```
#PROJECT- Classification model for ABG motors using predictive
analytics to enter the Indian Market
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import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix,
classification_report, roc_auc_score

# First we will load the excel file
file_path = r"C:\Users\chakr\OneDrive\Documents\
Capstone.datascience1.xlsx"

# Loading specific sheets into DataFrames
indian_df = pd.read_excel(file_path, sheet_name='indiandataset ')
japanese_df = pd.read_excel(file_path, sheet_name='japanesedataset ')


# Handle missing values (if any)
indian_df = indian_df.dropna()  # Drop rows with missing values in the
Indian dataset
japanese_df = japanese_df.dropna()  # Drop rows with missing values in
the Japanese dataset

# Display the first few rows of each DataFrame to verify
print("Indian Dataset after dropping missing values:")
print(indian_df.head())

print("\nJapanese Dataset after dropping missing values:")
print(japanese_df.head())
```

```
Indian Dataset after dropping missing values:
           ID  CURR_AGE GENDER  ANN_INCOME             DT_MAINT
0  20710B05XL        54      M     1425390            4/20/2018
1  89602T51HX        47      M     1678954  2018-08-06 00:00:00
2  70190Z52IP        60      M      931624            7/31/2017
3  25623V15MU        55      F     1106320            7/31/2017
4  36230I68CE        32      F      748465            1/27/2019

Japanese Dataset after dropping missing values:
Empty DataFrame
Columns: [ID, CURR_AGE, GENDER, ANN_INCOME, AGE_CAR, PURCHASE,
Unnamed: 6, Unnamed: 7, Unnamed: 8]
Index: []
```

```
indian_df = pd.read_excel(file_path, sheet_name='indiandataset ')
japanese_df = pd.read_excel(file_path, sheet_name='japanesedataset ')
```

```
# Strip any leading or trailing spaces from column names
indian_df.columns = indian_df.columns.str.strip()
japanese_df.columns = japanese_df.columns.str.strip()

# Verify column names
print("Indian Dataset Columns:", indian_df.columns)
print("Japanese Dataset Columns:", japanese_df.columns)

# We have done the segmentation of the age_car provided in the dataset
into four categories
def segment_age_car(age_car):
    if age_car < 200:
        return 1
    elif 200 <= age_car <= 360:
        return 2
    elif 360 < age_car <= 500:
        return 3
    else:
        return 4

# Applied the segmentation to the 'AGE_CAR' column in the Japanese
dataset
if 'AGE_CAR' in japanese_df.columns:
    japanese_df['age_car_segment'] =
japanese_df['AGE_CAR'].apply(segment_age_car)
    print(japanese_df[['AGE_CAR', 'age_car_segment']].head())
else:
    print("Column 'AGE_CAR' does not exist in the Japanese dataset.")
```

```
Indian Dataset Columns: Index(['ID', 'CURR_AGE', 'GENDER',
'ANN_INCOME', 'DT_MAINT'], dtype='object')
Japanese Dataset Columns: Index(['ID', 'CURR_AGE', 'GENDER',
'ANN_INCOME', 'AGE_CAR', 'PURCHASE',
       'Unnamed: 6', 'Unnamed: 7', 'Unnamed: 8'],
      dtype='object')
   AGE_CAR  age_car_segment
0      439                3
1      283                2
2      390                3
3      475                3
4      497                3
```

```
# We have the annual income of the customers in currency yen, so we
have converted into inr with a conversion rate of 0.64 as of year 2019
conversion_rate = 0.64

# Convert 'ANN_INCOME' from Yen to INR
japanese_df['ANN_INCOME_INR'] = japanese_df['ANN_INCOME'] *
conversion_rate
```

```
# Display the first few rows to check the conversion
print(japanese_df[['ANN_INCOME', 'ANN_INCOME_INR']].head())
```

```
   ANN_INCOME  ANN_INCOME_INR
0      445344       285020.16
1      107634        68885.76
2      502787       321783.68
3      585664       374824.96
4      705723       451662.72
```

```
# Calculated maximum and minimum values to calculate the range
max_income_inr = japanese_df['ANN_INCOME_INR'].max()
min_income_inr = japanese_df['ANN_INCOME_INR'].min()

# Print the results
print(f"Maximum Annual Income in INR: {max_income_inr}")
print(f"Minimum Annual Income in INR: {min_income_inr}")
```

```
Maximum Annual Income in INR: 511981.44
Minimum Annual Income in INR: 44856.96
```

```
# classify income groups based on the INR values for japanese dataset
def classify_income(income_inr):
    if income_inr <= 100000:
        return 1  # Low income
    elif 100000 < income_inr <= 200000:
        return 2  # Lower-middle income
    elif 200000 < income_inr <= 300000:
        return 3  # Upper-middle income
    else:
        return 4  # High income

# Apply the classification to the Japanese dataset
japanese_df['income_group'] =
japanese_df['ANN_INCOME_INR'].apply(classify_income)

# Check the classification
print(japanese_df[['ANN_INCOME_INR', 'income_group']].head())
```

```
   ANN_INCOME_INR  income_group
0       285020.16             3
1        68885.76             1
2       321783.68             4
3       374824.96             4
4       451662.72             4
```

```
# Calculate maximum and minimum age in the Japanese dataset
max_age_japanese = japanese_df['CURR_AGE'].max()
min_age_japanese = japanese_df['CURR_AGE'].min()

# Print the results
```

```python
print(f"Maximum Age in Japanese Dataset: {max_age_japanese}")
print(f"Minimum Age in Japanese Dataset: {min_age_japanese}")
```

```
Maximum Age in Japanese Dataset: 65
Minimum Age in Japanese Dataset: 25
```

```python
# Calculate maximum and minimum age in the indian dataset
max_age_indian = indian_df['CURR_AGE'].max()
min_age_indian = indian_df['CURR_AGE'].min()

# Print the results
print(f"Maximum Age in indian Dataset: {max_age_indian}")
print(f"Minimum Age in indian Dataset: {min_age_indian}")
```

```
Maximum Age in indian Dataset: 65
Minimum Age in indian Dataset: 25
```

```python
# Here we have classified age into four categories:
def classify_age_group(age):
    if 25 <= age < 35:
        return 1
    elif 35 <= age < 45:
        return 2
    elif 45 <= age < 55:
        return 3
    elif 55 <= age <= 65:
        return 4
    else:
        return None  # This handles any unexpected values

# Apply the classification to the 'CURR_AGE' column
indian_df['age_group'] =
indian_df['CURR_AGE'].apply(classify_age_group)

# Check the new classification
print(indian_df[['CURR_AGE', 'age_group']].head())
```

```
   CURR_AGE  age_group
0        54          3
1        47          3
2        60          4
3        55          4
4        32          1
```

```python
def classify_age_group(age):
    if 25 <= age < 35:
        return 1
    elif 35 <= age < 45:
        return 2
    elif 45 <= age < 55:
        return 3
```

```
    elif 55 <= age <= 65:
        return 4
    else:
        return None  # This handles any unexpected values

# Apply the classification to the 'CURR_AGE' column
japanese_df['age_group'] =
japanese_df['CURR_AGE'].apply(classify_age_group)

# Check the new classification
print(japanese_df[['CURR_AGE', 'age_group']].head())
```

```
   CURR_AGE  age_group
0        50          3
1        35          2
2        59          4
3        43          2
4        39          2
```

```
# Here we have converted the string value into binary of the gender
column
def convert_gender_indian(gender):
    if gender == 'M':
        return 0
    elif gender == 'F':
        return 1
    else:
        return None  # Handle unexpected values

# Apply the conversion to the Indian dataset
indian_df['gender_numeric'] =
indian_df['GENDER'].apply(convert_gender_indian)

# Define a function to convert gender into numerical values for the
Japanese dataset
def convert_gender_japanese(gender):
    if gender == 'M':
        return 0
    elif gender == 'F':
        return 1
    else:
        return None  # Handle unexpected values

# Apply the conversion to the Japanese dataset
japanese_df['gender_numeric'] =
japanese_df['GENDER'].apply(convert_gender_japanese)

# Check the new columns
print("Indian Dataset - GENDER and gender_numeric:")
print(indian_df[['GENDER', 'gender_numeric']].head())
```

```python
print("Japanese Dataset - GENDER and gender_numeric:")
print(japanese_df[['GENDER', 'gender_numeric']].head())
```

```
Indian Dataset - GENDER and gender_numeric:
  GENDER  gender_numeric
0      M               0
1      M               0
2      M               0
3      F               1
4      F               1
Japanese Dataset - GENDER and gender_numeric:
  GENDER  gender_numeric
0      M               0
1      M               0
2      F               1
3      M               0
4      F               1
```

```python
# Calculate the maximum and minimum of the annual income
max_income = indian_df['ANN_INCOME'].max()
min_income = indian_df['ANN_INCOME'].min()

print(f"Maximum Annual Income: {max_income}")
print(f"Minimum Annual Income: {min_income}")
```

```
Maximum Annual Income: 1999989
Minimum Annual Income: 300033
```

```python
# Convert DT_MAINT to datetime format (if not already in datetime)
indian_df['DT_MAINT'] = pd.to_datetime(indian_df['DT_MAINT'],
errors='coerce')

# Define the reference date (7th July 2019)
reference_date = pd.to_datetime('2019-07-07')

# Calculate the age of the car by subtracting DT_MAINT from the
reference date
# The result will be in days, so we can divide by 365 to get years
indian_df['age_car'] = (reference_date -
indian_df['DT_MAINT']).dt.days

# Display the updated dataframe with the new age_car column
print(indian_df[['ID', 'DT_MAINT', 'age_car']].head())
```

```
           ID   DT_MAINT  age_car
0  20710B05XL 2018-04-20      443
1  89602T51HX 2018-08-06      335
2  70190Z52IP 2017-07-31      706
3  25623V15MU 2017-07-31      706
4  36230I68CE 2019-01-27      161
```

```
# Define a function to segment the age_car values
def segment_age_car(age):
    if age < 200:
        return 1
    elif 200 <= age <= 360:
        return 2
    elif 360 < age <= 500:
        return 3
    else:
        return 4

# Apply the function to the age_car column and create a new column
with the segments
indian_df['age_car_segment'] =
indian_df['age_car'].apply(segment_age_car)

# Display the updated dataframe with the age_car and age_car_segment
columns
print(indian_df[['ID', 'DT_MAINT', 'age_car',
'age_car_segment']].head())
```

```
           ID   DT_MAINT  age_car  age_car_segment
0  20710B05XL 2018-04-20      443                3
1  89602T51HX 2018-08-06      335                2
2  70190Z52IP 2017-07-31      706                4
3  25623V15MU 2017-07-31      706                4
4  36230I68CE 2019-01-27      161                1
```

```
# Define a function to classify current age into age groups
def classify_age_group(age):
    if 25 <= age < 35:
        return 1
    elif 35 <= age < 45:
        return 2
    elif 45 <= age < 55:
        return 3
    elif 55 <= age <= 65:
        return 4

# Apply the function to the CURR_AGE column and create a new column
'age_group'
indian_df['age_group'] =
indian_df['CURR_AGE'].apply(classify_age_group)

# Display the updated dataframe with CURR_AGE and age_group columns
print(indian_df[['ID', 'CURR_AGE', 'age_group']].head())
```

```
           ID  CURR_AGE  age_group
0  20710B05XL        54          3
```

```
1  89602T51HX        47           3
2  70190Z52IP        60           4
3  25623V15MU        55           4
4  36230I68CE        32           1
```

```python
print(indian_df.head(10))
```

```
           ID  CURR_AGE GENDER  ANN_INCOME   DT_MAINT  age_group  \
0  20710B05XL        54      M     1425390 2018-04-20          3
1  89602T51HX        47      M     1678954 2018-08-06          3
2  70190Z52IP        60      M      931624 2017-07-31          4
3  25623V15MU        55      F     1106320 2017-07-31          4
4  36230I68CE        32      F      748465 2019-01-27          1
5  11264G01HZ        48      F     1051927 2018-11-24          3
6  74250S23UO        26      F     1076402 2018-09-22          1
7  26735J66DB        45      F     1481949 2018-05-04          3
8  93404P60ED        55      M     1725607 2018-02-01          4
9  56557A36QV        64      F      312323 2018-04-23          4

   gender_numeric  age_car  age_car_segment
0               0      443                3
1               0      335                2
2               0      706                4
3               1      706                4
4               1      161                1
5               1      225                2
6               1      288                2
7               1      429                3
8               0      521                4
9               1      440                3
```

```python
# Assuming `indian_df` is your DataFrame with the 'ANN_INCOME' column

# Step 1: Calculate mean and standard deviation of the 'ANN_INCOME'
column
mean_income = indian_df['ANN_INCOME'].mean()
std_income = indian_df['ANN_INCOME'].std()

# Step 2: Apply standardization formula (x - mean) / std
indian_df['income_standardized'] =
indian_df['ANN_INCOME'].apply(lambda x: (x - mean_income) /
std_income)

# Step 3: Check the result
print(indian_df[['ANN_INCOME', 'income_standardized']].head())
```

```
   ANN_INCOME  income_standardized
0     1425390             0.692730
1     1678954             1.327512
2      931624            -0.543383
```

```
3     1106320            -0.106042
4      748465            -1.001910
```

```python
#similarly we will do for japanese dataset
# Step 1: Calculate mean and standard deviation of the 'ANN_INCOME'
column
mean_income = japanese_df['ANN_INCOME'].mean()
std_income = japanese_df['ANN_INCOME'].std()

# Step 2: Apply standardization formula (x - mean) / std
japanese_df['income_standardized'] =
japanese_df['ANN_INCOME'].apply(lambda x: (x - mean_income) /
std_income)

# Step 3: Check the result
print(japanese_df[['ANN_INCOME', 'income_standardized']].head())
```

```
   ANN_INCOME  income_standardized
0      445344             0.490809
1      107634            -1.437759
2      502787             0.818849
3      585664             1.292137
4      705723             1.977760
```

```python
# Assume the 'DT_MAINT' column is already present in your dataset.
indian_df.columns = indian_df.columns.str.strip()
print("Indian Dataset Columns:", indian_df.columns)
# Step 1: Convert 'DT_MAINT' to datetime format
indian_df['DT_MAINT'] = pd.to_datetime(indian_df['DT_MAINT'])

# Step 2: Calculate the age of the car
reference_date = pd.to_datetime('2019-07-07')  # The fixed date for
calculation
indian_df['age_car'] = (reference_date -
indian_df['DT_MAINT']).dt.days

# Step 3: Function to categorize age_car
def categorize_age_car(age_car):
    if age_car < 200:
        return 1
    elif 200 <= age_car <= 360:
        return 2
    elif 360 < age_car <= 500:
        return 3
    else:
        return 4

# Apply the categorization function
indian_df['age_car_segment'] =
indian_df['age_car'].apply(categorize_age_car)
```

```
Indian Dataset Columns: Index(['ID', 'CURR_AGE', 'GENDER',
'ANN_INCOME', 'DT_MAINT', 'age_group',
       'gender_numeric', 'age_car', 'age_car_segment',
'income_standardized'],
      dtype='object')
```

```
print(indian_df.head(20))
```

```
            ID  CURR_AGE GENDER  ANN_INCOME   DT_MAINT  age_group  \
0   20710B05XL        54      M     1425390 2018-04-20          3
1   89602T51HX        47      M     1678954 2018-08-06          3
2   70190Z52IP        60      M      931624 2017-07-31          4
3   25623V15MU        55      F     1106320 2017-07-31          4
4   36230I68CE        32      F      748465 2019-01-27          1
5   11264G01HZ        48      F     1051927 2018-11-24          3
6   74250S23UO        26      F     1076402 2018-09-22          1
7   26735J66DB        45      F     1481949 2018-05-04          3
8   93404P60ED        55      M     1725607 2018-02-01          4
9   56557A36QV        64      F      312323 2018-04-23          4
10  38353F50LZ        53      M      546574 2019-05-06          3
11  54684T21RX        44      F     1203691 2017-12-07          2
12  46929E04HS        59      F      724688 2019-06-22          4
13  20647X82EQ        27      F      975130 2019-05-03          1
14  34956P25RT        57      F     1422399 2019-04-14          4
15  07090V20JQ        40      F     1558045 2018-06-02          2
16  78392T89DQ        33      M      669737 2019-05-31          1
17  07257K04CB        57      F      774593 2018-12-31          4
18  65658K80PS        59      F      993201 2019-05-03          4
19  69803K32CS        42      F     1050793 2016-10-21          2

    gender_numeric  age_car  age_car_segment  income_standardized
0                0      443                3             0.692730
1                0      335                2             1.327512
2                0      706                4            -0.543383
3                1      706                4            -0.106042
4                1      161                1            -1.001910
5                1      225                2            -0.242212
6                1      288                2            -0.180940
7                1      429                3             0.834322
8                0      521                4             1.444305
9                1      440                3            -2.093765
10               0       62                1            -1.507332
11               1      577                4             0.137720
12               1       15                1            -1.061434
13               1       65                1            -0.434468
14               1       84                1             0.685243
15               1      400                3             1.024824
16               0       37                1            -1.199001
17               1      188                1            -0.936500
```

```
18                 1       65                  1             -0.389229
19                 1      989                  4             -0.245050
```

```
import pandas as pd


# Step 1: Standardize the ANN_INCOME column
mean_income = indian_df['ANN_INCOME'].mean()
std_income = indian_df['ANN_INCOME'].std()
indian_df['ANN_INCOME'] = (indian_df['ANN_INCOME'] - mean_income) /
std_income

# Step 2: Replace DT_MAINT with age_car_segment
indian_df['DT_MAINT'] = indian_df['age_car_segment']

# Display the updated DataFrame with the first 50 rows
print(indian_df.head(50))
```

```
            ID  CURR_AGE GENDER  ANN_INCOME  DT_MAINT  age_group  \
0   20710B05XL        54      M    0.692730         3          3
1   89602T51HX        47      M    1.327512         2          3
2   70190Z52IP        60      M   -0.543383         4          4
3   25623V15MU        55      F   -0.106042         4          4
4   36230I68CE        32      F   -1.001910         1          1
5   11264G01HZ        48      F   -0.242212         2          3
6   74250S23UO        26      F   -0.180940         2          1
7   26735J66DB        45      F    0.834322         3          3
8   93404P60ED        55      M    1.444305         4          4
9   56557A36QV        64      F   -2.093765         3          4
10  38353F50LZ        53      M   -1.507332         1          3
11  54684T21RX        44      F    0.137720         4          2
12  46929E04HS        59      F   -1.061434         1          4
13  20647X82EQ        27      F   -0.434468         1          1
14  34956P25RT        57      F    0.685243         1          4
15  07090V20JQ        40      F    1.024824         3          2
16  78392T89DQ        33      M   -1.199001         1          1
17  07257K04CB        57      F   -0.936500         1          4
18  65658K80PS        59      F   -0.389229         1          4
19  69803K32CS        42      F   -0.245050         4          2
20  49525O29YH        40      M    1.124884         3          2
21  25740R14MI        63      M   -0.930973         4          4
22  84250L43IB        47      F    0.718028         3          3
23  84258G83EV        28      F   -0.903102         2          1
24  53254B39QD        55      F    1.799328         1          4
25  97021A36QC        40      F   -0.358081         1          2
26  47560Z98KV        44      F    0.465200         3          2
27  73529T58NE        64      M   -2.017858         3          4
28  30806A42VM        44      F    0.198266         1          2
29  00049S85RE        43      F    0.555001         1          2
30  26721D43SM        39      M    0.581926         4          2
```

31	82508W18LT	29	F	-0.019113	1	1
32	80438M73AV	63	M	-0.719885	1	4
33	67814A83LG	51	M	-0.175610	2	3
34	87070V97ZO	33	F	-0.657252	3	1
35	79093X41WL	45	F	-0.669774	1	3
36	80170A41DA	58	M	1.649910	2	4
37	92814K57MF	35	M	-0.345982	4	2
38	67811V23ZL	63	F	-0.589992	4	4
39	49928Y38OE	62	F	-0.580599	4	4
40	60766Z46OD	61	F	0.699457	2	4
41	65221A93PY	54	M	-0.735907	2	3
42	67305F19BO	47	M	-0.358554	3	3
43	11497L25KD	56	F	-0.674976	1	4
44	06436U96WN	33	F	-1.114174	3	1
45	00974O72DZ	59	F	-1.016883	1	4
46	09160K49TY	52	F	1.932804	1	3
47	75377M96JT	43	F	0.645703	3	2
48	50391O52JL	27	F	-0.596844	1	1
49	75750M01TD	40	M	0.165158	3	2

	gender_numeric	age_car	age_car_segment	income_standardized
0	0	443	3	0.692730
1	0	335	2	1.327512
2	0	706	4	-0.543383
3	1	706	4	-0.106042
4	1	161	1	-1.001910
5	1	225	2	-0.242212
6	1	288	2	-0.180940
7	1	429	3	0.834322
8	0	521	4	1.444305
9	1	440	3	-2.093765
10	0	62	1	-1.507332
11	1	577	4	0.137720
12	1	15	1	-1.061434
13	1	65	1	-0.434468
14	1	84	1	0.685243
15	1	400	3	1.024824
16	0	37	1	-1.199001
17	1	188	1	-0.936500
18	1	65	1	-0.389229
19	1	989	4	-0.245050
20	0	476	3	1.124884
21	0	712	4	-0.930973
22	1	429	3	0.718028
23	1	260	2	-0.903102
24	1	64	1	1.799328
25	1	13	1	-0.358081
26	1	445	3	0.465200
27	0	409	3	-2.017858

```
28                1      153              1           0.198266
29                1     -121              1           0.555001
30                0      861              4           0.581926
31                1      -61              1          -0.019113
32                0       84              1          -0.719885
33                0      304              2          -0.175610
34                1      409              3          -0.657252
35                1       41              1          -0.669774
36                0      301              2           1.649910
37                0      783              4          -0.345982
38                1      623              4          -0.589992
39                1      643              4          -0.580599
40                1      211              2           0.699457
41                0      350              2          -0.735907
42                0      446              3          -0.358554
43                1      102              1          -0.674976
44                1      423              3          -1.114174
45                1      131              1          -1.016883
46                1       98              1           1.932804
47                1      428              3           0.645703
48                1       92              1          -0.596844
49                0      477              3           0.165158
```

```python
# Count the number of rows in the indian_df
total_count = indian_df.shape[0]

# Display the count
print(f'Total number of records in indian_df: {total_count}')

# Optionally, you can also count the number of records for each column
data_count = indian_df.count()

# Display the count for each column
print("\nCount of non-null entries in each column:")
print(data_count)
```

```
Total number of records in indian_df: 70000

Count of non-null entries in each column:
ID                       70000
CURR_AGE                 70000
GENDER                   70000
ANN_INCOME               70000
DT_MAINT                 70000
age_group                70000
gender_numeric           70000
age_car                  70000
age_car_segment          70000
income_standardized      70000
dtype: int64
```

```python
# Defined features and target variables for the Japanese dataset
X_japanese = japanese_df[['CURR_AGE', 'gender_numeric',
'ANN_INCOME_INR', 'age_car_segment']]
y_japanese = japanese_df['PURCHASE']

# Split the Japanese dataset
X_train_japanese, X_test_japanese, y_train_japanese, y_test_japanese =
train_test_split(X_japanese, y_japanese, test_size=0.3,
random_state=42)

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the training data, and transform the testing data
X_train_japanese = scaler.fit_transform(X_train_japanese)
X_test_japanese = scaler.transform(X_test_japanese)

# Initialize the Logistic Regression model
model_japanese = LogisticRegression()

# Train the model
model_japanese.fit(X_train_japanese, y_train_japanese)

# Predict on the test set
y_pred_japanese = model_japanese.predict(X_test_japanese)

# Evaluate the model
print("Japanese Dataset Classification Report:")
print(classification_report(y_test_japanese, y_pred_japanese))
print("Accuracy:", accuracy_score(y_test_japanese, y_pred_japanese))
print("Confusion Matrix:")
print(confusion_matrix(y_test_japanese, y_pred_japanese))
print("ROC AUC Score:", roc_auc_score(y_test_japanese,
model_japanese.predict_proba(X_test_japanese)[:, 1]))
```

```
Japanese Dataset Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.60      0.62      5013
           1       0.72      0.76      0.74      6987

    accuracy                           0.69     12000
   macro avg       0.68      0.68      0.68     12000
weighted avg       0.69      0.69      0.69     12000

Accuracy: 0.69
Confusion Matrix:
[[2984 2029]
```

```
 [1691 5296]]
ROC AUC Score: 0.7500105422195408
```

```python
# Get feature importance
importance = model_japanese.coef_[0]
feature_names = X_japanese.columns

# Create a DataFrame for better visualization
importance_df = pd.DataFrame({'Feature': feature_names, 'Importance':
importance})
importance_df = importance_df.sort_values(by='Importance',
ascending=False)
print(importance_df)
```

```
           Feature  Importance
3  age_car_segment    0.872753
2   ANN_INCOME_INR    0.423752
0         CURR_AGE   -0.117223
1   gender_numeric   -0.118834
```

```python
# Import necessary libraries
from sklearn.metrics import precision_score, recall_score,
accuracy_score, roc_auc_score

# Evaluate model performance at different cutoffs
cutoffs = np.arange(0.01, 1, 0.01)  # Define cutoff values from 0.01
to 0.99
accuracy_jp = []
precision_jp = []
recall_jp = []
roc_auc_jp = []

# Loop through each cutoff value and calculate performance metrics
for cutoff in cutoffs:
    y_pred_jp = np.where(y_probs_jp > cutoff, 1, 0)  # Assign class
labels based on cutoff

    acc = accuracy_score(y_test_jp, y_pred_jp)
    prec = precision_score(y_test_jp, y_pred_jp, zero_division=0)  #
Avoid undefined precision
    rec = recall_score(y_test_jp, y_pred_jp)
    roc_auc = roc_auc_score(y_test_jp, y_probs_jp)

    accuracy_jp.append(acc)
    precision_jp.append(prec)
    recall_jp.append(rec)
    roc_auc_jp.append(roc_auc)

    # Print the cutoff value and corresponding performance metrics
    print(f"Cutoff: {cutoff:.2f} | Accuracy: {acc:.4f} | Precision:
```

```
{prec:.4f} | Recall: {rec:.4f} | ROC-AUC: {roc_auc:.4f}")

# Find the best cutoff based on desired metric (e.g., accuracy)
best_cutoff_index_jp = np.argmax(accuracy_jp)  # You can change this
to precision/recall depending on the metric
best_cutoff_jp = cutoffs[best_cutoff_index_jp]

print(f"\nBest cutoff value based on accuracy for Japanese dataset:
{best_cutoff_jp:.2f}")
```

```
Cutoff: 0.01 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.02 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.03 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.04 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.05 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.06 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.07 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.08 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.09 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.10 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.11 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.12 | Accuracy: 0.5823 | Precision: 0.5823 | Recall: 1.0000 |
ROC-AUC: 0.7493
Cutoff: 0.13 | Accuracy: 0.5824 | Precision: 0.5824 | Recall: 0.9997 |
ROC-AUC: 0.7493
Cutoff: 0.14 | Accuracy: 0.5847 | Precision: 0.5837 | Recall: 0.9994 |
ROC-AUC: 0.7493
Cutoff: 0.15 | Accuracy: 0.5877 | Precision: 0.5855 | Recall: 0.9989 |
ROC-AUC: 0.7493
Cutoff: 0.16 | Accuracy: 0.5906 | Precision: 0.5873 | Recall: 0.9981 |
ROC-AUC: 0.7493
Cutoff: 0.17 | Accuracy: 0.5934 | Precision: 0.5891 | Recall: 0.9970 |
ROC-AUC: 0.7493
Cutoff: 0.18 | Accuracy: 0.5958 | Precision: 0.5907 | Recall: 0.9963 |
ROC-AUC: 0.7493
Cutoff: 0.19 | Accuracy: 0.5979 | Precision: 0.5922 | Recall: 0.9934 |
ROC-AUC: 0.7493
Cutoff: 0.20 | Accuracy: 0.6012 | Precision: 0.5944 | Recall: 0.9923 |
ROC-AUC: 0.7493
```

```
Cutoff: 0.21 | Accuracy: 0.6045 | Precision: 0.5966 | Recall: 0.9901 |
ROC-AUC: 0.7493
Cutoff: 0.22 | Accuracy: 0.6102 | Precision: 0.6005 | Recall: 0.9874 |
ROC-AUC: 0.7493
Cutoff: 0.23 | Accuracy: 0.6152 | Precision: 0.6040 | Recall: 0.9847 |
ROC-AUC: 0.7493
Cutoff: 0.24 | Accuracy: 0.6174 | Precision: 0.6062 | Recall: 0.9785 |
ROC-AUC: 0.7493
Cutoff: 0.25 | Accuracy: 0.6204 | Precision: 0.6089 | Recall: 0.9729 |
ROC-AUC: 0.7493
Cutoff: 0.26 | Accuracy: 0.6224 | Precision: 0.6110 | Recall: 0.9672 |
ROC-AUC: 0.7493
Cutoff: 0.27 | Accuracy: 0.6248 | Precision: 0.6134 | Recall: 0.9615 |
ROC-AUC: 0.7493
Cutoff: 0.28 | Accuracy: 0.6255 | Precision: 0.6150 | Recall: 0.9541 |
ROC-AUC: 0.7493
Cutoff: 0.29 | Accuracy: 0.6306 | Precision: 0.6193 | Recall: 0.9485 |
ROC-AUC: 0.7493
Cutoff: 0.30 | Accuracy: 0.6338 | Precision: 0.6226 | Recall: 0.9420 |
ROC-AUC: 0.7493
Cutoff: 0.31 | Accuracy: 0.6381 | Precision: 0.6261 | Recall: 0.9393 |
ROC-AUC: 0.7493
Cutoff: 0.32 | Accuracy: 0.6401 | Precision: 0.6284 | Recall: 0.9346 |
ROC-AUC: 0.7493
Cutoff: 0.33 | Accuracy: 0.6435 | Precision: 0.6316 | Recall: 0.9302 |
ROC-AUC: 0.7493
Cutoff: 0.34 | Accuracy: 0.6456 | Precision: 0.6339 | Recall: 0.9260 |
ROC-AUC: 0.7493
Cutoff: 0.35 | Accuracy: 0.6476 | Precision: 0.6361 | Recall: 0.9226 |
ROC-AUC: 0.7493
Cutoff: 0.36 | Accuracy: 0.6512 | Precision: 0.6396 | Recall: 0.9181 |
ROC-AUC: 0.7493
Cutoff: 0.37 | Accuracy: 0.6538 | Precision: 0.6427 | Recall: 0.9127 |
ROC-AUC: 0.7493
Cutoff: 0.38 | Accuracy: 0.6584 | Precision: 0.6475 | Recall: 0.9071 |
ROC-AUC: 0.7493
Cutoff: 0.39 | Accuracy: 0.6628 | Precision: 0.6524 | Recall: 0.9011 |
ROC-AUC: 0.7493
Cutoff: 0.40 | Accuracy: 0.6675 | Precision: 0.6578 | Recall: 0.8941 |
ROC-AUC: 0.7493
Cutoff: 0.41 | Accuracy: 0.6719 | Precision: 0.6637 | Recall: 0.8849 |
ROC-AUC: 0.7493
Cutoff: 0.42 | Accuracy: 0.6750 | Precision: 0.6694 | Recall: 0.8728 |
ROC-AUC: 0.7493
Cutoff: 0.43 | Accuracy: 0.6793 | Precision: 0.6764 | Recall: 0.8612 |
ROC-AUC: 0.7493
Cutoff: 0.44 | Accuracy: 0.6827 | Precision: 0.6831 | Recall: 0.8490 |
ROC-AUC: 0.7493
Cutoff: 0.45 | Accuracy: 0.6845 | Precision: 0.6893 | Recall: 0.8343 |
```

```
ROC-AUC: 0.7493
Cutoff: 0.46 | Accuracy: 0.6831 | Precision: 0.6934 | Recall: 0.8169 |
ROC-AUC: 0.7493
Cutoff: 0.47 | Accuracy: 0.6844 | Precision: 0.6993 | Recall: 0.8035 |
ROC-AUC: 0.7493
Cutoff: 0.48 | Accuracy: 0.6855 | Precision: 0.7055 | Recall: 0.7895 |
ROC-AUC: 0.7493
Cutoff: 0.49 | Accuracy: 0.6884 | Precision: 0.7145 | Recall: 0.7742 |
ROC-AUC: 0.7493
Cutoff: 0.50 | Accuracy: 0.6913 | Precision: 0.7237 | Recall: 0.7598 |
ROC-AUC: 0.7493
Cutoff: 0.51 | Accuracy: 0.6903 | Precision: 0.7310 | Recall: 0.7407 |
ROC-AUC: 0.7493
Cutoff: 0.52 | Accuracy: 0.6880 | Precision: 0.7377 | Recall: 0.7202 |
ROC-AUC: 0.7493
Cutoff: 0.53 | Accuracy: 0.6888 | Precision: 0.7453 | Recall: 0.7073 |
ROC-AUC: 0.7493
Cutoff: 0.54 | Accuracy: 0.6898 | Precision: 0.7531 | Recall: 0.6951 |
ROC-AUC: 0.7493
Cutoff: 0.55 | Accuracy: 0.6897 | Precision: 0.7588 | Recall: 0.6846 |
ROC-AUC: 0.7493
Cutoff: 0.56 | Accuracy: 0.6880 | Precision: 0.7646 | Recall: 0.6705 |
ROC-AUC: 0.7493
Cutoff: 0.57 | Accuracy: 0.6881 | Precision: 0.7705 | Recall: 0.6612 |
ROC-AUC: 0.7493
Cutoff: 0.58 | Accuracy: 0.6866 | Precision: 0.7745 | Recall: 0.6514 |
ROC-AUC: 0.7493
Cutoff: 0.59 | Accuracy: 0.6853 | Precision: 0.7791 | Recall: 0.6415 |
ROC-AUC: 0.7493
Cutoff: 0.60 | Accuracy: 0.6836 | Precision: 0.7827 | Recall: 0.6320 |
ROC-AUC: 0.7493
Cutoff: 0.61 | Accuracy: 0.6817 | Precision: 0.7878 | Recall: 0.6206 |
ROC-AUC: 0.7493
Cutoff: 0.62 | Accuracy: 0.6793 | Precision: 0.7925 | Recall: 0.6084 |
ROC-AUC: 0.7493
Cutoff: 0.63 | Accuracy: 0.6770 | Precision: 0.7980 | Recall: 0.5961 |
ROC-AUC: 0.7493
Cutoff: 0.64 | Accuracy: 0.6736 | Precision: 0.8025 | Recall: 0.5828 |
ROC-AUC: 0.7493
Cutoff: 0.65 | Accuracy: 0.6676 | Precision: 0.8070 | Recall: 0.5639 |
ROC-AUC: 0.7493
Cutoff: 0.66 | Accuracy: 0.6606 | Precision: 0.8112 | Recall: 0.5436 |
ROC-AUC: 0.7493
Cutoff: 0.67 | Accuracy: 0.6521 | Precision: 0.8138 | Recall: 0.5218 |
ROC-AUC: 0.7493
Cutoff: 0.68 | Accuracy: 0.6458 | Precision: 0.8201 | Recall: 0.5018 |
ROC-AUC: 0.7493
Cutoff: 0.69 | Accuracy: 0.6370 | Precision: 0.8236 | Recall: 0.4792 |
ROC-AUC: 0.7493
```

```
Cutoff: 0.70 | Accuracy: 0.6285 | Precision: 0.8301 | Recall: 0.4551 |
ROC-AUC: 0.7493
Cutoff: 0.71 | Accuracy: 0.6184 | Precision: 0.8337 | Recall: 0.4305 |
ROC-AUC: 0.7493
Cutoff: 0.72 | Accuracy: 0.6098 | Precision: 0.8398 | Recall: 0.4075 |
ROC-AUC: 0.7493
Cutoff: 0.73 | Accuracy: 0.5991 | Precision: 0.8474 | Recall: 0.3798 |
ROC-AUC: 0.7493
Cutoff: 0.74 | Accuracy: 0.5873 | Precision: 0.8536 | Recall: 0.3514 |
ROC-AUC: 0.7493
Cutoff: 0.75 | Accuracy: 0.5777 | Precision: 0.8582 | Recall: 0.3290 |
ROC-AUC: 0.7493
Cutoff: 0.76 | Accuracy: 0.5701 | Precision: 0.8662 | Recall: 0.3094 |
ROC-AUC: 0.7493
Cutoff: 0.77 | Accuracy: 0.5622 | Precision: 0.8717 | Recall: 0.2908 |
ROC-AUC: 0.7493
Cutoff: 0.78 | Accuracy: 0.5541 | Precision: 0.8794 | Recall: 0.2714 |
ROC-AUC: 0.7493
Cutoff: 0.79 | Accuracy: 0.5463 | Precision: 0.8836 | Recall: 0.2542 |
ROC-AUC: 0.7493
Cutoff: 0.80 | Accuracy: 0.5377 | Precision: 0.8842 | Recall: 0.2372 |
ROC-AUC: 0.7493
Cutoff: 0.81 | Accuracy: 0.5293 | Precision: 0.8828 | Recall: 0.2210 |
ROC-AUC: 0.7493
Cutoff: 0.82 | Accuracy: 0.5228 | Precision: 0.8814 | Recall: 0.2084 |
ROC-AUC: 0.7493
Cutoff: 0.83 | Accuracy: 0.5155 | Precision: 0.8876 | Recall: 0.1922 |
ROC-AUC: 0.7493
Cutoff: 0.84 | Accuracy: 0.5060 | Precision: 0.8972 | Recall: 0.1712 |
ROC-AUC: 0.7493
Cutoff: 0.85 | Accuracy: 0.4944 | Precision: 0.9000 | Recall: 0.1481 |
ROC-AUC: 0.7493
Cutoff: 0.86 | Accuracy: 0.4823 | Precision: 0.9006 | Recall: 0.1245 |
ROC-AUC: 0.7493
Cutoff: 0.87 | Accuracy: 0.4707 | Precision: 0.9034 | Recall: 0.1018 |
ROC-AUC: 0.7493
Cutoff: 0.88 | Accuracy: 0.4599 | Precision: 0.9161 | Recall: 0.0797 |
ROC-AUC: 0.7493
Cutoff: 0.89 | Accuracy: 0.4528 | Precision: 0.9218 | Recall: 0.0658 |
ROC-AUC: 0.7493
Cutoff: 0.90 | Accuracy: 0.4478 | Precision: 0.9188 | Recall: 0.0567 |
ROC-AUC: 0.7493
Cutoff: 0.91 | Accuracy: 0.4449 | Precision: 0.9179 | Recall: 0.0512 |
ROC-AUC: 0.7493
Cutoff: 0.92 | Accuracy: 0.4397 | Precision: 0.9122 | Recall: 0.0416 |
ROC-AUC: 0.7493
Cutoff: 0.93 | Accuracy: 0.4343 | Precision: 0.9160 | Recall: 0.0312 |
ROC-AUC: 0.7493
Cutoff: 0.94 | Accuracy: 0.4278 | Precision: 0.9054 | Recall: 0.0192 |
```

```
ROC-AUC: 0.7493
Cutoff: 0.95 | Accuracy: 0.4206 | Precision: 0.9250 | Recall: 0.0053 |
ROC-AUC: 0.7493
Cutoff: 0.96 | Accuracy: 0.4178 | Precision: 0.0000 | Recall: 0.0000 |
ROC-AUC: 0.7493
Cutoff: 0.97 | Accuracy: 0.4178 | Precision: 0.0000 | Recall: 0.0000 |
ROC-AUC: 0.7493
Cutoff: 0.98 | Accuracy: 0.4178 | Precision: 0.0000 | Recall: 0.0000 |
ROC-AUC: 0.7493
Cutoff: 0.99 | Accuracy: 0.4178 | Precision: 0.0000 | Recall: 0.0000 |
ROC-AUC: 0.7493

Best cutoff value based on accuracy for Japanese dataset: 0.50
```

```
# Prepare your features and target variable
X_jp = japanese_df[['age_group', 'gender_numeric', 'age_car_segment',
'income_standardized']]
y_jp = japanese_df['PURCHASE']  # Replace with your target column name

# Split the dataset into training and testing sets
X_train_jp, X_test_jp, y_train_jp, y_test_jp = train_test_split(X_jp,
y_jp, test_size=0.2, random_state=42)

# Create and fit the logistic regression model
model_jp = LogisticRegression()
model_jp.fit(X_train_jp, y_train_jp)

# Get the intercept and coefficients
intercept_jp = model_jp.intercept_[0]  # Get the intercept
coefficients_jp = model_jp.coef_[0]  # Get the coefficients for each
feature

# Create a dictionary to display the intercept and coefficients
coefficients_dict_jp = {
    'Intercept': intercept_jp,
    'age_group': coefficients_jp[0],
    'gender_numeric': coefficients_jp[1],
    'age_car_segment': coefficients_jp[2],
    'income_standardized': coefficients_jp[3]
}

# Display the results
coefficients_df_jp = pd.DataFrame(coefficients_dict_jp, index=[0])
print("Intercept and Coefficients for the Japanese Dataset:")
print(coefficients_df_jp)
```

```
Intercept and Coefficients for the Japanese Dataset:
   Intercept  age_group  gender_numeric  age_car_segment
income_standardized
```

```
0  -1.573318  -0.099991       -0.229322         0.96041
0.419205



import numpy as np

# Coefficients from the logistic regression model trained on the
Japanese dataset
intercept_jp = -1.573318
coeff_age_group_jp = -0.099991
coeff_gender_jp = -0.229322
coeff_age_car_segment_jp = 0.96041
coeff_income_standardized_jp = 0.419205

# Function to calculate probability for each row using coefficients
from the Japanese dataset
def calculate_purchase_probability_jp(age_group, gender_numeric,
income_standardized, age_car_segment):
    # Logistic regression equation
    logit = (intercept_jp
             + coeff_age_group_jp * age_group
             + coeff_gender_jp * gender_numeric
             + coeff_income_standardized_jp * income_standardized
             + coeff_age_car_segment_jp * age_car_segment)

    # Apply logistic function
    probability = 1 / (1 + np.exp(-logit))

    return round(probability, 2)  # Round to 2 decimal places for
better precision

# Apply the function to the entire Indian dataset (indian_df)
indian_df['purchase_probability'] = indian_df.apply(
    lambda row: calculate_purchase_probability_jp(row['age_group'],

row['gender_numeric'],

row['income_standardized'],

row['age_car_segment']),
    axis=1
)

# View the first 5 rows of the updated dataframe
print(indian_df.head(5))

# Optionally, save the updated dataframe with probabilities to Excel
indian_df.to_excel("indian_df_with_purchase_probabilities.xlsx",
index=False)
```

```
            ID  CURR_AGE GENDER  ANN_INCOME  DT_MAINT  age_group  \
0  20710B05XL        54      M    0.692730         3          3
1  89602T51HX        47      M    1.327512         2          3
2  70190Z52IP        60      M   -0.543383         4          4
3  25623V15MU        55      F   -0.106042         4          4
4  36230I68CE        32      F   -1.001910         1          1

   gender_numeric  age_car  age_car_segment  income_standardized  \
0               0      443                3             0.692730
1               0      335                2             1.327512
2               0      706                4            -0.543383
3               1      706                4            -0.106042
4               1      161                1            -1.001910

   purchase_probability  purchase
0                  0.79         1
1                  0.65         1
2                  0.84         1
3                  0.83         1
4                  0.20         1

# Apply the if-else condition to assign 1 or 0 based on the cutoff
value of 0.2
indian_df['purchase'] = indian_df['purchase_probability'].apply(lambda
x: 1 if x > 0.2 else 0)

# Show the first 50 rows with the new 'purchase' column
print(indian_df[['CURR_AGE', 'gender_numeric', 'ANN_INCOME',
'age_car_segment', 'purchase_probability', 'purchase']].head(50))

# Optionally, save the updated dataframe to Excel
indian_df.to_excel("indian_df_with_purchase_predictions.xlsx",
index=False)


    CURR_AGE  gender_numeric  ANN_INCOME  age_car_segment  \
0         54               0    0.692730                3
1         47               0    1.327512                2
2         60               0   -0.543383                4
3         55               1   -0.106042                4
4         32               1   -1.001910                1
5         48               1   -0.242212                2
6         26               1   -0.180940                2
7         45               1    0.834322                3
8         55               0    1.444305                4
9         64               1   -2.093765                3
10        53               0   -1.507332                1
11        44               1    0.137720                4
12        59               1   -1.061434                1
13        27               1   -0.434468                1
```

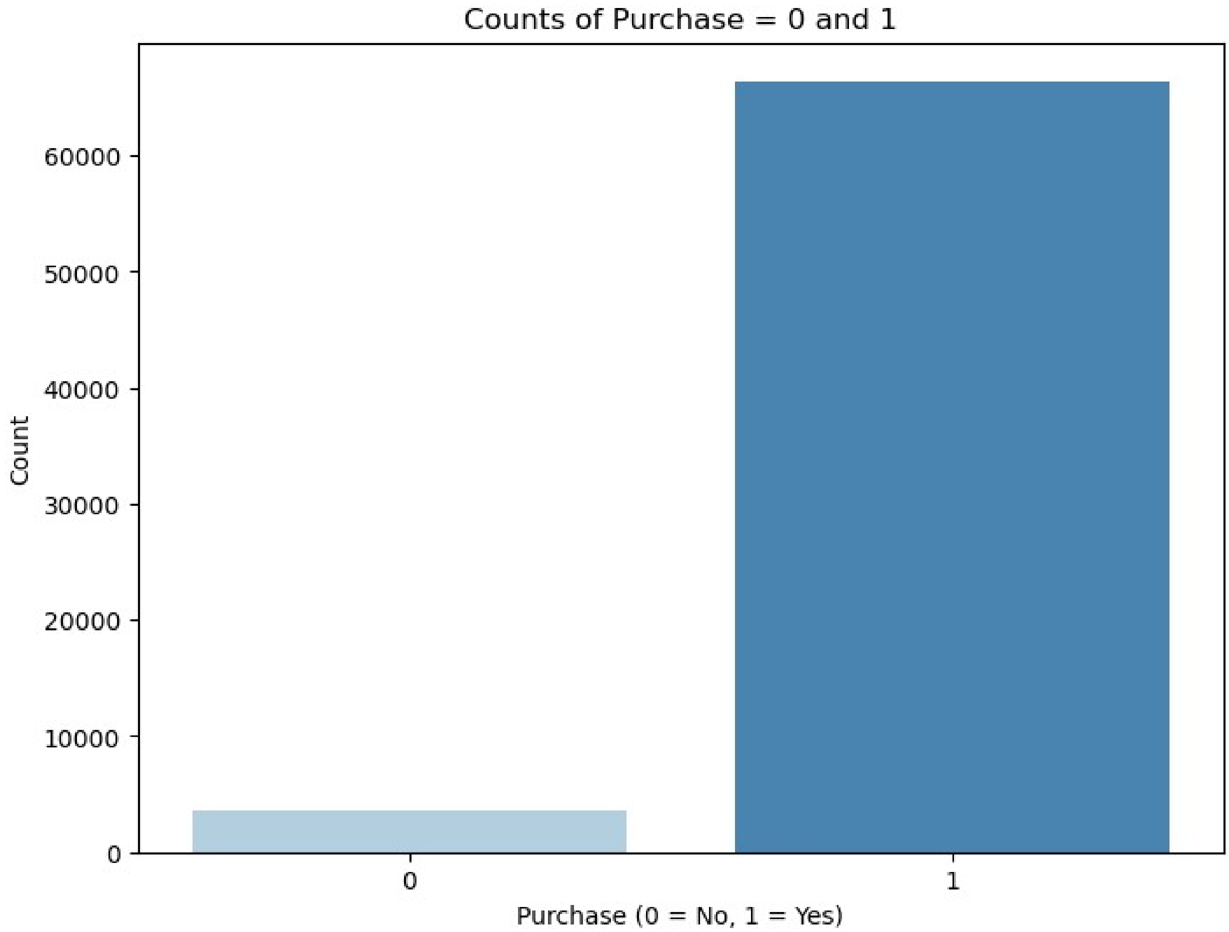
```
14        57                1    0.685243                 1
15        40                1    1.024824                 3
16        33                0   -1.199001                 1
17        57                1   -0.936500                 1
18        59                1   -0.389229                 1
19        42                1   -0.245050                 4
20        40                0    1.124884                 3
21        63                0   -0.930973                 4
22        47                1    0.718028                 3
23        28                1   -0.903102                 2
24        55                1    1.799328                 1
25        40                1   -0.358081                 1
26        44                1    0.465200                 3
27        64                0   -2.017858                 3
28        44                1    0.198266                 1
29        43                1    0.555001                 1
30        39                0    0.581926                 4
31        29                1   -0.019113                 1
32        63                0   -0.719885                 1
33        51                0   -0.175610                 2
34        33                1   -0.657252                 3
35        45                1   -0.669774                 1
36        58                0    1.649910                 2
37        35                0   -0.345982                 4
38        63                1   -0.589992                 4
39        62                1   -0.580599                 4
40        61                1    0.699457                 2
41        54                0   -0.735907                 2
42        47                0   -0.358554                 3
43        56                1   -0.674976                 1
44        33                1   -1.114174                 3
45        59                1   -1.016883                 1
46        52                1    1.932804                 1
47        43                1    0.645703                 3
48        27                1   -0.596844                 1
49        40                0    0.165158                 3

    purchase_probability  purchase
0                   0.79         1
1                   0.65         1
2                   0.84         1
3                   0.83         1
4                   0.20         0
5                   0.43         1
6                   0.49         1
7                   0.76         1
8                   0.92         1
9                   0.45         1
10                  0.18         0
```

```
11                    0.87         1
12                    0.16         0
13                    0.25         1
14                    0.28         1
15                    0.79         1
16                    0.23         1
17                    0.16         0
18                    0.20         0
19                    0.85         1
20                    0.83         1
21                    0.81         1
22                    0.75         1
23                    0.41         1
24                    0.38         1
25                    0.23         1
26                    0.75         1
27                    0.52         1
28                    0.28         1
29                    0.31         1
30                    0.91         1
31                    0.28         1
32                    0.21         1
33                    0.49         1
34                    0.67         1
35                    0.19         0
36                    0.65         1
37                    0.87         1
38                    0.80         1
39                    0.80         1
40                    0.50         1
41                    0.44         1
42                    0.70         1
43                    0.18         0
44                    0.63         1
45                    0.16         0
46                    0.42         1
47                    0.76         1
48                    0.23         1
49                    0.76         1
```

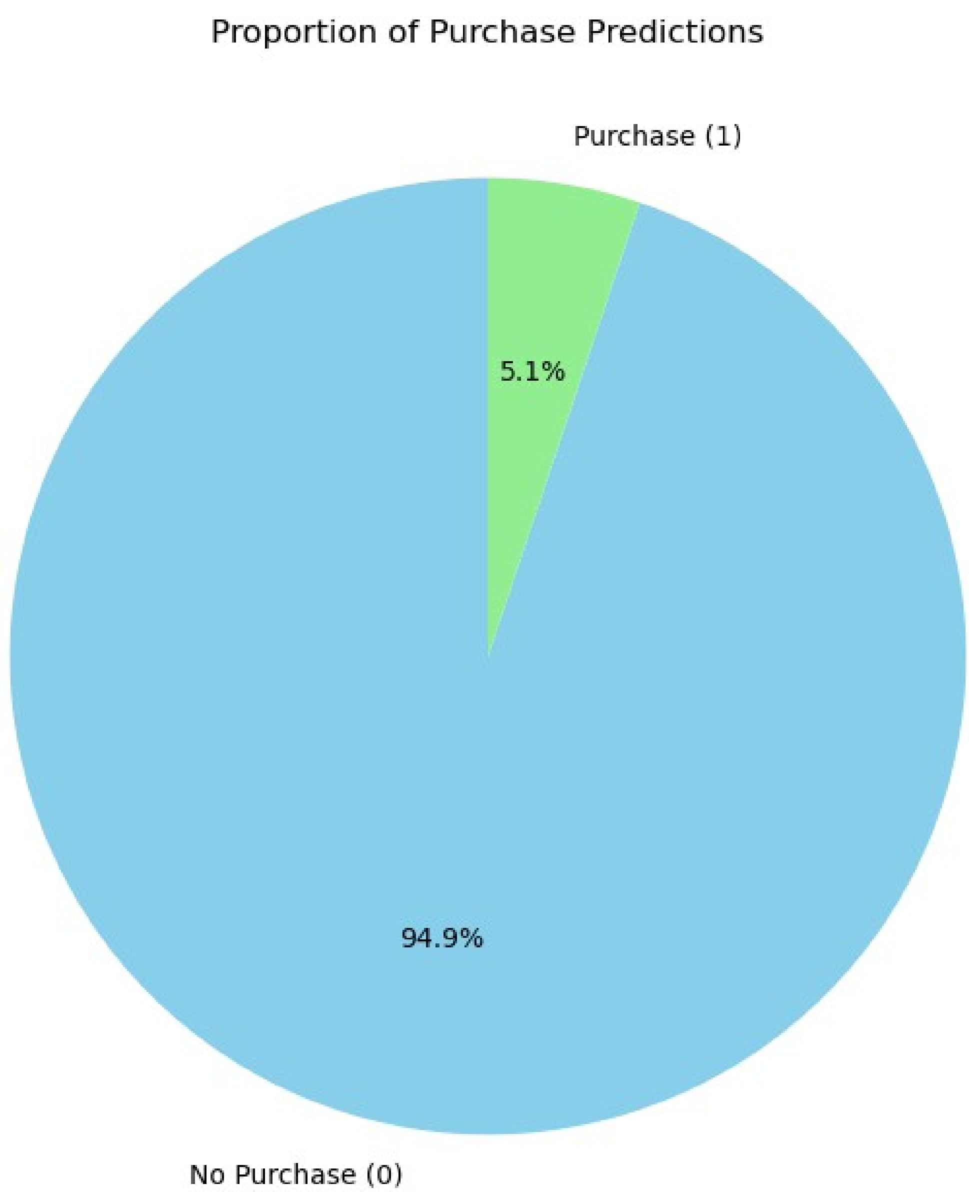
```
# Count the occurrences of 0 and 1 in the 'purchase' column
purchase_counts = indian_df['purchase'].value_counts()

# Print the count of 0 and 1
print("Count of Purchase = 0:", purchase_counts[0])
print("Count of Purchase = 1:", purchase_counts[1])
```

```
Count of Purchase = 0: 3601
Count of Purchase = 1: 66399
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# Bar plot of purchase counts
plt.figure(figsize=(8, 6))
sns.countplot(x='purchase', data=indian_df, palette='Blues')
plt.title('Counts of Purchase = 0 and 1')
plt.xlabel('Purchase (0 = No, 1 = Yes)')
plt.ylabel('Count')
plt.show()
```



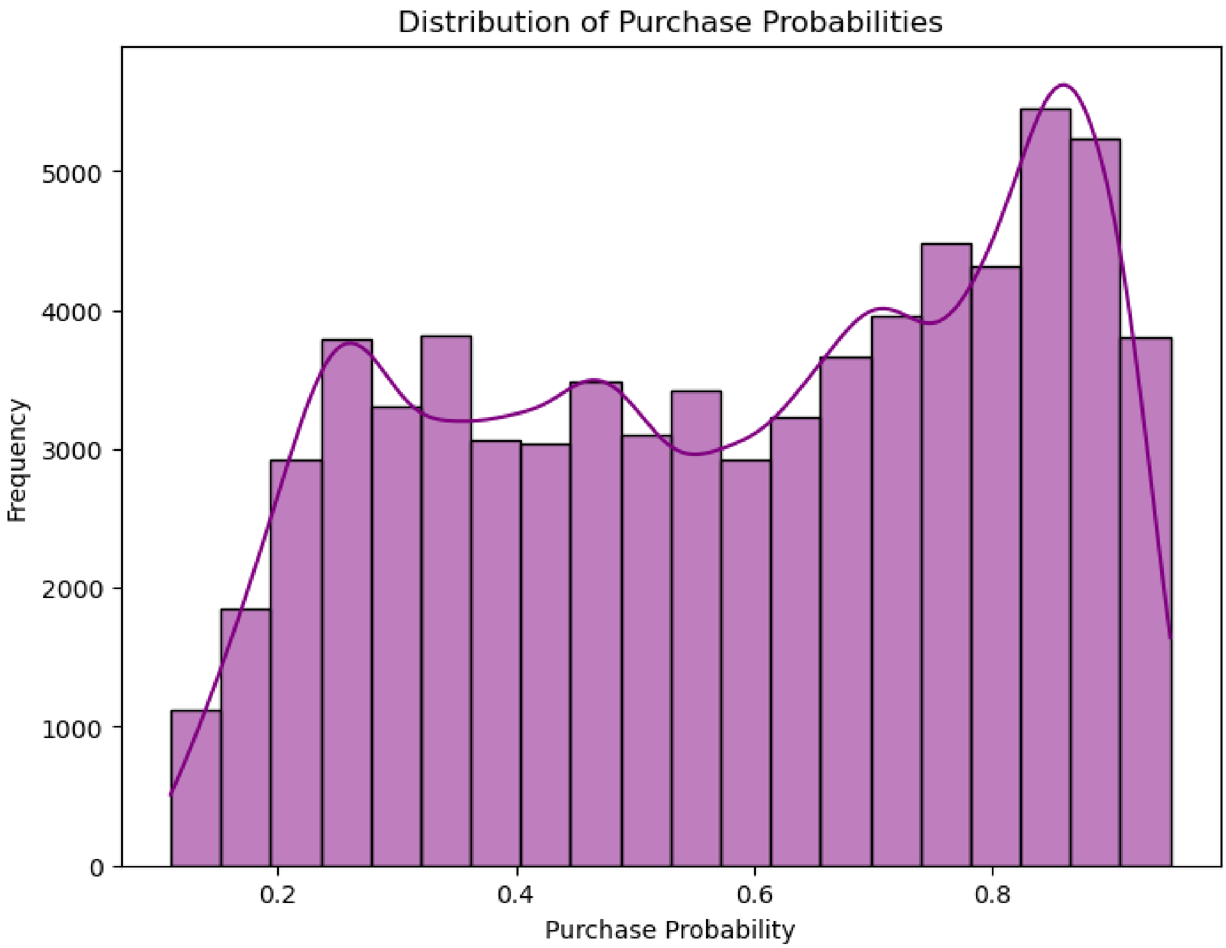

```
# Pie chart for purchase proportions
purchase_counts = indian_df['purchase'].value_counts()
plt.figure(figsize=(8, 8))
plt.pie(purchase_counts, labels=['No Purchase (0)', 'Purchase (1)'],
autopct='%1.1f%%', startangle=90, colors=['skyblue', 'lightgreen'])
plt.title('Proportion of Purchase Predictions')
plt.show()
```



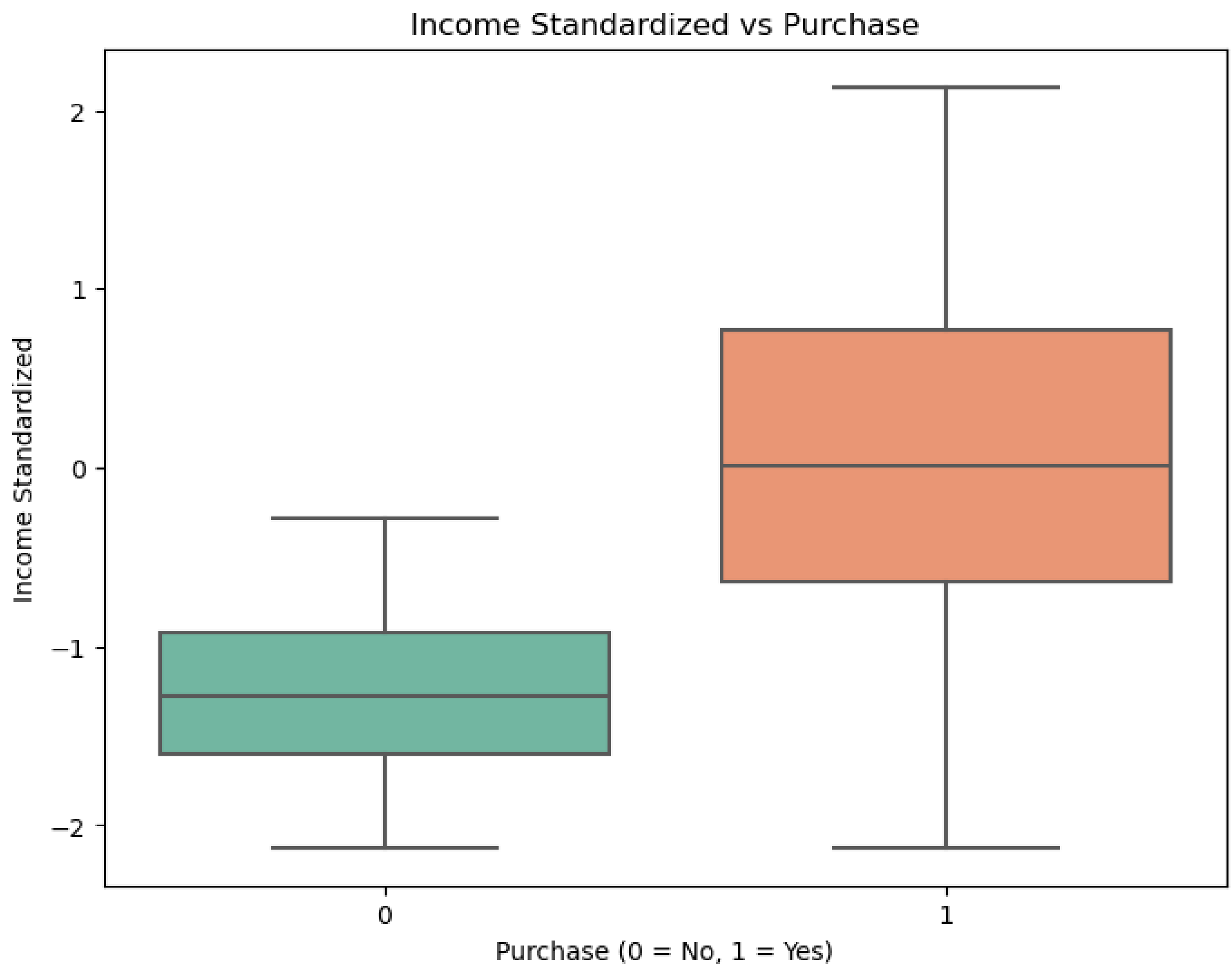

```
# Histogram of purchase probabilities
plt.figure(figsize=(8, 6))
sns.histplot(indian_df['purchase_probability'], bins=20, kde=True,
color='purple')
plt.title('Distribution of Purchase Probabilities')
plt.xlabel('Purchase Probability')
plt.ylabel('Frequency')
plt.show()

# Replace infinite values in the dataset with NaN
indian_df.replace([np.inf, -np.inf], np.nan, inplace=True)
```

```
# After replacing, you might also want to drop rows with NaN values or
fill them:
# Drop rows with NaN values (optional)
indian_df.dropna(inplace=True)
```

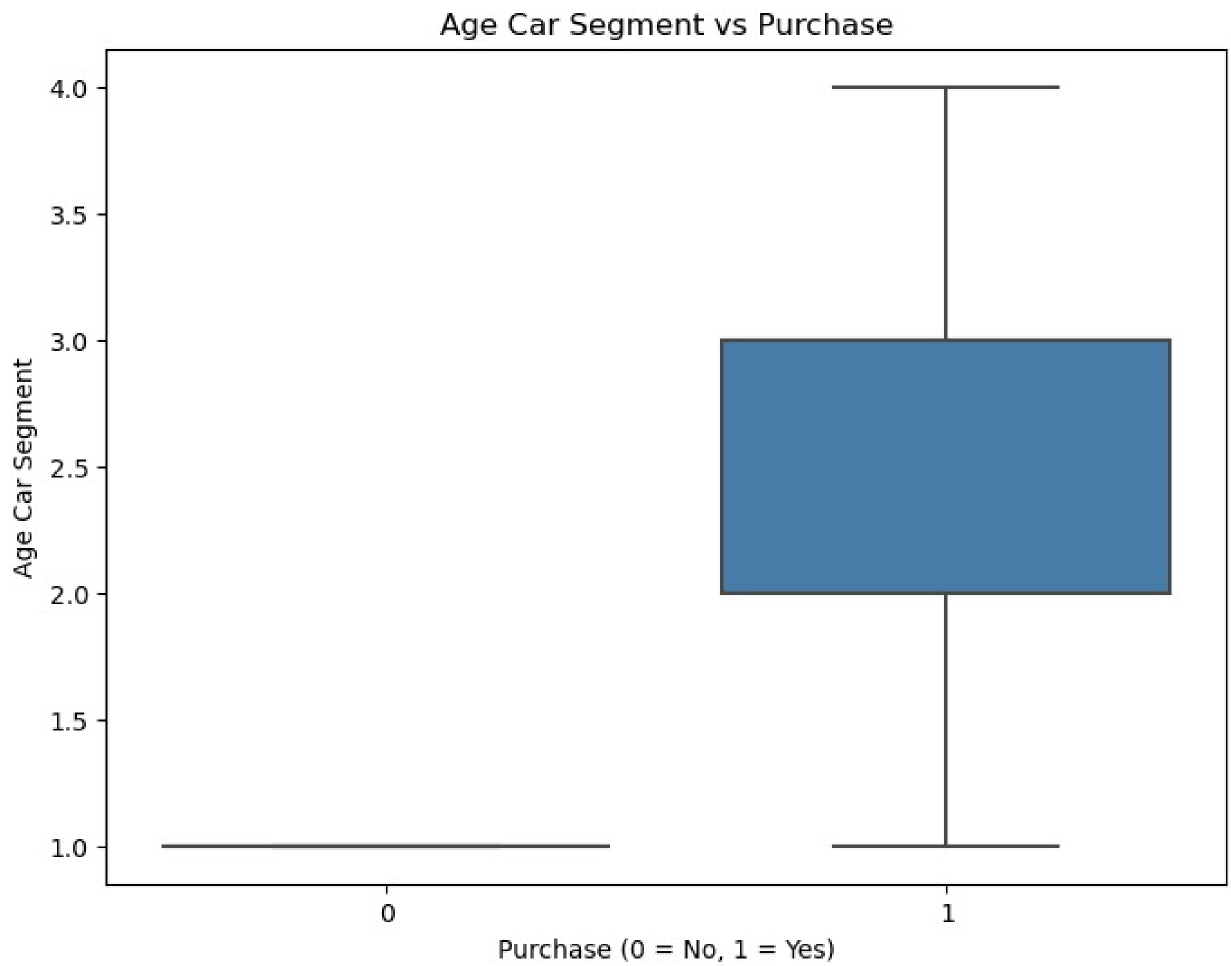
```
C:\Users\chakr\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed
in a future version. Convert inf values to NaN before operating
instead.
  with pd.option_context('mode.use_inf_as_na', True):
```




```
# Box plot of income_standardized vs purchase
plt.figure(figsize=(8, 6))
sns.boxplot(x='purchase', y='income_standardized', data=indian_df,
palette='Set2')
plt.title('Income Standardized vs Purchase')
plt.xlabel('Purchase (0 = No, 1 = Yes)')
plt.ylabel('Income Standardized')
plt.show()
```




```
# Box plot of age_car_segment vs purchase
plt.figure(figsize=(8, 6))
sns.boxplot(x='purchase', y='age_car_segment', data=indian_df,
palette='Set1')
plt.title('Age Car Segment vs Purchase')
plt.xlabel('Purchase (0 = No, 1 = Yes)')
plt.ylabel('Age Car Segment')
plt.show()
```


Age Car Segment vs Purchase
4.0
3.5
3.0
2.5
2.0
1.5
1.0
Age Car Segment
0
1
Purchase (0 = No, 1 = Yes)