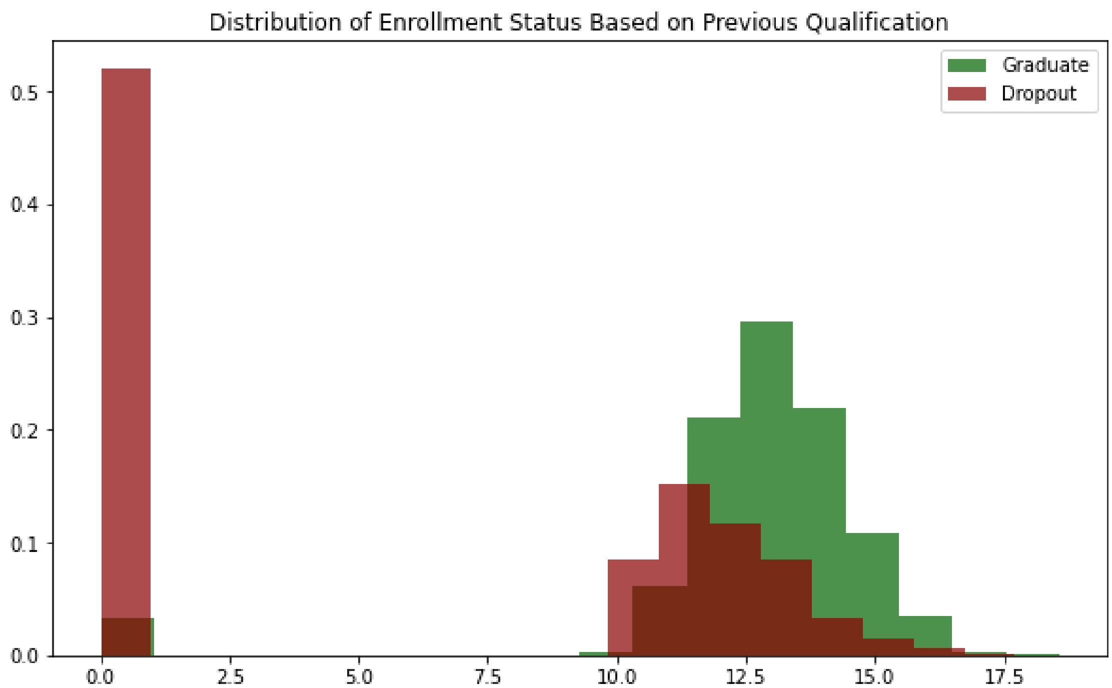
Likely an influential feature

### 2.0.16 Columns 31: Curricular units 2nd sem (grade)

[44]:
```
col = df.columns[31]

plt.figure(figsize=(10,6))
feature_ser = df[col]
for target_val in ['Graduate', 'Dropout']:
```

```
    plt.hist(feature_ser[df['Target'] == target_val], color=colors[target_val],
 ↪alpha=.7, bins=18, label=target_val, density=True)
plt.title('Distribution of Enrollment Status Based on Previous Qualification')
plt.legend()
plt.show()
```




**Observation: Not much fluctuation within this feature (distributions are nearly the same)**

Probably not an influential feature

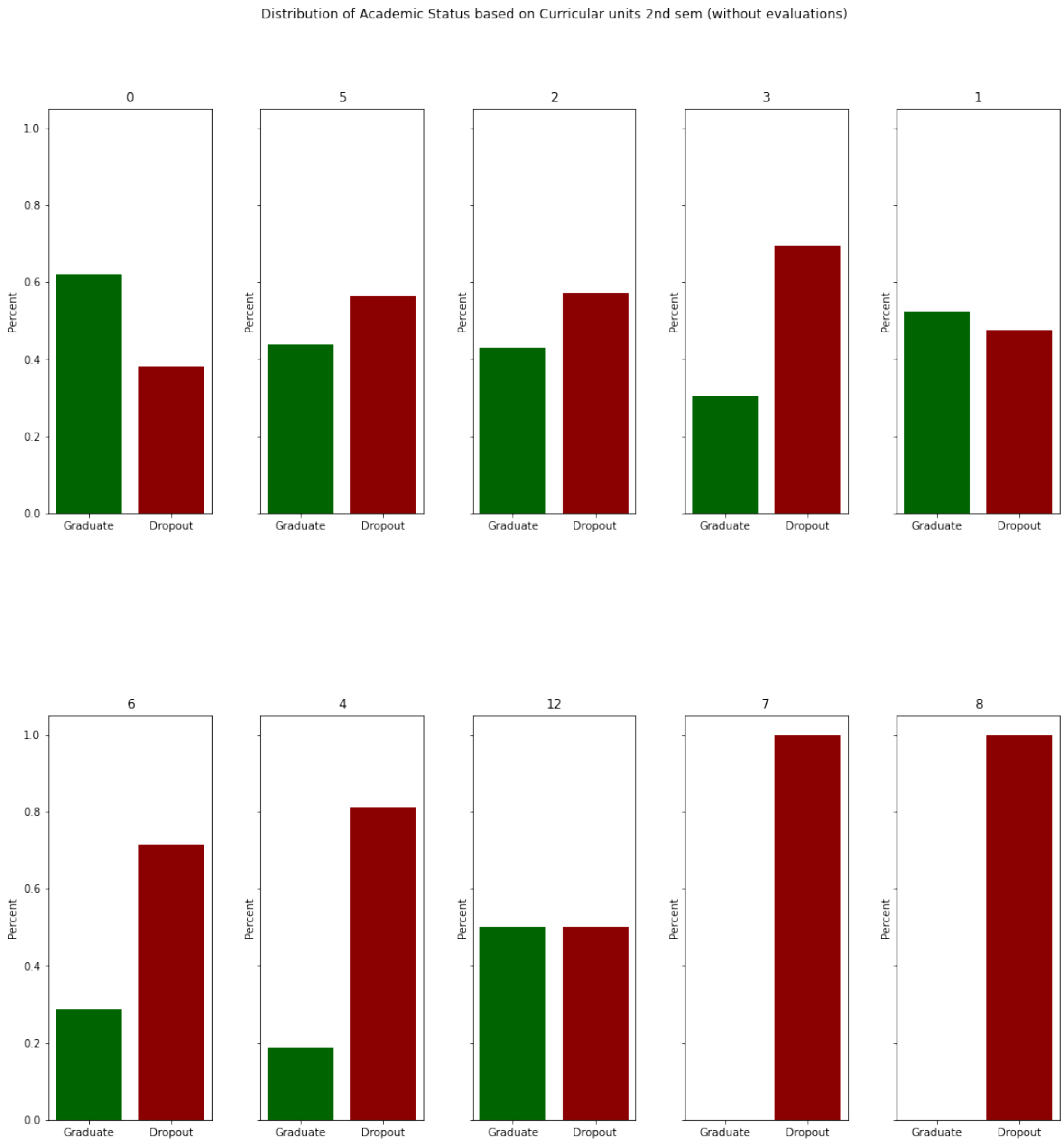
### 2.0.17 Columns 32: Curricular units 2nd sem (without evaluations)

[45]:
```
# select subset of dataset
col = df.columns[32]
# group by feature column values, find %makeup for each target val (Graduate,
 ↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)

subplots_height = 2
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),
 ↪sharey=True)
# reshape to make more readable
```

```
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Significant difference within some feature types**

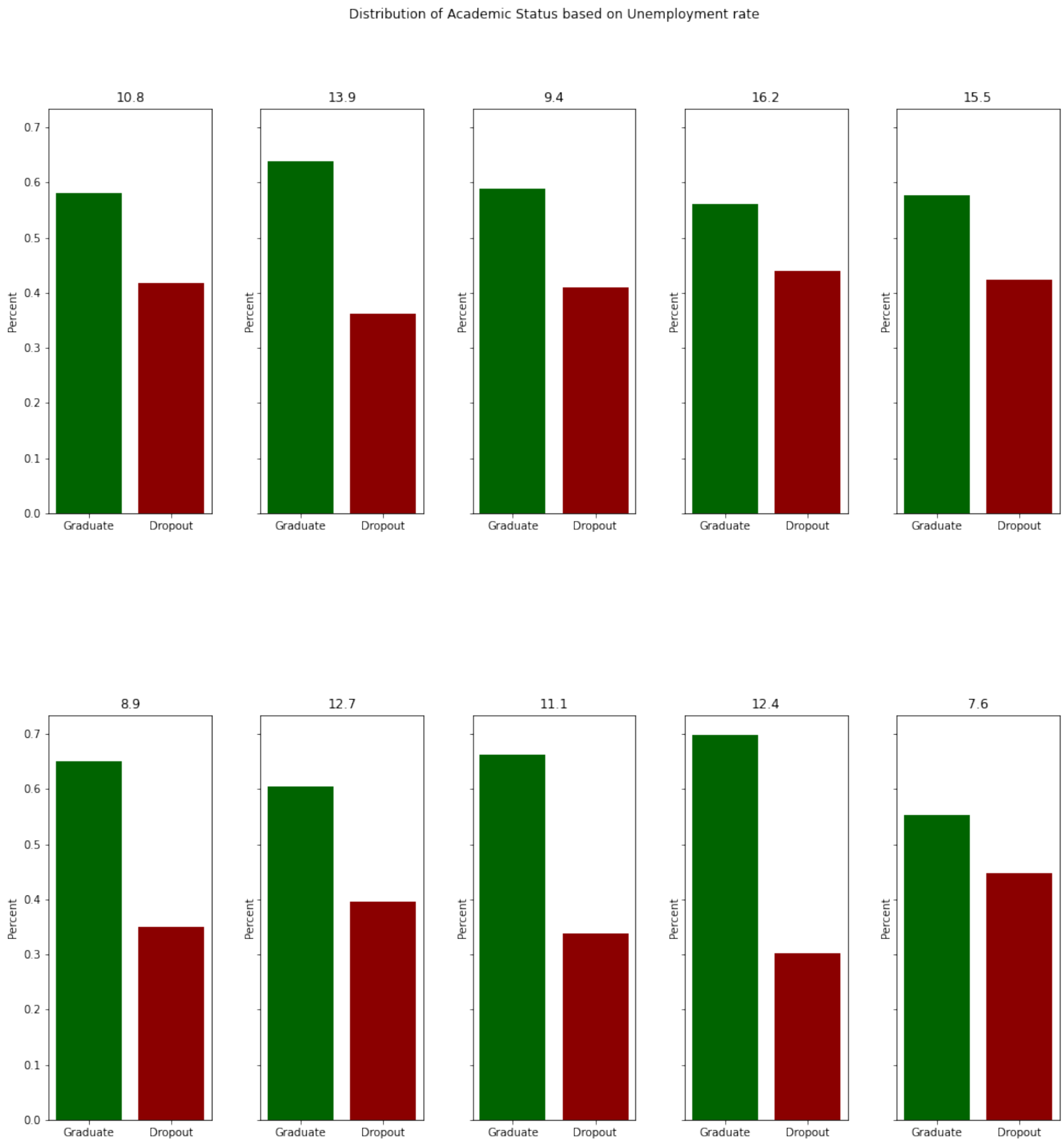
Likely an influential feature

### 2.0.18 Columns 33: Unemployment rate

[46]:
```
# select subset of dataset
col = df.columns[33]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 2
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16), sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val, dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Not much fluctuation within this feature**

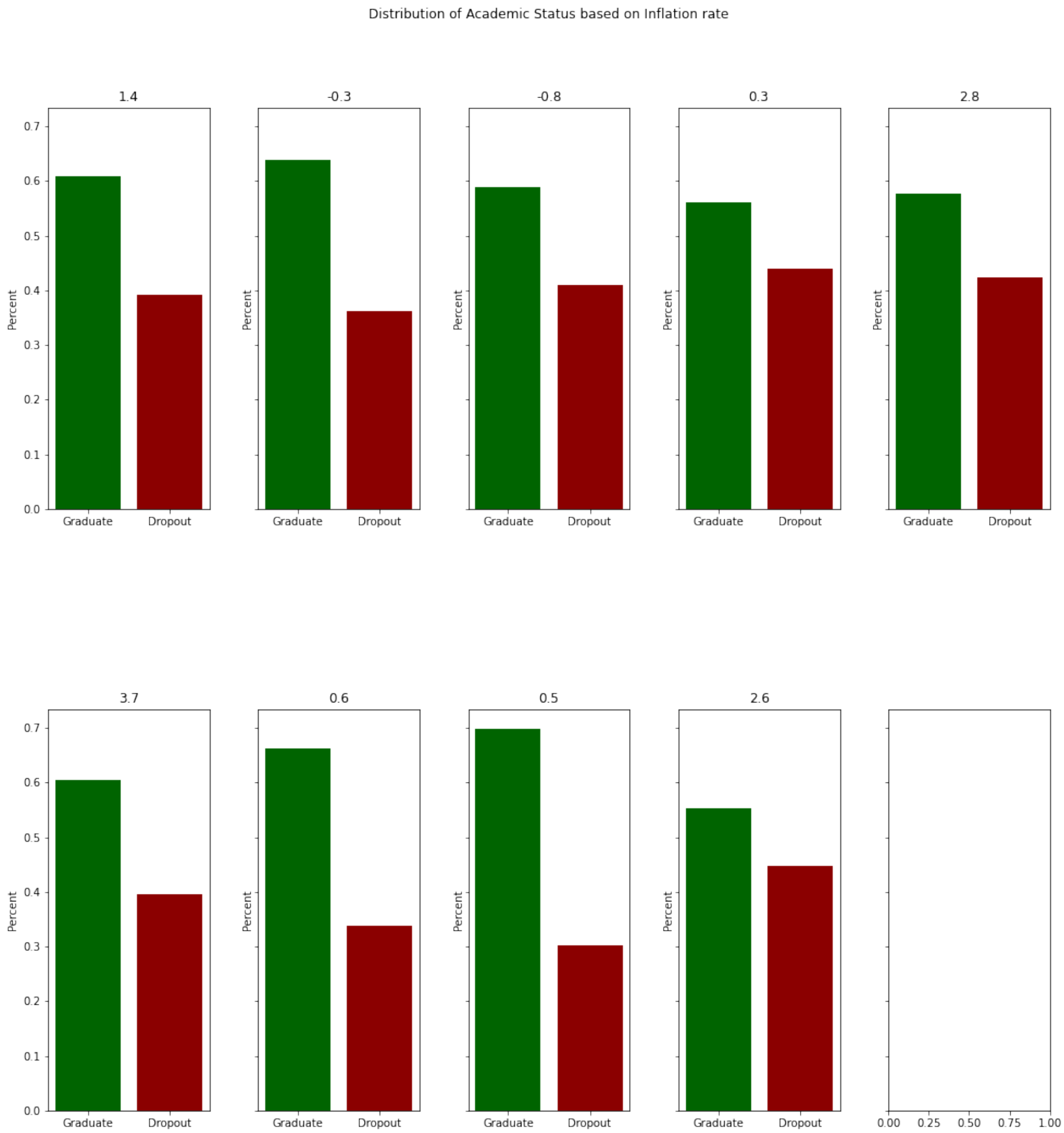
Probably not an influential feature

### 2.0.19 Columns 34: Inflation rate

[47]:
```
# select subset of dataset
col = df.columns[34]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```
subplots_height = 2
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate',  'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Not much fluctuation within this feature**

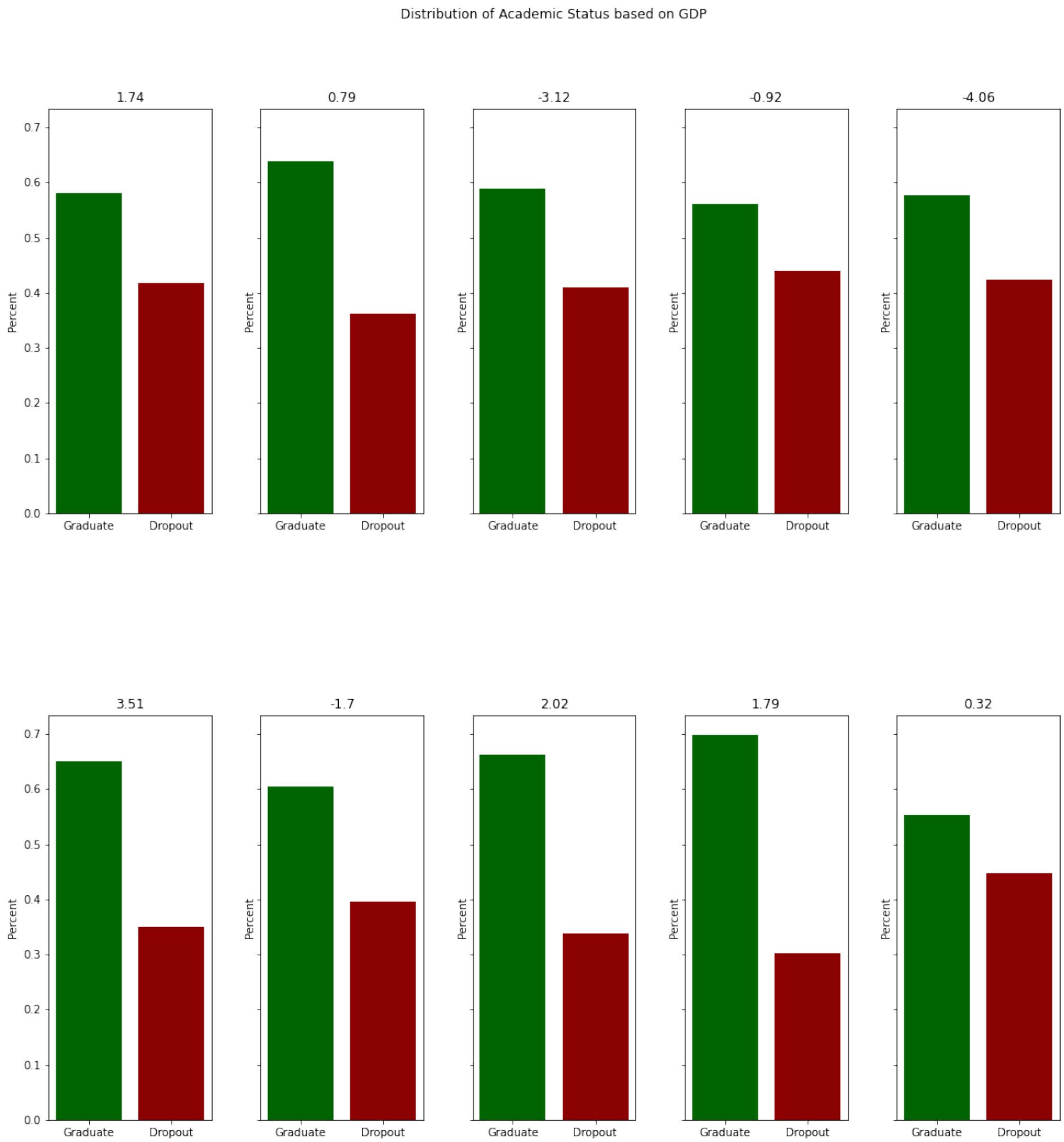
Probably not an influential feature

### 2.0.20 Columns 35: GDP

[48]:
```
# select subset of dataset
col = df.columns[35]
# group by feature column values, find %makeup for each target val (Graduate,␣
↪Dropout, Enrolled)
val_counts = df[[col, 'Target']].groupby(col).value_counts(normalize=True)
```

```python
subplots_height = 2
subplots_width = 5
# create #unique_feature_val subplots (hard-coded)
fig, axs = plt.subplots(subplots_height, subplots_width, figsize=(16, 16),␣
 ↪sharey=True)
# reshape to make more readable
plt.subplots_adjust(left=0.1,
                    bottom=0.1,
                    right=0.9,
                    top=0.9,
                    wspace=0.3,
                    hspace=0.5)

# generate a bar chart for each group; group for each unique value within␣
 ↪feature column
feature_vals = df[col].unique()
for i in range(len(feature_vals)):
    for target_val in ['Graduate', 'Dropout']:
        # create bar within barchart
        # extract value to map (may be 0)
        if (feature_vals[i], target_val) not in val_counts.index:
            dens = 0
        else:
            dens = val_counts.loc[(feature_vals[i], target_val)]
        axs[math.floor(i/subplots_width)][i%subplots_width].bar(target_val,␣
 ↪dens, color=colors[target_val])
    # set title to feature value
    axs[math.floor(i/subplots_width)][i%subplots_width].
 ↪set_title(feature_vals[i])
    # set y-axis title
    axs[math.floor(i/subplots_width)][i%subplots_width].set_ylabel('Percent')
fig.suptitle('Distribution of Academic Status based on ' + col)
plt.show()
```




**Observation: Not much fluctuation within this feature**

Probably not an influential feature

### 2.0.21 Summary on EDA for Columns 16-35:

- Columns #16; Tuition fees up to date: Likely
- Columns #17; Gender: Unlikely
- Columns #18; Scholarship holder: Likely
- Columns #19; Age at enrollment: Unlikely
- Columns #20; International: Unlikely
- Columns #21; Curricular units 1st sem (credited): Unlikely

- Columns #22; Curricular units 1st sem (enrolled): Likely
- Columns #23; Curricular units 1st sem (evaluations): Likely
- Columns #24; Curricular units 1st sem (approved): Likely
- Columns #25; Curricular units 1st sem (grade): Unlikely
- Columns #26; Curricular units 1st sem (without evaluations): Likely
- Columns #27; Curricular units 2nd sem (credited): Likely
- Columns #28; Curricular units 2nd sem (enrolled): Likely
- Columns #29; Curricular units 2nd sem (evaluations): Likely
- Columns #30; Curricular units 2nd sem (approved): Likely
- Columns #31; Curricular units 2nd sem (grade): Unlikely
- Columns #32; Curricular units 2nd sem (without evaluations): Likely
- Columns #33; Unemployment rate: Unlikely
- Columns #34; Inflation rate: Unlikely
- Columns #35; GDP: Unlikely

[8]:
```
df
```

[8]:
```
      Marital status  Application mode  Application order  \
0                  1                17                  5
1                  1                15                  1
2                  1                 1                  5
3                  1                17                  2
4                  2                39                  1
…                …                 …                 …
4419               1                 1                  6
4420               1                 1                  2
4421               1                 1                  1
4422               1                 1                  1
4423               1                10                  1

      Previous qualification  Nacionality  Mother's qualification  \
0                          1            1                      19
1                          1            1                       1
2                          1            1                      37
3                          1            1                      38
4                          1            1                      37
…                        …          …                     …
4419                       1            1                       1
4420                       1          105                       1
4421                       1            1                      37
4422                       1            1                      37
4423                       1           22                      38

      Father's qualification  Mother's occupation  Displaced  \
0                         12                    5          1
1                          3                    3          1
2                         37                    9          1
```

```
3                         37                    5          1
4                         38                    9          0
…                      …                  …        …
4419                       1                    5          0
4420                       1                    9          1
4421                      37                    9          1
4422                      37                    7          1
4423                      37                    5          1

      Educational special needs  …  Gender  Scholarship holder  \
0                             0  …       1                   0
1                             0  …       1                   0
2                             0  …       1                   0
3                             0  …       0                   0
4                             0  …       0                   0
…                          …  …     …                 …
4419                          0  …       1                   0
4420                          0  …       0                   0
4421                          0  …       0                   1
4422                          0  …       0                   1
4423                          0  …       0                   0

      International  Curricular units 1st sem (credited)  \
0                 0                                    0
1                 0                                    0
2                 0                                    0
3                 0                                    0
4                 0                                    0
…             …                                  …
4419              0                                    0
4420              1                                    0
4421              0                                    0
4422              0                                    0
4423              1                                    0

      Curricular units 1st sem (without evaluations)  \
0                                                  0
1                                                  0
2                                                  0
3                                                  0
4                                                  0
…                                              …
4419                                               0
4420                                               0
4421                                               0
4422                                               0
4423                                               0
```

```
      Curricular units 2nd sem (approved)  \
0                                       0
1                                       6
2                                       0
3                                       5
4                                       6
…                                   …
4419                                    5
4420                                    2
4421                                    1
4422                                    5
4423                                    6

      Curricular units 2nd sem (without evaluations)  Inflation rate   GDP  \
0                                                  0             1.4  1.74
1                                                  0            -0.3  0.79
2                                                  0             1.4  1.74
3                                                  0            -0.8 -3.12
4                                                  0            -0.3  0.79
…                                              …              …    …
4419                                               0             2.8 -4.06
4420                                               0             0.6  2.02
4421                                               0            -0.3  0.79
4422                                               0            -0.8 -3.12
4423                                               0             3.7 -1.70

        Target
0      Dropout
1     Graduate
2      Dropout
3     Graduate
4     Graduate
…         …
4419  Graduate
4420   Dropout
4421   Dropout
4422  Graduate
4423  Graduate

[3630 rows x 21 columns]
```

[34]:
```python
likely_cls = ['Marital status','Application mode','Course','Previous␣
↪qualification','Nacionality',
 "Father's qualification", "Mother's occupation","Father's occupation",
 'Debtor','Tuition fees up to date','Scholarship holder','Curricular units 1st␣
↪sem (enrolled)',
```

```
 'Curricular units 1st sem (evaluations)','Curricular units 1st sem (approved)',
 '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 (without␣
 ↪evaluations)',
'Target']

df = df[likely_cls]
df
```

[34]:

```
      Marital status  Application mode  Course  Previous qualification  \
0                  1                17     171                       1
1                  1                15    9254                       1
2                  1                 1    9070                       1
3                  1                17    9773                       1
4                  2                39    8014                       1
…                ...               ...     ...                     ...
4419               1                 1    9773                       1
4420               1                 1    9773                       1
4421               1                 1    9500                       1
4422               1                 1    9147                       1
4423               1                10    9773                       1

      Nacionality  Father's qualification  Mother's occupation  \
0               1                      12                    5
1               1                       3                    3
2               1                      37                    9
3               1                      37                    5
4               1                      38                    9
…             ...                     ...                  ...
4419            1                       1                    5
4420          105                       1                    9
4421            1                      37                    9
4422            1                      37                    7
4423           22                      37                    5

      Father's occupation  Debtor  Tuition fees up to date  …  \
0                       9       0                        1  …
1                       3       0                        0  …
2                       9       0                        0  …
3                       3       0                        1  …
4                       9       0                        1  …
…                     ...     ...                      ...  …
4419                    4       0                        1  …
4420                    9       1                        0  …
4421                    9       0                        1  …
```

```
4422                    4       0                        1  …
4423                    9       0                        1  …

      Curricular units 1st sem (enrolled)  \
0                                       0
1                                       6
2                                       6
3                                       6
4                                       6
…                                   …
4419                                    6
4420                                    6
4421                                    7
4422                                    5
4423                                    6

      Curricular units 1st sem (evaluations)  \
0                                          0
1                                          6
2                                          0
3                                          8
4                                          9
…                                      …
4419                                       7
4420                                       6
4421                                       8
4422                                       5
4423                                       8

      Curricular units 1st sem (approved)  \
0                                       0
1                                       6
2                                       0
3                                       6
4                                       5
…                                   …
4419                                    5
4420                                    6
4421                                    7
4422                                    5
4423                                    6

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

```
4                                                       0
…                                                   …
4419                                                    0
4420                                                    0
4421                                                    0
4422                                                    0
4423                                                    0

      Curricular units 2nd sem (credited)  \
0                                       0
1                                       0
2                                       0
3                                       0
4                                       0
…                                   …
4419                                    0
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)  \
0                                       0
1                                       6
2                                       0
3                                       5
4                                       6
…                                     …
4419                                    5
4420                                    2
4421                                    1
4422                                    5
4423                                    6

      Curricular units 2nd sem (without evaluations)    Target
0                                                  0   Dropout
1                                                  0  Graduate
2                                                  0   Dropout
3                                                  0  Graduate
4                                                  0  Graduate
…                                                …       …
4419                                               0  Graduate
4420                                               0   Dropout
4421                                               0   Dropout
4422                                               0  Graduate
4423                                               0  Graduate

[3630 rows x 21 columns]
```

[35]:

```
from statsmodels.stats.outliers_influence import variance_inflation_factor


def calculate_vif(df):
    vif_data = pd.DataFrame()
    vif_data["feature"] = df.columns[:-1]
    vif_data["VIF"] = [variance_inflation_factor(df.iloc[:, :-1].values, i) for␣
 ↪i in range(len(df.columns) - 1)]
    return vif_data

remove_columns_count = 0
while True:
    vif_data = calculate_vif(df)
    vif_data = vif_data.sort_values("VIF", ascending=False)

    if vif_data.iloc[0, 1] < 5:
        break

    column_to_remove = vif_data.iloc[0, 0]
```

```python
    print(f"column to remove: {column_to_remove}")
    df = df.drop(columns=[column_to_remove])
    remove_columns_count+=1

print(f"remove_columns_count is {remove_columns_count}")
df
```

```
column to remove: Curricular units 1st sem (enrolled)
column to remove: Curricular units 2nd sem (enrolled)
column to remove: Curricular units 1st sem (approved)
column to remove: Curricular units 1st sem (evaluations)
column to remove: Course
column to remove: Curricular units 2nd sem (evaluations)
column to remove: Tuition fees up to date
column to remove: Father's occupation
remove_columns_count is 8
```

[35]:

```
      Marital status  Application mode  Previous qualification  Nacionality  \
0                  1                17                       1            1
1                  1                15                       1            1
2                  1                 1                       1            1
3                  1                17                       1            1
4                  2                39                       1            1
…                …               …                     …          …
4419               1                 1                       1            1
4420               1                 1                       1          105
4421               1                 1                       1            1
4422               1                 1                       1            1
4423               1                10                       1           22

      Father's qualification  Mother's occupation  Debtor  Scholarship holder  \
0                         12                    5       0                   0
1                          3                    3       0                   0
2                         37                    9       0                   0
3                         37                    5       0                   0
4                         38                    9       0                   0
…                      …                   …     …                 …
4419                       1                    5       0                   0
4420                       1                    9       1                   0
4421                      37                    9       0                   1
4422                      37                    7       0                   1
4423                      37                    5       0                   0

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

```
3                                                 0
4                                                 0
…                                             …
4419                                              0
4420                                              0
4421                                              0
4422                                              0
4423                                              0

      Curricular units 2nd sem (credited)  \
0                                     0
1                                     0
2                                     0
3                                     0
4                                     0
…                                 …
4419                                  0
4420                                  0
4421                                  0
4422                                  0
4423                                  0

      Curricular units 2nd sem (approved)  \
0                                     0
1                                     6
2                                     0
3                                     5
4                                     6
…                                 …
4419                                  5
4420                                  2
4421                                  1
4422                                  5
4423                                  6

      Curricular units 2nd sem (without evaluations)    Target
0                                                 0   Dropout
1                                                 0  Graduate
2                                                 0   Dropout
3                                                 0  Graduate
4                                                 0  Graduate
…                                             …        …
4419                                              0  Graduate
4420                                              0   Dropout
4421                                              0   Dropout
4422                                              0  Graduate
4423                                              0  Graduate
```

```
[3630 rows x 13 columns]
```

## 2.1 Model

### 2.1.1 Logistic Regression

[36]:
```
# Check the proportion of each target in the population
df['Target'].value_counts()/df.shape[0]
```

[36]:
```
Target
Graduate    0.60854
Dropout     0.39146
Name: count, dtype: float64
```

[37]:
```
# Convert to Binary for modeling
df['Target'] = df['Target'].map({'Graduate': 1, 'Dropout': 0})
```

[23]:
```

```

[23]:
```
['Marital status',
 'Application mode',
 'Application order',
 'Previous qualification',
 'Nacionality',
 "Mother's qualification",
 "Father's qualification",
 "Mother's occupation",
 'Displaced',
 'Educational special needs',
 'Debtor',
 'Gender',
 'Scholarship holder',
 'International',
 'Curricular units 1st sem (credited)',
 'Curricular units 1st sem (without evaluations)',
 'Curricular units 2nd sem (approved)',
 'Curricular units 2nd sem (without evaluations)',
 'Inflation rate',
 'GDP',
 'Target']
```

[24]:
```

```

[24]:
```
12
```

```
[11]: df_cleaned = df[likely_cls]
      df_cleaned.head()
```

```
[11]:    Marital status  Application mode  Course  Previous qualification  \
      0               1                17     171                       1
      1               1                15    9254                       1
      2               1                 1    9070                       1
      3               1                17    9773                       1
      4               2                39    8014                       1

         Nacionality  Father's qualification  Mother's occupation  \
      0            1                      12                    5
      1            1                       3                    3
      2            1                      37                    9
      3            1                      37                    5
      4            1                      38                    9

         Father's occupation  Debtor  Tuition fees up to date  …  \
      0                    9       0                        1  …
      1                    3       0                        0  …
      2                    9       0                        0  …
      3                    3       0                        1  …
      4                    9       0                        1  …

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

         Curricular units 1st sem (evaluations)  \
      0                                       0
      1                                       6
      2                                       0
      3                                       8
      4                                       9

         Curricular units 1st sem (approved)  \
      0                                    0
      1                                    6
      2                                    0
      3                                    6
      4                                    5

         Curricular units 1st sem (without evaluations)  \
      0                                               0
```

```
1                                               0
2                                               0
3                                               0
4                                               0

   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)  \
0                                    0
1                                    6
2                                    0
3                                    5
4                                    6

   Curricular units 2nd sem (without evaluations)  Target
0                                               0       0
1                                               0       1
2                                               0       0
3                                               0       1
4                                               0       1

[5 rows x 21 columns]
```

[12]:
```
# Splitting the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(df_cleaned.drop('Target',␣
 ↪axis = 1),
                                                    df_cleaned['Target'],␣
 ↪test_size=0.2,
                                                    random_state=42)
```

[13]:
```
df_train = pd.DataFrame()
df_train = pd.concat([X_train, y_train], axis=1)
df_train
```

[13]:

```
      Marital status  Application mode  Course  Previous qualification  \
1116               1                 1    9070                       1
4372               1                39    9003                       1
4371               1                 1    9500                       1
2869               2                39    9991                      19
1638               1                39    9670                       9
…                …               …     …                     …
1359               1                42    9119                       1
1559               1                 1    9500                       1
1037               1                 1    9238                       1
4278               1                 1    9773                       1
3867               1                17    9500                       1

      Nacionality  Father's qualification  Mother's occupation  \
1116            1                      38                    1
4372            1                      12                    9
4371            1                      19                    3
2869            1                      37                    9
1638            1                      37                    5
…             …                     …                  …
1359            1                      37                    9
1559            1                      19                    2
1037            1                       3                    4
4278            1                       1                    4
3867            1                      19                    4

      Father's occupation  Debtor  Tuition fees up to date  …  \
1116                    9       0                        0  …
4372                    9       0                        1  …
4371                    3       0                        1  …
2869                    9       0                        1  …
1638                    3       1                        1  …
…                     …     …                      … …
1359                    9       0                        0  …
1559                   10       0                        1  …
1037                    2       0                        1  …
4278                    7       1                        1  …
3867                    9       0                        1  …

      Curricular units 1st sem (enrolled)  \
1116                                    5
4372                                    6
4371                                    7
2869                                    5
1638                                    5
…                                     …
1359                                    5
```

```
1559                               8
1037                               6
4278                               6
3867                               8

      Curricular units 1st sem (evaluations)  \
1116                                  5
4372                                  7
4371                                  7
2869                                  5
1638                                  5
…                                   …
1359                                  0
1559                                  8
1037                                  6
4278                                  6
3867                                  8

      Curricular units 1st sem (approved)  \
1116                               0
4372                               0
4371                               7
2869                               5
1638                               0
…                               …
1359                               0
1559                               8
1037                               6
4278                               6
3867                               7

      Curricular units 1st sem (without evaluations)  \
1116                                          0
4372                                          0
4371                                          0
2869                                          0
1638                                          0
…                                         …
1359                                          0
1559                                          0
1037                                          0
4278                                          0
3867                                          0

      Curricular units 2nd sem (credited)  \
1116                               0
4372                               0
```

```
4371                                     0
2869                                     0
1638                                     0
…                                      …
1359                                     0
1559                                     0
1037                                     0
4278                                     0
3867                                     0

      Curricular units 2nd sem (enrolled)  \
1116                                     6
4372                                     6
4371                                     8
2869                                     5
1638                                     5
…                                      …
1359                                     5
1559                                     8
1037                                     6
4278                                     6
3867                                     8

      Curricular units 2nd sem (evaluations)  \
1116                                        0
4372                                       10
4371                                        8
2869                                        5
1638                                        5
…                                         …
1359                                        0
1559                                        8
1037                                        6
4278                                        6
3867                                        8

      Curricular units 2nd sem (approved)  \
1116                                     0
4372                                     0
4371                                     8
2869                                     5
1638                                     0
…                                      …
1359                                     0
1559                                     8
1037                                     6
4278                                     6
```

```
3867                                        7

      Curricular units 2nd sem (without evaluations)  Target
1116                                                0       0
4372                                                0       0
4371                                                0       1
2869                                                0       1
1638                                                0       0
…                                               …       …
1359                                                0       0
1559                                                0       1
1037                                                0       1
4278                                                0       1
3867                                                0       1

[2904 rows x 21 columns]
```

[14]:

```
print(df_train.dtypes)
```

```
Marital status                                    int64
Application mode                                  int64
Course                                            int64
Previous qualification                            int64
Nacionality                                       int64
Father's qualification                            int64
Mother's occupation                               int64
Father's occupation                               int64
Debtor                                            int64
Tuition fees up to date                           int64
Scholarship holder                                int64
Curricular units 1st sem (enrolled)               int64
Curricular units 1st sem (evaluations)            int64
Curricular units 1st sem (approved)               int64
Curricular units 1st sem (without evaluations)    int64
Curricular units 2nd sem (credited)               int64
Curricular units 2nd sem (enrolled)               int64
Curricular units 2nd sem (evaluations)            int64
Curricular units 2nd sem (approved)               int64
Curricular units 2nd sem (without evaluations)    int64
Target                                            int64
dtype: object
```

[15]:

```
independent_vars = df_train.columns.difference(['Target']).tolist()

# Wrap column names with spaces or special characters
formula_parts = [f'Q("{x}")' if ' ' in x or '(' in x or ')' in x else x for x␣
 ↪in df_train.columns.difference(['Target'])]
```

```python
formula = 'Target ~ ' + ' + '.join(formula_parts)
```

[16]:
```python
base_logistic = smf.logit(formula=formula, data=df_train).fit()
print(base_logistic.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.234110
         Iterations 9
                           Logit Regression Results
==============================================================================
Dep. Variable:                 Target   No. Observations:                 2904
Model:                          Logit   Df Residuals:                     2883
Method:                           MLE   Df Model:                           20
Date:                Sun, 10 Mar 2024   Pseudo R-squ.:                  0.6508
Time:                        10:04:39   Log-Likelihood:                -679.86
converged:                       True   LL-Null:                       -1947.1
Covariance Type:            nonrobust   LLR p-value:                     0.000
================================================================================
=======================================
                                                          coef    std err
z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
---------------------------------------
Intercept                                              -2.6241      0.388
-6.768      0.000      -3.384      -1.864
Q("Application mode")                                  -0.0110      0.005
-2.208      0.027      -0.021      -0.001
Course                                              -9.727e-05    4.8e-05
-2.025      0.043      -0.000   -3.12e-06
Q("Curricular units 1st sem (approved)")                0.5487      0.084
6.517      0.000      0.384      0.714
Q("Curricular units 1st sem (enrolled)")               -0.3422      0.144
-2.372      0.018      -0.625      -0.059
Q("Curricular units 1st sem (evaluations)")             0.0204      0.041
0.502      0.616      -0.059      0.100
Q("Curricular units 1st sem (without evaluations)")     0.1409      0.175
0.807      0.420      -0.201      0.483
Q("Curricular units 2nd sem (approved)")                1.0646      0.075
14.124      0.000      0.917      1.212
Q("Curricular units 2nd sem (credited)")               -0.3481      0.066
-5.256      0.000      -0.478      -0.218
Q("Curricular units 2nd sem (enrolled)")               -0.6293      0.142
-4.426      0.000      -0.908      -0.351
Q("Curricular units 2nd sem (evaluations)")            -0.0495      0.037
-1.329      0.184      -0.123      0.024
Q("Curricular units 2nd sem (without evaluations)")     0.3765      0.158
2.388      0.017      0.067      0.685
```

```
Debtor                                                     -0.8281      0.263
-3.144      0.002      -1.344      -0.312
Q("Father's occupation")                                   -0.0010      0.007
-0.135      0.893      -0.015       0.013
Q("Father's qualification")                                 0.0057      0.005
1.187      0.235      -0.004      0.015
Q("Marital status")                                         0.1129      0.136
0.832      0.405      -0.153      0.379
Q("Mother's occupation")                                    0.0085      0.007
1.238      0.216      -0.005      0.022
Nacionality                                                -0.0102      0.009
-1.101      0.271      -0.028       0.008
Q("Previous qualification")                                 0.0174      0.008
2.231      0.026      0.002      0.033
Q("Scholarship holder")                                     0.8945      0.179
4.983      0.000      0.543      1.246
Q("Tuition fees up to date")                                2.6042      0.298
8.752      0.000      2.021      3.187
================================================================================
=======================================
```

[23]:

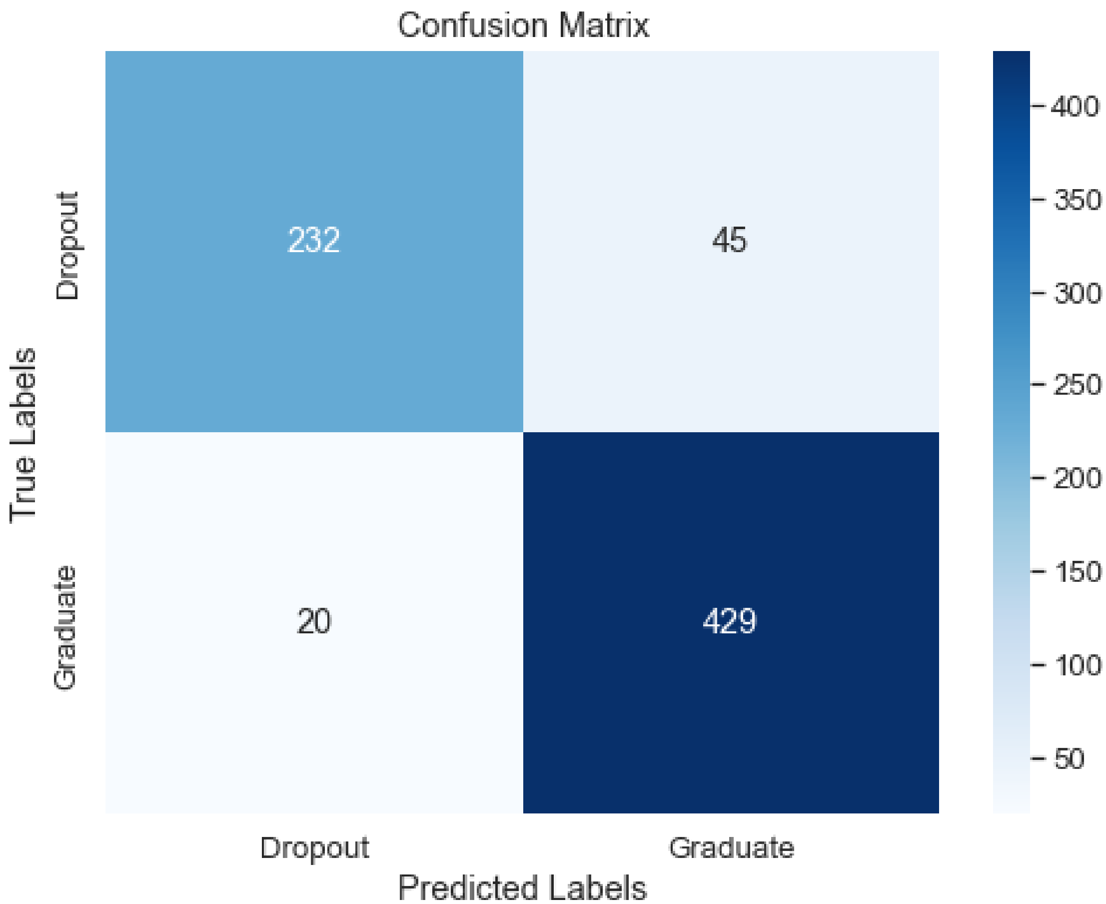
```python
probabilities_l = base_logistic.predict(X_test)
predictions_l = (probabilities_l >= 0.5).astype(int)
accuracy = accuracy_score(y_test, predictions_l)
print("Accuracy:", accuracy)
from sklearn.metrics import f1_score
f1 = f1_score(y_test, predicted_labels)
print("F1 Score:", f1)
```

```
Accuracy: 0.9104683195592287
F1 Score: 0.9295774647887324
```

[19]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

conf_matrix = confusion_matrix(y_test, predicted_labels)
plt.figure(figsize=(8, 6))
sns.set(font_scale=1.2)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=['Dropout','Graduate'], yticklabels=['Dropout','Graduate'])
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.title('Confusion Matrix')
plt.show()
```



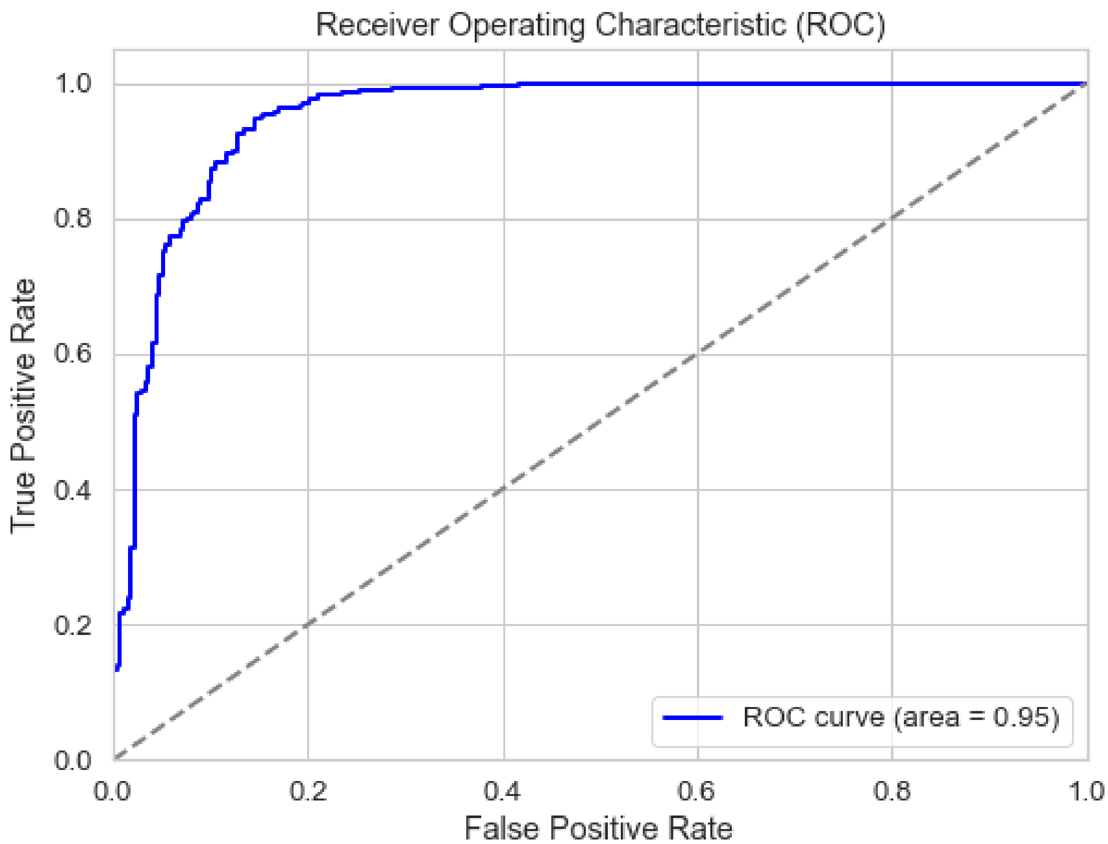

### 2.1.2 Evaluate the preformance of logistic regression

[26]:
```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import roc_curve, auc

# Compute ROC curve and AUC
fpr, tpr, thresholds = roc_curve(y_test, probabilities_l)
roc_auc = auc(fpr, tpr)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label='ROC curve (area = %0.2f)' %
 ↪roc_auc)
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
```

```
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```




**More Models - XGBOOST**

[47]:
```
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV
import xgboost as xgb
xgb_clf = XGBClassifier(objective='multi:softmax', num_class=2, verbosity=1)

# Define our parameter grid
param_grid = {
    'learning_rate': [0.01, 0.1, 0.2],  # Smaller values make the model robust␣
 ↪but slow to learn
    'max_depth': [4, 5, 6],  # Depth of the tree
    'min_child_weight': [1, 3, 5],  # Minimum sum of instance weight(hessian)␣
 ↪needed in a child
    'eta':[0.3,0.5]
```

```
}

# Setup GridSearchCV
grid_search = GridSearchCV(estimator=xgb_clf, param_grid=param_grid,␣
 ↪scoring='f1_weighted', n_jobs=-1, cv=3, verbose=3)

# Assuming X_train, y_train are defined as your feature matrix and target␣
 ↪vector from your dataset
grid_search.fit(X_train, y_train)

# Best parameters and best score
print("Best parameters found: ", grid_search.best_params_)
print("Best F1 score found: ", grid_search.best_score_)
```

```
Fitting 3 folds for each of 54 candidates, totalling 162 fits
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.886 total time=   0.7s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.896 total time=   0.7s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.890 total time=   0.7s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.897 total time=   0.7s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.888 total time=   0.7s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.893 total time=   0.7s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.888 total time=   0.7s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.893 total time=   0.7s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.885 total time=   0.7s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.895 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.901 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.892 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.894 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.888 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.896 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.892 total time=   0.9s
```

```
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.900 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.886 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.894 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.902 total time=   1.1s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.894 total time=   1.1s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.884 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.885 total time=   1.1s
[CV 1/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.892 total time=   1.3s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.908 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.900 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.904 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.895 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.907 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.896 total time=   1.3s
[CV 3/3] END eta=0.3, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.875 total time=   1.4s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.898 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.906 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.899 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.900 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.897 total time=   1.2s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.900 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.902 total time=   1.2s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=3;,
score=0.901 total time=   1.2s
```

```
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=3;,
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[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=5;,
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[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=3;,
score=0.902 total time=   1.3s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.3s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.4s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.7s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.904 total time=   1.7s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.7s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.904 total time=   1.4s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.899 total time=   1.5s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.901 total time=   1.5s
[CV 1/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.904 total time=   1.6s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.900 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.899 total time=   1.3s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.902 total time=   1.0s
[CV 3/3] END eta=0.3, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.898 total time=   1.4s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.894 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.904 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.896 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.898 total time=   0.9s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.907 total time=   0.9s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.902 total time=   0.9s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.900 total time=   0.8s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.892 total time=   1.0s
```

```
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.904 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.899 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.896 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.892 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.896 total time=   1.0s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.906 total time=   1.0s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.898 total time=   1.0s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.0s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.906 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.903 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.895 total time=   1.1s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.902 total time=   1.1s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.892 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.895 total time=   1.1s
[CV 1/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.904 total time=   1.1s
[CV 2/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.898 total time=   1.1s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.896 total time=   0.8s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.888 total time=   0.8s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=1;,
score=0.886 total time=   0.8s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.897 total time=   0.8s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.893 total time=   0.8s
[CV 3/3] END eta=0.3, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.897 total time=   1.1s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=3;,
score=0.888 total time=   0.7s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.890 total time=   0.7s
```

```
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.885 total time=   0.7s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=4, min_child_weight=5;,
score=0.893 total time=   0.7s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.895 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.896 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=1;,
score=0.888 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.894 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.901 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=3;,
score=0.892 total time=   1.1s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.0s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.892 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=5, min_child_weight=5;,
score=0.886 total time=   1.1s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.3s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.894 total time=   1.3s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.894 total time=   1.2s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=1;,
score=0.885 total time=   1.3s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.902 total time=   1.2s
[CV 1/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.892 total time=   1.3s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=3;,
score=0.884 total time=   1.3s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.900 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.896 total time=   1.3s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.908 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=1;,
score=0.895 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.904 total time=   0.8s
[CV 3/3] END eta=0.5, learning_rate=0.01, max_depth=6, min_child_weight=5;,
score=0.875 total time=   1.3s
```

```
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.907 total time=   0.7s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=3;,
score=0.898 total time=   0.7s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.899 total time=   0.7s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.906 total time=   0.7s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=4, min_child_weight=5;,
score=0.900 total time=   0.7s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.897 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.900 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=1;,
score=0.902 total time=   1.0s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=3;,
score=0.901 total time=   1.0s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=3;,
score=0.903 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=3;,
score=0.902 total time=   1.0s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.0s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=5;,
score=0.903 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=5, min_child_weight=5;,
score=0.900 total time=   1.0s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.904 total time=   1.2s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.2s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.904 total time=   1.2s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=1;,
score=0.898 total time=   1.2s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.901 total time=   1.3s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=3;,
score=0.899 total time=   1.2s
[CV 1/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.904 total time=   1.3s
[CV 2/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.899 total time=   1.3s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.900 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.894 total time=   0.9s
```

```
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=1;,
score=0.902 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.1, max_depth=6, min_child_weight=5;,
score=0.898 total time=   1.4s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.898 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.904 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=3;,
score=0.896 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.907 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.902 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=4, min_child_weight=5;,
score=0.900 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.892 total time=   1.1s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.899 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=1;,
score=0.896 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.904 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.892 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=3;,
score=0.896 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.906 total time=   0.9s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.898 total time=   0.9s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=5, min_child_weight=5;,
score=0.900 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.902 total time=   1.1s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.903 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=1;,
score=0.895 total time=   1.1s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.906 total time=   1.0s
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.895 total time=   1.0s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=3;,
score=0.892 total time=   0.9s
[CV 1/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.904 total time=   0.9s
```

```
[CV 2/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.898 total time=   0.7s
[CV 3/3] END eta=0.5, learning_rate=0.2, max_depth=6, min_child_weight=5;,
score=0.897 total time=   0.6s
Best parameters found:  {'eta': 0.3, 'learning_rate': 0.2, 'max_depth': 4,
'min_child_weight': 5}
Best F1 score found:  0.9029881326402945
```

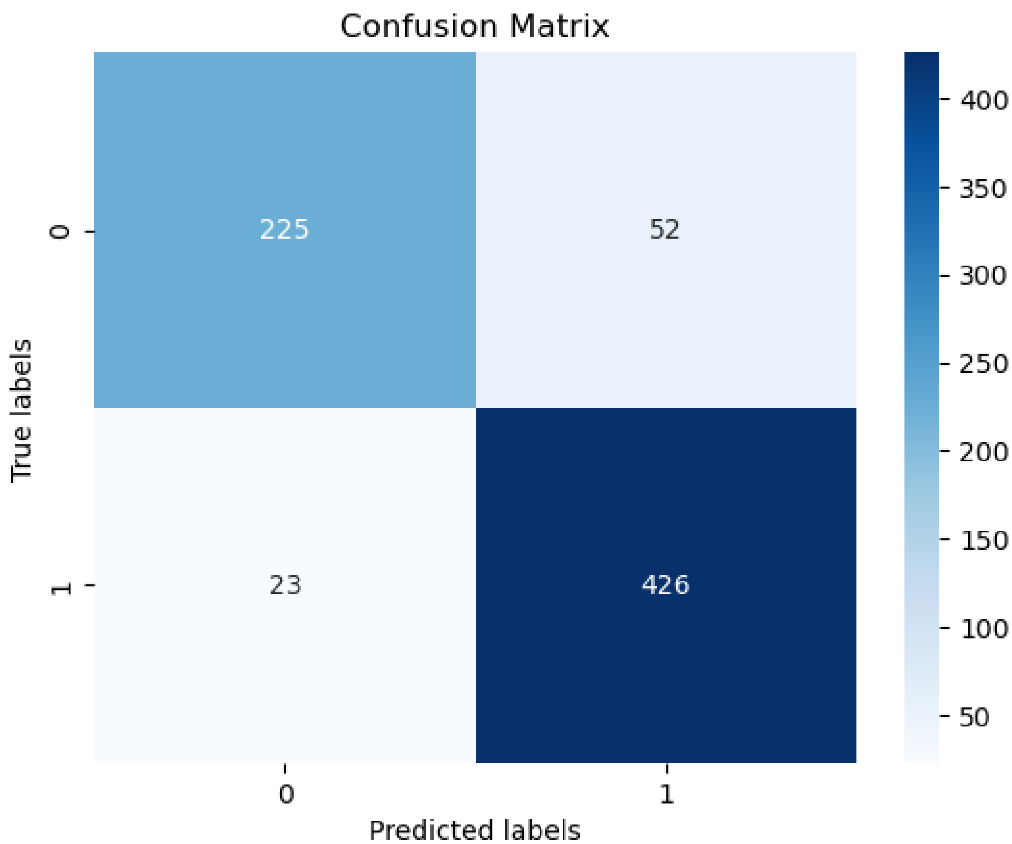
[49]:
```python
best_params = grid_search.best_params_

# Create a new XGBClassifier instance with the best parameters
best_xgb_clf = XGBClassifier(objective='multi:softmax', num_class=3,␣
 ↪verbosity=1, **best_params)

# Train the classifier on the entire training set
best_xgb_clf.fit(X_train, y_train)
```

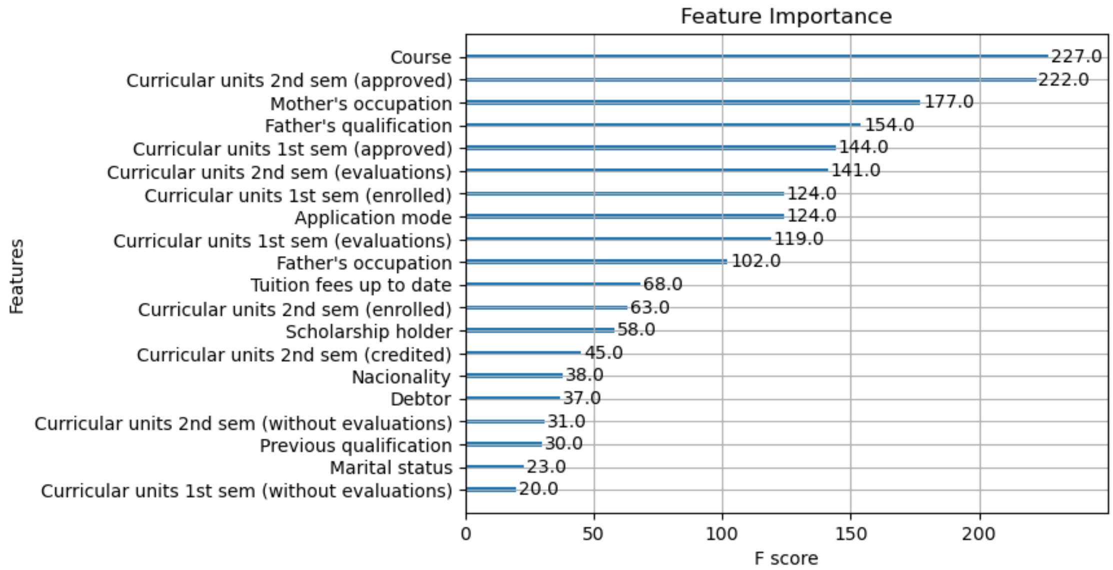
[49]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eta=0.3, eval_metric=None,
              feature_types=None, gamma=None, gpu_id=None, grow_policy=None,
              importance_type=None, interaction_constraints=None,
              learning_rate=0.2, max_bin=None, max_cat_threshold=None,
              max_cat_to_onehot=None, max_delta_step=None, max_depth=4,
              max_leaves=None, min_child_weight=5, missing=nan,
              monotone_constraints=None, n_estimators=100, n_jobs=None,
              num_class=3, num_parallel_tree=None, …)
```

[52]:
```python
# Making predictions
predictions = best_xgb_clf.predict(X_test)
accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy: {accuracy:.4f}')

f1 = f1_score(y_test, predictions, average='weighted')  # 'weighted' accounts␣
 ↪for label imbalance.
print(f'F1 Score: {f1:.2f}')

cm = confusion_matrix(y_test, predictions)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()

xgb.plot_importance(best_xgb_clf)
plt.title('Feature Importance')
```

```
plt.show()
```

```
Accuracy: 0.8967
F1 Score: 0.90
```






### More Models - SVM

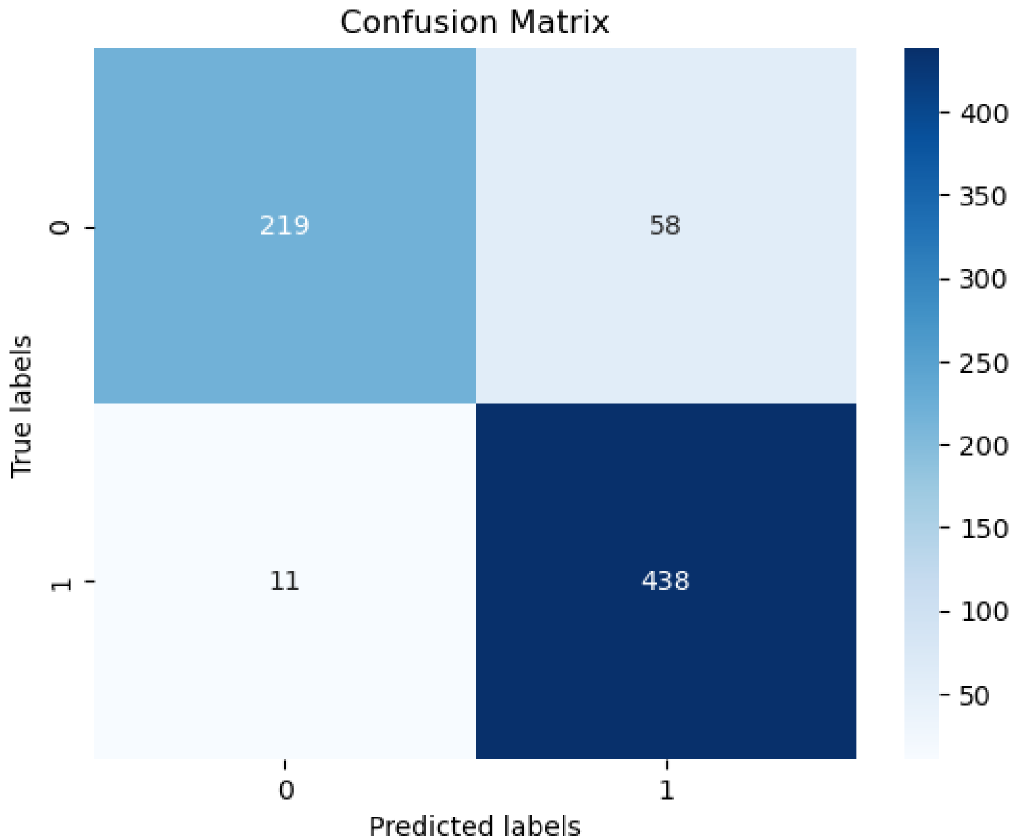
[53]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import classification_report

# Creating a SVM classifier using the RBF kernel
param_grid = {
    'svm__C': [0.1, 1, 10],
    'svm__gamma': [0.001, 0.01, 0.1, 1],
    'svm__kernel': ['rbf', 'linear', 'poly']
}
# Create a pipeline that scales the data then applies SVM
pipeline = Pipeline([
    ('scaler', StandardScaler()),
    ('svm', SVC())
])

# Create the GridSearchCV object
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy')
grid_search.fit(X_train, y_train)
print("Best parameters:", grid_search.best_params_)
print("Best cross-validation score: {:.2f}".format(grid_search.best_score_))

# Predict with the best found parameters
y_pred = grid_search.predict(X_test)
print("Classification report for best parameters:")
print(classification_report(y_test, y_pred))
```

```
Best parameters: {'svm__C': 0.1, 'svm__gamma': 0.001, 'svm__kernel': 'linear'}
Best cross-validation score: 0.91
Classification report for best parameters:
              precision    recall  f1-score   support

           0       0.95      0.79      0.86       277
           1       0.88      0.98      0.93       449

    accuracy                           0.90       726
   macro avg       0.92      0.88      0.90       726
weighted avg       0.91      0.90      0.90       726
```

[54]:
```
best_params = grid_search.best_params_
adjusted_best_params = {key.replace('svm__', ''): value for key, value in␣
 ↪best_params.items()}

# Create a new XGBClassifier instance with the best parameters
best_svm_clf = SVC(decision_function_shape='ovo',**adjusted_best_params)
# Train the classifier on the entire training set
best_svm_clf.fit(X_train, y_train)
print(f'Accuracy: {accuracy:.4f}')

f1 = f1_score(y_test, predictions, average='weighted')  # 'weighted' accounts␣
 ↪for label imbalance.
print(f'F1 Score: {f1:.2f}')
```

```
Accuracy: 0.8967
F1 Score: 0.90
```

[55]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.xlabel('Predicted labels')
plt.ylabel('True labels')
plt.title('Confusion Matrix')
plt.show()
```




## 2.2 Result

From the accuracy of the models being created, the one that is chosen as the final model to be used is the logistic regression model for its 91% accuracy. According to the logistic regression model, the variables that have the greatest impact on dropout are Tuition fees up to date (2.6042), Curricular units 2nd sem (approved) (1.0646), Scholarship holder (0.8945) and Debtor (-0.8281). These four variables have the greatest absolute values from the result of regression, meaning that for one single unit of change in the variable, there is going to be a large change in the final result. In the model, the threshold of dropout is set to be 0.5, meaning that for the regression results to be less than 0.5, the prediction is going to be "dropout" and not if the value is greater or equal to 0.5. Therefore it can be seen that these four variables have large influences on students' dropout. For an analysis of these four variables, they can be divided into two categories: expenses related and academic related. Debts, tuition and Scholarship all fall into the category of expenses. Thus it can be seen that expense is still the greatest reason that contributes to the dropout of students in college and the biggest problem that needs to be solved. This points the direction to the assignment of financial aid: with better and accurate assignment, the dropout can be significantly decreased. In fact, this model gives a practical solution to this problem: with the prediction on dropout of students, it can be found out that certain groups of students can be facing difficulties to graduate without financial aid, which means that the result of the model rise to a level from below 0.5 to above 0.5, then the possibility that the students graduate can be significantly improved. Such logic provides a practical solution to the financial problems provided by the model. For the units, it can be seen that the units students approved has a significant influence on the possibility of graduation. This means that students who enroll in more courses in their second semesters are more likely to graduate from college. This gives an intuition on a possible approach for improvement: improvement with advising. A possible interpretation is that students who do not enroll enough courses in their first year might lack planning for their college career, which can be improved by better advising. Students do not take sufficient courses early on, therefore they have a large workload that they cannot handle and leads to dropout. If students are provided with better advising, they might be able to get better planning from the beginning so they do not have to take too many courses later. By this result of the model, colleges can change the method of advising to provide students stronger guidance on the choice of courses in their first year.

### 2.3 Discussion and Conclusion

In conclusion, a reliable model that gives a high accuracy on the prediction of students' dropout rate given categories of variables is built. Based on such a model, colleges are able to have a better prediction of the students who are likely to drop out based on the data available and can take actions on advising and scholarships. Some possible future improvements can also be done to further improve the model. From observations on the variables that have significant influences on the result, it can be seen that some categories are related to each other. The financial reasons, for example, can be considered. Studies can be done on these variables about their correlations and how they behave when they appear at the same time to make influences on the final result can contribute to the improvement of the model. There are also more methods that can be added to the model like Gradient descent to reduce errors in the future.