Final Project Submission: Student Academic Success Classification Model Analysis

(Phase 3)

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- Program Pace: self paced
- Scheduled Project Review Time: Fri Jul 28, 2023 2pm
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- Blog post Url: https://medium.com/@tenicka.norwood/the-meaning-of-life-the-universe-and-everything-9423dcb79c06

Business Understanding

- **Stakeholder**: Instituto Politecnico de Portalegre
- **Business Case**: I am a new data scientist and have joined the challenge the Instituto Politecnico de Portalegre created to classify students' academic success. Researchers at the Instituto Politecnico de Portalegre want to reduce the rate of student academic failure in higher education.

The aim is to create a dependable model using machine learning techniques to spot students who may be at risk of dropping out of higher education after enrolling. By identifying these students early, we can implement strategies to

support them and reduce the likelihood of them leaving college.

The model was trained and tested with higher education student data from Portugal, but it is relevant for colleges and universities in the United States as well. We also face the challenge of identifying at-risk students and providing interventions to help them graduate on time and succeed in their studies.

> The completion rates of (US) undergraduates within six years of enrollment stand at only **62.3%** as of 2022.
>
> -- Hanneh Bareham and Chelsea Wing (bankrate.com)

Carnevale et al. (2021) Georgetown University in their study highlighted the substantial disparity in lifetime earnings based on educational attainment. In particular, the gist of this study showed that an average person with only a high school diploma or GED would earn an estimated **1.6 million dollars in their lifetime**, compared to a person with a bachelor's degree who potentially can make **~2.8 million dollars**. This profound disparity in earning potential underscores the transformative power of higher education and highlights the significance of timely graduation in enhancing students' long-term financial security.

Objectives

In this project, I will use the **OSEMiN pipeline** to:

- Obtain → Import the data.
- Scrub → Manage the datatypes, and resolve missing data or duplicates.
- Explore → Identify patterns within the relationships between variables in the data.
- Model → Create a set of predictive models.
- iNterpret → Identify insights and create visualizations of findings.

For our model we could prioritize:

- accuracy - the proportion of correctly predicted labels out of all of the samples in the testing dataset.
- precision - measures the model's accuracy in predicting true positives as a proportion of all positives.
- recall- measures the model's ability to measure all positive instances correctly.
- f1-score - the harmonic mean of precision and recall, used when we want to consider both false positives and false negatives

We will prioritize recall in this project over precision. By prioritizing recall, we aim to reduce the number of false negatives and increase the model's ability to correctly identify and intervene with students at risk of academic failure. Minimizing the number of false negatives will help to ensure that fewer students who need educational assistance slip through the cracks and are not appropriately identified and supported.

- True positives are the cases when a model predicts positive instances correctly.
  - Ex. students predicted to drop out and do drop out
- False negatives are the cases when a model mispredicts negative instances.
  - Ex. students predicted to drop out but do not drop out

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

A high recall means that our model can effectively detect a significant portion of students likely to fail academically. Crucially, determining which students are more likely to fail enables us to provide the necessary support and intervention programs to those students who need them the most.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

A high precision value indicates that when the model predicts a student is at risk, the student will likely experience academic failure. This feature is crucial as it helps prevent unnecessary intervention for students who may not need it, ensuring efficient allocation of resources.

Data Understanding

The machine learning repository at the University of California(Irvine) contains dataset for evaluating machine learning techniques. The dataset used in this exploration is from this repository and can be found here. This dataset was created as a part of a project to reduce academic dropout and failure rates in higher education. Using machine learning, this project aims to identify at-risk students early and provide support to improve their likelihood of on-time graduation.

The data includes essential information available from when a student enrolls, such as their:

- academic path
- demographics
- social-economic factors

There are three classifications of students within this dataset:

- dropout
- enrolled
- graduate

The data was preprocessed to address missing values and anomalies. The dataset has **37** columns with **4424** rows of data. I am going to use a minimum of 4 machine learning algorithms to classify this data and will also use exploration to determine:

- How does the number of credits students enrolled in each semester influece the likelihoon of students graduating on time?
- Does the timely payment of tuition fees have any impact on the graduation status of students?
- Is there are relationship between the age a students is at enrollment and the graduation status of students?

Features

Name	Role	Type	Data Type	Description
Marital status	Feature	Discrete	int	1 — single 2 — married 3 — widowed 4 — divorced 5 — facto union 6 — legally separated
Application mode	Feature	Discrete	int	1 – 1st phase – general contingent 2 –Ordinance No. 612/93 5 – 1st phase – special contingent (Azores Island) 7– Holders of other higher courses 10 – Ordinance No. 854-B/99 15 –International student (bachelor) 16 – 1st phase – special contingent (Madeira Island) 17 – 2nd phase – general contingent 18 – 3rd phase – general contingent 26 – Ordinance No. 533-A/99, item b2) (Different Plan) 27 - Ordinance No. 533-A/99, item b3 (Other Institution) 39 – Over 23 years old 42 – Transfer 43 – Change of course 44 – Technological specialization diploma holders 51 – Change of institution/course 53 – Short cycle diploma holders 57 – Change of institution/course (International)
Application order	Feature	Discrete	int	Application order between 0 - first choice; and 9 last choice
Course	Feature	Discrete	int	33 - Biofuel Production Technologies 171 - Animation and Multimedia Design 8014 - Social Service (evening attendance) 9003 - Agronomy 9070 - Communication Design 9085 - Veterinary Nursing 9119 - Informatics Engineering 9130 - Equinculture 9147 - Management 9238 - Social Service 9254 - Tourism 9500 - Nursing 9556 - Oral Hygiene 9670 - Advertising and Marketing Management 9773 - Journalism and Communication 9853 - Basic Education 9991 - Management (evening attendance)

Name	Role	Type	Data Type	Description
Daytime/evening attendance	Feature	Discrete	int	1 — daytime 0 — evening
Previous qualification	Feature	Discrete	int	1 – Secondary education 2 – Higher education - bachelor's degree 3 – Higher education - degree 4 – Higher education - master's 5– Higher education - doctorate 6 – Frequency of higher education 9 - 12th year of schooling - not completed 10 - 11th year of schooling - not completed 12 – Other – 11th year of schooling 14 – 10th year of schooling 15 – 10th year of schooling - not completed 19 - Basic education 3rd cycle (9th/10th/11th year) or equiv. 38 – Basic education 2nd cycle (6th/7th/8th year) or equiv. 39 – Technological specialization course 40 – Higher education - degree (1st cycle) 42 – Professional higher technical course 43 – Higher education - master (2nd cycle)
Previous qualification (grade)	Feature	Continuous	float	Grade of previous qualification between 0 and 200
Nacionality	Feature	Discrete		1 — Portuguese; 2 — German; 6 — Spanish; 11 — Italian; 13 — Dutch; 14 — English; 17 — Lithuanian; 21 — Angolan; 22 — Cape Verdean; 24 — Guinean; 25 — Mozambican; 26 — Santomean; 32 — Turkish; 41 — Brazilian; 62 — Romanian; 100 — Moldova (Republic of); 101 — Mexican; 103 — Ukrainian; 105 — Russian; 108 — Cuban; 109 — Colombian
Mother's qualification	Feature	Discrete	int	1 - Secondary Education - 12th Year of Schooling or Eq. 2 - Higher Education - Bachelor's Degree 3 - Higher Education - Degree 4 - Higher Education - Master's 5 - Higher Education - Doctorate 6 - Frequency of Higher Education 9 - 12th Year of Schooling - Not Completed 10 - 11th Year of Schooling - Not Completed 11 - 7th Year (Old) 12 - Other - 11th Year of Schooling 14 - 10th Year of Schooling 18 - General commerce course 19 - Basic Education 3rd Cycle (9th/10th/11th Year) or Equiv. 22 - Technical-professional course 26 - 7th year of schooling 27 - 2nd cycle of the general high school course 29 - 9th Year of Schooling - Not Completed 30 - 8th year of schooling 34 - Unknown 35 - Can't read or write 36 - Can read without having a 4th year of schooling 37 - Basic education 1st cycle (4th/5th year) or equiv. 38 - Basic Education 2nd Cycle (6th/7th/8th Year) or Equiv. 39 - Technological specialization course 40 - Higher education - degree (1st cycle) 41 - Specialized higher studies course 42 - Professional higher technical course 43 - Higher Education - Master (2nd cycle) 44 - Higher Education - Doctorate (3rd cycle)
Father's qualification	Feature	Discrete	int	1 - Secondary Education - 12th Year of Schooling or Eq. 2 - Higher Education - Bachelor's Degree 3 - Higher Education - Degree 4 - Higher Education - Master's 5 - Higher Education - Doctorate 6 - Frequency of Higher Education 9 - 12th Year of Schooling - Not Completed 10 - 11th Year of Schooling - Not Completed 11 - 7th Year (Old) 12 - Other - 11th Year of Schooling 13 - 2nd year complementary high school course 14 - 10th Year of Schooling 18 - General commerce course 19 - Basic Education 3rd Cycle (9th/10th/11th Year) or Equiv. 20 - Complementary High School Course 22 - Technical-professional course 25 - Complementary High School Course - not concluded 26 - 7th year of schooling 27 - 2nd cycle of the general high school course 29 - 9th Year of Schooling - Not Completed 30 - 8th year of schooling 31 - General Course of Administration and Commerce 33 - Supplementary Accounting and Administration 34 - Unknown 35 - Can't read or write 36 - Can read without having a 4th year of schooling 37 - Basic education 1st cycle (4th/5th year) or equiv. 38 - Basic Education 2nd Cycle (6th/7th/8th Year) or Equiv. 39 - Technological specialization course 40 - Higher education - degree (1st cycle) 41 - Specialized higher studies course 42 - Professional higher technical course 43 - Higher Education - Master (2nd cycle) 44 - Higher Education - Doctorate (3rd cycle
Mother's occupation	Feature	Discrete	int	0 – Student 1 – Representatives of the Legislative Power and Executive Bodies, Directors, Directors and Executive Managers 2 – Specialists in Intellectual and Scientific Activities 3 – Intermediate Level Technicians and Professions 4 – Administrative staff 5 – Personal Services, Security and Safety Workers and Sellers 6 – Farmers and Skilled Workers in Agriculture, Fisheries and Forestry 7 – Skilled Workers in Industry, Construction and Craftsmen 8 – Installation and Machine Operators and Assembly Workers 9 – Unskilled Workers 10 – Armed Forces Professions 90 – Other Situation 99– (blank) 122 – Health professionals 123 - teachers 125 - Specialists in information and communication technologies (ICT) 131 - Intermediate level

Name	Role	Type	Data Type	Description
				science and engineering technicians and professions 132 - Technicians and professionals, of intermediate level of health 134 - Intermediate level technicians from legal, social, sports, cultural and similar services 141 - Office workers, secretaries in general and data processing operators 143 - Data, accounting, statistical, financial services and registry-related operators 144 - Other administrative support staff 151 - personal service workers 152 - sellers 153 - Personal care workers and the like 171 - Skilled construction workers and the like, except electricians 173 - Skilled workers in printing, precision instrument manufacturing, jewelers, artisans and the like 175 - Workers in food processing, woodworking, clothing and other industries and crafts 191 - cleaning workers 192 - Unskilled workers in agriculture, animal production, fisheries and forestry 193 - Unskilled workers in extractive industry, construction, manufacturing and transport 194 - Meal preparation assistants
Father's occupation	Feature	Discrete	int	0 – Student 1 – Representatives of the Legislative Power and Executive Bodies, Directors, Directors and Executive Managers 2 – Specialists in Intellectual and Scientific Activities 3 –Intermediate Level Technicians and Professions 4 – Administrative staff 5 – Personal Services, Security and Safety Workers and Sellers 6 – Farmers and Skilled Workers in Agriculture, Fisheries and Forestry 7 – Skilled Workers in Industry, Construction and Craftsmen 8 – Installation and Machine Operators and Assembly Workers 9 – Unskilled Workers 10 – Armed Forces Professions 90 – Other Situation 99 – (blank) 101 – Armed Forces Officers 102 – Armed Forces Sergeants 103 – Other Armed Forces personnel 112 – Directors of administrative and commercial services 114 – Hotel, catering, trade and other services directors 121 - Specialists in the physical sciences, mathematics, engineering and related techniques 122 - Health professionals 123 - teachers 124 - Specialists in finance, accounting, administrative organization, public and commercial relations 131 - Intermediate level science and engineering technicians and professions 132 - Technicians and professionals, of intermediate level of health 134 - Intermediate level technicians from legal, social, sports, cultural and similar services 135 - Information and communication technology technicians 141 - Office workers, secretaries in general and data processing operators 143 - Data, accounting, statistical, financial services and registry-related operators 144 - Other administrative support staff 151 - personal service workers 152 - sellers 153 - Personal care workers and the like 154 - Protection and security services personnel 161 - Market-oriented farmers and skilled agricultural and animal production workers 163 - Farmers, livestock keepers, fishermen, hunters and gatherers, subsistence 171 - Skilled construction workers and the like, except electricians 172 - Skilled workers in metallurgy, metalworking and similar 174 - Skilled workers in electricity and electronics 175 - Workers in food processing, woodworking, clothing and other industries and crafts 181 - Fixed plant and machine operators 182 - assembly workers 183 - Vehicle drivers and mobile equipment operators 192 - Unskilled workers in agriculture, animal production, fisheries and forestry 193 - Unskilled workers in extractive industry, construction, manufacturing and transport 194 - Meal preparation assistants 195 - Street vendors (except food) and street service providers
Admission grade	Feature	Continuous	float	Admission grade (between 0 and 200)
Displaced	Feature	Discrete	int	1 — yes 0 — no
Educational special needs	Feature	Discrete	int	1 — yes 0 — no
Debtor	Feature	Discrete	int	1 — yes 0 — no
Tuition fees up to date	Feature	Discrete	int	1 — yes 0 — no
Gender	Feature	Discrete	int	1 — male 0 — female
Scholarship holder	Feature	Discrete	int	1 — yes 0 — no
Age at enrollment	Feature	Discrete	int	Age of studend at enrollment
Scholarship holder	Feature	Discrete	int	1 — yes 0 — no

Name	Role	Type	Data Type	Description
International	Feature	Discrete	int	1 — yes 0 — no
Curricular units 1st sem (credited)	Feature	Discrete	int	Number of curricular units credited in the 1st semester
Curricular units 1st sem (enrolled)	Feature	Discrete	int	Number of curricular units enrolled in the 1st semester
Curricular units 1st sem (evaluations)	Feature	Discrete	int	Number of evaluations to curricular units in the 1st semester
Curricular units 1st sem (approved)	Feature	Discrete	int	Number of curricular units approved in the 1st semester
Curricular units 1st sem (grade)	Feature	Discrete	float	Grade average in the 1st semester (between 0 and 20)
Curricular units 1st sem (without evaluations)	Feature	Discrete	int	Number of curricular units without evalutions in the 1st semester
Curricular units 2nd sem (credited)	Feature	Discrete	int	Number of curricular units credited in the 2nd semester
Curricular units 2nd sem (enrolled)	Feature	Discrete	int	Number of curricular units enrolled in the 2nd semester
Curricular units 2nd sem (evaluations)	Feature	Discrete	int	Number of evaluations to curricular units in the 2nd semester
Curricular units 2nd sem (approved)	Feature	Discrete	int	Number of curricular units approved in the 2nd semester
Curricular units 2nd sem (grade)	Feature	Discrete	float	Grade average in the 2nd semester (between 0 and 20)
Curricular units 2nd sem (without evaluations)	Feature	Discrete	int	Number of curricular units without evalutions in the 1st semester
Unemployment rate	Feature	Continuous	float	Unemployment rate (%)
Inflation rate	Feature	Continuous	float	Inflation rate (%)
GDP	Feature	Continuous	float	GDP
Target	Target	Categorical	string	Target. The problem is formulated as a three category classification task (dropout, enrolled, and graduate) at the end of the normal duration of the course

Obtain

The `ObtainData` class defines a constructor to initialize the data_path attribute and set data to None. It provides a method `load_data` to load the dataset from the specified data_path using pandas, assuming the dataset is in .csv format with semicolons as the separator, and assigns the loaded data to the data attribute. The `obtain_data` method calls the `load_data` method and returns the loaded dataset.

To determine answers to my guiding questions, first, I needed to import relevant libraries and packages.

Import libraries and Visualization Packages

Importing libraries at the beginning allows access to modules and other tools throughout this project that help to make the tasks within this project manageable to implement. The main libraries used within this project include:

- `pandas` : a data analysis and manipulation library which allows for flexible reading, writing, and reshaping of data
- `numpy` : a key library that brings the computational power of languages like C to Python
- `matplotlib` : a comprehensive visualization library
- `seaborn` : a data visualization library based on matplotlib
- `statsmodels` : a library used to understand statistical relationships between variables, often used in the field of economics.
- `sklearn` : a machine learning libary for data processing and modeling.

In [1]:
```
# Import libraries and visualization packages
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.ticker as ticker
import statsmodels.api as sm
import sklearn
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, recall_score
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.feature_selection import RFE
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

import warnings
warnings.filterwarnings("ignore")
warnings.simplefilter(action ='ignore', category = DeprecationWarning)
warnings.simplefilter(action ='ignore', category = FutureWarning)
warnings.filterwarnings("ignore", category=UserWarning, module="pandas")


# Allow plots to display and be stored inline within a notebook
%matplotlib inline

# Used for working with the z-score
from scipy import stats

# Used for working with long url
from urllib.parse import urlencode

# Set display option to readable format
pd.set_option('display.float_format', lambda x: '%.2f' % x)

# Filter warnings from pandas
pd.options.mode.chained_assignment = None
```

Check library versions:

One of the essential aspects of modeling is the ability to reproduce results. As we gather more information over time, science undoubtedly relies on models that continuously improve. Communicating the version of the tools used to generate a model is a crucial part of collaboration. Therefore, we take note of the version of key libraries so that other researchers have a starting point when attempting to reproduce this work.

In [2]:
```
# Check Pandas version
print ("Pandas version:")
pd.__version__
```

```
Pandas version:
'1.1.3'
```
Out[2]:

In [3]:
```
# Check Numpy version
print("Numpy version:")
np.__version__
```

```
Numpy version:
'1.24.4'
```
Out[3]:

In [4]:
```
# Check Seaborn version
print("Seaborn version:")
sns.__version__
```

```
Seaborn version:
'0.11.0'
```
Out[4]:

In [5]:
```
# Check Statsmodel version
print("Statsmodel version:")
sm.__version__
```

```
Statsmodel version:
'0.13.5'
```
Out[5]:

In [6]:
```
# Check sci-kit learn version
print("Sci-kit learn version:")
sklearn.__version__
```

```
Sci-kit learn version:
'1.3.0'
```
Out[6]:

In [7]:
```
class ObtainData:
    def __init__(self, data_path):
        """
        Constructor for the ObtainData class.

        Parameters:
        - data_path(string): Path to the dataset file.

        Initializes the data_path attribute and sets data to None.
        """

        self.data_path = data_path
        self.data = None

    def load_data(self):
        """
        Loads the dataset from the specified data_path using pandas.
        Assumes the dataset is in csv format with semicolons(;) as the separator.
        Assigns the loaded data to the data attribute.
        """
        self.data = pd.read_csv(self.data_path, sep = ';')

    def obtain_data(self):

        self.load_data()
        return self.data
```

In [8]:
```
# Main excution
```

```
if __name__ == '__main__':
    # Initialize the ObtainData object
    data_obtained = ObtainData(data_path = 'data/data.csv')

    # Obtain the data
    data_obtained.obtain_data()
```

Scrub

The `ScrubData` class defines a constructor to initialize the data attribute with a pandas DataFrame. It provides a method check_placeholders to check for placeholders *(e.g., '?', '#', 'NaN', 'null', 'N/A', '-')* and replaces them if found; otherwise, it prints a message indicating that no placeholders were detected.

Additionally, the class includes a `clean` method to perform data-cleaning operations. In this method, rows containing missing data are removed using `dropna` function and the resulting cleaned DataFrame is returned.

In [9]:
```
class ScrubData:
    def __init__(self, data):
        """
        Constructor for the ScrubData class.

        Parameters:
        - data (pandas DataFrame): The dataset to be explored

        Initializes the data attribute.
        """

        self.data = data


    def check_placeholders(self):
        """
        Checks and displays the presence of placeholders throughout the entire dataframe.
        Placeholders checked: '?', '#', 'NaN','null, 'N/A,'-'.
        """
        placeholders = ['?', '#', 'NaN', 'null', 'N/A', '-']
        placeholder_mask = self.data.isin(placeholders)

        if placeholder_mask.any().any():
            print('\nPlaceholders Detected:')
            display(placeholder_mask)
        else:
            print('\nNo Placeholders Detected.')

    def clean(self):
        """
        Perform data cleaning operations.
        """
        cleaned_data = self.data.dropna() # Drop rows with missing data

        return cleaned_data
```

After obtaining the dataset using the `ObtainData` class, the data is passed to the `ScrubData` class to perform data cleaning operations. The `clean` method of the `ScrubData` class is then applied to the dataset, resulting in the variable `cleaned_data` holding the cleaned version of the dataset.

In [10]:
```
# Create an instance of the Obtained Data Class
data = data_obtained.obtain_data()

# Create an instance of the "ScrubData" class and pass the obtained dataset as a parameter to initialize
scrubbed_data = ScrubData(data = data)

# Clean the dataset using the "clean" method of the "ScrubData" class and store the cleaned data in the
cleaned_data = scrubbed_data.clean()
```

Explore

After obtaining the dataset using the `ObtainData` class and cleaning it with the `ScrubData` class, the ExploreData</code> class can be used to analyze and explore the cleaned dataset further. The `ExploreData` class allows us to understand the data and identify any patterns or insights that could be beneficial for the subsequent analysis or decision-making processes.

In [11]:
```
class ExploreData:
    def __init__(self,data):
        """
        Constructor for the ExploreData class.

        Parameters:
        - data (pandas DataFrame): The dataset to be explored.

        Initializes the data attribute
        """
        self.data = data

    def examine_structure(self):
        """
        Prints the shape of the dataset and displays the first few rows.
        Also displays the data information including the number of rows and columns in the dataset.
        """
        print('Data Shape:')
        display(self.data.shape)

        print('Data Structure:')
        display(self.data.head())

        print('\nData Information:')
        display(self.data.info())

    def check_duplicates(self):

        """
        Checks and displays the number of duplicate rows in the dataset.
        """
        num_duplicates = self.data_duplicated().sum()
        print (f'\nNumber of Duplicate Rows: {num_duplicates}')

    def drop_duplicates(self):
        """
        Drops the duplicate rows from the dataset.
        """
        self.data.drop_duplicates(inplace = True)
        print("Duplicate rows dropped.")

    def generate_correlation_map(self, title):
        """
        Generates and displays a correlation matrix heatmap for the dataset.

        Parameters:
        -title(str): The title of the correlation map
        """

        correlation_matrix = self.data.corr()

        # Create a figure and set the title
        plt.figure(figsize = (30,25))
        plt.suptitle(title)

        # Generate the correlation heatmap
        sns.heatmap(correlation_matrix, annot = True, cmap = 'Blues')

        # Show the correlation map
        plt.show()
```

```
    def plot_pairplot(self, correlation_table):
        # Get the columns from the correlation table
        columns = list(correlation_table.index.levels[0])

        # Filter the data based on the columns
        data_filtered = self.data[columns]

        # Create a pairplot using the filtered data
        pairplot = sns.pairplot(data_filtered, diag_kind="kde", markers=".", height=2)

        # Customize the scatter matrix plot
        for ax in pairplot.axes.flat:
            ax.xaxis.label.set_rotation(90)
            ax.yaxis.label.set_rotation(0)
            ax.yaxis.label.set_ha('center')
            ax.get_yaxis().set_label_coords(-0.5, 0.5)
            ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=18)
            ax.set_yticklabels(ax.get_yticklabels(), rotation=90, ha='center', fontsize=18)

        # Show the plot
        plt.tight_layout()
        plt.show()

    def generate_correlation_table(self, threshold_min = 0.6, threshold_max = 1.0):
        """
        Generates a correlation table with filtered correlation pairs within specified thresholds.

        Parameters:
        - threshold_min (float): The minimum threshold for correlation values (inclusive). Default is 0.
        - threshold_max (float): The maximum threshold for correlation values (exclusive). Default is 1.

        Returns:

        - filtered_df (pandas DataFrame): The filtered correlation table.
        """

        correlation_matrix = self.data.corr().abs()

        correlation_df = correlation_matrix.stack().reset_index()
        correlation_df.columns = ['feature1', 'feature2', 'correlation']

        filtered_df = correlation_df[
            (correlation_df['correlation'] > threshold_min) & (correlation_df['correlation'] < threshold
        ]

        filtered_df.drop_duplicates(inplace = True)
        filtered_df.set_index(['feature1', 'feature2'], inplace = True)
        filtered_df.columns = ['correlation']

        return filtered_df

    def plot_gender_distribution(self):
        """
        Plots the gender distribution from the dataset.
        """
        plt.style.use('fivethirtyeight')
        gender_counts = self.data['Gender'].value_counts()
        gender_labels = ['Female', 'Male']
        gender_values = [gender_counts[0], gender_counts[1]]

        plt.figure(figsize = (8,6))
        ax = sns.barplot(x = gender_labels, y = gender_values, color = 'blue')

        plt.xlabel('Gender', fontsize = 14, weight = 'bold')
        plt.ylabel('Number of Students', fontsize = 14, weight = 'bold')
        plt.title('Gender Distribution of College Students',fontsize = 18, weight = 'bold')

        plt.show()
```

```
    def plot_dropout_by_gender(self):
        """
        Plots the gender distribution of students who dropout from the dataset.
        """
        plt.style.use('fivethirtyeight')
        dropout_data = self.data[self.data['Target']=='Dropout']
        dropout_data['Gender']= dropout_data['Gender'].map({1:'Male', 0:'Female'})


        plt.figure(figsize = (8,6))
        ax = sns.countplot(x = 'Gender', data = dropout_data, color = 'blue')

        plt.xlabel('Gender', fontsize = 14, weight = 'bold')
        plt.ylabel('Number of Students', fontsize = 14, weight = 'bold')
        plt.title('Distribution of Dropouts by Gender',fontsize = 18, weight = 'bold')

        plt.show()

    def plot_target_distribution(self):
        """
        Plots the gender distribute of the target variable from the dataset.
        """

        target_data = self.data['Target']
        target_labels = ['Dropout', 'Enrolled', 'Graduate']


        plt.figure(figsize = (8,6))
        ax = sns.countplot(x = target_labels, data = target_data, color = 'blue')

        plt.xlabel('Status', fontsize = 14, weight = 'bold')
        plt.ylabel('Percentage of Students', fontsize = 14, weight = 'bold')
        plt.title('Progress to Graduation Distribution of College Students',fontsize = 18, weight = 'bol

        plt.show()
```

Next, we create an instance of the `ExploreData` class and pass the cleaned dataset as a parameter to initialize the class, stored in the variable `data_exploration`. We then call the `examine_structure(` method of the `ExploreData` class to examine the structure of the dataset, including its size, data types, and presence of missing values. Finally, we use the `generate_correlation_map()` method of the `ExploreData` class to generate a correlation map, which visualizes the correlations between features related to student academic success.

In [12]:
```
# Create an instance of the ExploreData class and pass the cleaned dataset as a parameter to initialize
data_exploration = ExploreData(data=cleaned_data)

# Examine the structure of the dataset, such as the number of rows, columns, data types, and missing val
data_exploration.examine_structure()
```

```
Data Shape:
(4424, 37)
Data Structure:
```

	Marital status	Application mode	Application order	Course	Daytime/evening attendance\t	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	F qualif
0	1	17	5	171	1	1	122.00	1	19	
1	1	15	1	9254	1	1	160.00	1	1	
2	1	1	5	9070	1	1	122.00	1	37	
3	1	17	2	9773	1	1	122.00	1	38	
4	2	39	1	8014	0	1	100.00	1	37	

5 rows × 37 columns

```
Data Information:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4424 entries, 0 to 4423
Data columns (total 37 columns):
 #   Column                                          Non-Null Count  Dtype
---  ------                                          --------------  -----
 0   Marital status                                  4424 non-null   int64
 1   Application mode                                4424 non-null   int64
 2   Application order                               4424 non-null   int64
 3   Course                                          4424 non-null   int64
 4   Daytime/evening attendance                      4424 non-null   int64
 5   Previous qualification                          4424 non-null   int64
 6   Previous qualification (grade)                  4424 non-null   float64
 7   Nacionality                                     4424 non-null   int64
 8   Mother's qualification                          4424 non-null   int64
 9   Father's qualification                          4424 non-null   int64
 10  Mother's occupation                             4424 non-null   int64
 11  Father's occupation                             4424 non-null   int64
 12  Admission grade                                 4424 non-null   float64
 13  Displaced                                       4424 non-null   int64
 14  Educational special needs                       4424 non-null   int64
 15  Debtor                                          4424 non-null   int64
 16  Tuition fees up to date                         4424 non-null   int64
 17  Gender                                          4424 non-null   int64
 18  Scholarship holder                              4424 non-null   int64
 19  Age at enrollment                               4424 non-null   int64
 20  International                                   4424 non-null   int64
 21  Curricular units 1st sem (credited)             4424 non-null   int64
 22  Curricular units 1st sem (enrolled)             4424 non-null   int64
 23  Curricular units 1st sem (evaluations)          4424 non-null   int64
 24  Curricular units 1st sem (approved)             4424 non-null   int64
 25  Curricular units 1st sem (grade)                4424 non-null   float64
 26  Curricular units 1st sem (without evaluations)  4424 non-null   int64
 27  Curricular units 2nd sem (credited)             4424 non-null   int64
 28  Curricular units 2nd sem (enrolled)             4424 non-null   int64
 29  Curricular units 2nd sem (evaluations)          4424 non-null   int64
 30  Curricular units 2nd sem (approved)             4424 non-null   int64
 31  Curricular units 2nd sem (grade)                4424 non-null   float64
 32  Curricular units 2nd sem (without evaluations)  4424 non-null   int64
 33  Unemployment rate                               4424 non-null   float64
 34  Inflation rate                                  4424 non-null   float64
 35  GDP                                             4424 non-null   float64
 36  Target                                          4424 non-null   object
dtypes: float64(7), int64(29), object(1)
memory usage: 1.3+ MB
```

The data contains **4424 entries and 37 columns**. It includes various features related to student academic success, such as economic stability (debt, timely tuition payments), demographics, and curriculuar units. TThe data is stored in a DataFrame format, providing information on data types and non-null counts for each column. The data is well-structured and does not contain any missing values.

The ratio below shows the Pearson correlation :

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2}\sqrt{\sum(Y_i - \bar{Y})^2}}$$

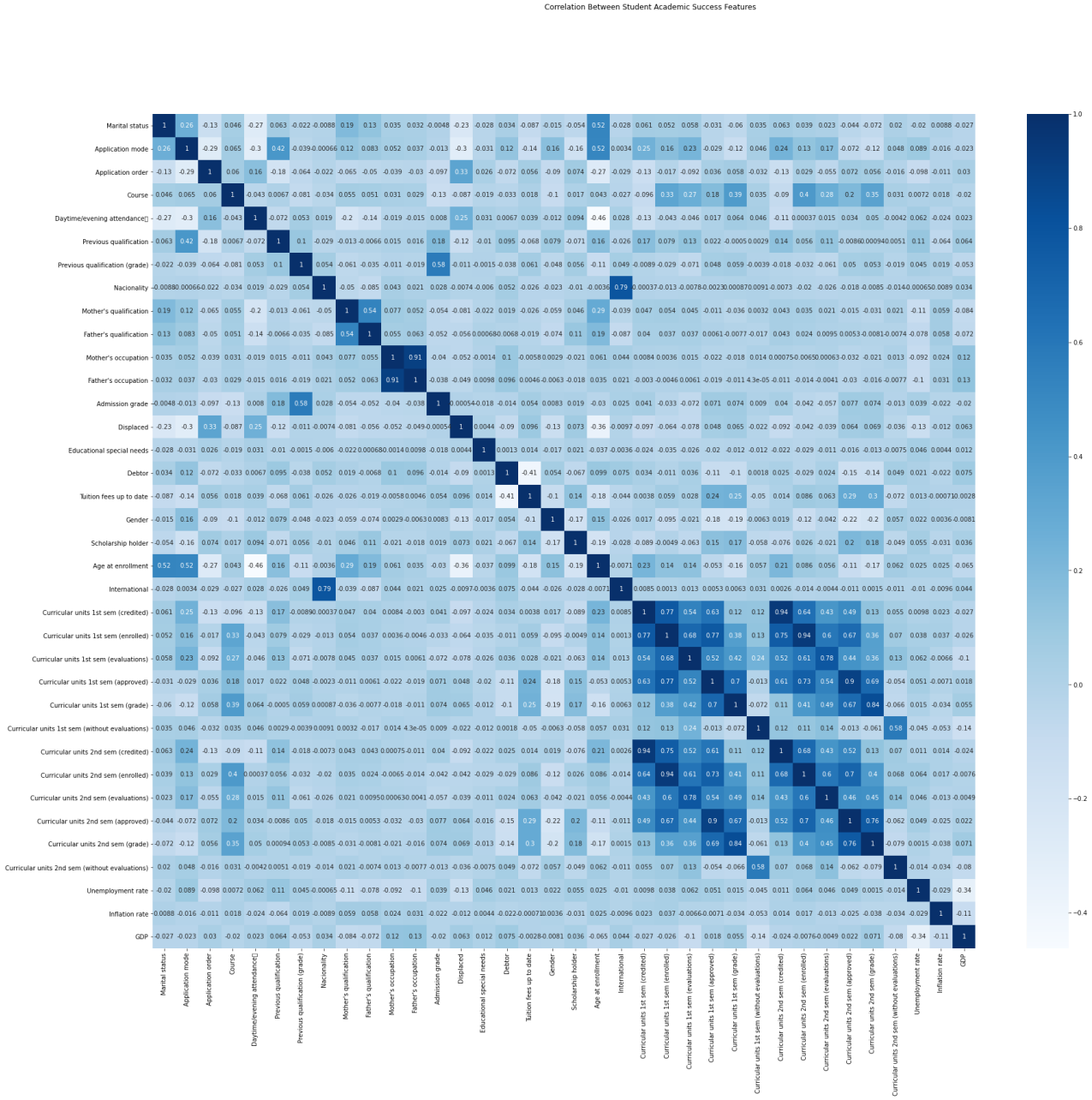
- X_i - individual point in dataset X
- Y_i - individual point in dataset Y
- $\bar{X}$- mean of dataset X
- $\bar{Y}$ - mean of dataset Y

The Pearson correlation coefficient r measures the linear relationship between two datasets X and Y by computing how closely data points cluster around their respective means.

A commonly held rule for interpreting the Pearson correlation is that:

- Very strong correlation → 0.8 to 1
- Strong correlation → 0.6 to 0.799
- Moderate correlation → 0.4 to 0.599
- Weak correlation → 0.2 to 0.399
- Very weak correlation → 0 to 0.199

In [13]:
```
# Generate a correlation map for the dataset to visualize the correlations between features related to s
data_exploration.generate_correlation_map("Correlation Between Student Academic Success Features")
```



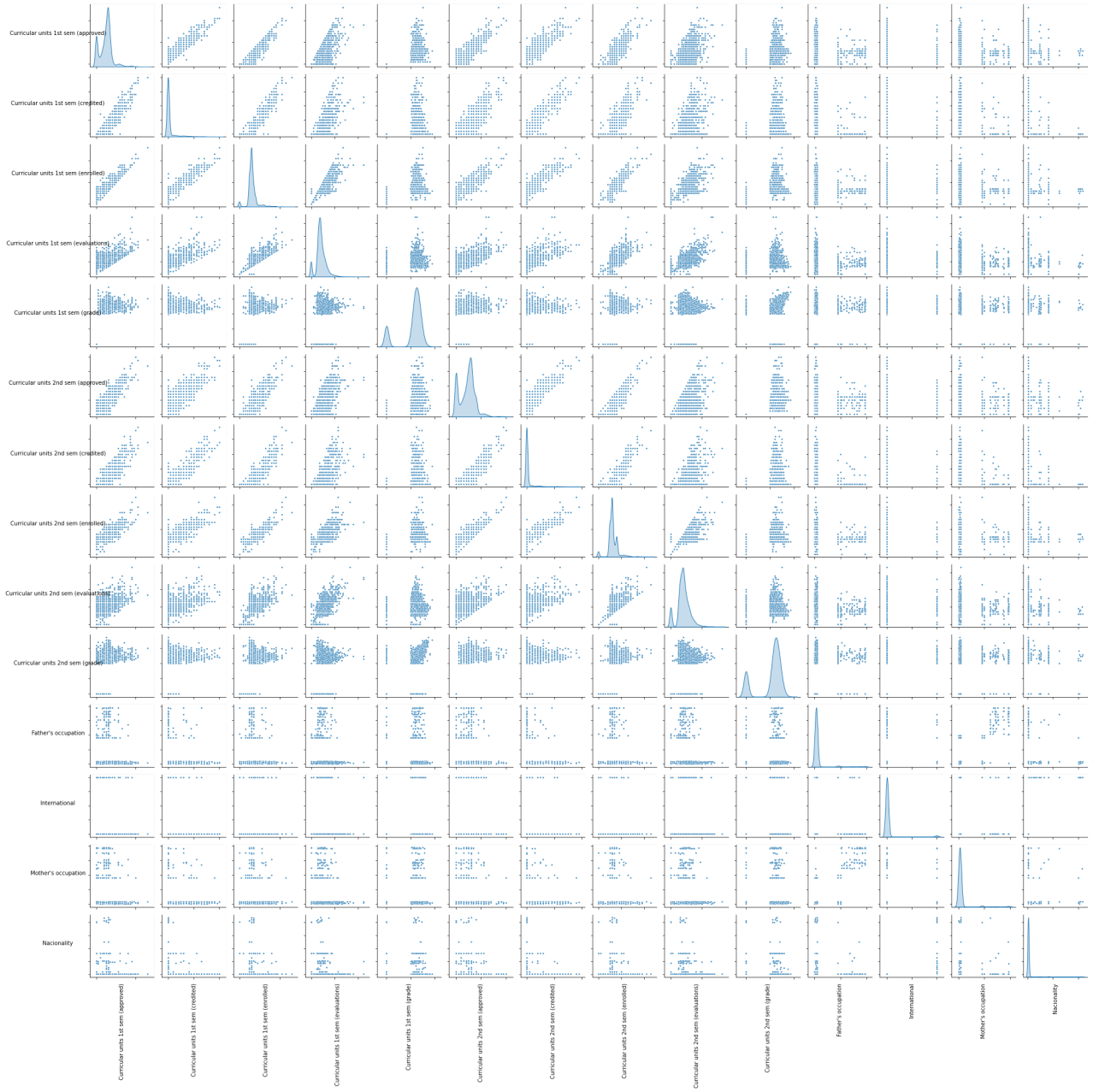
This correlation heat map seems complicated to analyze, so let's simplify it to something more useful.

In [14]:
```
# Generate a correlation table for the cleaned dataset using the "generate_correlation_table" method of
# The correlation table will include only correlations between 0.6 and 1.0.
correlation_table = data_exploration.generate_correlation_table(0.6, 1.0)

# Display the correlation table using the "display" function.
display(correlation_table)
```

feature1	feature2	correlation
Nacionality	**International**	0.79
Mother's occupation	**Father's occupation**	0.91
Father's occupation	**Mother's occupation**	0.91
International	**Nacionality**	0.79
Curricular units 1st sem (credited)	**Curricular units 1st sem (enrolled)**	0.77
	Curricular units 1st sem (approved)	0.63
	Curricular units 2nd sem (credited)	0.94
	Curricular units 2nd sem (enrolled)	0.64
Curricular units 1st sem (enrolled)	**Curricular units 1st sem (credited)**	0.77
	Curricular units 1st sem (evaluations)	0.68
	Curricular units 1st sem (approved)	0.77
	Curricular units 2nd sem (credited)	0.75
	Curricular units 2nd sem (enrolled)	0.94
	Curricular units 2nd sem (approved)	0.67
Curricular units 1st sem (evaluations)	**Curricular units 1st sem (enrolled)**	0.68
	Curricular units 2nd sem (enrolled)	0.61
	Curricular units 2nd sem (evaluations)	0.78
Curricular units 1st sem (approved)	**Curricular units 1st sem (credited)**	0.63
	Curricular units 1st sem (enrolled)	0.77
	Curricular units 1st sem (grade)	0.70
	Curricular units 2nd sem (credited)	0.61
	Curricular units 2nd sem (enrolled)	0.73
	Curricular units 2nd sem (approved)	0.90
	Curricular units 2nd sem (grade)	0.69
Curricular units 1st sem (grade)	**Curricular units 1st sem (approved)**	0.70
	Curricular units 2nd sem (approved)	0.67
	Curricular units 2nd sem (grade)	0.84
Curricular units 2nd sem (credited)	**Curricular units 1st sem (credited)**	0.94
	Curricular units 1st sem (enrolled)	0.75
	Curricular units 1st sem (approved)	0.61
	Curricular units 2nd sem (enrolled)	0.68
Curricular units 2nd sem (enrolled)	**Curricular units 1st sem (credited)**	0.64
	Curricular units 1st sem (enrolled)	0.94
	Curricular units 1st sem (evaluations)	0.61
	Curricular units 1st sem (approved)	0.73
	Curricular units 2nd sem (credited)	0.68
	Curricular units 2nd sem (evaluations)	0.60
	Curricular units 2nd sem (approved)	0.70
Curricular units 2nd sem (evaluations)	**Curricular units 1st sem (evaluations)**	0.78

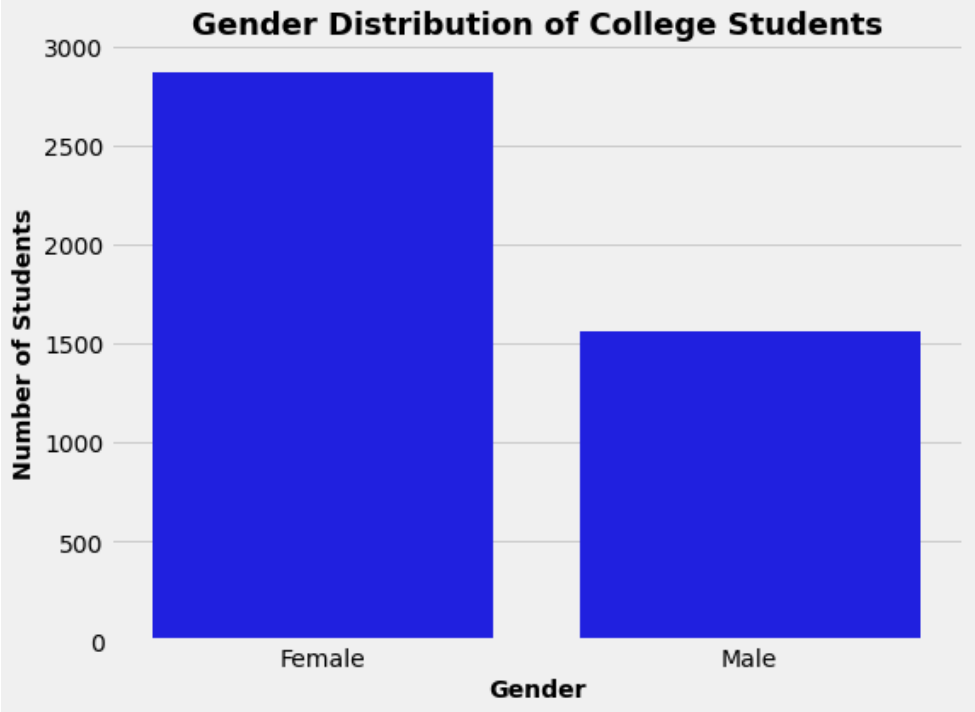
feature1	feature2	correlation
	Curricular units 2nd sem (enrolled)	0.60
Curricular units 2nd sem (approved)	Curricular units 1st sem (enrolled)	0.67
	Curricular units 1st sem (approved)	0.90
	Curricular units 1st sem (grade)	0.67
	Curricular units 2nd sem (enrolled)	0.70
	Curricular units 2nd sem (grade)	0.76
Curricular units 2nd sem (grade)	Curricular units 1st sem (approved)	0.69
	Curricular units 1st sem (grade)	0.84
	Curricular units 2nd sem (approved)	0.76

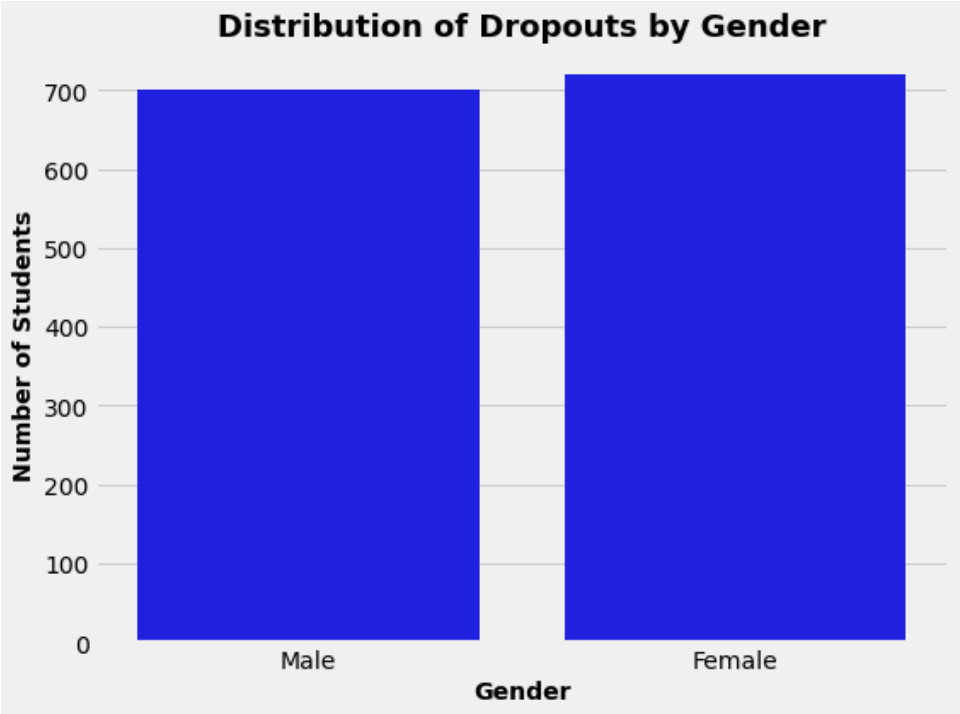
In [15]:
```
%%time
# Plot pairplot using the correlation table
data_exploration.plot_pairplot(correlation_table)
```

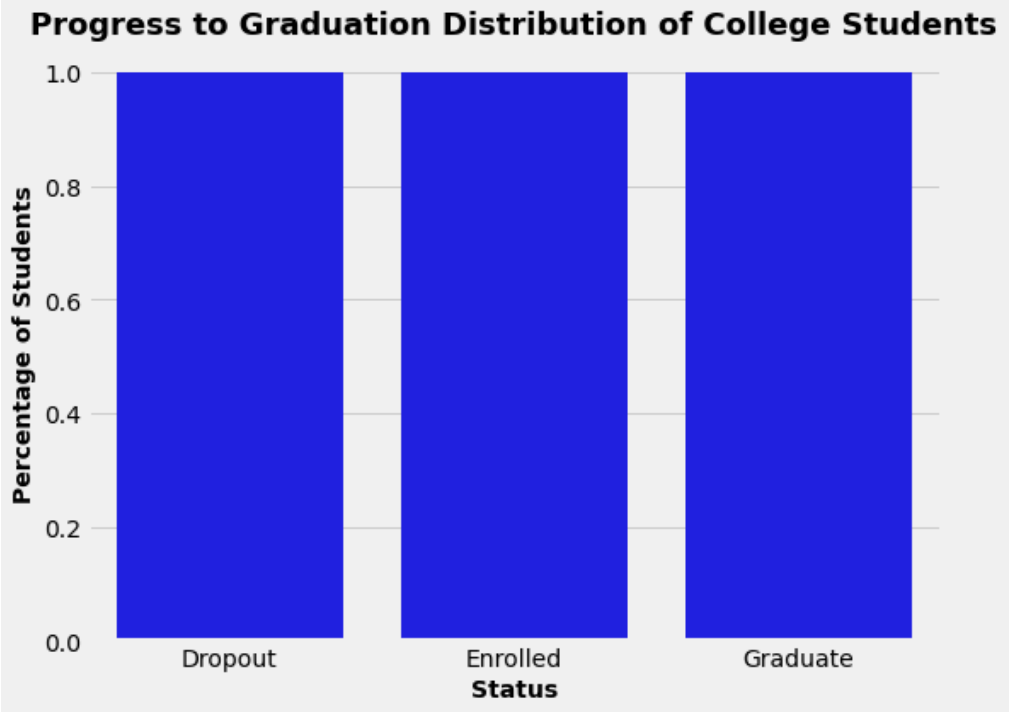


```
Wall time: 1min 54s
```

In [16]:
```python
if __name__ == '__main__':
    # Plot the gender distribution of the data
    data_exploration.plot_gender_distribution()

    # Plot the dropout distribution by gender
    data_exploration.plot_dropout_by_gender()

    # Plote the Progress to graduation distribution by gender
    data_exploration.plot_target_distribution()
```







While there are ~1500 more female students than male students in the dataset, there are equal numbers of each gender (approx 700 students) who dropped out of college. The data has similar numbers of students in each class.

The AnalyzeData class has the following functions:

- `analyze` : Maps relevant variables to their corresponding labels and performs data analysis to explore factors influencing student graduation status.
- `plot_bar_chart` : Plots bar charts to visualize the impact of categorical variables on graduation status.
- `plot_boxplot` : Plots box plots to visualize the relationship between target variables and numerical features.
- `plot_horizontal_bar_chart` : Plots horizontal bar charts to explore the influence of 'Previous qualification' on graduation status.

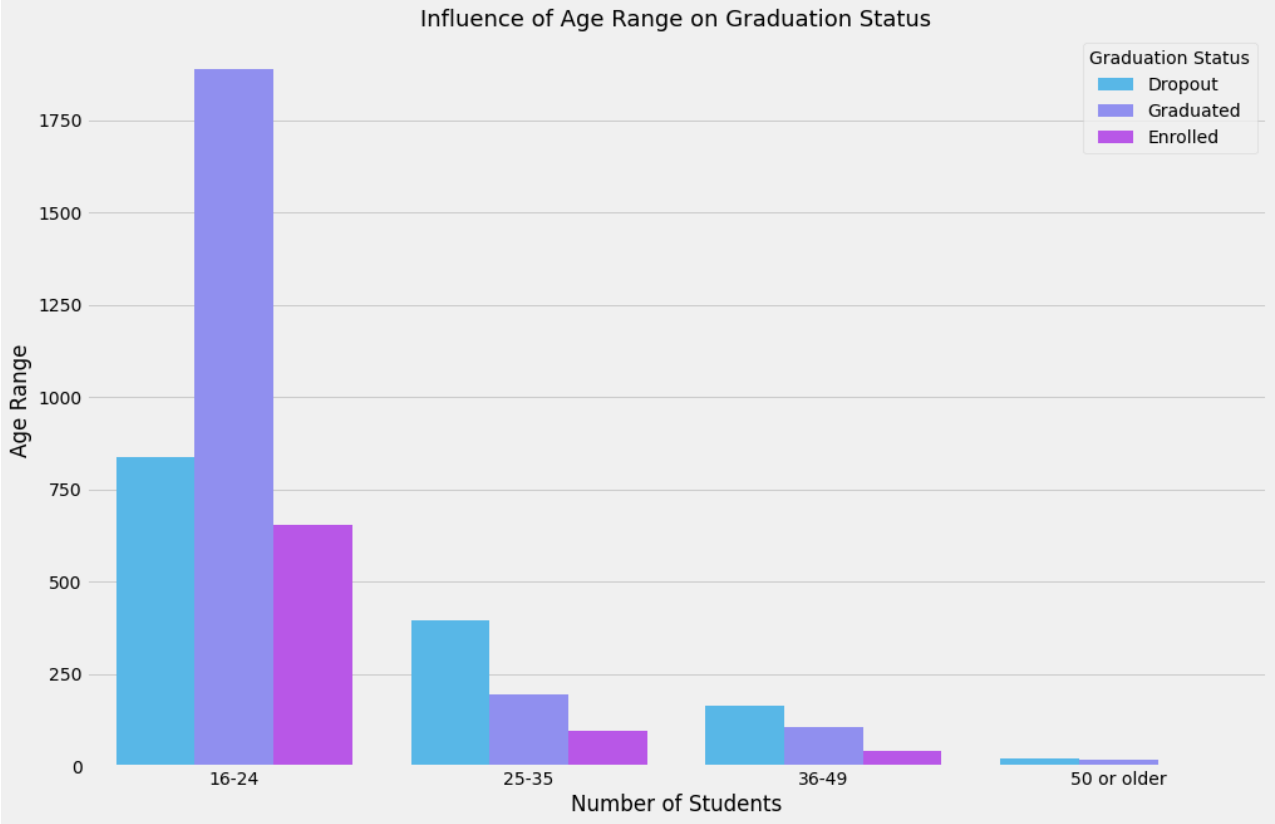
By using these functions, we can begin to explore the factors affecting graduation outcomes.

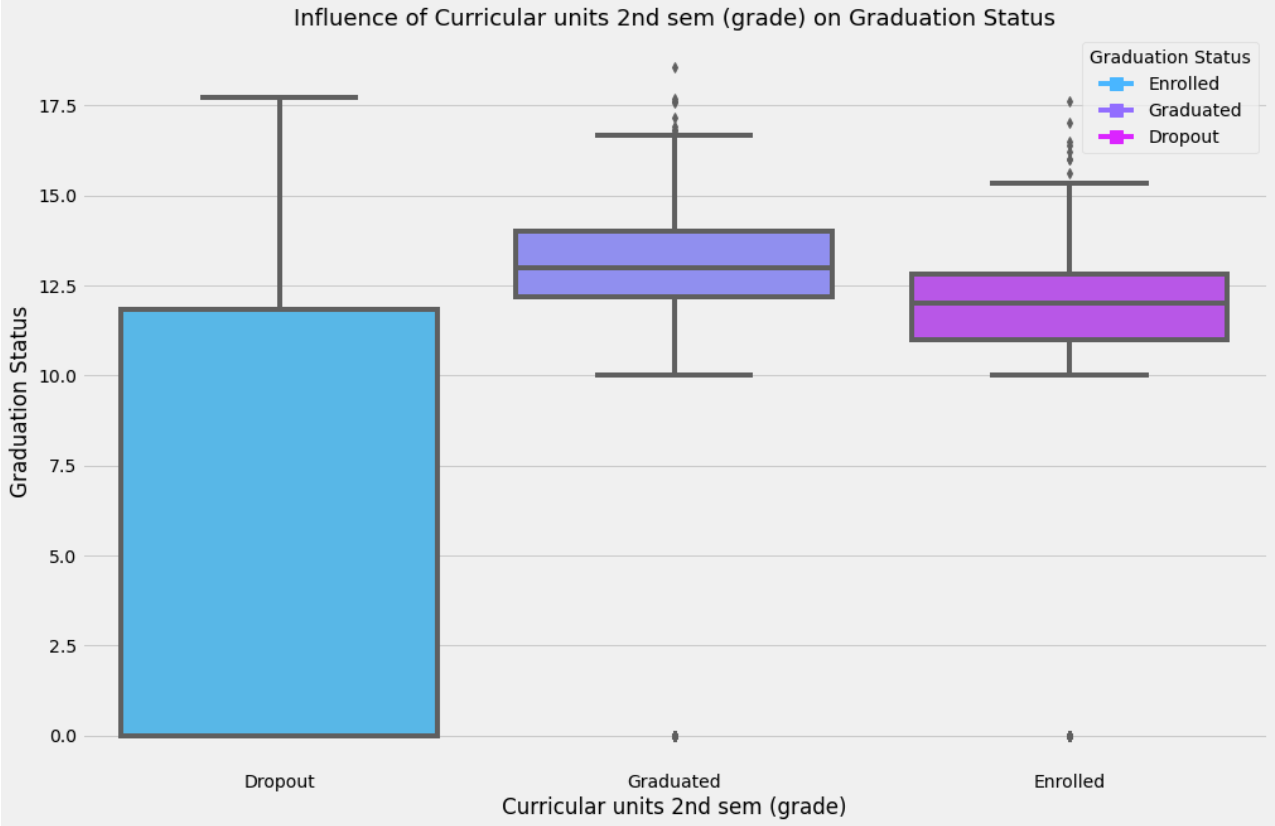
In [17]:
```
class AnalyzeData:
    def __init__(self, data):
        self.data = data

    def analyze(self):
        # Map the revised target variable values to their corresponding labels
        target_labels = {
            "Enrolled": "Enrolled",
            "Graduate": "Graduated",
            "Dropout": "Dropout"
        }

        # Map the revised "Tuition fees up to date" variable values to their corresponding labels
        tuition_fees_labels = {
            1: "Yes",
            0: "No"
        }

        # Map the revised "Marital status" variable values to their corresponding labels
        marital_status_labels = {
            1: "Single",
            2: "Married",
            3: "Widower",
            4: "Divorced",
            5: "Facto Union",
            6: "Legally Separated"
```

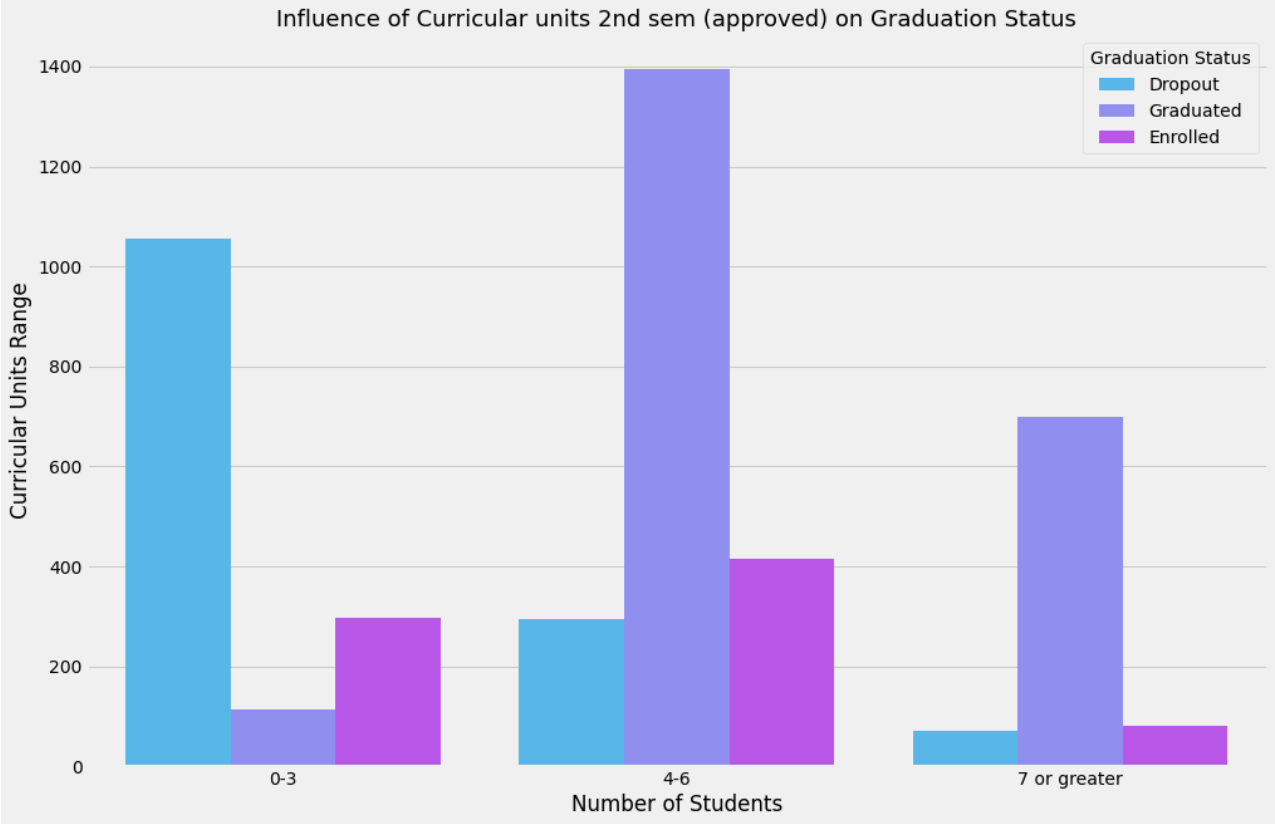
```
        }

        # Map the revised "Marital status" variable values to their corresponding labels
        attendance_labels = {
            1: "daytime",
            0: "evening",
        }

        # Map the revised "Debtor" variable values to their corresponding labels
        debtor_labels = {
            1: "Yes",
            0: "No"
        }

        # Map the revised "Scholarship holder" variable values to their corresponding labels
        scholarship_labels = {
            1: "Yes",
            0: "No"
        }
        # Map the revised "Previous qualification" variable values to their corresponding labels
        previous_qualification_labels = {
            1: "Secondary education",
            2: "Higher education - bachelor's degree",
            3: "Higher education - degree",
            4: "Higher education - master's",
            5: "Higher education - doctorate",
            6: "Frequency of higher education",
            9: "12th year of schooling - not completed",
            10: "11th year of schooling - not completed",
            12: "Other - 11th year of schooling",
            14: "10th year of schooling",
            15: "10th year of schooling - not completed",
            19: "Basic education 3rd cycle (9th/10th/11th year) or equiv.",
            38: "Basic education 2nd cycle (6th/7th/8th year) or equiv.",
            39: "Technological specialization course",
            40: "Higher education - degree (1st cycle)",
            42: "Professional higher technical course",
            43: "Higher education - master (2nd cycle)"
        }

        # Filter the data for relevant columns
        relevant_columns = ['Marital status',
                            'Curricular units 1st sem (credited)',
                            'Curricular units 2nd sem (approved)',
                            'Tuition fees up to date',
                            'Curricular units 2nd sem (grade)',
                            "Debtor",
                            "Age at enrollment",
                            'Target',
                            'Scholarship holder',
                            'Displaced',
                            'Unemployment rate',
                            'Previous qualification']

        data_subset = self.data[relevant_columns]

        data_subset['Target'] = data_subset['Target'].map(target_labels)
        data_subset['Marital status'] = data_subset['Marital status'].map(marital_status_labels)
        data_subset['Tuition fees up to date'] = data_subset['Tuition fees up to date'].map(tuition_fees
        data_subset['Debtor'] = data_subset['Debtor'].map(debtor_labels)
        data_subset['Previous qualification'] = data_subset['Previous qualification'].map(previous_quali
        data_subset['Scholarship holder'] = data_subset['Scholarship holder'].map(scholarship_labels)

        age_ranges = [16, 25, 36, 50, 100]
        data_subset['Age Range'] = pd.cut(data_subset['Age at enrollment'], bins=age_ranges, labels=["16
                                                                                                     "25
                                                                                                     "36
                                                                                                     "50


        approved_units_bins = [-1, 3, 6, float('inf')]
```

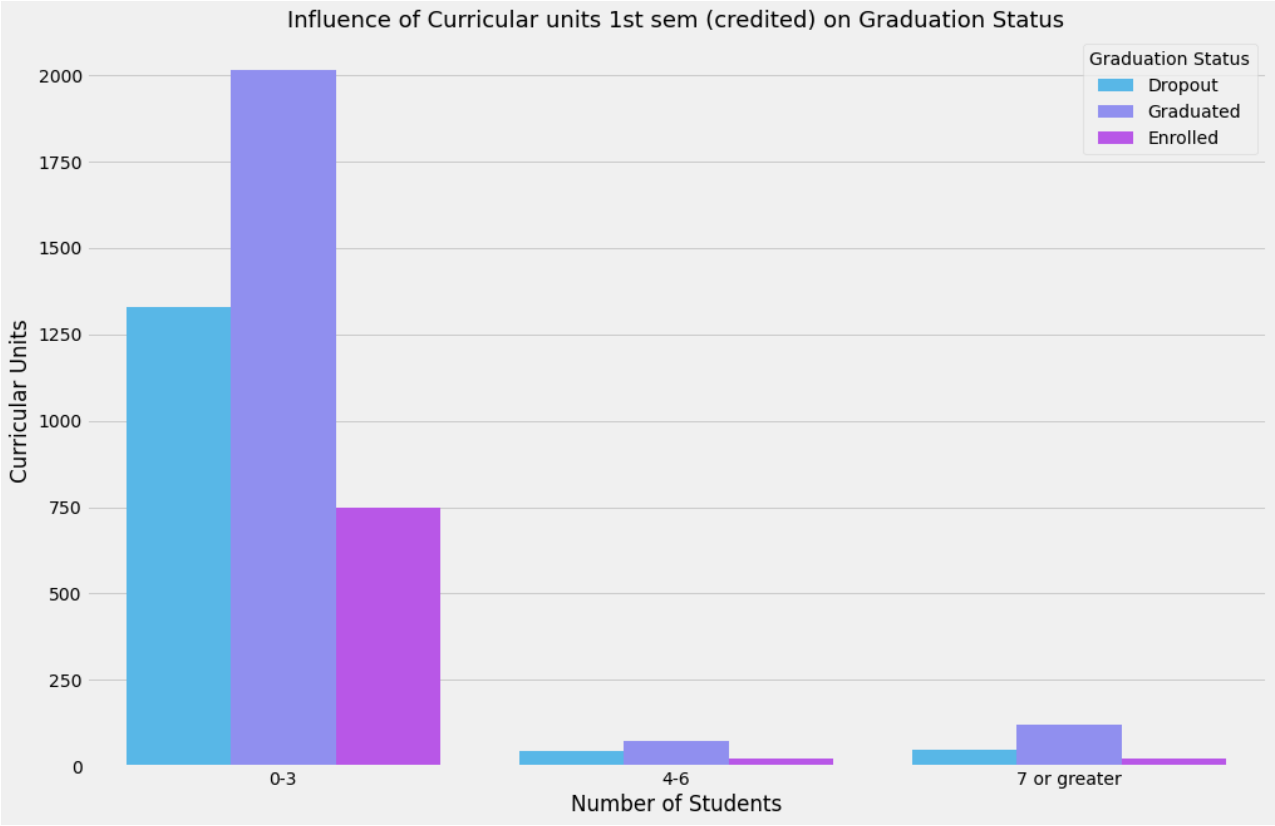
```
        approved_units_labels = ["0-3", "4-6", "7 or greater"]
        data_subset['Approved Units Range'] = pd.cut(data_subset['Curricular units 2nd sem (approved)'],
                                                     bins = approved_units_bins,
                                                     labels = approved_units_labels)
        data_subset['Credited Units'] = pd.cut(data_subset['Curricular units 1st sem (credited)'],
                                                     bins = approved_units_bins,
                                                     labels = approved_units_labels)
        # Plot the results
        self.plot_bar_chart(data_subset,
                            'Age Range',
                            'Influence of Age Range on Graduation Status',
                            'Number of Students',
                            'Age Range')
        self.plot_boxplot(data_subset,
                          'Curricular units 2nd sem (grade)',
                          'Influence of Curricular units 2nd sem (grade) on Graduation Status',
                          'Curricular units 2nd sem (grade)',
                          'Graduation Status')
        self.plot_bar_chart(data_subset,
                            'Approved Units Range',
                            'Influence of Curricular units 2nd sem (approved) on Graduation Status',
                            'Number of Students',
                            'Curricular Units Range')

        self.plot_bar_chart(data_subset,
                            'Credited Units',
                            'Influence of Curricular units 1st sem (credited) on Graduation Status',
                            'Number of Students',
                            'Curricular Units')

        self.plot_bar_chart(data_subset,
                            'Scholarship holder',
                            'Influence of Scholarship Status on Graduation Status',
                            'Number of Students',
                            'Scholarship holder')
        self.plot_bar_chart(data_subset,
                            'Tuition fees up to date',
                            'Influence of Tuition Fees on Graduation Status',
                            'Tuition Fees Up to Date',
                            'Number of Students')
        self.plot_horizontal_bar_chart(data_subset,
                                       'Previous qualification',
                                       'Influence of Previous qualification on Graduation Status',
                                       'Number of Students',
                                       'Graduation Status')

    def plot_bar_chart(self, data, x, title, xlabel, ylabel):
        plt.figure(figsize=(15, 10))
        sns.countplot(data=data, x=x, hue='Target', palette='cool')
        plt.legend(title="Graduation Status")
        plt.xlabel(xlabel)
        plt.ylabel(ylabel)
        plt.title(title, fontsize=18)
        plt.show()

    def plot_boxplot(self, data, x, title, xlabel, ylabel):
        plt.figure(figsize=(15, 10))
        sns.boxplot(data=data, x='Target', y=x, palette='cool')
        custom_legend = [plt.Line2D([], [], color=sns.color_palette('cool')[1], marker='s',
                                    markersize=10, label='Enrolled'),
                         plt.Line2D([], [], color=sns.color_palette('cool')[3], marker='s',
                                    markersize=10, label='Graduated'),
                         plt.Line2D([], [], color=sns.color_palette('cool')[5], marker='s',
                                    markersize=10, label='Dropout')]
        plt.legend(handles=custom_legend, title="Graduation Status")
        plt.xlabel(xlabel)
        plt.ylabel(ylabel)
        plt.title(title, fontsize=18)
        plt.show()
```

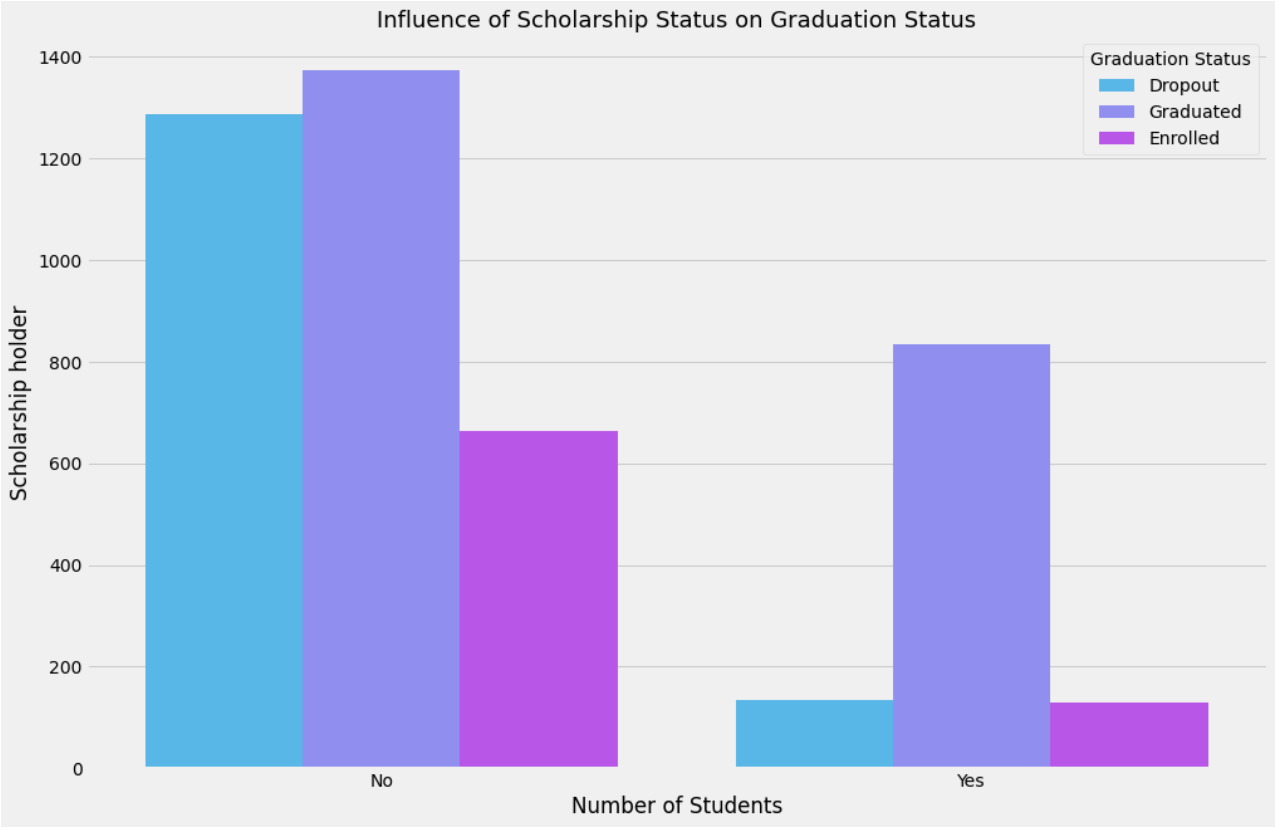
```
    def plot_horizontal_bar_chart(self, data, x, title, xlabel, ylabel):
        plt.figure(figsize=(15, 10))
        sns.countplot(data=data, y=x, hue='Target', palette='cool')
        plt.legend(title="Graduation Status")
        plt.xlabel(xlabel)
        plt.ylabel(ylabel)
        plt.title(title, fontsize=18)
        plt.show()

# Instantiate the AnalyzeData class with the data
analysis = AnalyzeData(data)

# Perform the analysis
analysis.analyze()
```

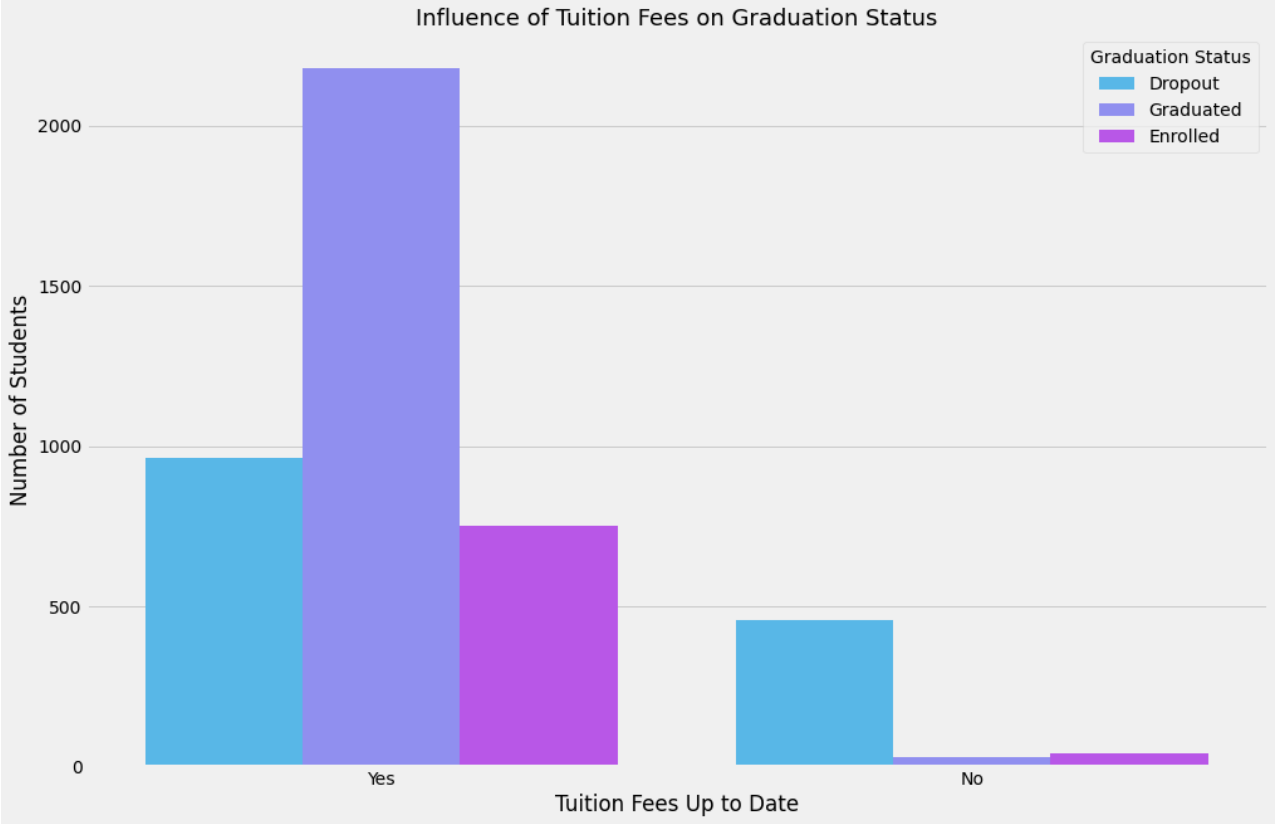


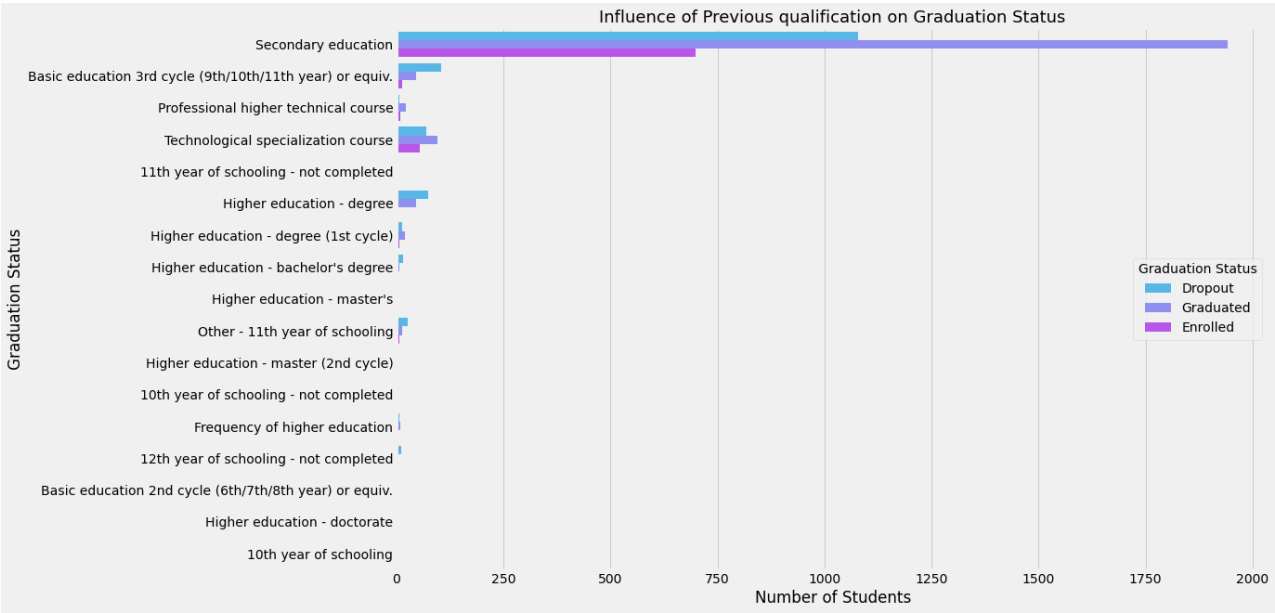

Influence of Curricular units 2nd sem (grade) on Graduation Status
Graduation Status
Enrolled
Graduated
Dropout
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
Graduation Status
Dropout
Graduated
Enrolled
Curricular units 2nd sem (grade)


Influence of Curricular units 2nd sem (approved) on Graduation Status
Graduation Status
Dropout
Graduated
Enrolled
1400
1200
1000
800
600
400
200
0
Curricular Units Range
0-3
4-6
7 or greater
Number of Students


Influence of Curricular units 1st sem (credited) on Graduation Status
Graduation Status
Dropout
Graduated
Enrolled
Curricular Units
2000
1750
1500
1250
1000
750
500
250
0
0-3
4-6
7 or greater
Number of Students


Influence of Scholarship Status on Graduation Status
Graduation Status
Dropout
Graduated
Enrolled
Scholarship holder
1400
1200
1000
800
600
400
200
0
No
Yes
Number of Students





During exploration, we identified the following trends:

- Age Range and Graduation: 25-35 age group has higher enrollment and graduation rates. Age 50+ has higher dropout.
- Curricular Units and Graduation: 4-6 units show highest graduation rate, 7+ slightly lower, 0-3 lower.
- Tuition Fees and Graduation: Up-to-date fees link to significantly higher graduation rates.
- Marital Status and Graduation: Married/in a union have higher graduation rate.
- Previous Qualification: Higher education levels have higher graduation rates. Basic education lower rates.

I will combine this information with the results of a ternary classifier that is trained on 80% of the dataset to idenify insights that will make an impact on decreasing failure rates for students in higher education.

Model

The TernaryClassifier class handles classification tasks on datasets with three categories of a target variable. It provides:

- Methods for data preprocessing.
- Training multiple classification models.
- Making predictions.
- Tuning hyperparameters to optimize model performance.

The name "TernaryClassifier" is derived from the term "ternary," which refers to systems or situations that involve three elements or options. A ternary classification problem consists in predicting one of three possible classes or categories for each data instance.

This project uses recall as the scoring metric to evaluate the models. The reason behind this choice is our primary objective of minimizing the academic failure rate.

In particular, missing students who need academic support can seriously affect their educational outcomes and prospects. A high recall score indicates that the model effectively identifies a large proportion of at-risk students who are prone to academic failure.

We can correctly identify students who need support and provide them with interventions.

The `TernaryClassifier` class includes:

- Constructor: Takes a DataFrame (`data`) containing features (X) and ternary target variable (y).
- Preprocessing: Separates X and y, scales features using `StandardScaler` , encodes y with `LabelEncoder` , and returns the scaled features as a DataFrame.
- Model Library: Defines models for training, including `Logistic Regression` , `K-Nearest Neighbors` , `Support Vector Machine` , `Decision Trees` , and `Random Forests` .
- Training: Trains each model in the library on preprocessed data (X and y), making them ready for prediction.
- Prediction: Predicts target variable values using all trained models on testing data (X_test), returning a dictionary of model predictions.
- Hyperparameter Tuning: Uses `tune_parameters()` method to optimize model performance by finding the best hyperparameters for each classifier using `GridSearchCV` .
- Training with Parameter Tuning: Trains models with tuned hyperparameters using `GridSearchCV` . Returns a dictionary of best models and identifies the most performative one based on recall scores.

Each of the models was trained using an 80/20 split and then evaluated using recall.

In [18]:
```
class TernaryClassifier:
    def __init__(self, data):
        """
        Constructor for the TernaryClassifier class.

        Parameters:
        - data (pandas DataFrame): The dataset for the classifier.
        """

        self.data = data
        self.scaler = StandardScaler()
        # Define a library of models
        self.models = {
            'Logistic Regression': LogisticRegression(max_iter=1000),
            'K-Nearest Neighbors': KNeighborsClassifier(),
            'Support Vector Machine': SVC(),
```

```
            'Decision Trees': DecisionTreeClassifier(),
            'Random Forest': RandomForestClassifier()
        }

    def preprocess_data(self):
        # Separate features (X) and target variable (y)
        X = self.data.drop('Target', axis=1)
        y = self.data['Target']

        # Scale the input features
        scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)

        # Encode the target variable
        label_encoder = LabelEncoder()
        y_encoded = label_encoder.fit_transform(y)

        # Convert X_scaled to DataFrame and set column names
        X_scaled_df = pd.DataFrame(X_scaled, columns=X.columns)

        return X_scaled_df, y_encoded

    def train_model(self, X, y):
        """
        Trains the ternary classifier model on the preprocessed data.

        Parameters:
        - X (pandas DataFrame): The preprocessed feature data.
        - y (pandas DataFrame): The preprocessed target variable.

        Returns:
        - model: The trained ternary classifier model.
        """
        # Train each model in the library
        for model_name, model in self.models.items():
            model.fit(X, y)

        # Return the trained models dictionary
        return self.models

    def predict(self, X_test):
        """
        Predicts the target variable values using all the trained models.

        Parameters:
        - X_test (pandas DataFrame): Testing feature data.

        Returns:
        - predictions (dict): Dictionary containing the predictions of each model.
        """
        predictions = {}

        for model_name, model in self.models.items():
            model_predictions = model.predict(X_test)
            predictions[model_name] = model_predictions

        return predictions

    def tune_parameters(self, classifier, param_grid, X, y, scorer):
        """
        Tune hyperparameters of the given classifier using GridSearchCV.

        Parameters:
        - classifier: The classifier to be tuned.
        - param_grid: The dictionary containing hyperparameter grids for the classifier.
        - X (pandas DataFrame): The preprocessed feature data.
        - y (pandas DataFrame): The preprocessed target variable.
        - scorer: Scorer function to evaluate the models.

        Returns:
```

```
        - best_params: The best hyperparameters found by GridSearchCV.
        - best_score: The best recall score achieved by the classifier.
        """
        grid_search = GridSearchCV(estimator=classifier, param_grid=param_grid, scoring=scorer, cv=5)
        grid_search.fit(X, y)
        best_params = grid_search.best_params_
        best_score = grid_search.best_score_

        return best_params, best_score

    def train_model_with_parameter_tuning(self, X, y):
        """
        Trains the ternary classifier model with parameter tuning on the preprocessed data.

        Parameters:

        - X (pandas DataFrame): The preprocessed feature data.
        - y (pandas DataFrame): The preprocessed target variable.

        Returns:
        - model: The trained ternary classifier model with tuned hyperparameters.
        """
        # Define a library of models with default parameters
        models = {
            'Logistic Regression': LogisticRegression(),
            'K-Nearest Neighbors': KNeighborsClassifier(),
            'Support Vector Machine': SVC(),
            'Decision Trees': DecisionTreeClassifier(),
            'Random Forest': RandomForestClassifier()
        }

        # Create an empty dictionary to store the best models with tuned parameters
        best_models = {}
        best_recall_scores = {}

        # Iterate through each model in the library and perform grid search for parameter tuning
        for model_name, model in models.items():
            # Get the corresponding parameter grid for the model
            model_param_grid = param_grid[model_name]

            # Perform parameter tuning using the tune_parameters function
            best_params, best_score = self.tune_parameters(model, model_param_grid, X, y,
                                                           scorer=make_scorer(recall_score, average='wei

            # Set the best hyperparameters to the model
            model.set_params(**best_params)

            # Train the model with the best hyperparameters
            model.fit(X, y)

            # Store the best model in the dictionary
            best_models[model_name] = model
            best_recall_scores[model_name] = best_score

        # Store the trained models with tuned parameters
        self.models = best_models

        # Identify the most performative model
        most_performative_model = max(best_recall_scores, key=best_recall_scores.get)

        # Return the dictionary of best models and the most performative model
        return best_models, most_performative_model
```

Evaluation

I created a `ModelEvaluation` class to evaluate different classifier models for a ternary classification problem. The class contains:

- methods to calculate evaluation metrics such as accuracy, precision, recall, and F1 score for each trained model.
- functions to analyze feature importances for the `RandomForestClassifier` and identify the best hyperparameters that yield the best recall score for each model using cross-validation.

The class includes the following functions:

- `evaluate_models` → takes a trained `TernaryClassifier` instance, performs predictions on the test data, and calculates various evaluation metrics for each model.
- `analyze_feature_importances` → analyzes feature importances for the `RandomForestClassifier` and stores them in a data frame.
- `calculate_best_scores` → `GridSearchCV` to find the best hyperparameters for each model based on a specified scoring metric.
- `identify_best_parameters` → identifies the best hyperparameters and their corresponding recall scores for each model.
- `plot_feature_importances` → plots the feature importances of the trained models using bar plots.

In [19]:
```
class ModelEvaluation:
    def __init__(self, X_train, y_train, X_test, y_test):
        """
        Constructor for the ModelEvaluation class.

        Parameters:
        - X_train (pandas DataFrame): Training feature data.
        - y_train (pandas Series or numpy array): Training target variable.
        - X_test (pandas DataFrame): Testing feature data.
        - y_test (pandas Series or numpy array): Testing target variable.
        """
        self.X_train = X_train
        self.y_train = y_train
        self.X_test = X_test
        self.y_test = y_test
        self.models = None
        self.evaluation_df = None
        self.feature_importance_df = None


    def evaluate_models(self, classifier):
        """
        Evaluates different classifier models and stores the evaluation results in a dataframe.

        Parameters:
        - classifier (TernaryClassifier): The TernaryClassifier instance.

        Returns:
        - evaluation_df (pandas DataFrame): The evaluation results dataframe.
        """
        models = classifier.train_model(self.X_train, self.y_train)
        self.models = models

        evaluation_results = []
        for model_name, model in models.items():
            y_pred = model.predict(self.X_test)

            accuracy = accuracy_score(self.y_test, y_pred)
            precision = precision_score(self.y_test, y_pred, average='weighted')
            recall = recall_score(self.y_test, y_pred, average='weighted')
            f1 = f1_score(self.y_test, y_pred, average='weighted')

            evaluation_results.append({
                'Model': model_name,
                'Accuracy': accuracy,
```

```
            'Precision': precision,
            'Recall': recall,
            'F1 Score': f1
        })

    evaluation_df = pd.DataFrame(evaluation_results)
    self.evaluation_df = evaluation_df

    return evaluation_df

def analyze_feature_importances(self):
    """
    Analyzes and stores feature importances for the RandomForestClassifier.

    Returns:
    - feature_importance_df (pandas DataFrame): The feature importances dataframe.
    """
    if 'Random Forest' in self.models:
        random_forest_model = self.models['Random Forest']
        if hasattr(random_forest_model, 'feature_importances_'):
            feature_importances = random_forest_model.feature_importances_
            feature_importance_df = pd.DataFrame({'Feature': self.X_train.columns, 'Importance': fea
            self.feature_importance_df = feature_importance_df
            return feature_importance_df.info()
        else:
            print("Random Forest model does not have feature importances.")
    else:
        print("Random Forest model not found in trained models.")

    return None

def calculate_best_scores(self, param_grids, scoring):
    """
    Calculate the best scores using cross-validation with recall scoring for all specified models.

    Parameters:
    - param_grids (dict): Dictionary containing the parameter grids for each model.
    - scoring (str or callable): The scoring metric to use for evaluation.

    Returns:
    - best_scores (dict): Dictionary containing the best recall scores for each model.
    """

    best_scores = {}

    for model_name, model in self.models.items():
        param_grid = param_grids.get(model_name)

        if param_grid is not None:
            grid_search = GridSearchCV(estimator=model, param_grid=param_grid, scoring=scoring, cv=5
            grid_search.fit(self.X_train, self.y_train)

            best_scores[model_name] = grid_search.best_score_

    return best_scores

def calculate_confusion_matrices(self, X_test, y_test):
    """
    Calculates and returns the confusion matrices for all evaluated models.

    Parameter:

    - X_test (pandas DataFrame): Testing feature data.
    - y_test (pandas Series/ numpy array): Testing target variable.

    Returns:
    - confusion_matrices (dict): Dictionary containing confusion matrices
    """
    confusion_matrices = {}
```

```
        for model_name, model in self.models.items():
            y_pred = model.predict(X_test)
            cm = confusion_matrix(y_test, y_pred)
            confusion_matrices[model_name] = cm
        return confusion_matrices

    def plot_confusion_matrices(self, X_test, y_test):
        """
        Plots normalized confusion matrix for each evaluated model.

        Parameter:
        - X_test(pandas DataFrame): Testing feature data.
        - y_test(pandas Series or numpy array): Testing target variable.
        """

        for model_name, model in self.models.items():
            if hasattr(model, 'predict'):
                y_pred = model.predict(X_test)

                # Compute the confusion matrix
                cm = confusion_matrix(y_test, y_pred)


                # Print the confusion matrix
                print(f"Confusion Matrix - {model_name}:")
                print(cm)

                # Calculate normalized confusion matrix
                cm_normed = cm.astype('float') / cm.sum(axis = 1)[:, np.newaxis]


                # Set the plot title and and labels
                plt.figure()
                sns.heatmap(cm_normed, annot = True, cmap = 'Blues', ax = plt.gca(), fmt = ".2f",
                            xticklabels = ["Dropout", "Enrolled", "Graduated"],
                            yticklabels = ["Dropout", "Enrolled", "Graduated"])

                plt.title(f"Confusion Matrix - {model_name}")
                plt.xlabel("Predicted Label")
                plt.ylabel("True Label")

                # Show the plot
                plt.show()


    def plot_feature_importances(self, trained_models, feature_names):
        # Create a DataFrame to store feature importances
        feature_importances_df = pd.DataFrame(index=feature_names)

        for model_name, model in trained_models.items():
            if hasattr(model, 'feature_importances_'):
                # Get the feature importances from the model
                feature_importances = model.feature_importances_

                # Store the feature importances in the DataFrame
                feature_importances_df[model_name] = feature_importances

        # Plot the feature importances
        plt.figure(figsize=(12, 8))
        sns.barplot(data=feature_importances_df.T, x=feature_importances_df.columns,
                    y=feature_importances_df.T.mean(axis=1))
        plt.title('Feature Importances')
        plt.xticks(rotation=45, ha='right')
        plt.show()


    def identify_best_parameters(self, param_grids, scoring):
        """
        Identify the best parameters that yield the best recall score for all specified models.
```

```
        Parameters:
        - param_grids (dict): Dictionary containing the parameter grids for each model.
        - scoring (str or callable): The scoring metric to use for evaluation.

        Returns:
        - best_parameters (dict): Dictionary containing the best parameters for each model.
        - best_recall_scores (dict): Dictionary containing the best recall scores for each model.
        """

        best_parameters = {}
        best_recall_scores = {}

        for model_name, model in self.models.items():
            param_grid = param_grids.get(model_name)

            if param_grid is not None:
                grid_search = GridSearchCV(estimator=model, param_grid=param_grid, scoring=scoring, cv=5
                grid_search.fit(self.X_train, self.y_train)

                best_parameters[model_name] = grid_search.best_params_
                best_recall_scores[model_name] = grid_search.best_score_

        return best_parameters, best_recall_scores
```

In [20]:

```
%%time
# Instantiate the TernaryClassifier class with data
ternary_classifier = TernaryClassifier(data)

# Preprocess the data using the TernaryClassifier class
X_scaled, y_encoded = ternary_classifier.preprocess_data()

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_encoded, test_size=0.2, random_state=42)

# Define parameter grids for each model
param_grid = {
    'Logistic Regression': {'C': [0.1, 1.0, 10.0]},
    'K-Nearest Neighbors': {'n_neighbors': [3, 5, 7]},
    'Support Vector Machine': {'C': [0.1, 1.0, 10.0],
                               'kernel': ['linear', 'rbf']},
    'Decision Trees': {'max_depth': [None, 5, 10]},
    'Random Forest': {'n_estimators': [50, 100, 200],
                      'max_depth': [None, 5, 10]}
}


# Train models with parameter tuning
best_models, most_performative_model = ternary_classifier.train_model_with_parameter_tuning(X_train, y_t
# Print the best hyperparameters for each model
for model_name, model in best_models.items():
    print(f"Model: {model_name}")
    print("Best Hyperparameters:", model.get_params())
    print("------------------------------")

print (f" Most Performative Model", most_performative_model)
```

```
Model: Logistic Regression
Best Hyperparameters: {'C': 1.0, 'class_weight': None, 'dual': False, 'fit_intercept': True, 'intercept
_scaling': 1, 'l1_ratio': None, 'max_iter': 100, 'multi_class': 'auto', 'n_jobs': None, 'penalty': 'l
2', 'random_state': None, 'solver': 'lbfgs', 'tol': 0.0001, 'verbose': 0, 'warm_start': False}
------------------------------
Model: K-Nearest Neighbors
Best Hyperparameters: {'algorithm': 'auto', 'leaf_size': 30, 'metric': 'minkowski', 'metric_params': No
ne, 'n_jobs': None, 'n_neighbors': 7, 'p': 2, 'weights': 'uniform'}
------------------------------
Model: Support Vector Machine
Best Hyperparameters: {'C': 0.1, 'break_ties': False, 'cache_size': 200, 'class_weight': None, 'coef0':
0.0, 'decision_function_shape': 'ovr', 'degree': 3, 'gamma': 'scale', 'kernel': 'linear', 'max_iter': -
1, 'probability': False, 'random_state': None, 'shrinking': True, 'tol': 0.001, 'verbose': False}
------------------------------
Model: Decision Trees
Best Hyperparameters: {'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini', 'max_depth': 5, 'ma
x_features': None, 'max_leaf_nodes': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 1, 'min_sa
mples_split': 2, 'min_weight_fraction_leaf': 0.0, 'random_state': None, 'splitter': 'best'}
------------------------------
Model: Random Forest
Best Hyperparameters: {'bootstrap': True, 'ccp_alpha': 0.0, 'class_weight': None, 'criterion': 'gini',
'max_depth': None, 'max_features': 'sqrt', 'max_leaf_nodes': None, 'max_samples': None, 'min_impurity_d
ecrease': 0.0, 'min_samples_leaf': 1, 'min_samples_split': 2, 'min_weight_fraction_leaf': 0.0, 'n_estim
ators': 200, 'n_jobs': None, 'oob_score': False, 'random_state': None, 'verbose': 0, 'warm_start': Fals
e}
------------------------------
 Most Performative Model Random Forest
```

The Random Forest model is the most performative.

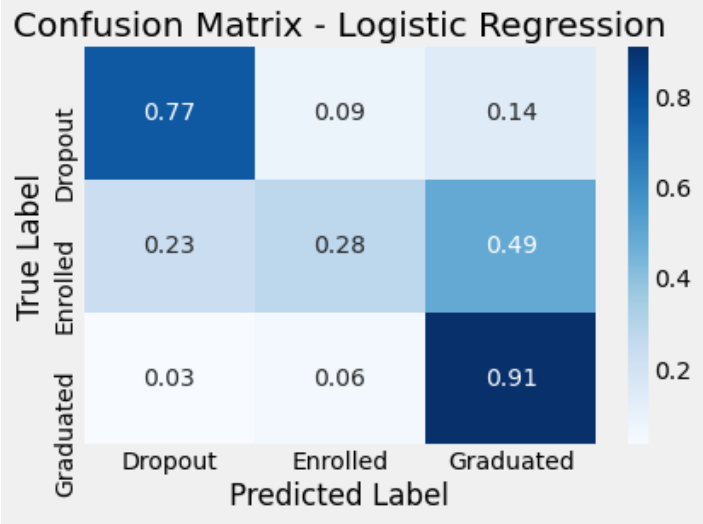
In [21]:
```python
# Instantiate the ModelEvaluation class
model_evaluation = ModelEvaluation(X_train, y_train, X_test, y_test)

# Evaluate models
evaluation_results = model_evaluation.evaluate_models(ternary_classifier)


# Display evaluation results
display(evaluation_results)
```

	Model	Accuracy	Precision	Recall	F1 Score
0	Logistic Regression	0.75	0.73	0.75	0.74
1	K-Nearest Neighbors	0.70	0.69	0.70	0.68
2	Support Vector Machine	0.75	0.74	0.75	0.73
3	Decision Trees	0.73	0.73	0.73	0.72
4	Random Forest	0.76	0.75	0.76	0.75

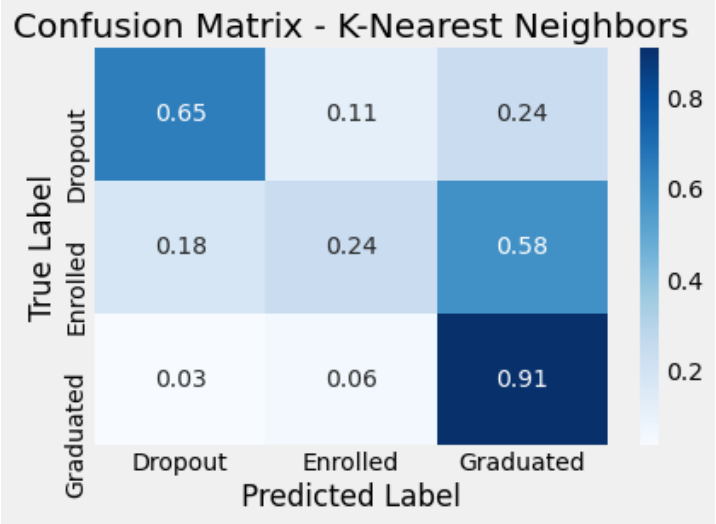
Let's look at the confusion matrices for the models trained using the `ternaryClassifier` class.

In [22]:
```python
# Calculate and plot the confusion matrices
model_evaluation.plot_confusion_matrices(X_test, y_test)
```

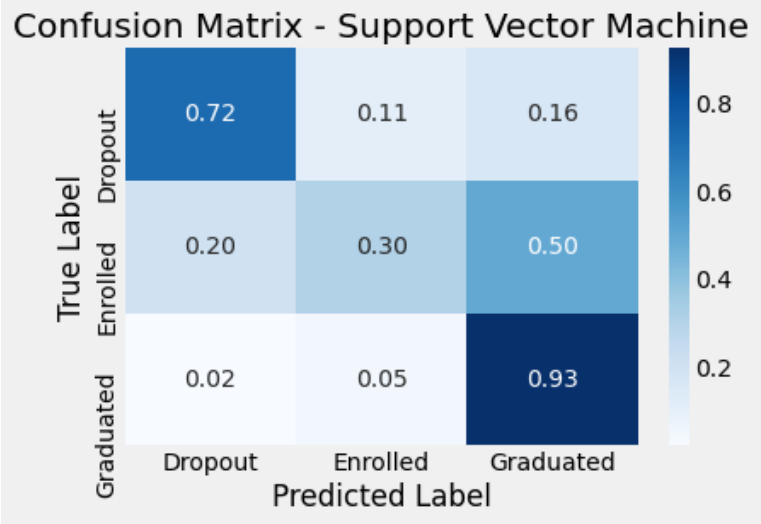
```
Confusion Matrix - Logistic Regression:
[[244  27  45]
 [ 35  42  74]
 [ 14  24 380]]
```



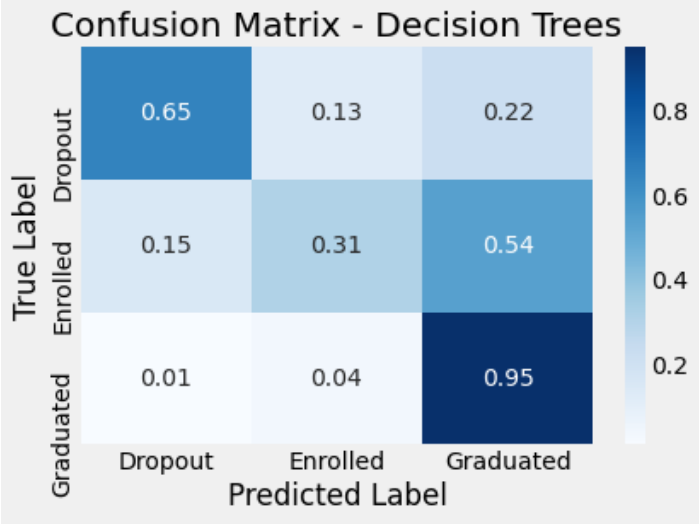

```
Confusion Matrix - K-Nearest Neighbors:
[[205  36  75]
 [ 27  36  88]
 [ 14  23 381]]
```



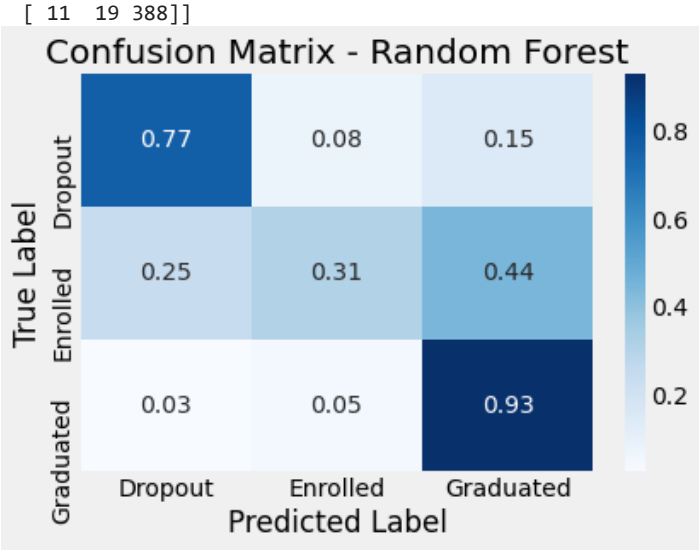

```
Confusion Matrix - Support Vector Machine:
[[228  36  52]
 [ 30  46  75]
 [  9  22 387]]
```




```
Confusion Matrix - Decision Trees:
[[206  40  70]
 [ 23  47  81]
 [  5  16 397]]
```




```
Confusion Matrix - Random Forest:
[[242  26  48]
 [ 37  47  67]
 [ 11  19 388]]
```



iNterpret

Our code displays a confusion matrix, the most pertinent features, and their corresponding feature importances for each model. If a model does not have feature importances, the code alerts the user accordingly.

- The top 5 feature importances are identified and displayed for various models (Random Forest, SVM, Decision Trees, K Nearest neighbors), with a notification for models without feature importances.
- The `Random Forest` is the most performative model with a recall score of **0.76**
- The confusion matrix for random forest suggests that our predicts student dropouts and graduates much better than it predicts students who are enrolled:
  - Dropout as Dropout prediction: correct 76 out of 100 times
  - Graduate as Graduate prediction: correct 93 out of 100 times
  - Enrolled as Enrolled prediction: correct 30 out of 100 times
  - Enrolled as Dropout prediction: correct 26 out of 100 times
  - Graduated as Dropout prediction: correct 3 out of 100 times

In [23]:
```
# Get the best model for each classifier
logistic_regression_model = best_models['Logistic Regression']
random_forest_model = best_models['Random Forest']
svm_model = best_models['Support Vector Machine']
decision_tree_model = best_models['Decision Trees']
```

```
knn_model = best_models['K-Nearest Neighbors']

# Get the top 10 coefficients for Logistic Regression
if hasattr(logistic_regression_model, 'coef_'):
    coef_abs = abs(logistic_regression_model.coef_[0])
    top_5_coefficients = sorted(list(zip(ternary_classifier.data.drop('Target', axis=1).columns, coef_ab
                                key=lambda x: x[1], reverse=True)[:5]
    print("Top 5 Coefficients for Logistic Regression:")
    for feature, coef in top_5_coefficients:
        print(f"{feature}: {coef}")
    print("\n")
else:
    print("Logistic Regression model does not have coefficients.")

# Get the top 5 feature importances for Random Forest, Support Vector Machines, Decision Trees, and K-Ne
models_to_analyze = [random_forest_model, svm_model, decision_tree_model, knn_model]
model_names = ['Random Forest', 'Support Vector Machine', 'Decision Trees', 'K-Nearest Neighbors']
#print('trace11')
for model, model_name in zip(models_to_analyze, model_names):
    if hasattr(model, 'feature_importances_'):
        feature_importances = model.feature_importances_
        top_5_features = sorted(list(zip(ternary_classifier.data.drop('Target', axis=1).columns,
                                         feature_importances)), key=lambda x: x[1], reverse=True)[:5]
        print(f"Top 5 Feature Importances for {model_name}:")
        for feature, importance in top_5_features:
            print(f"{feature}: {importance}")
        print("\n")
    else:
        print(f"{model_name} model does not have feature importances.")
```

```
Top 5 Coefficients for Logistic Regression:
Curricular units 2nd sem (approved): 1.4406130311414413
Curricular units 2nd sem (enrolled): 0.9379467613448992
Curricular units 1st sem (approved): 0.9284216462299857
Tuition fees up to date: 0.5393465430753019
Curricular units 2nd sem (grade): 0.479125037413678


Top 5 Feature Importances for Random Forest:
Curricular units 2nd sem (approved): 0.14227396871758963
Curricular units 2nd sem (grade): 0.10641414150823442
Curricular units 1st sem (approved): 0.09432502180925087
Curricular units 1st sem (grade): 0.06249169894863917
Curricular units 2nd sem (evaluations): 0.04533733129763811


Support Vector Machine model does not have feature importances.
Top 5 Feature Importances for Decision Trees:
Curricular units 2nd sem (approved): 0.7340676173420965
Tuition fees up to date: 0.08683122950372858
Curricular units 1st sem (enrolled): 0.04759970663468778
Curricular units 1st sem (evaluations): 0.027786992188045787
Curricular units 2nd sem (enrolled): 0.019011659271296687


K-Nearest Neighbors model does not have feature importances.
```

In [24]:

```
# Instantiate the TernaryClassifier class with your data
# ternary_classifier = TernaryClassifier(cleaned_data)

# Preprocess the data using the TernaryClassifier class
# X_scaled, y_encoded = ternary_classifier.preprocess_data()

# Split the data into training and testing sets
# X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_encoded, test_size=0.2, random_state=4

# Assuming you have already trained the KNN model in the TernaryClassifier class
# knn_model = ternary_classifier.models['K-Nearest Neighbors']

# Perform feature scaling on the training data
scaler = MinMaxScaler()
```

```
X_train_scaled = scaler.fit_transform(X_train)

# Create a SelectKBest selector and fit it with the training data
k_best_selector = SelectKBest(score_func=chi2, k=5)
X_train_k_best = k_best_selector.fit_transform(X_train_scaled, y_train)

# Get the support (selected) features from SelectKBest
selected_features_indices = k_best_selector.get_support(indices=True)
selected_features = X_train.columns[selected_features_indices]

# Print the top 3 selected features
print("Top 5 selected features by SelectKBest with KNN:")
for feature in selected_features:
    print(feature)
```

```
Top 5 selected features by SelectKBest with KNN:
Debtor
Scholarship holder
Curricular units 1st sem (grade)
Curricular units 2nd sem (approved)
Curricular units 2nd sem (grade)
```

In [25]:
```
# Instantiate the TernaryClassifier class with your data
# ternary_classifier = TernaryClassifier(cleaned_data)

# Preprocess the data using the TernaryClassifier class
# X_scaled, y_encoded = ternary_classifier.preprocess_data()

# Split the data into training and testing sets
# X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_encoded, test_size=0.2, random_state=4

# Assuming you have already trained the SVM model in the TernaryClassifier class
# svm_model = ternary_classifier.models['Support Vector Machine']

# Perform feature scaling on the training data
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)

# Create an RFE selector and fit it with the trained SVM model
rfe_selector = RFE(estimator=SVC(kernel='linear'), n_features_to_select=5)
rfe_selector.fit(X_train_scaled, y_train)

# Get the support (selected) features from RFE
selected_features_indices = rfe_selector.get_support(indices=True)
selected_features = X_train.columns[selected_features_indices]

# Print the top 5 selected features
print("Top 5 selected features by RFE with SVM:")
for feature in selected_features:
    print(feature)
```

```
Top 5 selected features by RFE with SVM:
Curricular units 1st sem (enrolled)
Curricular units 1st sem (approved)
Curricular units 2nd sem (credited)
Curricular units 2nd sem (enrolled)
Curricular units 2nd sem (approved)
```

Insights

Based on the information from the confusion matrices and feature analysis, we recommend the following:

- Adopting a multifaceted strategy that includes academic support and interventions.
- Monitoring tuition fee payments to mitigate academic failure.
- Providing early interventions between 1st and 2nd semester.

Insight 1: Curricular Units in 2nd Semester Matter

- Students with more approved units in the 2nd semester have a higher chance of academic success.
- The number of enrolled units in the 2nd semester also positively impacts academic outcomes.
- Encouraging students to pass more units in the 2nd semester can lead to a reduced rate of academic failure.

Focusing on students' progress and success in their 2nd-semester curricular units can significantly contribute to reducing the rate of academic failure.

Insight 2: Monitoring Tuition Fee Payments is Pivotal

Being up-to-date with tuition fees is crucial for predicting academic success. Timely tuition fee payments correlate with better student outcomes. Implementing strategies to ensure prompt tuition fee payments can positively impact academic performance and reduce failure rates.

By closely monitoring and supporting students to stay on track with tuition fee payments, institutions can foster an environment that reduces the rate of academic failure.

Insight 3: Evaluations and Grades are Crucial

Academic performance in the 1st and 2nd semester evaluations significantly influences students' likelihood of success. Students who achieve higher grades tend to have better academic outcomes overall. Early identification and intervention for students struggling with evaluations or grades can improve academic performance and decrease failure rates.

Prioritizing academic support and intervention based on early evaluations and grades can effectively contribute to minimizing the rate of academic failure.

Future Work

I am interested in exploring how to apply XGBoost, a robust gradient boosting algorithm to a ternary (3-class) classification model. XGBoost handles large datasets and captures complex interactions between features. This could enhance predictive modeling for academic success, improving accuracy and interpretability. Employing a robust hyperparameter tuning process, like grid search or Bayesian optimization, can fine-tune model parameters for better results.

Extending the analysis to include US universities may also provide valuable insights. Identifying common factors influencing student success across diverse contexts is possible. Understand how these factors vary between institutions. I would like to strengthen both the generalizability and the ability to tailor interventions that are research driven to address academic challenges.

By leveraging advanced techniques and cross-institutional analyses, educational research advances that leverage evidence-based practices, we can systematically improve student outcomes.

I want to craft a set of informed decisions and targeted interventions that reduce the rate of academic failure effectively.