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January 21, 2025

0.1 Problem Statement

0.1.1 Context

AllLife Bank is a US bank that has a growing customer base. The majority of these customers are liability customers (depositors) with varying sizes of deposits. The number of customers who are also borrowers (asset customers) is quite small, and the bank is interested in expanding this base rapidly to bring in more loan business and in the process, earn more through the interest on loans. In particular, the management wants to explore ways of converting its liability customers to personal loan customers (while retaining them as depositors).

A campaign that the bank ran last year for liability customers showed a healthy conversion rate of over 9% success. This has encouraged the retail marketing department to devise campaigns with better target marketing to increase the success ratio.

You as a Data scientist at AllLife bank have to build a model that will help the marketing department to identify the potential customers who have a higher probability of purchasing the loan.

0.1.2 Objective

To predict whether a liability customer will buy personal loans, to understand which customer attributes are most significant in driving purchases, and identify which segment of customers to target more.

0.1.3 Data Dictionary

- `ID`: Customer ID
- `Age`: Customer's age in completed years
- `Experience`: #years of professional experience
- `Income`: Annual income of the customer (in thousand dollars)
- `ZIP Code`: Home Address ZIP code.
- `Family`: the Family size of the customer
- `CCAvg`: Average spending on credit cards per month (in thousand dollars)
- `Education`: Education Level. 1: Undergrad; 2: Graduate;3: Advanced/Professional
- `Mortgage`: Value of house mortgage if any. (in thousand dollars)
- `Personal_Loan`: Did this customer accept the personal loan offered in the last campaign? (0: No, 1: Yes)
- `Securities_Account`: Does the customer have securities account with the bank? (0: No, 1: Yes)
- `CD_Account`: Does the customer have a certificate of deposit (CD) account with the bank? (0: No, 1: Yes)

- `Online`: Do customers use internet banking facilities? (0: No, 1: Yes)
- `CreditCard`: Does the customer use a credit card issued by any other Bank (excluding All life Bank)? (0: No, 1: Yes)

0.2 Please read the instructions carefully before starting the project.

This is a commented Jupyter IPython Notebook file in which all the instructions and tasks to be performed are mentioned. * Blanks '_______' are provided in the notebook that needs to be filled with an appropriate code to get the correct result. With every '_______' blank, there is a comment that briefly describes what needs to be filled in the blank space. * Identify the task to be performed correctly, and only then proceed to write the required code. * Fill the code wherever asked by the commented lines like "# write your code here" or "# complete the code". Running incomplete code may throw error. * Please run the codes in a sequential manner from the beginning to avoid any unnecessary errors. * Add the results/observations (wherever mentioned) derived from the analysis in the presentation and submit the same.

0.3 Importing necessary libraries

[ ]:
```
# Installing the libraries with the specified version.
!pip install numpy==1.25.2 pandas==2.2.2 matplotlib==3.8.1 seaborn==0.13.1␣
↪scikit-learn==1.3.2 sklearn-pandas==2.2.0 -q --user
```

```
                         18.2/18.2 MB
77.6 MB/s eta 0:00:00
                         11.6/11.6 MB
60.2 MB/s eta 0:00:00
                         294.8/294.8 kB
22.6 MB/s eta 0:00:00
                         10.9/10.9 MB
80.5 MB/s eta 0:00:00
  WARNING: The scripts f2py, f2py3 and f2py3.11 are installed in
'/root/.local/bin' which is not on PATH.
  Consider adding this directory to PATH or, if you prefer to suppress this
warning, use --no-warn-script-location.
```

Note:

1. After running the above cell, kindly restart the notebook kernel (for Jupyter Notebook) or runtime (for Google Colab) and run all cells sequentially from the next cell.
2. On executing the above line of code, you might see a warning regarding package dependencies. This error message can be ignored as the above code ensures that all necessary libraries and their dependencies are maintained to successfully execute the code in this notebook.

[ ]:
```
# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np
```

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

# Library to split data
from sklearn.model_selection import train_test_split

# To build model for prediction
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree

# To get diferent metric scores
from sklearn.metrics import (
    f1_score,
    accuracy_score,
    recall_score,
    precision_score,
    confusion_matrix,
)

# to suppress unnecessary warnings
import warnings
warnings.filterwarnings("ignore")
```

0.4 Loading the dataset

[ ]:
```
# uncomment the following lines if Google Colab is being used
# from google.colab import drive
# drive.mount('/content/drive')
```

[ ]:
```
Loan = pd.read_csv("/content/Loan_Modelling.csv")   ##  Complete the code to␣
↪read the data
```

[ ]:
```
# copying data to another variable to avoid any changes to original data
data = Loan.copy()
```

0.5 Data Overview

0.5.1 View the first and last 5 rows of the dataset.

[ ]:
```
data.head()  ##  Complete the code to view top 5 rows of the data
```

[ ]:
```
   ID  Age  Experience  Income  ZIPCode  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
```

[ ]:
```
data.tail() ##  Complete the code to view last 5 rows of the data
```

[ ]:
```
        ID  Age  Experience  Income  ZIPCode  Family  CCAvg  Education  \
4995  4996   29           3      40    92697       1    1.9          3
4996  4997   30           4      15    92037       4    0.4          1
4997  4998   63          39      24    93023       2    0.3          3
4998  4999   65          40      49    90034       3    0.5          2
4999  5000   28           4      83    92612       3    0.8          1

      Mortgage  Personal_Loan  Securities_Account  CD_Account  Online  \
4995         0              0                   0           0       1
4996        85              0                   0           0       1
4997         0              0                   0           0       0
4998         0              0                   0           0       1
4999         0              0                   0           0       1

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

0.5.2 Understand the shape of the dataset.

[ ]:
```
data.shape ## Complete the code to get the shape of the data
```

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

0.5.3 Check the data types of the columns for the dataset

[ ]:
```
data.info()  ##  Complete the code to view the datatypes of the data
```

```
<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   ZIPCode             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
```

0.5.4 Checking the Statistical Summary

[ ]:
```
data.describe().T  ## Complete the code to print the statistical summary of the data
```

[ ]:
```
                     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
ZIPCode             5000.0  93169.257000  1759.455086  90005.0  91911.00
Family              5000.0      2.396400     1.147663      1.0      1.00
CCAvg               5000.0      1.937938     1.747659      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
ZIPCode             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
```

0.5.5 Dropping columns

[ ]:
```
data = data.drop(['ID'], axis=1)  ## Complete the code to drop a column from
 ↪the dataframe
```

0.6 Data Preprocessing

0.6.1 Checking for Anomalous Values

[ ]:
```
data["Experience"].unique()
```

[ ]:
```
array([ 1, 19, 15,  9,  8, 13, 27, 24, 10, 39,  5, 23, 32, 41, 30, 14, 18,
       21, 28, 31, 11, 16, 20, 35,  6, 25,  7, 12, 26, 37, 17,  2, 36, 29,
        3, 22, -1, 34,  0, 38, 40, 33,  4, -2, 42, -3, 43])
```

[ ]:
```
# checking for experience <0
data[data["Experience"] < 0]["Experience"].unique()
```

[ ]:
```
array([-1, -2, -3])
```

[ ]:
```
# Correcting the experience values
data["Experience"].replace(-1, 1, inplace=True)
data["Experience"].replace(-2, 2, inplace=True)
data["Experience"].replace(-3, 3, inplace=True)
```

[ ]:
```
data["Education"].unique()
```

[ ]:
```
array([1, 2, 3])
```

0.6.2 Feature Engineering

[ ]:
```
# checking the number of uniques in the zip code
data["ZIPCode"].nunique()
```

[ ]:
```
467
```

[ ]:
```
data["ZIPCode"] = data["ZIPCode"].astype(str)
print(
    "Number of unique values if we take first two digits of ZIPCode: ",
```

```
    data["ZIPCode"].str[0:2].nunique(),
)
data["ZIPCode"] = data["ZIPCode"].str[0:2]

data["ZIPCode"] = data["ZIPCode"].astype("category")
```

```
Number of unique values if we take first two digits of ZIPCode:  7
```

[ ]:
```
## Converting the data type of categorical features to 'category'
cat_cols = [
    "Education",
    "Personal_Loan",
    "Securities_Account",
    "CD_Account",
    "Online",
    "CreditCard",
    "ZIPCode",
]
data[cat_cols] = data[cat_cols].astype("category")
```

0.7 Exploratory Data Analysis (EDA)

0.7.1 Univariate Analysis

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

    data: dataframe
    feature: dataframe column
    figsize: size of figure (default (12,7))
    kde: whether to show the density curve (default False)
    bins: number of bins for histogram (default None)
    """
    f2, (ax_box2, ax_hist2) = plt.subplots(
        nrows=2,  # Number of rows of the subplot grid= 2
        sharex=True,  # x-axis will be shared among all subplots
        gridspec_kw={"height_ratios": (0.25, 0.75)},
        figsize=figsize,
    )  # creating the 2 subplots
    sns.boxplot(
        data=data, x=feature, ax=ax_box2, showmeans=True, color="violet"
    )  # boxplot will be created and a star will indicate the mean value of the␣
↪column
    sns.histplot(
        data=data, x=feature, kde=kde, ax=ax_hist2, bins=bins, palette="winter"
    ) if bins else sns.histplot(
```

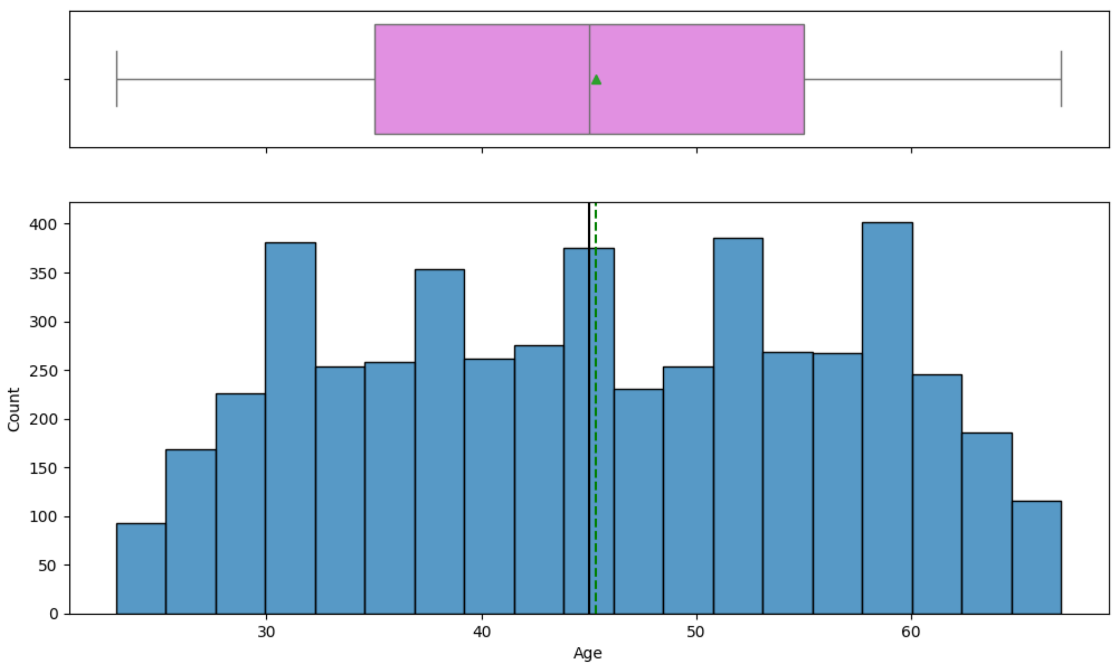
```
        data=data, x=feature, kde=kde, ax=ax_hist2
    )  # For histogram
    ax_hist2.axvline(
        data[feature].mean(), color="green", linestyle="--"
    )  # Add mean to the histogram
    ax_hist2.axvline(
        data[feature].median(), color="black", linestyle="-"
    )  # Add median to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

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


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

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

    total = len(data[feature])  # length of the column
    count = data[feature].nunique()
    if n is None:
        plt.figure(figsize=(count + 1, 5))
    else:
        plt.figure(figsize=(n + 1, 5))

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

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

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

```
        y = p.get_height()  # height of the plot

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

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

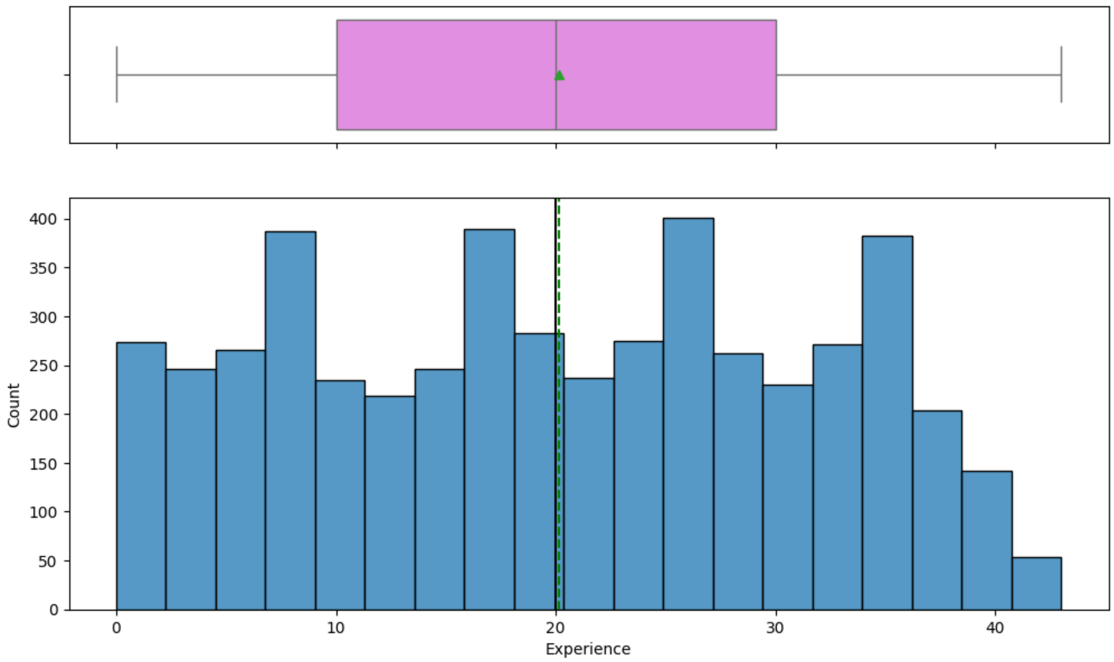
Observations on Age

[ ]:
```
histogram_boxplot(data, "Age")
```



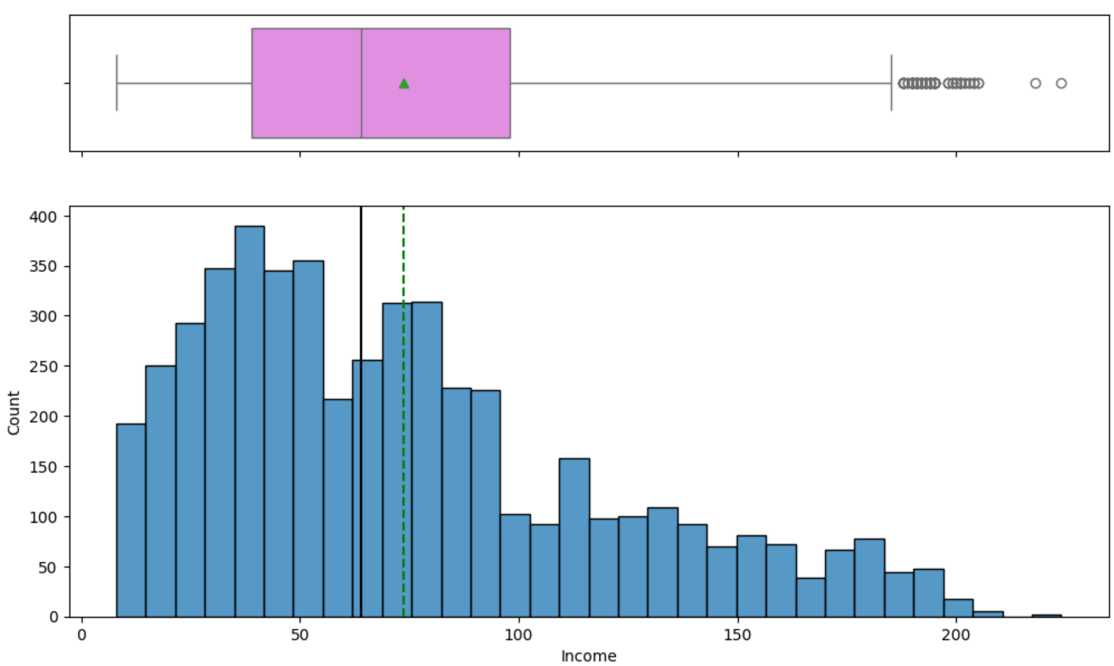
Observations on Experience

[ ]:
```
histogram_boxplot(data, "Experience") ## Complete the code to create␣
↪histogram_boxplot for experience
```



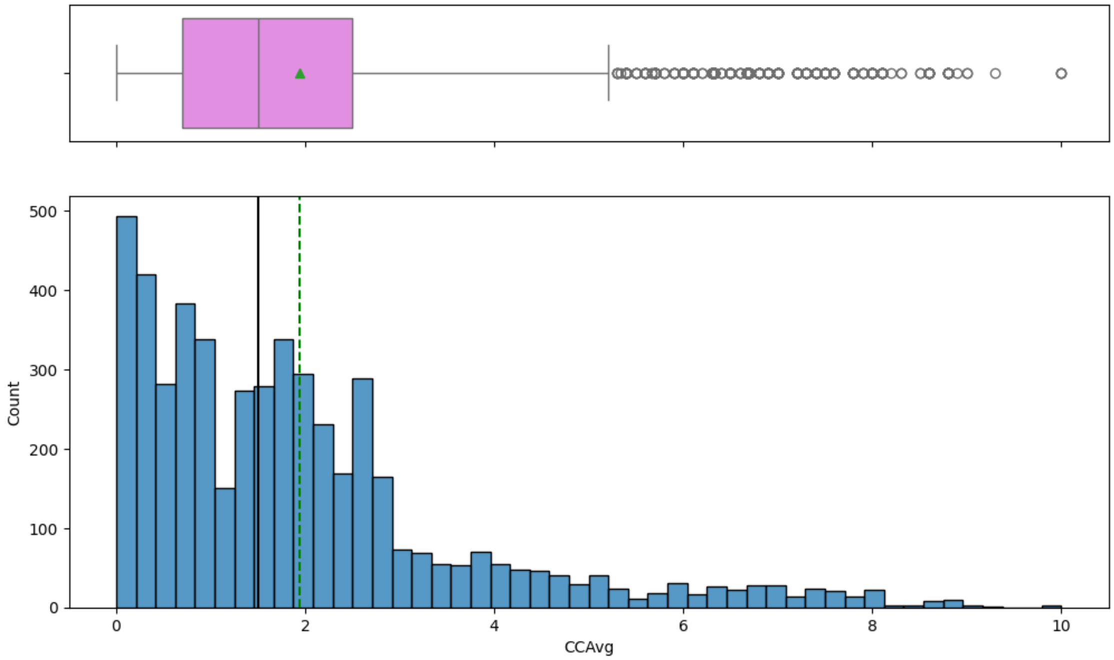
Observations on Income

```
[ ]: histogram_boxplot(data,"Income")  ## Complete the code to create
     ↪histogram_boxplot for Income
```



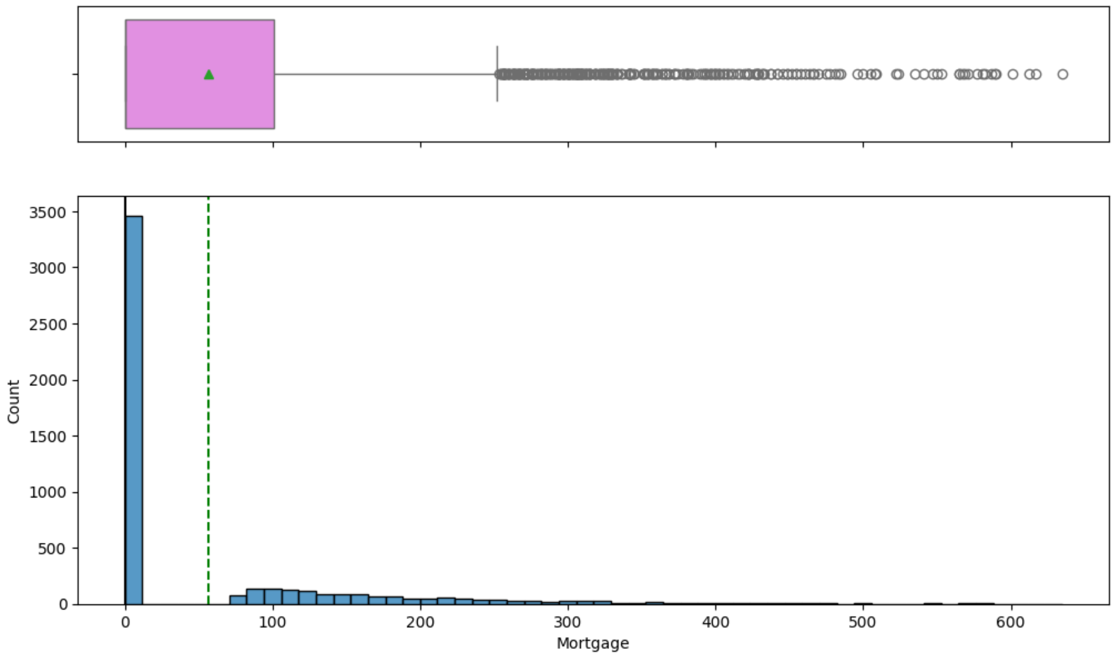
Observations on CCAvg

```
[ ]: histogram_boxplot(data, "CCAvg")  ## Complete the code to create
     ↪histogram_boxplot for CCAvg
```



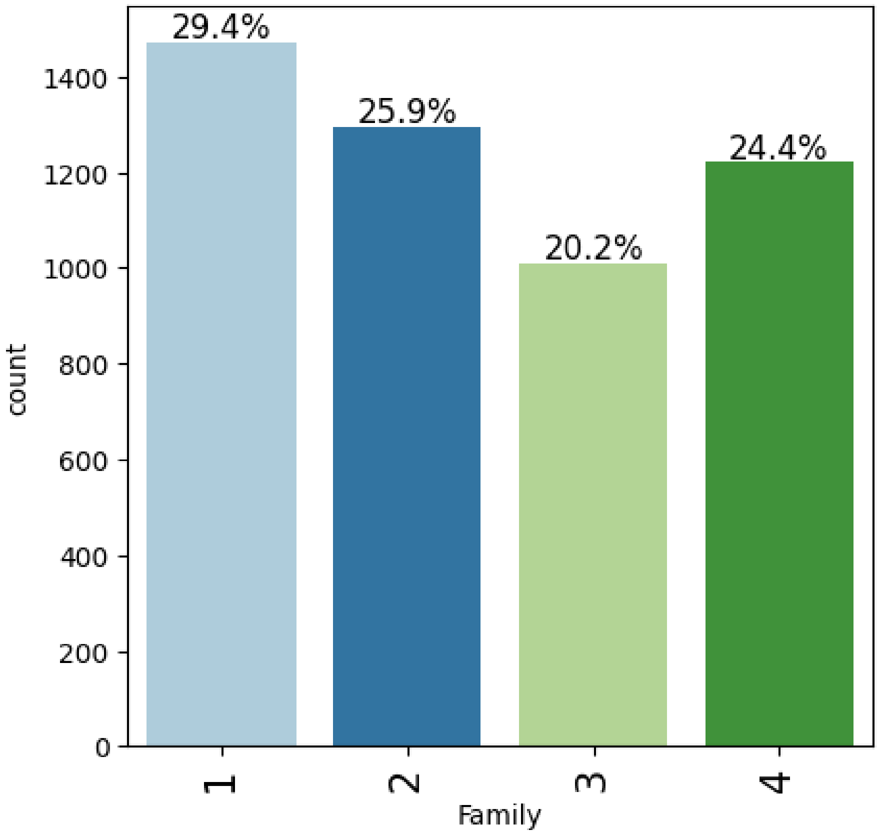
Observations on Mortgage

```
[ ]: histogram_boxplot(data, "Mortgage")  ## Complete the code to create
     ↪histogram_boxplot for Mortgage
```



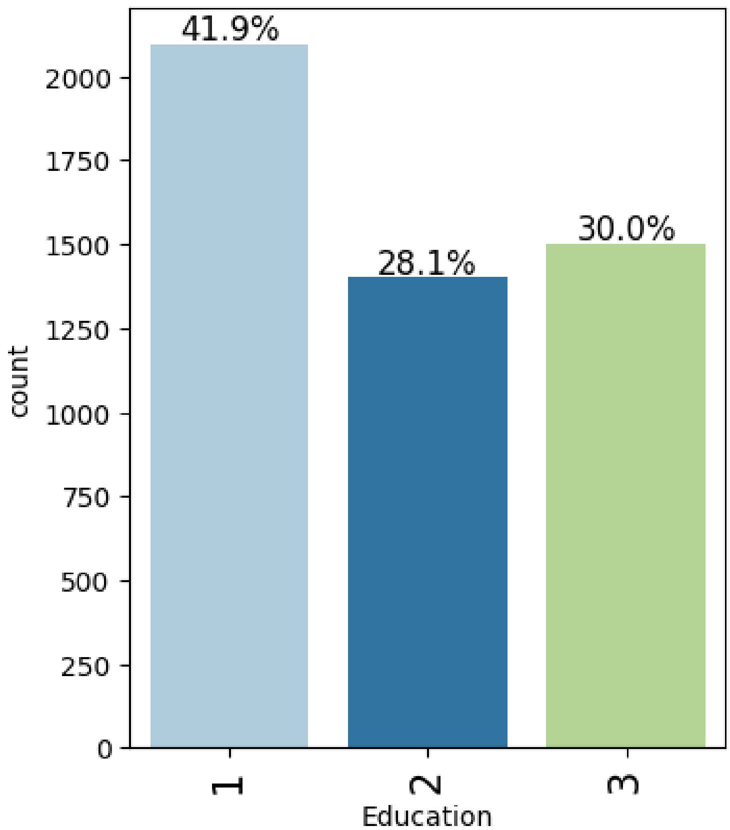
Observations on Family

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



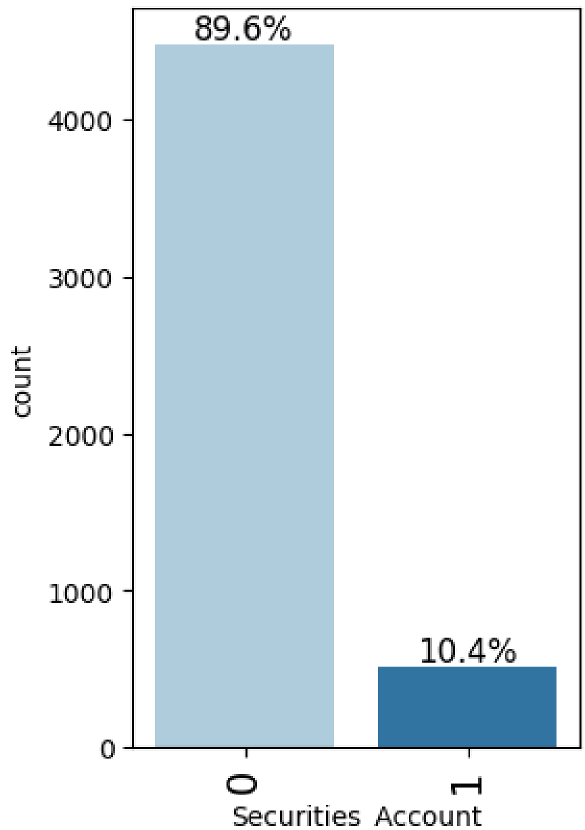
Observations on Education

```
[ ]: labeled_barplot( data, "Education", perc=True)   ## Complete the code to create
     ↪labeled_barplot for Education
```



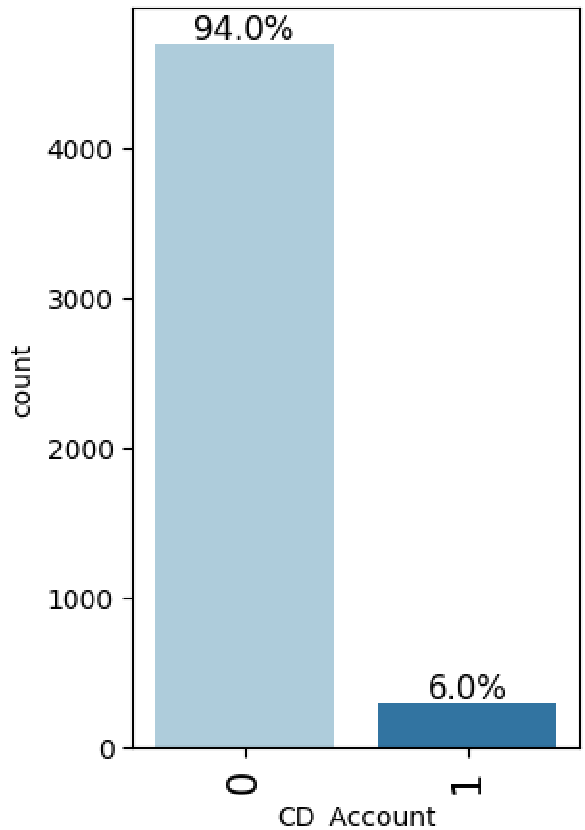
Observations on Securities_Account

```
[ ]: labeled_barplot(data, "Securities_Account", perc=True)    ## Complete the code␣
     ↪to create labeled_barplot for Securities_Account
```



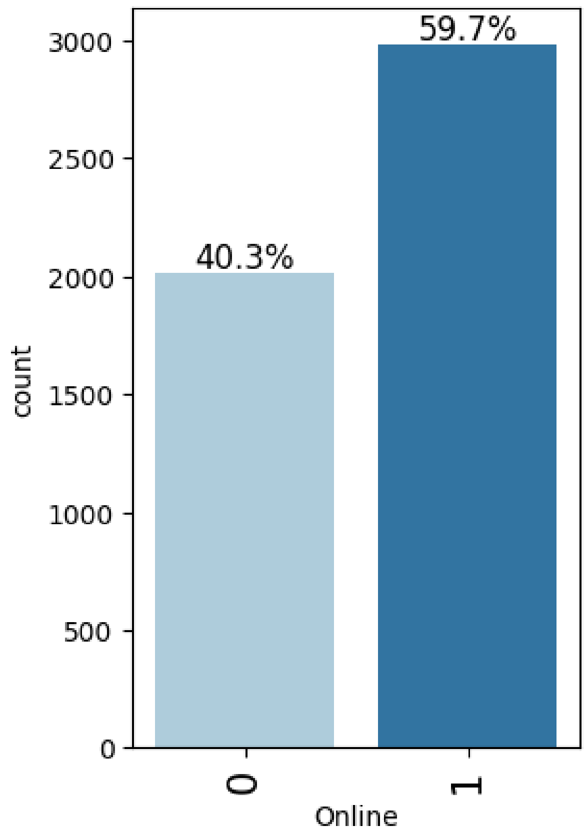
Observations on CD_Account

```
[ ]: labeled_barplot(data, "CD_Account", perc=True)    ## Complete the code to create␣
     ↪labeled_barplot for CD_Account
```



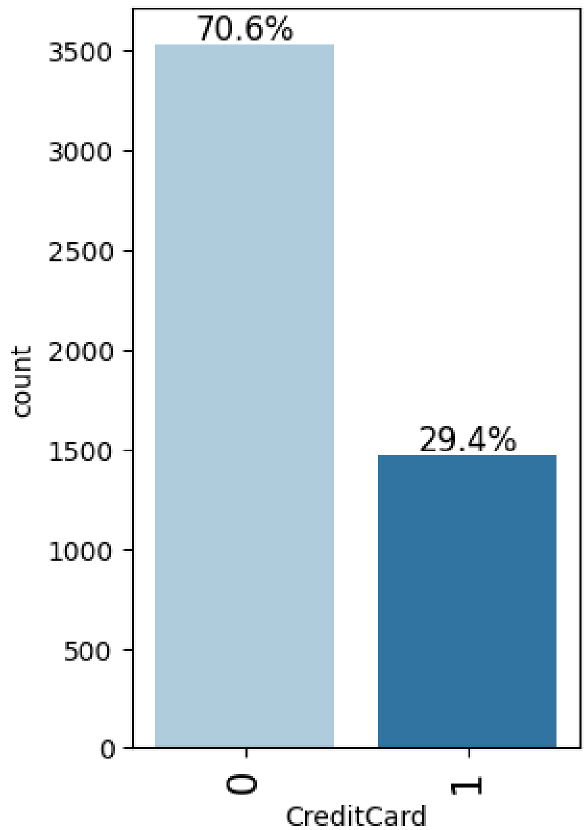
Observations on Online

```
[ ]: labeled_barplot(data, "Online", perc=True)    ## Complete the code to create␣
     ↪labeled_barplot for Online
```



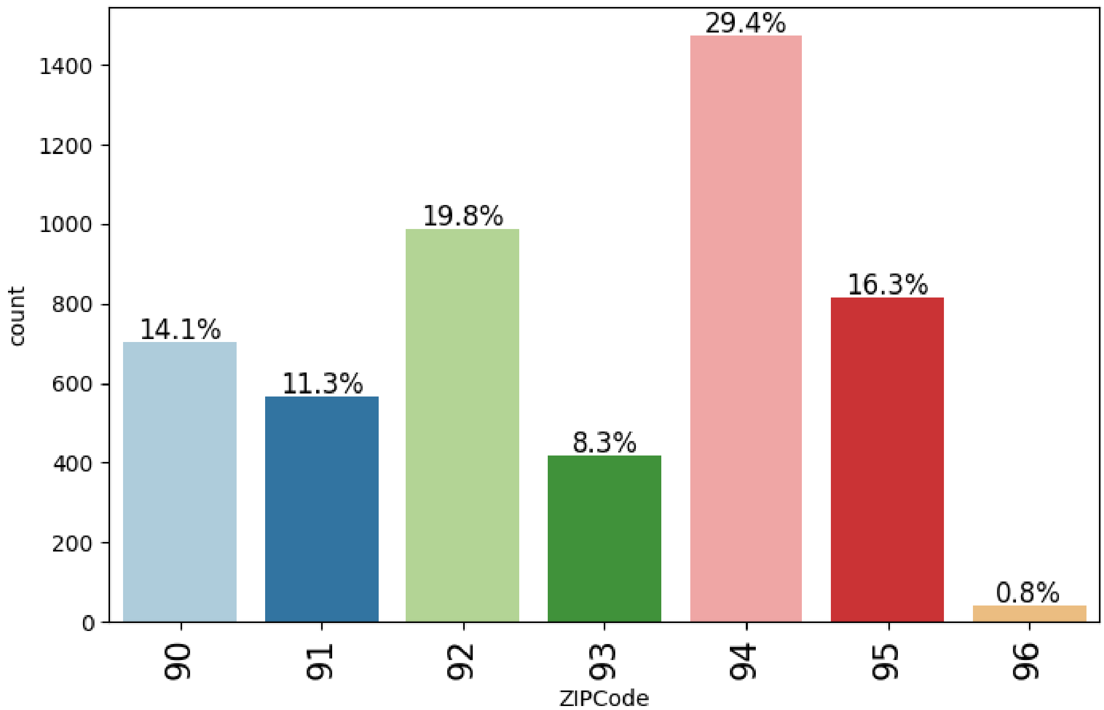
Observation on CreditCard

```
[ ]: labeled_barplot(data, "CreditCard", perc=True)    ## Complete the code to create
     ↪labeled_barplot for CreditCard
```



Observation on ZIPCode

```
[ ]: labeled_barplot(data, "ZIPCode", perc=True)   ## Complete the code to create␣
     ↪labeled_barplot for ZIPCode
```



0.7.2 Bivariate Analysis

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

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

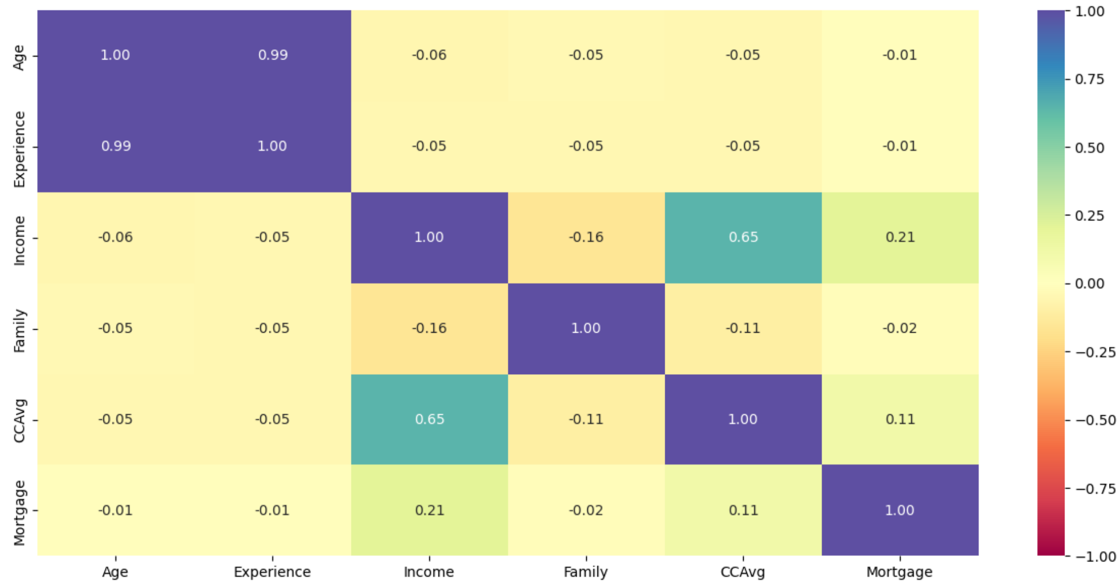
```
        loc="lower left", frameon=False,
    )
    plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
    plt.show()
```

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


def distribution_plot_wrt_target(data, predictor, target):

    fig, axs = plt.subplots(2, 2, figsize=(12, 10))

    target_uniq = data[target].unique()

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

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

    axs[1, 0].set_title("Boxplot w.r.t target")
    sns.boxplot(data=data, x=target, y=predictor, ax=axs[1, 0],␣
 ↪palette="gist_rainbow")

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

```
        palette="gist_rainbow",
    )

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

Correlation check

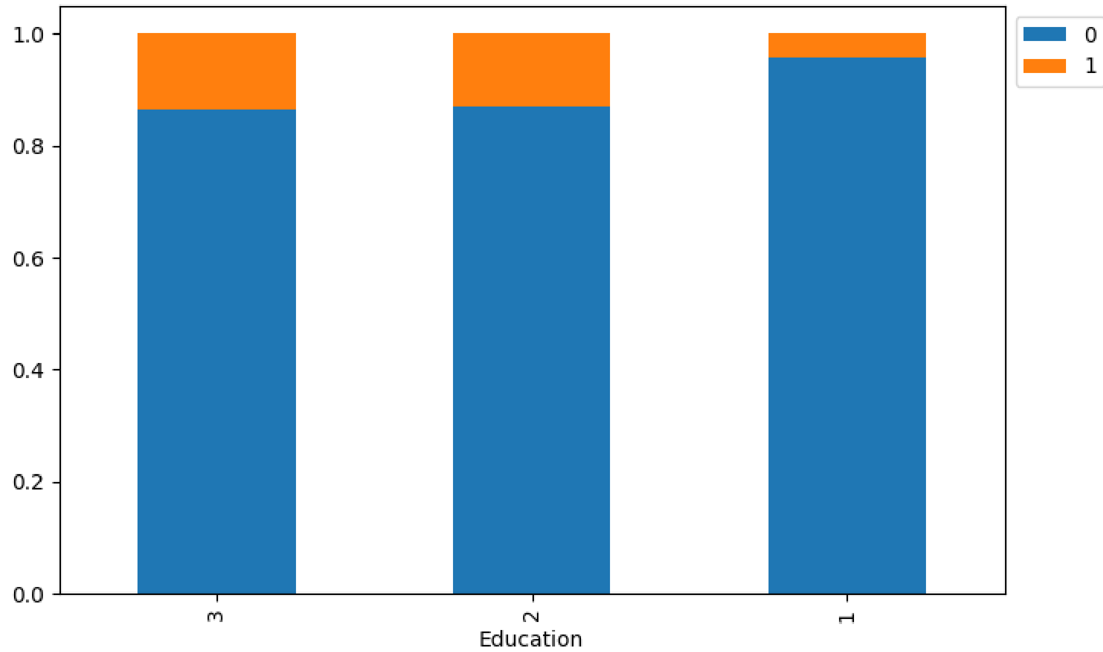
[ ]:
```
plt.figure(figsize=(15, 7))
sns.heatmap(data.corr(numeric_only=True), annot=True, vmin=-1, vmax=1, fmt=".
↪2f", cmap="Spectral") # Complete the code to get the heatmap of the data
plt.show()
```



Let's check how a customer's interest in purchasing a loan varies with their education

[ ]:
```
stacked_barplot(data, "Education", "Personal_Loan")
```

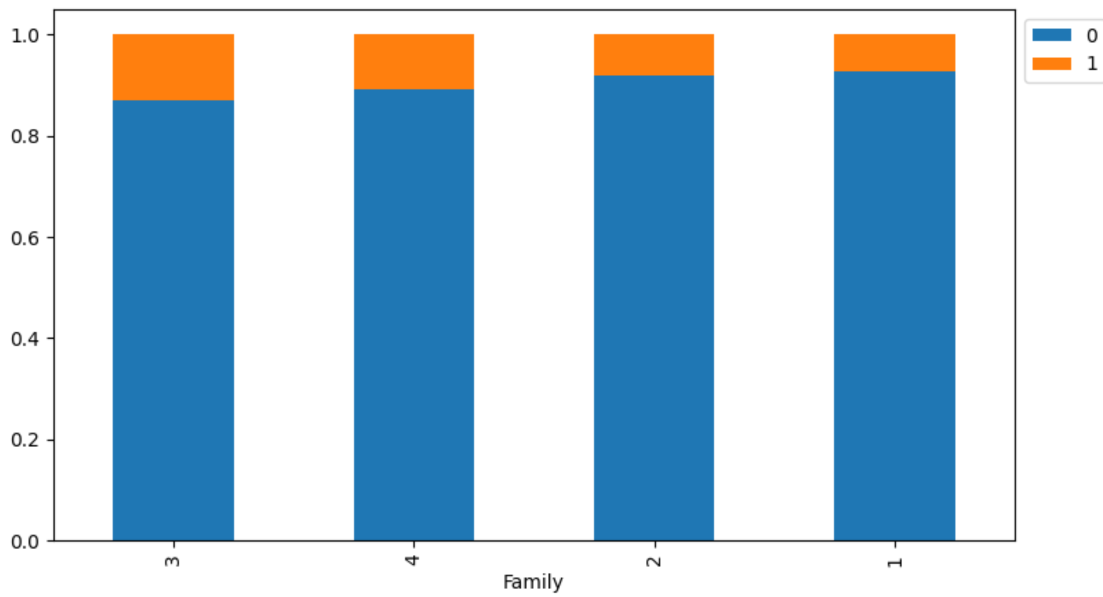
```
Personal_Loan      0    1   All
Education
All             4520  480  5000
3               1296  205  1501
2               1221  182  1403
1               2003   93  2096
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs Family

```
[ ]: stacked_barplot(data, "Family", "Personal_Loan")  ## Complete the code to plot␣
     ↪stacked barplot for Personal Loan and Family
```

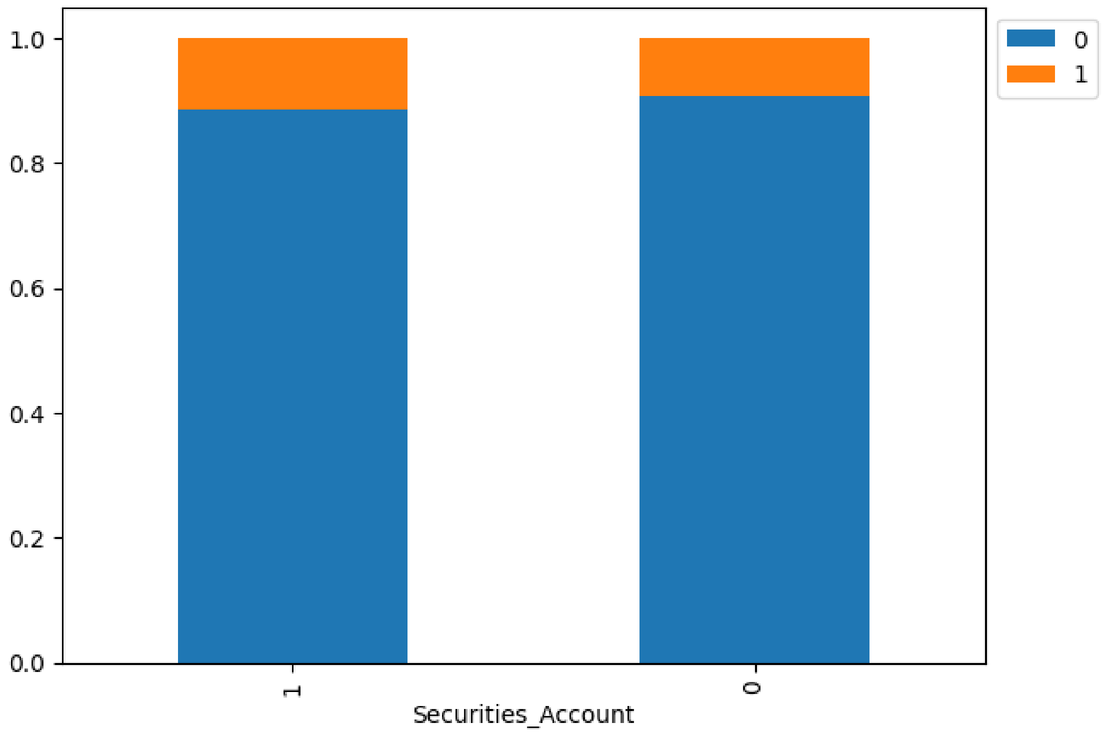
```
Personal_Loan     0    1   All
Family
All            4520  480  5000
4              1088  134  1222
3               877  133  1010
1              1365  107  1472
2              1190  106  1296
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs Securities_Account

[ ]:
```
stacked_barplot(data, "Securities_Account", "Personal_Loan") ## Complete the␣
↪code to plot stacked barplot for Personal Loan and Securities_Account
```

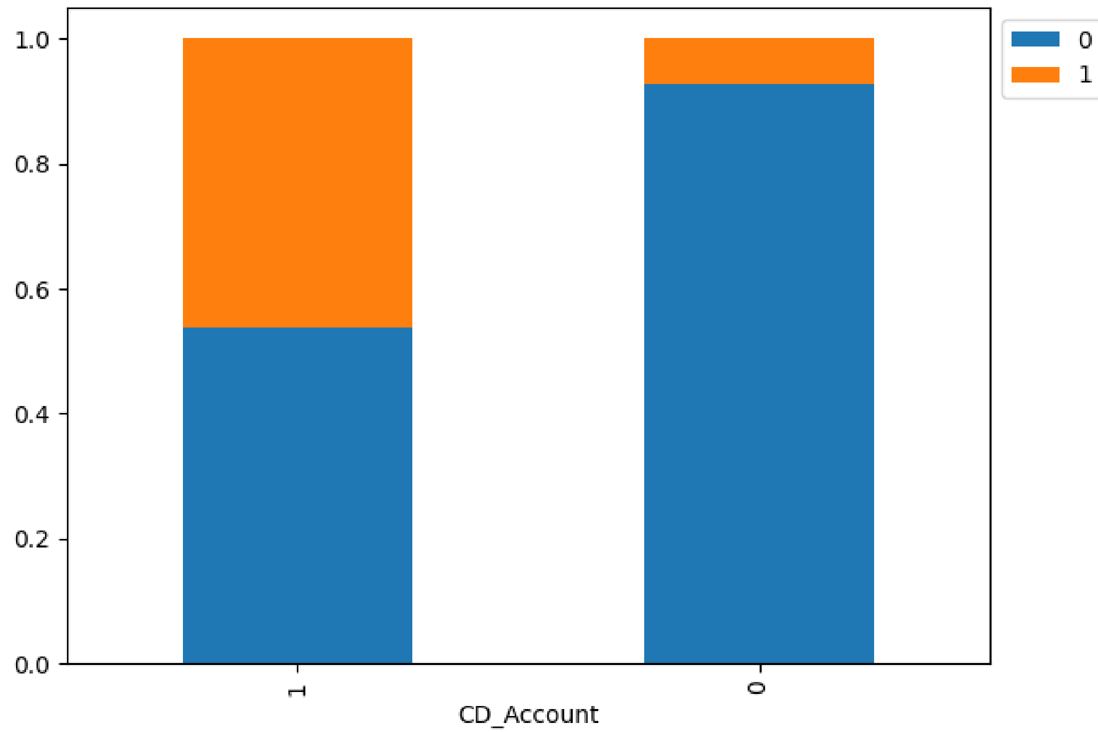
```
Personal_Loan          0    1   All
Securities_Account
All                 4520  480  5000
0                   4058  420  4478
1                    462   60   522
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs CD_Account

[ ]:
```
stacked_barplot(data, "CD_Account", "Personal_Loan") ## Complete the code to␣
↪plot stacked barplot for Personal Loan and CD_Account
```

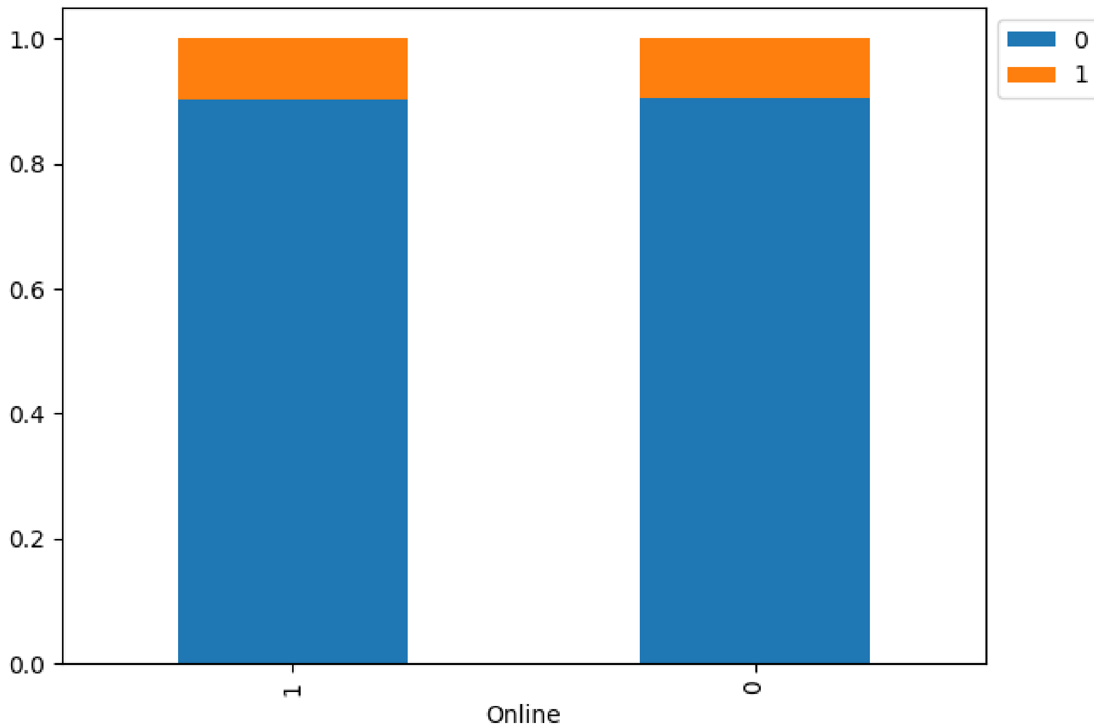
```
Personal_Loan      0    1   All
CD_Account
All             4520  480  5000
0               4358  340  4698
1                162  140   302
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs Online

[ ]:
```
stacked_barplot(data, "Online", "Personal_Loan") ## Complete the code to plot␣
↪stacked barplot for Personal Loan and Online
```

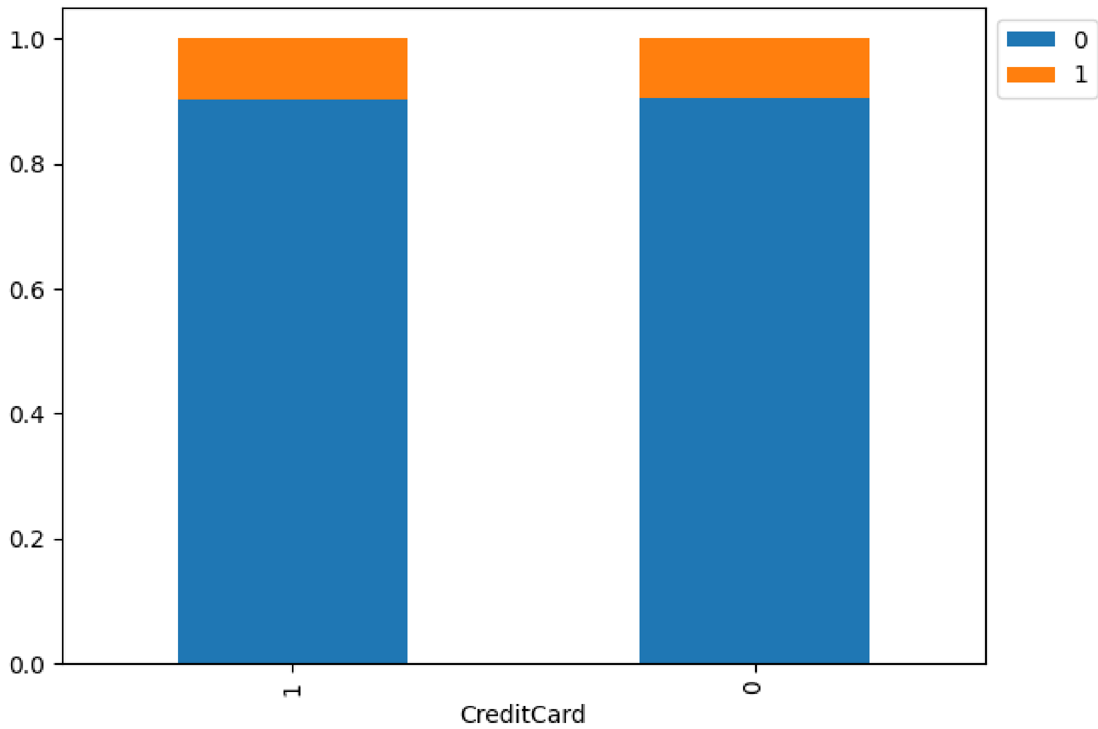
```
Personal_Loan     0    1   All
Online
All            4520  480  5000
1              2693  291  2984
0              1827  189  2016
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs CreditCard

```
[ ]: stacked_barplot(data, "CreditCard", "Personal_Loan") ## Complete the code to␣
     ↪plot stacked barplot for Personal Loan and CreditCard
```

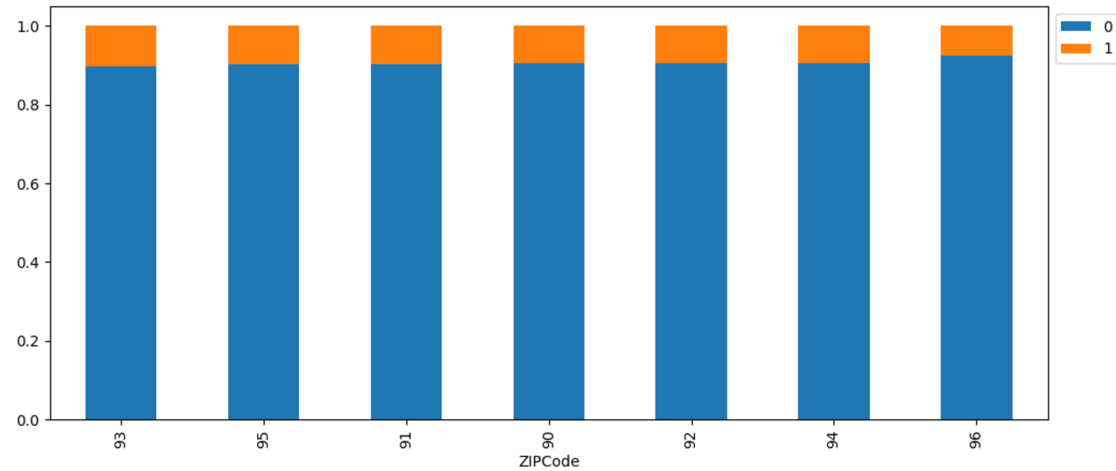
```
Personal_Loan     0    1   All
CreditCard
All            4520  480  5000
0              3193  337  3530
1              1327  143  1470
--------------------------------------------------------------------------------
----------------------------------------
```



Personal_Loan vs ZIPCode

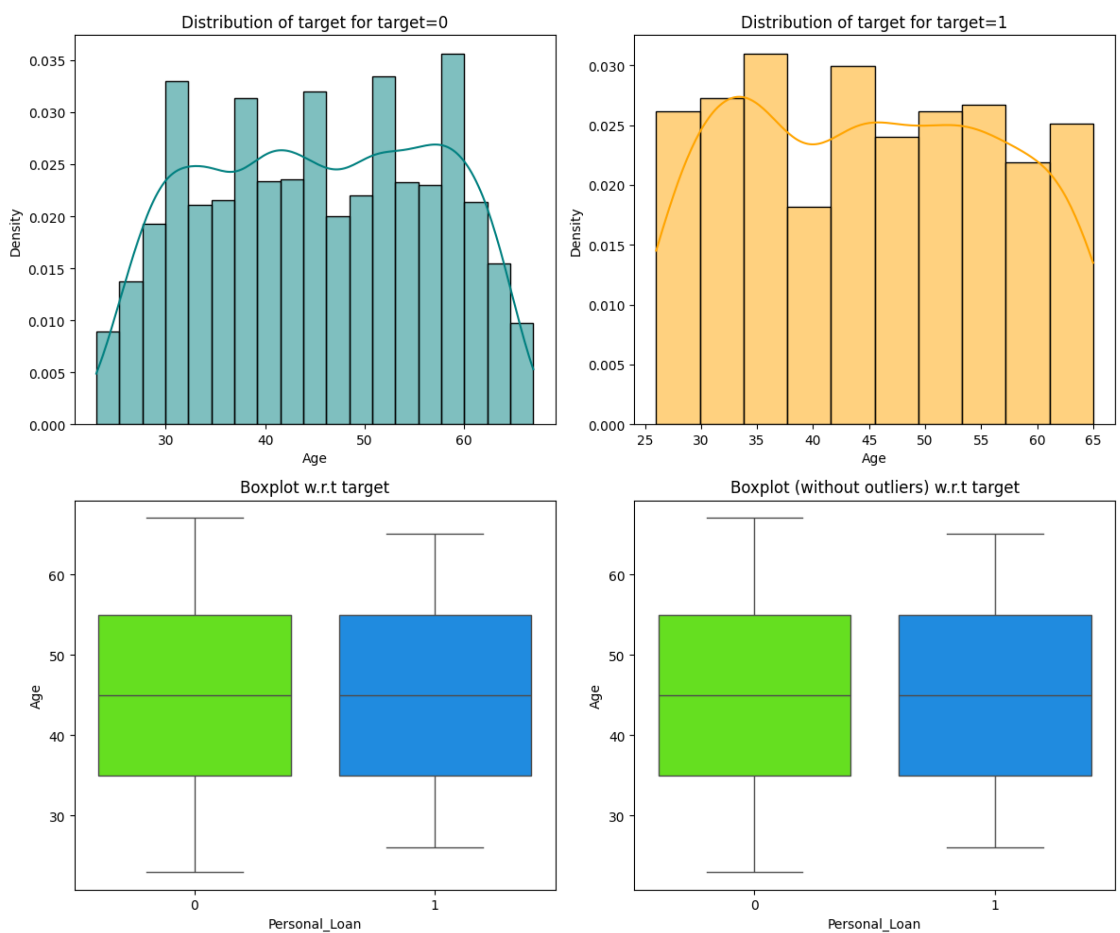
```
[ ]: stacked_barplot(data, "ZIPCode", "Personal_Loan") ## Complete the code to plot␣
     ↪stacked barplot for Personal Loan and ZIPCode
```

```
Personal_Loan     0    1   All
ZIPCode
All            4520  480  5000
94             1334  138  1472
92              894   94   988
95              735   80   815
90              636   67   703
91              510   55   565
93              374   43   417
96               37    3    40
--------------------------------------------------------------------------------
----------------------------------------
```



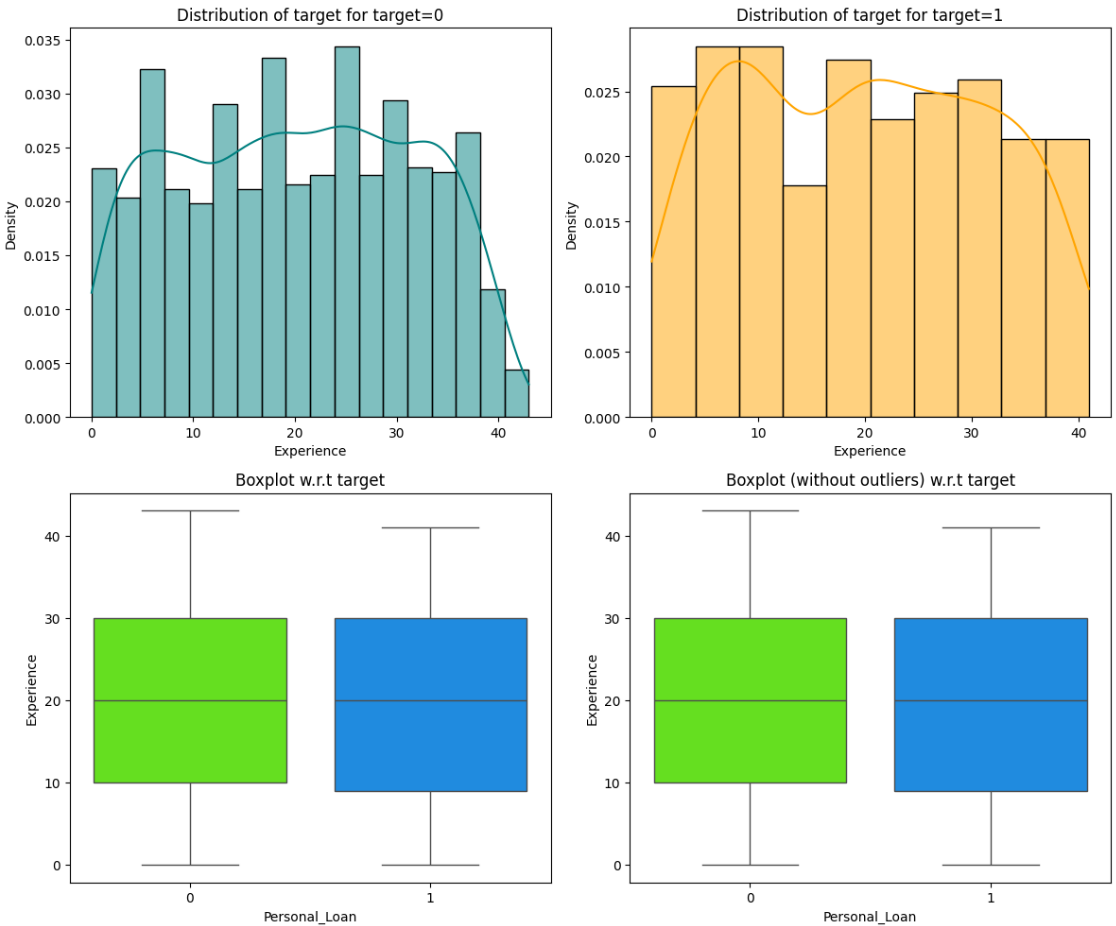
Let's check how a customer's interest in purchasing a loan varies with their age

[ ]:
```
distribution_plot_wrt_target(data, "Age", "Personal_Loan")
```



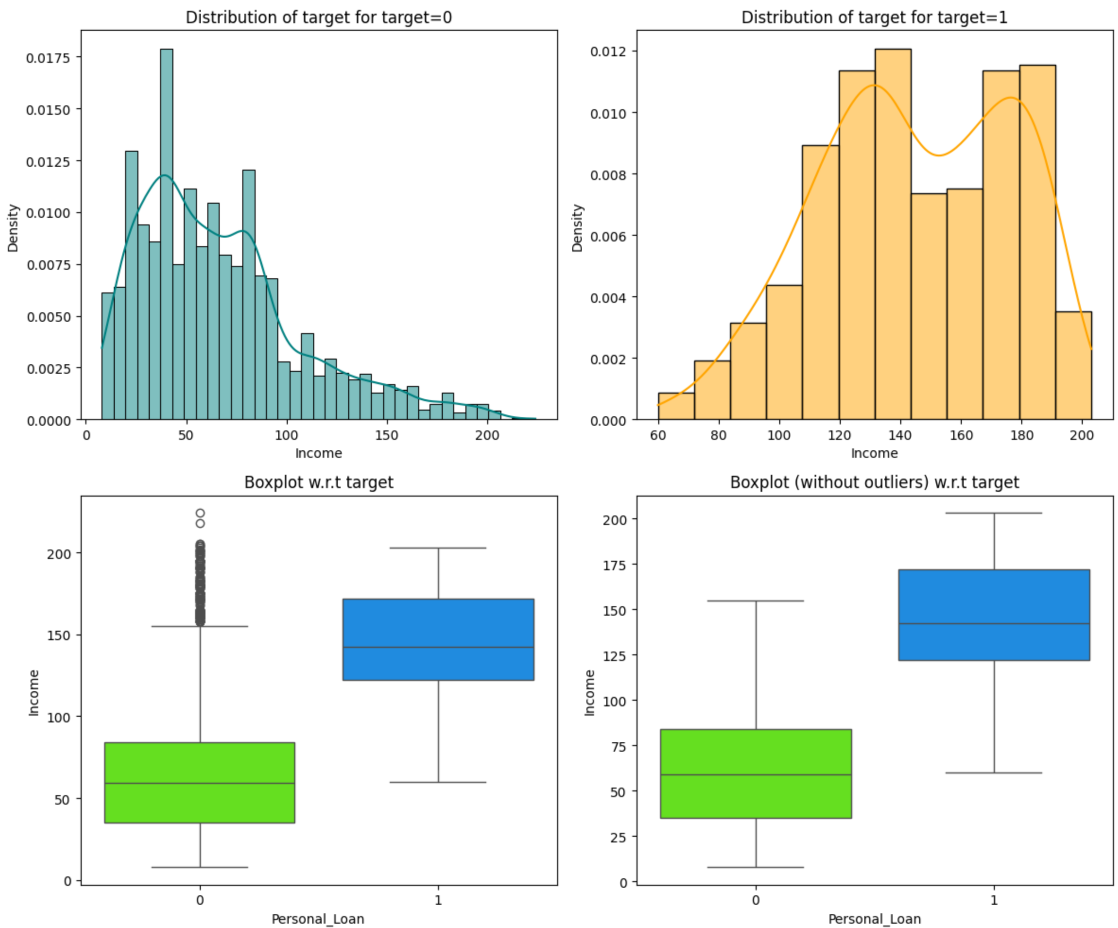
Personal Loan vs Experience

[ ]:
```
distribution_plot_wrt_target(data, "Experience", "Personal_Loan") ## Complete␣
↪the code to plot stacked barplot for Personal Loan and Experience
```



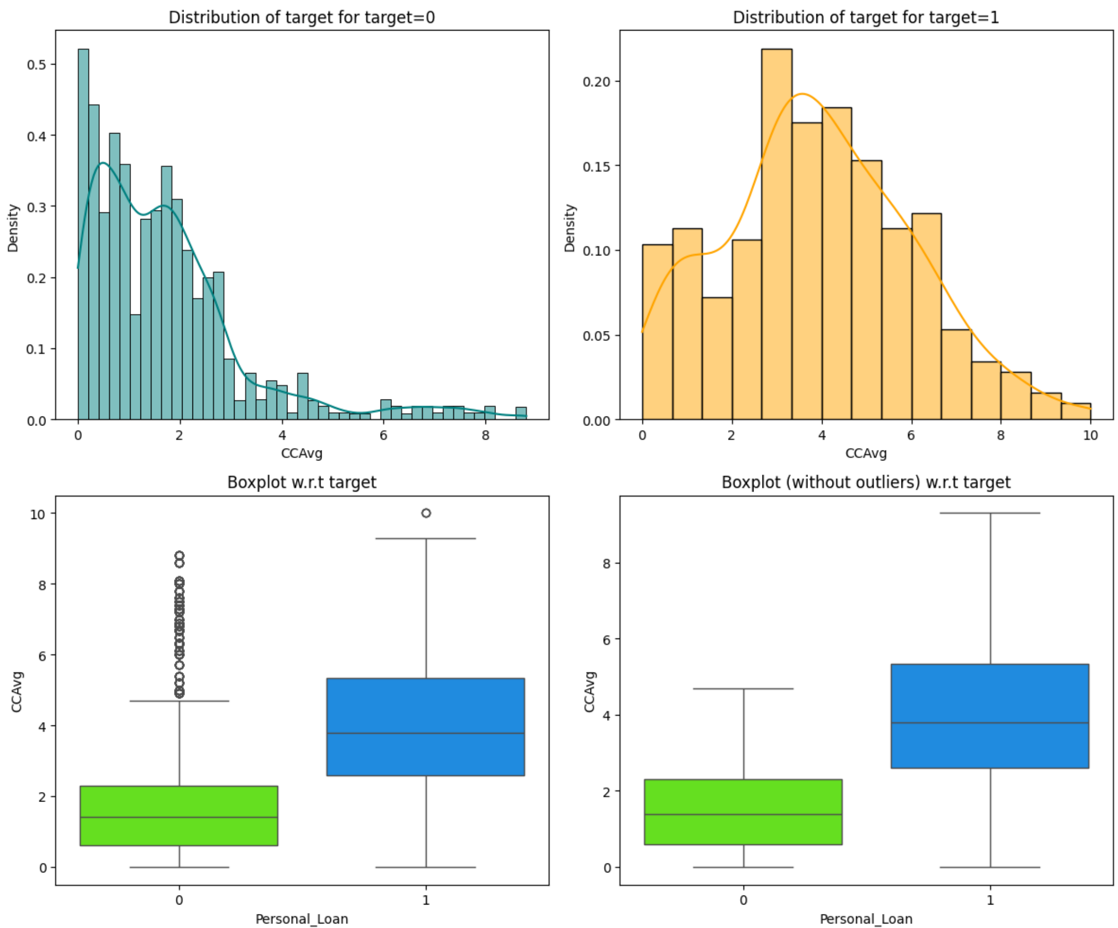
Personal Loan vs Income

[ ]:
```
distribution_plot_wrt_target(data, "Income", "Personal_Loan") ## Complete the␣
↪code to plot stacked barplot for Personal Loan and Income
```



Personal Loan vs CCAvg

[ ]:
```
distribution_plot_wrt_target(data, "CCAvg", "Personal_Loan") ## Complete the␣
↪code to plot stacked barplot for Personal Loan and CCAvg
```



0.8 Data Preprocessing (contd.)

0.8.1 Outlier Detection

```
[ ]: Q1 = data.select_dtypes(include=["float64", "int64"]).quantile(0.25)  # To find␣
     ↪the 25th percentile and 75th percentile.
     Q3 = data.select_dtypes(include=["float64", "int64"]).quantile(0.75)

     IQR = Q3 - Q1  # Inter Quantile Range (75th perentile - 25th percentile)

     lower = (
         Q1 - 1.5 * IQR
     )  # Finding lower and upper bounds for all values. All values outside these␣
     ↪bounds are outliers
     upper = Q3 + 1.5 * IQR
```

```
[ ]: (
         (data.select_dtypes(include=["float64", "int64"]) < lower)
```

```
    | (data.select_dtypes(include=["float64", "int64"]) > upper)
).sum() / len(data) * 100
```

[ ]:
```
Age           0.00
Experience    0.00
Income        1.92
Family        0.00
CCAvg         6.48
Mortgage      5.82
dtype: float64
```

0.8.2 Data Preparation for Modeling

[ ]:
```
# dropping Experience as it is perfectly correlated with Age
X = data.drop(["Personal_Loan", "Experience"], axis=1)
Y = data["Personal_Loan"]

X = pd.get_dummies(X, columns=["ZIPCode", "Education"], drop_first=True)

X = X.astype(float)

# Splitting data in train and test sets
X_train, X_test, y_train, y_test = train_test_split(
    X, Y, test_size=0.30, random_state=1
)
```

[ ]:
```
print("Shape of Training set : ", X_train.shape)
print("Shape of test set : ", X_test.shape)
print("Percentage of classes in training set:")
print(y_train.value_counts(normalize=True))
print("Percentage of classes in test set:")
print(y_test.value_counts(normalize=True))
```

```
Shape of Training set :  (3500, 17)
Shape of test set :  (1500, 17)
Percentage of classes in training set:
Personal_Loan
0    0.905429
1    0.094571
Name: proportion, dtype: float64
Percentage of classes in test set:
Personal_Loan
0    0.900667
1    0.099333
Name: proportion, dtype: float64
```

0.9 Model Building

0.9.1 Model Evaluation Criterion

- *mention the model evaluation criterion here with proper reasoning*

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

- The model_performance_classification_sklearn function will be used to check the model performance of models.
- The confusion_matrix_sklearnfunction will be used to plot confusion matrix.

[ ]:
```python
# defining a function to compute different metrics to check performance of a␣
↪classification model built using sklearn
def model_performance_classification_sklearn(model, predictors, target):
    """
    Function to compute different metrics to check classification model␣
↪performance

    model: classifier
    predictors: independent variables
    target: dependent variable
    """

    # predicting using the independent variables
    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred)  # to compute Recall
    precision = precision_score(target, pred)  # to compute Precision
    f1 = f1_score(target, pred)  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f1,},
        index=[0],
    )

    return df_perf
```

[ ]:
```python
def confusion_matrix_sklearn(model, predictors, target):
    """
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
```

```
    y_pred = model.predict(predictors)
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().
↪sum())]
            for item in cm.flatten()
        ]
    ).reshape(2, 2)

    plt.figure(figsize=(6, 4))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

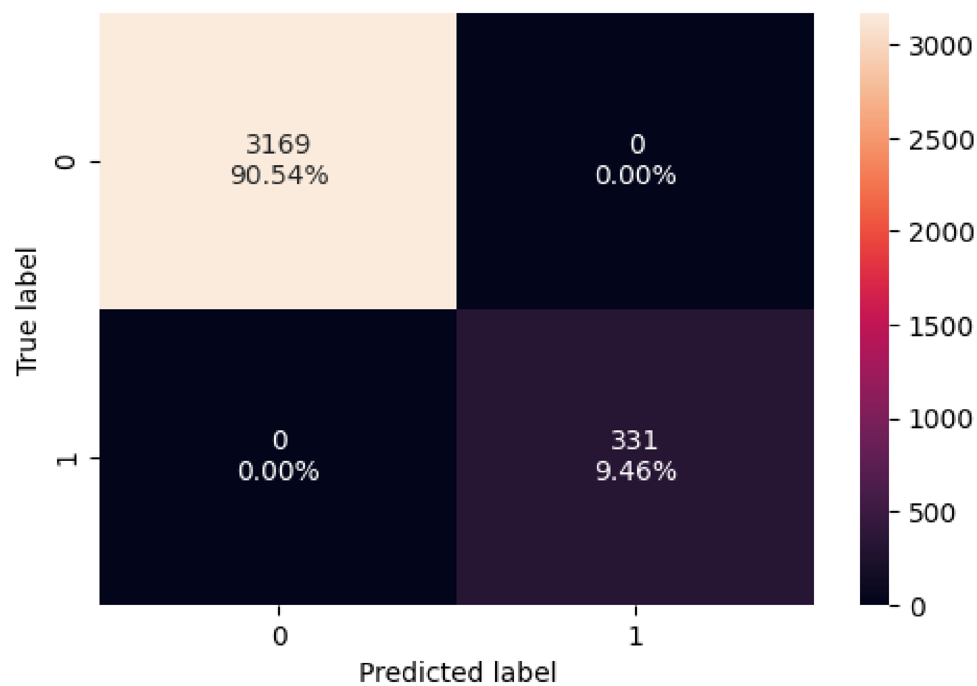
0.9.2 Decision Tree (sklearn default)

[ ]:
```
model = DecisionTreeClassifier(criterion="gini", random_state=1)
model.fit(X_train, y_train)
```

[ ]: DecisionTreeClassifier(random_state=1)

Checking model performance on training data

[ ]:
```
confusion_matrix_sklearn(model, X_train, y_train)
```



```
[ ]: decision_tree_perf_train = model_performance_classification_sklearn(
         model, X_train, y_train
     )
     decision_tree_perf_train
```

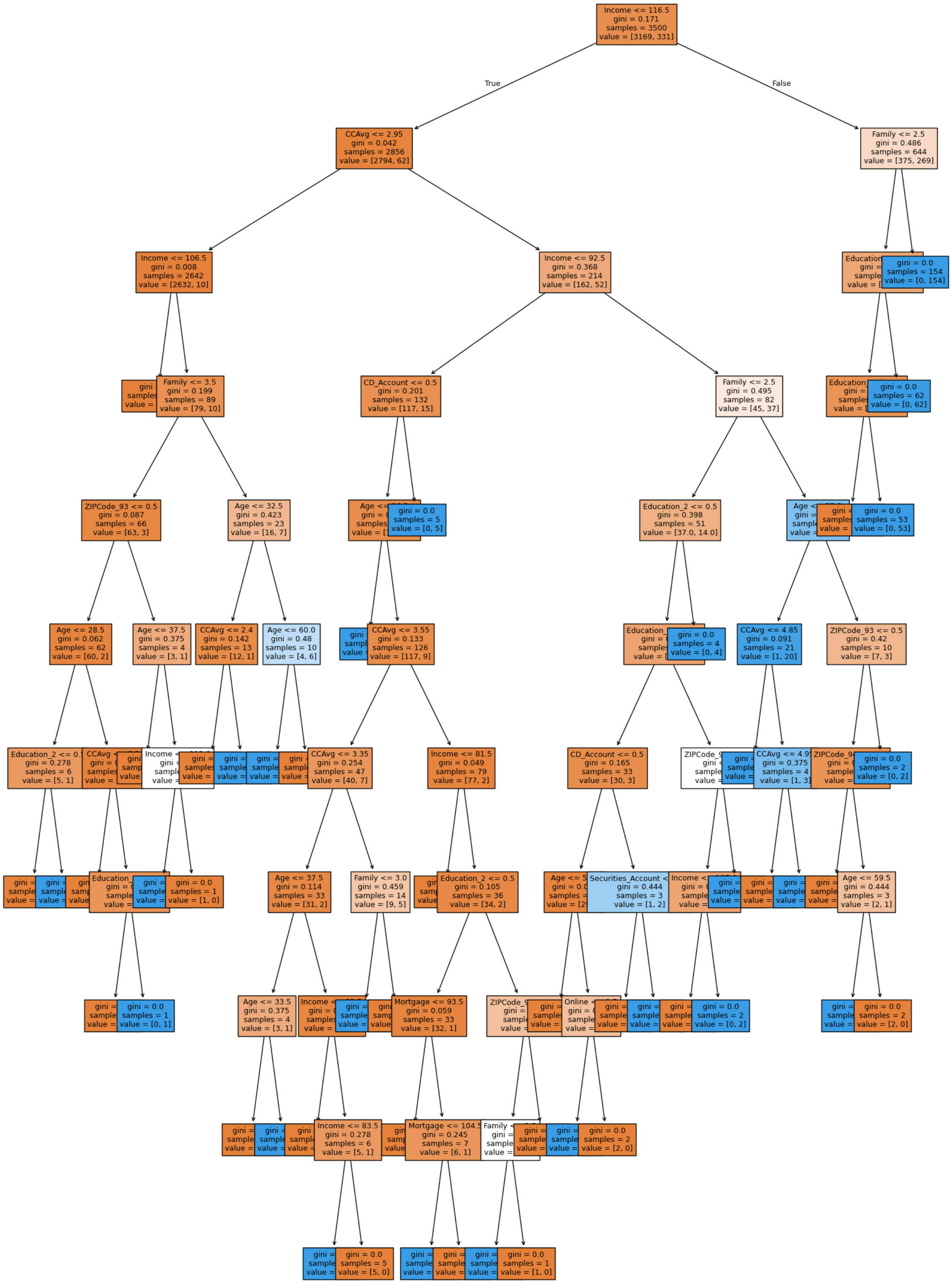
```
[ ]:    Accuracy  Recall  Precision   F1
     0       1.0     1.0        1.0  1.0
```

Visualizing the Decision Tree

```
[ ]: feature_names = list(X_train.columns)
     print(feature_names)
```

```
['Age', 'Income', 'Family', 'CCAvg', 'Mortgage', 'Securities_Account',
'CD_Account', 'Online', 'CreditCard', 'ZIPCode_91', 'ZIPCode_92', 'ZIPCode_93',
'ZIPCode_94', 'ZIPCode_95', 'ZIPCode_96', 'Education_2', 'Education_3']
```

```
[ ]: plt.figure(figsize=(20, 30))
     out = tree.plot_tree(
         model,
         feature_names=feature_names,
         filled=True,
         fontsize=9,
         node_ids=False,
         class_names=None,
     )
     # below code will add arrows to the decision tree split if they are missing
     for o in out:
         arrow = o.arrow_patch
         if arrow is not None:
             arrow.set_edgecolor("black")
             arrow.set_linewidth(1)
     plt.show()
```



[ ]:
```python
# Text report showing the rules of a decision tree -

print(tree.export_text(model, feature_names=feature_names, show_weights=True))
```

```
|--- Income <= 116.50
|   |--- CCAvg <= 2.95
|   |   |--- Income <= 106.50
|   |   |   |--- weights: [2553.00, 0.00] class: 0
|   |   |--- Income >  106.50
|   |   |   |--- Family <= 3.50
|   |   |   |   |--- ZIPCode_93 <= 0.50
|   |   |   |   |   |--- Age <= 28.50
|   |   |   |   |   |   |--- Education_2 <= 0.50
|   |   |   |   |   |   |   |--- weights: [5.00, 0.00] class: 0
|   |   |   |   |   |   |--- Education_2 >  0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |--- Age >  28.50
|   |   |   |   |   |   |--- CCAvg <= 2.20
|   |   |   |   |   |   |   |--- weights: [48.00, 0.00] class: 0
|   |   |   |   |   |   |--- CCAvg >  2.20
|   |   |   |   |   |   |   |--- Education_3 <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [7.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- Education_3 >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- ZIPCode_93 >  0.50
|   |   |   |   |   |--- Age <= 37.50
|   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |--- Age >  37.50
|   |   |   |   |   |   |--- Income <= 112.00
|   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |--- Income >  112.00
|   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |--- Family >  3.50
|   |   |   |   |--- Age <= 32.50
|   |   |   |   |   |--- CCAvg <= 2.40
|   |   |   |   |   |   |--- weights: [12.00, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  2.40
|   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- Age >  32.50
|   |   |   |   |   |--- Age <= 60.00
|   |   |   |   |   |   |--- weights: [0.00, 6.00] class: 1
|   |   |   |   |   |--- Age >  60.00
|   |   |   |   |   |   |--- weights: [4.00, 0.00] class: 0
|   |--- CCAvg >  2.95
|   |   |--- Income <= 92.50
|   |   |   |--- CD_Account <= 0.50
|   |   |   |   |--- Age <= 26.50
```

```
|   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |--- Age >  26.50
|   |   |   |   |   |--- CCAvg <= 3.55
|   |   |   |   |   |   |--- CCAvg <= 3.35
|   |   |   |   |   |   |   |--- Age <= 37.50
|   |   |   |   |   |   |   |   |--- Age <= 33.50
|   |   |   |   |   |   |   |   |   |--- weights: [3.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Age >  33.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- Age >  37.50
|   |   |   |   |   |   |   |   |--- Income <= 82.50
|   |   |   |   |   |   |   |   |   |--- weights: [23.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Income >  82.50
|   |   |   |   |   |   |   |   |   |--- Income <= 83.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |--- Income >  83.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [5.00, 0.00] class: 0
|   |   |   |   |   |   |--- CCAvg >  3.35
|   |   |   |   |   |   |   |--- Family <= 3.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 5.00] class: 1
|   |   |   |   |   |   |   |--- Family >  3.00
|   |   |   |   |   |   |   |   |--- weights: [9.00, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  3.55
|   |   |   |   |   |   |--- Income <= 81.50
|   |   |   |   |   |   |   |--- weights: [43.00, 0.00] class: 0
|   |   |   |   |   |   |--- Income >  81.50
|   |   |   |   |   |   |   |--- Education_2 <= 0.50
|   |   |   |   |   |   |   |   |--- Mortgage <= 93.50
|   |   |   |   |   |   |   |   |   |--- weights: [26.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Mortgage >  93.50
|   |   |   |   |   |   |   |   |   |--- Mortgage <= 104.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |--- Mortgage >  104.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [6.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- Education_2 >  0.50
|   |   |   |   |   |   |   |   |--- ZIPCode_91 <= 0.50
|   |   |   |   |   |   |   |   |   |--- Family <= 3.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |   |--- Family >  3.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- ZIPCode_91 >  0.50
|   |   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |--- CD_Account >  0.50
|   |   |   |   |--- weights: [0.00, 5.00] class: 1
|   |   |--- Income >  92.50
|   |   |   |--- Family <= 2.50
|   |   |   |   |--- Education_2 <= 0.50
|   |   |   |   |   |--- Education_3 <= 0.50
```

```
|   |   |   |   |   |   |--- CD_Account <= 0.50
|   |   |   |   |   |   |   |--- Age <= 56.50
|   |   |   |   |   |   |   |   |--- weights: [27.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- Age >  56.50
|   |   |   |   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |   |--- CD_Account >  0.50
|   |   |   |   |   |   |   |--- Securities_Account <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- Securities_Account >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|   |   |   |   |   |--- Education_3 >  0.50
|   |   |   |   |   |   |--- ZIPCode_94 <= 0.50
|   |   |   |   |   |   |   |--- Income <= 107.00
|   |   |   |   |   |   |   |   |--- weights: [7.00, 0.00] class: 0
|   |   |   |   |   |   |   |--- Income >  107.00
|   |   |   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|   |   |   |   |   |   |--- ZIPCode_94 >  0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 5.00] class: 1
|   |   |   |   |--- Education_2 >  0.50
|   |   |   |   |   |--- weights: [0.00, 4.00] class: 1
|   |   |   |--- Family >  2.50
|   |   |   |   |--- Age <= 57.50
|   |   |   |   |   |--- CCAvg <= 4.85
|   |   |   |   |   |   |--- weights: [0.00, 17.00] class: 1
|   |   |   |   |   |--- CCAvg >  4.85
|   |   |   |   |   |   |--- CCAvg <= 4.95
|   |   |   |   |   |   |   |--- weights: [1.00, 0.00] class: 0
|   |   |   |   |   |   |--- CCAvg >  4.95
|   |   |   |   |   |   |   |--- weights: [0.00, 3.00] class: 1
|   |   |   |   |--- Age >  57.50
|   |   |   |   |   |--- ZIPCode_93 <= 0.50
|   |   |   |   |   |   |--- ZIPCode_94 <= 0.50
|   |   |   |   |   |   |   |--- weights: [5.00, 0.00] class: 0
|   |   |   |   |   |   |--- ZIPCode_94 >  0.50
|   |   |   |   |   |   |   |--- Age <= 59.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.00] class: 1
|   |   |   |   |   |   |   |--- Age >  59.50
|   |   |   |   |   |   |   |   |--- weights: [2.00, 0.00] class: 0
|   |   |   |   |   |--- ZIPCode_93 >  0.50
|   |   |   |   |   |   |--- weights: [0.00, 2.00] class: 1
|--- Income >  116.50
|   |--- Family <= 2.50
|   |   |--- Education_3 <= 0.50
|   |   |   |--- Education_2 <= 0.50
|   |   |   |   |--- weights: [375.00, 0.00] class: 0
```

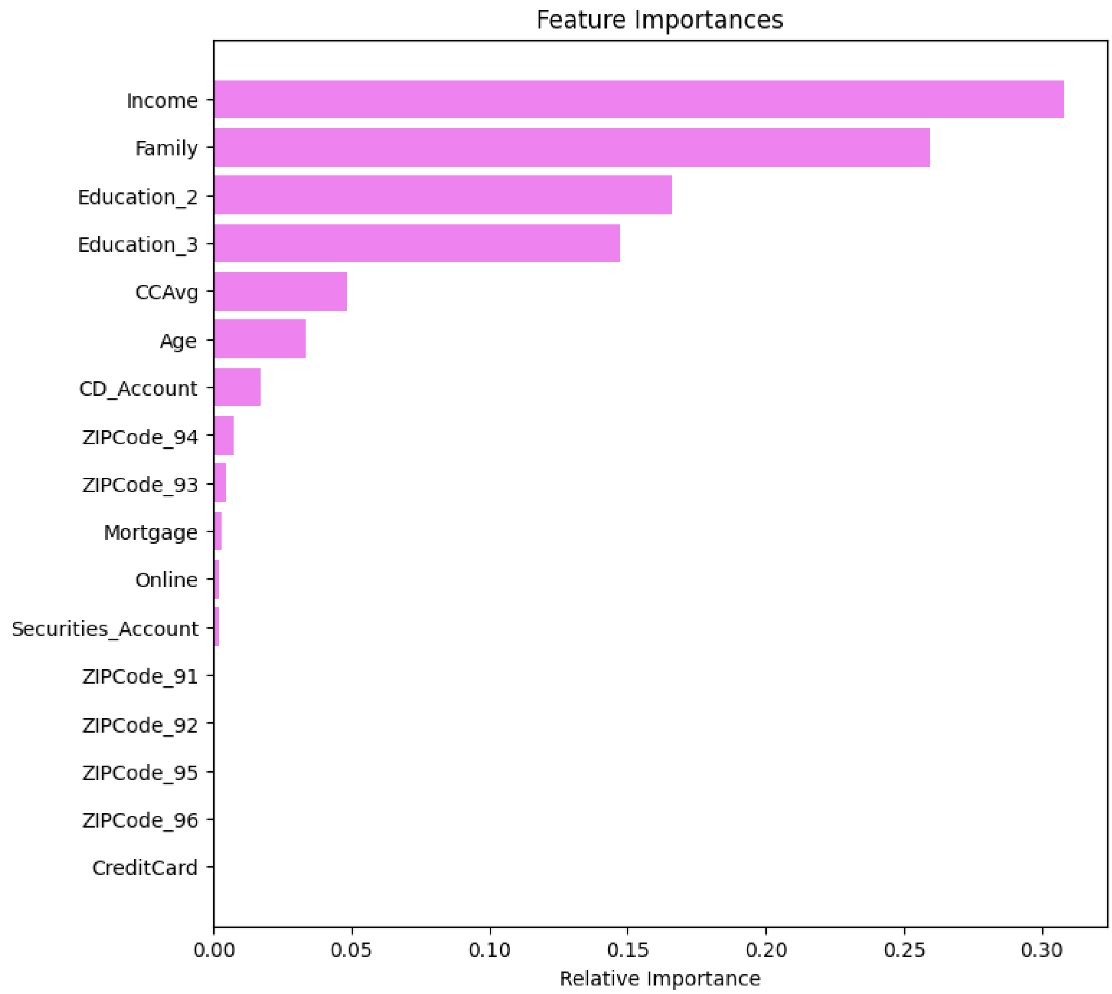
```
|   |   |   |--- Education_2 >  0.50
|   |   |   |   |--- weights: [0.00, 53.00] class: 1
|   |   |--- Education_3 >  0.50
|   |   |   |--- weights: [0.00, 62.00] class: 1
|   |--- Family >  2.50
|   |   |--- weights: [0.00, 154.00] class: 1
```

[ ]:
```
# importance of features in the tree building ( The importance of a feature is␣
↪computed as the
# (normalized) total reduction of the criterion brought by that feature. It is␣
↪also known as the Gini importance )

print(
    pd.DataFrame(
        model.feature_importances_, columns=["Imp"], index=X_train.columns
    ).sort_values(by="Imp", ascending=False)
)
```

```
                         Imp
Income              0.308098
Family              0.259255
Education_2         0.166192
Education_3         0.147127
CCAvg               0.048798
Age                 0.033150
CD_Account          0.017273
ZIPCode_94          0.007183
ZIPCode_93          0.004682
Mortgage            0.003236
Online              0.002224
Securities_Account  0.002224
ZIPCode_91          0.000556
ZIPCode_92          0.000000
ZIPCode_95          0.000000
ZIPCode_96          0.000000
CreditCard          0.000000
```

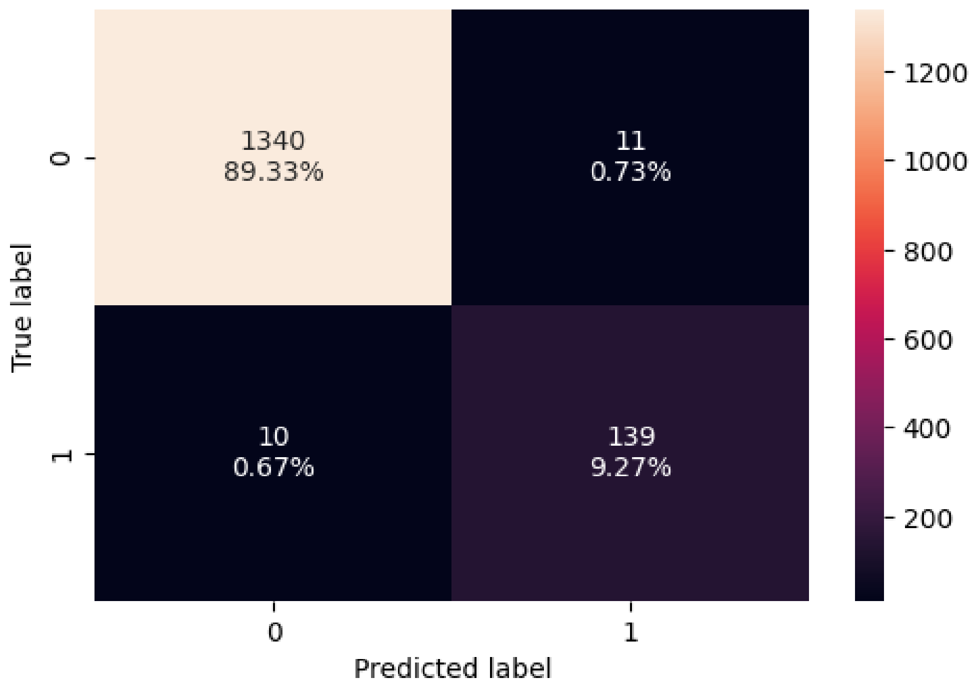
[ ]:
```
importances = model.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(8, 8))
plt.title("Feature Importances")
plt.barh(range(len(indices)), importances[indices], color="violet",␣
↪align="center")
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
```

```
plt.show()
```



Checking model performance on test data

[ ]:
```
confusion_matrix_sklearn(model, X_test, y_test) ## Complete the code to create
↪confusion matrix for test data
```



[ ]:
```
decision_tree_perf_test = model_performance_classification_sklearn(model,␣
    ↪X_train, y_train) ## Complete the code to check performance on test data
decision_tree_perf_test
```

[ ]:

	Accuracy	Recall	Precision	F1
0	1.0	1.0	1.0	1.0

0.10 Model Performance Improvement

Pre-pruning **Note**: The parameters provided below are a sample set. You can feel free to update the same and try out other combinations.

[ ]:
```
# Define the parameters of the tree to iterate over
max_depth_values = np.arange(2, 7, 2)
max_leaf_nodes_values = [50, 75, 150, 250]
min_samples_split_values = [10, 30, 50, 70]

# Initialize variables to store the best model and its performance
best_estimator = None
best_score_diff = float('inf')
best_test_score = 0.0

# Iterate over all combinations of the specified parameter values
for max_depth in max_depth_values:
```

```
    for max_leaf_nodes in max_leaf_nodes_values:
        for min_samples_split in min_samples_split_values:

            # Initialize the tree with the current set of parameters
            estimator = DecisionTreeClassifier(
                max_depth=max_depth,
                max_leaf_nodes=max_leaf_nodes,
                min_samples_split=min_samples_split,
                class_weight='balanced',
                random_state=42
            )

            # Fit the model to the training data
            estimator.fit(X_train, y_train)

            # Make predictions on the training and test sets
            y_train_pred = estimator.predict(X_train)
            y_test_pred = estimator.predict(X_test)

            # Calculate recall scores for training and test sets
            train_recall_score = recall_score(y_train, y_train_pred)
            test_recall_score = recall_score(y_test, y_test_pred)

            # Calculate the absolute difference between training and test␣
 ↪recall scores
            score_diff = abs(train_recall_score - test_recall_score)

            # Update the best estimator and best score if the current one has a␣
 ↪smaller score difference
            if (score_diff < best_score_diff) & (test_recall_score >␣
 ↪best_test_score):
                best_score_diff = score_diff
                best_test_score = test_recall_score
                best_estimator = estimator

# Print the best parameters
print("Best parameters found:")
print(f"Max depth: {best_estimator.max_depth}")
print(f"Max leaf nodes: {best_estimator.max_leaf_nodes}")
print(f"Min samples split: {best_estimator.min_samples_split}")
print(f"Best test recall score: {best_test_score}")
```

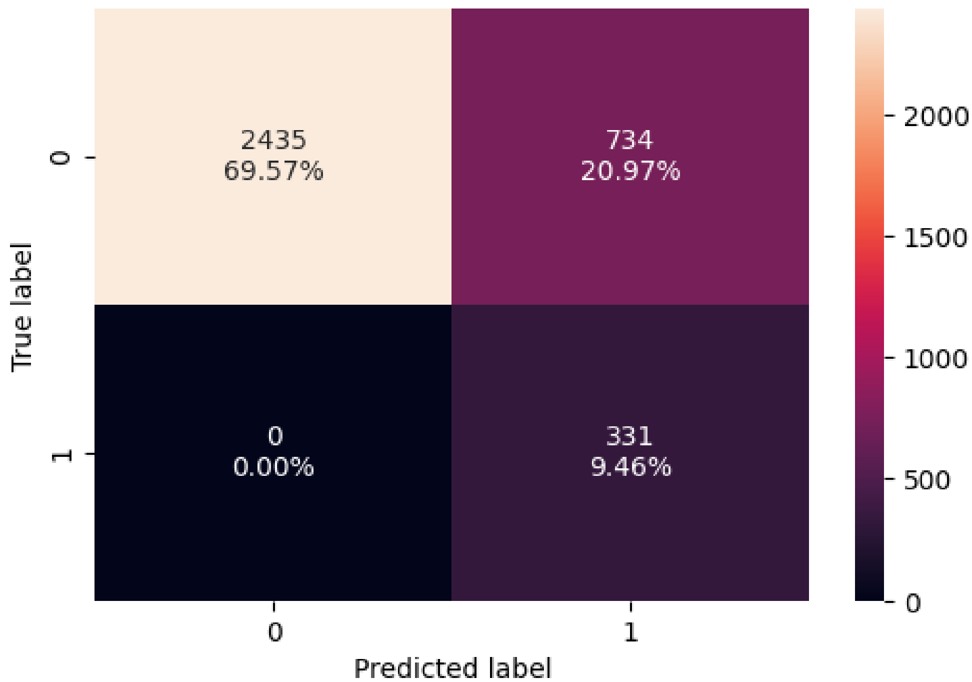
```
Best parameters found:
Max depth: 2
Max leaf nodes: 50
Min samples split: 10
Best test recall score: 1.0
```

```
[ ]: # Fit the best algorithm to the data.
estimator = best_estimator
estimator.fit(X_train, y_train) ## Complete the code to fit model on train data
```

```
[ ]: DecisionTreeClassifier(class_weight='balanced', max_depth=2, max_leaf_nodes=50,
                            min_samples_split=10, random_state=42)
```

Checking performance on training data

```
[ ]: confusion_matrix_sklearn(estimator,X_train, y_train) ## Complete the code to␣
 ↪create confusion matrix for train data
```



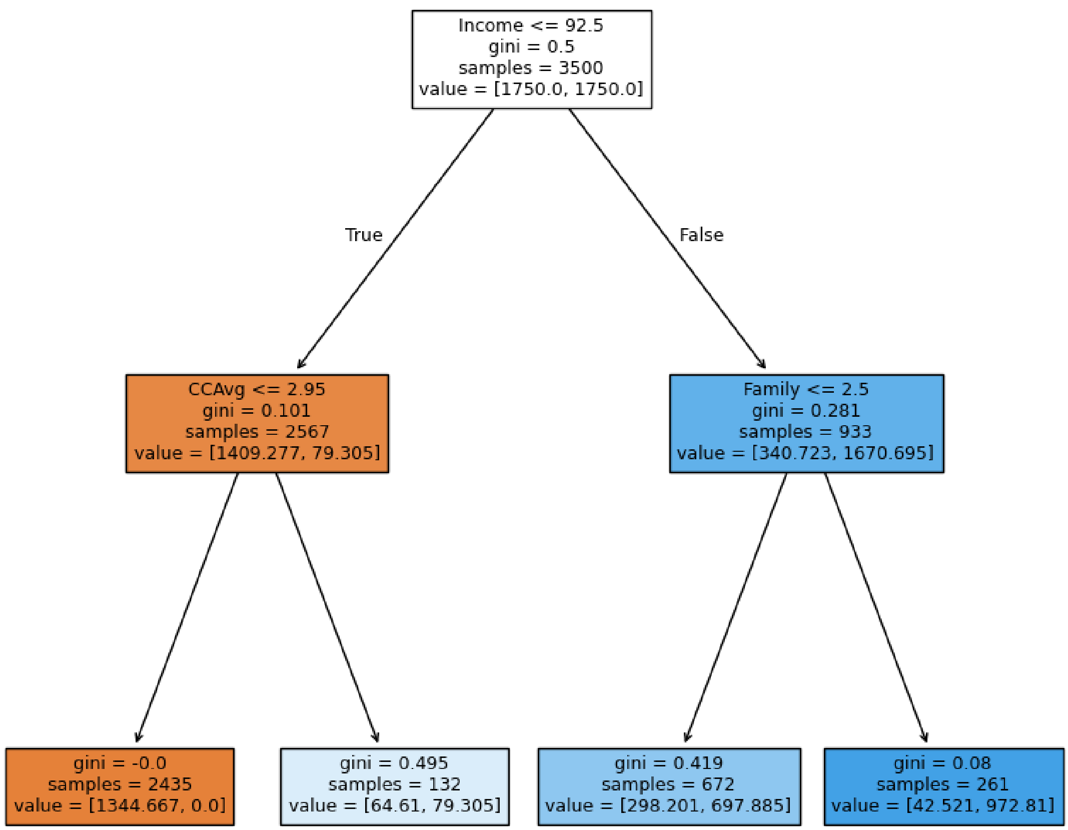

```
[ ]: decision_tree_tune_perf_train =␣
 ↪model_performance_classification_sklearn(estimator,X_train, y_train) ##␣
 ↪Complete the code to check performance on train data
decision_tree_tune_perf_train
```

```
[ ]:    Accuracy  Recall  Precision        F1
     0  0.790286     1.0   0.310798  0.474212
```

Visualizing the Decision Tree

```
[ ]: plt.figure(figsize=(10, 10))
out = tree.plot_tree(
    estimator,
```

```
    feature_names=feature_names,
    filled=True,
    fontsize=9,
    node_ids=False,
    class_names=None,
)
# below code will add arrows to the decision tree split if they are missing
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor("black")
        arrow.set_linewidth(1)
plt.show()
```



[ ]:
```
# Text report showing the rules of a decision tree -

print(tree.export_text(estimator, feature_names=feature_names,␣
 ↪show_weights=True))
```

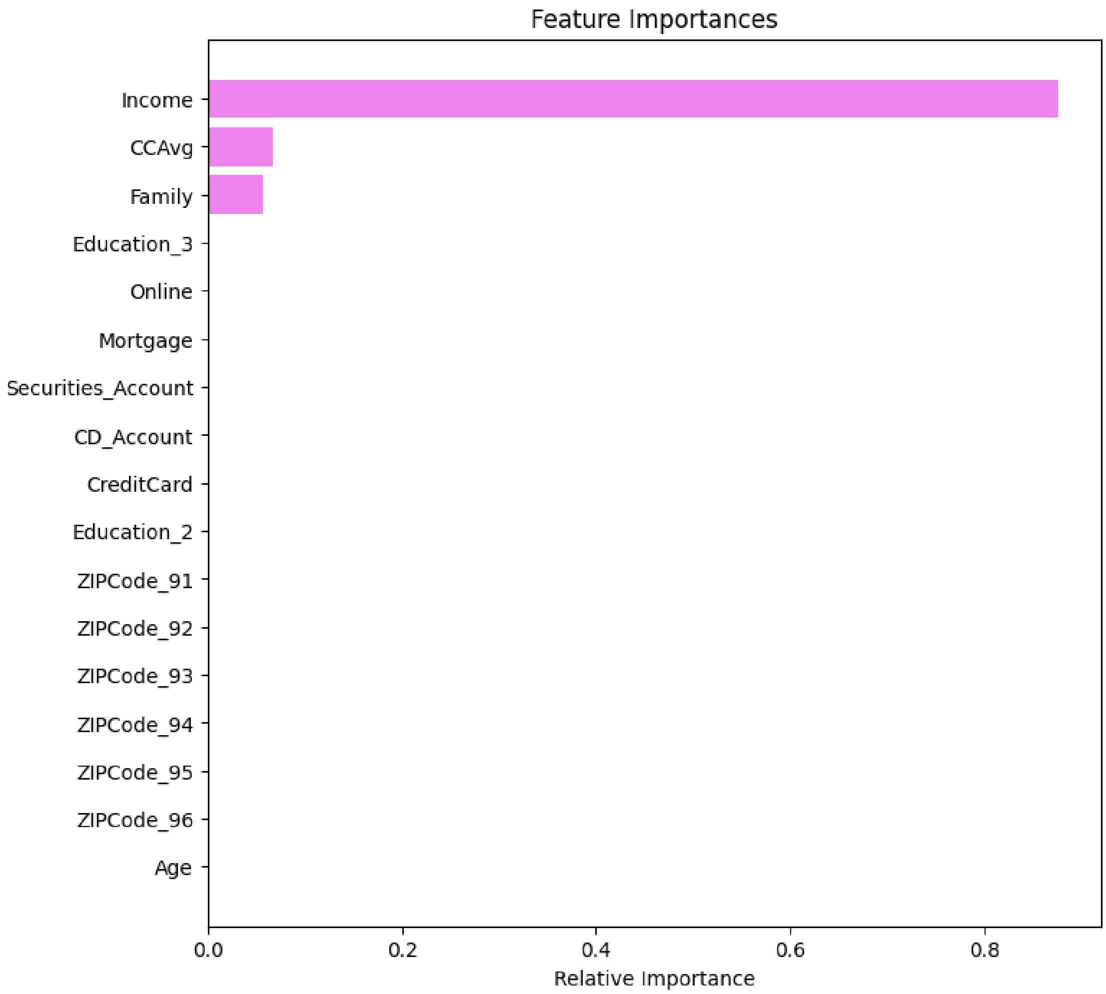
```
|--- Income <= 92.50
|   |--- CCAvg <= 2.95
|   |   |--- weights: [1344.67, 0.00] class: 0
|   |--- CCAvg >  2.95
|   |   |--- weights: [64.61, 79.31] class: 1
|--- Income >  92.50
|   |--- Family <= 2.50
|   |   |--- weights: [298.20, 697.89] class: 1
|   |--- Family >  2.50
|   |   |--- weights: [42.52, 972.81] class: 1
```

[ ]:
```
# importance of features in the tree building ( The importance of a feature is␣
 ↪computed as the
# (normalized) total reduction of the criterion brought by that feature. It is␣
 ↪also known as the Gini importance )

print(
    pd.DataFrame(
        estimator.feature_importances_, columns=["Imp"], index=X_train.columns
    ).sort_values(by="Imp", ascending=False)
)
```

```
                         Imp
Income              0.876529
CCAvg               0.066940
Family              0.056531
Age                 0.000000
ZIPCode_92          0.000000
Education_2         0.000000
ZIPCode_96          0.000000
ZIPCode_95          0.000000
ZIPCode_94          0.000000
ZIPCode_93          0.000000
CreditCard          0.000000
ZIPCode_91          0.000000
Online              0.000000
CD_Account          0.000000
Securities_Account  0.000000
Mortgage            0.000000
Education_3         0.000000
```

[ ]:

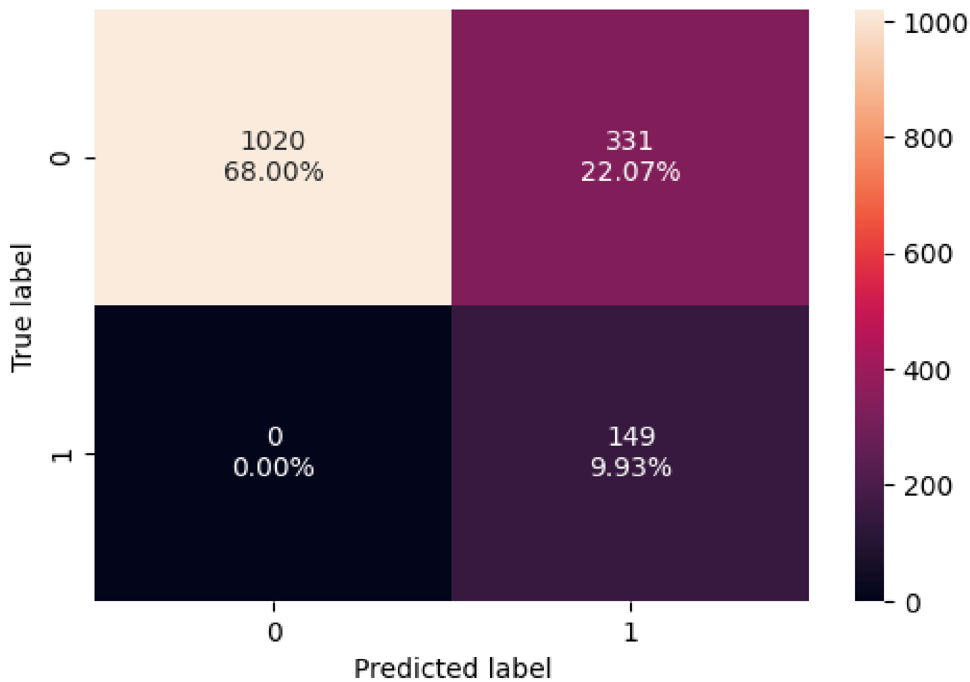
```
importances = estimator.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(8, 8))
plt.title("Feature Importances")
plt.barh(range(len(indices)), importances[indices], color="violet",␣
 ↪align="center")
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
plt.show()
```



Checking performance on test data

[ ]:

```
confusion_matrix_sklearn(estimator,X_test, y_test)  # Complete the code to get␣
 ↪the confusion matrix on test data
```



[ ]:
```
decision_tree_tune_perf_test =␣
  ↪model_performance_classification_sklearn(estimator,X_test, y_test) ##␣
  ↪Complete the code to check performance on test data
decision_tree_tune_perf_test
```

[ ]:

	Accuracy	Recall	Precision	F1
0	0.779333	1.0	0.310417	0.473768

Post-pruning

[ ]:
```
clf = DecisionTreeClassifier(random_state=1)
path = clf.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas, impurities = path.ccp_alphas, path.impurities
```

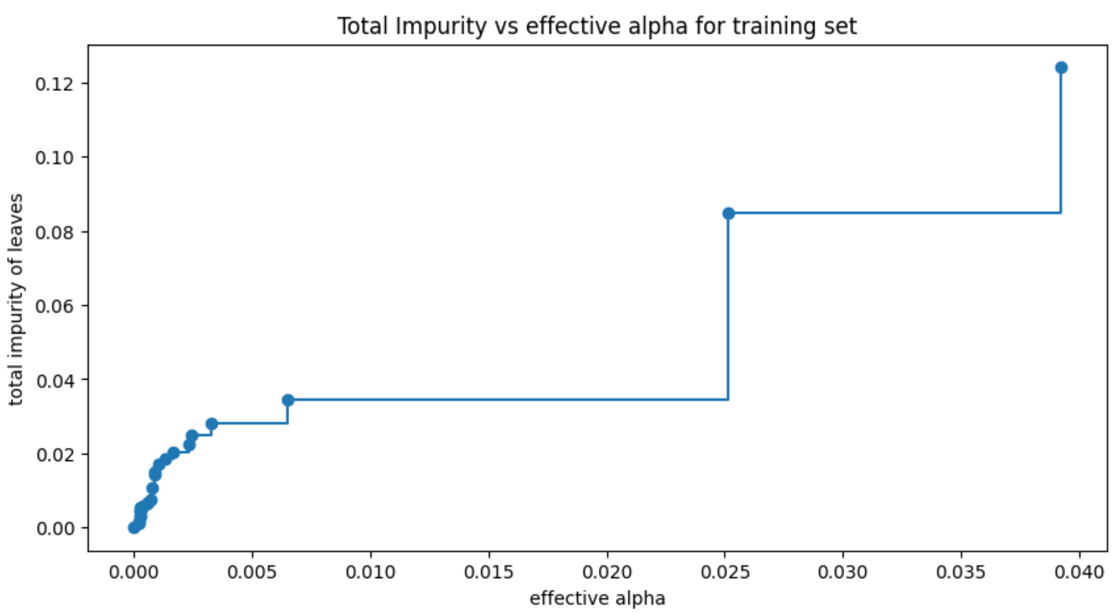
[ ]:
```
pd.DataFrame(path)
```

[ ]:

	ccp_alphas	impurities
0	0.000000	0.000000
1	0.000186	0.001114
2	0.000214	0.001542
3	0.000242	0.002750
4	0.000250	0.003250
5	0.000268	0.004324
6	0.000272	0.004868

```
7      0.000276    0.005420
8      0.000381    0.005801
9      0.000527    0.006329
10     0.000625    0.006954
11     0.000700    0.007654
12     0.000769    0.010731
13     0.000882    0.014260
14     0.000889    0.015149
15     0.001026    0.017200
16     0.001305    0.018505
17     0.001647    0.020153
18     0.002333    0.022486
19     0.002407    0.024893
20     0.003294    0.028187
21     0.006473    0.034659
22     0.025146    0.084951
23     0.039216    0.124167
24     0.047088    0.171255
```

[ ]:
```
fig, ax = plt.subplots(figsize=(10, 5))
ax.plot(ccp_alphas[:-1], impurities[:-1], marker="o", drawstyle="steps-post")
ax.set_xlabel("effective alpha")
ax.set_ylabel("total impurity of leaves")
ax.set_title("Total Impurity vs effective alpha for training set")
plt.show()
```

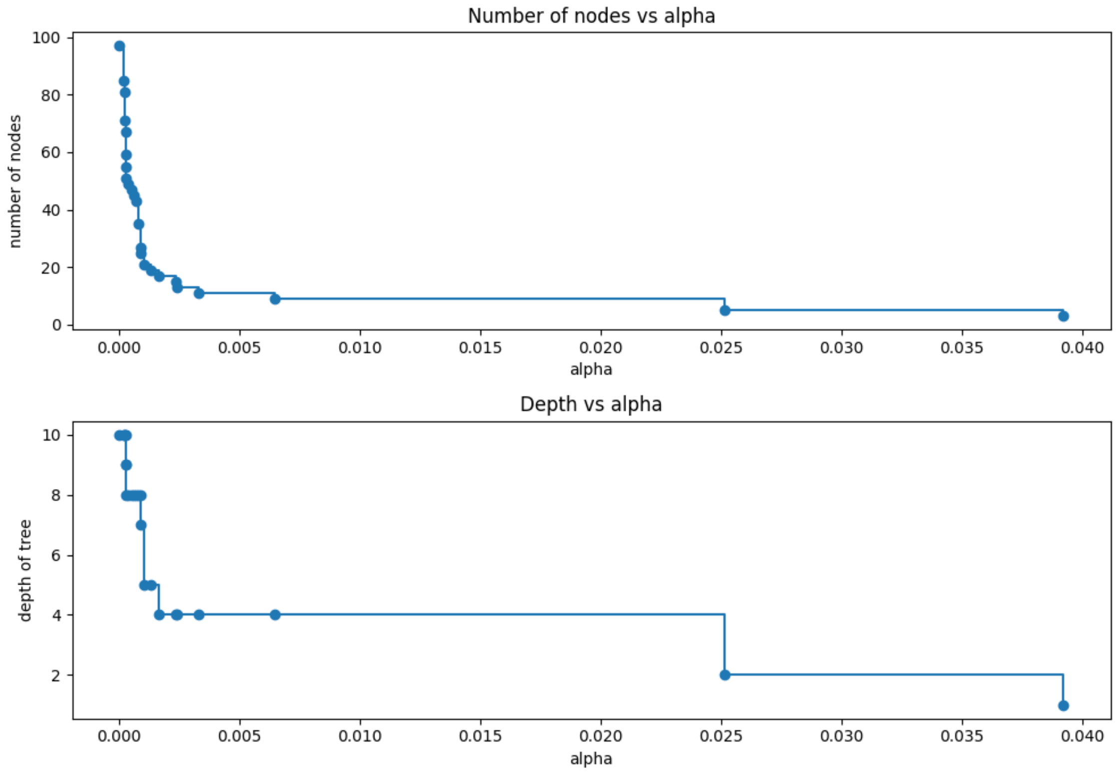


Next, we train a decision tree using effective alphas. The last value in `ccp_alphas` is the alpha value that prunes the whole tree, leaving the tree, `clfs[-1]`, with one node.

[ ]:
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(random_state=1, ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train,)     ## Complete the code to fit decision tree on␣
 ↪training data
    clfs.append(clf)
print(
    "Number of nodes in the last tree is: {} with ccp_alpha: {}".format(
        clfs[-1].tree_.node_count, ccp_alphas[-1]
    )
)
```

```
Number of nodes in the last tree is: 1 with ccp_alpha: 0.04708834100596766
```

[ ]:
```
clfs = clfs[:-1]
ccp_alphas = ccp_alphas[:-1]

node_counts = [clf.tree_.node_count for clf in clfs]
depth = [clf.tree_.max_depth for clf in clfs]
fig, ax = plt.subplots(2, 1, figsize=(10, 7))
ax[0].plot(ccp_alphas, node_counts, marker="o", drawstyle="steps-post")
ax[0].set_xlabel("alpha")
ax[0].set_ylabel("number of nodes")
ax[0].set_title("Number of nodes vs alpha")
ax[1].plot(ccp_alphas, depth, marker="o", drawstyle="steps-post")
ax[1].set_xlabel("alpha")
ax[1].set_ylabel("depth of tree")
ax[1].set_title("Depth vs alpha")
fig.tight_layout()
```



Recall vs alpha for training and testing sets

[ ]:
```
recall_train = []
for clf in clfs:
    pred_train = clf.predict(X_train)
    values_train = recall_score(y_train, pred_train)
    recall_train.append(values_train)

recall_test = []
for clf in clfs:
    pred_test = clf.predict(X_test)
    values_test = recall_score(y_test, pred_test)
    recall_test.append(values_test)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15, 5))
ax.set_xlabel("alpha")
ax.set_ylabel("Recall")
ax.set_title("Recall vs alpha for training and testing sets")
ax.plot(ccp_alphas, recall_train, marker="o", label="train",␣
 ↪drawstyle="steps-post")
ax.plot(ccp_alphas, recall_test, marker="o", label="test",␣
 ↪drawstyle="steps-post")
```

```
ax.legend()
plt.show()
```

[ ]:
```
index_best_model = np.argmax(recall_test)
best_model = clfs[index_best_model]
print(best_model)
```

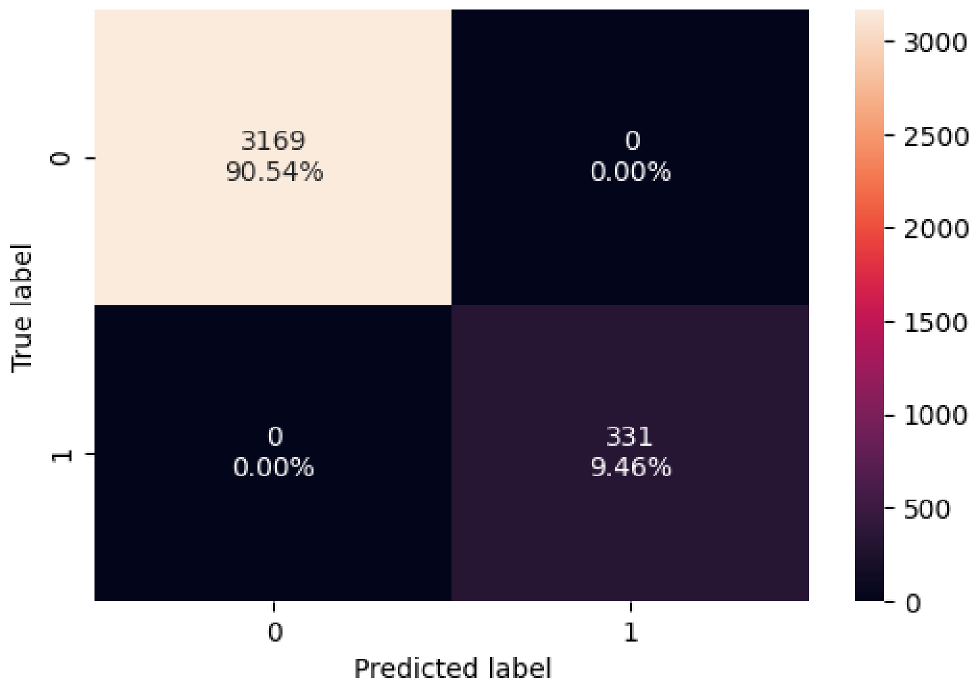
```
DecisionTreeClassifier(random_state=1)
```

[ ]:
```
estimator_2 = DecisionTreeClassifier(
    ccp_alpha=ccp_alphas[index_best_model], class_weight={0: 0.15, 1: 0.85},␣
 ↪random_state=1         ## Complete the code by adding the correct ccp_alpha␣
 ↪value
)
estimator_2.fit(X_train, y_train)
```

[ ]:
```
DecisionTreeClassifier(class_weight={0: 0.15, 1: 0.85}, random_state=1)
```

Checking performance on training data

[ ]:
```
confusion_matrix_sklearn(estimator_2, X_train, y_train) ## Complete the code to␣
 ↪create confusion matrix for train data
```



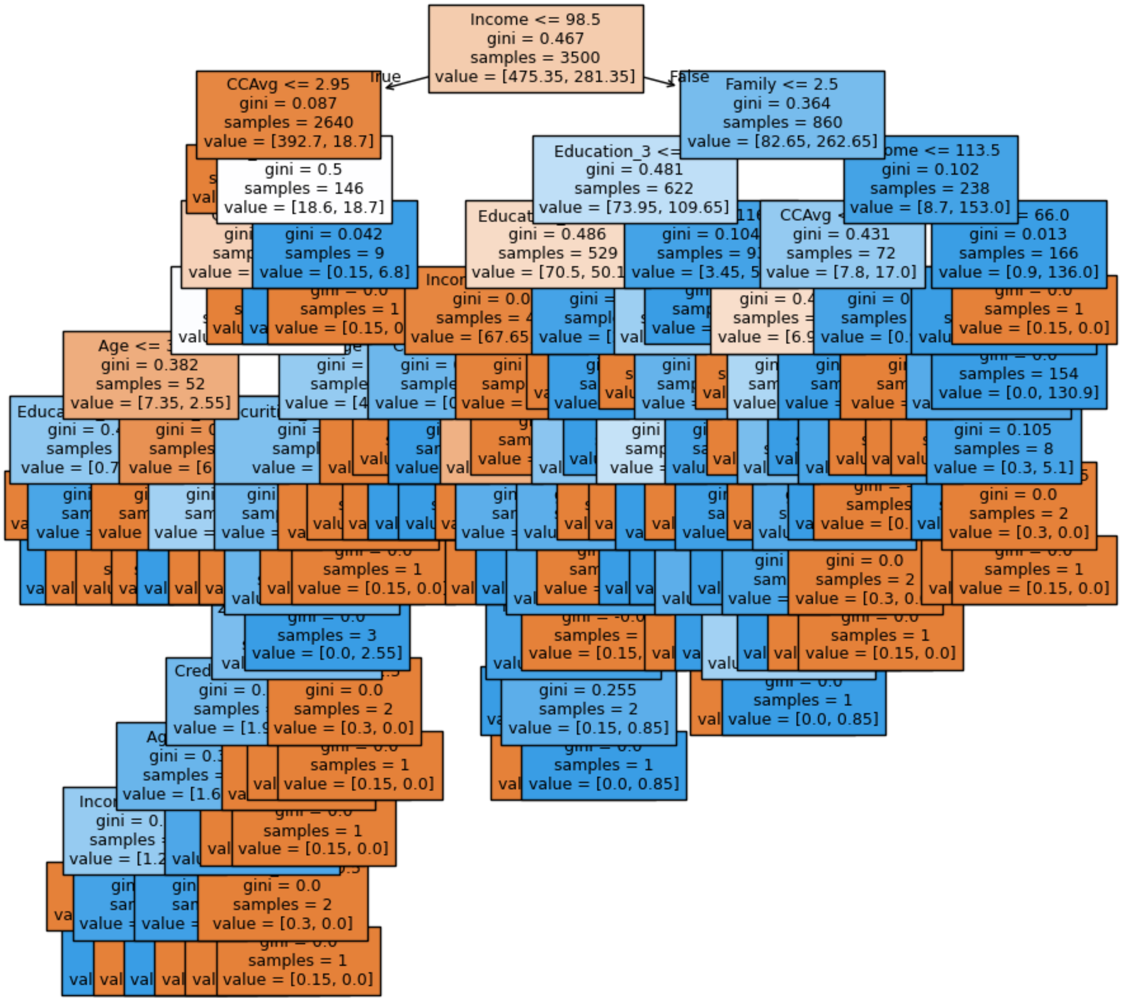

```
[ ]: decision_tree_tune_post_train =␣
     ↪model_performance_classification_sklearn(estimator_2, X_train, y_train) ##␣
     ↪Complete the code to check performance on train data
     decision_tree_tune_post_train
```

```
[ ]:    Accuracy  Recall  Precision   F1
     0       1.0     1.0        1.0  1.0
```

Visualizing the Decision Tree

```
[ ]: plt.figure(figsize=(10, 10))
     out = tree.plot_tree(
         estimator_2,
         feature_names=feature_names,
         filled=True,
         fontsize=9,
         node_ids=False,
         class_names=None,
     )
     # below code will add arrows to the decision tree split if they are missing
     for o in out:
         arrow = o.arrow_patch
         if arrow is not None:
             arrow.set_edgecolor("black")
```

```
        arrow.set_linewidth(1)
plt.show()
```



[ ]:
```
# Text report showing the rules of a decision tree -

print(tree.export_text(estimator_2, feature_names=feature_names,
 ↪show_weights=True))
```

```
|--- Income <= 98.50
|   |--- CCAvg <= 2.95
|   |   |--- weights: [374.10, 0.00] class: 0
|   |--- CCAvg >  2.95
|   |   |--- CD_Account <= 0.50
|   |   |   |--- CCAvg <= 3.95
|   |   |   |   |--- Income <= 81.50
|   |   |   |   |   |--- Age <= 36.50
```

```
|   |   |   |   |   |   |--- Education_2 <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |   |--- Education_2 >  0.50
|   |   |   |   |   |   |   |--- ZIPCode_91 <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |   |--- ZIPCode_91 >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Age >  36.50
|   |   |   |   |   |   |--- ZIPCode_91 <= 0.50
|   |   |   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [2.55, 0.00] class: 0
|   |   |   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |   |   |--- weights: [3.60, 0.00] class: 0
|   |   |   |   |   |   |--- ZIPCode_91 >  0.50
|   |   |   |   |   |   |   |--- Education_3 <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |--- Education_3 >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |--- Income >  81.50
|   |   |   |   |   |--- Mortgage <= 152.00
|   |   |   |   |   |   |--- Securities_Account <= 0.50
|   |   |   |   |   |   |   |--- CCAvg <= 3.05
|   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |   |--- CCAvg >  3.05
|   |   |   |   |   |   |   |   |--- CCAvg <= 3.85
|   |   |   |   |   |   |   |   |   |--- ZIPCode_91 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- CreditCard <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 4
|   |   |   |   |   |   |   |   |   |   |--- CreditCard >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |--- ZIPCode_91 >  0.50
|   |   |   |   |   |   |   |   |   |   |--- Family <= 1.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- Family >  1.50
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- CCAvg >  3.85
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 2.55] class: 1
|   |   |   |   |   |   |--- Securities_Account >  0.50
|   |   |   |   |   |   |   |--- CreditCard <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |   |--- CreditCard >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |--- Mortgage >  152.00
|   |   |   |   |   |   |--- ZIPCode_94 <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |--- ZIPCode_94 >  0.50
|   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |--- CCAvg >  3.95
```

```
|   |   |   |   |--- weights: [6.75, 0.00] class: 0
|   |   |--- CD_Account >  0.50
|   |   |   |--- CCAvg <= 4.50
|   |   |   |   |--- weights: [0.00, 6.80] class: 1
|   |   |   |--- CCAvg >  4.50
|   |   |   |   |--- weights: [0.15, 0.00] class: 0
|--- Income >  98.50
|   |--- Family <= 2.50
|   |   |--- Education_3 <= 0.50
|   |   |   |--- Education_2 <= 0.50
|   |   |   |   |--- Income <= 100.00
|   |   |   |   |   |--- CCAvg <= 4.20
|   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  4.20
|   |   |   |   |   |   |--- Age <= 54.50
|   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |--- Age >  54.50
|   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |--- Income >  100.00
|   |   |   |   |   |--- Income <= 103.50
|   |   |   |   |   |   |--- CCAvg <= 3.06
|   |   |   |   |   |   |   |--- weights: [2.10, 0.00] class: 0
|   |   |   |   |   |   |--- CCAvg >  3.06
|   |   |   |   |   |   |   |--- ZIPCode_91 <= 0.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- ZIPCode_91 >  0.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |--- Income >  103.50
|   |   |   |   |   |   |--- weights: [64.95, 0.00] class: 0
|   |   |   |--- Education_2 >  0.50
|   |   |   |   |--- Income <= 110.00
|   |   |   |   |   |--- weights: [1.80, 0.00] class: 0
|   |   |   |   |--- Income >  110.00
|   |   |   |   |   |--- Income <= 116.50
|   |   |   |   |   |   |--- Mortgage <= 141.50
|   |   |   |   |   |   |   |--- Income <= 114.50
|   |   |   |   |   |   |   |   |--- Age <= 48.50
|   |   |   |   |   |   |   |   |   |--- Income <= 113.00
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |   |   |   |--- Income >  113.00
|   |   |   |   |   |   |   |   |   |   |--- CCAvg <= 3.10
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |   |--- CCAvg >  3.10
|   |   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |   |--- Age >  48.50
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- Income >  114.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
```

```
|   |   |   |   |   |   |--- Mortgage >  141.50
|   |   |   |   |   |   |   |--- weights: [0.60, 0.00] class: 0
|   |   |   |   |   |--- Income >  116.50
|   |   |   |   |   |   |--- weights: [0.00, 45.05] class: 1
|   |   |--- Education_3 >  0.50
|   |   |   |--- Income <= 116.50
|   |   |   |   |--- CCAvg <= 1.10
|   |   |   |   |   |--- weights: [1.95, 0.00] class: 0
|   |   |   |   |--- CCAvg >  1.10
|   |   |   |   |   |--- Age <= 41.50
|   |   |   |   |   |   |--- ZIPCode_94 <= 0.50
|   |   |   |   |   |   |   |--- weights: [1.20, 0.00] class: 0
|   |   |   |   |   |   |--- ZIPCode_94 >  0.50
|   |   |   |   |   |   |   |--- Mortgage <= 74.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |--- Mortgage >  74.50
|   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |--- Age >  41.50
|   |   |   |   |   |   |--- Income <= 100.00
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |--- Income >  100.00
|   |   |   |   |   |   |   |--- CCAvg <= 1.85
|   |   |   |   |   |   |   |   |--- Mortgage <= 206.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Mortgage >  206.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
|   |   |   |   |   |   |   |--- CCAvg >  1.85
|   |   |   |   |   |   |   |   |--- weights: [0.00, 4.25] class: 1
|   |   |   |--- Income >  116.50
|   |   |   |   |--- weights: [0.00, 52.70] class: 1
|   |--- Family >  2.50
|   |   |--- Income <= 113.50
|   |   |   |--- CCAvg <= 2.75
|   |   |   |   |--- Income <= 106.50
|   |   |   |   |   |--- weights: [3.90, 0.00] class: 0
|   |   |   |   |--- Income >  106.50
|   |   |   |   |   |--- Age <= 28.50
|   |   |   |   |   |   |--- weights: [1.35, 0.00] class: 0
|   |   |   |   |   |--- Age >  28.50
|   |   |   |   |   |   |--- Family <= 3.50
|   |   |   |   |   |   |   |--- weights: [0.90, 0.00] class: 0
|   |   |   |   |   |   |--- Family >  3.50
|   |   |   |   |   |   |   |--- Age <= 60.00
|   |   |   |   |   |   |   |   |--- Age <= 35.00
|   |   |   |   |   |   |   |   |   |--- Education_3 <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |   |   |   |   |--- Education_3 >  0.50
|   |   |   |   |   |   |   |   |   |   |--- weights: [0.00, 0.85] class: 1
```

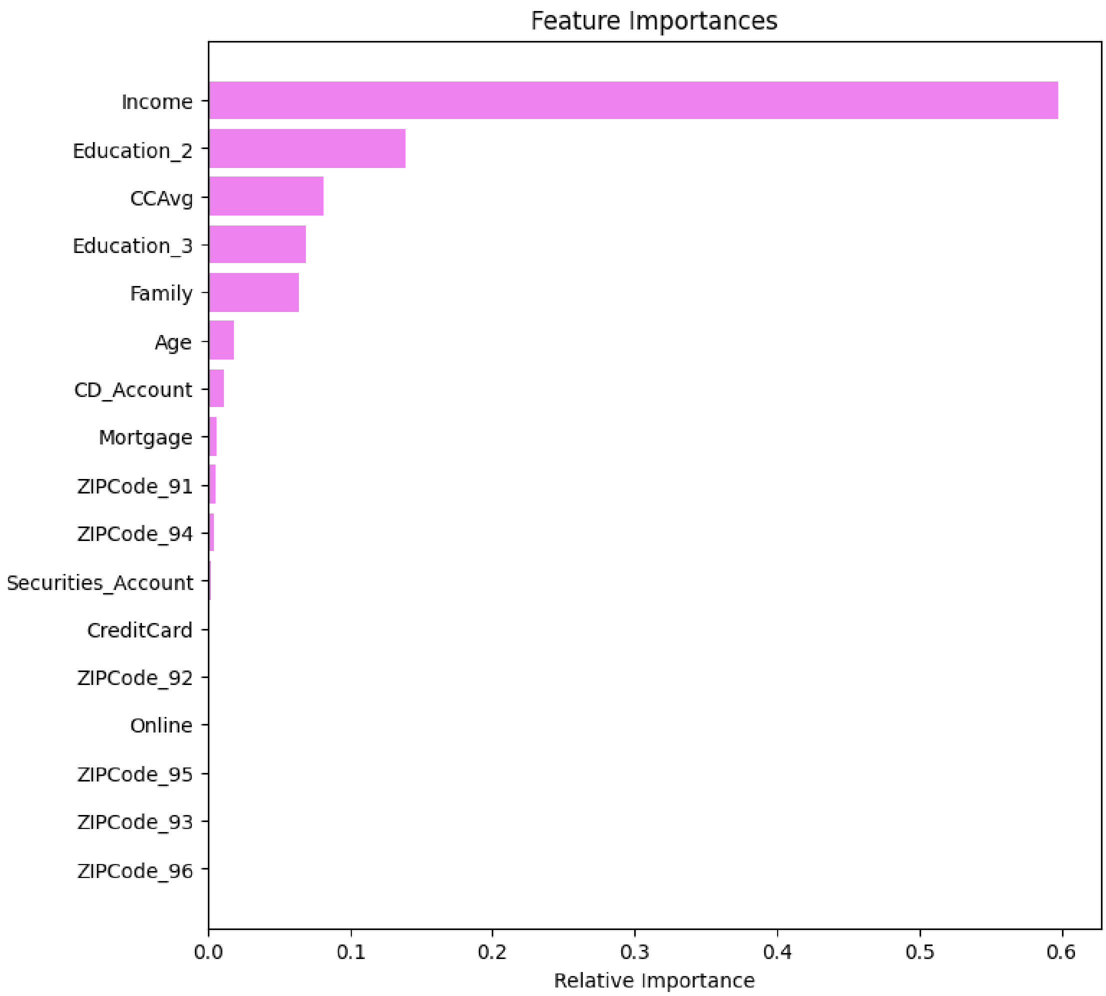
```
|   |   |   |   |   |   |   |   |--- Age >  35.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.00, 4.25] class: 1
|   |   |   |   |   |   |   |--- Age >  60.00
|   |   |   |   |   |   |   |   |--- Age <= 64.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |   |--- Age >  64.00
|   |   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |--- CCAvg >  2.75
|   |   |   |   |--- Age <= 57.00
|   |   |   |   |   |--- Age <= 49.50
|   |   |   |   |   |   |--- weights: [0.00, 10.20] class: 1
|   |   |   |   |   |--- Age >  49.50
|   |   |   |   |   |   |--- Online <= 0.50
|   |   |   |   |   |   |   |--- weights: [0.00, 1.70] class: 1
|   |   |   |   |   |   |--- Online >  0.50
|   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- Age >  57.00
|   |   |   |   |   |--- Education_2 <= 0.50
|   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |--- Education_2 >  0.50
|   |   |   |   |   |   |--- weights: [0.30, 0.00] class: 0
|   |   |--- Income >  113.50
|   |   |   |--- Age <= 66.00
|   |   |   |   |--- Income <= 116.50
|   |   |   |   |   |--- CCAvg <= 2.50
|   |   |   |   |   |   |--- weights: [0.45, 0.00] class: 0
|   |   |   |   |   |--- CCAvg >  2.50
|   |   |   |   |   |   |--- Age <= 60.50
|   |   |   |   |   |   |   |--- weights: [0.00, 5.10] class: 1
|   |   |   |   |   |   |--- Age >  60.50
|   |   |   |   |   |   |   |--- Income <= 114.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |   |   |   |--- Income >  114.50
|   |   |   |   |   |   |   |   |--- weights: [0.15, 0.00] class: 0
|   |   |   |   |--- Income >  116.50
|   |   |   |   |   |--- weights: [0.00, 130.90] class: 1
|   |   |   |--- Age >  66.00
|   |   |   |   |--- weights: [0.15, 0.00] class: 0
```

[ ]:
```
# importance of features in the tree building ( The importance of a feature is␣
↪computed as the
# (normalized) total reduction of the criterion brought by that feature. It is␣
↪also known as the Gini importance )

print(
    pd.DataFrame(
```

```
        estimator_2.feature_importances_, columns=["Imp"], index=X_train.columns
    ).sort_values(by="Imp", ascending=False)
)
```

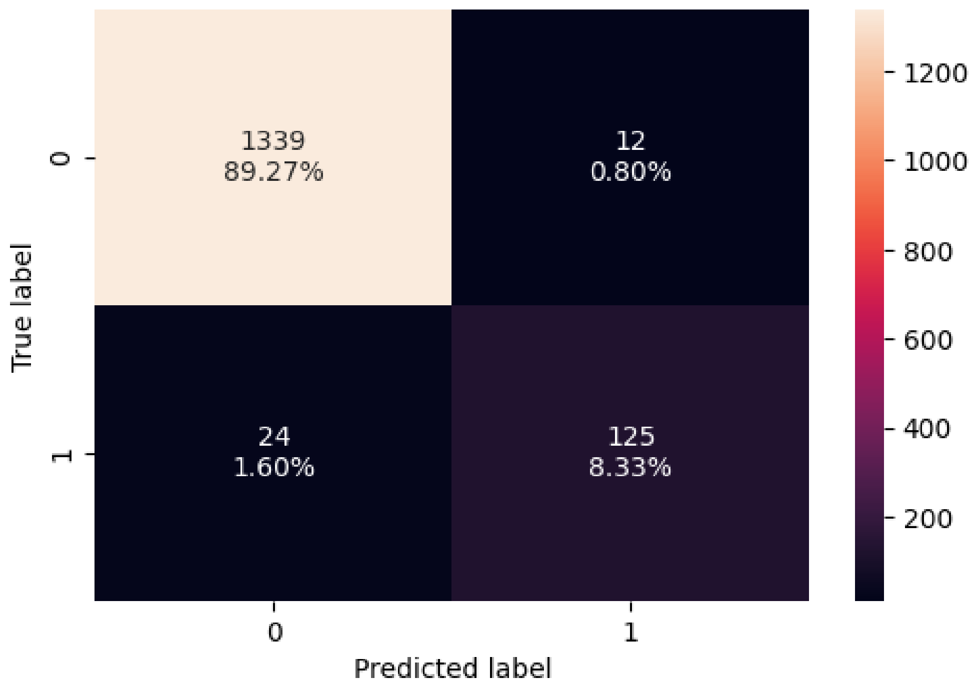
```
                              Imp
Income                5.979097e-01
Education_2           1.388508e-01
CCAvg                 8.152996e-02
Education_3           6.895824e-02
Family                6.407969e-02
Age                   1.825151e-02
CD_Account            1.099955e-02
Mortgage              5.762198e-03
ZIPCode_91            5.088280e-03
ZIPCode_94            3.980114e-03
Securities_Account    1.946974e-03
CreditCard            1.061543e-03
ZIPCode_92            8.015507e-04
Online                7.798872e-04
ZIPCode_95            3.768988e-18
ZIPCode_93            0.000000e+00
ZIPCode_96            0.000000e+00
```

[ ]:
```
importances = estimator_2.feature_importances_
indices = np.argsort(importances)

plt.figure(figsize=(8, 8))
plt.title("Feature Importances")
plt.barh(range(len(indices)), importances[indices], color="violet",␣
 ↪align="center")
plt.yticks(range(len(indices)), [feature_names[i] for i in indices])
plt.xlabel("Relative Importance")
plt.show()
```



Checking performance on test data

[ ]:
```
confusion_matrix_sklearn(estimator_2, X_test, y_test)  # Complete the code to
↪get the confusion matrix on test data
```




```
[ ]: decision_tree_tune_post_test =
     ↪model_performance_classification_sklearn(estimator_2, X_test, y_test) ##
     ↪Complete the code to get the model performance on test data
     decision_tree_tune_post_test
```

[ ]:

	Accuracy	Recall	Precision	F1
0	0.976	0.838926	0.912409	0.874126

0.11 Model Performance Comparison and Final Model Selection

```
[ ]: # training performance comparison

     models_train_comp_df = pd.concat(
         [decision_tree_perf_train.T, decision_tree_tune_perf_train.T,
     ↪decision_tree_tune_post_train.T], axis=1,
     )
     models_train_comp_df.columns = ["Decision Tree (sklearn default)", "Decision
     ↪Tree (Pre-Pruning)", "Decision Tree (Post-Pruning)"]
     print("Training performance comparison:")
     models_train_comp_df
```

Training performance comparison:

```
[ ]:            Decision Tree (sklearn default)  Decision Tree (Pre-Pruning)  \
Accuracy                                    1.0                     0.790286
Recall                                      1.0                     1.000000
Precision                                   1.0                     0.310798
F1                                          1.0                     0.474212

           Decision Tree (Post-Pruning)
Accuracy                            1.0
Recall                              1.0
Precision                           1.0
F1                                  1.0
```

```
[ ]: # testing performance comparison

models_test_comp_df = pd.concat(
    [decision_tree_perf_test.T, decision_tree_tune_perf_test.T,␣
 ↪decision_tree_tune_post_test.T], axis=1,
)
models_test_comp_df.columns = ["Decision Tree (sklearn default)", "Decision␣
 ↪Tree (Pre-Pruning)", "Decision Tree (Post-Pruning)"]
print("Test set performance comparison:")
models_test_comp_df
```

```
Test set performance comparison:
```

```
[ ]:            Decision Tree (sklearn default)  Decision Tree (Pre-Pruning)  \
Accuracy                                    1.0                     0.779333
Recall                                      1.0                     1.000000
Precision                                   1.0                     0.310417
F1                                          1.0                     0.473768

           Decision Tree (Post-Pruning)
Accuracy                       0.976000
Recall                         0.838926
Precision                      0.912409
F1                             0.874126
```

0.12 Actionable Insights and Business Recommendations

What recommedations would you suggest to the bank?

The **Decision Tree with Post-Pruning** appears to be the best model. Here's why:

1. **Balanced Performance:** The code demonstrates that post-pruning leads to a more balanced performance between training and testing sets, reducing overfitting which is evident in the default decision tree model. This balance suggests better generalization to unseen data.

2. **Recall Optimization:** The code explicitly searches for the best model based on recall score and the difference between training and testing recall scores. Post-pruning leads to a higher recall score on the test data, indicating its better capability of identifying customers likely to accept a personal loan (positive class). In a banking context, identifying potential customers accurately is crucial.

3. **Performance Comparison:** The final model comparison tables (models_train_comp_df and models_test_comp_df) show how the post-pruning model often produces competitive or superior scores. A careful examination of the Recall, Precision, and F1 scores provides a concrete picture.

Based on the analysis using the Decision Tree model (especially the post-pruning version), here are some actionable insights and recommendations for the bank:

1. Focus on High-Income , Graduate Education and High-CCAvg Customers:

- The model highlights "Income" , "Education" and "CCAvg" (average credit card spending) as highly important features in predicting loan acceptance.
- The bank should prioritize marketing and outreach efforts towards customers with higher incomes education and credit card spending. These customers demonstrate a higher likelihood of accepting a personal loan.

2. Targeted Marketing Campaigns Based on Demographics:

- Although not as prominent as Income and CCAvg, the model considers Advanced/Professional Education and "Family" as influential.
- Segment customers based on these factors. Create tailored marketing campaigns or offers that address the specific needs and financial situations of different customer segments (e.g., offers for families, education-related loans, higher loan amounts for higher earners).

3. Optimize Customer Relationship Management (CRM) Strategies:

- Use the model's predictions as part of a broader CRM system to identify potential loan applicants proactively.
- Proactively reach out to customers with high predicted probabilities of loan acceptance.
- Offer personalized incentives or pre-approved loans to these customers.

4. Monitor and Refine Model Performance:

- The model's performance should be monitored over time. Customer behavior and market conditions can change, potentially affecting the model's accuracy.
- Periodically retrain the model with updated data to ensure its continued relevance and effectiveness.

5. Explore Other Relevant Features:

- Investigate additional customer data points that might improve the model's predictive power (e.g., loan history, debt-to-income ratio, recent transactions, online banking usage etc.). Consider including these features in future model iterations.

6. Balance Cost and Benefit:

- Understand the cost associated with each marketing effort and the potential profit from securing a loan.

- Ensure the targeting strategy is optimized for net profit by considering the probability of loan acceptance versus the costs associated with the campaigns.
- Use A/B testing to determine the best allocation of marketing budget to different customer segments.

7. Consider Explainability and Transparency:

- Since the decision tree is fairly interpretable, be transparent with the reasons for the loan offers or marketing outreach.
- Providing reasons why they were targeted for the loan offer can increase customer trust and improve acceptance rates.