Notebook

June 6, 2025

1 LOAN APPROVAL CLASSIFICATION

Author: Brian Kanyenje

1.1 Business Understanding

In today's financial sector, lending institutions are facing increasing pressure to make accurate, data driven decisions when approving loans applications. This makes it vital to correctly distinguish creditworthy people from high-risk ones to maximize profitability and reduce the chances of loan defaults.

This project aims to build a model capable of evaluating the repayment likelihood of loans from an applicant's demographic, financial and behavioral information. Thanks to data science techniques, the model will provide actionable insights that will support lenders in the loan approval process and help them make more accurate decisions thus increasing the institution's risk management framework.

1.2 Project Objectives

1. To examine demographic factors associated with high loan default rates

2. Determine whether there is a statistically significant relationship between an applicant's credit score and their loan approval status.

3. Build accurate models to predict whether a loan applicant will default on the loan.

4. Validate the model's performance on unseen data to guarantee robustness and reliability in real-world applications.

1.3 Importing libraries

[1]:
```python
# Data manipulation and utility libraries
import pandas as pd
import numpy as np
import math
import zipfile

# Visualization libraries
import seaborn as sns
import matplotlib.pyplot as plt
```

```python
from sklearn.tree import plot_tree
from sklearn.metrics import ConfusionMatrixDisplay

# Statistical analysis
import scipy.stats as stats

# Data preprocessing
from sklearn.preprocessing import LabelEncoder, OrdinalEncoder, OneHotEncoder,␣
↪label_binarize, MinMaxScaler

# Model selection and evaluation tools
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪StratifiedKFold, GridSearchCV, RandomizedSearchCV
from sklearn.metrics import classification_report, accuracy_score,␣
↪precision_score, f1_score, roc_curve, auc, root_mean_squared_error,␣
↪confusion_matrix

# Feature selection and pipeline construction
from sklearn.pipeline import Pipeline
from sklearn.feature_selection import RFECV

# Machine learning models
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier

# Handling imbalanced datasets
from imblearn.over_sampling import SMOTE

# Warning suppression
import warnings
warnings.filterwarnings('ignore')
```

1.4 Data Understanding

The data for this project was found on Kaggle,aleading site for data science resources. The file contains detailed records loan applications which include personal information, details of a person's finances and the current status of the loan. This dataset provides a solid foundation to develop a predictive models to assess credit risk effectively.

To begin, let's import the dataset:

[2]:
```python
# Extract the dataset from the archive_8 zipfile and save it as df
with zipfile.ZipFile('./Data/archive_8.zip') as z:
    with z.open('loan_data.csv') as f:
        df = pd.read_csv(f)
```

[3]:
```python
# Preview the first five records
df.head()
```

[3]:
```
   person_age person_gender person_education  person_income  person_emp_exp  \
0        22.0        female           Master        71948.0               0
1        21.0        female      High School        12282.0               0
2        25.0        female      High School        12438.0               3
3        23.0        female         Bachelor        79753.0               0
4        24.0          male           Master        66135.0               1

  person_home_ownership  loan_amnt loan_intent  loan_int_rate  \
0                  RENT    35000.0    PERSONAL          16.02
1                   OWN     1000.0   EDUCATION          11.14
2              MORTGAGE     5500.0     MEDICAL          12.87
3                  RENT    35000.0     MEDICAL          15.23
4                  RENT    35000.0     MEDICAL          14.27

   loan_percent_income  cb_person_cred_hist_length  credit_score  \
0                 0.49                         3.0           561
1                 0.08                         2.0           504
2                 0.44                         3.0           635
3                 0.44                         2.0           675
4                 0.53                         4.0           586

  previous_loan_defaults_on_file  loan_status
0                             No            1
1                            Yes            0
2                             No            1
3                             No            1
4                             No            1
```

Next, let's create a function that provides an initial overview of the dataset and prints three key pieces of information: 1. `summary(dataframe)` * Dataframe Shape - `df.shape` * Dataframe info - `df.info()` * Descriptive Statistics - `df.describe()`

[4]:
```python
# Create a function to display the dataframe's summary and descriptive statistics
def summary(dataframe):
    print('-------- Dataframe Shape -------\n')
    print(f'The dataframe has {df.shape[0]} rows and {df.shape[1]} columns\n')
    print('-------- Dataframe Info --------\n')
    print(df.info()) # dataframe summary
    print('\n')
    print('-------- Dataframe Descriptive Statistics --------\n')
    print(df.describe()) # dataframe descriptive statistics
    print('\n')
```

[5]:
```python
# Call out the summary function
summary(df)
```

```
-------- Dataframe Shape -------

The dataframe has 45000 rows and 14 columns

-------- Dataframe Info --------

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45000 entries, 0 to 44999
Data columns (total 14 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   person_age                      45000 non-null  float64
 1   person_gender                   45000 non-null  object
 2   person_education                45000 non-null  object
 3   person_income                   45000 non-null  float64
 4   person_emp_exp                  45000 non-null  int64
 5   person_home_ownership           45000 non-null  object
 6   loan_amnt                       45000 non-null  float64
 7   loan_intent                     45000 non-null  object
 8   loan_int_rate                   45000 non-null  float64
 9   loan_percent_income             45000 non-null  float64
 10  cb_person_cred_hist_length      45000 non-null  float64
 11  credit_score                    45000 non-null  int64
 12  previous_loan_defaults_on_file  45000 non-null  object
 13  loan_status                     45000 non-null  int64
dtypes: float64(6), int64(3), object(5)
memory usage: 4.8+ MB
None


-------- Dataframe Descriptive Statistics --------

        person_age  person_income  person_emp_exp     loan_amnt  \
count  45000.000000   4.500000e+04    45000.000000  45000.000000
mean      27.764178   8.031905e+04        5.410333   9583.157556
std        6.045108   8.042250e+04        6.063532   6314.886691
min       20.000000   8.000000e+03        0.000000    500.000000
25%       24.000000   4.720400e+04        1.000000   5000.000000
50%       26.000000   6.704800e+04        4.000000   8000.000000
75%       30.000000   9.578925e+04        8.000000  12237.250000
max      144.000000   7.200766e+06      125.000000  35000.000000

       loan_int_rate  loan_percent_income  cb_person_cred_hist_length  \
count   45000.000000         45000.000000                45000.000000
mean       11.006606             0.139725                    5.867489
```

```
std          2.978808          0.087212                        3.879702
min          5.420000          0.000000                        2.000000
25%          8.590000          0.070000                        3.000000
50%         11.010000          0.120000                        4.000000
75%         12.990000          0.190000                        8.000000
max         20.000000          0.660000                       30.000000

       credit_score   loan_status
count  45000.000000  45000.000000
mean     632.608756      0.222222
std       50.435865      0.415744
min      390.000000      0.000000
25%      601.000000      0.000000
50%      640.000000      0.000000
75%      670.000000      0.000000
max      850.000000      1.000000
```

The dataset contains 45,000 rows and 14 columns, covering a range of features from personal to financial information.

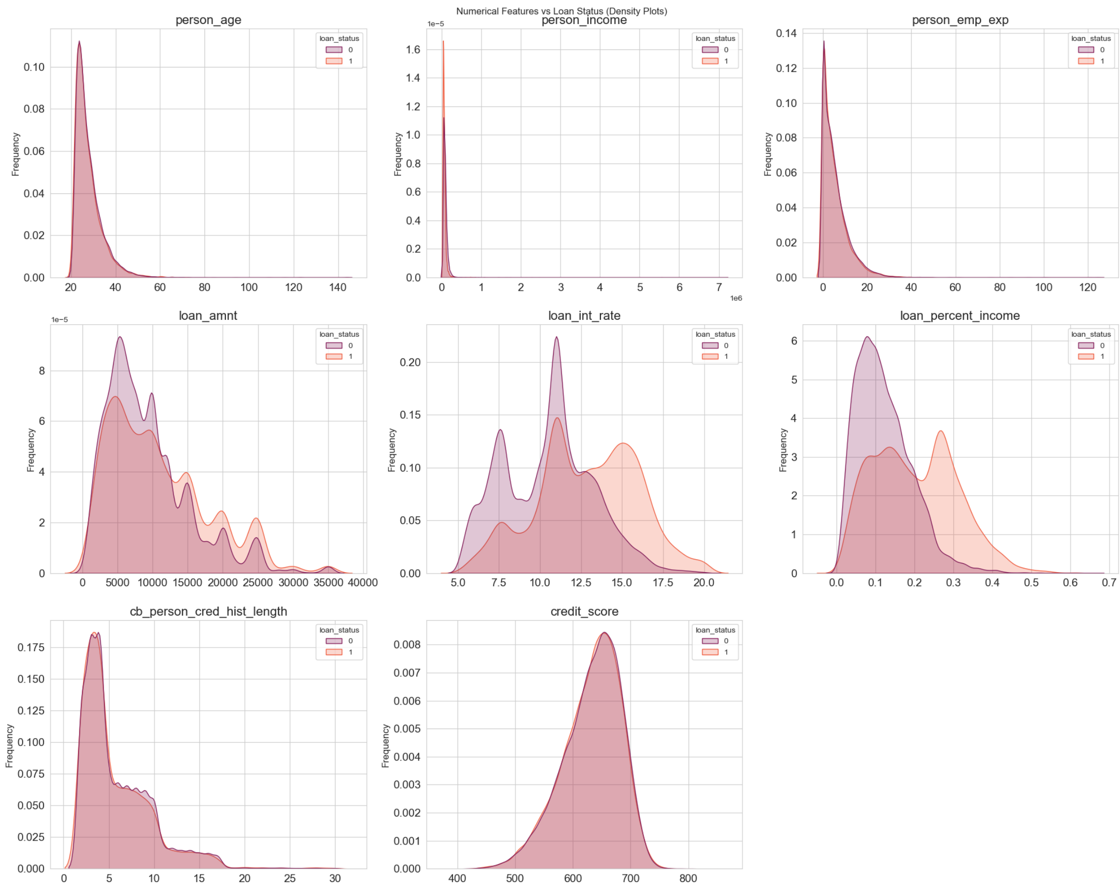
Below is a **brief description** of each column:

#	Column	Description	Type
1	person_age	Age of the person	Float
2	person_gender	Gender of the person	Categorical
3	person_education	Highest education level	Categorical
4	person_income	Annual income	Float
5	person_emp_exp	Years of employment experience	Integer
6	person_home_ownership	Home ownership status (e.g., rent, own, mortgage)	Categorical
7	loan_amnt	Loan amount requested	Float
8	loan_intent	Purpose of the loan	Categorical
9	loan_int_rate	Loan interest rate	Float
10	loan_percent_income	Loan as a percentage of annual income	Float
11	cb_person_cred_hist_length	Length of credit history in years	Float
12	credit_score	Credit score of the person	Integer
13	previous_loan_defaults_on_file	Indicator of previous loan defaults	Categorical
14	loan_status (target variable)	Loan approval status: 1 = approved; 0 = rejected	Integer

After getting a layout of how the data looks like, the next step is to get an understanding of how each numerical variable behaves for different classes of the target variable `loan_status`. This will help identify the variables' **distribution, potential patterns** and **important features** that could contribute to a model. This will be done using a Kernel Distribution plot (KDE).

[6]:

```python
# Select all columns with numeric data types (int or float)
numerical_cols = df.select_dtypes('number').columns

# Set seaborn plot style to 'whitegrid' for a cleaner background
sns.set_style('whitegrid')

# Create a figure with 3 rows and 3 columns of subplots (to fit 9 numerical␣
↪features)
fig, axes = plt.subplots(nrows=3, ncols=3, figsize=(20, 16))

# Add a super title for the entire figure
fig.suptitle('Numerical Features vs Loan Status (Density Plots)')

# Flatten the 2D array of axes to make iteration easier
axes = axes.flatten()

# Loop over all numerical columns and plot each one
for i, col in enumerate(numerical_cols):
    sns.kdeplot(
        x=col,
        data=df,
        ax=axes[i],
        hue='loan_status',
        fill=True,
        common_norm=False,
        palette='rocket'
    )

    axes[i].set_title(col, fontsize=16)        # Set plot title to the column␣
↪name
    axes[i].set_xlabel('', fontsize=12)        # Remove x-axis label for clean␣
↪visuals
    axes[i].set_ylabel('Frequency', fontsize=12)  # Label y-axis as Frequency
    axes[i].tick_params(axis='x', labelsize=14)   # Adjust font size for x-axis␣
↪ticks
    axes[i].tick_params(axis='y', labelsize=14)   # Adjust font size for y-axis␣
↪ticks

# Remove any empty/unfilled subplots (if there are fewer features than subplots)
for j in range(len(numerical_cols) - 1, len(axes)):
    fig.delaxes(axes[j])

# Adjust spacing between plots to avoid overlap
plt.tight_layout()

# Display the complete figure with all subplots
plt.show()
```



From the above visualization, we can already derive a lot of information about the different features and their relationship with the target variable `loan_status`. Key notable takeaways from this visualization are:

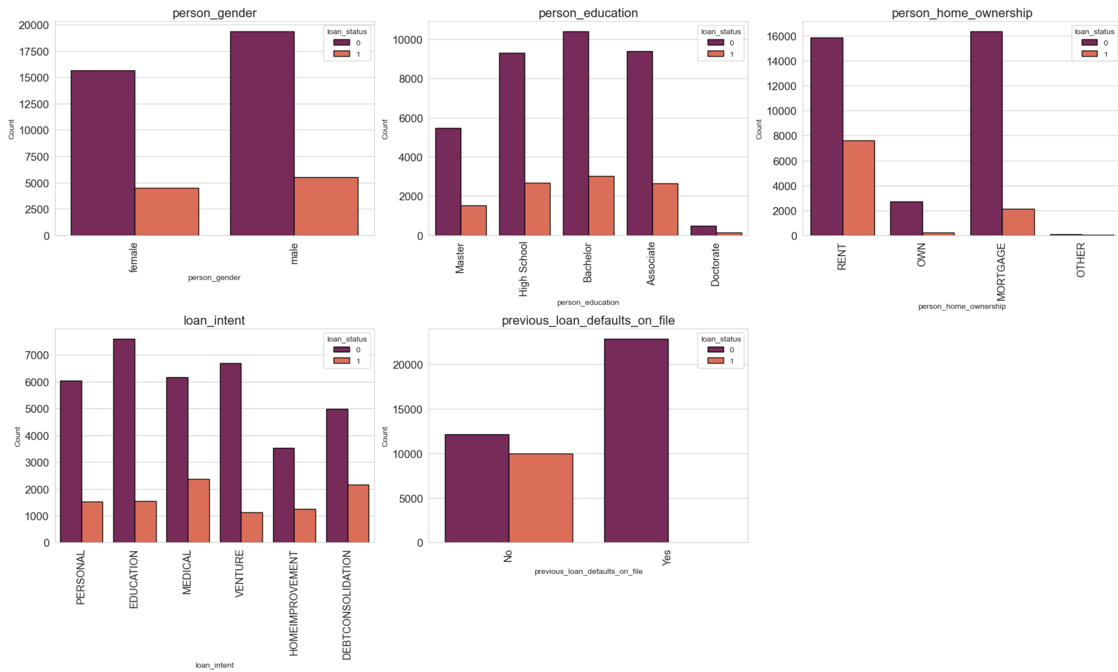
- `person_age` column has a distribution that is right-skewed. Most applicants are between the age of 25–35.
- `person_income` column is extremely right-skewed probably due to outliers
- `person_emp_exp column` is also right-skewed. It brings to light that most applicants have 0–20 years of experience.
- `loan_amnt` columns shows that more lower amount loans are rejected. Most applicants seems to apply loans between 2500 to 10,000
- `loan_int_rate` column is a strong indicator with rejected loans (0) clustering at higher interest rates. Approved loans (1) have peaks at lower interest rates (around 11%). This seems to be a **good potential predictor**.
- `loan_percent_income` column is a also a **very useful feature**. Approved loans tend to have lower loan-to-income ratios while rejections increase as the ratio increases.
- `cb_person_cred_hist_length` brings to light that most applicants have credit histories be-

tween 0 - 5 years. The curves mostly overlap. This is a **weak indicator**.

- `credit_score` column appears normally distributed with the two curves overlapping perfectly. This also seems to be a **weak indicator**.

Similar to the numerical columns, let's get a clear view of the value counts for each categorical feature. This will help in detecting imbalanced categories and understand the dominant classes.

[7]:
```
# Identify all categorical columns (e.g., object or category data types)
categorical_cols = df.select_dtypes(include=['object', 'category']).columns

# Set Seaborn style to white grid for better aesthetics
sns.set_style('whitegrid')

# Create a 2-row by 3-column grid of subplots (can show up to 6 plots)
fig, axes = plt.subplots(nrows=2, ncols=3, figsize=(20, 12))

# Flatten the 2D subplot array into a 1D list for easier looping
axes = axes.flatten()

# Loop through each categorical column to plot its value counts
for i, col in enumerate(categorical_cols):
    sns.countplot(
        data=df,
        x=col,
        hue='loan_status',
        ax=axes[i],      # Assign each plot to one subplot axis
        edgecolor='black',     # Add black borders to bars
        palette='rocket'
    )

    axes[i].set_title(col, fontsize=16)              # Set the title of the␣
 ↪subplot
    axes[i].set_ylabel('Count', fontsize=10)
    axes[i].tick_params(axis='x', labelrotation=90, labelsize=13)  # Rotate x␣
 ↪labels for better readability
    axes[i].tick_params(axis='y', labelsize=14)       # Set font size of y-axis␣
 ↪ticks

# If fewer plots than axes, delete the unused subplot(s)
for j in range(len(categorical_cols), len(axes)):
    fig.delaxes(axes[j])

# Adjust spacing between plots and display the figure
plt.tight_layout()
plt.show()
```



From this visualization, the key notable takeaways are: * From the `person_gender` feature, the data shows that the male gender has the highest loan rejections and loan approvals. This indicates that more males apply for loans increasing their chances of getting approved or rejected. This doesn't necessarily imply gender-based bias in approval. * In the `person_education` column, the data shows that the Doctorate degree holders have the lowest loan applications. This could be due to the fact that Doctorate degree holders make up a small portion of the population or they are financially stable and don't require loans. * The `previous_loan_defaults_on_file` feature is probably **the strongest predictor** as no person who had a previous loan default got a loan approval.

1.5 Data Preparation

The data preparation step aims to prepare the data for modelling and visualization. Key steps include normalizing the data, splitting the data into train and testing data to prevent data leakage, categorical encoding andchecking for multicollinearity.

1.5.1 Data Splitting

Data splitting is a crucial step in building a reliable and unbiased prediction model. It involves dividing the data into training and testing datasets - one for training the model and one for validating the dataset. Splitting ensures that the model is tested on data it hasn't interacted with before. This will simulate how it will perform in the real world.

[8]:
```python
# Separate the features (X) and the target variable (y) from the dataframe
X = df.drop('loan_status', axis=1)
y = df['loan_status']
```

```
# Split the dataset into training and testing sets
# 80% of data goes to training, 20% to testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Combine X_train and y_train back into a single DataFrame for easier handling␣
↪of training data
train_df = pd.concat([X_train, y_train], axis=1)

# Combine X_test and y_test back into a single DataFrame for easier handling of␣
↪testing data
test_df = pd.concat([X_test, y_test], axis=1)
```

1.5.2 Data Cleaning

To handle missing and duplicate values, let's create a function that outputs: * Missing values - `df.isna().sum()` * Duplicate values - `df.duplicated().value_counts()`

[9]:
```
# Create a function to display the dataframe's missing and duplicate values
def discrepancies(dataframe):
    print('-------- DataFrame Missing Values --------\n')
    print(df.isna().sum()) # Check for missing values
    print('\n')
    print('-------- Dataframe Duplicate Values --------\n')
    print(df.duplicated().value_counts()) # Check for duplicate values
```

[10]:
```
# Call out the function to check for missing and duplicate values
discrepancies(train_df)
```

```
-------- DataFrame Missing Values --------

person_age                        0
person_gender                     0
person_education                  0
person_income                     0
person_emp_exp                    0
person_home_ownership             0
loan_amnt                         0
loan_intent                       0
loan_int_rate                     0
loan_percent_income               0
cb_person_cred_hist_length        0
credit_score                      0
previous_loan_defaults_on_file    0
loan_status                       0
dtype: int64
```

```
-------- Dataframe Duplicate Values --------

False    45000
Name: count, dtype: int64
```

The dataframe has no missing and duplicate values. Next, let's validate the contents of the categorical columns for any discrepancies such as placeholders or characters.

[11]:
```python
# Identify categorical columns in the training dataset
categorical_cols = train_df.select_dtypes(include=['object', 'category']).
↪columns

# Loop through each categorical column and display value counts
for col in categorical_cols:
    print(f"\n--- Value counts for column: {col} ---")
    print(train_df[col].value_counts())
```

```
--- Value counts for column: person_gender ---
person_gender
male      19817
female    16183
Name: count, dtype: int64

--- Value counts for column: person_education ---
person_education
Bachelor       10772
Associate       9607
High School     9508
Master          5609
Doctorate        504
Name: count, dtype: int64

--- Value counts for column: person_home_ownership ---
person_home_ownership
RENT        18727
MORTGAGE    14795
OWN          2379
OTHER          99
Name: count, dtype: int64

--- Value counts for column: loan_intent ---
loan_intent
EDUCATION            7381
MEDICAL              6818
VENTURE              6227
PERSONAL             6030
```

```
DEBTCONSOLIDATION    5731
HOMEIMPROVEMENT      3813
Name: count, dtype: int64

--- Value counts for column: previous_loan_defaults_on_file ---
previous_loan_defaults_on_file
Yes    18253
No     17747
Name: count, dtype: int64
```

The columns have their perceived values and there doesn't seem to be presence of placeholders or unknown characters.

1.5.3 Scaling

Scaling will transform features by scaling them to a given range (Usually [0,1] with minmax scaling). This is important as it scales all the numerical features to the same scale. Minmax scaling is preferred as it does not distort the shape of the original distribution. This is good for data visualization.

To ease the process, it will be best to create two almost similar features; one for the training data that outputs the scaled dataframe and the fitted scaler, and one for the testing data that takes in both the dataframe to be scaled and the pre fitted scaler to apply the same transformation.

[12]:
```python
# Fit a MinMaxScaler on the numeric columns of training data.
# Return the fitted scaler and the scaled training data.
def fit_scaler_on_train(train_df):

    # Select numeric columns to scale
    numeric_cols = train_df.select_dtypes(include='number').columns

    # Select categorical columns to preserve (they won't be scaled)
    categorical_cols = train_df.select_dtypes('object')

    # Initialize the MinMaxScaler
    scaler = MinMaxScaler()

    # Fit the scaler on training numeric data and transform it
    scaled_train = scaler.fit_transform(train_df[numeric_cols])

    # Create a new DataFrame from the scaled numeric data, keeping original␣
 ↪column names and indices
    scaled_train_df = pd.DataFrame(scaled_train, columns=numeric_cols,␣
 ↪index=train_df.index)

    # Concatenate the unscaled categorical columns with the scaled numeric␣
 ↪columns
    concated_df = pd.concat([categorical_cols, scaled_train_df], axis=1)
```

```python
    # Return both the fitted scaler and the transformed training DataFrame
    return scaler, concated_df


# Apply an existing fitted scaler to numeric columns of test data.
# Return a scaled test DataFrame.

def apply_scaler_on_test(test_df, scaler):

    # Select numeric columns to scale
    numeric_cols = test_df.select_dtypes(include='number').columns

    # Select categorical columns to preserve
    categorical_cols = test_df.select_dtypes('object')

    # Apply the previously fitted scaler to the numeric test data
    scaled_test = scaler.transform(test_df[numeric_cols])

    # Create a new DataFrame from the scaled numeric data
    scaled_test_df = pd.DataFrame(scaled_test, columns=numeric_cols,␣
 ↪index=test_df.index)

    # Concatenate the unscaled categorical columns with the scaled numeric␣
 ↪columns
    concated_df = pd.concat([categorical_cols, scaled_test_df], axis=1)

    # Return the fully prepared (scaled + categorical) test DataFrame
    return concated_df
```

[13]:
```python
# Transform the training data and preserve the scaler for the testing dataset
scaler, scaled_df = fit_scaler_on_train(train_df)
# Preview the results
scaled_df.head()
```

[13]:
```
      person_gender person_education person_home_ownership      loan_intent  \
25180        female         Bachelor              MORTGAGE         PERSONAL
12555          male      High School                  RENT          VENTURE
29153        female           Master              MORTGAGE         PERSONAL
23838          male        Associate                  RENT        EDUCATION
35686          male           Master                  RENT  HOMEIMPROVEMENT

      previous_loan_defaults_on_file  person_age  person_income  \
25180                             No    0.112903       0.012410
12555                            Yes    0.040323       0.009030
29153                            Yes    0.169355       0.043738
23838                             No    0.056452       0.011989
35686                            Yes    0.056452       0.010688
```

```
       person_emp_exp  loan_amnt  loan_int_rate  loan_percent_income  \
25180           0.088   0.420290       0.501372             0.238095
12555           0.024   0.333333       0.441701             0.253968
29153           0.144   0.681159       0.339506             0.111111
23838           0.032   0.263768       0.803841             0.158730
35686           0.056   0.190116       0.517833             0.126984

       cb_person_cred_hist_length  credit_score  loan_status
25180                    0.250000      0.523913          0.0
12555                    0.071429      0.584783          0.0
29153                    0.321429      0.636957          0.0
23838                    0.178571      0.545652          0.0
35686                    0.035714      0.686957          0.0
```

1.5.4 Encoding

The aim of encoding is to convert categorical data into numerical format which is necessary because most machine learning models require numerical input. Let's check the values in the categorical columns in order to figure out which type of encoder to use.

[14]:
```python
# Loop through each categorical column and display value counts
for col in categorical_cols:
    print(f"\n--- Value counts for column: {col} ---")
    print(train_df[col].value_counts())
```

```
--- Value counts for column: person_gender ---
person_gender
male      19817
female    16183
Name: count, dtype: int64

--- Value counts for column: person_education ---
person_education
Bachelor       10772
Associate       9607
High School     9508
Master          5609
Doctorate        504
Name: count, dtype: int64

--- Value counts for column: person_home_ownership ---
person_home_ownership
RENT        18727
MORTGAGE    14795
OWN          2379
OTHER          99
```

```
Name: count, dtype: int64

--- Value counts for column: loan_intent ---
loan_intent
EDUCATION            7381
MEDICAL              6818
VENTURE              6227
PERSONAL             6030
DEBTCONSOLIDATION    5731
HOMEIMPROVEMENT      3813
Name: count, dtype: int64

--- Value counts for column: previous_loan_defaults_on_file ---
previous_loan_defaults_on_file
Yes    18253
No     17747
Name: count, dtype: int64
```

`previous_loan_defaults_on_file`, `person_home_ownership`, `person_gender`, `loan_intent` columns will require one-hot encoding since the values don't possess any hierarchy or rank. The `person_education` column contains information about the level of education of the applicants and as such, it will require ordinal encoding.

Let's create a function that will be used on both training and testing data for encoding.

[15]:
```
# Create a function to be used by both the training and testing data for␣
↪encoding
def encode_df(df):
    """
    Encode categorical features in the input DataFrame using:
    - Ordinal encoding for 'person_education'
    - One-hot encoding for selected nominal features
    Return the encoded DataFrame.
    """

    # Make a copy to avoid modifying the original DataFrame
    df_encoded = df.copy()

    # --- Ordinal Encoding ---
    # Define the order for the 'person_education' column
    education_order = [['High School', 'Associate', 'Bachelor', 'Master',␣
↪'Doctorate']]

    # Check if the column exists before encoding
    if 'person_education' in df_encoded.columns:
        # Create and fit an OrdinalEncoder with the specified order
        ord_enc = OrdinalEncoder(categories=education_order)
```

```
        # Transform the 'person_education' column and add it as a new feature
        df_encoded['person_education_encoded'] = ord_enc.
 ↪fit_transform(df_encoded[['person_education']])


    # --- One-Hot Encoding ---
    # Columns to be one-hot encoded (nominal categories, no inherent order)
    onehot_cols = [
        'person_gender',
        'person_home_ownership',
        'loan_intent',
        'previous_loan_defaults_on_file'
    ]

    for col in onehot_cols:
        if col in df_encoded.columns:
            # Create OneHotEncoder instance
            ohe = OneHotEncoder(sparse_output=False, drop='first',␣
 ↪handle_unknown='ignore')

            # Fit and transform the column
            transformed = ohe.fit_transform(df_encoded[[col]])

            # Get new column names for the encoded variables
            col_names = ohe.get_feature_names_out([col])

            # Create a DataFrame from the transformed output
            onehot_df = pd.DataFrame(transformed, columns=col_names,␣
 ↪index=df_encoded.index)

            # Concatenate the one-hot encoded columns with the original␣
 ↪DataFrame
            df_encoded = pd.concat([df_encoded, onehot_df], axis=1)

    # Return the fully encoded DataFrame
    return df_encoded
```

[16]:

```
# Create a function for easier dropping of the categorical columns that were␣
 ↪encoded
def drop_columns(df):

    # A list of columns to drop
    columns_to_drop = [
        'person_gender', 'person_education',
        'person_home_ownership', 'age_bin',
        'loan_intent','Loan_Status_Encoded',
        'previous_loan_defaults_on_file'
```

```
    ]

    return df.drop(columns=columns_to_drop, errors='ignore')
```

[17]:
```
# Apply the function on the scaled dataframe
encoded_df = encode_df(scaled_df)
# Create a df with the dropped categorical columns
num_df = drop_columns(encoded_df)
```

We will also need a second dataframe with the categorical columns for visualization. In this case we will use the initial training dataframe that hasn't been normalized for better visualizations.

[18]:
```
# Create a copy of the training df for visualization
eda_df = train_df.copy()
# Encode the target variable for easier visualization
eda_df['Loan_Status_Encoded'] = eda_df['loan_status'].map({1: 'Approved', 0:␣
↪'Rejected'})
```

[19]:
```
# Preview the dataframe
eda_df.head()
```

[19]:
```
       person_age person_gender person_education  person_income  \
25180        34.0        female         Bachelor        97265.0
12555        25.0          male      High School        72953.0
29153        41.0        female           Master       322597.0
23838        27.0          male        Associate        94232.0
35686        27.0          male           Master        84873.0

       person_emp_exp person_home_ownership  loan_amnt      loan_intent  \
25180              11              MORTGAGE    15000.0         PERSONAL
12555               3                  RENT    12000.0          VENTURE
29153              18              MORTGAGE    24000.0         PERSONAL
23838               4                  RENT     9600.0        EDUCATION
35686               7                  RENT     7059.0  HOMEIMPROVEMENT

       loan_int_rate  loan_percent_income  cb_person_cred_hist_length  \
25180          12.73                 0.15                         9.0
12555          11.86                 0.16                         4.0
29153          10.37                 0.07                        11.0
23838          17.14                 0.10                         7.0
35686          12.97                 0.08                         3.0

       credit_score previous_loan_defaults_on_file  loan_status  \
25180           631                             No            0
12555           659                            Yes            0
29153           683                            Yes            0
23838           641                             No            0
35686           706                            Yes            0
```

```
      Loan_Status_Encoded
25180            Rejected
12555            Rejected
29153            Rejected
23838            Rejected
35686            Rejected
```

1.5.5 Multicollinearity Check

Multicollinearity occurs when two or more independent variables are **highly correlated** with each other. This can cause models to fit the noise rather than the signal espesially in models such as logistic regression. Multicollinearity also causes redundancy and removing features that are highly correlated increases the model performance.

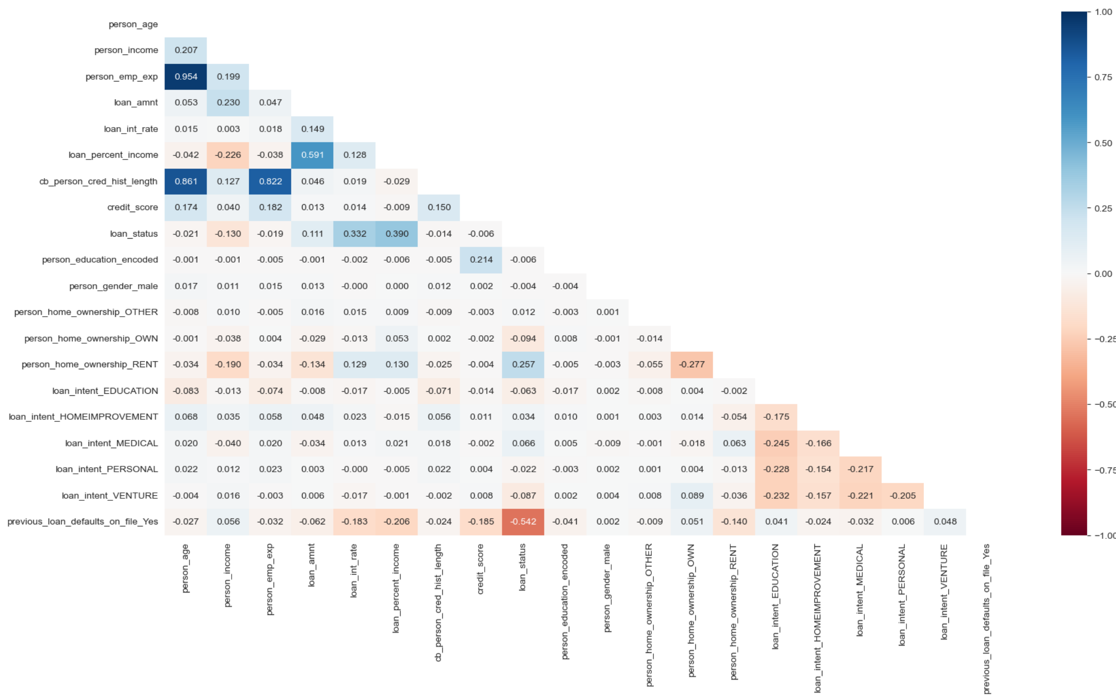
[20]:
```
# Loop through each column in the numeric DataFrame
for index, col in enumerate(num_df.columns):

    # Check if the corresponding column in correlation_df is of type 'object'␣
 ↪(i.e., categorical)
    if num_df[col].dtypes == 'object':
        print(col, 'Column has categorical values')

    # If this is the last column in the loop and no categorical column was␣
 ↪found earlier print no columns were found to be categorical
    elif index + 1 == len(num_df.columns):
        print('There are no columns with categorical values')
```

```
There are no columns with categorical values
```

Now that we have affirmed that there are no categorical columns in the dataframe, let's create a heatmap visualizing the level of correlation between the different columns.

[21]:
```
# Calculate the correlation matrix for numeric columns in the DataFrame
correlation_matrix = num_df.corr()

# Create a mask for the upper triangle of the matrix
# This avoids showing duplicate correlations since the matrix is symmetric
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))

# Set the figure size for better readability
plt.figure(figsize=(20, 10))
sns.set_style('white')

# Plot a heatmap of the correlation matrix
sns.heatmap(correlation_matrix, mask=mask, # - hide redundant info
            annot=True, fmt=".3f", # format the annotations to 3 decimal places
            annot_kws={"fontsize": 10}, # set the font size of the annotations
```

```
              cmap="RdBu", vmin=-1, vmax=1) # set the color scale range from -1␣
↪(perfect negative) to 1 (perfect positive)

# Display the heatmap
plt.show()
```



The heatmap shows that the `cb_person_cred_hist_length`, `person_age` and `person_emp_exp` are highly correlated. All the remaining features don't exhibit multicollinearity.

Next step will be to create a dataframe with each column pair in the dataframe and their corresponding correlation value.

[22]:
```
# Take the absolute value of the correlation matrix to consider strength␣
↪regardless of direction
# Use .stack() to convert the matrix into a Series with a MultiIndex (pairs of␣
↪variables)
# Reset the index to convert the MultiIndex into columns
# Sort the values by the correlation strength in descending order
correlated = correlation_matrix.abs().stack().reset_index().sort_values(0,␣
↪ascending=False)

# Create a new column 'pairs' that contains tuples of the variable pairs␣
↪(level_0 and level_1)
correlated['pairs'] = list(zip(correlated['level_0'], correlated['level_1']))
```

```python
# Set the new 'pairs' column as the index of the DataFrame
correlated.set_index(['pairs'], inplace=True)

# Drop the original 'level_0' and 'level_1' columns as they are now redundant
correlated.drop(columns=['level_0', 'level_1'], axis=1, inplace=True)

# Preview the results
correlated.head()
```

[22]:

```
                                            0
pairs
(person_age, person_age)                  1.0
(person_gender_male, person_gender_male)  1.0
(loan_amnt, loan_amnt)                    1.0
(loan_int_rate, loan_int_rate)            1.0
(loan_percent_income, loan_percent_income)  1.0
```

[23]:

```python
# Rename the remaining column (which contains the correlation values) to␣
↪'Correlation'
correlated.columns = ['Correlation']

# Filter for pairs where correlation is strong (> 0.75) but exclude perfect␣
↪correlation (1.0)
highly_correlated = correlated[(correlated['Correlation'] > 0.75) &␣
↪(correlated['Correlation'] < 1)]

# Display the filtered highly correlated pairs
highly_correlated
```

[23]:

```
                                              Correlation
pairs
(person_age, person_emp_exp)                     0.953926
(person_emp_exp, person_age)                     0.953926
(person_age, cb_person_cred_hist_length)         0.861121
(cb_person_cred_hist_length, person_age)         0.861121
(person_emp_exp, cb_person_cred_hist_length)     0.822347
(cb_person_cred_hist_length, person_emp_exp)     0.822347
```

Now that we have identified the columns with a correlation value greater than 0.75, the next step is to drop one of the columns. Todecide which feature to drop, we will asses their relevance to the target variable. This will de done by performing a **two-sample t-test** to check whether the feature values differ significantly between the two target classes (0 - Rejected and 1 - Approved). This statistical test will help us determine which feature contributes more meaningfully to predicting the target, guiding us in selecting the feature to retain.

[24]:

```python
# List of selected correlated numeric columns to test against the target
correlated_cols = ['person_age', 'cb_person_cred_hist_length', 'person_emp_exp']
```

```python
# Get unique values of the target variable (loan status)
loan_statuses = num_df['loan_status'].unique()

# Initialize lists to store test statistics and feature names
F_statistic = []  # (Note: variable should be t_stat instead of F_stat)
P_value = []
column = []

# Loop through each correlated feature column
for col in correlated_cols:

    # Select values of the feature where loan status is 'Approved'
    approved = eda_df[eda_df['Loan_Status_Encoded'] == 'Approved'][col]

    # Select values of the feature where loan status is 'Rejected'
    rejected = eda_df[eda_df['Loan_Status_Encoded'] == 'Rejected'][col]

    # Perform two-sample t-test (Welch's t-test) between approved and rejected␣
 ↪groups
    t_stat, p_value = stats.ttest_ind(approved, rejected, equal_var=False)

    # Append t-statistic and p-value to their respective lists
    F_statistic.append(t_stat)  # Corrected variable name from f_stat to t_stat
    P_value.append(p_value)

    # Append current column name to list
    column.append(col)

# Create a DataFrame to summarize the t-test results for each feature
results = pd.DataFrame({'Feature': column, 'T_Statistic': F_statistic,␣
 ↪'P_Value': P_value})

# Sort the results by ascending p-value to identify features with significant␣
 ↪differences first
results.sort_values('P_Value')
```

[24]:

	Feature	T_Statistic	P_Value
0	person_age	-3.930913	0.000085
2	person_emp_exp	-3.579399	0.000346
1	cb_person_cred_hist_length	-2.562495	0.010404

All three features have a p-value below our significance level (0.05) indicating that they are statistically significant with respect to the target variable. In this case it will be better to retain all the features and apply an **L1 penalty** when modelling in order to combat the multicollinearity. The L1 penalty requires all the features to be on the same scale in order to avoid penalising features with greater coefficients. Fortunately, the data was already normalized using MinMaxScaler.

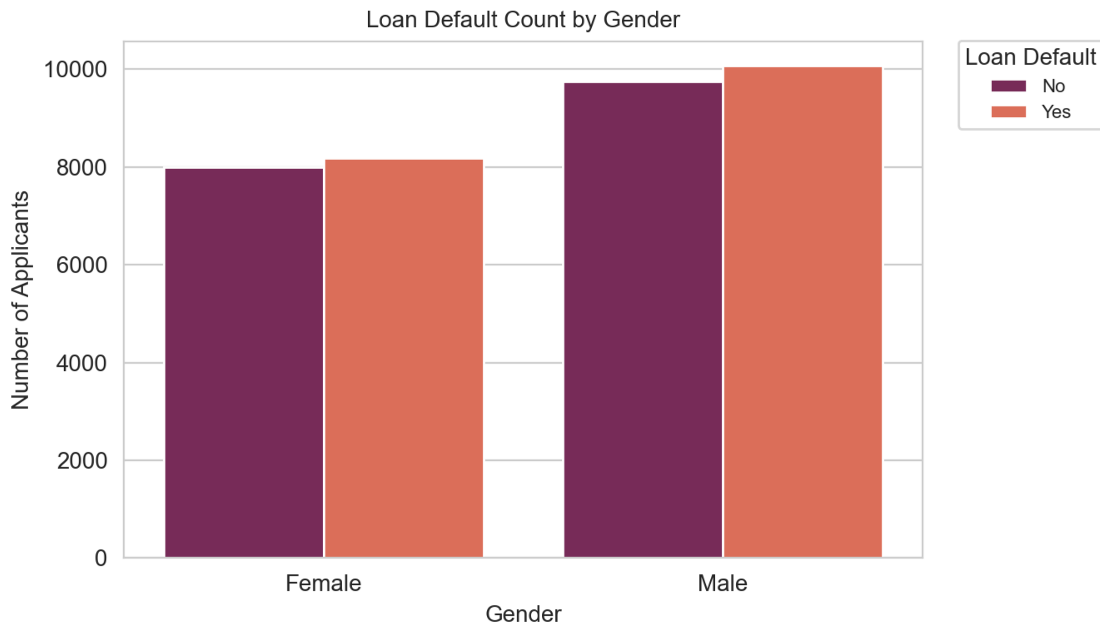
1.6 Exploratory Data Analysis

1.6.1 Objective 1: To examine demographic factors associated with high loan default rates

This objective will help to uncover which demographic groups are more likely to default on loans. The insight gotten from this will help lenders to segment risk by implementing this insight into their approval process.

[25]:
```
# Set the figure size for the plot
plt.figure(figsize=(7, 4), dpi=200)
sns.set_style('whitegrid')

# Create a count plot showing the number of applicants by gender,
# further separated by whether they had previous loan defaults
sns.countplot(
    x='person_gender',
    hue='previous_loan_defaults_on_file',       # Hue: Split by previous loan␣
 ↪default status
    data=eda_df,
    palette='rocket'
)

# Add a title and axis labels
plt.title('Loan Default Count by Gender', fontsize=10)
plt.xlabel('Gender', fontsize=10)
plt.ylabel('Number of Applicants', fontsize=10)

# Customize the ticks
plt.xticks(ticks=[0, 1], labels=['Female', 'Male'], fontsize=10)
plt.yticks(fontsize=10)

# Customize the legend
plt.legend(
    title='Loan Default',
    frameon=True,                               # Draw a box around the legend
    loc='upper right',                          # Anchor the legend to the␣
 ↪upper right of the plot area
    bbox_to_anchor=[1.23, 1.005],                # Offset the legend position␣
 ↪outside the plot
    borderaxespad=0.1,                          # Padding between the legend␣
 ↪content and its border
    fontsize=8)

# Adjust plot layout to prevent overlap or clipping
plt.tight_layout()

# Display the final plot
```

```
plt.show()
```



From the visualization, we observe that the male gender had the highest propensity to default on loans compared to females. The males also had the highest number of applicants who didn't default on loans. This trent reflects that males consitute the highest proportion of applicants applying for loans which leads to higher count of males defaulting and not defaulting on loans.

Another notable thing is that the proportion of applicants who had defaulted on a previous loan was higher compared to those who hadn't.

Let's perform a chi-square statistical test to test whether loan default status is dependent on gender.

> **Alternate Hypothesis** - The loan default status is dependent on gender
>
> **Null Hypothesis** - The loan default status is independent of the gender

[26]:
```
# Create a contingency table
contingency = pd.crosstab(encoded_df['person_gender'],␣
 ↪encoded_df['previous_loan_defaults_on_file'])

# Perform the Chi-Square test of independence on the contingency table
chi2, p_value, dof, expected = stats.chi2_contingency(contingency)

# Print the p-value from the test to assess statistical significance
if p_value < 0.05:
    print('Reject Null Hypothesis - The loan default status is dependent on␣
 ↪gender')
else:
```

```
    print('Fail to Reject Null Hypothesis -  The loan default status is␣
 ↪independent of gender')
print(f"P_value: {p_value:.3f}")
```

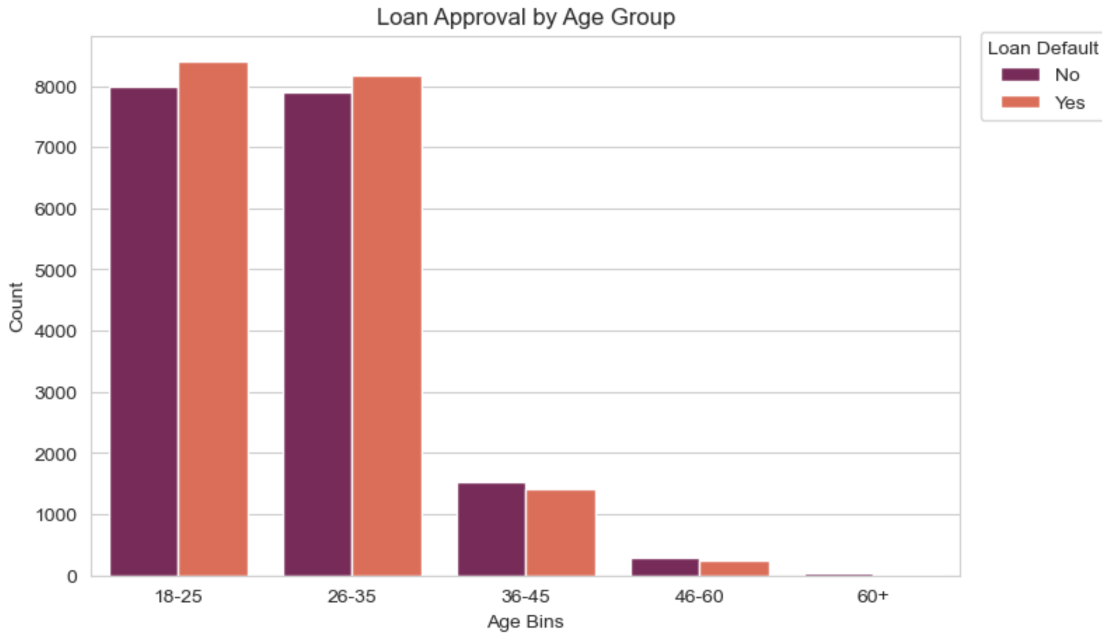
```
Fail to Reject Null Hypothesis -  The loan default status is independent of
gender
P_value: 0.676
```

The statistical test has a p_value of 0.676 which greatly exceeds our significance level. We can conclude from this that the loan defaulting status is not affected by gender.

Next, let's delve into the **age of the applicants** and how it affects the loan defaulting status. The aim of this is to analyze whether certain ge groups may be more or less likely to default. This can help financial institutions tailor loan terms and approvals by age group.

[27]:
```
# Create age bins by segmenting 'person_age' into specified ranges with labels
eda_df['age_bin'] = pd.cut(
    eda_df['person_age'],                     # The age column to bin
    bins=[18, 25, 35, 45, 60, 100],          # Define age intervals (bins)
    labels=['18-25', '26-35', '36-45', '46-60', '60+']  # Labels for each bin
)

# Set the figure size for the plot
plt.figure(figsize=(8, 5))

sns.set_style('whitegrid')

# Create a count plot showing the number of applicants per age group,
# separated by their previous loan default status
sns.countplot(
    x='age_bin',                             # Use the binned age groups on the␣
 ↪x-axis
    hue='previous_loan_defaults_on_file',
    data=eda_df,
    palette='rocket'
)

# Add a title to the plot
plt.title('Loan Approval by Age Group')
plt.xlabel('Age Bins')
plt.ylabel('Count')

# Customize the legend appearance and location
plt.legend(
    title='Loan Default',
    frameon=True,
    loc='upper right',                      # Position the legend in the upper␣
 ↪right corner
```

```
    bbox_to_anchor=[1.18,1.024]
)
plt.show()
```



From this visualization, it is observed that the 18 - 25 age range has the most loan defaults followed closely by the 26 - 35 age range. The age range of 36 - 45, the number of applicants without loan defaults exceeds those who defaulted, indicating a shift toward more responsible repayment behavior. Beyond the age of 45, loan applications drop sharply, with significantly fewer individuals applying for or receiving loans. Notably, the 60+ age group has minimal loan activity, suggesting that older individuals are either less likely to apply for loans or are less frequently approved.

Next, let's test whether there is a statistically significant difference between the average age of people who have defaulted on loans before and those who haven't. This helps assess if age is a predictor or associated factor for previous defaults.

> **Alternate Hypothesis** - There is a difference in the mean age between the two groups.
>
> **Null hypothesis** - There is no difference in the mean age of individuals with previous loan defaults and those without.

[28]:
```
# Split data into two groups based on loan default history
no_default = eda_df[eda_df['previous_loan_defaults_on_file'] ==␣
 ↪'No']['person_age']
default = eda_df[eda_df['previous_loan_defaults_on_file'] ==␣
 ↪'Yes']['person_age']

# Perform an independent t-test
```

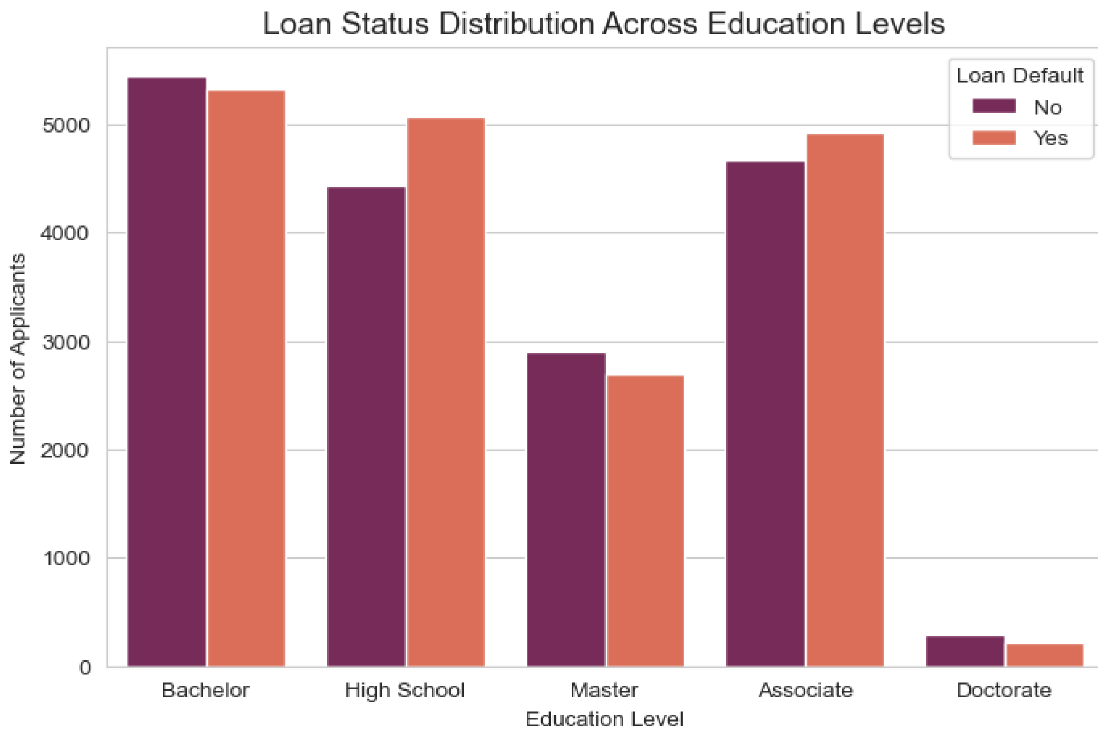
```
t_stat, p_value = stats.ttest_ind(no_default, default, equal_var=False)  #␣
↪Welch's t-test is safer if variances are unequal

# Interpretation
if p_value < 0.05:
    print('Reject Null Hypothesis - There is a difference in the mean age␣
↪between the two groups.')
else:
    print('Fail to Reject Null Hypothesis -There is no difference in the mean␣
↪age of individuals with previous loan defaults and those without.')
print(f'P-value: {p_value:.4f}')
```

```
Reject Null Hypothesis - There is a difference in the mean age between the two
groups.
P-value: 0.0000
```

The age feature has a p-value of 0.00 meaning that there is **a statistical significant difference** between the average age of people who have defaulted on loans before and those who haven't.

The final part in addressing this objective involves analyzing the relationship between a person's education level and their loan status using a stacked bar chart. This helps identify how loan approval or default varies across different education categories.

[29]:
```
# Set the visual style for the seaborn plots
sns.set_style('whitegrid')

# Create a countplot showing counts of loan default status for each education␣
↪level
plt.figure(figsize=(8, 5))
sns.countplot(
    data=eda_df,
    x='person_education',
    hue='previous_loan_defaults_on_file',      # Hue: loan default status to␣
↪split counts by this variable
    palette='rocket'
)

# Add title and axis labels
plt.title('Loan Status Distribution Across Education Levels', fontsize=14)
plt.xlabel('Education Level')
plt.ylabel('Number of Applicants')

# Add legend with a title and location
plt.legend(title='Loan Default', frameon=True, loc='upper right')

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



From this visualization it can be observed that the Bachelor's degree holdershave the highest number of loan applicants, with a slightly higher number of defaults compared to those without defaults. Majority of those with only high school qualifications loan defaults compared to those who don't, similar to those with Assiciate qualifications. Doctorate holders are the fewest in number, and their defaults are minimal suggesting lower risk.

Loan default rates are relatively high across most education levels, especially in Bachelor's, Associate, High School, indicating that higher education does not necessarily reduce the likelihood of defaulting. However, extremely low defaults among Doctorate holders may imply better creditworthiness.

Next, let's determine whether there is a statistically significant association between a person's education level and their previous loan default status.

> **Alternative hypothesis** : There is an association between education level and loan default status.
>
> **Null hypothesis**: Education level and loan default status are independent.

[30]:
```
# Create a contingency table (cross-tabulation) between education and loan␣
↪default status
contingency = pd.crosstab(
    encoded_df['person_education'],          # Rows: education levels (encoded)
    encoded_df['previous_loan_defaults_on_file']  # Columns: loan default␣
↪status (encoded)
```

```
)

# Perform Chi-square test of independence on the contingency table
chi2, p_value, dof, expected = stats.chi2_contingency(contingency)

# Interpretation
if p_value < 0.05:
    print('Reject Null Hypothesis - There is an association between education␣
 ↪level and loan default status.')
else:
    print('Fail to Reject Null Hypothesis -  Education level and loan default␣
 ↪status are independent.')
print(f'P-value: {p_value:.3f}')
```

```
Reject Null Hypothesis - There is an association between education level and
loan default status.
P-value: 0.000
```

1.6.2 Objective 2: Determine whether there is a statistically significant relationship between an applicant's credit score and their loan approval status.

This objective seeks to find out if an applicant's credit score influences whether their loan application gets approved or not.

[31]:
```
# Set the figure size to 8 inches wide and 5 inches tall
plt.figure(figsize=(8, 5))

sns.set_style('whitegrid')

# Create a boxplot to show the distribution of credit scores for each loan␣
 ↪status category
sns.boxplot(
    x='Loan_Status_Encoded',
    y='credit_score',
    data=eda_df,
    palette='rocket'
)

# Add a title to the plot
plt.title('Credit Score Distribution by Loan Status')

# Label the x-axis
plt.xlabel('Loan Status')

# Label the y-axis
plt.ylabel('Credit Score')

# Display the plot
```

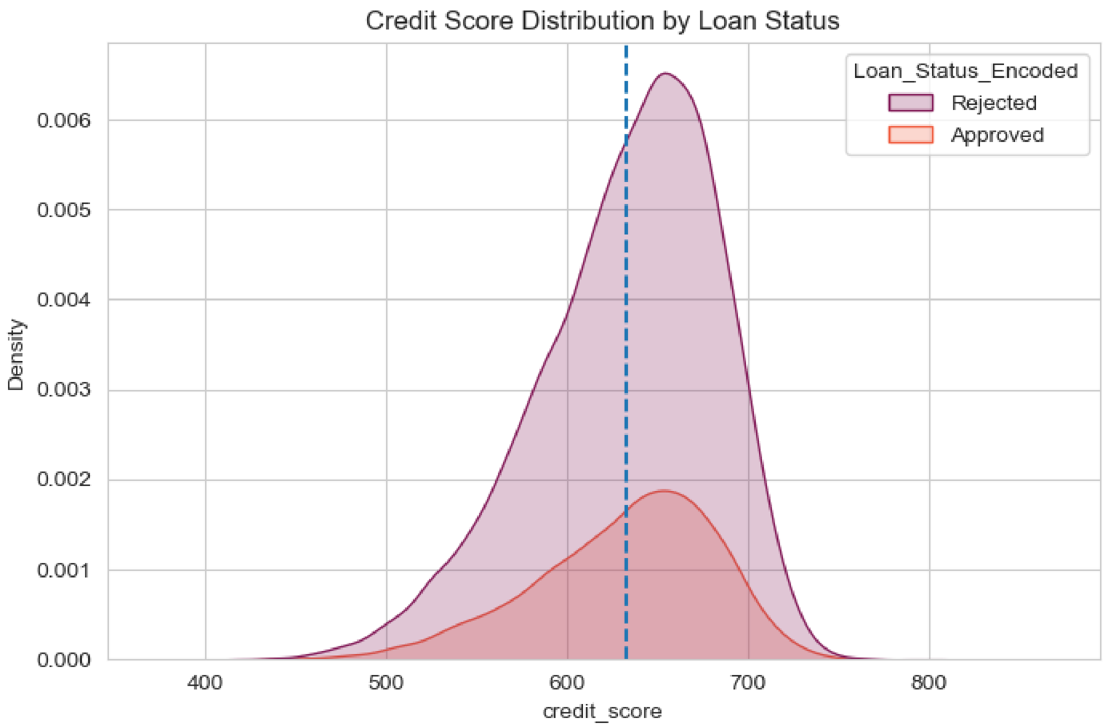
```
plt.show()
```

The median credit score and interquartile ranges of these two categories are nearly indentical and lie aroung the 650 mark. However, it can be observed that the rejected group had some applicants with high credit scores that had their application rejected.

Let's plot the distribution plots of these two categories to better pick up on the nuances.

[32]:
```
# Set the figure size for the plot
plt.figure(figsize=(8, 5))
sns.set_style('whitegrid')

# Create a KDE plot (Kernel Density Estimate) to show the distribution of␣
↪credit scores

sns.kdeplot(x='credit_score',
            hue='Loan_Status_Encoded',  # separate the plot by Loan Status
            data=eda_df,
            fill=True,
            palette='rocket')

# Add a line for the mean
plt.axvline(eda_df['credit_score'].mean(), linestyle='--')
```

```python
# Add a title to the plot
plt.title('Credit Score Distribution by Loan Status')

# Display the plot
plt.show()
```



Both groups have peaks around 650. The curves also overlap with borrowers with 'good' credit scores still get rejected while their similar counterparts are approved. This shows that this is not a reliable feature for predicting whether an applicant will get approved or rejected. Let's perform a statistical test to analyze whether there is a statistical sinificance between the two groups.

> **Alternative Hypothesis** - There is a significant difference in the mean credit scores between approved and rejected applicants.
>
> **Null Hypothesis** - There is no difference in the mean credit scores of approved and rejected loan applicants.

[33]:
```python
# Filter credit scores for approved loan applicants
approved = eda_df[eda_df['Loan_Status_Encoded'] == 'Approved']['credit_score']

# Filter credit scores for rejected loan applicants
rejected = eda_df[eda_df['Loan_Status_Encoded'] == 'Rejected']['credit_score']
```

```python
# Perform an independent two-sample t-test assuming unequal variances (Welch's␣
↪t-test)
t_stat, p_value = stats.ttest_ind(approved, rejected, equal_var=False)

# Display the p-value with 3 decimal places
if p_value < 0.05:
    print('Reject Null Hypothesis - There is a significant difference in the␣
↪mean credit scores between approved and rejected applicants.')
else:
    print('Fail to Reject Null Hypothesis - There is no difference in the mean␣
↪credit scores of approved and rejected loan applicants.')
print(f"P-value: {p_value:.3f}")
```

```
Fail to Reject Null Hypothesis - There is no difference in the mean credit
scores of approved and rejected loan applicants.
P-value: 0.218
```

1.7 Feature Selection

The aim of this section is to identify and retain only the features in the dataset that constribute to the outcome of the target variable. This will help improve model performance by focusing only on the relevant columns. This will also reduce overfitting by eliminating noise.

Since this project will utilise different models, the most important features may vary depending on the model at hand. To better choose the best features for a particular model, we will use **RFECV(Recursive Feature Elimination with Cross Validation)** which helps select features based on model performance. To streamline the process, we will incorporate RFECV into a pipeline for each model

[34]:
```python
def model_pipeline(model):

    # Creates a pipeline with RFECV for feature selection and a classifier.

    pipeline = Pipeline([
        # Step 1: Recursive Feature Elimination with Cross-Validation using the␣
↪given model
        ('feature_selection', RFECV(estimator=model, cv=StratifiedKFold(5))),

        # Step 2: Final classification using the same model
        ('classifier', model)
    ])

    return pipeline
```

1.8 Modelling

In this section, we will develop and evaluate three models to accurately predict whether the applicant will have their loan approved or rejected. The models will be validated using the test data and the model with the highest accuracy score will be chosen The models to be used are: * Logistic Regression * Decision Trees * XGBoost

The models will be evaluated using the **F1-Score** which provides a balanced measureof both precision and recall. This is important because in loan approval to not only minimise false positives (approving loans to risky applicants) but also avoid false negatives (rejecting creditworthy applicants). The F1-score is particularly useful in cases of class imbalance, where one outcome occurs more frequently than the other.

1.8.1 Data Preparation

This step involves preparing the training and testing data for modelling. Let's create a function to apply to the test data all the processing done on the training data.

[35]:
```
# Create a function to apply to the test data all the processing done on the␣
↪training data.
def prepare_test_data(test_df, scaler):

    target_column='loan_status'

    # Apply scaling
    scaled_test = apply_scaler_on_test(test_df, scaler)

    # Apply encoding
    encoded_test = encode_df(scaled_test)

    # Drop irrelevant columns
    dropped_df = drop_columns(encoded_test)

    # Split into features and target
    X_test = dropped_df.drop(target_column, axis=1)
    y_test = encoded_test[target_column]

    return X_test, y_test


# Apply the function
X_test, y_test = prepare_test_data(test_df, scaler)

#
X_train = num_df.drop('loan_status', axis=1)
y_train = num_df['loan_status']
```

Now that we have the final dataset for modelling, let's check for class imbalance in the target variable.

[36]:
```
# Check for class imbalance
y_train.value_counts()
```

[36]:
```
loan_status
0.0    28010
1.0     7990
Name: count, dtype: int64
```

The rejected category has four times more data compared to the approved category. To combat thos, let's resample the data tomake it more inclusive for all categories. The best way to do this is by using **SMOTE**.

[37]:
```python
# Insantiate SMOTE and set the minority class to have 27000 records
smote = SMOTE(random_state=42, sampling_strategy = {1: 25000})
# Fit SMOTE to the training dataset
X_resampled, y_resampled = smote.fit_resample(X_train, y_train)
# Verify the results
y_resampled.value_counts()
```

[37]:
```
loan_status
0.0    28010
1.0    25000
Name: count, dtype: int64
```

1.8.2 1. Logistic Regression (Baseline Model)

This will act as the baseline model in order to provide a simple benchmark out of which all other models can be compared and also set the expectations on the performance.

Let's begin modelling. To start, let's instantiate a Logistic Regression model and fit it to the resampled data.

[38]:
```python
# Instantiate the model
logreg = LogisticRegression(solver='liblinear', fit_intercept=False)
# Create a pipeline with the model
pipeline = model_pipeline(logreg)
# Fit the pipeline to the resampled data
pipeline.fit(X_resampled, y_resampled)
```

[38]:
```
Pipeline(steps=[('feature_selection',
                 RFECV(cv=StratifiedKFold(n_splits=5, random_state=None,
shuffle=False),
                       estimator=LogisticRegression(fit_intercept=False,
                                                    solver='liblinear'))),
                ('classifier',
                 LogisticRegression(fit_intercept=False, solver='liblinear'))])
```

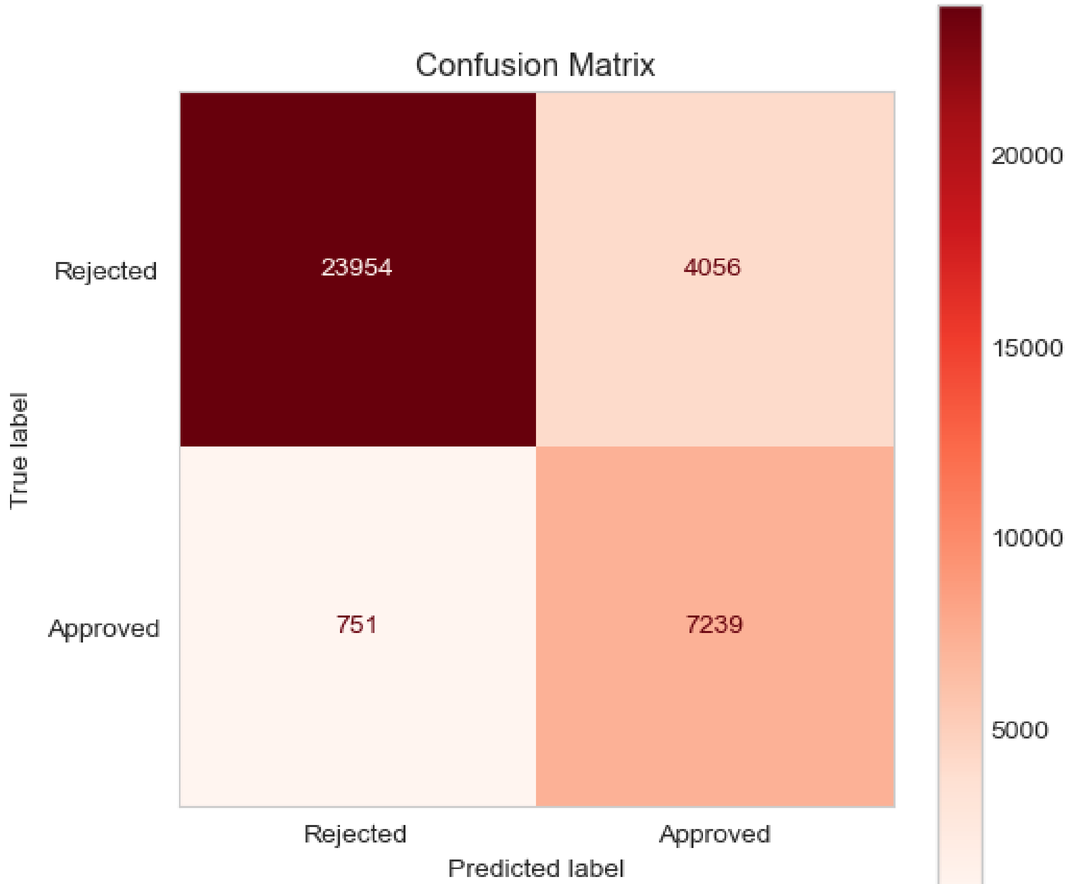
To better view the results, a function will be created that outputs the model's classification report (F1 Score, recall, precision and accuracy) together with the confusion matrix and the ROC curve.

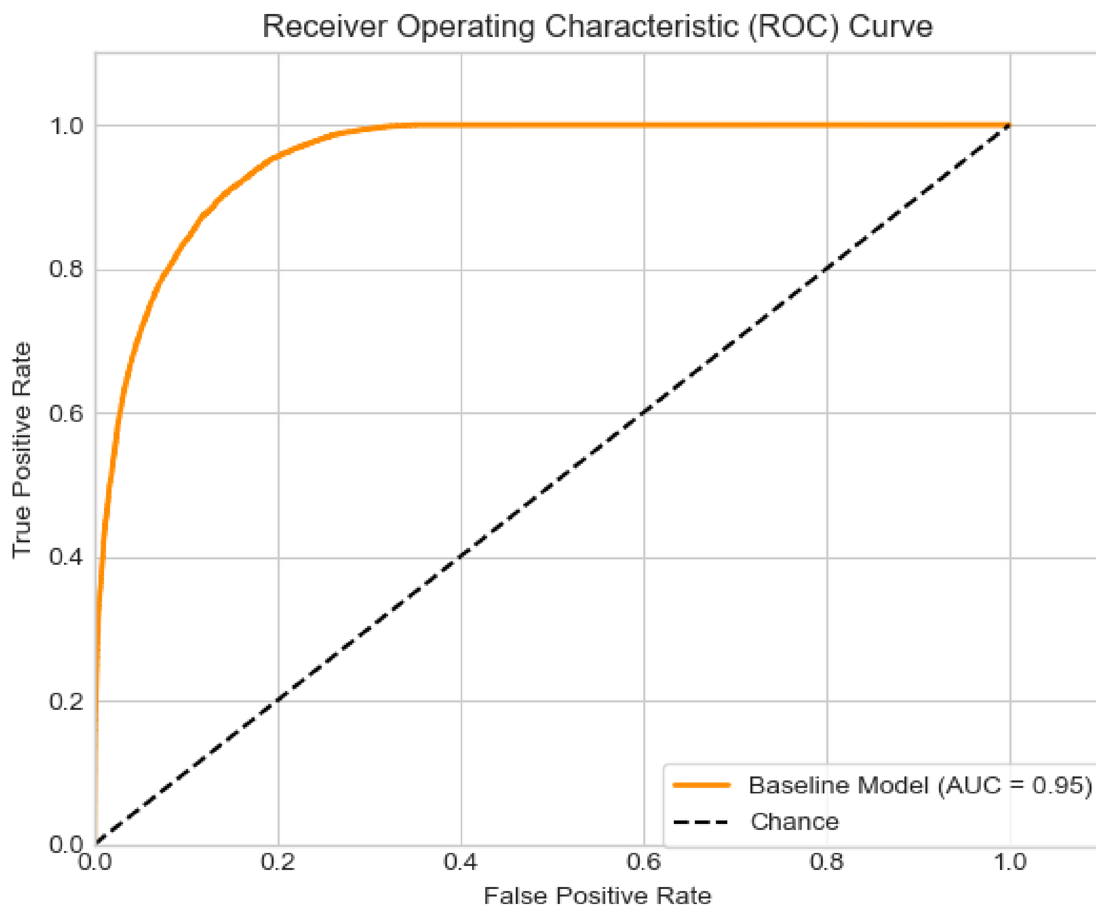
[39]:
```python
# Create a model that outputs the classification report, confusion matrix, ROC␣
↪curve and the AUC score
```

```python
def evaluate_model(model, X, y_true, model_name='Model'):

    # Set labels
    class_labels=['Rejected', 'Approved']

    # Predict labels
    y_pred = model.predict(X)

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm,␣
 ↪display_labels=class_labels)

    # Plot confusion matrix
    fig, ax = plt.subplots(figsize=(6, 6))
    plt.style.use('seaborn-v0_8-whitegrid')
    disp.plot(ax=ax, cmap='Reds')
    ax.grid(False)
    plt.title("Confusion Matrix")
    plt.show()

    # Compute ROC curve and AUC
    if model_name in ['XGBoost', 'Decision Tree'] :
        y_scores = model.predict_proba(X)[:, 1]
    else:
        y_scores = model.decision_function(X)
    fpr, tpr, _ = roc_curve(y_true, y_scores)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.figure(figsize=(6, 5))
    plt.style.use('seaborn-v0_8-whitegrid')
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'{model_name} (AUC =␣
 ↪{roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='black', linestyle='--', label='Chance')
    plt.xlim(0, 1.1)
    plt.ylim(0, 1.1)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend(loc='lower right', frameon=True, bbox_to_anchor=[1.015,-0.02])
    plt.grid(True)
    plt.tight_layout()
    plt.show()

    # Print classification report
    print('-------------- Classification Report --------------\n')
```

```
    print(classification_report(y_true, y_pred, target_names=class_labels))
    print('\n-------------- AUC Score --------------\n')
    print(f'AUC Score: {roc_auc:.4f}')
```

[40]:
```
# Apply the function to evalaute the model and get the scores
evaluate_model(pipeline, X_train, y_train, model_name='Baseline Model')
```



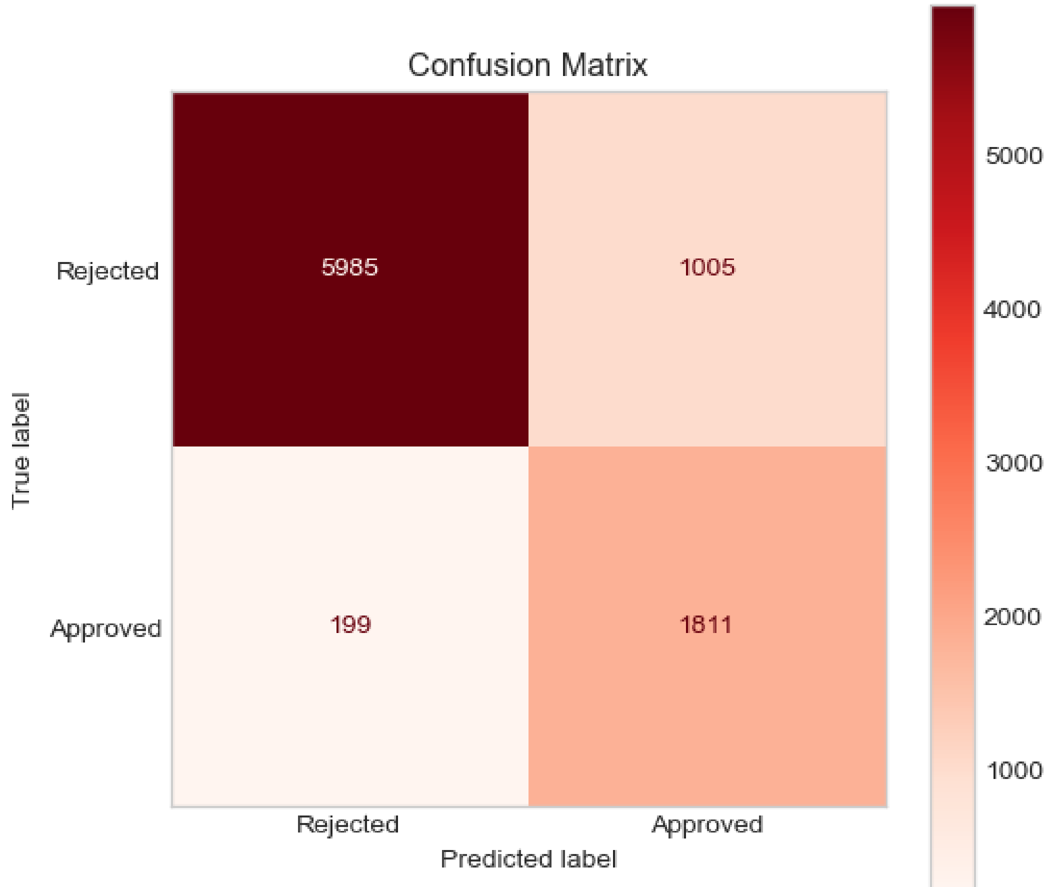


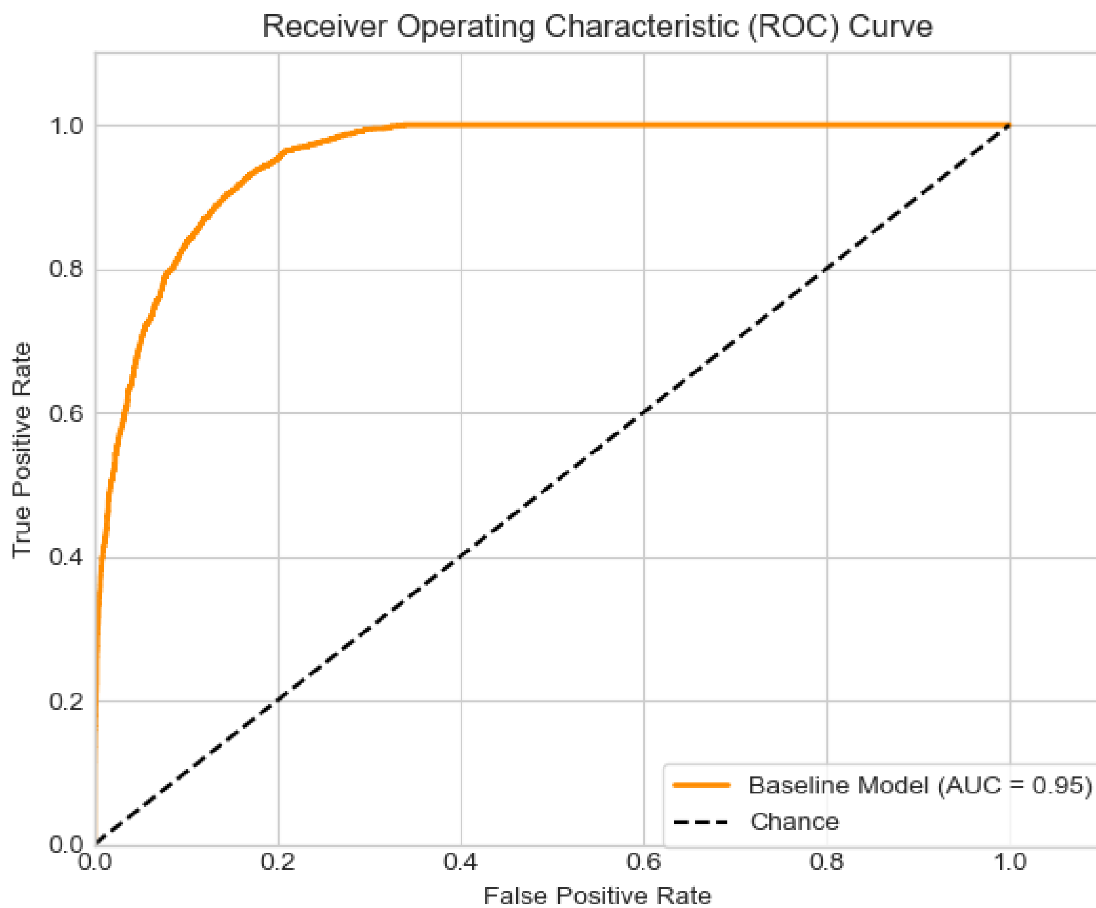

```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.97      0.86      0.91     28010
    Approved       0.64      0.91      0.75      7990

    accuracy                           0.87     36000
   macro avg       0.81      0.88      0.83     36000
weighted avg       0.90      0.87      0.87     36000


-------------- AUC Score --------------

AUC Score: 0.9544
```

The model has 87 % prediction accuracy. The f1 score is 91% for rejected data and 75% for approved data.

Let's now validate the model on the unseen test data. A significantly lower performance compared to the training set would indicate potential overfitting.

[41]:
```
# Validate the model using the test data
evaluate_model(pipeline,X_test, y_test, model_name='Baseline Model')
```






```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.97      0.86      0.91      6990
    Approved       0.64      0.90      0.75      2010

    accuracy                           0.87      9000
   macro avg       0.81      0.88      0.83      9000
weighted avg       0.90      0.87      0.87      9000


-------------- AUC Score --------------

AUC Score: 0.9524
```

1.8.3 Model Results

The model performs similarly for both the training and testing data. This is a good sign as it means there is no overfitting. However, the model perfored poorly when predicting the rejected applications. This led to a high number of false positive predictions which drove the precision score to 64% and ultimately driving down the approved class f1-score to 75% . A likely contributing factor is the oversampling. The oversampling introduced too many duplicated instances of approved applications causing the model to become biased towards predicting approvals. This made it hard for the model to correctly recognize patterns associated with rejected applications.

To address this, the step will be to fine tune the logistic regression model by using different **class weights** that will penalizing misclassification of rejected applications more heavily.

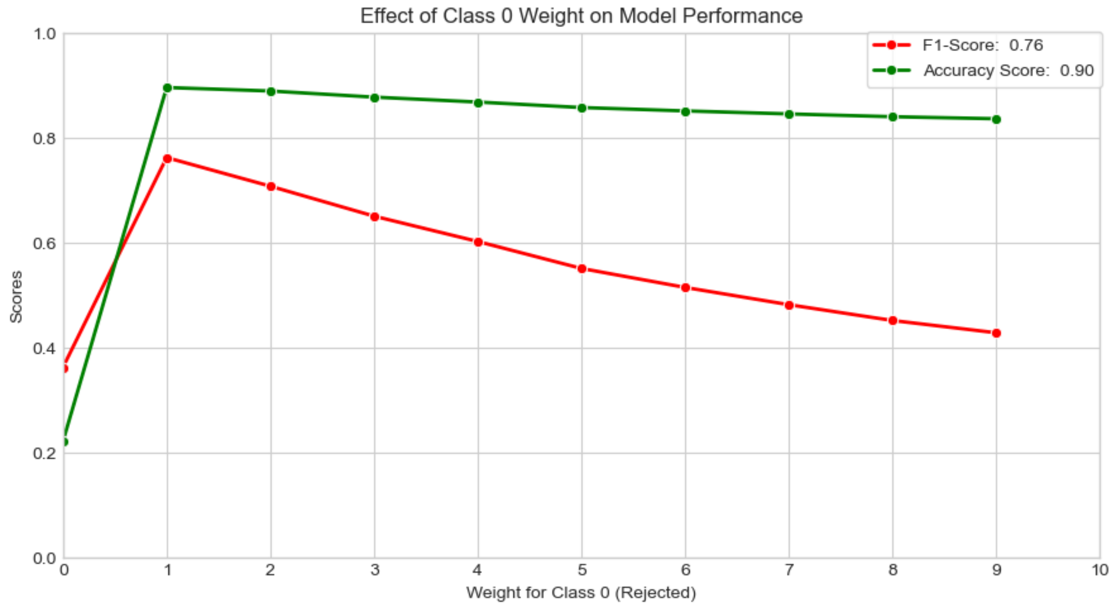
1.8.4 Logistic Regression Fine Tuning

Let's investigate how different class weights impact the overall model performance. To ensure a fair comparison, we will use the same features selected by the baseline model.

[42]:
```
# Get the mask of selected features
selected_mask = pipeline.named_steps['feature_selection'].support_

# Get the feature names
selected_logreg = X_resampled.columns[selected_mask].tolist()
```

[43]:
```
# Define the range of weights to test for class 0 (rejected applications)
class_0_weights = np.arange(0, 10, 1)

# Lists to store evaluation results for each weight setting
accuracy_scores = []
f1_scores = []
weight_labels = []

# Loop through each weight for class 0
for w0 in class_0_weights:
    weights = {0: w0, 1: 1}  # Fix weight of class 1 (approved) at 1, vary␣
 ↪weight of class 0

    # Train logistic regression model with L1 penalty and specified class␣
 ↪weights
    model = LogisticRegression(solver='liblinear', class_weight=weights)
    model.fit(X_train[selected_logreg], y_train)

    # Predict on training data
    y_pred = model.predict(X_train[selected_logreg])

    # Evaluate performance using F1-score and accuracy
    f1 = f1_score(y_train, y_pred)
    accuracy = accuracy_score(y_train, y_pred)
```

```python
    # Store results for plotting
    f1_scores.append(f1)
    accuracy_scores.append(accuracy)
    weight_labels.append(w0)

# Plot the effect of class 0 weight on model performance
plt.figure(figsize=(9, 5))

# Plot F1-scores
accuracy_max = max(accuracy_scores)
f1_max = max(f1_scores)
sns.lineplot(x=weight_labels, y=f1_scores,
             marker='o', linewidth=2,
             color='red',
             label=f'F1-Score: {f1_max: .2f}')

# Plot Accuracy scores
sns.lineplot(x=weight_labels, y=accuracy_scores,
             marker='o', linewidth=2,
             color='green',
             label=f'Accuracy Score: {accuracy_max: .2f}')

# Set plot labels and formatting
plt.xlabel('Weight for Class 0 (Rejected)')
plt.ylabel('Scores')
plt.xlim([0, 10])
plt.xticks(range(0,11,1))
plt.ylim([0, 1])

# Add a title and grid
plt.title('Effect of Class 0 Weight on Model Performance')
plt.grid(True)

# Adjust layout
plt.tight_layout()
plt.legend(frameon=True, bbox_to_anchor=[1.01, 1.02])

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

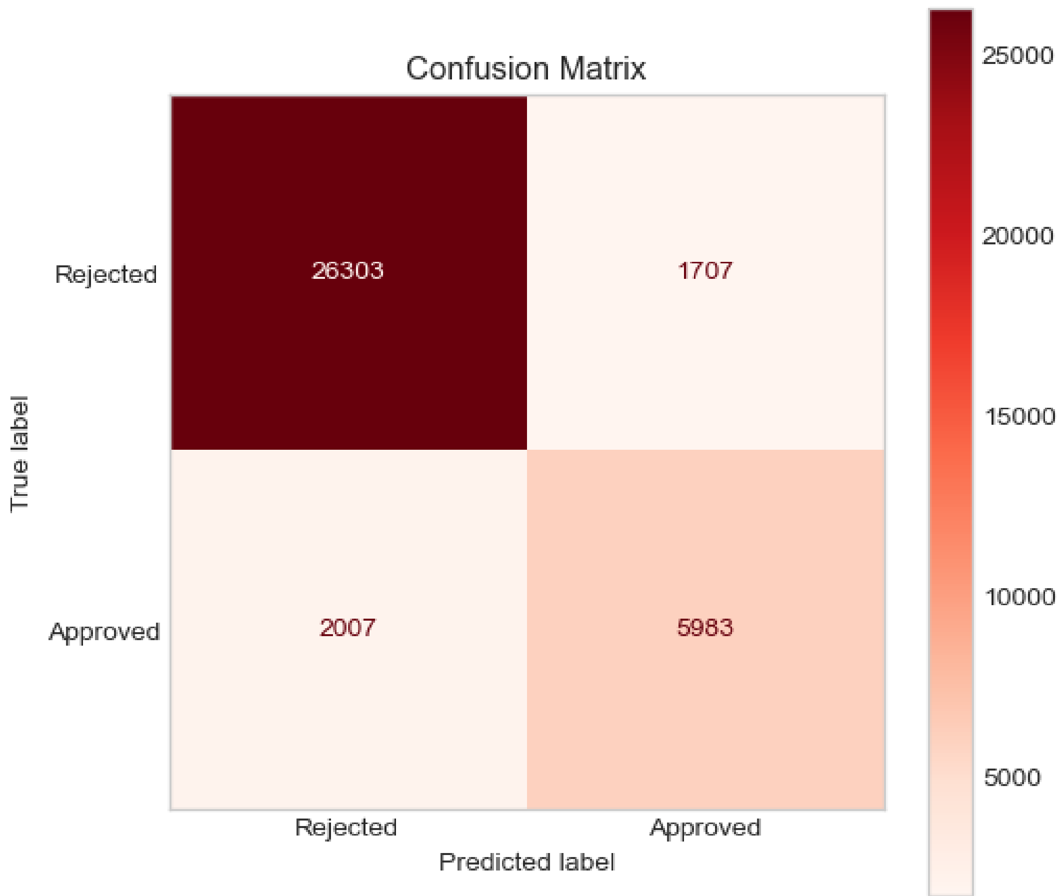


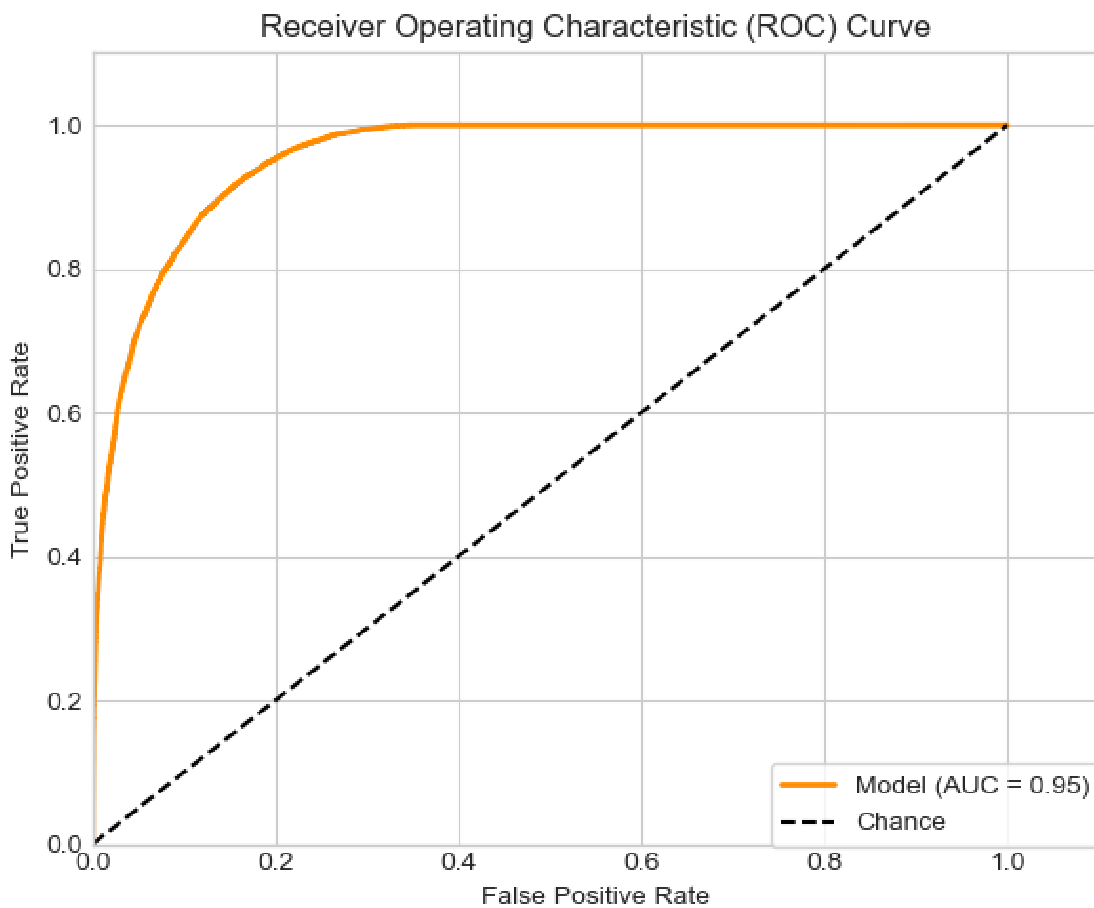
From the plot above, the model performed slightly better terms of f1-score than before when using balanced class weights ({0:1, 1:1}). While accuracy reached a high of 90%, f1-score peaked at 76% indicating a more balanced performance across classes. This shows that for this model, using the imbalanced dataset as it is is much better tha using resampled data. Next, let's create a new model and employ **GridSearchCV** to tune the hyperparameters and find the best parameter combinations.

[44]:
```
# Define the hyperparameter grid to search for Logistic Regression
parameters = {
    'solver': ['liblinear'],            # supports L1 regularization
    'penalty': ['l1'],                  # apply a penalty to combat␣
 ↪multicollinearity
    'fit_intercept': [True, False],     # Test whether including an intercept␣
 ↪improves model performance
    'C': [0.5, 1e12]                    # Regularization strength
}

# Initialize a base Logistic Regression model with balanced class weights
tuned_model = LogisticRegression(solver='liblinear', class_weight={0:1, 1:1})

# Perform Grid Search with 5-fold cross-validation
# Run in parallel using all available cores (n_jobs=-1)
grid_logreg = GridSearchCV(logreg, parameters, cv=5, scoring='accuracy',␣
 ↪n_jobs=-1)

# Fit the model on the selected features and training labels
grid_logreg.fit(X_train[selected_logreg], y_train)
```

[44]:
```
GridSearchCV(cv=5,
             estimator=LogisticRegression(fit_intercept=False,
                                          solver='liblinear'),
             n_jobs=-1,
             param_grid={'C': [0.5, 1000000000000.0],
                         'fit_intercept': [True, False], 'penalty': ['l1'],
                         'solver': ['liblinear']},
             scoring='accuracy')
```

[45]:
```
# Evaluate the model
evaluate_model(grid_logreg.best_estimator_, X_train[selected_logreg], y_train)
```



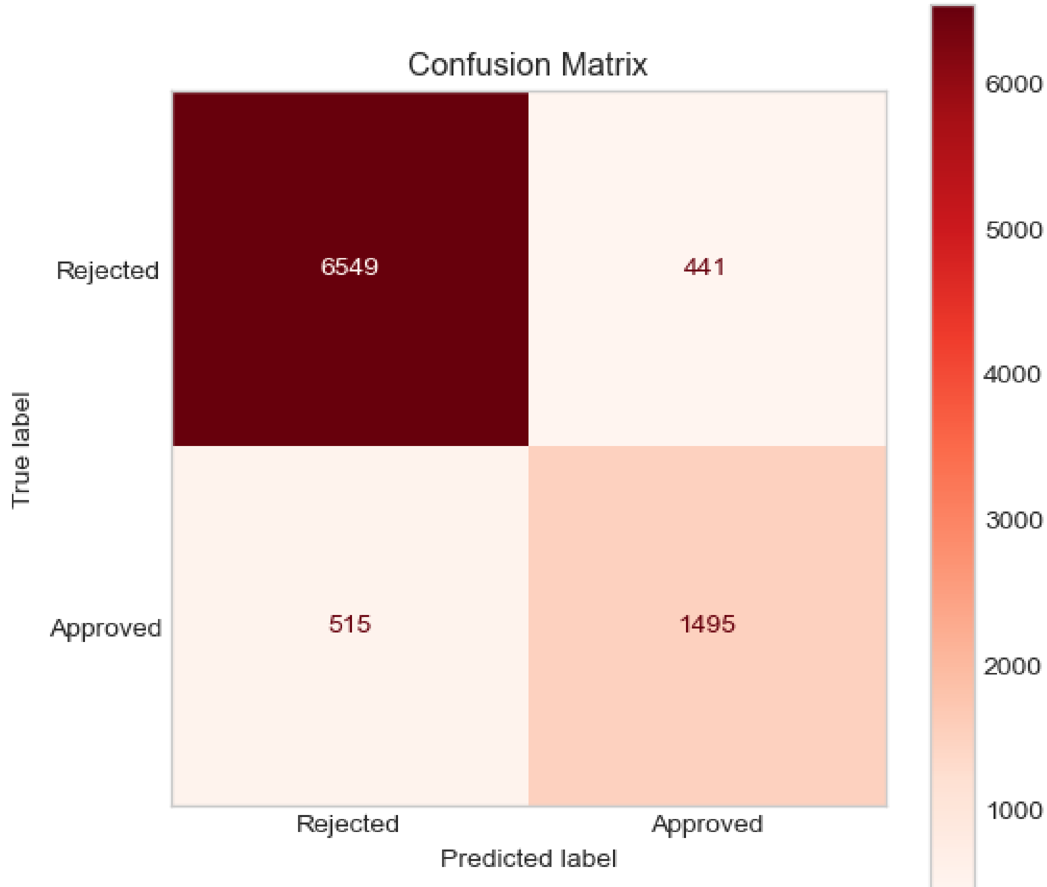


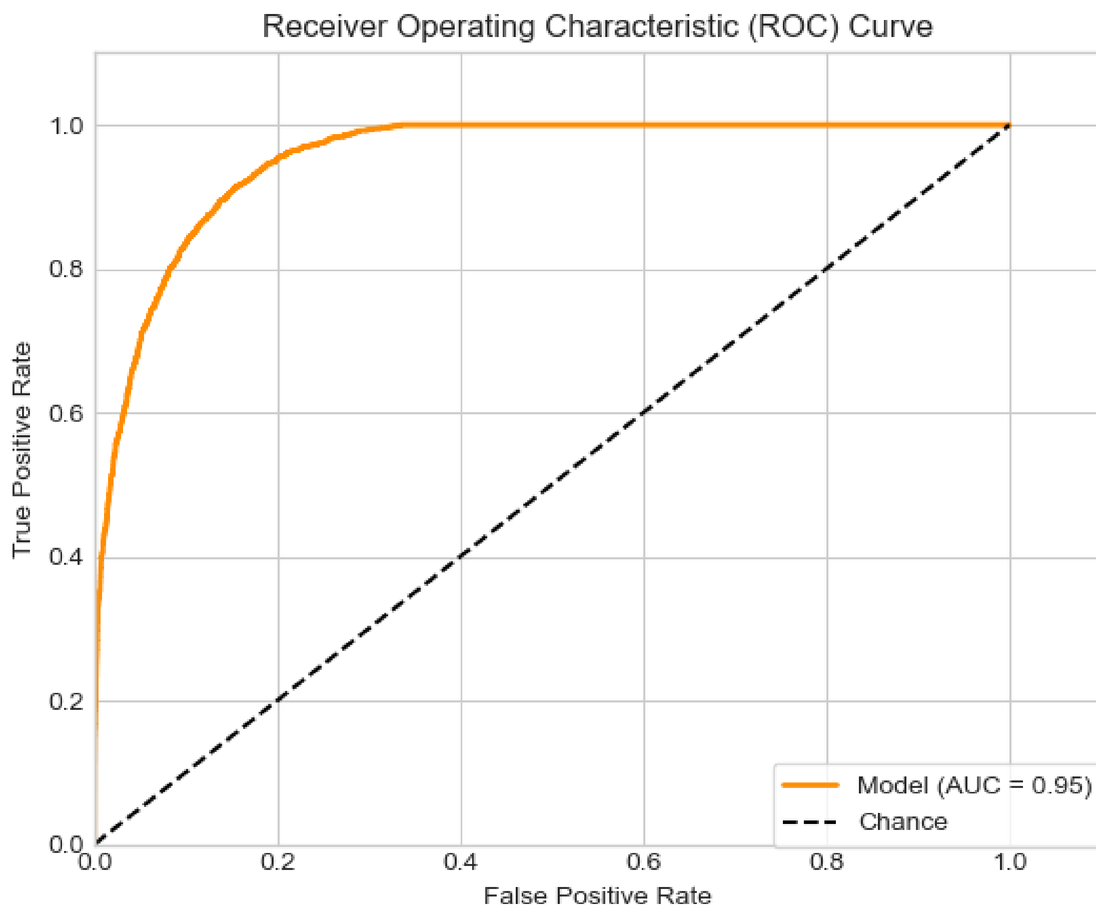

```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.93      0.94      0.93     28010
    Approved       0.78      0.75      0.76      7990

    accuracy                           0.90     36000
   macro avg       0.85      0.84      0.85     36000
weighted avg       0.90      0.90      0.90     36000


-------------- AUC Score --------------

AUC Score: 0.9547
```

After using **GridSearchCV** the model has performed smilar to the last model with 90% accuracy and 85% f1 score. The model also had an **AUC Score** of 95% . Next let's validate the tuned model on the test data.

[46]:

```
# Evaluate the model on the test data
evaluate_model(grid_logreg.best_estimator_,X_test[selected_logreg], y_test)
```






```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.93      0.94      0.93      6990
    Approved       0.77      0.74      0.76      2010

    accuracy                           0.89      9000
   macro avg       0.85      0.84      0.84      9000
weighted avg       0.89      0.89      0.89      9000


-------------- AUC Score --------------

AUC Score: 0.9527
```

1.8.5 Model Results

The logistic regression was chosen for its simplicity ain interpretability in binary classification tasks. After validating the model on the test data, the model garnered scores almost similar to the training data. The scores are as follows: * Overall Accuracy: 89% * Macro F1-score: 84% (average across both classes) * AUC Score: 0.9527 — Excellent separability between the classes.

The model performed very well (93% F1-Score) on the majority class (Rejected) and reasonably well (76% F1-Score) on the minority class (Approved). The average F1-Score for both classes was 84%.

Limitations: The minority class still lags behind in recall and F1-Score mainly because of the class imbalance. Logisticregression also assumes a linear relationshp between the target and predictor variables. This restricts the model from capturing complex patterns

Reccomendations: The thresholds will need to be optimized based on the institution's needs. The threshold may be raised if the loan institution views false positives as more costly and dropped in the institution views false negatives as more costly. Exploring more flexible models such as Decision Forest and XGBoost could further improve the performance of the minority class.

1.8.6 2. Decision Tree

Decision Tree was chosen to be the next model because it can model complex, non-linear decision boundaries. This is a drawback of logistic regression which assumes a linear relationship between the predictors and the target variable. Decision trees also automatically handle interactions between variables; something that has to be done manually with logistic regression.

Let's start off by using **RFECV (Recursive Feature Elimination with Cross-Validation)** in the pipeline to select the most important features in order to reduce some of the noise in the dataset. We will then compare the results with a new model using all the features

[47]:
```
# Instantiate a Decision Tree classifier with a fixed random state for␣
↪reproducibility
tree = DecisionTreeClassifier(random_state=42)

# Create a pipeline with RFECV feature selection and the decision tree model
pipeline_tree = model_pipeline(tree)

# Fit the pipeline to the resampled training data
pipeline_tree.fit(X_train, y_train)

# Get a list of features that were selected by RFECV
selected_mask = pipeline_tree.named_steps['feature_selection'].support_

selected_tree = X_train.columns[selected_mask].tolist()
```

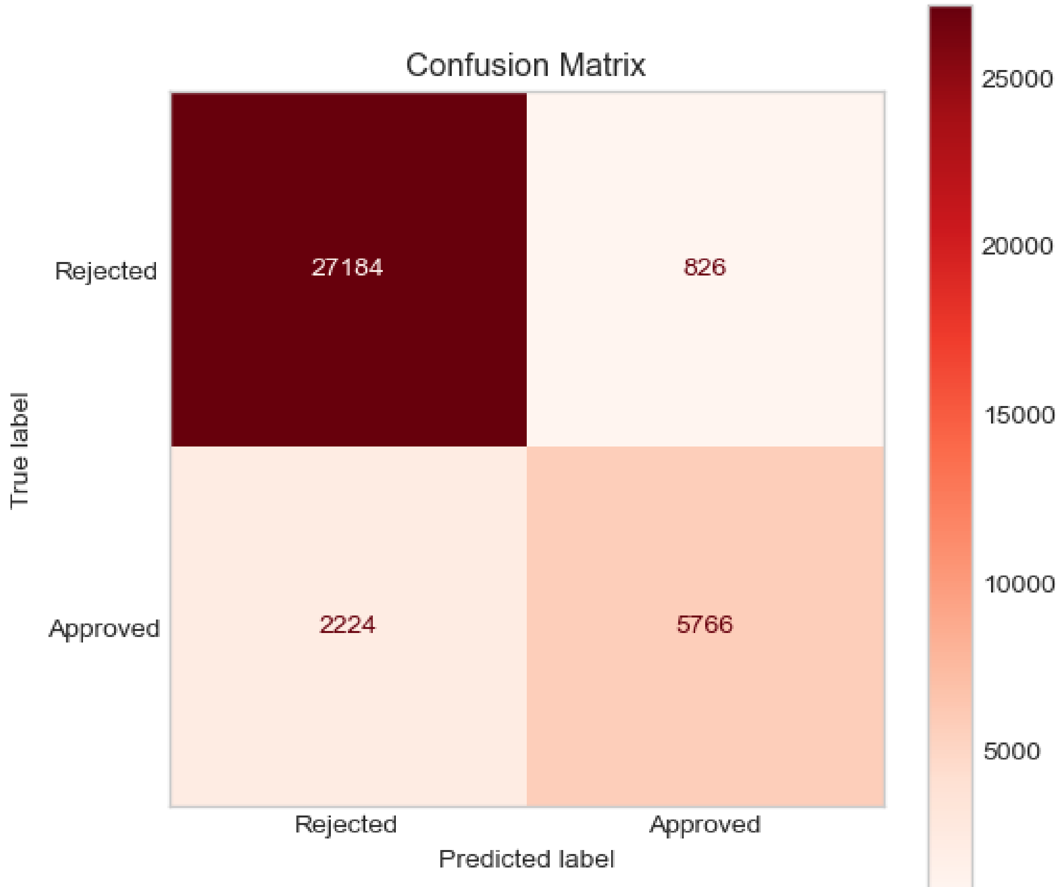
[48]:
```
# Parameter grid
parameters = {
    'criterion': ['entropy'],           # Use entropy (information gain) for␣
↪splitting
```

```
    'max_depth': [3, 5, 7],             # Limit tree depth to control complexity␣
 ↪and prevent overfitting
    'min_samples_split': [2, 5],        # Minimum number of samples required to␣
 ↪split an internal node
    'min_samples_leaf': [1, 2],         # Minimum number of samples required to␣
 ↪be at a leaf node
    'max_leaf_nodes': [None, 10]        # Maximum number of leaf nodes to limit␣
 ↪tree size (None means unlimited)
}

# Initialize GridSearchCV with the Decision Tree estimator and the parameter␣
 ↪grid
grid_tree = GridSearchCV(tree, parameters, cv=5, scoring='accuracy', n_jobs=-1)

# Fit GridSearchCV on the training data using only the selected features
grid_tree.fit(X_train[selected_tree], y_train)
```

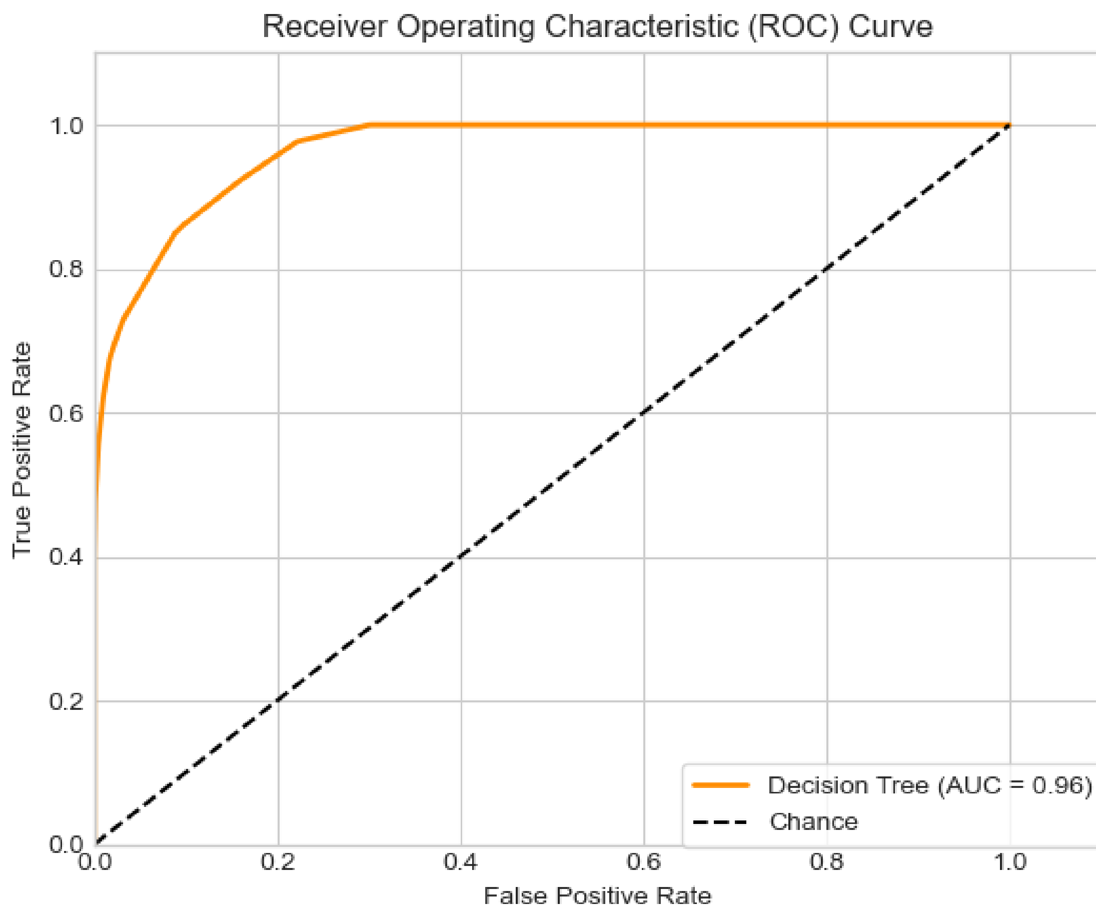
[48]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42), n_jobs=-1,
             param_grid={'criterion': ['entropy'], 'max_depth': [3, 5, 7],
                         'max_leaf_nodes': [None, 10],
                         'min_samples_leaf': [1, 2],
                         'min_samples_split': [2, 5]},
             scoring='accuracy')
```

After getting the best features and parameters, let's evaluate the best estimator.

[49]:
```
# Validate the model
evaluate_model(grid_tree.best_estimator_, X_train[selected_tree], y_train,␣
 ↪model_name='Decision Tree')
```



Confusion Matrix
Rejected
Approved
True label
27184
826
2224
5766
Rejected
Approved
Predicted label
25000
20000
15000
10000
5000




```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.92      0.97      0.95     28010
    Approved       0.87      0.72      0.79      7990

    accuracy                           0.92     36000
   macro avg       0.90      0.85      0.87     36000
weighted avg       0.91      0.92      0.91     36000


-------------- AUC Score --------------

AUC Score: 0.9647
```

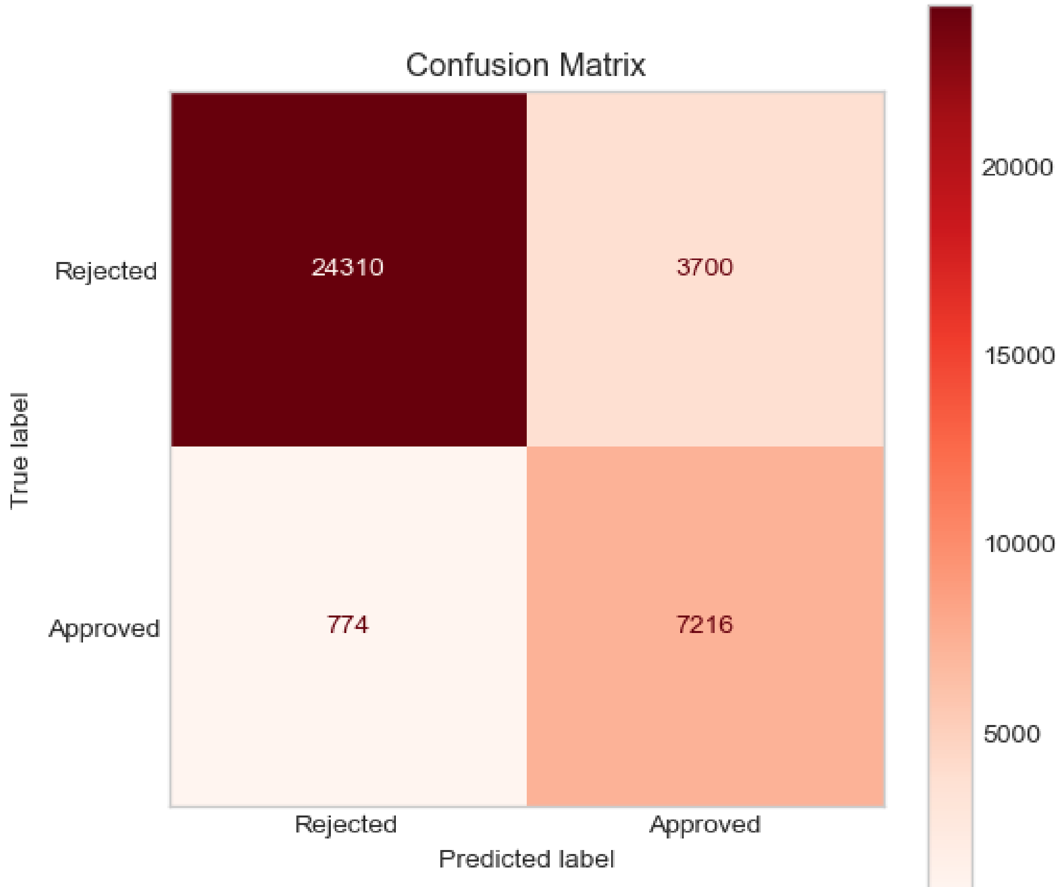
The model has performed very well with an F1-Score of 95% for the rejected class and 79% for the approved class and a 92% accuracy. The model has also scored 96.5% on the AUC Score. This model begs the question of will the number of false negatives reduce when we use the resampled data. The model currently is using the normal imbalanced data which is incorrectly classifyinng the approval class as rejected because of the rejected class is the majority class. Will using th resampled data help the model better classify the approved classes? Let's find out.

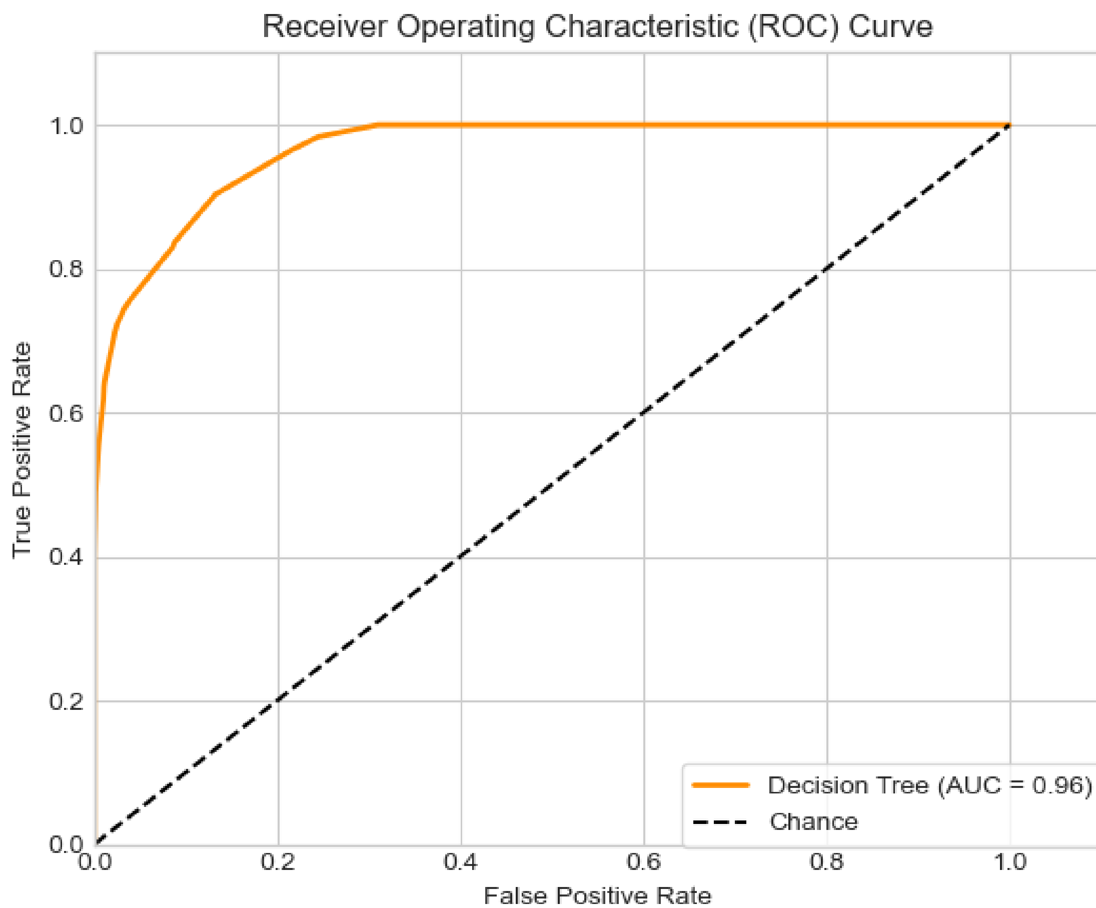
We'll create a new model and compare this to the previous model using the imbalanced data:

[50]:
```
# Perform Grid Search with 5-fold cross-validation
grid_tree_2 = GridSearchCV(tree, parameters, cv=5, scoring='accuracy',␣
 ↪n_jobs=-1)

# Fit the model on the selected features
grid_tree_2.fit(X_resampled[selected_tree], y_resampled)
```

[50]:
```
GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42), n_jobs=-1,
             param_grid={'criterion': ['entropy'], 'max_depth': [3, 5, 7],
                         'max_leaf_nodes': [None, 10],
                         'min_samples_leaf': [1, 2],
                         'min_samples_split': [2, 5]},
             scoring='accuracy')
```

[51]:
```
# Validate the model on the training data
evaluate_model(grid_tree_2.best_estimator_, X_train[selected_tree], y_train,␣
 ↪model_name='Decision Tree')
```


Confusion Matrix
Rejected
Approved
True label
24310
3700
774
7216
Rejected
Approved
Predicted label
20000
15000
10000
5000

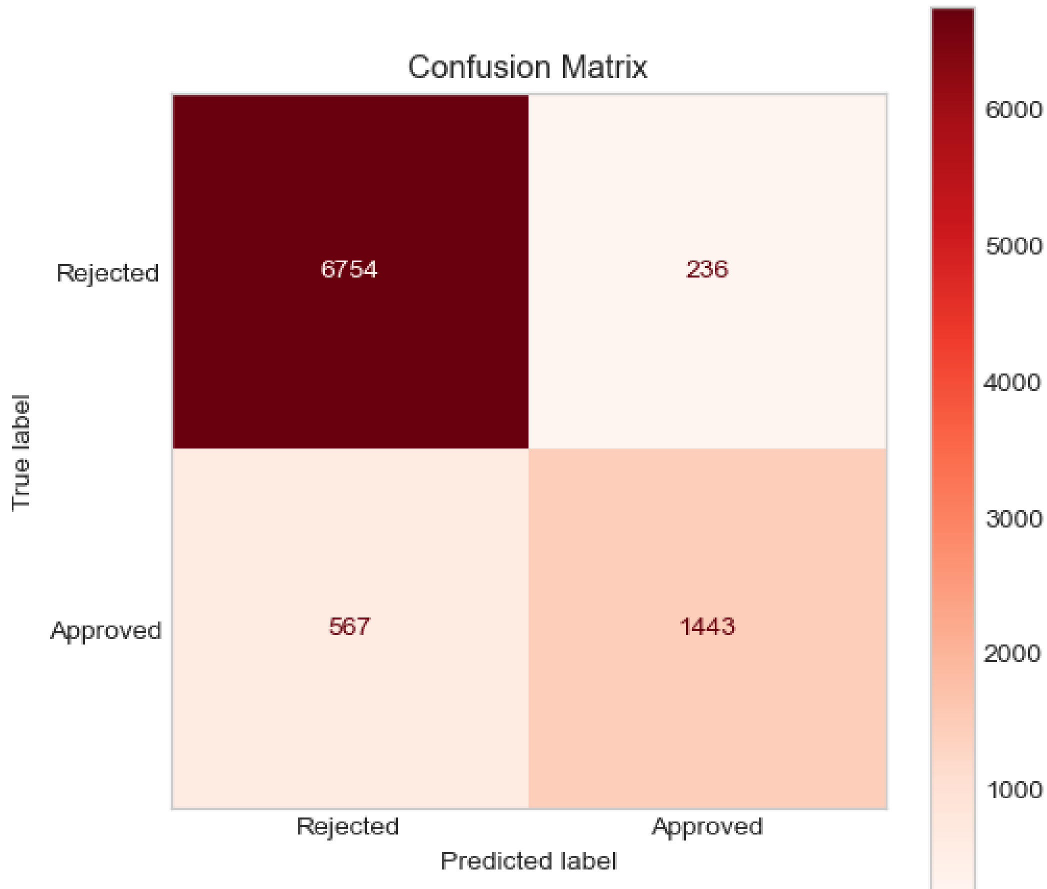


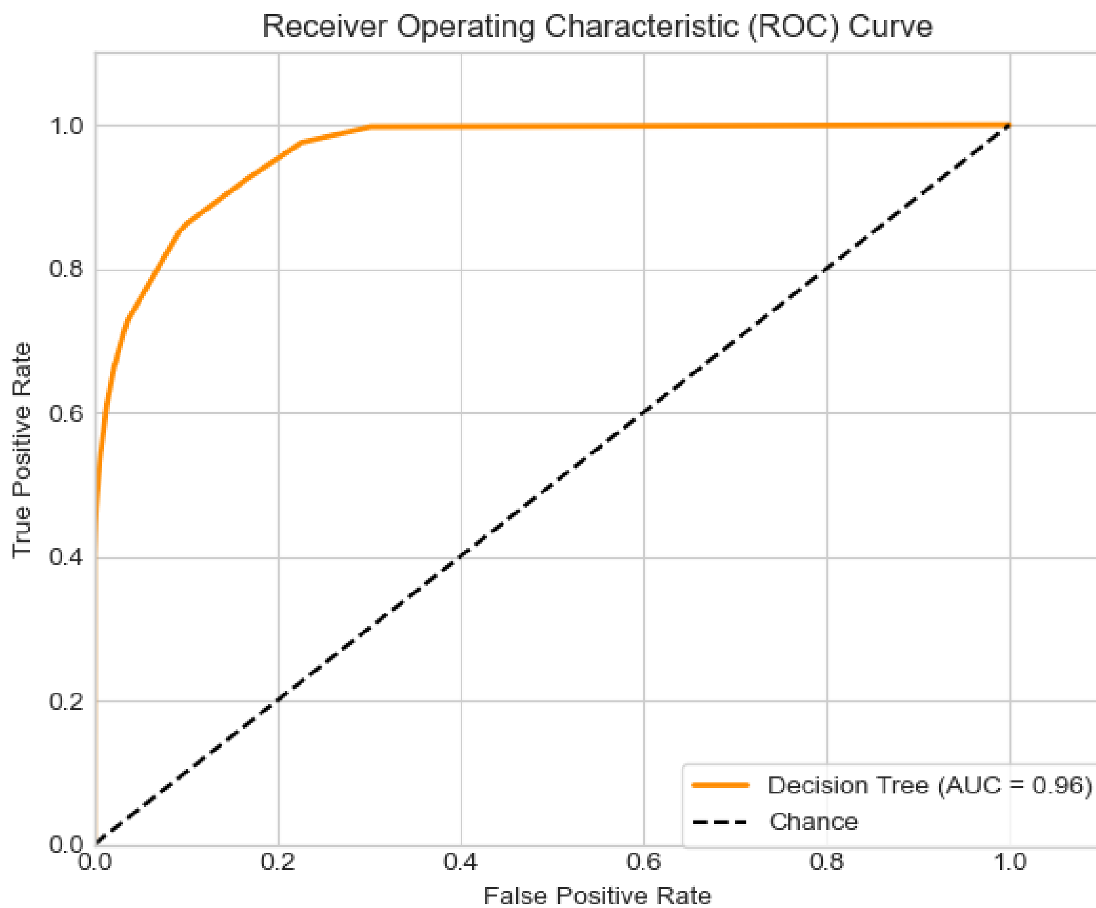

```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.97      0.87      0.92     28010
    Approved       0.66      0.90      0.76      7990

    accuracy                           0.88     36000
   macro avg       0.82      0.89      0.84     36000
weighted avg       0.90      0.88      0.88     36000


-------------- AUC Score --------------

AUC Score: 0.9644
```

Using the resampled data has caused a decrease in model performance, having the F1-Score drop to 84% and the accuracy to 88%. This is evident that in this model, using the normal data is much better since resampling the data leads to the model overfitting on the minority class.

[52]:

```
# Validate the model on the test data
evaluate_model(grid_tree.best_estimator_, X_test[selected_tree], y_test,␣
↪model_name='Decision Tree')
```






```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.92      0.97      0.94      6990
    Approved       0.86      0.72      0.78      2010

    accuracy                           0.91      9000
   macro avg       0.89      0.84      0.86      9000
weighted avg       0.91      0.91      0.91      9000


-------------- AUC Score --------------

AUC Score: 0.9612
```

1.8.7 Model Results

Decision Trees were selected for their ability to capture non-linear relationships; a drawback of logistic regression.

After validating the model on the test datathe scores are as follows:

- Overall Accuracy: 91%
- Macro F1-score: 86%
- AUC Score: 0.9612 — Excellent class separation ability

The Approved class achieved an F1-score of 78%, meaning the model balances precision and recall relatively well, though some positive cases are still being missed..

Limitations: The recall on the Approved class is low meaning some true Approved cases are being misclassified, lowering the F1-Score. Decision Trees are prone to overfitting and thus the model has to be pruned to avoid this, which might somewhat impact the performance.

Recommendations: Try models such as XGBoost which typically produces higher and more stale F1-Scores across classes.

1.8.8 3. XGBoost

This model was chosen because it has the potential to achieve higher accuracy, F1-score and better generalization on data compared to Decision Trees. XGboost also uses sequential learning which makes it significantly more powerful than a single Decision Tree.

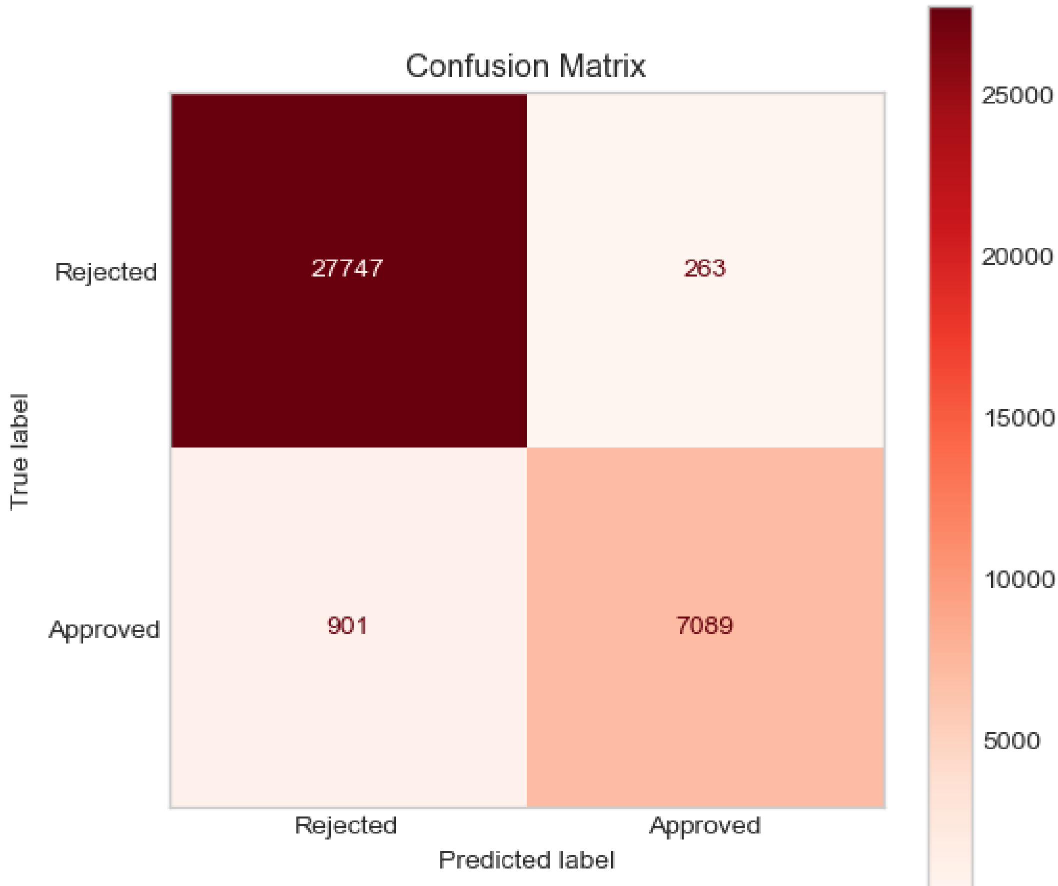
Same as the previous steps, let's get a list of the best features to use with the model:

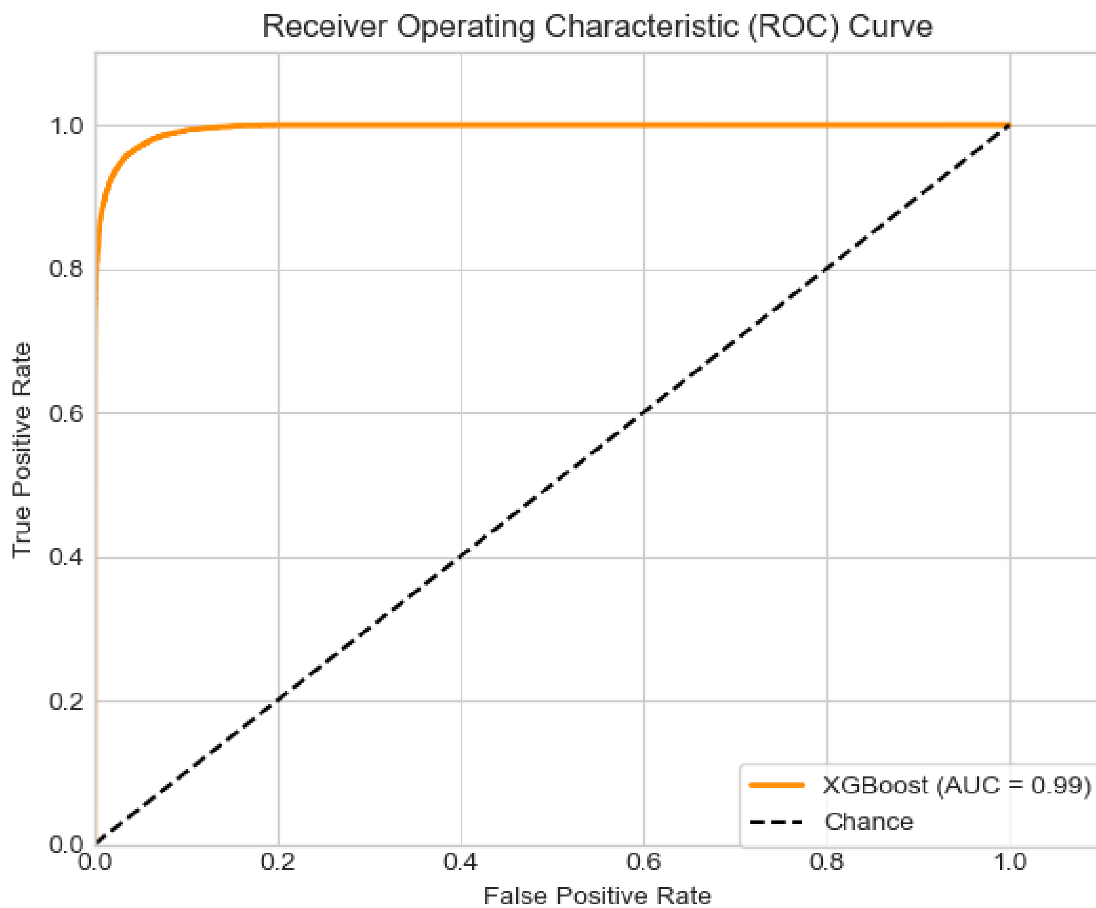
[53]:
```
# Instantiate an XGBoost classifier with a fixed random state for␣
 ↪reproducibility
boost = XGBClassifier(random_state=42)

# Create a pipeline with RFECV feature selection
pipeline_boost= model_pipeline(boost)

# Fit the pipeline to the resampled training data
pipeline_boost.fit(X_train, y_train)

# Get a list of features that were selected by RFECV
selected_mask = pipeline_tree.named_steps['feature_selection'].support_
selected_boost = X_resampled.columns[selected_mask].tolist()

# Fit the model to the dataset with the selected features
boost.fit(X_train[selected_boost], y_train)
```

[53]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
```

```
                feature_weights=None, gamma=None, grow_policy=None,
                importance_type=None, interaction_constraints=None,
                learning_rate=None, max_bin=None, max_cat_threshold=None,
                max_cat_to_onehot=None, max_delta_step=None, max_depth=None,
                max_leaves=None, min_child_weight=None, missing=nan,
                monotone_constraints=None, multi_strategy=None, n_estimators=None,
                n_jobs=None, num_parallel_tree=None, …)
```

[54]:
```
# Evaluate the model performance
evaluate_model(boost, X_train[selected_boost], y_train, model_name='XGBoost')
```



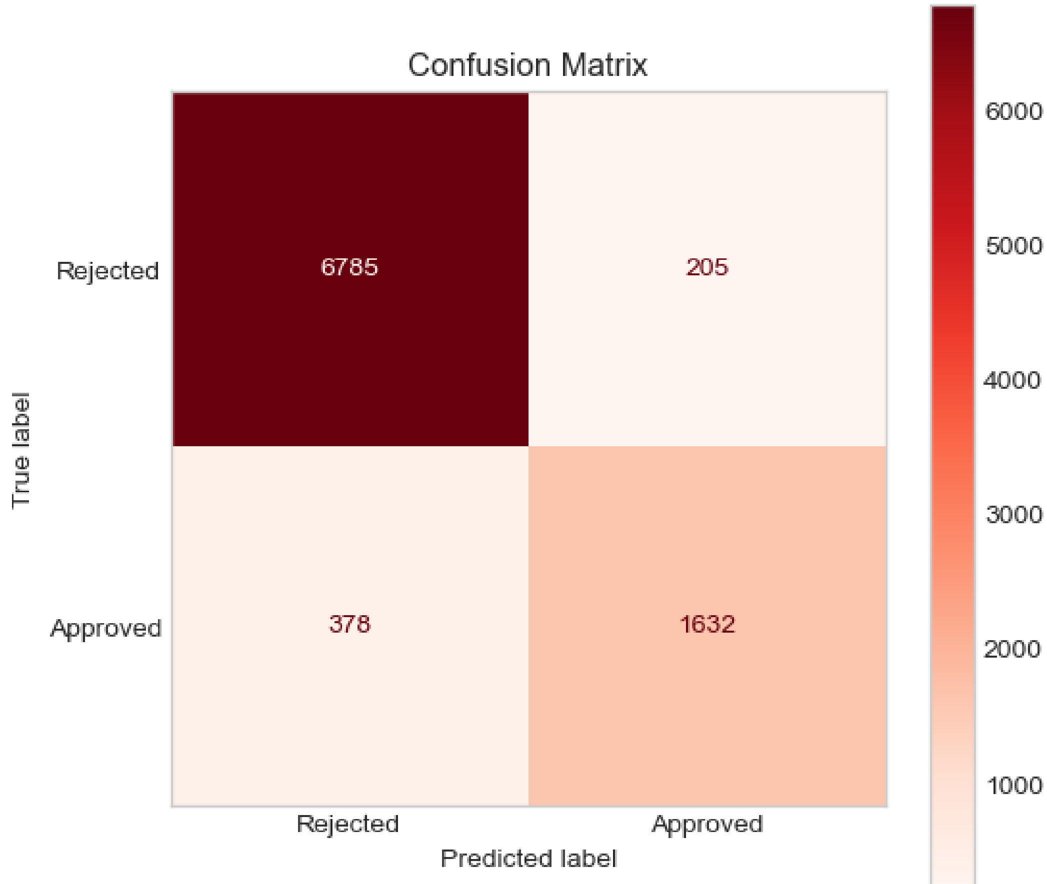


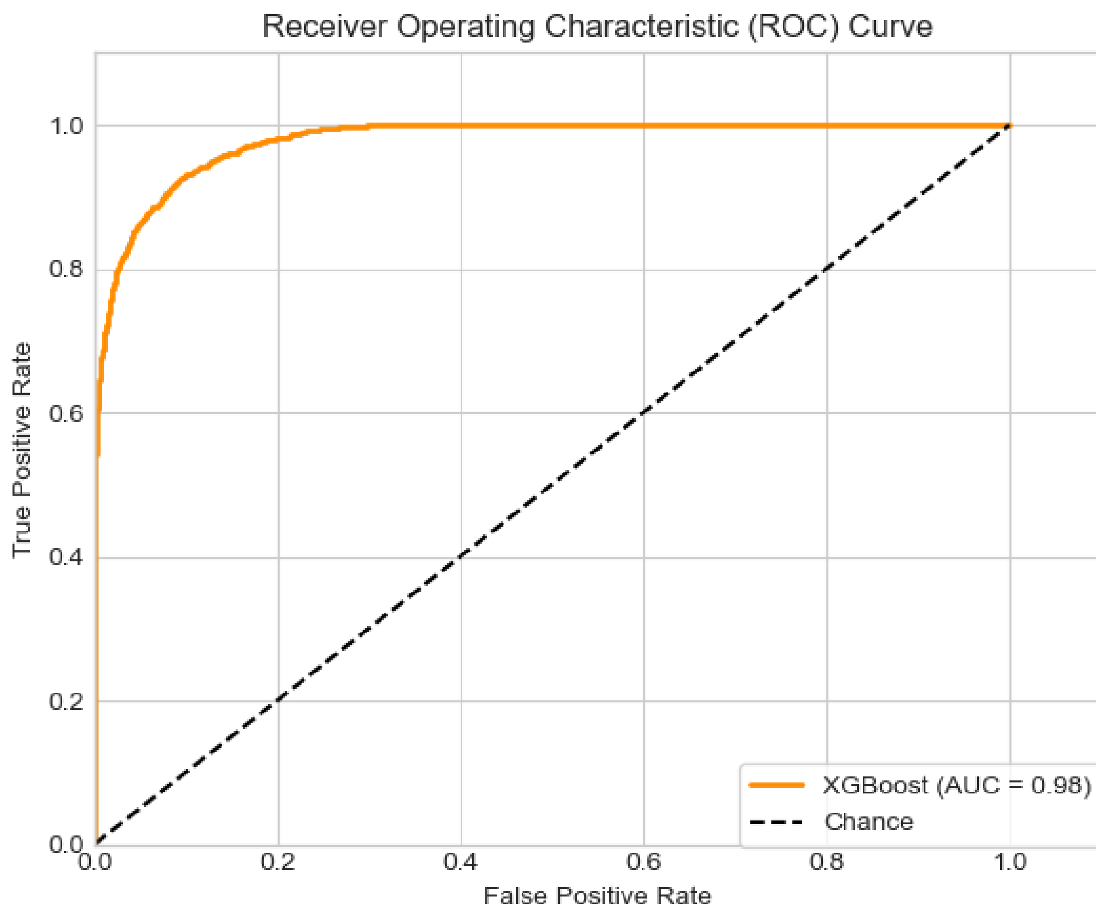

```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.97      0.99      0.98     28010
    Approved       0.96      0.89      0.92      7990

    accuracy                           0.97     36000
   macro avg       0.97      0.94      0.95     36000
weighted avg       0.97      0.97      0.97     36000


-------------- AUC Score --------------

AUC Score: 0.9949
```

The model has scored an F1-Score of 95%, the highest score so far. The model has also gotten a 97% accuracy score and an AUC score of 99.49%. Overall this model has performed far better than all the other models.

The final step is to validate the model on the step data to ensure that there is no overfitting.

[55]:
```python
# Validate the model on the test data
evaluate_model(boost, X_test[selected_boost], y_test, model_name='XGBoost')
```






```
-------------- Classification Report --------------

              precision    recall  f1-score   support

    Rejected       0.95      0.97      0.96      6990
    Approved       0.89      0.81      0.85      2010

    accuracy                           0.94      9000
   macro avg       0.92      0.89      0.90      9000
weighted avg       0.93      0.94      0.93      9000


-------------- AUC Score --------------

AUC Score: 0.9783
```

On the test data, the model has gotten an F1-Score of 84% and an accuracy score of 93%. There is no substantial decrease in performance meaning the model is not overfitting.

This will now be the **final model**.

1.8.9 Final Model Performance

XGBoost was selected due to its strong performance in classification tasks, especially in imbalanced datasets. The test scores for this model were as follows:

- Macro F1-score: 90%
- Accuracy: 94%
- AUC Score: 0.9783 – Excellent separability between classes.

The Approved class got an F1-Score of 84%, indicating a strong balance between precision and recall. This score was significantly better than Decision Trees or Logistic Regression.

Limitations: The Approved class got a recall of 80% suggesting that there was presence of some false negatives, though fewer than the other models.This model also saw an increase in training time as compared to the baseline model and Decision Trees.

Recommendations: Tune some parameters such as `max_depth`, `learning_rate` and `n_estimators` inorder to improve recall without sacrificing precision or F1-Score.

1.9 Findings and Recommendations

Objective 1: To examine demographic factors associated with high loan default rates

a) Gender vs Loan Default Status

Findings:

A **Chi-Square Test** was done and the p-value gotten was 0.676. We failed to reject the null hypothesis which was Loan default status is independent of gender.

b) Age vs. Loan Default Status

Findings:

A **Two-sample T-test** was done and the test got a p-value less than the sgnificant level. The null hypothesis was dropped and the alternative adopted which stated that there is a significant difference in the average age between those who have defaulted and those who haven't.

c) Education Level vs. Loan Default Status

Findings:

A **Chi-Square Test** was done and the test got a p-value significantly less than the significance level. The null hypothesis was rejected and the alternative adopted which stated that there is a significant association between education level and default status.

Recommendations

The loan institutions should include age and the level of educations into their loan approval process. However, they should do this cautiously to avoid discrimination.

**Objective 2: To determine whether there is a statistically significant relationship between an applicant's credit score and their loan approval status.

Findings: A **Two-sample T-test** was done and the test had a p-value greater than the significance level. Failed to reject the null hypothesis which stated that there is no statistically significant difference in credit scores between the two groups.

Recommendations

Do not use credit score alone as determining factor of loan approval

Objective 3: Build accurate models to predict whether a loan applicant will default on the loan.

The final model got an F1-Score of 95% and an accuracy score of 97% on training data. This shows high accuracy in predicting whether loan approval or rejection.

Objective 4: Validate the model's performance on unseen data to guarantee robustness and reliability in real-world applications.

The final model was validated on the test data and got an F1-Score of 90% and an accuracy of 94%. This proved rubustness of the model and reliability in real-world applications.

[ ]:
```

```

This notebook was converted with convert.ploomber.io