AML_Group_18_Section_2_FinalProject

April 29, 2023

[ ]:
```
!pip install category_encoders
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Collecting category_encoders
  Downloading category_encoders-2.6.0-py2.py3-none-any.whl (81 kB)
                           81.2/81.2 kB
9.0 MB/s eta 0:00:00
Requirement already satisfied: statsmodels>=0.9.0 in
/usr/local/lib/python3.9/dist-packages (from category_encoders) (0.13.5)
Requirement already satisfied: patsy>=0.5.1 in /usr/local/lib/python3.9/dist-
packages (from category_encoders) (0.5.3)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.9/dist-
packages (from category_encoders) (1.22.4)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.9/dist-
packages (from category_encoders) (1.10.1)
Requirement already satisfied: scikit-learn>=0.20.0 in
/usr/local/lib/python3.9/dist-packages (from category_encoders) (1.2.2)
Requirement already satisfied: pandas>=1.0.5 in /usr/local/lib/python3.9/dist-
packages (from category_encoders) (1.5.3)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.9/dist-packages (from pandas>=1.0.5->category_encoders)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.9/dist-
packages (from pandas>=1.0.5->category_encoders) (2022.7.1)
Requirement already satisfied: six in /usr/local/lib/python3.9/dist-packages
(from patsy>=0.5.1->category_encoders) (1.16.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.9/dist-packages (from scikit-
learn>=0.20.0->category_encoders) (3.1.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.9/dist-
packages (from scikit-learn>=0.20.0->category_encoders) (1.2.0)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.9/dist-
packages (from statsmodels>=0.9.0->category_encoders) (23.1)
Installing collected packages: category_encoders
Successfully installed category_encoders-2.6.0
```

```
[ ]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     import warnings
     from sklearn.preprocessing import KBinsDiscretizer, OneHotEncoder,␣
      ↪StandardScaler
     warnings.filterwarnings('ignore')
```

```
[ ]: !ls
```

```
sample_data
```

```
[ ]: from google.colab import drive
     drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

```
[ ]: !ls
```

```
drive   sample_data
```

```
[ ]: loan_data = data = pd.read_excel('/content/drive/MyDrive/
      ↪AML_FinalProject_Group18/Bank_Personal_Loan_Modelling.xlsx','Data')
```

1 Exploratory Data Analysis

```
[ ]: loan_data.head()
```

```
[ ]:    ID  Age  Experience  Income  ZIP Code  Family  CCAvg  Education  Mortgage  \
     0   1   25           1      49     91107       4    1.6          1         0
     1   2   45          19      34     90089       3    1.5          1         0
     2   3   39          15      11     94720       1    1.0          1         0
     3   4   35           9     100     94112       1    2.7          2         0
     4   5   35           8      45     91330       4    1.0          2         0

        Personal Loan  Securities Account  CD Account  Online  CreditCard
     0              0                   1           0       0           0
     1              0                   1           0       0           0
     2              0                   0           0       0           0
     3              0                   0           0       0           0
     4              0                   0           0       0           1
```

```
[ ]: loan_data.shape
```

```
[ ]: (5000, 14)
```

[ ]:
```
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 14 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   ID                  5000 non-null   int64
 1   Age                 5000 non-null   int64
 2   Experience          5000 non-null   int64
 3   Income              5000 non-null   int64
 4   ZIP Code            5000 non-null   int64
 5   Family              5000 non-null   int64
 6   CCAvg               5000 non-null   float64
 7   Education           5000 non-null   int64
 8   Mortgage            5000 non-null   int64
 9   Personal Loan       5000 non-null   int64
 10  Securities Account  5000 non-null   int64
 11  CD Account          5000 non-null   int64
 12  Online              5000 non-null   int64
 13  CreditCard          5000 non-null   int64
dtypes: float64(1), int64(13)
memory usage: 547.0 KB
```

1.1 Data Analysis

[ ]:
```
edu_exp = loan_data.groupby("Education").Experience.mean().
 ↪sort_values(ascending=True)
edu_exp
```

[ ]:
```
Education
2    19.770492
1    20.065363
3    20.471686
Name: Experience, dtype: float64
```

[ ]:
```
age_exp = loan_data.groupby('Age')['Experience'].mean().
 ↪sort_values(ascending=False).reset_index()
age_exp
```

[ ]:

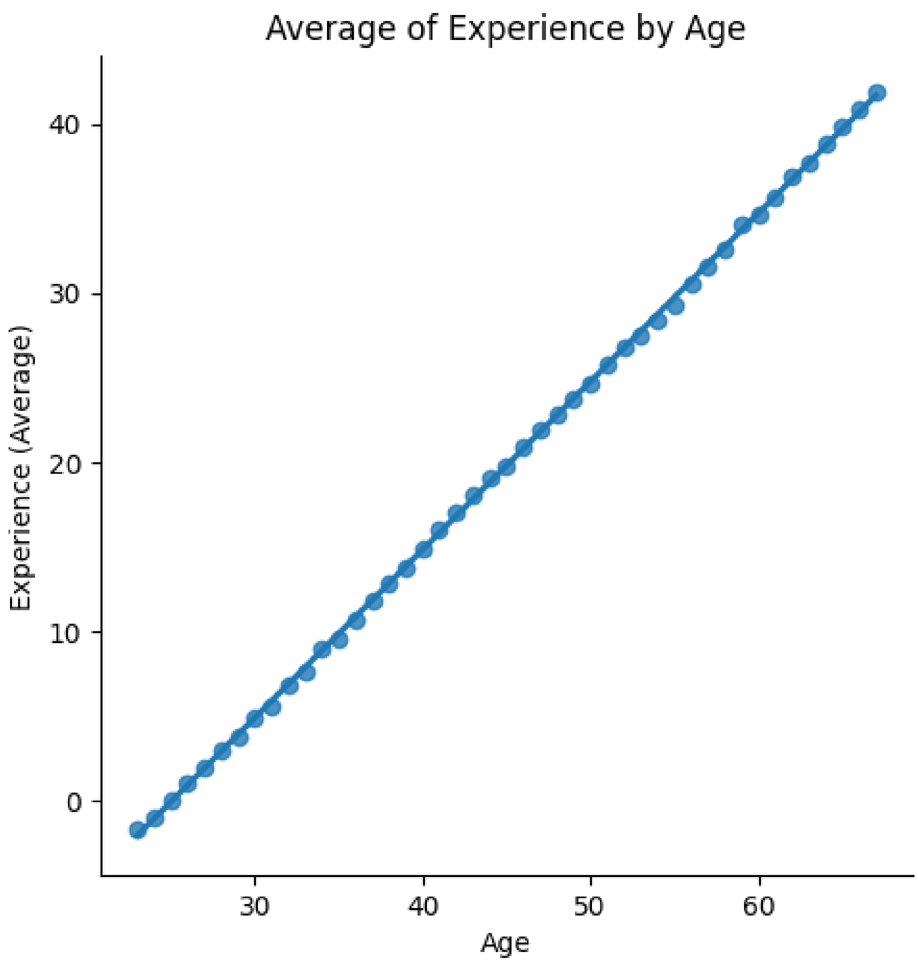
	Age	Experience
0	67	41.833333
1	66	40.875000
2	65	39.812500
3	64	38.846154
4	63	37.638889
5	62	36.829268

```
6    61   35.672131
7    60   34.645669
8    59   34.000000
9    58   32.559441
10   57   31.590909
11   56   30.488889
12   55   29.312000
13   54   28.412587
14   53   27.464286
15   52   26.813793
16   51   25.806202
17   50   24.652174
18   49   23.756522
19   48   22.838983
20   47   21.893805
21   46   20.834646
22   45   19.724409
23   44   19.057851
24   43   18.033557
25   42   17.000000
26   41   16.029412
27   40   14.904000
28   39   13.766917
29   38   12.860870
30   37   11.820755
31   36   10.635514
32   35    9.556291
33   34    8.932836
34   33    7.641667
35   32    6.850000
36   31    5.552000
37   30    4.860294
38   29    3.715447
39   28    2.961165
40   27    1.923077
41   26    0.961538
42   25   -0.018868
43   24   -1.071429
44   23   -1.666667
```

[ ]:
```
plt.figure(figsize=(10,7))
sns.lmplot(x="Age", y="Experience", data=age_exp)
plt.ylabel("Experience (Average)")
plt.title("Average of Experience by Age")
```

[ ]:
```
Text(0.5, 1.0, 'Average of Experience by Age')
```

<Figure size 1000x700 with 0 Axes>



Notice there are inconsistent data in our dataset. The number of years of experience couldn't be a negative number. After exploring the dataset, we found there are only few entries containing negative years of experience. Removing few entries will not influence our later model and prediction. So we'll remove these entries in data preprocessing part.

[ ]:
```
summ = loan_data.describe()
pd.DataFrame(summ, columns=summ.columns).transpose()
```

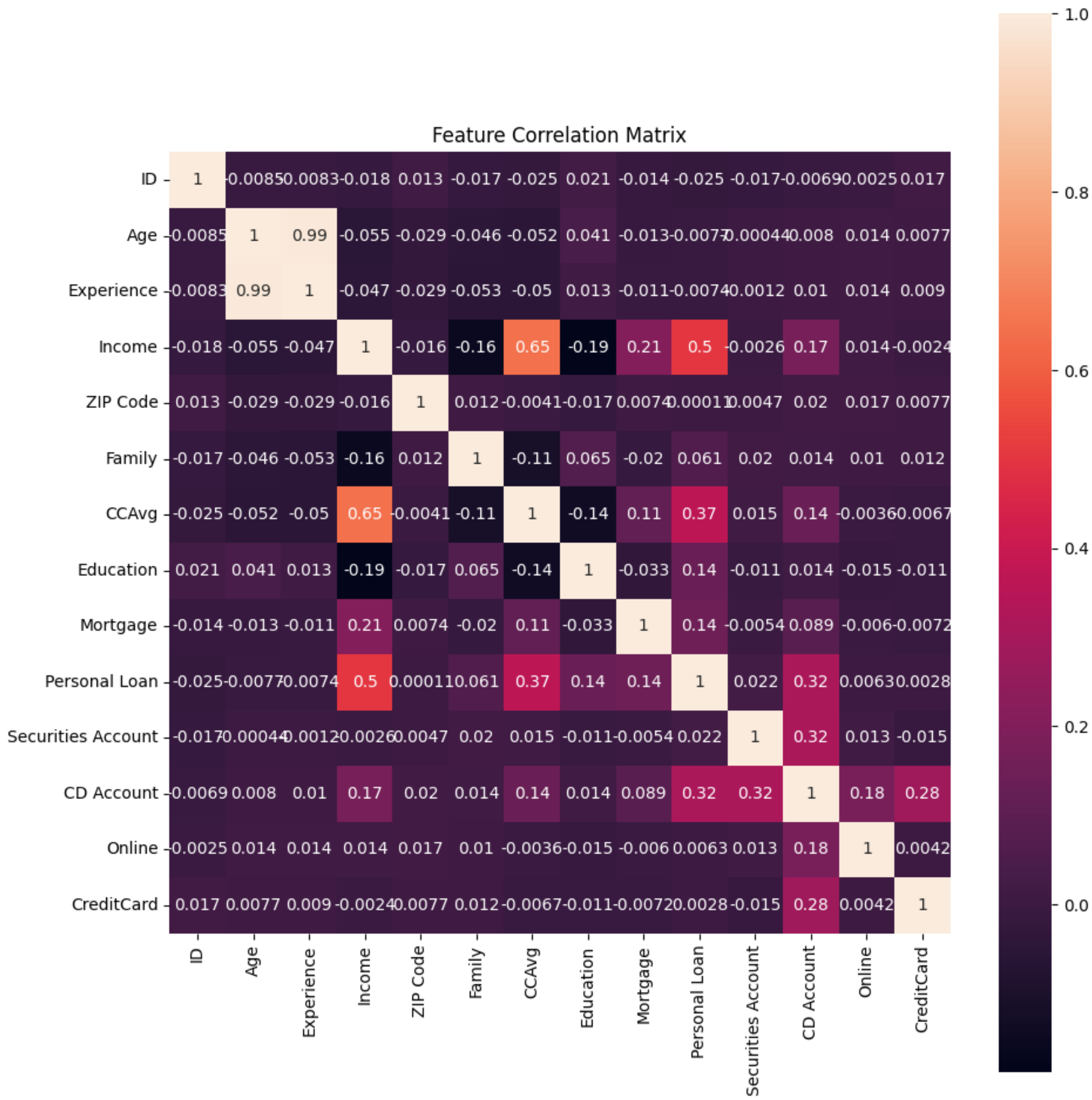
[ ]:

	count	mean	std	min	25%	\
ID	5000.0	2500.500000	1443.520003	1.0	1250.75	
Age	5000.0	45.338400	11.463166	23.0	35.00	
Experience	5000.0	20.104600	11.467954	-3.0	10.00	
Income	5000.0	73.774200	46.033729	8.0	39.00	
ZIP Code	5000.0	93152.503000	2121.852197	9307.0	91911.00	
Family	5000.0	2.396400	1.147663	1.0	1.00	

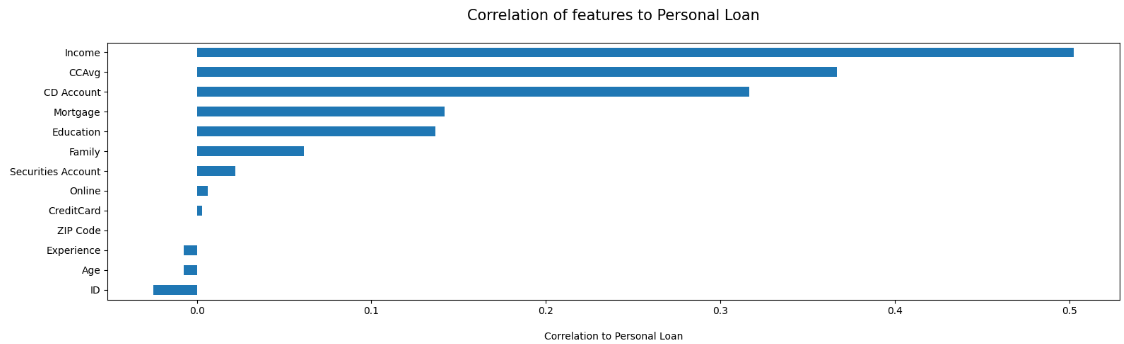
```
CCAvg               5000.0      1.937913     1.747666     0.0        0.70
Education           5000.0      1.881000     0.839869     1.0        1.00
Mortgage            5000.0     56.498800   101.713802     0.0        0.00
Personal Loan       5000.0      0.096000     0.294621     0.0        0.00
Securities Account  5000.0      0.104400     0.305809     0.0        0.00
CD Account          5000.0      0.060400     0.238250     0.0        0.00
Online              5000.0      0.596800     0.490589     0.0        0.00
CreditCard          5000.0      0.294000     0.455637     0.0        0.00

                        50%       75%      max
ID                   2500.5   3750.25   5000.0
Age                    45.0     55.00     67.0
Experience             20.0     30.00     43.0
Income                 64.0     98.00    224.0
ZIP Code            93437.0  94608.00  96651.0
Family                  2.0      3.00      4.0
CCAvg                   1.5      2.50     10.0
Education               2.0      3.00      3.0
Mortgage                0.0    101.00    635.0
Personal Loan           0.0      0.00      1.0
Securities Account      0.0      0.00      1.0
CD Account              0.0      0.00      1.0
Online                  1.0      1.00      1.0
CreditCard              0.0      1.00      1.0
```

1.2 Feature Correlation Analysis

[ ]:
```
corr = loan_data.corr()
plt.subplots(figsize=(10,10));
sns.heatmap(corr, annot=True, square=True)
plt.title("Feature Correlation Matrix")
plt.tight_layout()
```




```
[ ]: plt.figure(figsize=(16,5))
corr["Personal Loan"].sort_values(ascending=True)[:-1].plot(kind="barh")
plt.title("Correlation of features to Personal Loan\n", fontsize=15)
plt.xlabel("\nCorrelation to Personal Loan")
plt.tight_layout()
plt.show()
```



Analysis:

According to the correlation heatmap and the bar graph we plot above, we have the following initial observations:

1. The top 3 most important features to Personal_Loan is "Income", "CCAvg", and "CD Account"
2. "ZIP Code" have no correlation with our target variable "Personal_Loan".
3. From the Data Analysis part and the correlation heatmap, we can find "Age" and "Experience" are highly correlated and almost linearly related to each other, with correlation 0.99 with each other. Thus, we processing our data for model training, we can consider this pair of features as "Multicollinearity" and drop either one of them to avoid some negative influence on our model.

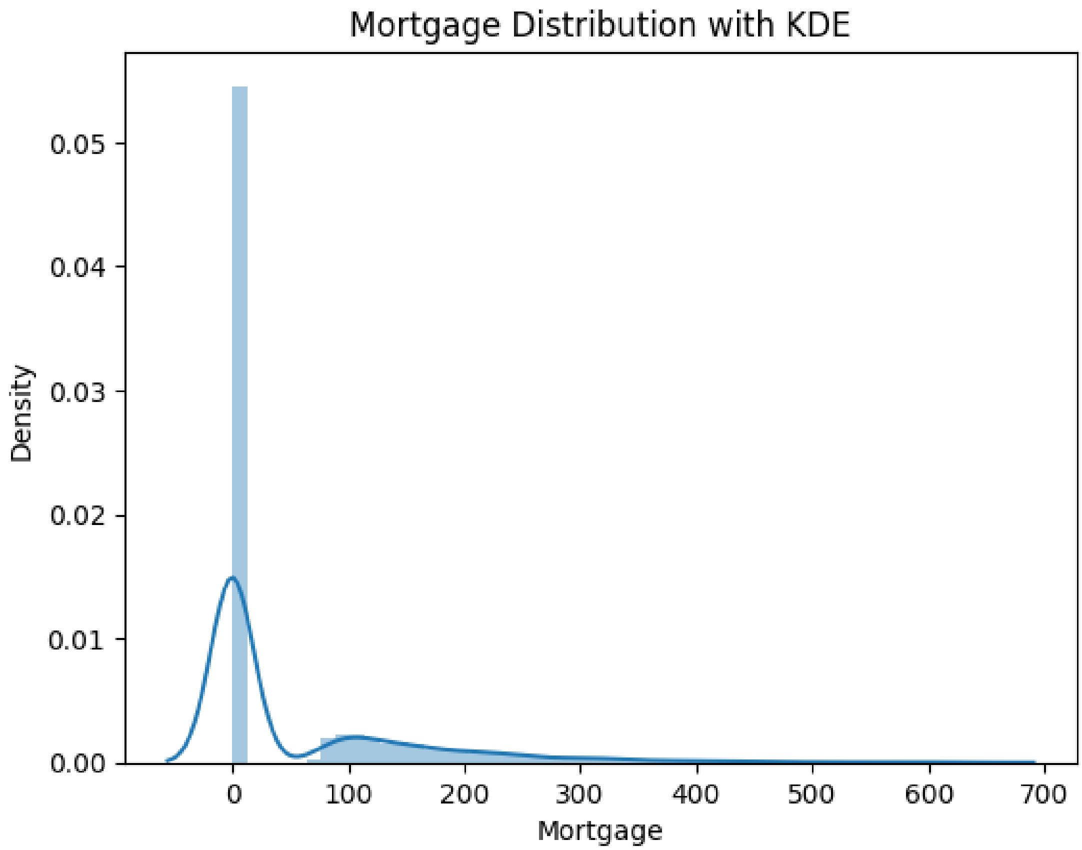
1.3 Univariate Analysis

1.3.1 Numerical Feature Distribution

Mortgage

[ ]:
```
sns.distplot(loan_data["Mortgage"])
plt.title("Mortgage Distribution with KDE")
```

[ ]:
```
Text(0.5, 1.0, 'Mortgage Distribution with KDE')
```

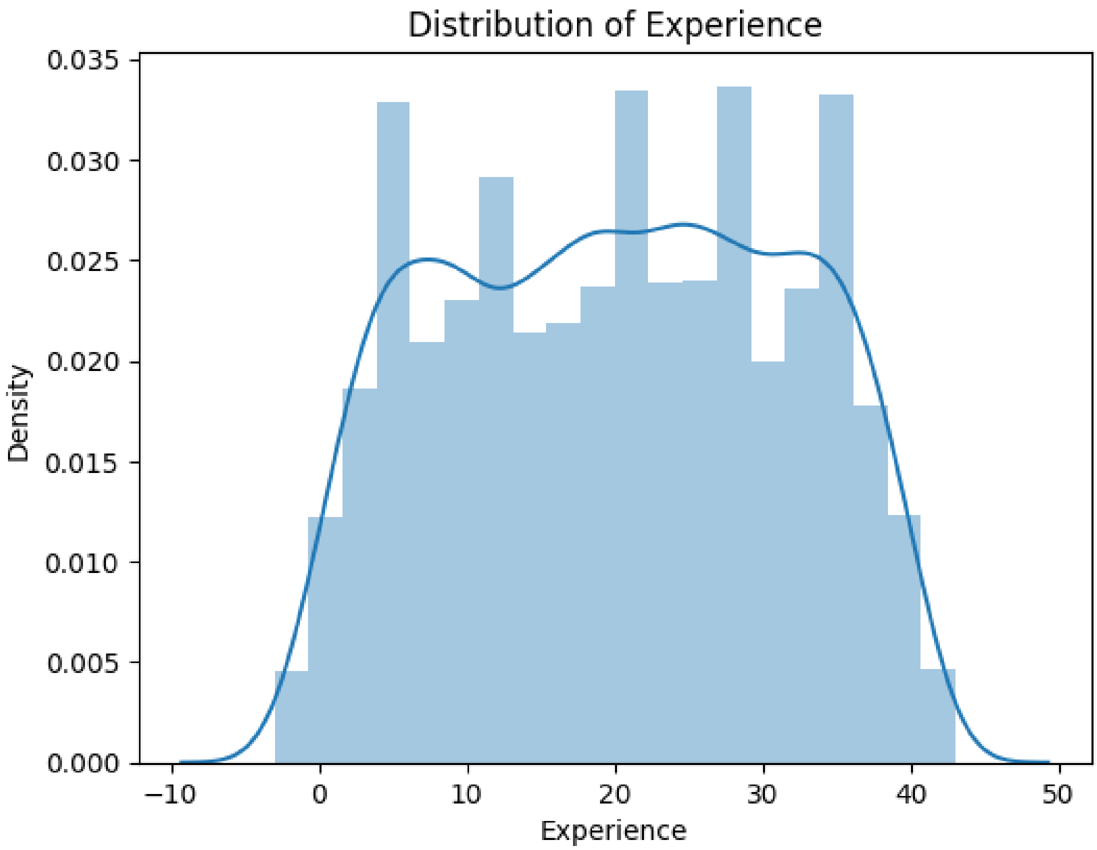


According to the plot above, we can find this plot of "Mortgage" is skewed to the right, meaning most people have no or only little mortgage. From this observation, we know we need to transform/standardize/normalize this feature for later data processing to avoid bias/distortation in our prediction results.

Experience

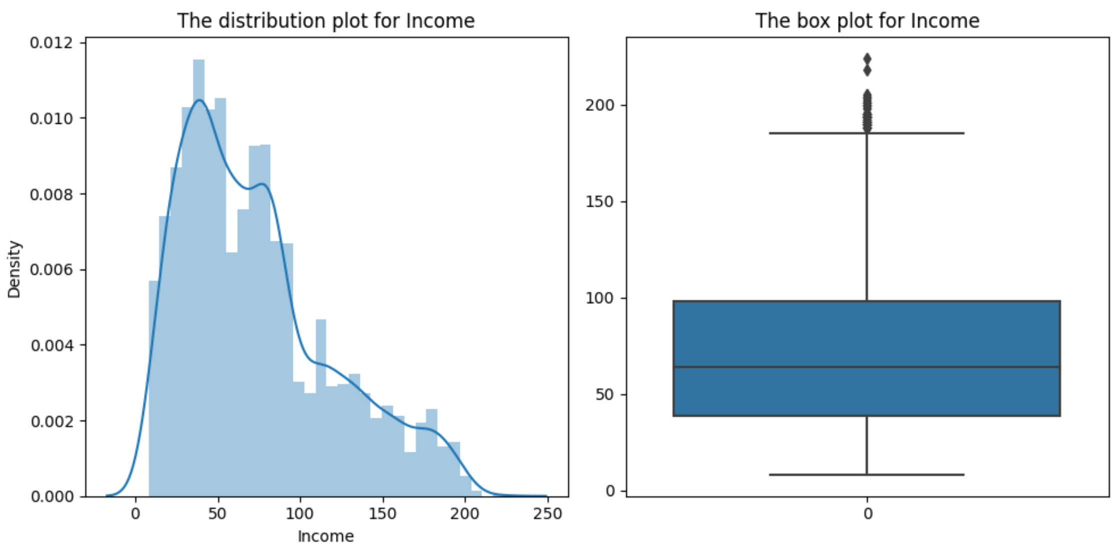
[ ]:
```
sns.distplot(loan_data['Experience'])
plt.title("Distribution of Experience")
```

[ ]: Text(0.5, 1.0, 'Distribution of Experience')



Income

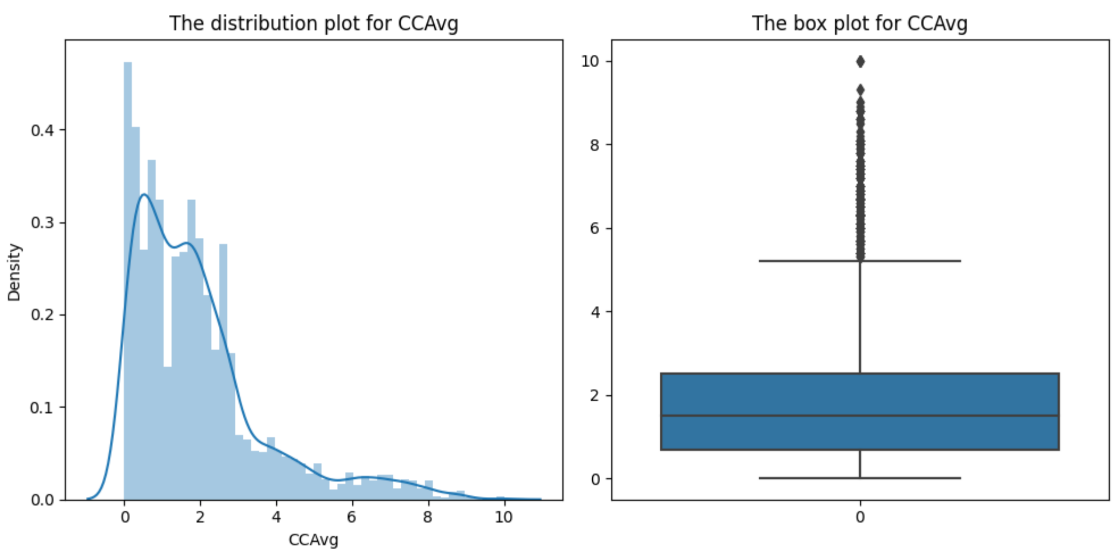
[ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(10,5))
sns.distplot(loan_data['Income'], ax=axes[0])
axes[0].title.set_text("The distribution plot for Income")
sns.boxplot(loan_data['Income'], orient="v", ax=axes[1])
axes[1].title.set_text("The box plot for Income")
plt.tight_layout()
```



Notice that the "Income" feature is also a little bit right skewed. From its box plot, we can find there are some outliers. So we also need to normalize this feature when feeding data into our model.

CCAvg

[ ]:
```
fig, axes = plt.subplots(1, 2, figsize=(10,5))
sns.distplot(loan_data['CCAvg'], ax=axes[0])
sns.boxplot(loan_data['CCAvg'], orient="v", ax=axes[1])
axes[0].title.set_text("The distribution plot for CCAvg")
axes[1].title.set_text("The box plot for CCAvg")
plt.tight_layout()
```



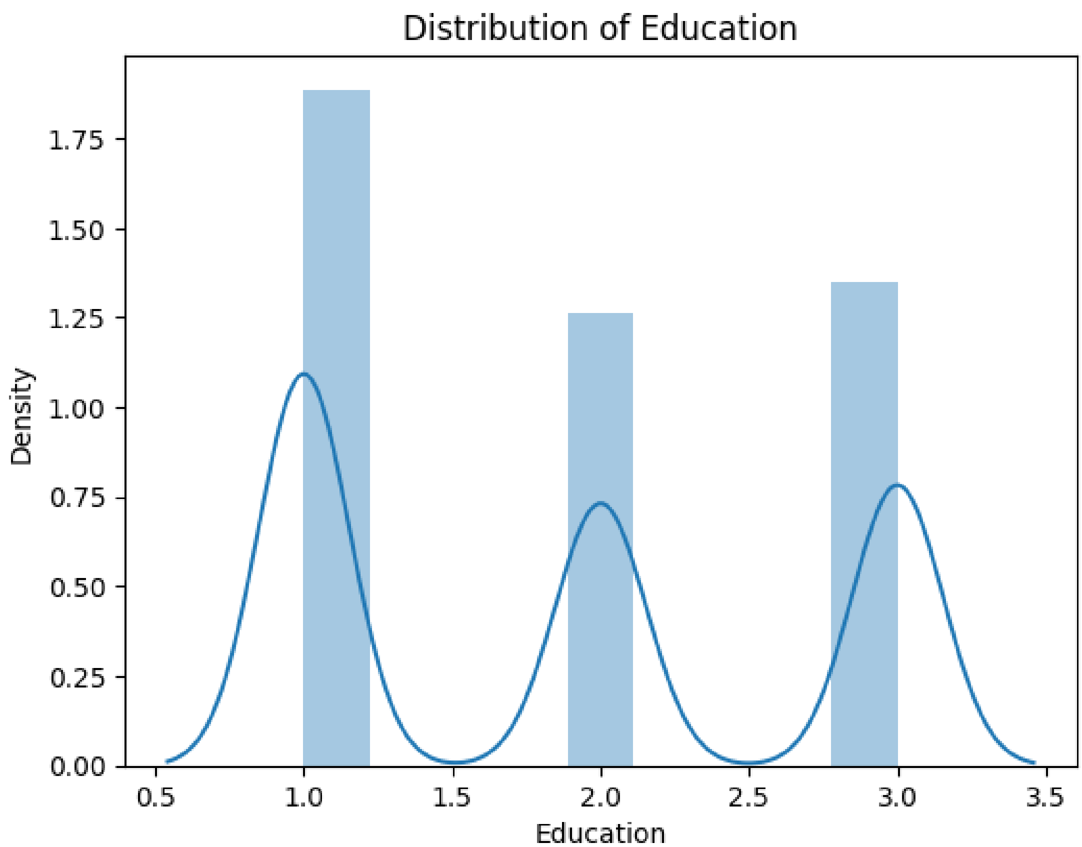
According to the distribution and the box plot above, we can also find "CCAvg" is also right skewed. Moreover, outliers exist in the box plot. So we need to do normalization to avoid data imbalance issues.

1.3.2 Categorical Feature Analysis

Education

[ ]:
```
sns.distplot(loan_data['Education'])
plt.title("Distribution of Education")
```

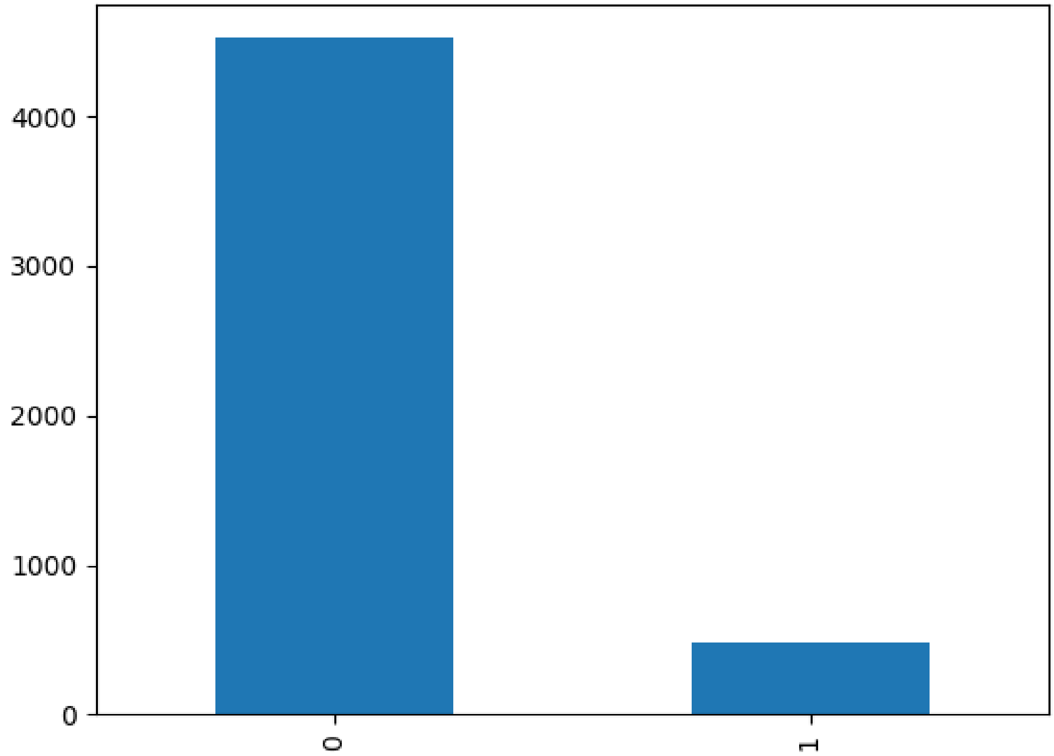
[ ]:
```
Text(0.5, 1.0, 'Distribution of Education')
```



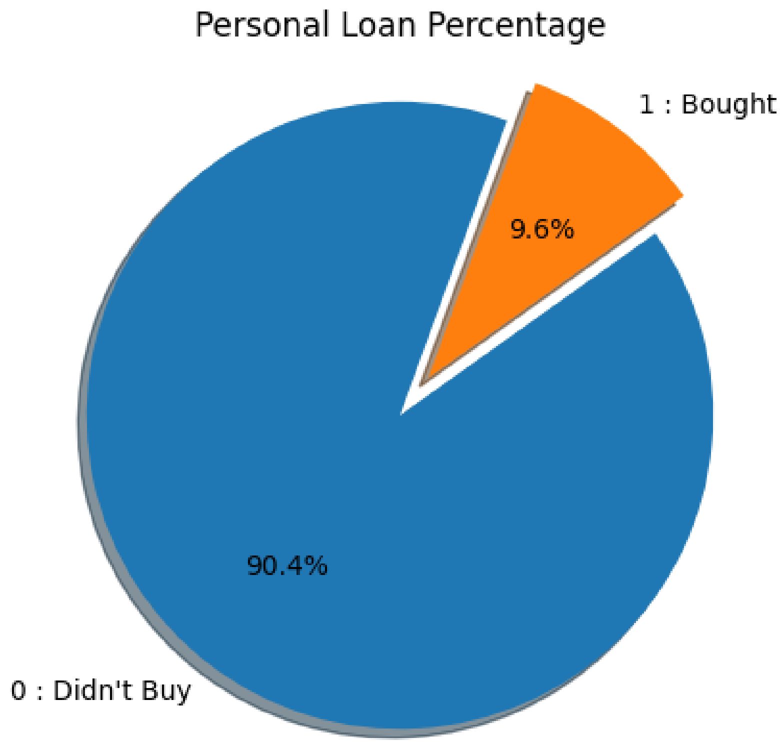
Personal Loan

[ ]:
```
loan_data["Personal Loan"].value_counts().plot(kind='bar')
```

[ ]:
```
<Axes: >
```



[ ]:
```
fig1, ax1 = plt.subplots()
explode = (0, 0.15)
ax1.pie(loan_data["Personal Loan"].value_counts(), explode=explode, labels=["0 :
 ↪ Didn't Buy", "1 : Bought"], autopct='%1.1f%%',
        shadow=True, startangle=70)
ax1.axis('equal')
plt.title("Personal Loan Percentage")
plt.show()
```

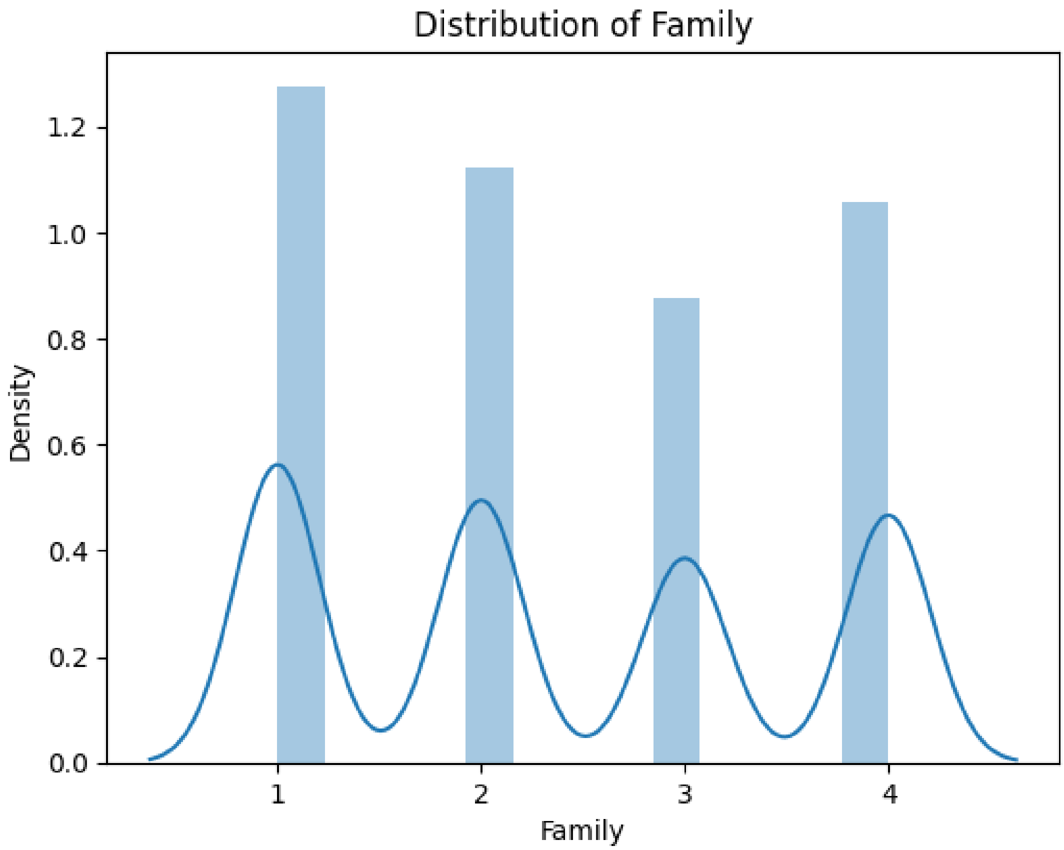


According to the pie chart above, we can find out of all customers, only 9.6% customers bought loan in the last campaign. So data imbalance issues exist in our dataset. We need to deal with this imbalance issue in the later part.

Family

[ ]:
```
sns.distplot(loan_data['Family'])
plt.title("Distribution of Family")
```

[ ]:
```
Text(0.5, 1.0, 'Distribution of Family')
```

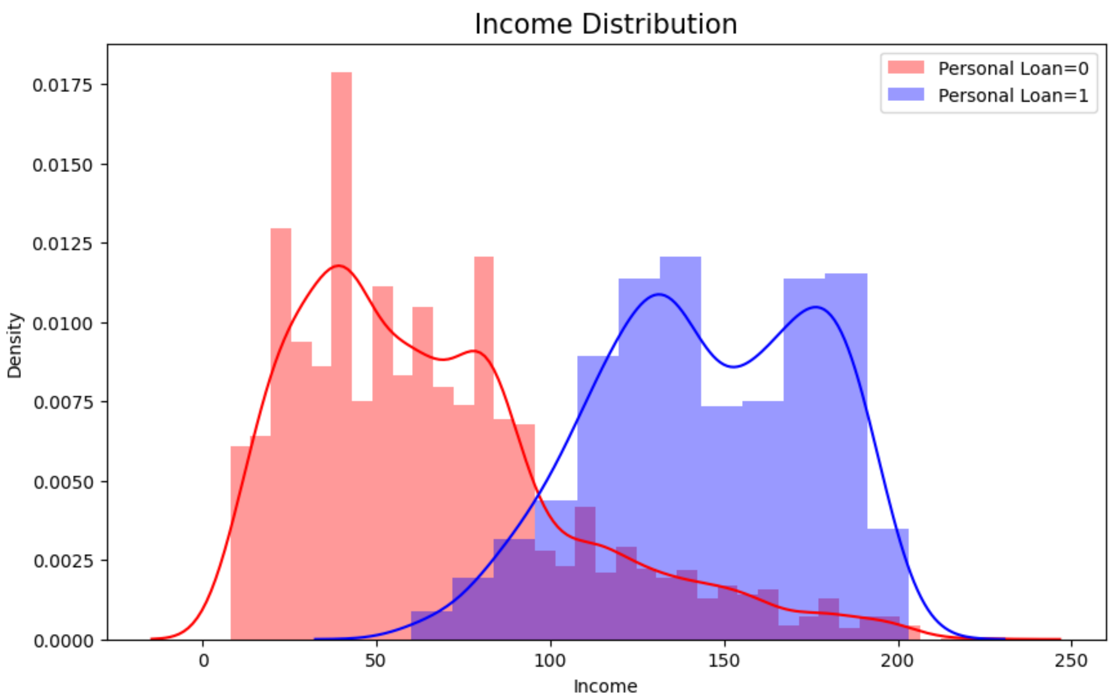


1.4 Bivariate Analysis

1.4.1 Income VS. Peronal Loan

[ ]:
```
plt.figure(figsize=(10,6))
sns.distplot(loan_data[loan_data["Personal Loan"] == 0]['Income'], color =␣
 ↪'r',label='Personal Loan=0',kde=True)
sns.distplot(loan_data[loan_data["Personal Loan"] == 1]['Income'], color =␣
 ↪'b',label='Personal Loan=1',kde=True)
plt.legend()
plt.title("Income Distribution", fontsize=15)
```

[ ]: Text(0.5, 1.0, 'Income Distribution')

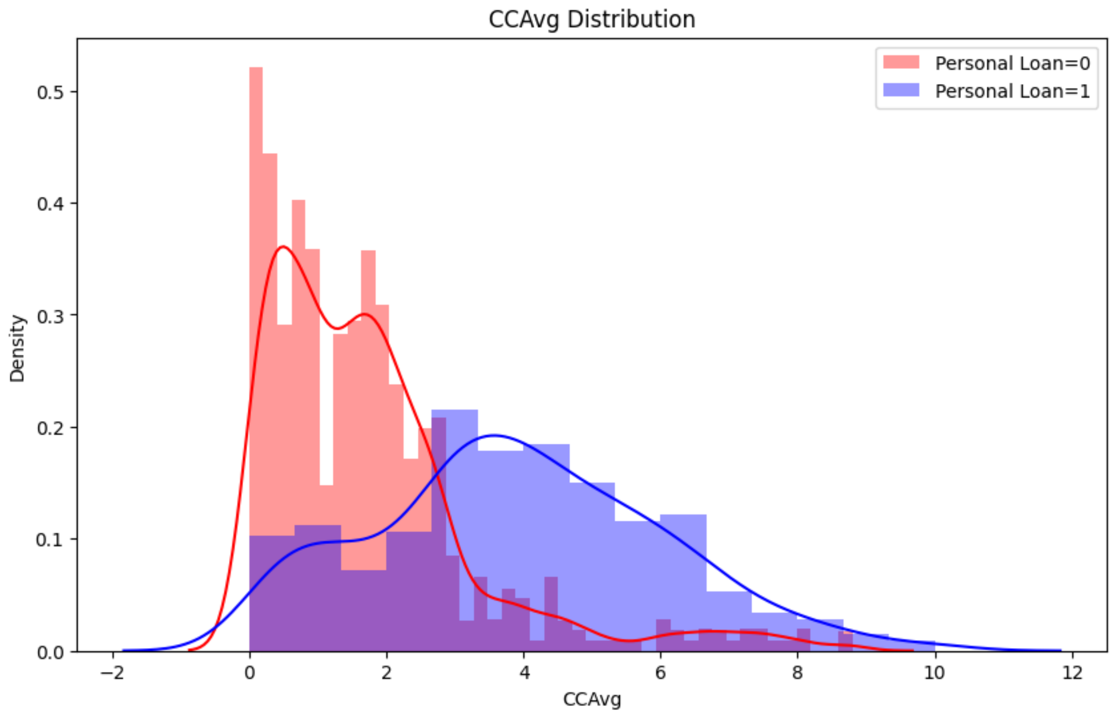


According to the distrubition graph between income and personal loan, we can find people who has personal load usually have higher income. For people whose income is lower, they are less likely to have personal loan.

1.4.2 CCAvg VS. Personal Loan

[ ]:
```
plt.figure(figsize=(10,6))
sns.distplot(loan_data[loan_data["Personal Loan"] == 0]['CCAvg'], color =␣
 ↪'r',label='Personal Loan=0',kde=True)
sns.distplot(loan_data[loan_data["Personal Loan"] == 1]['CCAvg'], color =␣
 ↪'b',label='Personal Loan=1',kde=True)
plt.legend()
plt.title("CCAvg Distribution")
```

[ ]:
```
Text(0.5, 1.0, 'CCAvg Distribution')
```

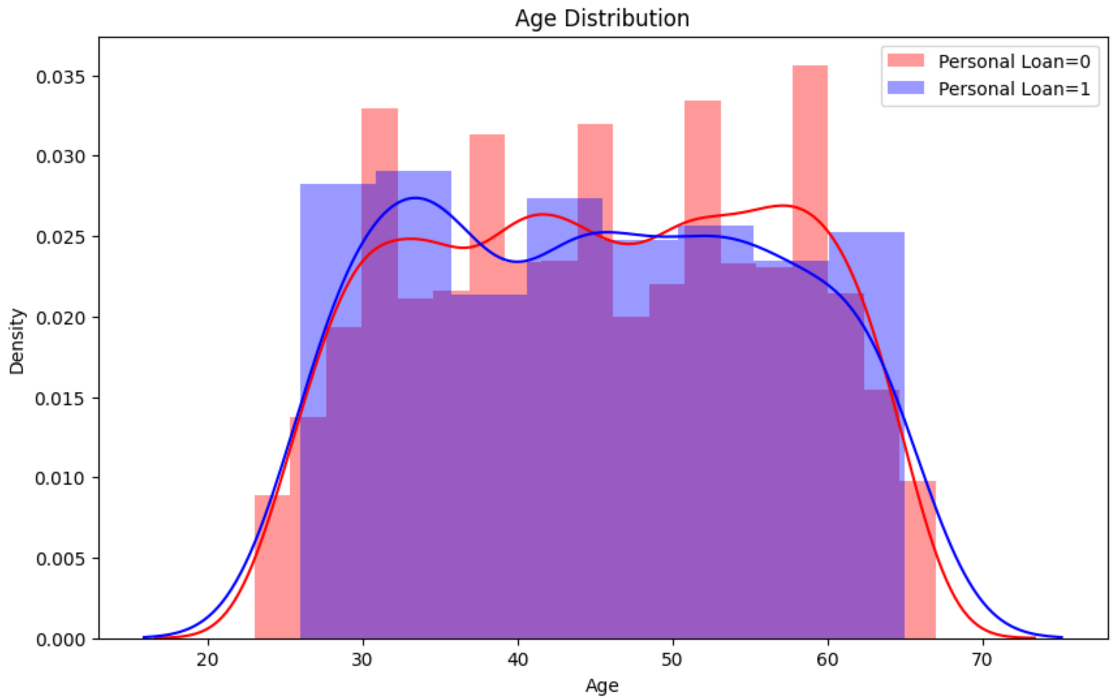


According to the distrubition graph between CCAvg and personal loan, we can find people who has personal load usually have higher monthly spending with the credit card. For people whose income is lower, they spend less with the credit card each month.

1.4.3 Age & Experience VS. Personal Loan

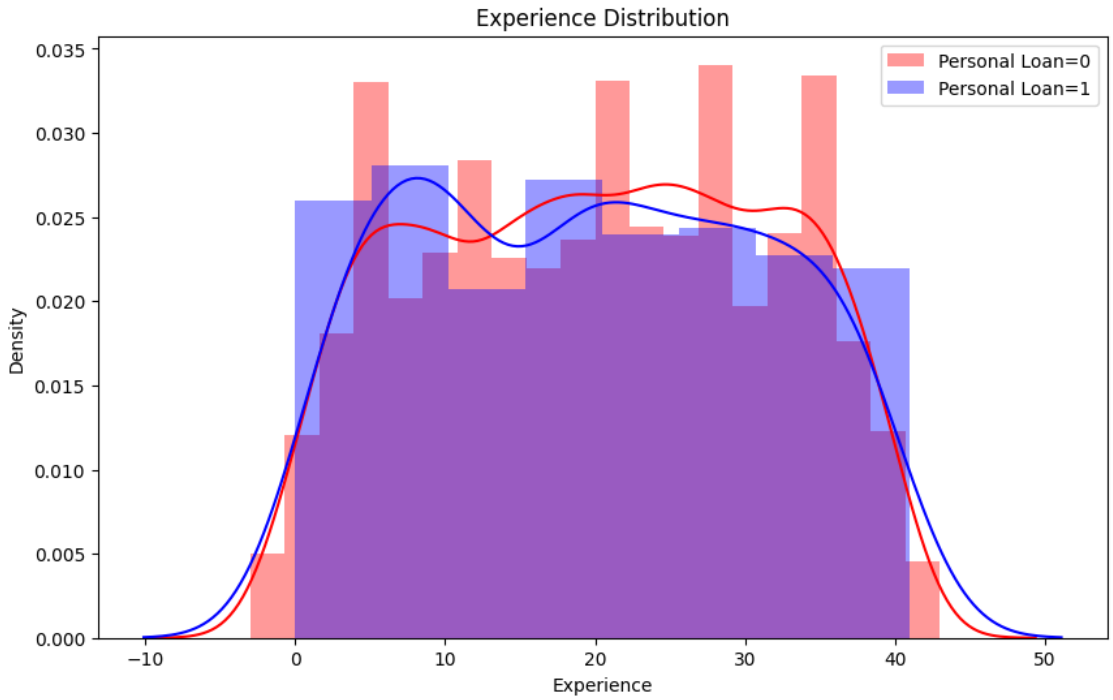
[ ]:
```
plt.figure(figsize=(10,6))
sns.distplot(loan_data[loan_data["Personal Loan"] == 0]['Age'], color =␣
 ↪'r',label='Personal Loan=0',kde=True)
sns.distplot(loan_data[loan_data["Personal Loan"] == 1]['Age'], color =␣
 ↪'b',label='Personal Loan=1',kde=True)
plt.legend()
plt.title("Age Distribution")
```

[ ]:
```
Text(0.5, 1.0, 'Age Distribution')
```




```
[ ]: plt.figure(figsize=(10,6))
     sns.distplot(loan_data[loan_data["Personal Loan"] == 0]['Experience'], color =␣
      ↪'r',label='Personal Loan=0',kde=True)
     sns.distplot(loan_data[loan_data["Personal Loan"] == 1]['Experience'], color =␣
      ↪'b',label='Personal Loan=1',kde=True)
     plt.legend()
     plt.title("Experience Distribution")
```

```
[ ]: Text(0.5, 1.0, 'Experience Distribution')
```

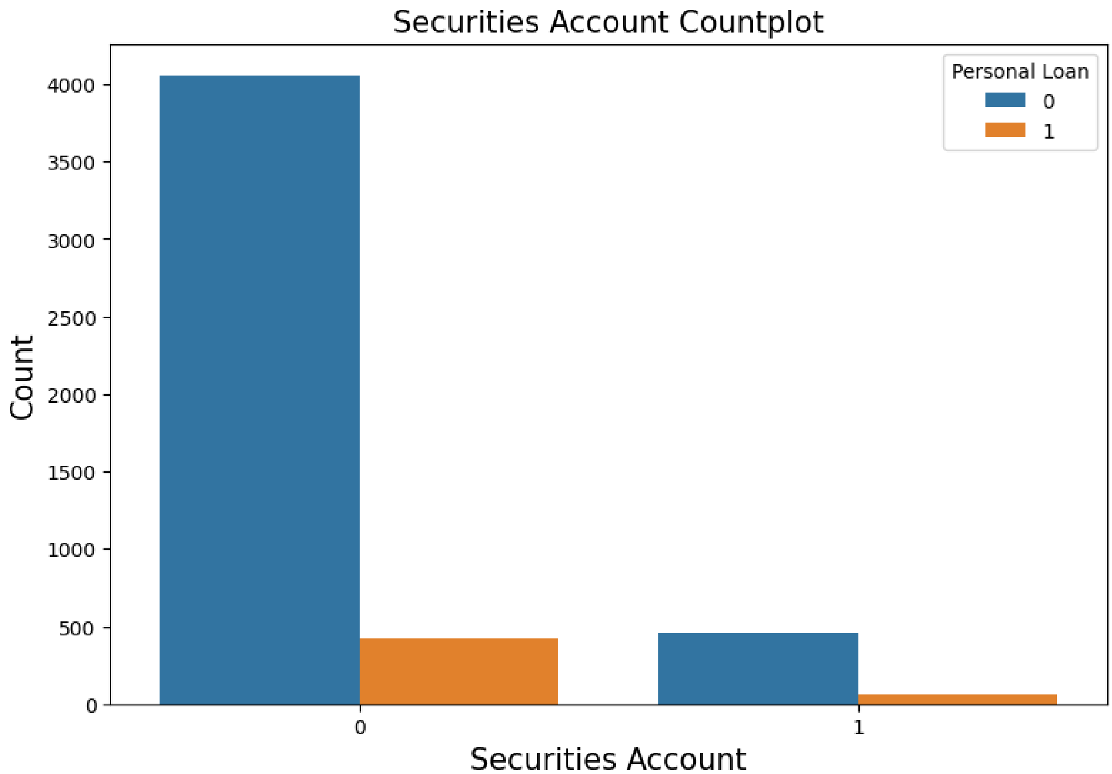


Based on our previous conclusion, we know age and year of experience are closed positively related to each other. So their distribution graphs show roughly the same pattern. Moreover, the distribution are kind of average for these two features vs. personal loan. Thus, these two features might not influence our target variable too much.

1.4.4 Securities Account VS. Personal Loan

[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="Securities Account", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('Securities Account Countplot', fontsize=15)
plt.xlabel('Securities Account', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]:
```
Text(0, 0.5, 'Count')
```

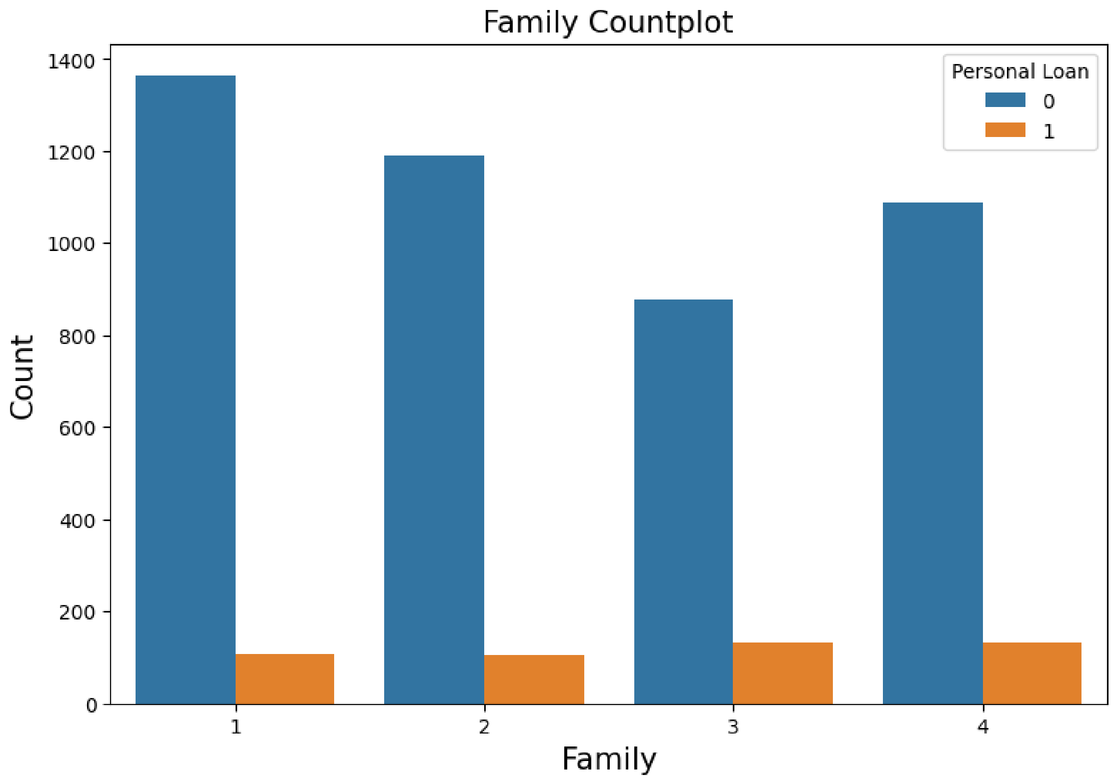


From the count plot above, we can find most people do not have securities account. Moreover, out of which, most people do not have personal loans either.

1.4.5 Family Countplot VS. Personal Loan

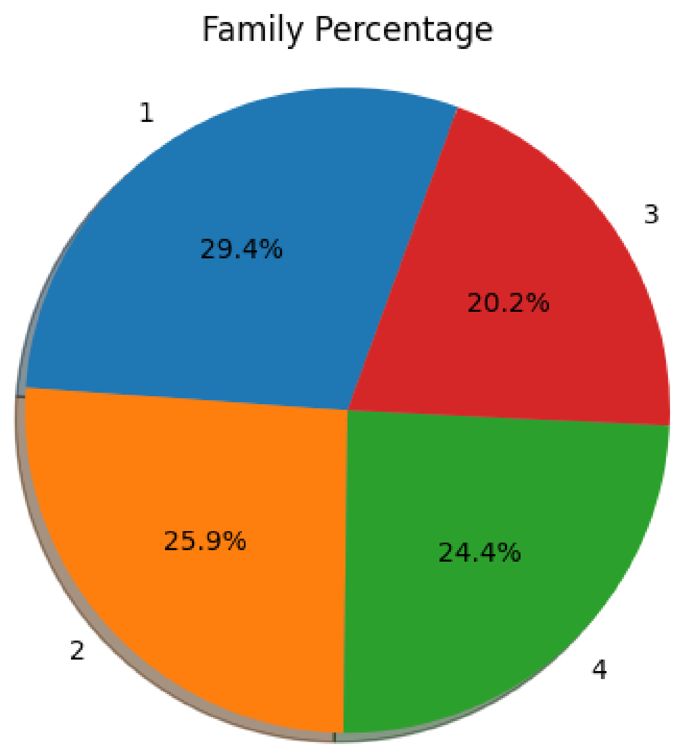
[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="Family", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('Family Countplot', fontsize=15)
plt.xlabel('Family', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]:
```
Text(0, 0.5, 'Count')
```



From the countplot above, we can find from the person who do not have personal loan, their family size tend to be 1, followed by 2. This is a reasonable observation sincc their expense is less than other categories of customers. Then for people who have personal loan, they usually have a larger family size.

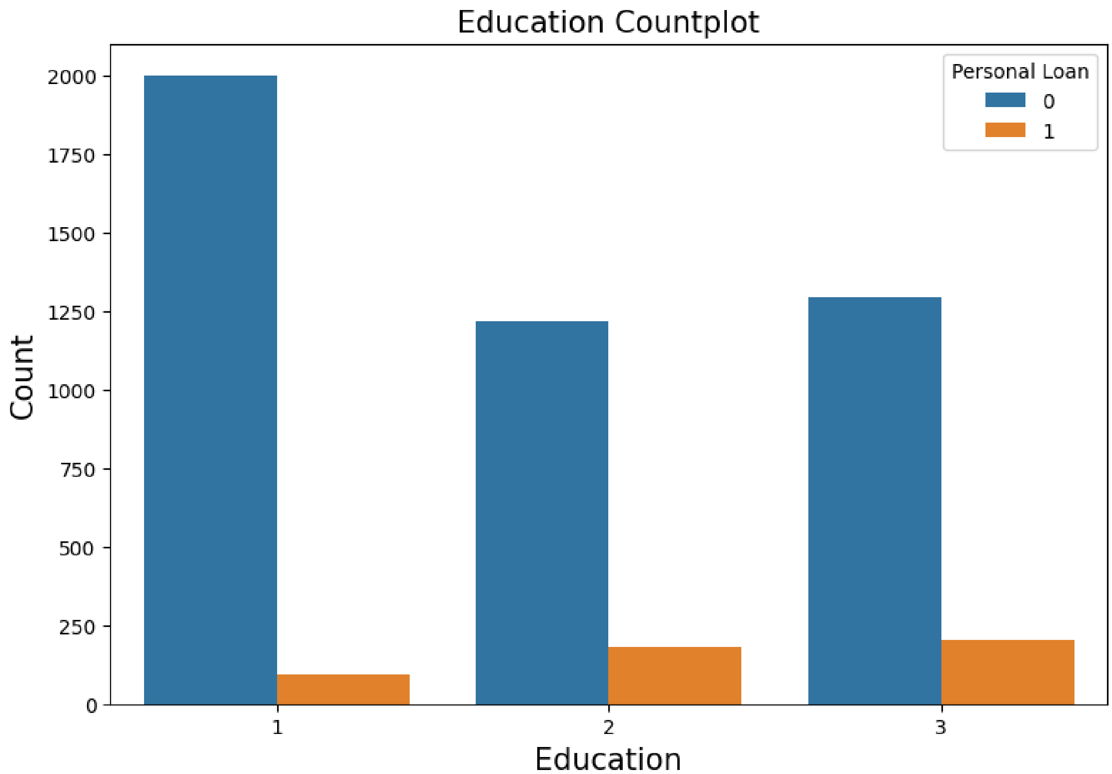
[ ]:
```
fig1, ax1 = plt.subplots()
explode = (0, 0.15)
# count the number of occurrences of each education level
counts = loan_data['Family'].value_counts()
ax1.pie(counts, labels=counts.index, autopct='%1.1f%%',
        shadow=True, startangle=70)
ax1.axis('equal')
plt.title("Family Percentage")
plt.show()
```



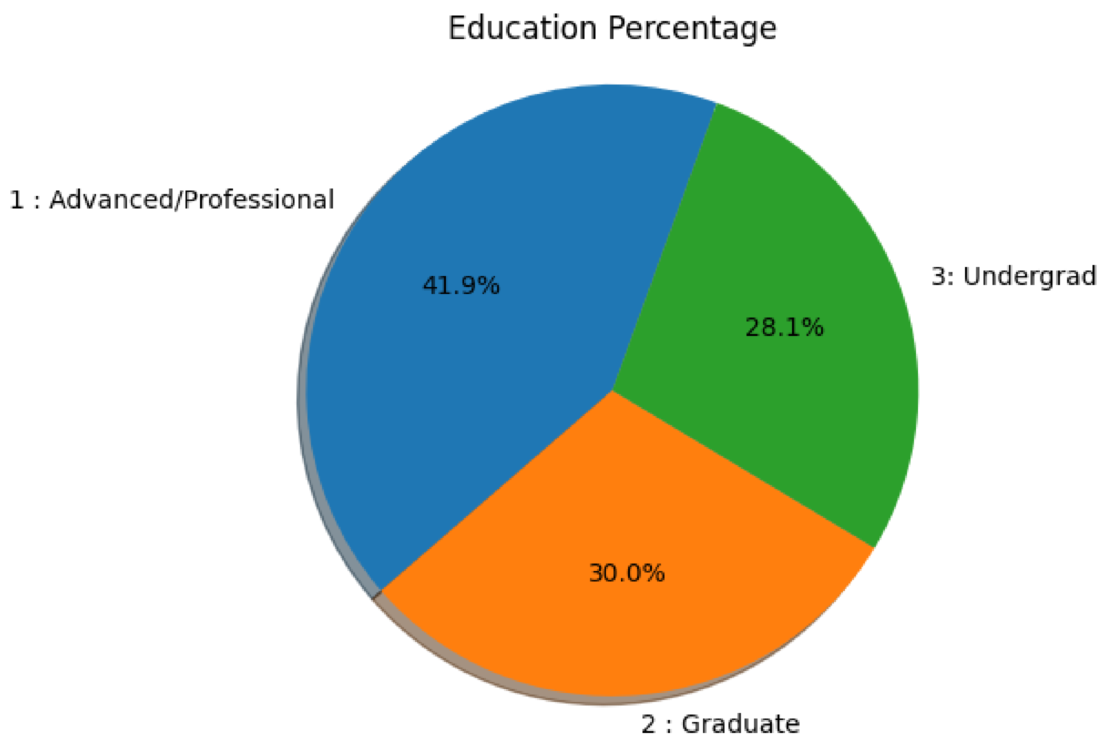
1.4.6 Education VS. Personal Loan

[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="Education", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('Education Countplot', fontsize=15)
plt.xlabel('Education', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]:
```
Text(0, 0.5, 'Count')
```



[ ]:
```
fig1, ax1 = plt.subplots()
explode = (0, 0.15)
# count the number of occurrences of each education level
counts = loan_data['Education'].value_counts()
ax1.pie(counts, labels=["1 : Advanced/Professional", "2 : Graduate", "3:␣
↪Undergrad"], autopct='%1.1f%%',
        shadow=True, startangle=70)
ax1.axis('equal')
plt.title("Education Percentage")
plt.show()
```

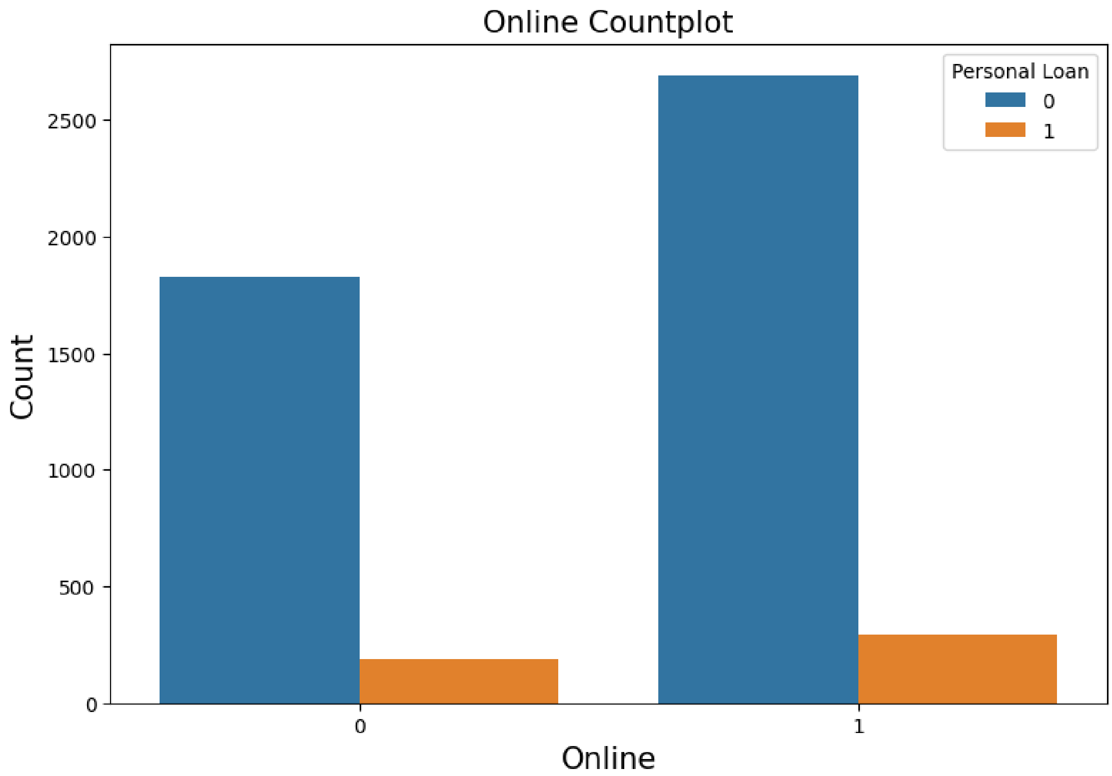


Customers with lower educational qualification are more likely to buy personal loan. As they should have a lower income. But customers who have high qualified education background are less prone to buy personal loan.

1.4.7 Online VS. Personal Loan

[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="Online", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('Online Countplot', fontsize=15)
plt.xlabel('Online', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]:
```
Text(0, 0.5, 'Count')
```

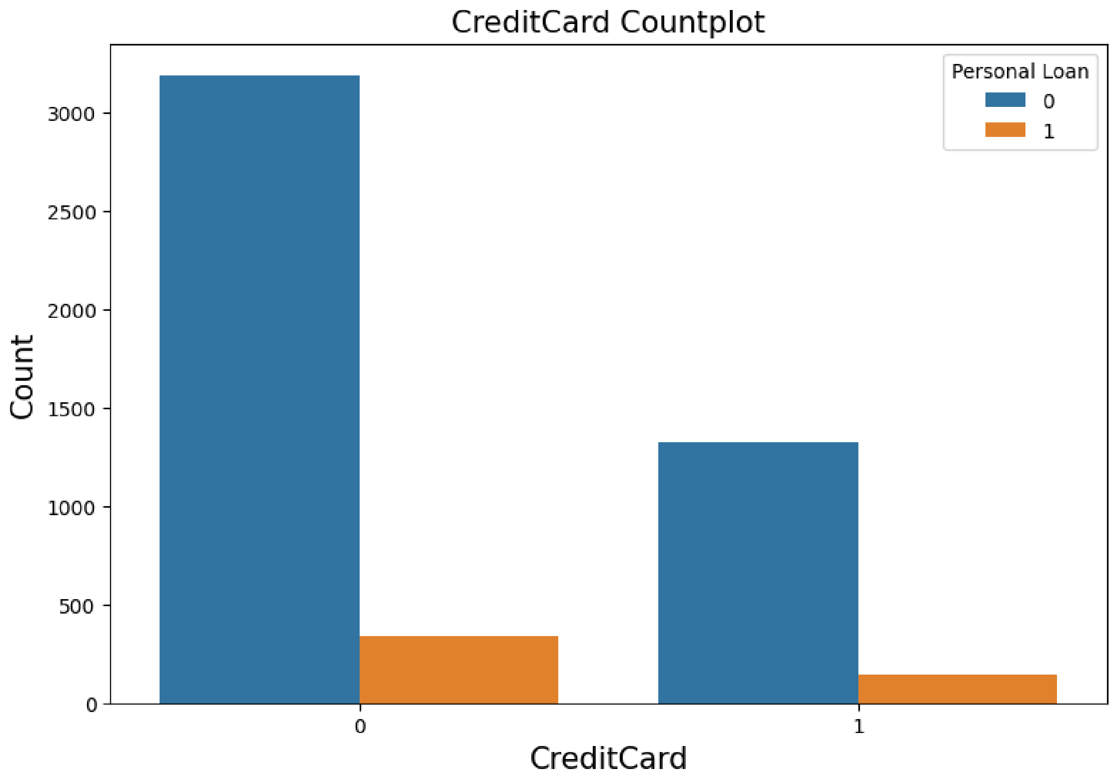


Most customers has online internet banking facility and the people who have these facility have bought more number of personal loans.

1.4.8 Credit Card VS. Personal Loan

[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="CreditCard", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('CreditCard Countplot', fontsize=15)
plt.xlabel('CreditCard', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]: Text(0, 0.5, 'Count')

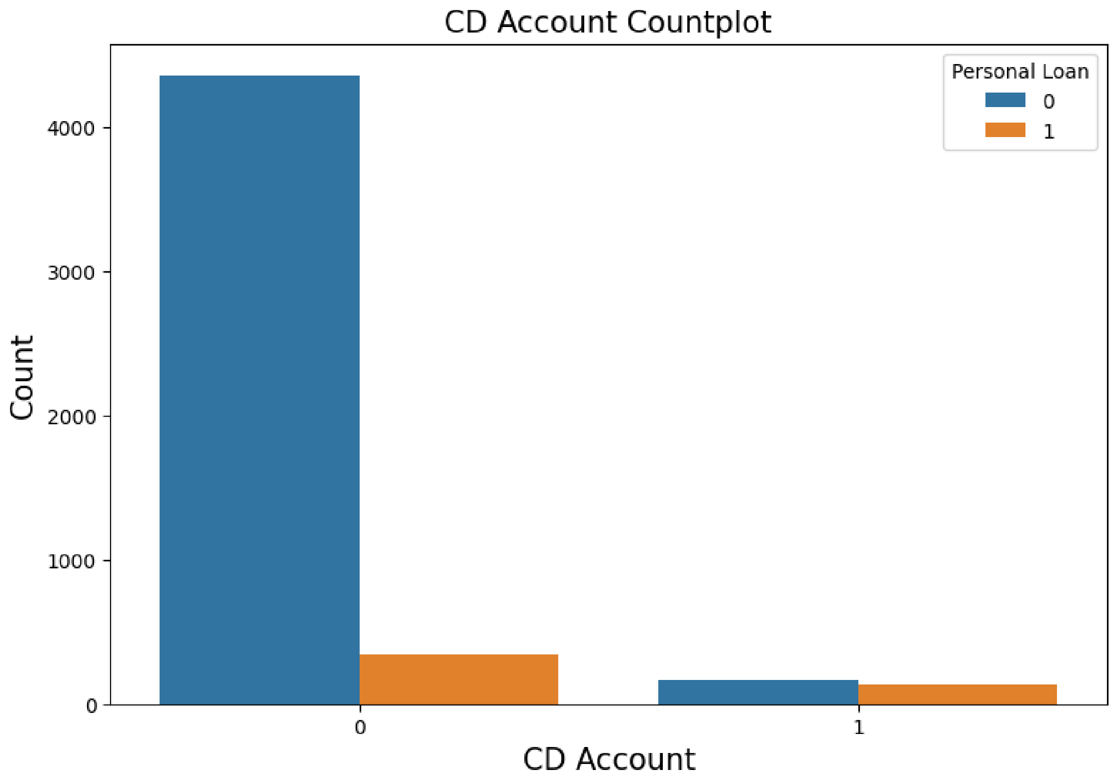


Most customers don't have a credit card. And the maximum number of customers who bought personal loan falls in this category, as they don't have the privilage to buy anything on credit using credit card. So they are more likely to buy things with personal loan.

1.4.9 CD Account VS. Personal Loan

[ ]:
```
plt.figure(figsize=(9,6))
sns.countplot(x="CD Account", hue="Personal Loan", data=loan_data)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.title('CD Account Countplot', fontsize=15)
plt.xlabel('CD Account', fontsize=15)
plt.ylabel('Count', fontsize=15)
```

[ ]:
```
Text(0, 0.5, 'Count')
```



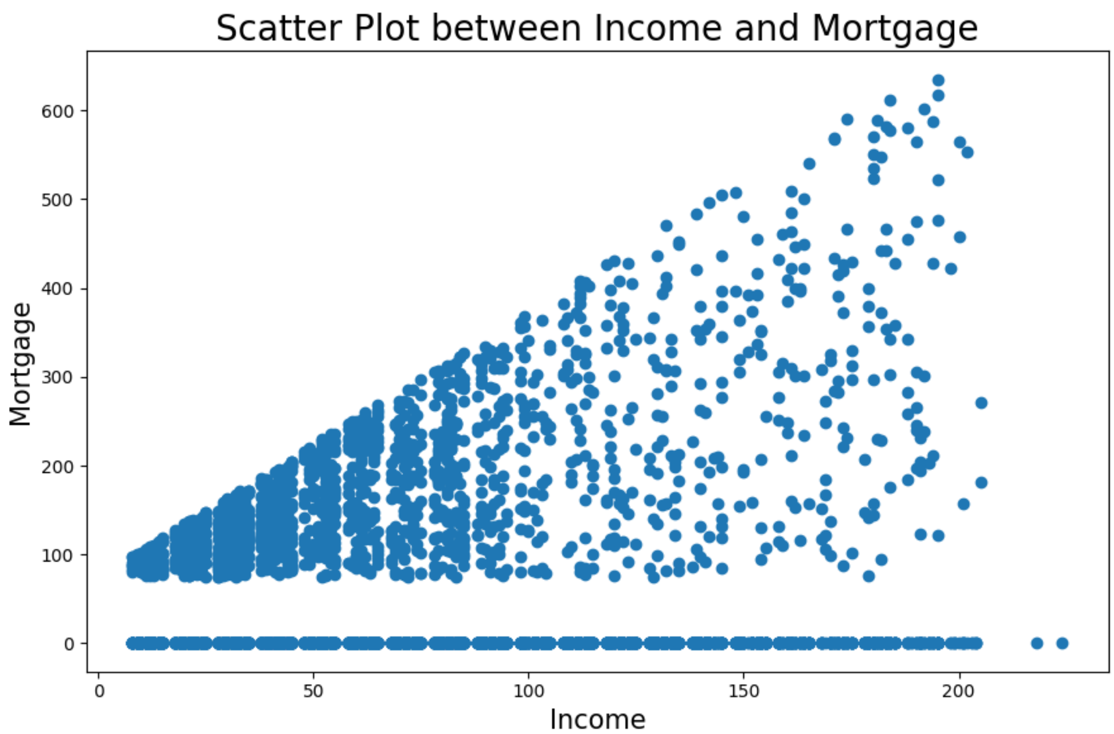
[ ]:

```

```

1.4.10 Income VS. Mortgage

[ ]:

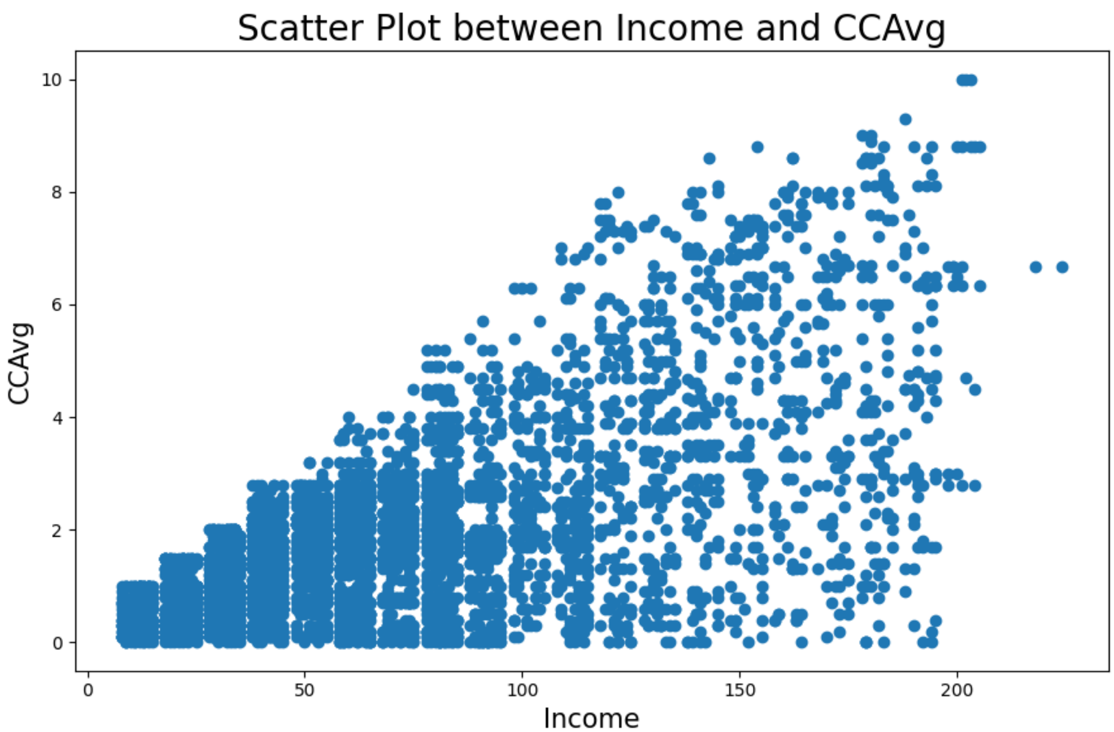
```
plt.figure(figsize=(9,6))
plt.scatter(x=loan_data["Income"], y=loan_data["Mortgage"])
plt.title("Scatter Plot between Income and Mortgage", fontsize=20)
plt.xlabel("Income", fontsize=15)
plt.ylabel("Mortgage", fontsize=15)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.tight_layout()
```



Many of the customers don't have any mortgage in their name. So we can observe a line along the mortgage value zero. And the mortgage value for the customers increases with increase in their income.

1.4.11 Income VS. CCAvg

[ ]:
```
plt.figure(figsize=(9,6))
plt.scatter(x=loan_data["Income"], y=loan_data["CCAvg"])
plt.title("Scatter Plot between Income and CCAvg", fontsize=20)
plt.xlabel("Income", fontsize=15)
plt.ylabel("CCAvg", fontsize=15)
plt.xticks(horizontalalignment='center')
plt.yticks(horizontalalignment='right')
plt.tight_layout()
```



2 Data Preprocessing

2.1 Data Cleaning

1. After the initial data exploration, we found that the dataset doesn't contain any missing or duplicate values.
2. Based on the Univariate Analysis, we need to drop all the noise records whose 'Experience' <0 or 'ZIP Code' < 5 digits.
3. Drop The variable ID, since it only acts as a customer identifier without adding any useful information to the dataset.
4. Drop 'Age' (strongly correlated with Experience.)

[ ]:
```
# No missing Values
loan_data.isnull().sum().sum()
```

[ ]: 0

[ ]:
```
# No duplicated Values
loan_data[loan_data.duplicated(keep=False)].sum().sum()
```

[ ]: 0.0

[ ]:
```
loan_data[loan_data['Experience']<0]['Experience'].value_counts()
```

[ ]:
```
-1    33
-2    15
-3     4
Name: Experience, dtype: int64
```

[ ]:
```
loan_data[loan_data['ZIP Code']<10000]
```

[ ]:
```
      ID  Age  Experience  Income  ZIP Code  Family  CCAvg  Education  \
384  385   51          25      21      9307       4    0.6          3

     Mortgage  Personal Loan  Securities Account  CD Account  Online  \
384         0              0                   0           0       1

     CreditCard
384           1
```

[ ]:
```
# Drop 'Experience' <0 or 'ZIP Code' < 5 digits.
loan_data = loan_data[loan_data['Experience'] >=0]

loan_data = loan_data[loan_data['ZIP Code'] >= 10000]
```

[ ]:
```
# Drop The variable ID, since it only acts as a customer identifier without␣
↪adding any useful information to the dataset.
loan_data.drop(columns = {'ID'}, inplace = True)
```

[ ]:
```
# Drop 'Age' (strongly correlated with Experience.)
loan_data.drop(columns = {'Age'}, inplace = True)
```

[ ]:
```
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4947 entries, 0 to 4999
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Experience          4947 non-null   int64
 1   Income              4947 non-null   int64
 2   ZIP Code            4947 non-null   int64
 3   Family              4947 non-null   int64
 4   CCAvg               4947 non-null   float64
 5   Education           4947 non-null   int64
 6   Mortgage            4947 non-null   int64
 7   Personal Loan       4947 non-null   int64
 8   Securities Account  4947 non-null   int64
 9   CD Account          4947 non-null   int64
```

```
 10  Online                4947 non-null   int64
 11  CreditCard            4947 non-null   int64
dtypes: float64(1), int64(11)
memory usage: 502.4 KB
```

2.2 Feature Enginneering

1. Log transformation will be applied to remove the right skewness in 'Income', "CCAvg', and 'Mortgage'(too many zeros and plus one before log transformation).
2. Convert 'CCAvg' average monthly credit card spending to annual spending by times 12 (Equal the unit in the Income)
3. Category Encoding will be selected to convert 'Family', 'Education' and 'Zip Code' into numerical values.

[ ]:
```
# Log transformation removes the right skewness in 'Income', ''CCAvg', and␣
↪'Mortgage'
# (too many zeros and plus one before log transformation)

for i in ['Income', 'CCAvg', 'Mortgage']:
    loan_data[i] = (loan_data[i] + 1).apply(np.log10)
```

[ ]:
```
# Convert 'CCAvg' average monthly credit card spending to annual spending by␣
↪times 12
loan_data['CCAvg'] = loan_data['CCAvg']*12
```

[ ]:
```
loan_data
```

[ ]:
```
      Experience    Income  ZIP Code  Family     CCAvg  Education  Mortgage  \
0              1  1.698970     91107       4  4.979680          1  0.000000
1             19  1.544068     90089       3  4.775280          1  0.000000
2             15  1.079181     94720       1  3.612360          1  0.000000
3              9  2.004321     94112       1  6.818421          2  0.000000
4              8  1.662758     91330       4  3.612360          2  0.000000
…            …         …        …       …         …          …
4995           3  1.612784     92697       1  5.548776          3  0.000000
4996           4  1.204120     92037       4  1.753536          1  1.934498
4997          39  1.397940     93023       2  1.367320          3  0.000000
4998          40  1.698970     90034       3  2.113095          2  0.000000
4999           4  1.924279     92612       3  3.063270          1  0.000000

      Personal Loan  Securities Account  CD Account  Online  CreditCard
0                 0                   1           0       0           0
1                 0                   1           0       0           0
2                 0                   0           0       0           0
3                 0                   0           0       0           0
4                 0                   0           0       0           1
…              …                   …          …      …          …
```

```
4995                0                   0           0       1           0
4996                0                   0           0       1           0
4997                0                   0           0       0           0
4998                0                   0           0       1           0
4999                0                   0           0       1           1

[4947 rows x 12 columns]
```

[ ]:
```
# Category Encoding on ‘Family’, ‘Education’ and ‘Zip Code’ into numerical␣
 ↪values
import category_encoders as ce
from category_encoders import TargetEncoder

loan_data_X = loan_data.drop(columns = ['Personal Loan'])
loan_data_y = loan_data['Personal Loan']

te_features = ['Family', 'Education', 'ZIP Code']
te_df = ce.TargetEncoder(cols = te_features).fit_transform(loan_data_X,␣
 ↪loan_data_y)
```

[ ]:
```
te_df = pd.concat((te_df, loan_data_y) , axis = 1)
te_df.head(5)
```

[ ]:
```
   Experience    Income  ZIP Code    Family     CCAvg  Education  Mortgage  \
0           1  1.698970  0.113775  0.111481  4.979680   0.044712       0.0
1          19  1.544068  0.174766  0.132867  4.775280   0.044712       0.0
2          15  1.079181  0.115854  0.072789  3.612360   0.044712       0.0
3           9  2.004321  0.068982  0.072789  6.818421   0.131218       0.0
4           8  1.662758  0.067417  0.111481  3.612360   0.131218       0.0

   Securities Account  CD Account  Online  CreditCard  Personal Loan
0                   1           0       0           0              0
1                   1           0       0           0              0
2                   0           0       0           0              0
3                   0           0       0           0              0
4                   0           0       0           1              0
```

[ ]:
```
te_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4947 entries, 0 to 4999
Data columns (total 12 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Experience          4947 non-null   int64
 1   Income              4947 non-null   float64
 2   ZIP Code            4947 non-null   float64
```

```
 3   Family              4947 non-null   float64
 4   CCAvg               4947 non-null   float64
 5   Education           4947 non-null   float64
 6   Mortgage            4947 non-null   float64
 7   Securities Account  4947 non-null   int64
 8   CD Account          4947 non-null   int64
 9   Online              4947 non-null   int64
 10  CreditCard          4947 non-null   int64
 11  Personal Loan       4947 non-null   int64
dtypes: float64(6), int64(6)
memory usage: 502.4 KB
```

2.3 Address Imbalanced Data

1. Target Variable: Personal Loan (Whether the potential customers have a higher probability of purchasing the loan)
2. Only 9.6% customers bought loan in the last campaign
3. Synthetic Minority Oversampling Technique & Train-Test Split (80:20)- Reduce Overfitting incurred by Oversampling
4. After All the above steps:
    1. The shape of my development set is (3957, 11)
    2. The shape of my test set is (990, 11)
    3. The shape of my development set after SMOTE is (5588, 11)
    4. The shape of my development target after SMOTE is (5588,)
    5. The number of positive labels in the development set are 2794
    6. The number of negative labels in the development set are 2794

[ ]:
```python
from sklearn.model_selection import train_test_split
X = te_df.drop(columns = 'Personal Loan')
y = te_df['Personal Loan']

X_dev, X_test, y_dev, y_test = train_test_split(X,y, test_size=0.2,
                                                stratify = y, random_state=42)
print('The shape of my development set is {}'.format(X_dev.shape) )
print('The shape of my test set is {}'.format(X_test.shape) )
print("*****************************************************************")
print('The shape of my development target is {}'.format(y_dev.shape) )
print('The shape of my test target is {}'.format(y_test.shape) )
```

```
The shape of my development set is (3957, 11)
The shape of my test set is (990, 11)
*****************************************************************
The shape of my development target is (3957,)
The shape of my test target is (990,)
```

[ ]:
```python
te_df['Personal Loan'].value_counts(normalize = True)
```

[ ]:
```
0    0.902971
1    0.097029
Name: Personal Loan, dtype: float64
```

[ ]:
```
y_dev.value_counts(normalize = True)
```

[ ]:
```
0    0.902957
1    0.097043
Name: Personal Loan, dtype: float64
```

[ ]:
```
y_test.value_counts(normalize = True)
```

[ ]:
```
0    0.90303
1    0.09697
Name: Personal Loan, dtype: float64
```

[ ]:
```
from imblearn.over_sampling import SMOTE

smote = SMOTE(random_state=42)
X_dev_subsample_smote, y_dev_subsample_smote = smote.fit_resample(X_dev,y_dev)
print('The shape of my development set after SMOTE is {}'.
 ↪format(X_dev_subsample_smote.shape))
print('The shape of my development target after SMOTE is {}'.
 ↪format(y_dev_subsample_smote.shape))
print("The number of positive labels in the development set are {}".
 ↪format(y_dev_subsample_smote.value_counts()[1]))
print("The number of negative labels in the development set are {}".
 ↪format(y_dev_subsample_smote.value_counts()[0]))
```

```
The shape of my development set after SMOTE is (7146, 11)
The shape of my development target after SMOTE is (7146,)
The number of positive labels in the development set are 3573
The number of negative labels in the development set are 3573
```

3 ML Techniques

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, recall_score, precision_score,␣
 ↪f1_score, roc_auc_score
from sklearn.model_selection import GridSearchCV, StratifiedKFold,␣
 ↪cross_val_score
```

```
from sklearn.metrics import classification_report, RocCurveDisplay,␣
↪ConfusionMatrixDisplay
from sklearn.svm import SVC
```

To train machine learning models for classifying personal loans, we will define several functions that help select best hyperparameters for each model.

```
[ ]: def f1_metric(model, X_train, y_train):
         return f1_score(y_train, model.predict(X_train), average='binary')

     def tune_hyperparameters(MLclf, hyper_params, X_train, y_train):
         cross_validation = StratifiedKFold(n_splits=5, shuffle=True, random_state=0)
         MLclf_search = GridSearchCV(MLclf, hyper_params, cv=cross_validation,␣
      ↪scoring=f1_metric, n_jobs=-1)
         MLclf_search.fit(X_train, y_train)
         print("Best hyperparameters based on the 5-fold corss-validation:\n",␣
      ↪MLclf_search.best_params_)
         return MLclf_search.best_estimator_
```

3.1 Logistic Regression Model

Logistic Regression ML classifier:

To train logistric regression classifier, we will follow the below steps: 1. Train and test the classifier using the dataset after SMOTE method 2. Visulize the confusion metric and ROC plot of the trained classifer in test dataset

3. Train and test the classifier using the dataset without using SMOTE method
4. Visulize the confusion metric and ROC plot of the trained classifer in test dataset

3.1.1 With SMOTE Technique

Training Dataset With SMOTE Technique

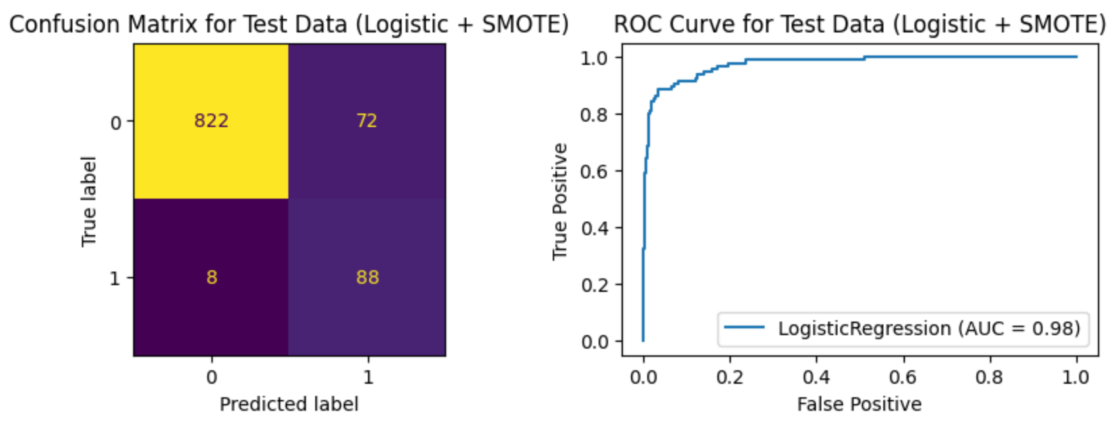
```
[ ]: hyper_params = [{'solver':['saga'], 'penalty':['l1','l2','elasticnet'], 'C': np.
      ↪logspace(-1, 1, 10), 'l1_ratio': np.arange(0,0.4,0.1)},
                     {'solver':['lbfgs','liblinear','newton','saga'], 'penalty':␣
      ↪['l1','l2'], 'C': np.logspace(-1, 1, 10), 'l1_ratio': np.arange(0,0.4,0.1)}]
     logistic = LogisticRegression(max_iter=666)
     logistic_smote_opt = tune_hyperparameters(logistic, hyper_params,␣
      ↪X_dev_subsample_smote, y_dev_subsample_smote)
```

```
Best hyperparameters based on the 5-fold corss-validation:
 {'C': 5.994842503189409, 'l1_ratio': 0.0, 'penalty': 'l1', 'solver':
'liblinear'}
```

```
[ ]: y_pred_train_smote = logistic_smote_opt.predict(X_dev_subsample_smote)
     print("Classification performance (logistic regression) for SMOTE-based␣
      ↪training dataset")
```

```python
print("-"*60)
print(classification_report(y_dev_subsample_smote, y_pred_train_smote))

y_pred_test_smote = logistic_smote_opt.predict(X_test)
print('')
print("Classification performance (logistic regression) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_smote))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(logistic_smote_opt, X_test, y_test,␣
↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (Logistic + SMOTE)')

# ROC Curve
RocCurveDisplay.from_estimator(logistic_smote_opt, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (Logistic + SMOTE)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (logistic regression) for SMOTE-based training
dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.92      0.93      3573
           1       0.92      0.94      0.93      3573

    accuracy                           0.93      7146
   macro avg       0.93      0.93      0.93      7146
weighted avg       0.93      0.93      0.93      7146


Classification performance (logistic regression) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      0.92      0.95       894
           1       0.55      0.92      0.69        96

    accuracy                           0.92       990
   macro avg       0.77      0.92      0.82       990
weighted avg       0.95      0.92      0.93       990
```



3.1.2 Without SMOTE Technique

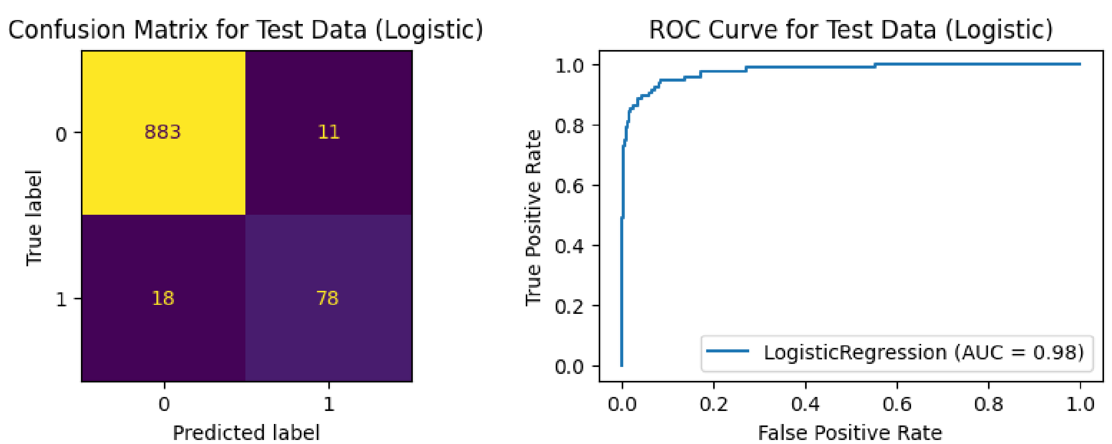
```
[ ]: hyper_params = [{'solver':['saga'], 'penalty':['l1','l2','elasticnet'], 'C': np.
     ↪logspace(-1, 1, 10), 'l1_ratio': np.arange(0,0.4,0.1)},
                    {'solver':['lbfgs','liblinear','newton','saga'], 'penalty':␣
     ↪['l1','l2'], 'C': np.logspace(-1, 1, 10), 'l1_ratio': np.arange(0,0.4,0.1)}]
     logistic_ori = LogisticRegression(max_iter=666)
     logistic_ori_opt = tune_hyperparameters(logistic_ori, hyper_params, X_dev,␣
     ↪y_dev)
```

```
Best hyperparameters based on the 5-fold corss-validation:
 {'C': 10.0, 'l1_ratio': 0.0, 'penalty': 'l1', 'solver': 'liblinear'}
```

```
[ ]: y_pred_train_ori = logistic_ori_opt.predict(X_dev)
     print("Classification performance (logistic regression) for training dataset␣
     ↪without SMOTE technique")
     print("-"*60)
     print(classification_report(y_dev, y_pred_train_ori))

     y_pred_test_ori = logistic_ori_opt.predict(X_test)
     print('')
     print("Classification performance (logistic regression) for test dataset")
     print("-"*60)
     print(classification_report(y_test, y_pred_test_ori))

     # Confusion Matrix
     fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
     ConfusionMatrixDisplay.from_estimator(logistic_ori_opt, X_test, y_test,␣
     ↪colorbar=False, ax=ax1)
     ax1.set_title('Confusion Matrix for Test Data (Logistic)')

     # ROC Curve
```

```
RocCurveDisplay.from_estimator(logistic_ori_opt, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (Logistic)')
ax2.set_xlabel('False Positive Rate')
ax2.set_ylabel('True Positive Rate')
plt.show()
```

```
Classification performance (logistic regression) for training dataset without
SMOTE technique
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.97      0.99      0.98      3573
           1       0.91      0.76      0.82       384

    accuracy                           0.97      3957
   macro avg       0.94      0.87      0.90      3957
weighted avg       0.97      0.97      0.97      3957


Classification performance (logistic regression) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       894
           1       0.88      0.81      0.84        96

    accuracy                           0.97       990
   macro avg       0.93      0.90      0.91       990
weighted avg       0.97      0.97      0.97       990
```



3.2 Random Forest Model

Random Forest ML classifier:

To train Random Forest classifier, we will follow the below steps: 1. Train and test the RF classifier using the SMOTE-based dataset 2. Visulize the confusion metric and ROC plot of the trained RF classifer in test dataset

3. Train and test the RF classifier using the dataset without SMOTE technique
4. Visulize the confusion metric and ROC plot of the trained classifer in test dataset

3.2.1 With SMOTE Technique

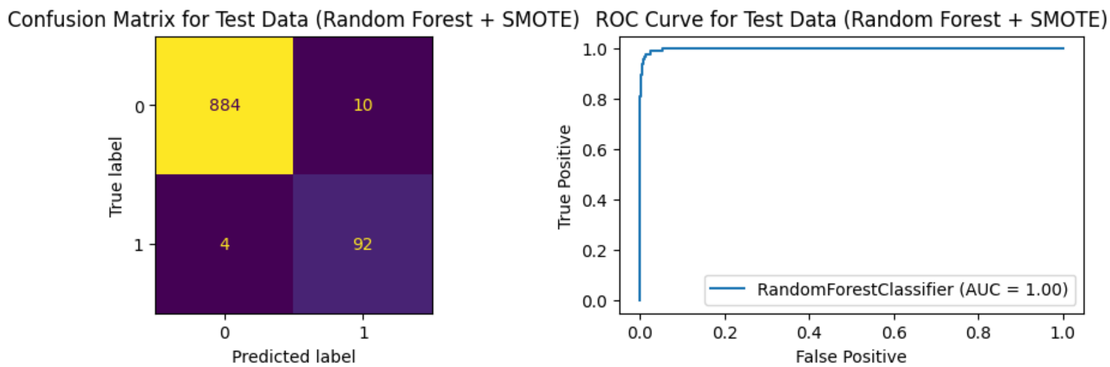
SMOTE-based Dataset (Random Forest)

[ ]:
```
hyper_params = {'max_depth': np.arange(4, 10), 'n_estimators': [10, 20, 50,␣
↪100], 'min_samples_split': [2, 3, 4], 'min_samples_leaf': [1, 2, 3]}
rf_smote = RandomForestClassifier(criterion='gini', random_state=0)
rf_opt_smote = tune_hyperparameters(rf_smote, hyper_params,␣
↪X_dev_subsample_smote, y_dev_subsample_smote)
```

```
Best hyperparameters based on the 5-fold corss-validation:
 {'max_depth': 9, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators':
100}
```

[ ]:
```
y_pred_train_smote = rf_opt_smote.predict(X_dev_subsample_smote)
print("Classification performance (Random Forest) for SMOTE-based training␣
↪dataset")
print("-"*60)
print(classification_report(y_dev_subsample_smote, y_pred_train_smote))

y_pred_test_smote = rf_opt_smote.predict(X_test)
print('')
print("Classification performance (Random Forest) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_smote))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(11, 3))
ConfusionMatrixDisplay.from_estimator(rf_opt_smote, X_test, y_test,␣
↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (Random Forest + SMOTE)')

# ROC Curve
RocCurveDisplay.from_estimator(rf_opt_smote, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (Random Forest + SMOTE)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (Random Forest) for SMOTE-based training dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3573
           1       1.00      1.00      1.00      3573

    accuracy                           1.00      7146
   macro avg       1.00      1.00      1.00      7146
weighted avg       1.00      1.00      1.00      7146


Classification performance (Random Forest) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       894
           1       0.90      0.96      0.93        96

    accuracy                           0.99       990
   macro avg       0.95      0.97      0.96       990
weighted avg       0.99      0.99      0.99       990
```



3.2.2 Without SMOTE Technique

Dataset without using SMOTE technique (Random Forest)

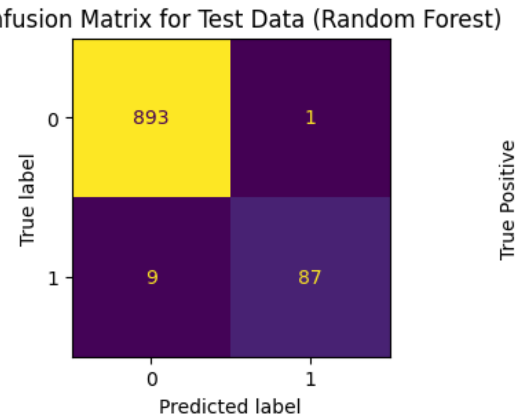
```
[ ]: hyper_params = {'max_depth': np.arange(4, 10), 'n_estimators': [20, 50, 100],
     ↪'min_samples_split': [2, 3, 4], 'min_samples_leaf': [1, 2, 3]}
     rf_ori = RandomForestClassifier(criterion='gini', random_state=0)
     rf_opt_ori = tune_hyperparameters(rf_ori, hyper_params, X_dev, y_dev)
```

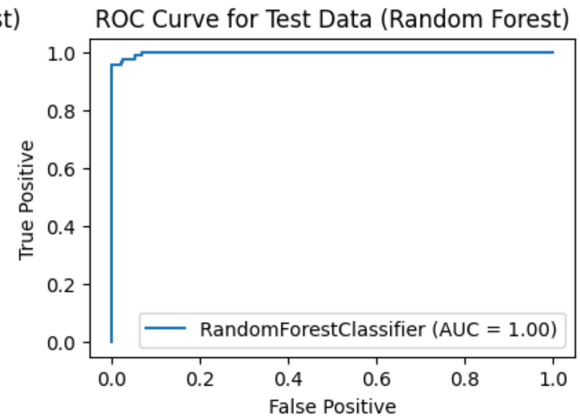
```
Best hyperparameters based on the 5-fold corss-validation:
 {'max_depth': 9, 'min_samples_leaf': 1, 'min_samples_split': 4, 'n_estimators':
100}
```

[ ]:
```python
y_pred_train_ori = rf_opt_ori.predict(X_dev)
print("Classification performance (Random Forest) for training dataset without␣
 ↪SMOTE technique")
print("-"*60)
print(classification_report(y_dev, y_pred_train_ori))

y_pred_test_ori = rf_opt_ori.predict(X_test)
print('')
print("Classification performance (Random Forest) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_ori))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(rf_opt_ori, X_test, y_test,␣
 ↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (Random Forest)')

# ROC Curve
RocCurveDisplay.from_estimator(rf_opt_ori, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (Random Forest)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (Random Forest) for training dataset without SMOTE
technique
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3573
           1       1.00      0.96      0.98       384

    accuracy                           1.00      3957
   macro avg       1.00      0.98      0.99      3957
weighted avg       1.00      1.00      1.00      3957


Classification performance (Random Forest) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      1.00      0.99       894
           1       0.99      0.91      0.95        96
```

```
    accuracy                           0.99       990
   macro avg       0.99      0.95      0.97       990
weighted avg       0.99      0.99      0.99       990
```





3.3 XGBoost Model

XGBoost ML classifier:

To train XGBoost classifier, we will follow the below steps:

1. Train and test the XGBoost classifier using the SMOTE-based dataset
2. Visulize the confusion metric and ROC plot of the trained *XGBoost* classifer in test dataset
3. Train and test the XGBoost classifier using the dataset without SMOTE technique
4. Visulize the confusion metric and ROC plot of the trained classifer in test dataset

3.3.1 With SMOTE Technique

SMOTE-based Dataset

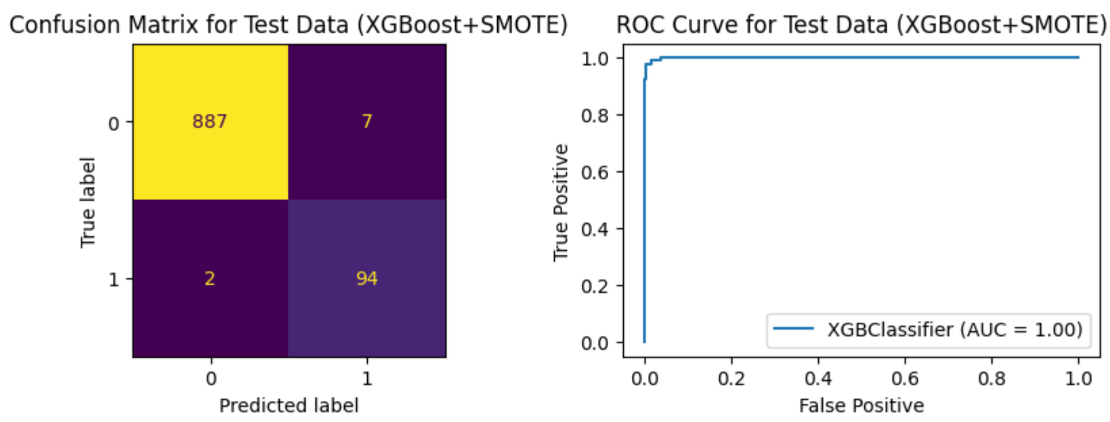
[ ]:
```python
hyper_params = {'learning_rate': [0.05, 0.1, 0.2], 'n_estimators': [30, 50],'subsample': [0.6, 0.8, 1.0],'reg_alpha': [0, 0.1, 1],'reg_lambda': [0, 0.1, 1]}
xgb_smote = XGBClassifier(random_state=0)
xgb_opt_smote = tune_hyperparameters(xgb_smote, hyper_params, X_dev_subsample_smote, y_dev_subsample_smote)
```

```
Best hyperparameters based on the 5-fold corss-validation:
 {'learning_rate': 0.2, 'n_estimators': 50, 'reg_alpha': 0, 'reg_lambda': 1,
'subsample': 1.0}
```

[ ]:
```python
y_pred_train_smote = xgb_opt_smote.predict(X_dev_subsample_smote)
print("Classification performance (XGBoost) for SMOTE-based training dataset")
```

```python
print("-"*60)
print(classification_report(y_dev_subsample_smote, y_pred_train_smote))

y_pred_test_smote = xgb_opt_smote.predict(X_test)
print('')
print("Classification performance (XGBoost) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_smote))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(xgb_opt_smote, X_test, y_test,␣
 ↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (XGBoost+SMOTE)')

# ROC Curve
RocCurveDisplay.from_estimator(xgb_opt_smote, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (XGBoost+SMOTE)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (XGBoost) for SMOTE-based training dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3573
           1       1.00      1.00      1.00      3573

    accuracy                           1.00      7146
   macro avg       1.00      1.00      1.00      7146
weighted avg       1.00      1.00      1.00      7146


Classification performance (XGBoost) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      0.99      0.99       894
           1       0.93      0.98      0.95        96

    accuracy                           0.99       990
   macro avg       0.96      0.99      0.97       990
weighted avg       0.99      0.99      0.99       990
```



3.3.2 Without SMOTE Technique

Dataset without using SMOTE technique

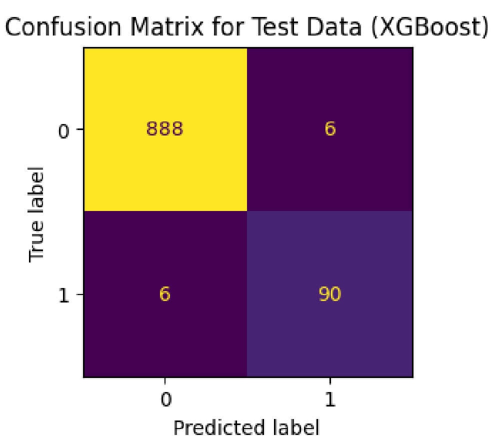
[ ]:
```
hyper_params = {'learning_rate': [0.05, 0.1, 0.2], 'n_estimators': [30, 50],'subsample': [0.6, 0.8, 1.0],'reg_alpha': [0, 0.1, 1],'reg_lambda': [0, 0.1, 1]}
xgb_ori = XGBClassifier(random_state=0)
xgb_opt_ori = tune_hyperparameters(xgb_ori, hyper_params, X_dev, y_dev)
```

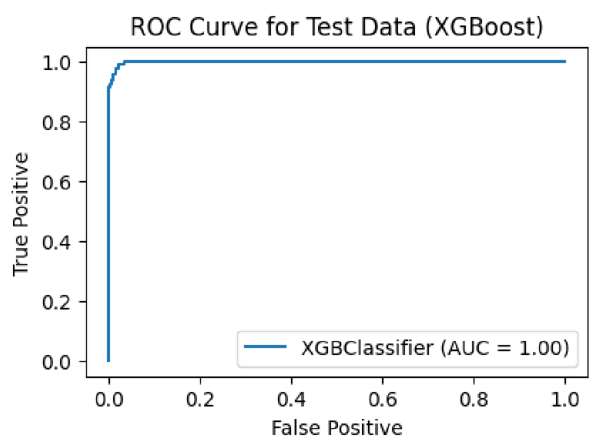
```
Best hyperparameters based on the 5-fold corss-validation:
 {'learning_rate': 0.2, 'n_estimators': 30, 'reg_alpha': 0, 'reg_lambda': 0,
'subsample': 0.6}
```

[ ]:
```
y_pred_train_ori = xgb_opt_ori.predict(X_dev)
print("Classification performance (XGBoost) for training dataset without SMOTE technique")
print("-"*60)
print(classification_report(y_dev, y_pred_train_ori))

y_pred_test_ori = xgb_opt_ori.predict(X_test)
print('')
print("Classification performance (XGBoost) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_ori))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(xgb_opt_ori, X_test, y_test, colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (XGBoost)')
```

```python
# ROC Curve
RocCurveDisplay.from_estimator(xgb_opt_ori, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (XGBoost)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (XGBoost) for training dataset without SMOTE
technique
------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      3573
           1       0.99      0.98      0.99       384

    accuracy                           1.00      3957
   macro avg       1.00      0.99      0.99      3957
weighted avg       1.00      1.00      1.00      3957


Classification performance (XGBoost) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       894
           1       0.94      0.94      0.94        96

    accuracy                           0.99       990
   macro avg       0.97      0.97      0.97       990
weighted avg       0.99      0.99      0.99       990
```





3.4 Support Vector Machine(SVM)

SVM ML classifier:

To train SVM classifier, we will follow the below steps:

1. Train and test the SVM classifier using the SMOTE-based dataset
2. Visulize the confusion metric and ROC plot of the trained SVM classifer in test dataset
3. Train and test the SVM classifier using the dataset without SMOTE technique
4. Visulize the confusion metric and ROC plot of the trained classifer in test dataset

3.4.1 With SMOTE Technique

SMOTE-based Dataset

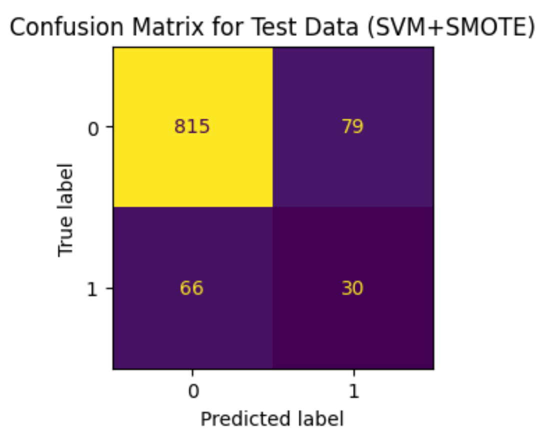
[ ]:
```
hyper_params = [{'kernel': ['rbf'],'gamma': [1, 0.1, 0.01, 0.001], 'C': [100,␣
↪10, 0.1,1, 1000]}, {'kernel': ['linear'], 'C': [10, 0.1, 1, 100, 1000]}]
svm_smote = SVC(probability=True, max_iter=600)
svm_opt_smote = tune_hyperparameters(svm_smote, hyper_params,␣
↪X_dev_subsample_smote, y_dev_subsample_smote)
```

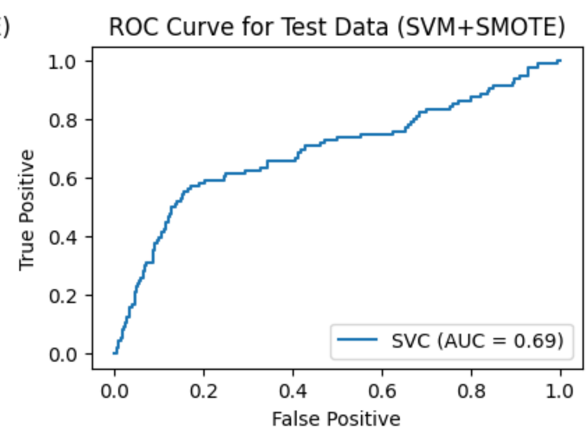
```
Best hyperparameters based on the 5-fold corss-validation:
 {'C': 10, 'gamma': 1, 'kernel': 'rbf'}
```

[ ]:
```
y_pred_train_smote = svm_opt_smote.predict(X_dev_subsample_smote)
print("Classification performance (SVM) for SMOTE-based training dataset")
print("-"*60)
print(classification_report(y_dev_subsample_smote, y_pred_train_smote))

y_pred_test_smote = svm_opt_smote.predict(X_test)
print('')
print("Classification performance (SVM) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_smote))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(svm_opt_smote, X_test, y_test,␣
↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (SVM+SMOTE)')

# ROC Curve
RocCurveDisplay.from_estimator(svm_opt_smote, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (SVM+SMOTE)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (SVM) for SMOTE-based training dataset
------------------------------------------------------------
```

```
              precision    recall  f1-score   support

           0       0.95      0.98      0.96      3573
           1       0.98      0.95      0.96      3573

    accuracy                           0.96      7146
   macro avg       0.96      0.96      0.96      7146
weighted avg       0.96      0.96      0.96      7146


Classification performance (SVM) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.93      0.91      0.92       894
           1       0.28      0.31      0.29        96

    accuracy                           0.85       990
   macro avg       0.60      0.61      0.61       990
weighted avg       0.86      0.85      0.86       990
```





3.4.2 Without SMOTE Technique

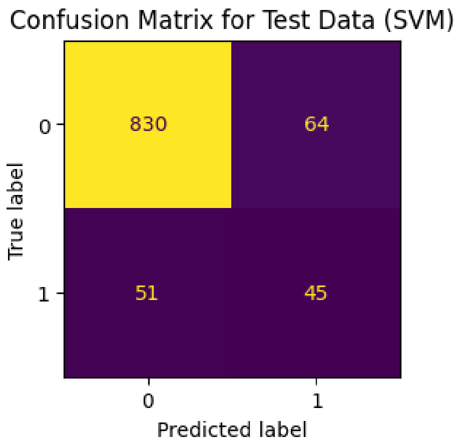
```
[ ]: hyper_params = [{'kernel': ['rbf'],'gamma': [1, 0.1, 0.01, 0.001], 'C': [0.1,␣
     ↪1, 10, 100, 1000]}, {'kernel': ['linear'], 'C': [0.1, 1, 10, 100, 1000]}]
     svm_ori = SVC(probability=True, max_iter=600)
     svm_opt_ori = tune_hyperparameters(svm_smote, hyper_params, X_dev, y_dev)
```

```
Best hyperparameters based on the 5-fold corss-validation:
 {'C': 1000, 'gamma': 0.1, 'kernel': 'rbf'}
```

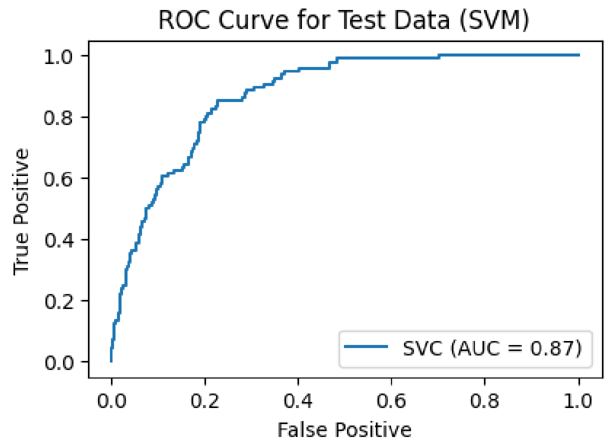
[ ]:

```python
y_pred_train_ori = svm_opt_ori.predict(X_dev)
print("Classification performance (SVM) for training dataset without SMOTE␣
↪technique")
print("-"*60)
print(classification_report(y_dev, y_pred_train_ori))

y_pred_test_ori = svm_opt_ori.predict(X_test)
print('')
print("Classification performance (SVM) for test dataset")
print("-"*60)
print(classification_report(y_test, y_pred_test_ori))

# Confusion Matrix
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(10, 3))
ConfusionMatrixDisplay.from_estimator(svm_opt_ori, X_test, y_test,␣
↪colorbar=False, ax=ax1)
ax1.set_title('Confusion Matrix for Test Data (SVM)')

# ROC Curve
RocCurveDisplay.from_estimator(svm_opt_ori, X_test, y_test, ax=ax2)
ax2.set_title('ROC Curve for Test Data (SVM)')
ax2.set_xlabel('False Positive')
ax2.set_ylabel('True Positive')
plt.show()
```

```
Classification performance (SVM) for training dataset without SMOTE technique
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.97      0.95      0.96      3573
           1       0.59      0.70      0.64       384

    accuracy                           0.92      3957
   macro avg       0.78      0.83      0.80      3957
weighted avg       0.93      0.92      0.93      3957


Classification performance (SVM) for test dataset
------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.94      0.93      0.94       894
           1       0.41      0.47      0.44        96

    accuracy                           0.88       990
   macro avg       0.68      0.70      0.69       990
weighted avg       0.89      0.88      0.89       990
```



Confusion Matrix for Test Data (SVM)
830
64
51
45
0
1
True label
0
1
Predicted label



ROC Curve for Test Data (SVM)
1.0
0.8
0.6
0.4
0.2
0.0
True Positive
0.0
0.2
0.4
0.6
0.8
1.0
False Positive
SVC (AUC = 0.87)