Claxon competition 2024-Copy1

January 4, 2025

[1]:
```
<h2>Financial institutions face significant risks due to loan defaults.␣
↪Accurately predicting the
probability of default (PD) on loans is critical for risk management and␣
↪strategic planning.
In this competition, participants are tasked with developing a predictive model␣
↪that estimates the
probability of default on loans using historical loan data.<h2>

### Objective:
The objective is to build a predictive model on this data to help the bank␣
↪decide on whether to approve a loan to a prospective applicant.

###Data Dictionary

    unnamed-observation number.
    loan_id - unique identifier for each loan.
    Sex (Categories: male, female, other)
    disbursemet_date-date when loan funds were released and made available to␣
↪the borrower.
    currency-currency in which the loan was issued(USD).
    country- country of origin for the borrower.
    sex - gender of the customer.
    is_employed- Not employed(False), employed(True).
    job- the job of the customer.
    location- place of residency of the client.
    loan_amount - amount for which loan is requested.
    number_of_defaults- the count of defaulted times of a customer.
    outstanding_balance- the amount not yet paid by the customer.
    interest_rate-percentage of loan amount that a customer pays to the bank as␣
↪interest over a year.
    age - age of the customer.
    remaining term- amount of time remaining for the loan to be fully repaid.
    salary-income of the customer.
    marital_status- 1-married, 0-single.
    Loan Status- 1-defaulted, 0-Did not default.
```

```
  Cell In[1], line 1
    <h2>Financial institutions face significant risks due to loan defaults.␣
 ↪Accurately predicting the
    ^

SyntaxError: invalid syntax
```

[3]:
```
### Import necessary libraries
```

[5]:
```
# this will help in making the Python code more structured automatically (good␣
 ↪coding practice)
import jupyter_black

jupyter_black.load()

# To filter the warnings
import warnings

warnings.filterwarnings("ignore")

# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# Removes the limit for the number of displayed columns
pd.set_option("display.max_columns", None)
# Sets the limit for the number of displayed rows
pd.set_option("display.max_rows", 200)

# libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Library to split data
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# To build model for prediction
import statsmodels.stats.api as sms
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
from statsmodels.tools.tools import add_constant
from sklearn.linear_model import LogisticRegression  # Logistic Regression
from sklearn.tree import DecisionTreeClassifier  # Decision Tree
from sklearn.ensemble import (
```

```
    RandomForestClassifier,
    GradientBoostingClassifier,
)  # Random Forest, Gradient Boosting Machines
from sklearn.svm import SVC  # Support Vector Machines

import pickle

# To get diferent metric scores
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score,
    ConfusionMatrixDisplay,
    precision_recall_curve,
    roc_curve,
)
import pandas as pd

pd.set_option("display.max_columns", None)
```

```
<IPython.core.display.HTML object>
```

[7]:
```
# Loading the dataset - sheet_name parameter is used if there are multiple tabs␣
↪in the excel file.
```

[9]:
```
df = pd.read_csv(
    "C:/Users/Munashe Muchinako/OneDrive/Desktop/data science/Data Science␣
↪Competion Question and Data/data_science_competition_2024.csv"
)
```

[11]:
```
# copy the data into duplicate variable 'data' to avoid making changes to the␣
↪original data
```

[13]:
```
data_raw = df.copy()
```

[15]:
```
# show top 5 rows in the data
```

[17]:
```
data_raw.head(4)
```

[17]:
```
   Unnamed: 0                               loan_id  gender disbursemet_date  \
0           0  8d05de78-ff32-46b1-aeb5-b3190f9c158a  female       2022 10 29
1           1  368bf756-fcf2-4822-9612-f445d90b485b   other       2020 06 06
2           2  6e3be39e-49b5-45b5-aab6-c6556de53c6f   other       2023 09 29
3           3  191c62f8-2211-49fe-ba91-43556b307871  female       2022 06 22
```

```
  currency   country     sex  is_employed      job    location  loan_amount  \
0      USD  Zimbabwe  female         True  Teacher  Beitbridge      39000.0
1      USD  Zimbabwe   other         True  Teacher      Harare      27000.0
2      USD  Zimbabwe   other         True    Nurse       Gweru      35000.0
3      USD  Zimbabwe  female         True   Doctor      Rusape      24000.0

   number_of_defaults  outstanding_balance  interest_rate  age  \
0                   0         48653.011473           0.22   37
1                   2         28752.062237           0.20   43
2                   1         44797.554126           0.22   43
3                   0         35681.496413           0.23   47

   number_of_defaults.1 remaining term       salary marital_status  age.1  \
0                     0             47  3230.038869        married     37
1                     2             62  3194.139103         single     43
2                     1             57  3330.826656        married     43
3                     0             42  2246.797020       divorced     47

       Loan Status
0  Did not default
1  Did not default
2  Did not default
3  Did not default
```

[19]:
```
# Display last 3 rows of the data
```

[21]:
```
data_raw.tail(3)
```

[21]:
```
       Unnamed: 0                               loan_id  gender  \
99997       99997  4f10e845-8f75-4cd5-9f3a-3dad3e04a483  female
99998       99998  eded01ca-79d2-4e86-a1e3-2ea1354edca7    male
99999       99999  a37561ec-0901-4350-8a13-634f80ece55d   other

      disbursemet_date currency   country     sex  is_employed          job  \
99997       2021 10 20      USD  Zimbabwe  female         True  Data Analyst
99998       2021 08 22      USD  Zimbabwe    male         True      Engineer
99999       2022 04 29      USD  Zimbabwe   other         True      Engineer

      location  loan_amount  number_of_defaults  outstanding_balance  \
99997   Kadoma      48000.0                   0         34266.224130
99998   Mutare      36000.0                   2         71546.024917
99999    Gweru      46000.0                   0         43141.102930

       interest_rate  age  number_of_defaults.1 remaining term       salary  \
99997           0.23   43                     0             53  3535.599759
99998           0.22   49                     2             59  3082.407123
99999           0.21   47                     0             47  2670.766532
```

```
      marital_status  age.1       Loan Status
99997        married     43  Did not default
99998         single     49  Did not default
99999        married     47  Did not default
```

[23]:
```
# Understand the data shape
```

[25]:
```
data_raw.shape
```

[25]:
```
(100000, 21)
```

[27]:
```
# There are 100000 observations and 21 columns in the dataset
```

[29]:
```
### Check the data types of the columns in the dataset.
data_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 21 columns):
 #   Column                 Non-Null Count   Dtype
---  ------                 --------------   -----
 0   Unnamed: 0             100000 non-null  int64
 1   loan_id                100000 non-null  object
 2   gender                 100000 non-null  object
 3   disbursemet_date       100000 non-null  object
 4   currency               100000 non-null  object
 5   country                99900 non-null   object
 6   sex                    100000 non-null  object
 7   is_employed            100000 non-null  bool
 8   job                    95864 non-null   object
 9   location               99405 non-null   object
 10  loan_amount            100000 non-null  float64
 11  number_of_defaults     100000 non-null  int64
 12  outstanding_balance    100000 non-null  float64
 13  interest_rate          100000 non-null  float64
 14  age                    100000 non-null  int64
 15  number_of_defaults.1   100000 non-null  int64
 16  remaining term         100000 non-null  object
 17  salary                 100000 non-null  float64
 18  marital_status         100000 non-null  object
 19  age.1                  100000 non-null  int64
 20  Loan Status            100000 non-null  object
dtypes: bool(1), float64(4), int64(5), object(11)
memory usage: 15.4+ MB
```

[31]:
```
-We have 8 continuous variables(age.1, age, salary, Unnamed,  loan_amount,
↪number_of_defaults, outstanding_balance, number_of_defaults.1
```

```
-All other are categorical
-We can see that there are missing records in the dataset
```

```
  Cell In[31], line 1
    -We have 8 continuous variables(age.1, age, salary, Unnamed,  loan_amount,␣
↪number_of_defaults, outstanding_balance, number_of_defaults.1
        ^
SyntaxError: invalid syntax
```

[33]:
```
###Summary of the data
```

[35]:
```
data_raw.describe().T
```

[35]:
```
                         count          mean           std      min  \
Unnamed: 0            100000.0  49999.500000  28867.657797      0.0
loan_amount           100000.0  31120.000000  15895.093631   1000.0
number_of_defaults    100000.0      0.441970      0.688286      0.0
outstanding_balance   100000.0  36964.909763  10014.758477      0.0
interest_rate         100000.0      0.210435      0.018725      0.1
age                   100000.0     43.570690      4.863760     21.0
number_of_defaults.1  100000.0      0.441970      0.688286      0.0
salary                100000.0   2781.804324    696.450055    250.0
age.1                 100000.0     43.570690      4.863760     21.0

                               25%           50%           75%       max
Unnamed: 0            24999.750000  49999.500000  74999.250000   99999.0
loan_amount           21000.000000  31000.000000  40000.000000  273000.0
number_of_defaults        0.000000      0.000000      1.000000       2.0
outstanding_balance   29625.227472  35063.852394  42133.388817  150960.0
interest_rate             0.200000      0.210000      0.220000       0.3
age                      40.000000     44.000000     47.000000      65.0
number_of_defaults.1      0.000000      0.000000      1.000000       2.0
salary                 2273.929349   2665.441567   3146.577655   10000.0
age.1                    40.000000     44.000000     47.000000      65.0
```

[37]:
```
Observations

    Mean value for the age column is approx 44 and the median is 44. This shows␣
↪that majority of the customers are under 44 years of age.
    Mean loan_amount is approx 31120 but it has a wide range with values from␣
↪1000 to 273000. We will explore this further in univariate analysis.
    Mean salary is 2782 and median is approx 2665.This shows that majority of␣
↪the customers earn salaries below 2782.
    Mean value for outstanding balance is 36965.
```

```
  Cell In[37], line 3
    Mean value for the age column is approx 44 and the median is 44. This shows
 ↪that majority of the customers are under 44 years of age.
    ^
IndentationError: unexpected indent
```

[39]:
```
###Display number of missing values per each column
```

[41]:
```
data_raw.isna().sum()
```

[41]:
```
Unnamed: 0               0
loan_id                  0
gender                   0
disbursemet_date         0
currency                 0
country                100
sex                      0
is_employed              0
job                   4136
location               595
loan_amount              0
number_of_defaults       0
outstanding_balance      0
interest_rate            0
age                      0
number_of_defaults.1     0
remaining term           0
salary                   0
marital_status           0
age.1                    0
Loan Status              0
dtype: int64
```

[43]:
```
-The country, job and location variables has some missing values, we will
 ↪impute them using mode(most frequent value) since there relatively few
 ↪missing values compared to total dataset size
```

```
  Cell In[43], line 1
    -The country, job and location variables has some missing values, we will
 ↪impute them using mode(most frequent value) since there relatively few missing
 ↪values compared to total dataset size
         ^
SyntaxError: invalid syntax
```

[45]:
```
###Data Cleaning
```

[47]:
```
# Handling missing data
```

[49]:
```
mode_country = data_raw["country"].mode()[0]  # calculate mode for country
mode_job = data_raw["job"].mode()[0]  # calculate mode for job
mode_location = data_raw["location"].mode()[0]  # calculate mode for location

# Fill missing values with mode
data_raw["country"].fillna(mode_country, inplace=True)
data_raw["job"].fillna(mode_job, inplace=True)
data_raw["location"].fillna(mode_location, inplace=True)
```

[51]:
```
# Checking missing data again
data_raw.isnull().values.any()
```

[51]: False

[53]:
```
# We can see that there are nolonger missing records
```

[55]:
```
# Changing the target column loan status from string datatype to␣
↪bolean-(defaulted=1 otherwise 0)
data_raw["Loan Status"] = np.where(data_raw["Loan Status"] == "Defaulted", 1, 0)
```

[57]:
```
# Check for data row duplication between "age" and "age.1"
duplicate_rows = data_raw["age"].equals(data_raw["age.1"])
# Print the result (True if duplication, False otherwise)
print(duplicate_rows)
```

True

[59]:
```
# Check for data row duplication between "gender" and "sex"
duplicate_rows = data_raw["gender"].equals(data_raw["sex"])
# Print the result (True if duplication, False otherwise)
print(duplicate_rows)
```

True

[61]:
```
# The columns age and age.1 are duplicates as shown by the result above
```

[63]:
```
# Check for data row duplication between "number_of_defaults" and␣
↪"number_of_defaults.1"
duplicate_rows = data_raw["number_of_defaults"].
↪equals(data_raw["number_of_defaults.1"])
# Print the result (True if duplication, False otherwise)
print(duplicate_rows)
```

True

[65]:
```
# The columns number_of_defaults and number_of_defaults.1 are duplicates as␣
↪shown by the result above
```

[67]:
```
# Romove the duplicated columns, leaving original column and remove the unnamed␣
↪column replace 'Unnamed' with the actual label)
data_raw.drop(
    ["age.1", "number_of_defaults.1", "sex", data_raw.columns[0]], axis=1,␣
↪inplace=True
)
```

[69]:
```
# Convert 'date' column to datetime from string
data_raw["disbursemet_date"] = pd.to_datetime(data_raw["disbursemet_date"])
```

[71]:
```
##converting remaining term from string type to float
data_raw["remaining term"] = data_raw["remaining term"].str.replace("_", "")
data_raw["remaining term"] = data_raw["remaining term"].astype(float)
```

[73]:
```
# check for duplicate rows based on all columns
duplicate_rows = data_raw[data_raw.duplicated()]
print(duplicate_rows)
```

```
Empty DataFrame
Columns: [loan_id, gender, disbursemet_date, currency, country, is_employed,
job, location, loan_amount, number_of_defaults, outstanding_balance,
interest_rate, age, remaining term, salary, marital_status, Loan Status]
Index: []
```

[75]:
```
# There are no more duplicates
```

[77]:
```
# Taking a  closer look on currency column
data_raw["currency"].value_counts()
```

[77]:
```
currency
USD     99980
$USD       20
Name: count, dtype: int64
```

[79]:
```
# Formatting value $USD to USD
data_raw["currency"] = data_raw["currency"].str.replace("$USD", "USD")
data_raw["currency"].value_counts()
```

[79]:
```
currency
USD    100000
Name: count, dtype: int64
```

[81]:
```
# getting rid of empty spaces before each location
data_raw["location"] = data_raw["location"].str.strip()
data_raw["location"].value_counts()
```

[81]:
```
location
Harare            9148
Bulawayo          8263
Mutare            8262
Gweru             7983
Masvingo          7665
Marondera         7513
Rusape            6506
Chivhu            6411
Plumtree          5552
Beitbridge        5311
Chipinge          4447
Chimanimani       4388
Kwekwe            3491
Chiredzi          3199
Kadoma            3118
Nyanga            2142
Karoi             1899
Shurugwi          1359
Zvishavane        1301
Gokwe              920
Kariba             671
Victoria Falls     219
Redcliff           191
Hwange              41
Name: count, dtype: int64
```

[83]:
```
# checking counts of data values in the country column
data_raw["country"].value_counts()
```

[83]:
```
country
Zimbabwe    99887
zimbabwe      100
Zim            13
Name: count, dtype: int64
```

[85]:
```
# Correcting the all the values to become Zimbabwe
data_raw["country"] = data_raw["country"].str.title()
data_raw["country"] = data_raw["country"].str.replace("Zim", "Zimbabwe")
data_raw["country"] = data_raw["country"].str.replace("Zimbabwebabwe",␣
↪"Zimbabwe")
data_raw["country"].value_counts()
```

[85]:
```
country
Zimbabwe    100000
Name: count, dtype: int64
```

[87]:
```python
# Taking a closer look on various customer jobs
data_raw["job"].value_counts()
```

[87]:
```
job
Engineer              20660
Nurse                 15284
Data Analyst          13204
Doctor                12186
Software Developer    11932
Teacher                8950
Accountant             7802
SoftwareDeveloper      3564
Data Scientist         3521
Lawyer                 2862
Data Scintist            35
Name: count, dtype: int64
```

[89]:
```python
##Correcting typing errors in job values
data_raw["job"] = data_raw["job"].replace("Data Scintist", "Data Scientist")
data_raw["job"] = data_raw["job"].replace("SoftwareDeveloper", "Software␣
↪Developer")
```

[91]:
```python
data_raw.head()
```

[91]:
```
                                loan_id  gender disbursemet_date currency  \
0  8d05de78-ff32-46b1-aeb5-b3190f9c158a  female       2022-10-29      USD
1  368bf756-fcf2-4822-9612-f445d90b485b   other       2020-06-06      USD
2  6e3be39e-49b5-45b5-aab6-c6556de53c6f   other       2023-09-29      USD
3  191c62f8-2211-49fe-ba91-43556b307871  female       2022-06-22      USD
4  477cd8a1-3b01-4623-9318-8cd6122a8346    male       2023-02-08      USD

    country  is_employed      job    location  loan_amount  \
0  Zimbabwe         True  Teacher  Beitbridge      39000.0
1  Zimbabwe         True  Teacher      Harare      27000.0
2  Zimbabwe         True    Nurse       Gweru      35000.0
3  Zimbabwe         True   Doctor      Rusape      24000.0
4  Zimbabwe         True    Nurse    Chipinge      19000.0

   number_of_defaults  outstanding_balance  interest_rate  age  \
0                   0         48653.011473           0.22   37
1                   2         28752.062237           0.20   43
2                   1         44797.554126           0.22   43
3                   0         35681.496413           0.23   47
4                   0         34156.055882           0.20   42

   remaining term       salary marital_status  Loan Status
0            47.0  3230.038869        married            0
```

```
1             62.0  3194.139103         single            0
2             57.0  3330.826656        married            0
3             42.0  2246.797020       divorced            0
4             45.0  2310.858441        married            0
```

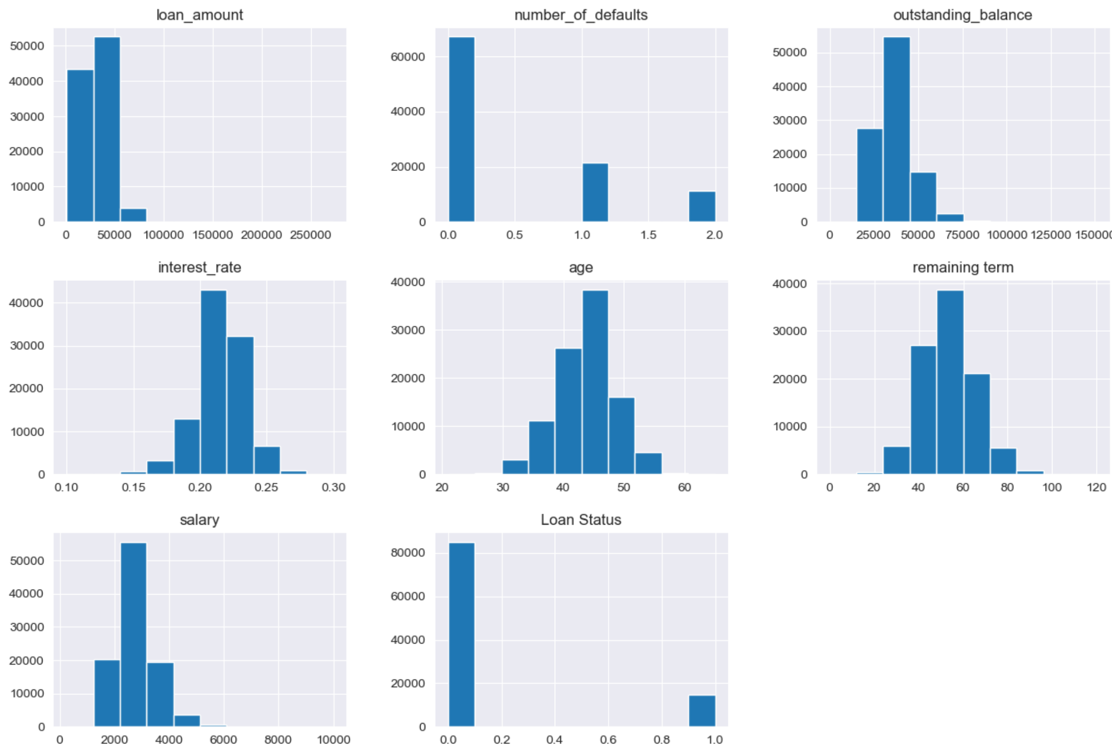
[93]:
```python
data_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 17 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   loan_id              100000 non-null  object
 1   gender               100000 non-null  object
 2   disbursemet_date     100000 non-null  datetime64[ns]
 3   currency             100000 non-null  object
 4   country              100000 non-null  object
 5   is_employed          100000 non-null  bool
 6   job                  100000 non-null  object
 7   location             100000 non-null  object
 8   loan_amount          100000 non-null  float64
 9   number_of_defaults   100000 non-null  int64
 10  outstanding_balance  100000 non-null  float64
 11  interest_rate        100000 non-null  float64
 12  age                  100000 non-null  int64
 13  remaining term       100000 non-null  float64
 14  salary               100000 non-null  float64
 15  marital_status       100000 non-null  object
 16  Loan Status          100000 non-null  int32
dtypes: bool(1), datetime64[ns](1), float64(5), int32(1), int64(2), object(7)
memory usage: 11.9+ MB
```

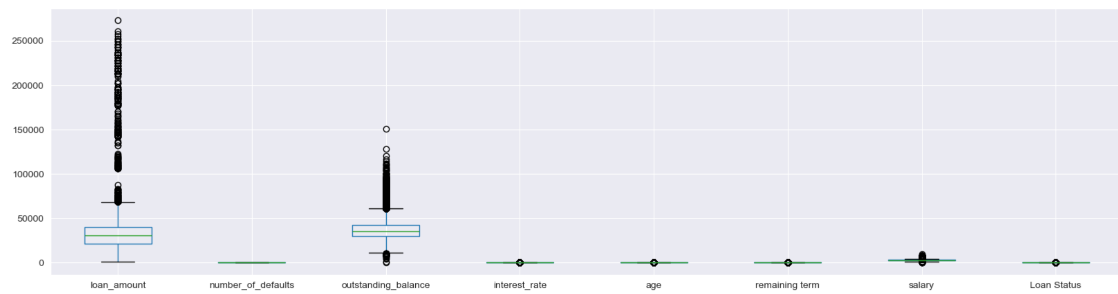
[95]:
```python
data = data_raw.copy()
```

[97]:
```python
#### Distribution of variables in the data
```

[99]:
```python
## Univariate analysis
sns.set_style("darkgrid")
data.iloc[:, 8:17].hist(figsize=(15, 10))
plt.show()
```



[100]:
```
data.iloc[:, 8:17].boxplot(figsize=(20, 5))
plt.show()
```



[102]:
```
# Checking the loan Status distibution amoung defaults and non defaults
data["Loan Status"].value_counts(1)
```

[102]:
```
Loan Status
0    0.85134
1    0.14866
Name: proportion, dtype: float64
```

[105]:
```
# It can be clearly seen that there is only 14.9% of defaulters, compared to␣
↪85% who did not default
```

[107]:
```
# Cross-table of gender and Loan Status
round(data.groupby(["gender"])["Loan Status"].value_counts(1), 2).unstack()
```

[107]:
```
Loan Status     0     1
gender
female       0.88  0.12
male         0.84  0.16
other        0.84  0.16
```

[109]:
```
# It seems that among gendor the proportion of women who defaults is lower,␣
↪compared to the other gender
```

[111]:
```
# check if any value in each column is zero
has_zeros_in_loan_amount = (data["loan_amount"] == 0).any()
print(has_zeros_in_loan_amount)
```

```
False
```

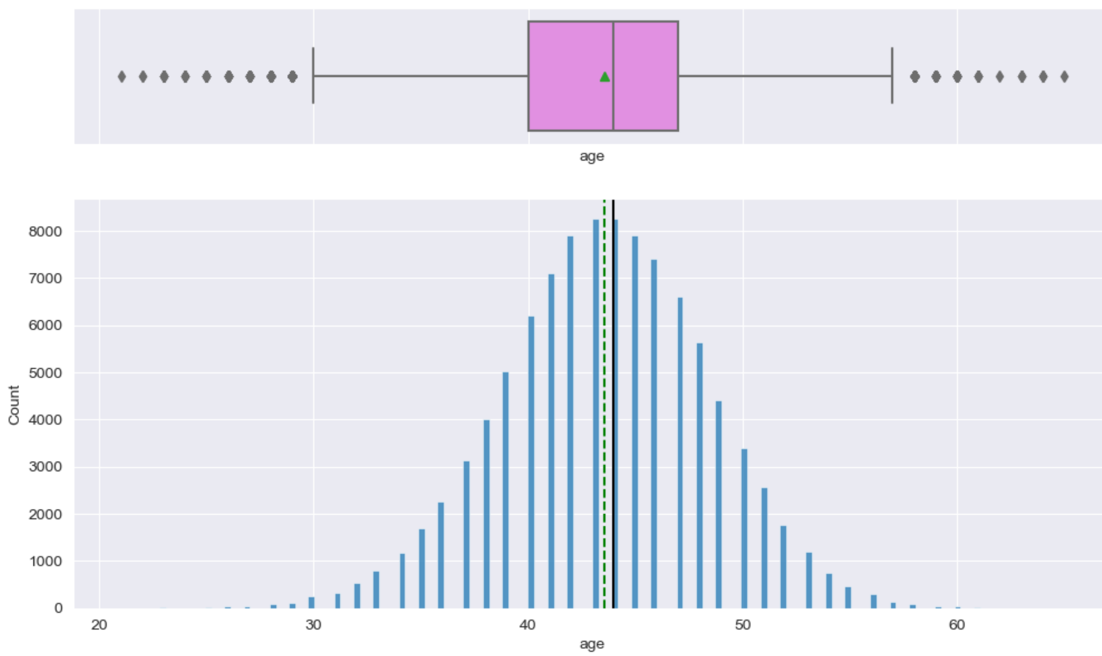
[113]:
```
# There is no observations with zero values
```

[115]:
```
def histogram_boxplot(data, feature, figsize=(12, 7), kde=False, bins=None):
    """
    Boxplot and histogram combined

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to show the density curve (default False)
    bins: number of bins for histogram (default None)
    """

    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a star will indicate the mean value of the␣
↪column
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="winter"
    ) if bins else sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2
```

```
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to the histogram
```

[117]:
```
### Observation on Age
```

[119]:
```
histogram_boxplot(data, "age")
```



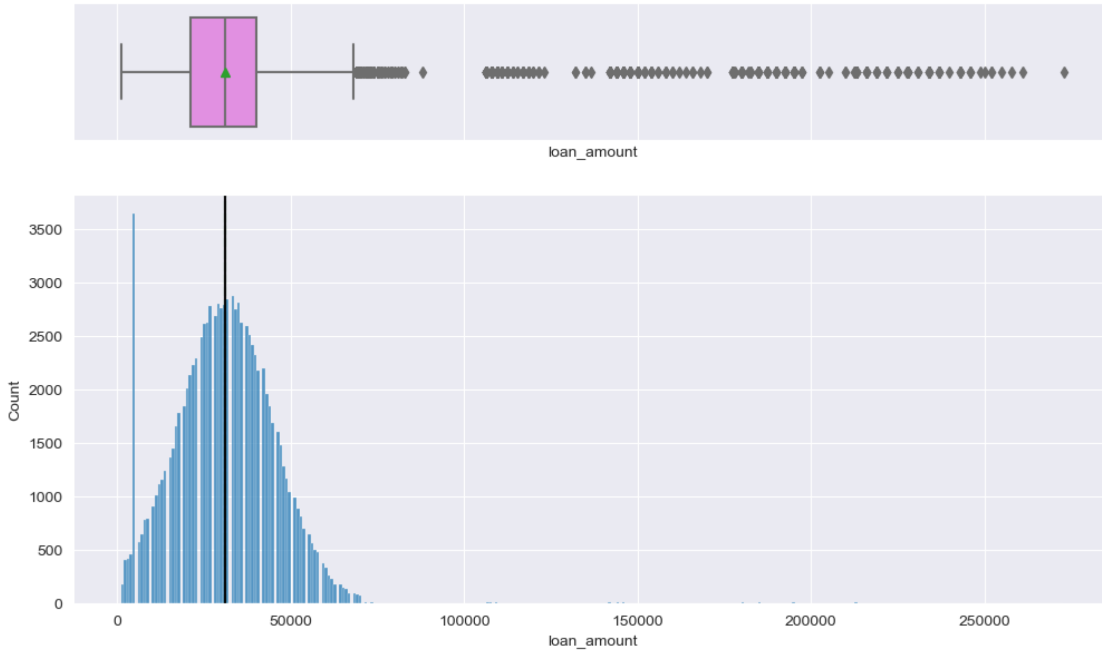
[120]:
```
- The distribution of age is equal
- The boxplot shows that there are outliers at both  ends
- We will not treat these outliers as they represent the real market trend
```

```
  Cell In[120], line 1
    - The distribution of age is equal
          ^
SyntaxError: invalid syntax
```

[122]:
```
### Observation on Credit Amount
```

[124]:

```
histogram_boxplot(data, "loan_amount")
```



[125]:

```
    The distribution of the loan_amount is right-skewed
    The boxplot shows that there are outliers at the right end
    We will not treat these outliers as they represent the real market trend
```

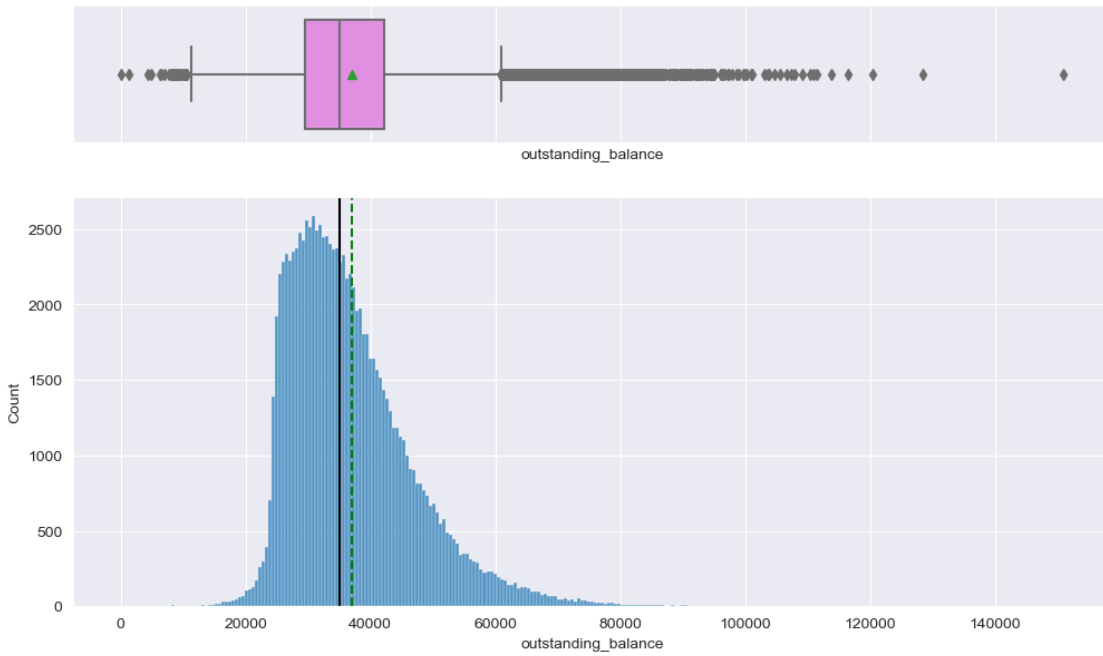
```
  Cell In[125], line 1
    The distribution of the loan_amount is right-skewed
        ^
SyntaxError: invalid syntax
```

[ ]:

```
### Observations on Duration
```

[128]:

```
histogram_boxplot(data, "outstanding_balance")
```

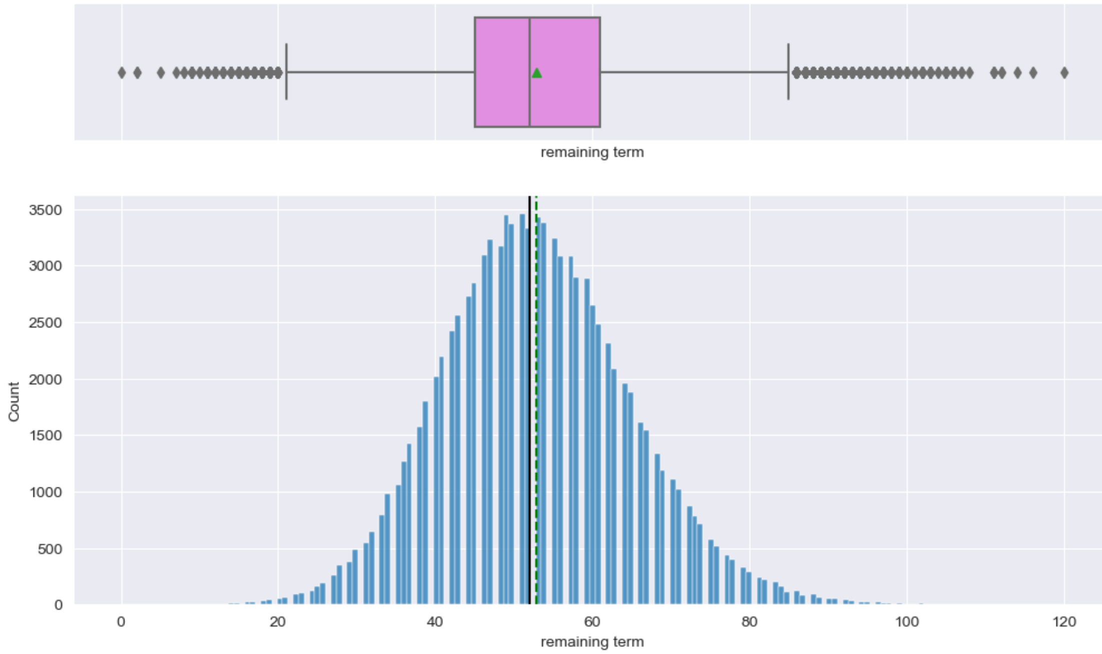


[129]:
```
    The distribution of the outstanding_balance is right-skewed
    The boxplot shows that there are outliers at both ends
    We will not treat these outliers as they represent the real market trend
```

```
  Cell In[129], line 1
    The distribution of the outstanding_balance is right-skewed
        ^
SyntaxError: invalid syntax
```

[131]:
```
### Observations on remaining term for the loan to be fully repaid
```

[133]:
```
histogram_boxplot(data, "remaining term")
```



[135]:
```
-The remaining time is equally distributed
```

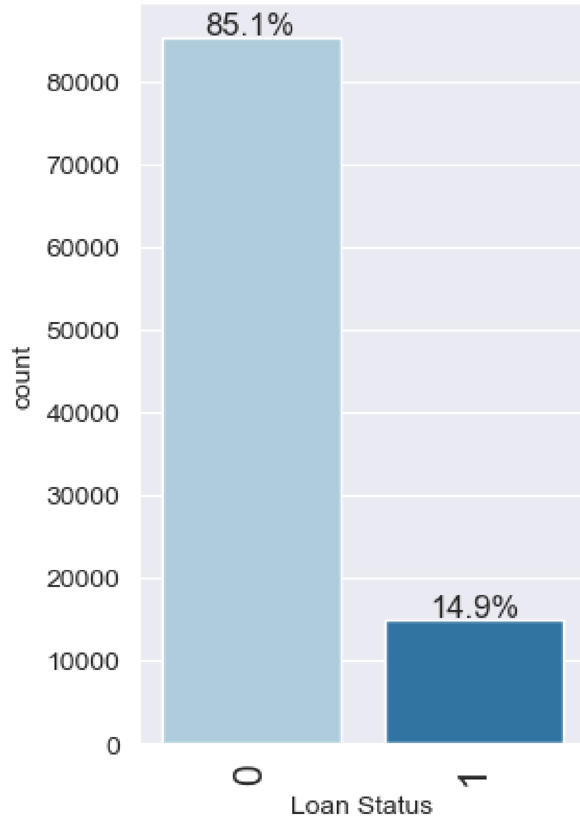
```
  Cell In[135], line 1
    -The remaining time is equally distributed
         ^
SyntaxError: invalid syntax
```

[137]:
```
# function to create labeled barplots


def labeled_barplot(data, feature, perc=False, n=None):
    """
    Barplot with percentage at the top

    data: dataframe
    feature: dataframe column
    perc: whether to display percentages instead of count (default is False)
    n: displays the top n category levels (default is None, i.e., display all␣
 ↪levels)
    """

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
```

```python
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

    plt.xticks(rotation=90, fontsize=15)
    ax = sns.countplot(
        data=data,
        x=feature,
        palette="Paired",
        order=data[feature].value_counts().index[:n].sort_values(),
    )

    for p in ax.patches:
        if perc == True:
            label = "{:.1f}%".format(
                100 * p.get_height() / total
            )  # percentage of each class of the category
        else:
            label = p.get_height()  # count of each level of the category

        x = p.get_x() + p.get_width() / 2  # width of the plot
        y = p.get_height()  # height of the plot

        ax.annotate(
            label,
            (x, y),
            ha="center",
            va="center",
            size=12,
            xytext=(0, 5),
            textcoords="offset points",
        )  # annotate the percentage

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

[139]:
```python
### Observations on loan status
```

[141]:
```python
labeled_barplot(data, "Loan Status", perc=True)
```



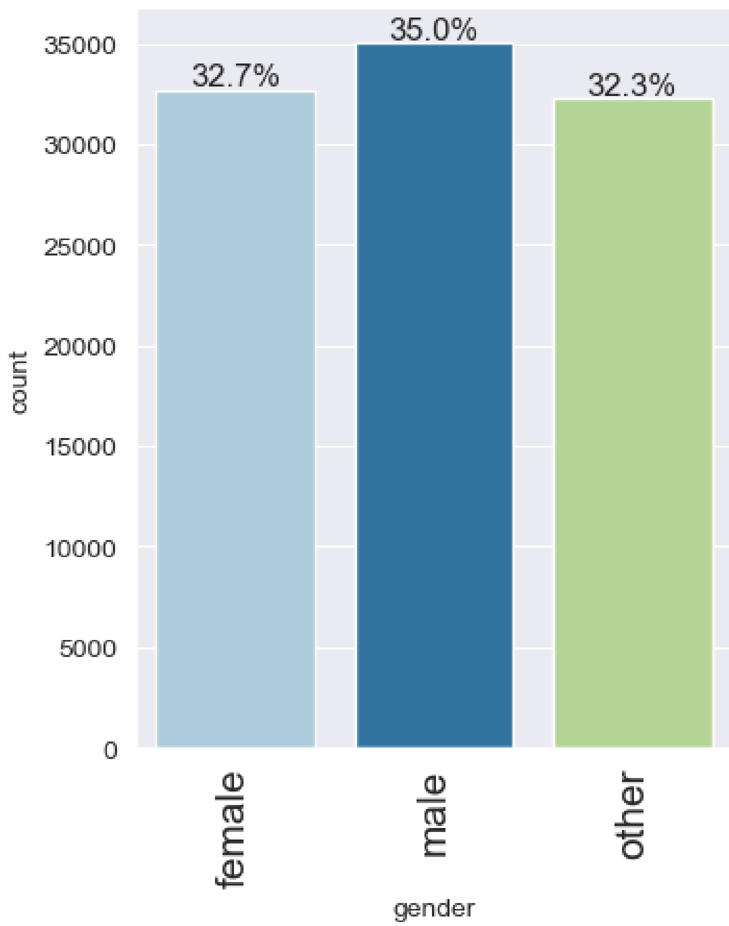
[143]:
```
- The class distribution in the target variable is imbalanced.
- We have 85.1% observations for non-defaulters and 14.9% observations for␣
↪defaulters.
```

```
  Cell In[143], line 1
    - The class distribution in the target variable is imbalanced.
          ^
SyntaxError: invalid syntax
```

[ ]:

[146]:
```
###Observation on sex
```

[148]:
```
labeled_barplot(data, "gender", perc=True)
```

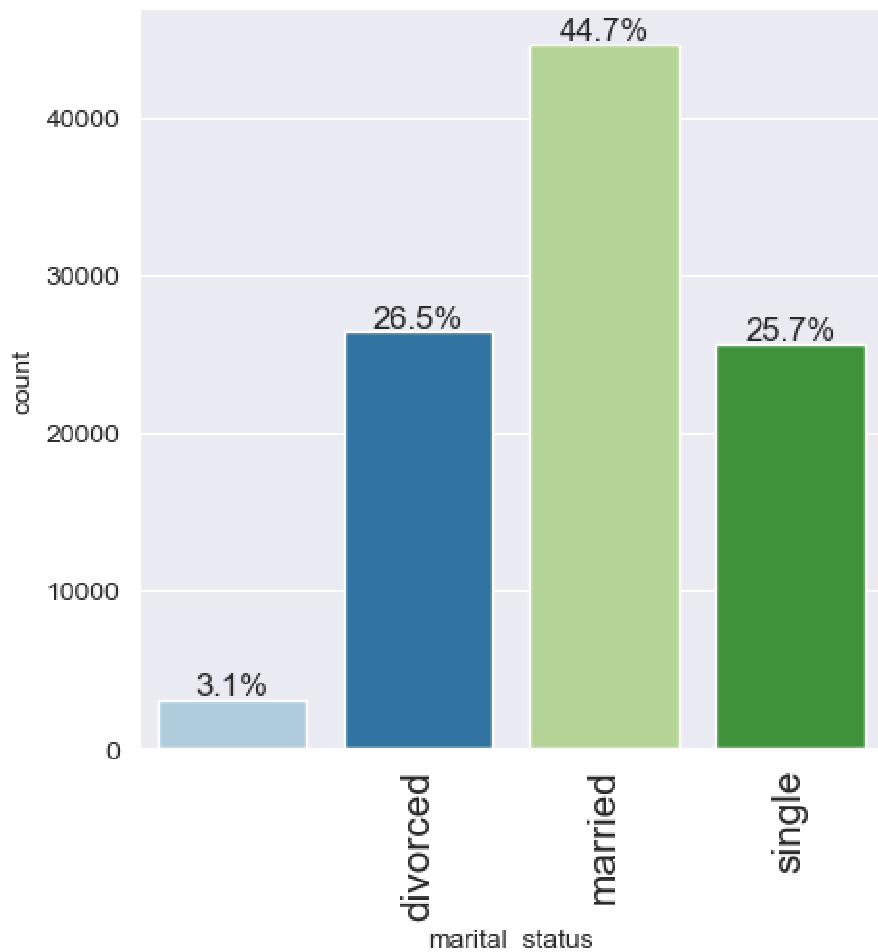


[150]:
```
- Male customers are taking more credit than female customers
- There are 35% male customers and 32.7% female customers
-The other portion belongs to 'other' class
```

```
  Cell In[150], line 1
    - Male customers are taking more credit than female customers
           ^
SyntaxError: invalid syntax
```

[152]:
```
###Observation on marriage status
```

[154]:
```
labeled_barplot(data, "marital_status", perc=True)
```



[156]:
```
    """Majority of the customers i.e. 44% fall into the married category which␣
↪makes sense as these may be the persons who require loans to help them␣
↪supply family needs.
    There are only approx 27% customers that lie in divorced category.
    There are only approx 27% observations  that fall under single category.
    There are very few persons with unknown marital status."""
```

[156]:
```
'Majority of the customers i.e. 44% fall into the married category which makes
sense as these may be the persons who require loans to help them supply family
needs.\nThere are only approx 27% customers that lie in divorced
category.\nThere are only approx 27% observations  that fall under single
category.\nThere are very few persons with unknown marital status.'
```

[158]:
```
###Bivariate Analysis
# Checking variable distribution in the data
```

[160]:
```
"""sns.pairplot(data, hue="Loan Status")
plt.show()"""
```

[160]:
```
'sns.pairplot(data, hue="Loan Status")\nplt.show()'
```

[162]:
```
- There are overlaps i.e., no clear distinction in the distribution of␣
↪variables for people who have defaulted and did not default.
- Let's explore this further with the help of other plots.
```

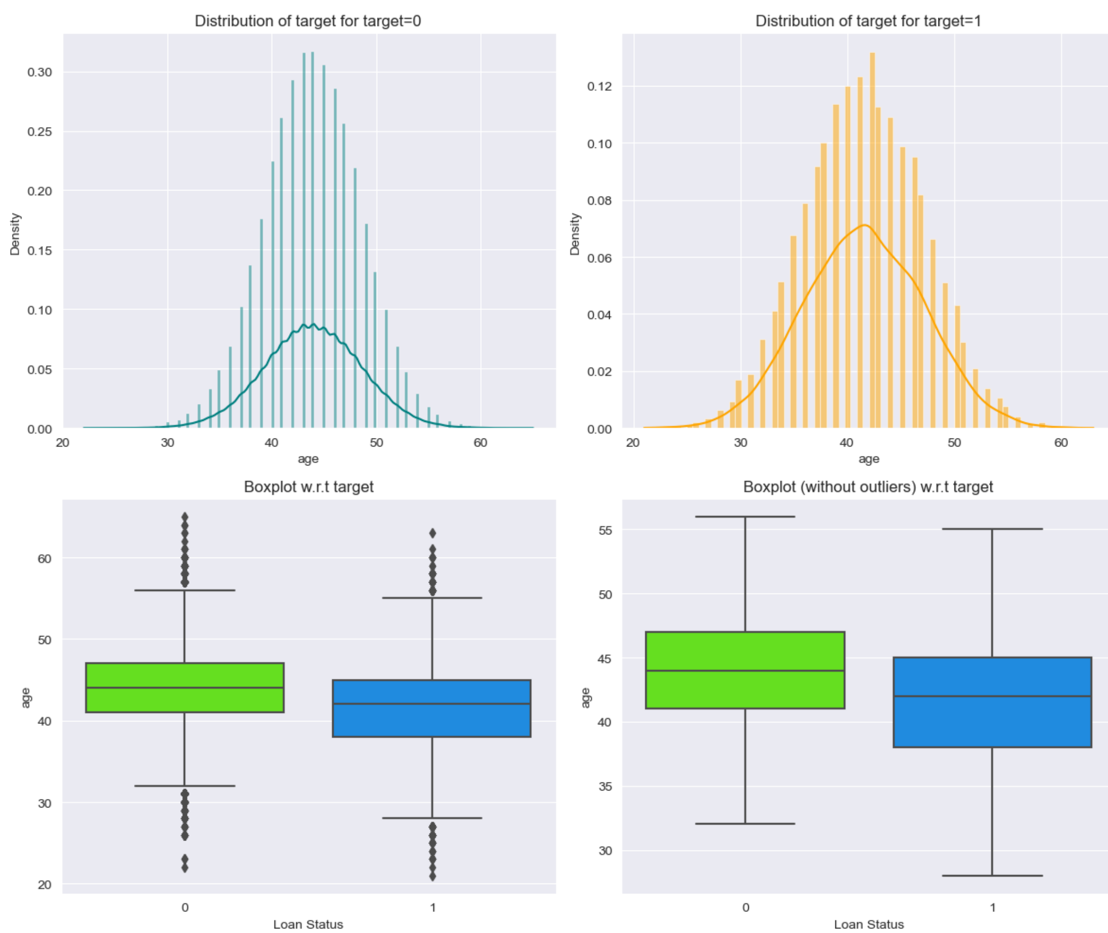
```
  Cell In[162], line 2
    - Let's explore this further with the help of other plots.
         ^
SyntaxError: unterminated string literal (detected at line 2)
```

[164]:
```
### function to plot distributions wrt target


def distribution_plot_wrt_target(data, predictor, target):
    fig, axs = plt.subplots(2, 2, figsize=(12, 10))

    target_uniq = data[target].unique()

    axs[0, 0].set_title("Distribution of target for target=" +␣
↪str(target_uniq[0]))
    sns.histplot(
        data=data[data[target] == target_uniq[0]],
        x=predictor,
        kde=True,
        ax=axs[0, 0],
        color="teal",
        stat="density",
    )

    axs[0, 1].set_title("Distribution of target for target=" +␣
↪str(target_uniq[1]))
    sns.histplot(
        data=data[data[target] == target_uniq[1]],
        x=predictor,
        kde=True,
        ax=axs[0, 1],
        color="orange",
        stat="density",
    )

    axs[1, 0].set_title("Boxplot w.r.t target")
```

```
    sns.boxplot(data=data, x=target, y=predictor, ax=axs[1, 0], palette="gist_rainbow")

    axs[1, 1].set_title("Boxplot (without outliers) w.r.t target")
    sns.boxplot(
        data=data,
        x=target,
        y=predictor,
        ax=axs[1, 1],
        showfliers=False,
        palette="gist_rainbow",
    )

    plt.tight_layout()
    plt.show()
```

[166]:
```
### Loan status vs Age
```

[168]:
```
distribution_plot_wrt_target(data, "age", "Loan Status")
```

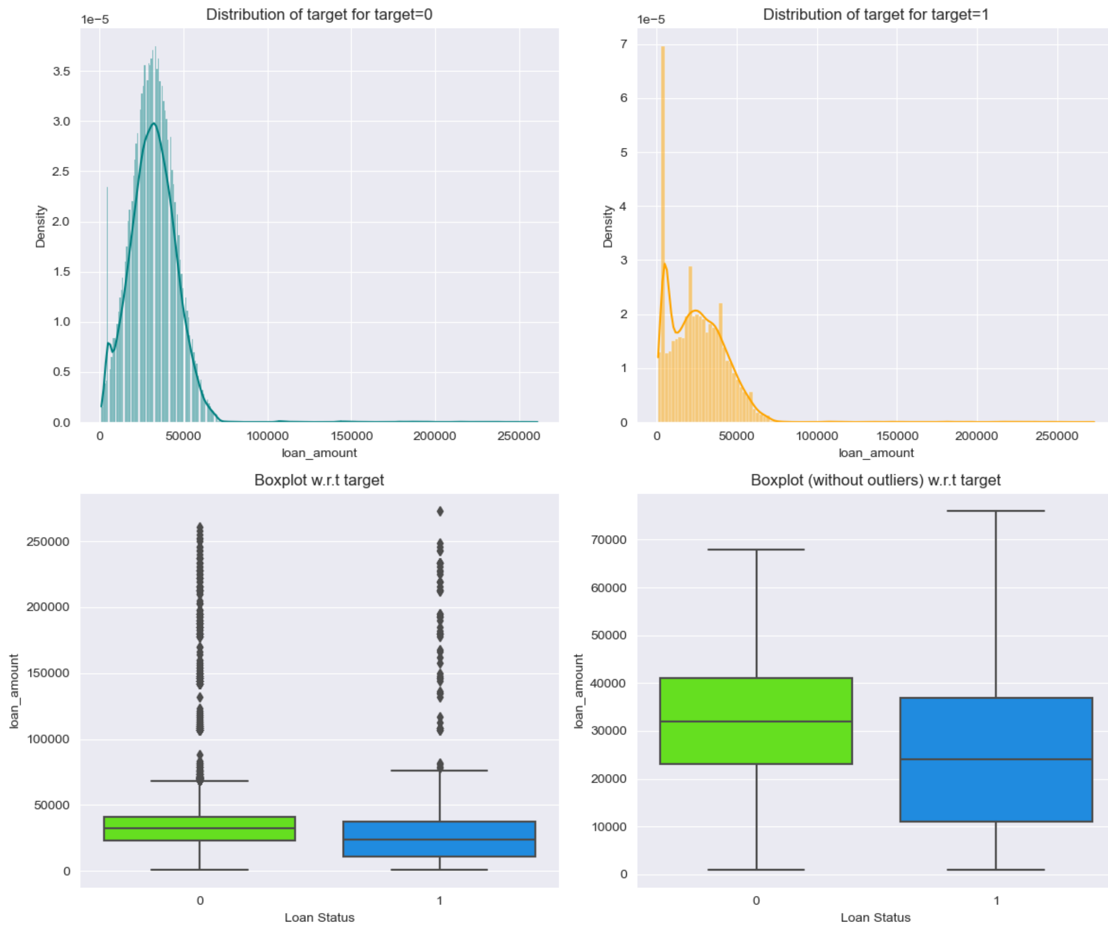


[169]:
```
- We can see that the median age of defaulters is less than the median age of non-defaulters.
- This shows that younger customers are more likely to default.
- There are outliers in boxplots of both class distributions
```

```
  Cell In[169], line 1
    - We can see that the median age of defaulters is less than the median age of non-defaulters.
               ^
SyntaxError: invalid syntax
```

[171]:
```
### Loan Status vs loan amount
```

[173]:
```
distribution_plot_wrt_target(data, "loan_amount", "Loan Status")
```



[174]:
```
- We can see that the lower quartile loan amount of defaulters is much less␣
↪than the lower quartile amount of non-defaulters.
- This shows that customers with low loan amount are more likely to default.
- The bank may need to be more cautious when approving smaller loans
- There are outliers in boxplots of both class distributions
```

```
  Cell In[174], line 1
    - We can see that the lower quartile loan amount of defaulters is much less␣
↪than the lower quartile amount of non-defaulters.
          ^
SyntaxError: invalid syntax
```

[ ]:
```
### Risk vs remaining term
```

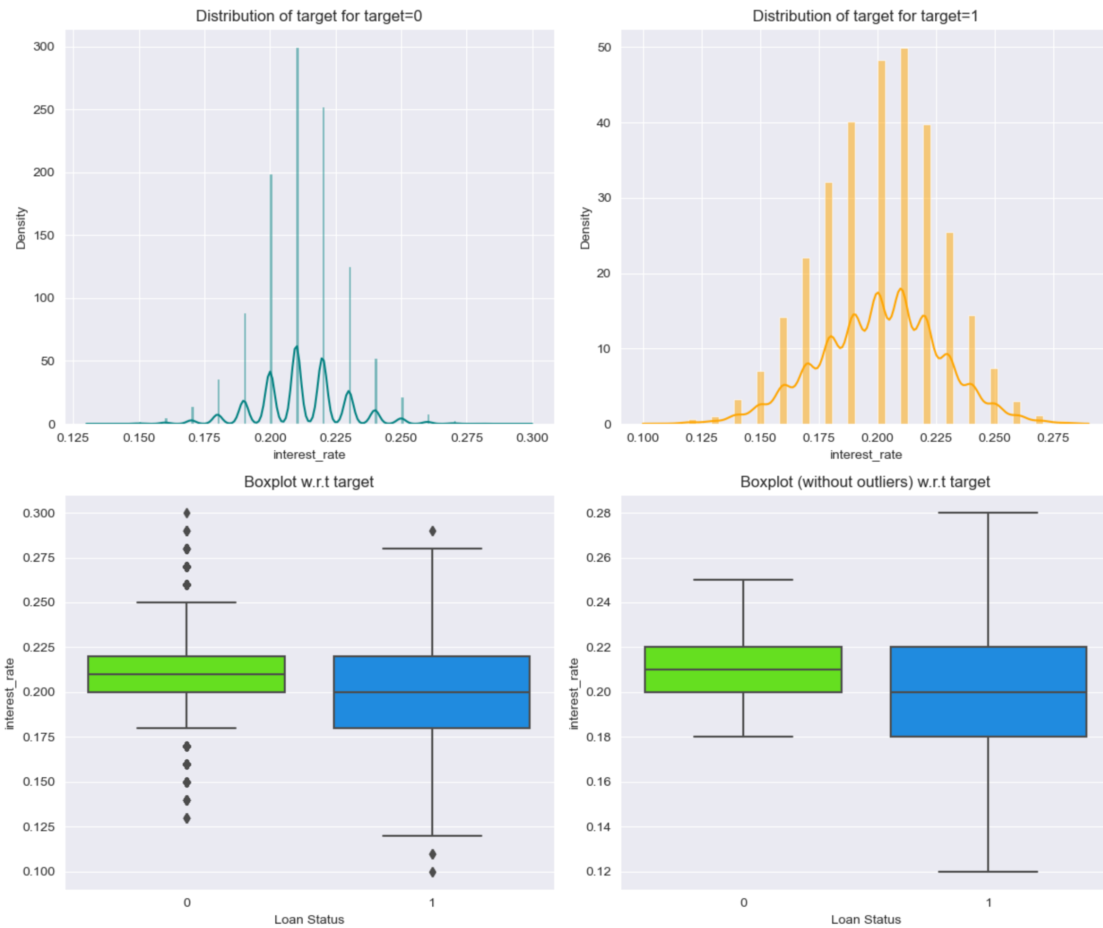
[ ]:
```
distribution_plot_wrt_target(data, "remaining term", "Loan Status")
```

[178]:
```
-The median remaining term of non defaulters is equal to the median remaining␣
↪term of defaulters
-This shows that the remaining term  may not be a significant factor in␣
↪distinguishing between defaulters and non defaulters
```

```
  Cell In[178], line 1
    -The median remaining term of non defaulters is equal to the median␣
↪remaining term of defaulters
          ^
SyntaxError: invalid syntax
```

[180]:
```
## Interest vs Loan Status
```

[182]:
```
distribution_plot_wrt_target(data, "interest_rate", "Loan Status")
```

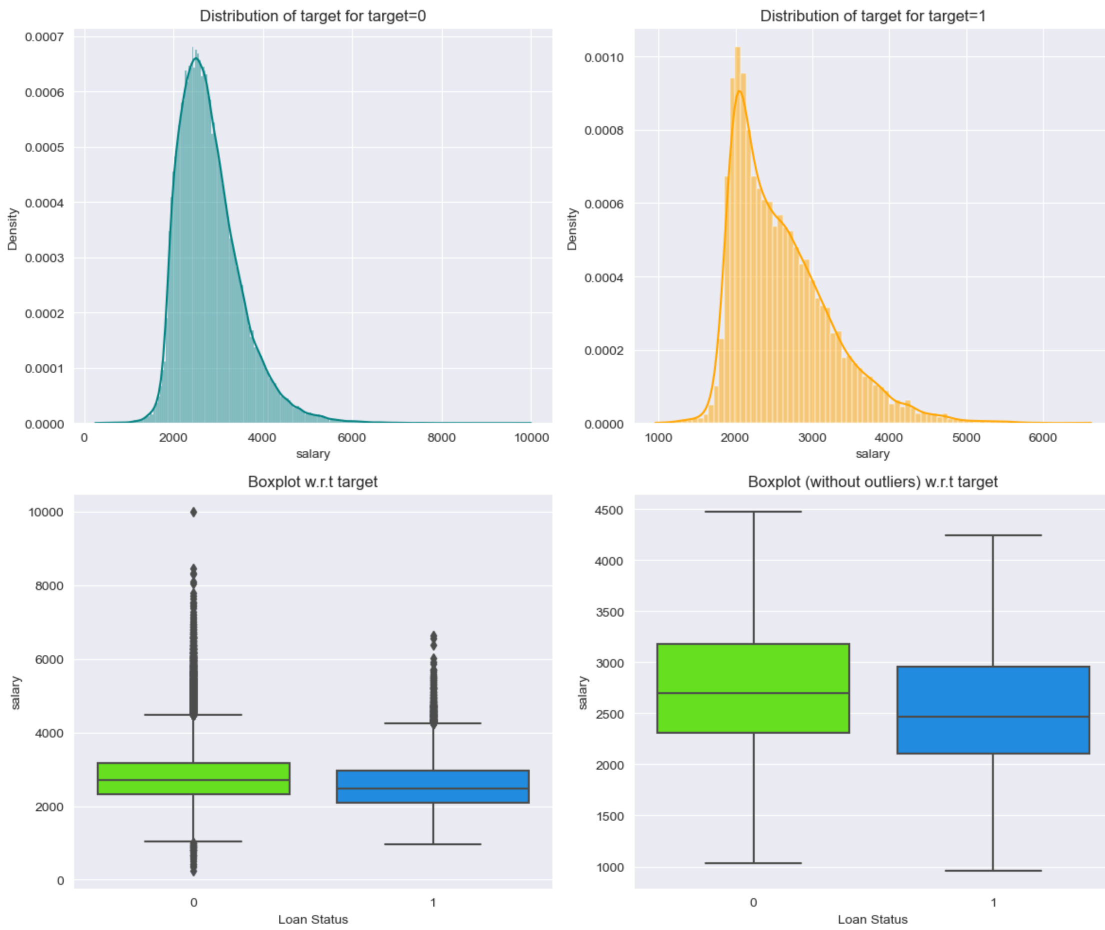


[183]:
```
-Lower meadian interest rate for defaulters compared to non defaulters
-Lower lower quatile Q1 interest rate for defaulters compared to non defaulters
-This implies that lower interest rate may not necesssarily a guarantee of loan␣
 ↪repayment
-The defaulters may be more likely to have lower creditworthiness despite␣
 ↪having lower interest rates
```

```
  Cell In[183], line 1
    -Lower meadian interest rate for defaulters compared to non defaulters
           ^
SyntaxError: invalid syntax
```

[ ]:
```
##Salary vs Loan Status
```

[186]:
```
distribution_plot_wrt_target(data, "salary", "Loan Status")
```



[187]:
```
-The median salary for defaulters is much lower than the median salary for non␣
↪defaulters
-This means that lower income customers are more likely to default on loan
-It also shows that higher income customers tend to have greater financial␣
↪stability and ability to repay loans
```

```
  Cell In[187], line 1
    -The median salary for defaulters is much lower than the median salary for␣
↪non defaulters
         ^

SyntaxError: invalid syntax
```

[ ]:
```
##Number_of_defaults vs Loan Status
```

[ ]:
```
distribution_plot_wrt_target(data, "outstanding_balance", "Loan Status")
```

[ ]:
```
-The median outstanding balance for defaulters is lower than that of non␣
↪defaulters
-This shows that defaulters tend to have lower outstanding balances but still␣
↪struggle to repay their loans
-Non defaulters have higher oustanding balance but still manages to repay their␣
↪loans
```

[ ]:
```python
# function to plot stacked bar chart


def stacked_barplot(data, predictor, target):
    """
    Print the category counts and plot a stacked bar chart

    data: dataframe
    predictor: independent variable
    target: target variable
    """
    count = data[predictor].nunique()
    sorter = data[target].value_counts().index[-1]
    tab1 = pd.crosstab(data[predictor], data[target], margins=True).sort_values(
        by=sorter, ascending=False
    )
    print(tab1)
    print("-" * 120)
    tab = pd.crosstab(data[predictor], data[target], normalize="index").
↪sort_values(
        by=sorter, ascending=False
    )
    tab.plot(kind="bar", stacked=True, figsize=(count + 5, 6))
    plt.legend(
        loc="lower left",
        frameon=False,
    )
    plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
    plt.show()
```

[193]:
```python
###Loan Status vs Sex
```

[195]:
```python
stacked_barplot(data, "gender", "Loan Status")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[195], line 1
----> 1 stacked_barplot(data, "gender", "Loan Status")
```

```
NameError: name 'stacked_barplot' is not defined
```

[197]:
```
- We saw earlier that the percentage of male customers is more than the female␣
↪customers. This plot shows that male customers are more likely to default as␣
↪compared to female customers.
```

```
  Cell In[197], line 1
    - We saw earlier that the percentage of male customers is more than the␣
↪female customers. This plot shows that male customers are more likely to␣
↪default as compared to female customers.
          ^

SyntaxError: invalid syntax
```

[199]:
```
##Loan amount vs Loan Status
```

[201]:
```
stacked_barplot(data, "marital_status", "Loan Status")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[201], line 1
----> 1 stacked_barplot(data, "marital_status", "Loan Status")

NameError: name 'stacked_barplot' is not defined
```

[203]:
```
-This plot shows that divorced customers are more likely to default as compared␣
↪to single and married customers.
```

```
  Cell In[203], line 1
    -This plot shows that divorced customers are more likely to default as␣
↪compared to single and married customers.
          ^

SyntaxError: invalid syntax
```

[205]:
```
##Job vs Loan status
```

[207]:
```
stacked_barplot(data, "job", "Loan Status")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[207], line 1
----> 1 stacked_barplot(data, "job", "Loan Status")
```

```
NameError: name 'stacked_barplot' is not defined
```

[209]:
```
# The plot above shows that lawyers are more likely to default followed by Data␣
↪Scientists
```

[211]:
```
# location vs loan status
stacked_barplot(data, "location", "Loan Status")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[211], line 2
      1 # location vs loan status
----> 2 stacked_barplot(data, "location", "Loan Status")

NameError: name 'stacked_barplot' is not defined
```

[213]:
```
As we can see from above, customers from above customers from Hwange followed␣
↪by victoria falls, Gokwe etc are more likely to default
```

```
  Cell In[213], line 1
    As we can see from above, customers from above customers from Hwange␣
 ↪followed by victoria falls, Gokwe etc are more likely to default
       ^
SyntaxError: invalid syntax
```

[215]:
```
# Employment status  vs loan status
stacked_barplot(data, "is_employed", "Loan Status")
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[215], line 2
      1 # Employment status  vs loan status
----> 2 stacked_barplot(data, "is_employed", "Loan Status")

NameError: name 'stacked_barplot' is not defined
```

[217]:
```
# More customers who are unemployed are likely to default
```

[219]:
```
# number of defaults vs loan status
stacked_barplot(data, "number_of_defaults", "Loan Status")
```

```
---------------------------------------------------------------------------
```

```
NameError                                 Traceback (most recent call last)
Cell In[219], line 2
      1 # number of defaults vs loan status
----> 2 stacked_barplot(data, "number_of_defaults", "Loan Status")

NameError: name 'stacked_barplot' is not defined
```

[221]:
```
# Customers who have 2 records of defaults are more prone to default followed␣
↪by one
```

[223]:
```
###Model evaluation criterion
Model can make wrong predictions as:

    Model predicted a non-defaulter as a defaulter - False Positive
    Model predicted a defaulter as a non-defaulter - False Negative

How to reduce this loss i.e need to reduce False Negatives ?

    Bank would want to reduce false negatives, this can be done by maximizing␣
↪the Recall. Greater the recall lesser the chances of false negatives.
```

```
  Cell In[223], line 2
    Model can make wrong predictions as:
          ^
SyntaxError: invalid syntax
```

[225]:
```
First, let's create functions to calculate different metrics and confusion␣
↪matrix so that we don't have to use the same code repeatedly for each model.

    The model_performance_classification_statsmodels function will be used to␣
↪check the model performance of models.
    The confusion_matrix_statsmodels function will be used to plot confusion␣
↪matrix.
```

```
  Cell In[225], line 1
    First, let's create functions to calculate different metrics and confusion␣
↪matrix so that we don't have to use the same code repeatedly for each model.
           ^
SyntaxError: invalid syntax
```

[ ]:

[ ]:

```

```

[229]:

```
### Data Preparation
```

[231]:

```
### Logistic Regression (with statsmodels library)
```

[233]:

```
X = data[
    [
        "gender",
        "is_employed",
        "job",
        "remaining term",
        "loan_amount",
        "number_of_defaults",
        "outstanding_balance",
        "interest_rate",
        "age",
        "salary",
        "marital_status",
    ]
]
Y = data["Loan Status"]
```

[235]:

```
# creating dummy variables
X = pd.get_dummies(X, drop_first=True)

# standardising continuous variables
scaler = StandardScaler()
X[
    [
        "interest_rate",
        "remaining term",
        "salary",
        "outstanding_balance",
        "age",
        "loan_amount",
    ]
] = scaler.fit_transform(
    X[
        [
            "interest_rate",
            "remaining term",
            "salary",
            "outstanding_balance",
            "age",
            "loan_amount",
        ]
```

```
    ]
)

# Saving the Standard Scaler
pickle.dump(
    scaler,
    open(
        "C:/Users/Munashe Muchinako/OneDrive/Desktop/data science/Data Science␣
↪Competion Question and Data/fastapi endpoints/ML Models/StandardScaler.pkl",
        "wb",
    ),
)



# adding constant
X = sm.add_constant(X)



# splitting in training and test set
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=1)
```

[237]:
```
print(X_train.shape, X_test.shape)
```

```
(80000, 22) (20000, 22)
```

[239]:
```
# Initialising  models
```

[241]:
```
"""models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(n_estimators=100),
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100),
    "SVM": SVC(probability=True),
}"""
```

[241]:
```
'models = {\n    "Logistic Regression": LogisticRegression(max_iter=1000),\n
"Decision Tree": DecisionTreeClassifier(),\n    "Random Forest":
RandomForestClassifier(n_estimators=100),\n    "Gradient Boosting":
GradientBoostingClassifier(n_estimators=100),\n    "SVM":
SVC(probability=True),\n}'
```

[243]:
```
# Define model parameters
model_params = {
    "Logistic Regression": [
        {"solver": "liblinear", "C": 0.1},
        {"solver": "liblinear", "C": 1.0},
        {"solver": "liblinear", "C": 10.0},
```

```
        {"solver": "newton-cg", "C": 1.0},
        {"solver": "saga", "C": 1.0},
    ],
    "Decision Tree": [
        {"max_depth": 5, "min_samples_split": 10},
        {"max_depth": 10, "min_samples_split": 5},
        {"max_depth": None, "min_samples_split": 10},
        {"max_depth": 5, "min_samples_split": 2},
        {"max_depth": 15, "min_samples_split": 5},
    ],
    "Random Forest": [
        {"n_estimators": 50, "max_depth": 10},
        {"n_estimators": 100, "max_depth": 15},
        {"n_estimators": 200, "max_depth": None},
        {"n_estimators": 100, "max_depth": 10},
        {"n_estimators": 150, "max_depth": 20},
    ],
    "Gradient Boosting": [
        {"n_estimators": 50, "learning_rate": 0.1},
        {"n_estimators": 100, "learning_rate": 0.1},
        {"n_estimators": 150, "learning_rate": 0.05},
        {"n_estimators": 100, "learning_rate": 0.01},
        {"n_estimators": 200, "learning_rate": 0.1},
    ],
}
```

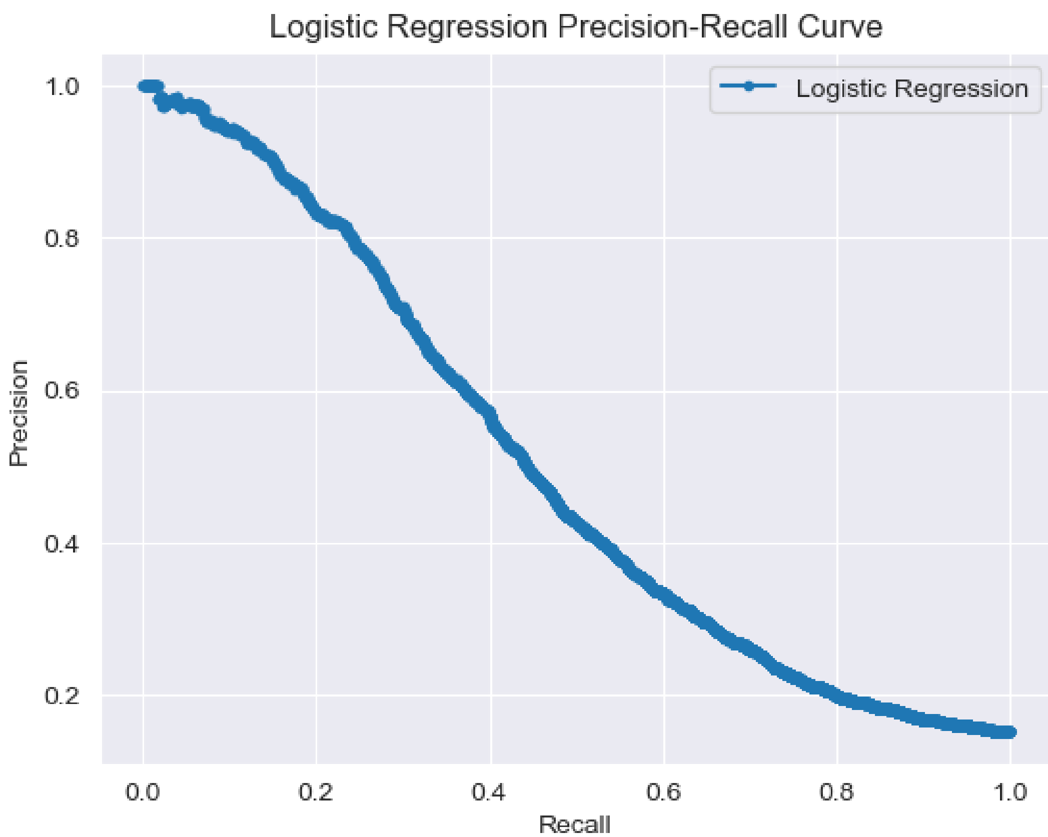
[245]:
```
# Train and Evaluate the models
```

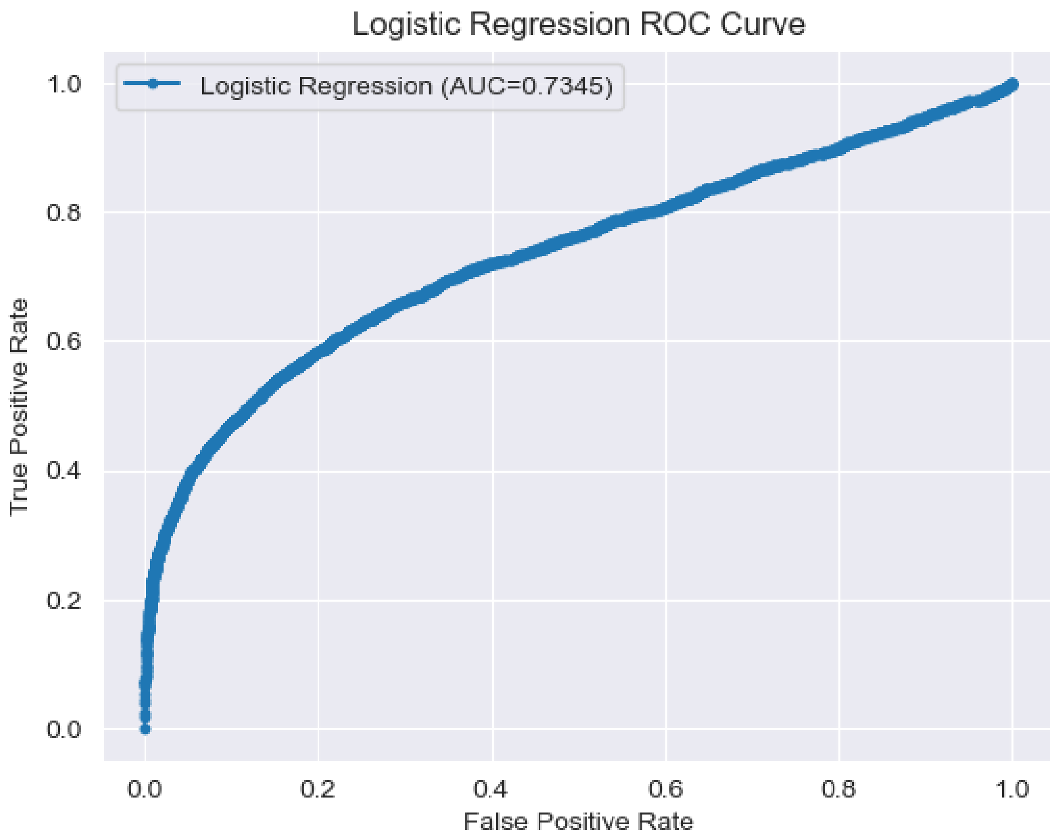
[247]:
```
for algorithm, params_list in model_params.items():
    print(f"\n{algorithm} Models:")
    for i, params in enumerate(params_list):
        print(f"\nModel {i+1} with parameters: {params}")

        if algorithm == "Logistic Regression":
            model = LogisticRegression(max_iter=1000, **params)
        elif algorithm == "Decision Tree":
            model = DecisionTreeClassifier(**params)
            model.fit(X_train, y_train)
            # Saving the Decision Tree
            pickle.dump(
                model,
                open(
                    "C:/Users/Munashe Muchinako/OneDrive/Desktop/data science/
↪Data Science Competion Question and Data/fastapi endpoints/ML Models/
↪DecisionTree.pkl",
                    "wb",
                ),
```

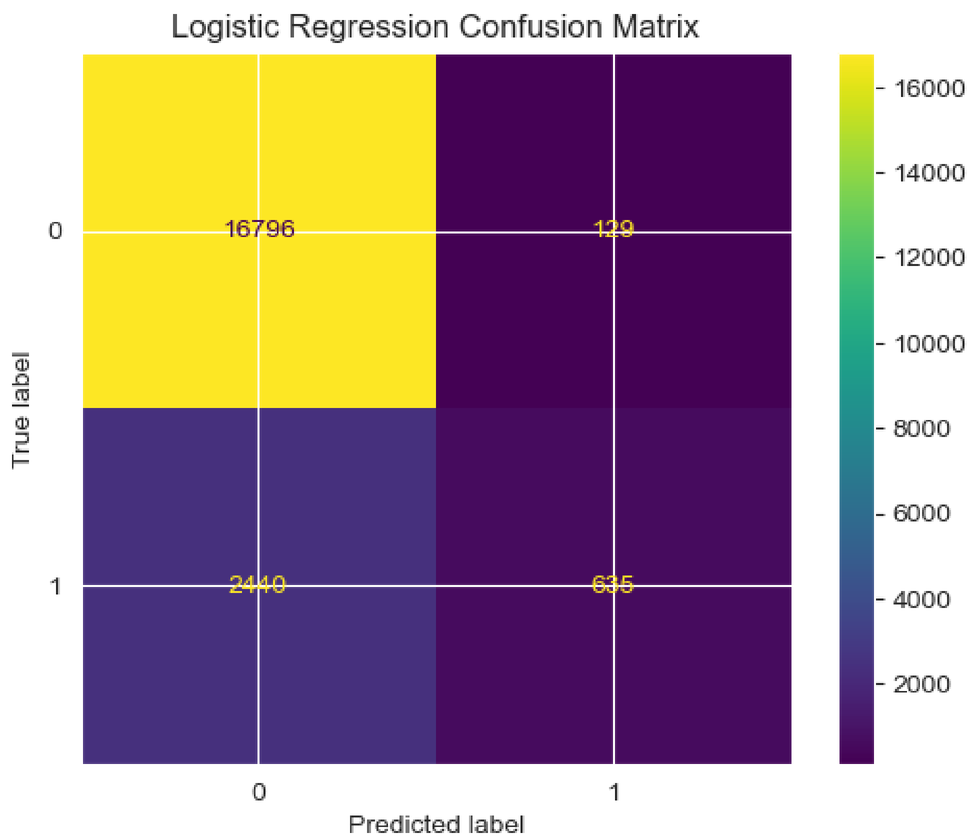
```python
        )

    elif algorithm == "Random Forest":
        model = RandomForestClassifier(**params)
    elif algorithm == "Gradient Boosting":
        model = GradientBoostingClassifier(**params)
    elif algorithm == "SVM":
        model = SVC(probability=True, **params)

    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_pred_prob = (
        model.predict_proba(X_test)[:, 1]
        if hasattr(model, "predict_proba")
        else model.decision_function(X_test)
    )

    # Function for Metrics
    accuracy = accuracy_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred_prob)
    cm = confusion_matrix(y_test, y_pred)

# Displaying the outcomes
print(f"{algorithm}:")
print(f"Accuracy:{accuracy:.4f}")
print(f"F1 Score:{f1:.4f}")
print(f"Recall:{recall:.4f}")
print(f"Precision:{precision:.4f}")
print(f"ROC AUC:{roc_auc:.4f}")
"""print("Confusion Matrix:")
#print(cm)"""

# Plot precision-Recall curve
precision_vals, recall_vals, _ = precision_recall_curve(y_test, y_pred_prob)
plt.plot(recall_vals, precision_vals, marker=".", label=f"{algorithm}")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title(f"{algorithm} Precision-Recall Curve")
plt.legend()
plt.show()

# Plot Roc Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
plt.plot(fpr, tpr, marker=".", label=f"{algorithm} (AUC={roc_auc:.4f})")
```

```
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title(f"{algorithm} ROC Curve")
    plt.legend()
    plt.show()

    # defining a function to plot the confusion_matrix of a classification model
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=model.
 ↪classes_)
    """plt.figure(figsize=(7, 5))
    sns.heatmap(cm, annot=True, fmt="g")
    plt.xlabel("Predicted Values")
    plt.ylabel("Actual Values")"""
    disp.plot()
    plt.title(f"{algorithm} Confusion Matrix")
    plt.show()
    """
    cm = confusion_matrix(y_train, pred_train)
    plt.figure(figsize=(7, 5))
    sns.heatmap(cm, annot=True, fmt="g")
    plt.xlabel("Predicted Values")
    plt.ylabel("Actual Values")
    plt.show()"""
```

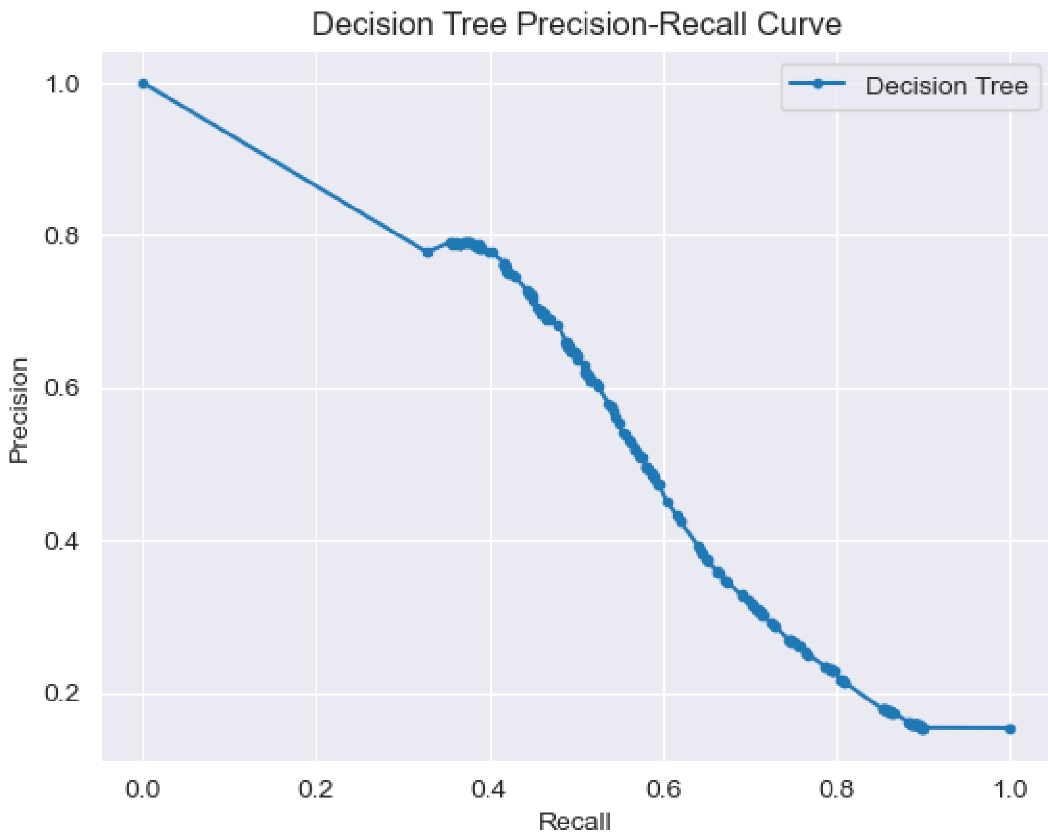
```
Logistic Regression Models:

Model 1 with parameters: {'solver': 'liblinear', 'C': 0.1}

Model 2 with parameters: {'solver': 'liblinear', 'C': 1.0}

Model 3 with parameters: {'solver': 'liblinear', 'C': 10.0}

Model 4 with parameters: {'solver': 'newton-cg', 'C': 1.0}

Model 5 with parameters: {'solver': 'saga', 'C': 1.0}
Logistic Regression:
Accuracy:0.8716
F1 Score:0.3308
Recall:0.2065
Precision:0.8312
ROC AUC:0.7345
```

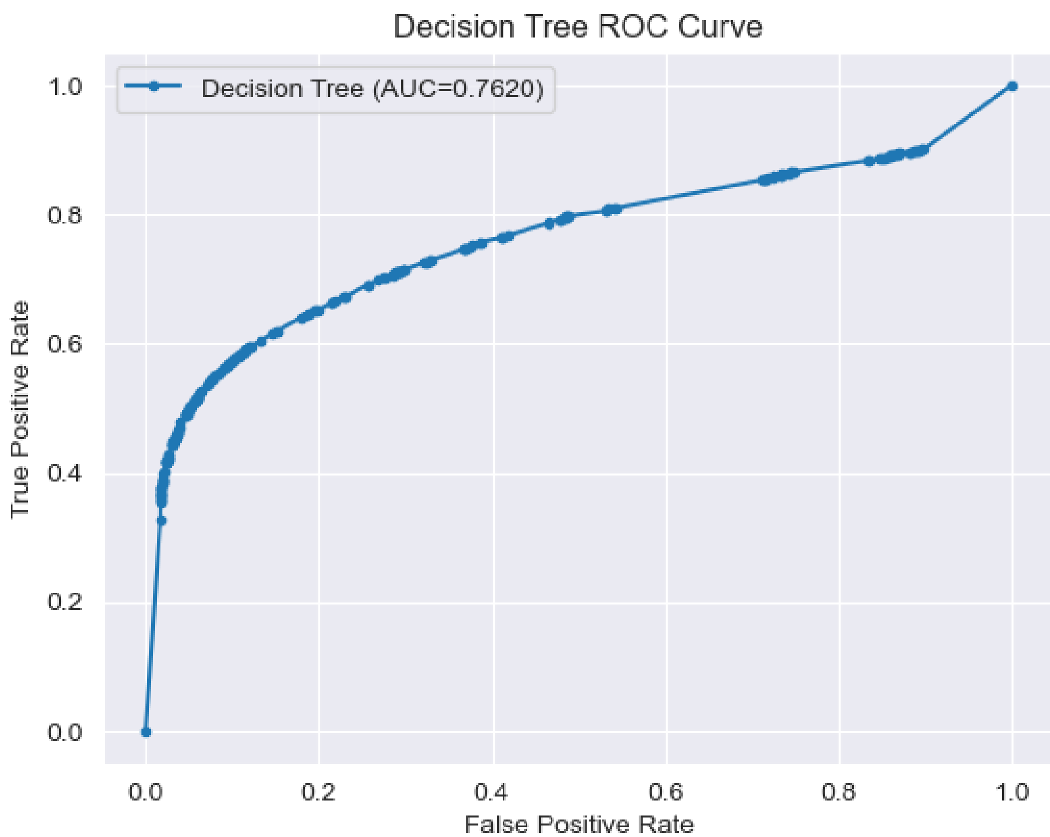

Logistic Regression Precision-Recall Curve
Logistic Regression
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0

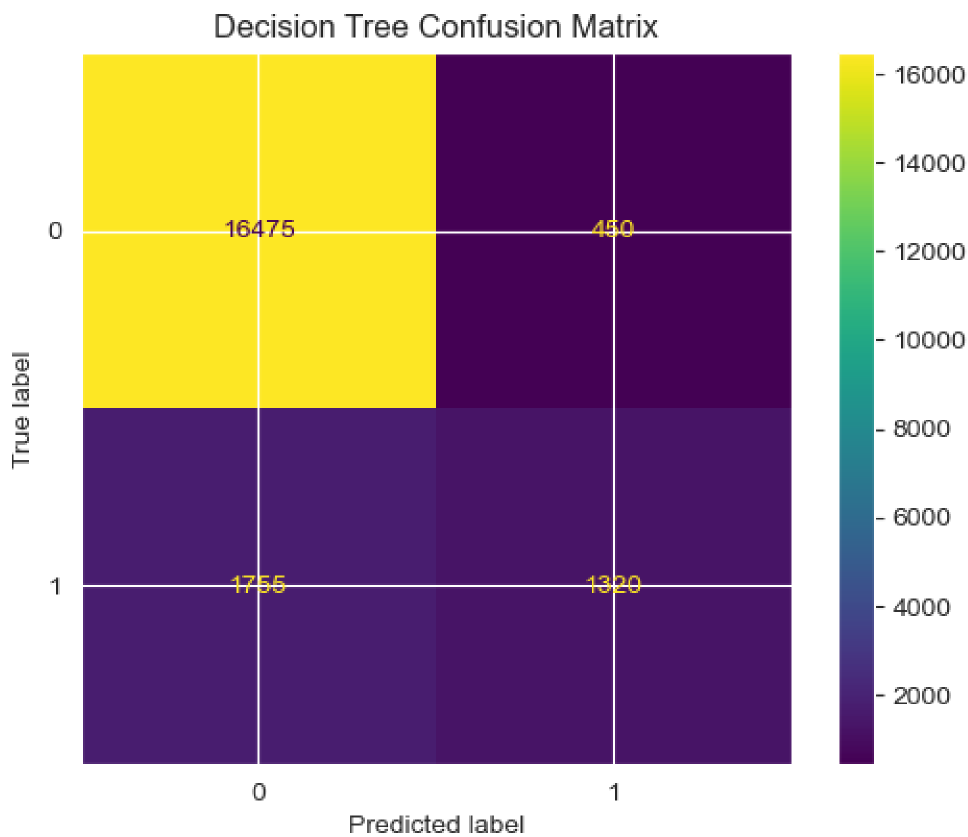

Logistic Regression ROC Curve
Logistic Regression (AUC=0.7345)
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate



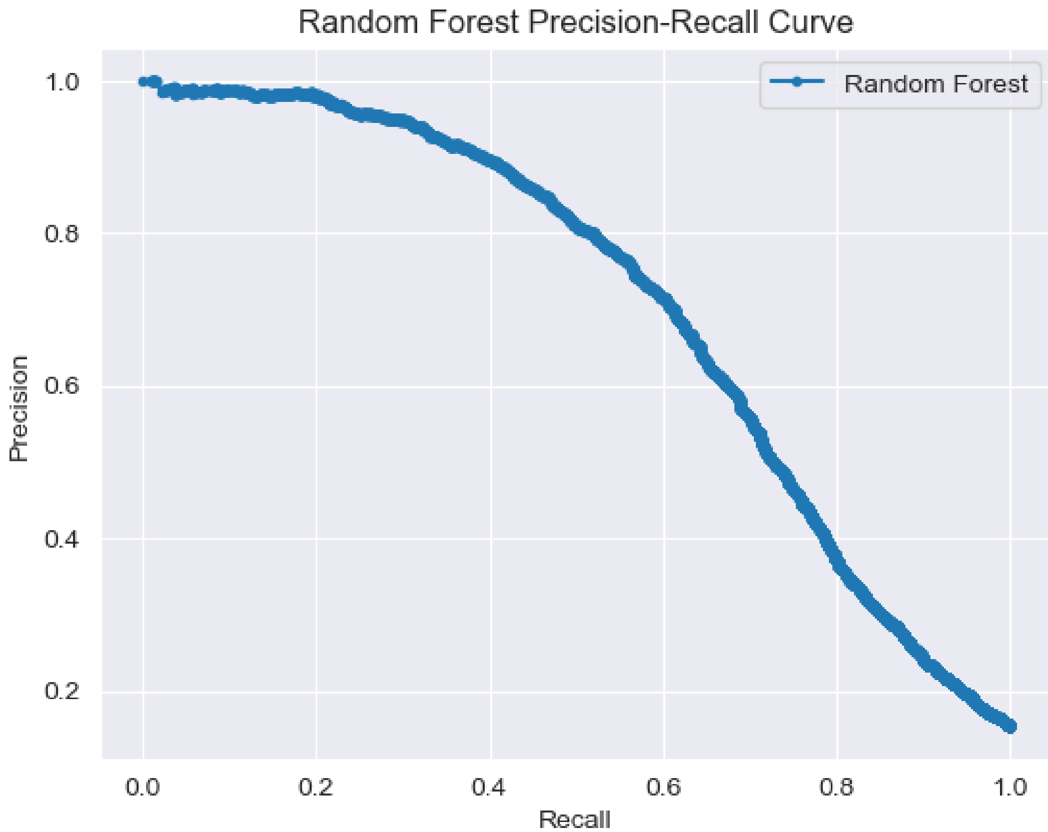

```
Decision Tree Models:

Model 1 with parameters: {'max_depth': 5, 'min_samples_split': 10}

Model 2 with parameters: {'max_depth': 10, 'min_samples_split': 5}

Model 3 with parameters: {'max_depth': None, 'min_samples_split': 10}

Model 4 with parameters: {'max_depth': 5, 'min_samples_split': 2}

Model 5 with parameters: {'max_depth': 15, 'min_samples_split': 5}
Decision Tree:
Accuracy:0.8898
F1 Score:0.5449
Recall:0.4293
Precision:0.7458
ROC AUC:0.7620
```

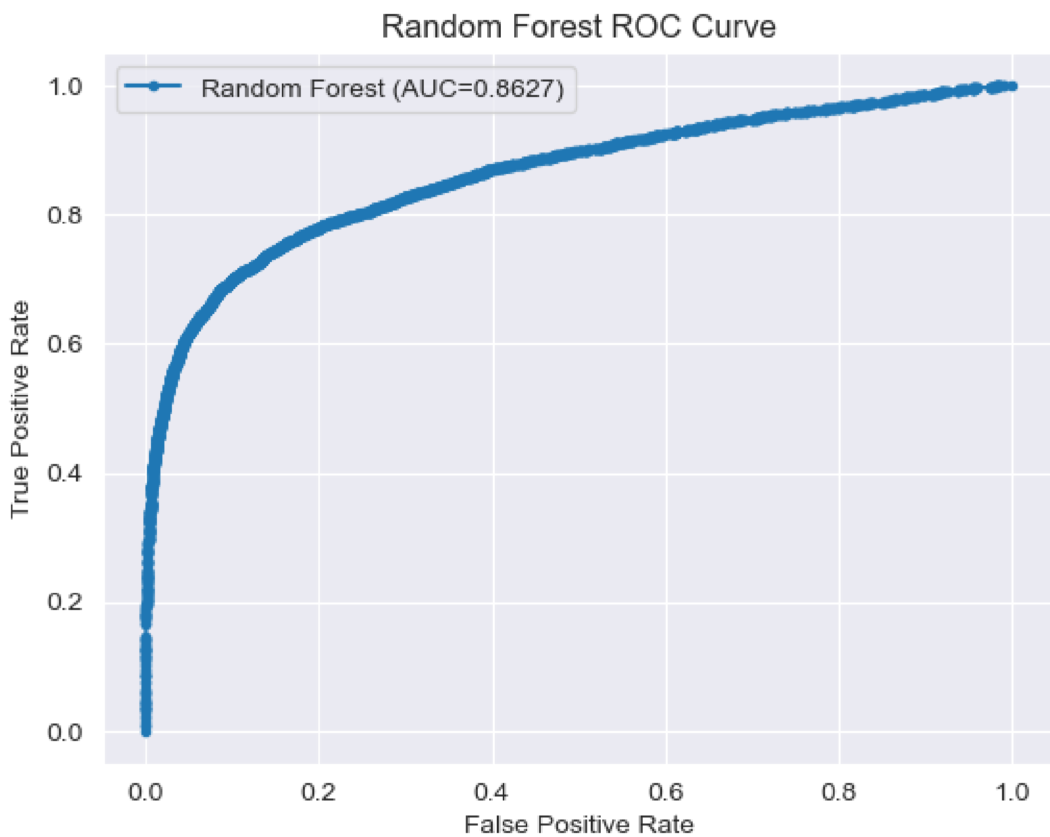

Decision Tree Precision-Recall Curve
Decision Tree
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0

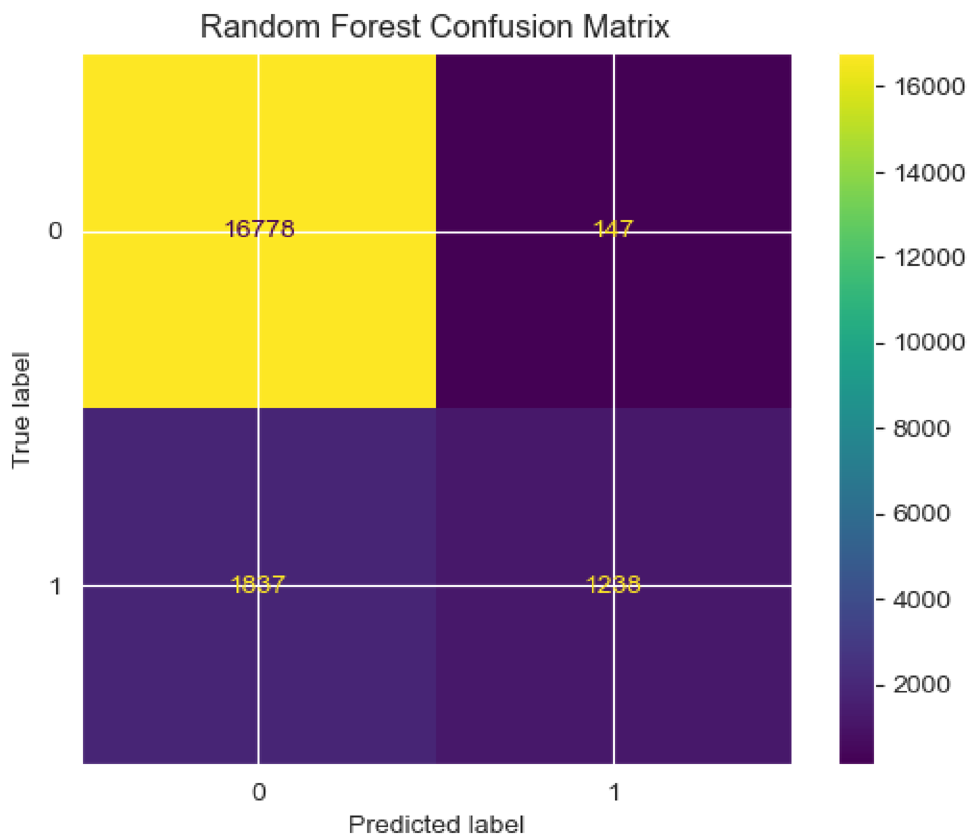

Decision Tree ROC Curve
Decision Tree (AUC=0.7620)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0



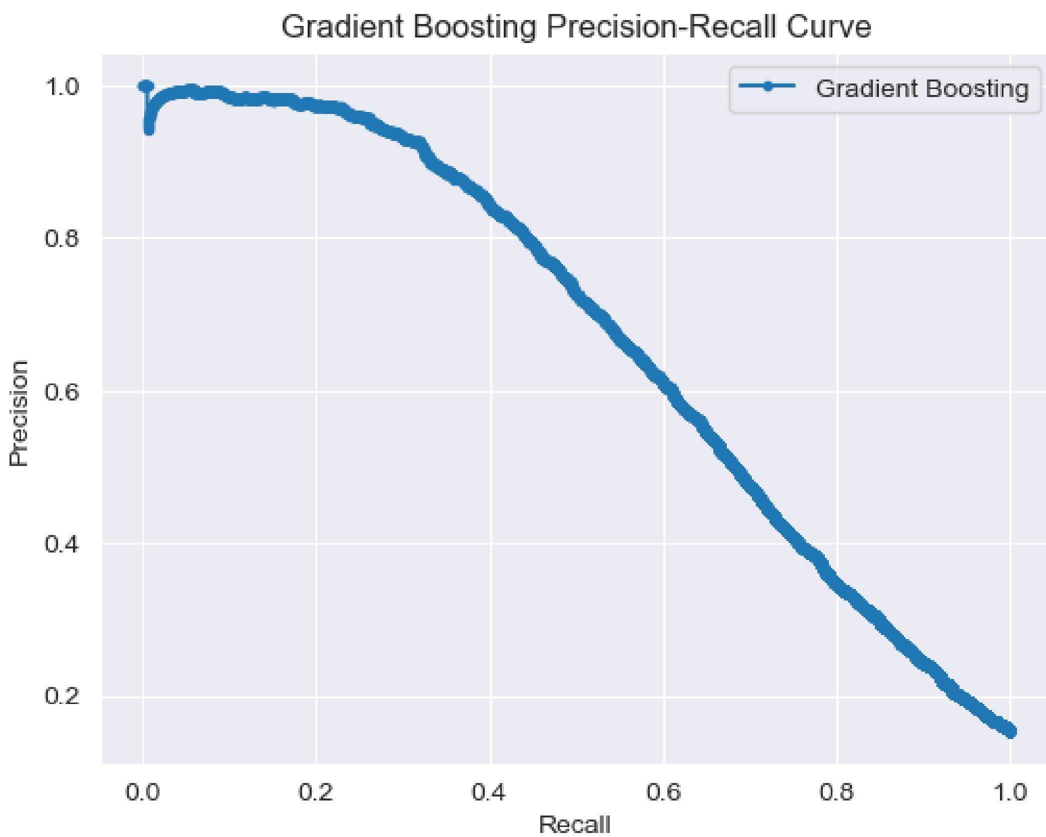

```
Random Forest Models:

Model 1 with parameters: {'n_estimators': 50, 'max_depth': 10}

Model 2 with parameters: {'n_estimators': 100, 'max_depth': 15}

Model 3 with parameters: {'n_estimators': 200, 'max_depth': None}

Model 4 with parameters: {'n_estimators': 100, 'max_depth': 10}

Model 5 with parameters: {'n_estimators': 150, 'max_depth': 20}
Random Forest:
Accuracy:0.9008
F1 Score:0.5552
Recall:0.4026
Precision:0.8939
ROC AUC:0.8627
```

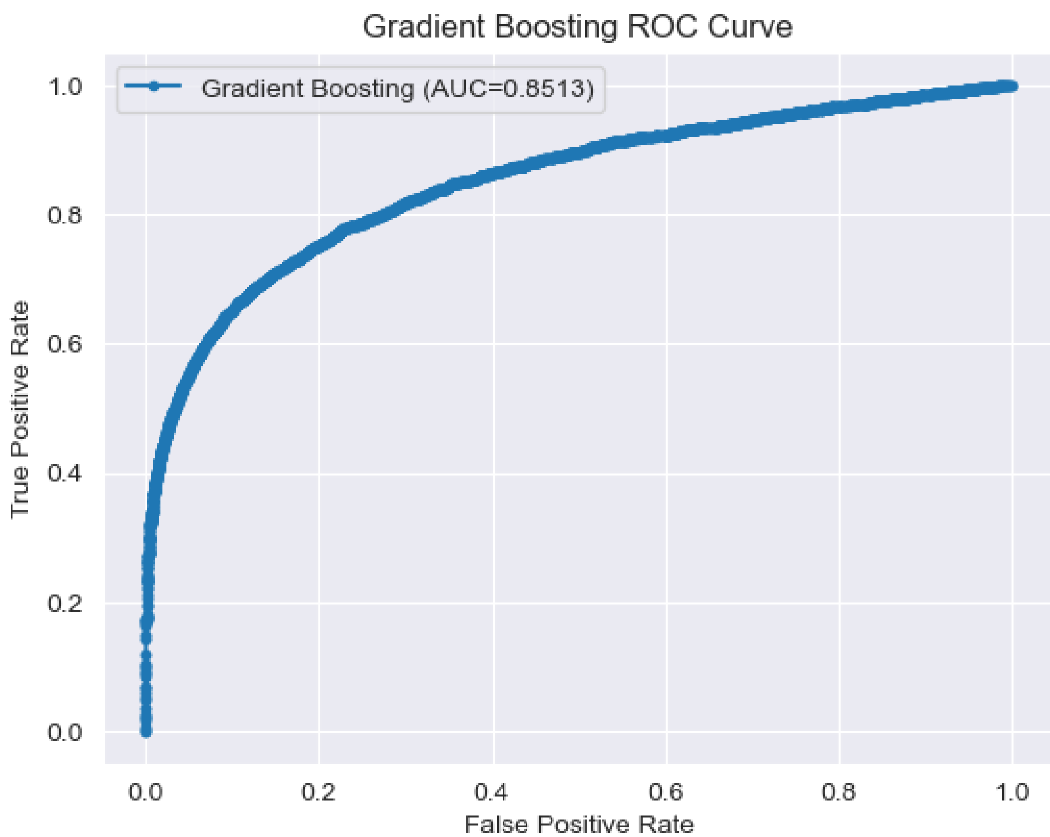

Random Forest Precision-Recall Curve
Random Forest
Precision
Recall
1.0
0.8
0.6
0.4
0.2
0.0
0.2
0.4
0.6
0.8
1.0

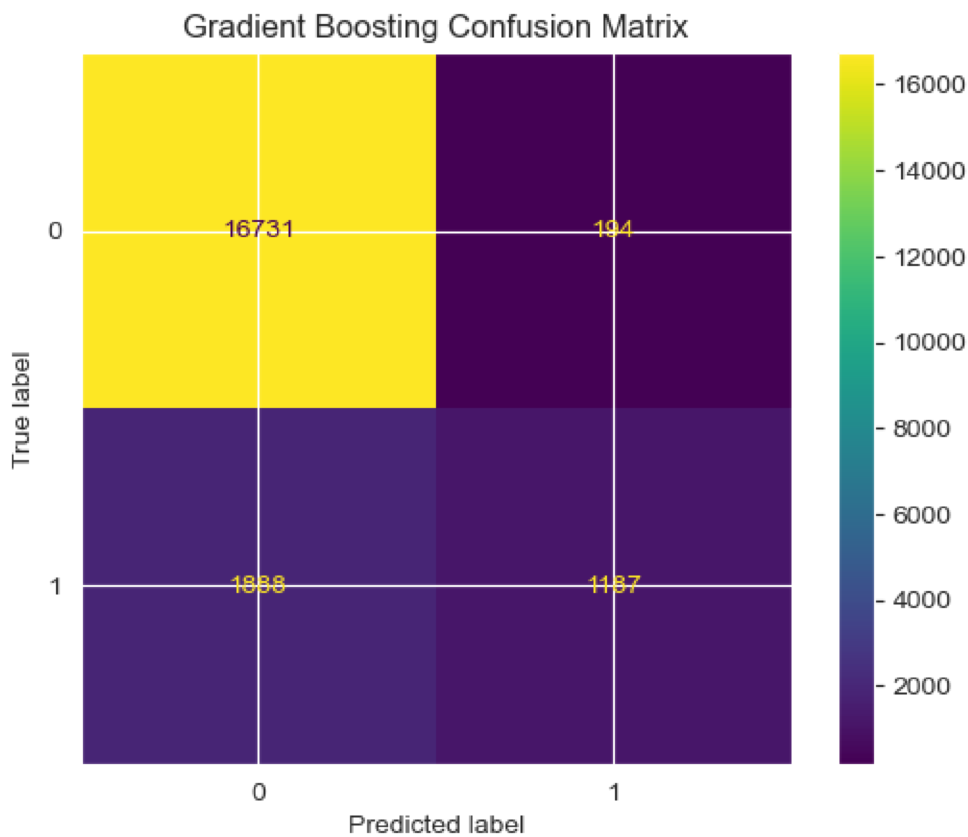

Random Forest ROC Curve
Random Forest (AUC=0.8627)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0




```
Gradient Boosting Models:

Model 1 with parameters: {'n_estimators': 50, 'learning_rate': 0.1}

Model 2 with parameters: {'n_estimators': 100, 'learning_rate': 0.1}

Model 3 with parameters: {'n_estimators': 150, 'learning_rate': 0.05}

Model 4 with parameters: {'n_estimators': 100, 'learning_rate': 0.01}

Model 5 with parameters: {'n_estimators': 200, 'learning_rate': 0.1}
Gradient Boosting:
Accuracy:0.8959
F1 Score:0.5328
Recall:0.3860
Precision:0.8595
ROC AUC:0.8513
```


Gradient Boosting Precision-Recall Curve
Gradient Boosting
1.0
0.8
0.6
0.4
0.2
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall


Gradient Boosting ROC Curve
Gradient Boosting (AUC=0.8513)
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0


Gradient Boosting Confusion Matrix
16731
194
1888
1187
0
1
True label
0
1
Predicted label
16000
14000
12000
10000
8000
6000
4000
2000

```
[ ]:
```

```
[ ]:
```