Problem Statement

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.

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.

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)

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.**

Importing necessary libraries

In [200]:

```
# Installing the libraries with the specified version.
!pip install numpy==1.25.2 pandas==1.5.3 matplotlib==3.7.1 seaborn==0.13.1 scikit-learn=
=1.2.2 sklearn-pandas==2.2.0 -q --user
```

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.**

In [201]:

```
# 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")
```

Loading the dataset

In [202]:

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount
("/content/drive", force_remount=True).
```

In [203]:

```
Loan = pd.read_csv("/content/drive/MyDrive/chap2_machine_learning/Loan_Modelling.csv")
##  Complete the code to read the data
```

In [204]:

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

Data Overview

View the first and last 5 rows of the dataset.

In [205]:

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

Out[205]:

	ID	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage	Personal_Loan	Securities_Account	CD_Acc
0	1	25	1	49	91107	4	1.6	1	0	0	1	
1	2	45	19	34	90089	3	1.5	1	0	0	1	
2	3	39	15	11	94720	1	1.0	1	0	0	0	
3	4	35	9	100	94112	1	2.7	2	0	0	0	
4	5	35	8	45	91330	4	1.0	2	0	0	0	

In [206]:

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

Out[206]:

	ID	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage	Personal_Loan	Securities_Account	CI
4995	4996	29	3	40	92697	1	1.9	3	0	0	0	
4996	4997	30	4	15	92037	4	0.4	1	85	0	0	
4997	4998	63	39	24	93023	2	0.3	3	0	0	0	
4998	4999	65	40	49	90034	3	0.5	2	0	0	0	
4999	5000	28	4	83	92612	3	0.8	1	0	0	0	

Understand the shape of the dataset.

In [207]:

```
data.shape   ## Complete the code to get the shape of the data
```

Out[207]:

```
(5000, 14)
```

Check the data types of the columns for the dataset

In [208]:

```
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
```

```
 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
```

Checking the Statistical Summary

In [209]:

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

Out[209]:

	count	mean	std	min	25%	50%	75%	max
ID	5000.0	2500.500000	1443.520003	1.0	1250.75	2500.5	3750.25	5000.0
Age	5000.0	45.338400	11.463166	23.0	35.00	45.0	55.00	67.0
Experience	5000.0	20.104600	11.467954	-3.0	10.00	20.0	30.00	43.0
Income	5000.0	73.774200	46.033729	8.0	39.00	64.0	98.00	224.0
ZIPCode	5000.0	93169.257000	1759.455086	90005.0	91911.00	93437.0	94608.00	96651.0
Family	5000.0	2.396400	1.147663	1.0	1.00	2.0	3.00	4.0
CCAvg	5000.0	1.937938	1.747659	0.0	0.70	1.5	2.50	10.0
Education	5000.0	1.881000	0.839869	1.0	1.00	2.0	3.00	3.0
Mortgage	5000.0	56.498800	101.713802	0.0	0.00	0.0	101.00	635.0
Personal_Loan	5000.0	0.096000	0.294621	0.0	0.00	0.0	0.00	1.0
Securities_Account	5000.0	0.104400	0.305809	0.0	0.00	0.0	0.00	1.0
CD_Account	5000.0	0.060400	0.238250	0.0	0.00	0.0	0.00	1.0
Online	5000.0	0.596800	0.490589	0.0	0.00	1.0	1.00	1.0
CreditCard	5000.0	0.294000	0.455637	0.0	0.00	0.0	1.00	1.0

Dropping columns

In [210]:

```
data = data.drop(["ID"], axis=1)   ## Complete the code to drop a column from the datafram
e
```

In [211]:

```
data.sample(2)
```

Out[211]:

	Age	Experience	Income	ZIPCode	Family	CCAvg	Education	Mortgage	Personal_Loan	Securities_Account	CD_Acco
599	28	4	103	94720	2	2.5	1	0	0	0	
4460	47	22	78	92093	1	0.2	2	0	0	0	

Data Preprocessing

Checking for Anomalous Values

In [212]:

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

Out[212]:

```
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])
```

In [213]:

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

Out[213]:

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

In [214]:

```
# 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)
```

In [215]:

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

Out[215]:

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

Feature Engineering

In [216]:

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

Out[216]:

```
467
```

In [217]:

```
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
```

In [218]:

```
## 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")
```

Exploratory Data Analysis (EDA)

Univariate Analysis

In [219]:

```
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
```

In [220]:

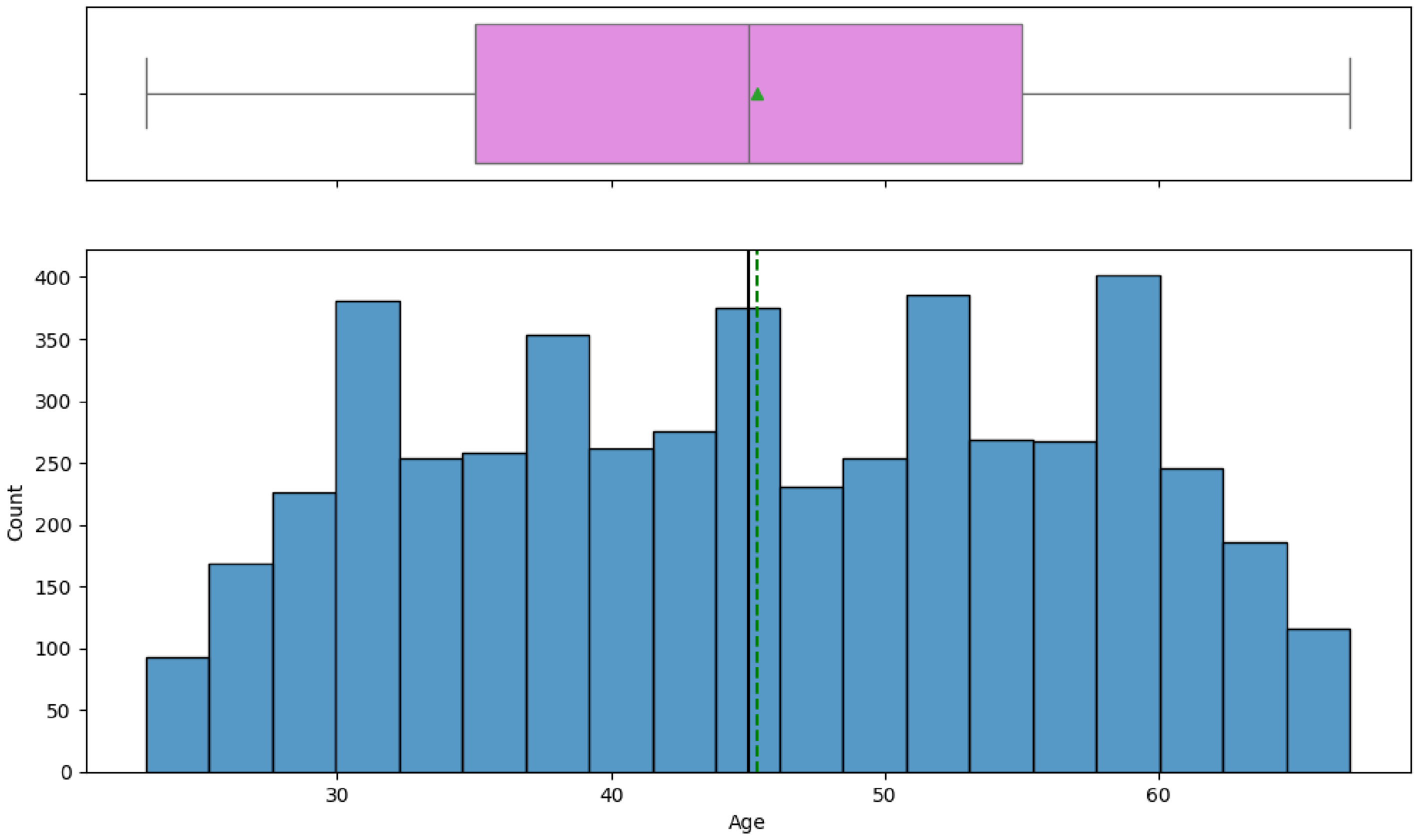
```
# function to create labeled barplots


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

In [221]:

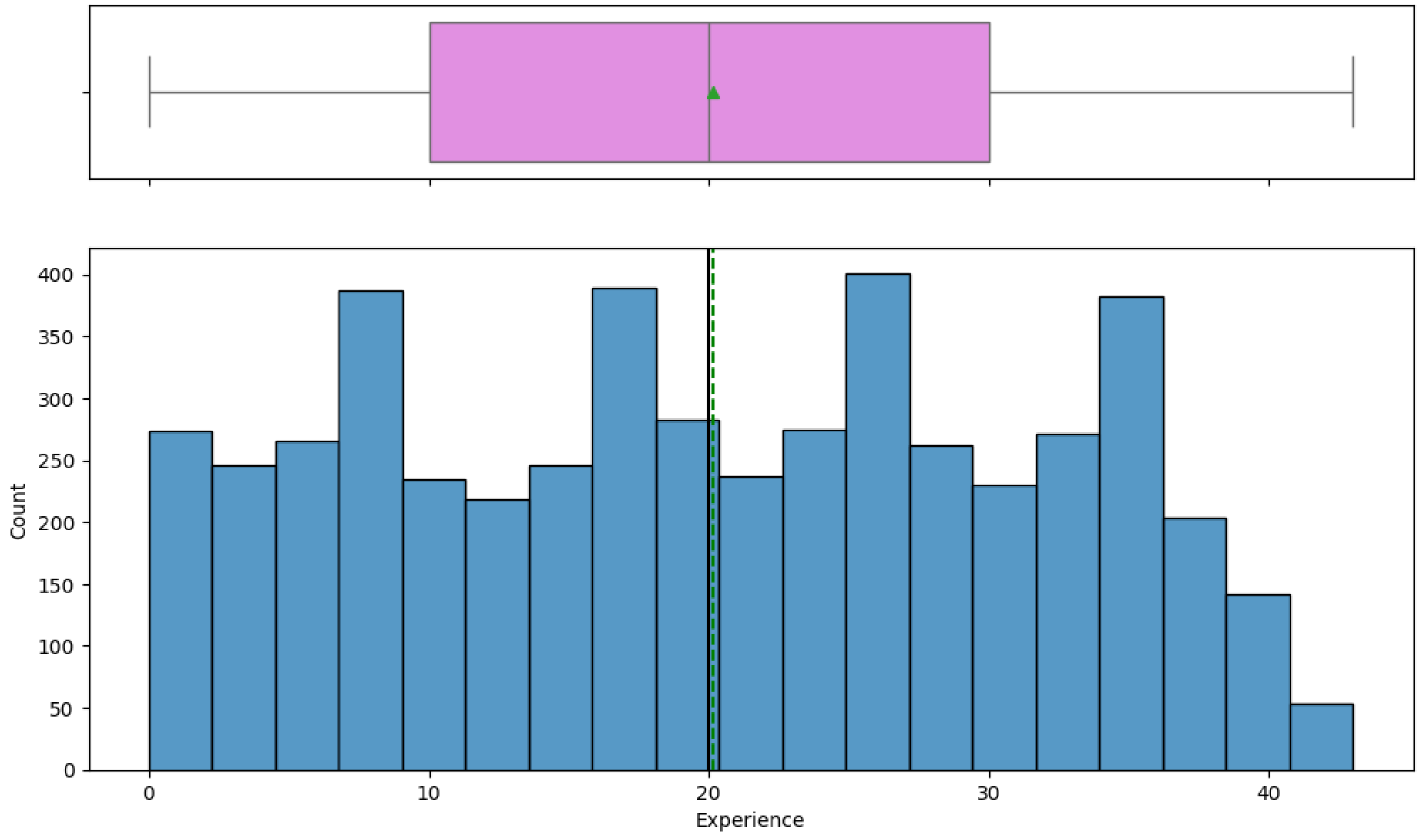
```
histogram_boxplot(data, "Age")
```



Observations on Experience

In [222]:

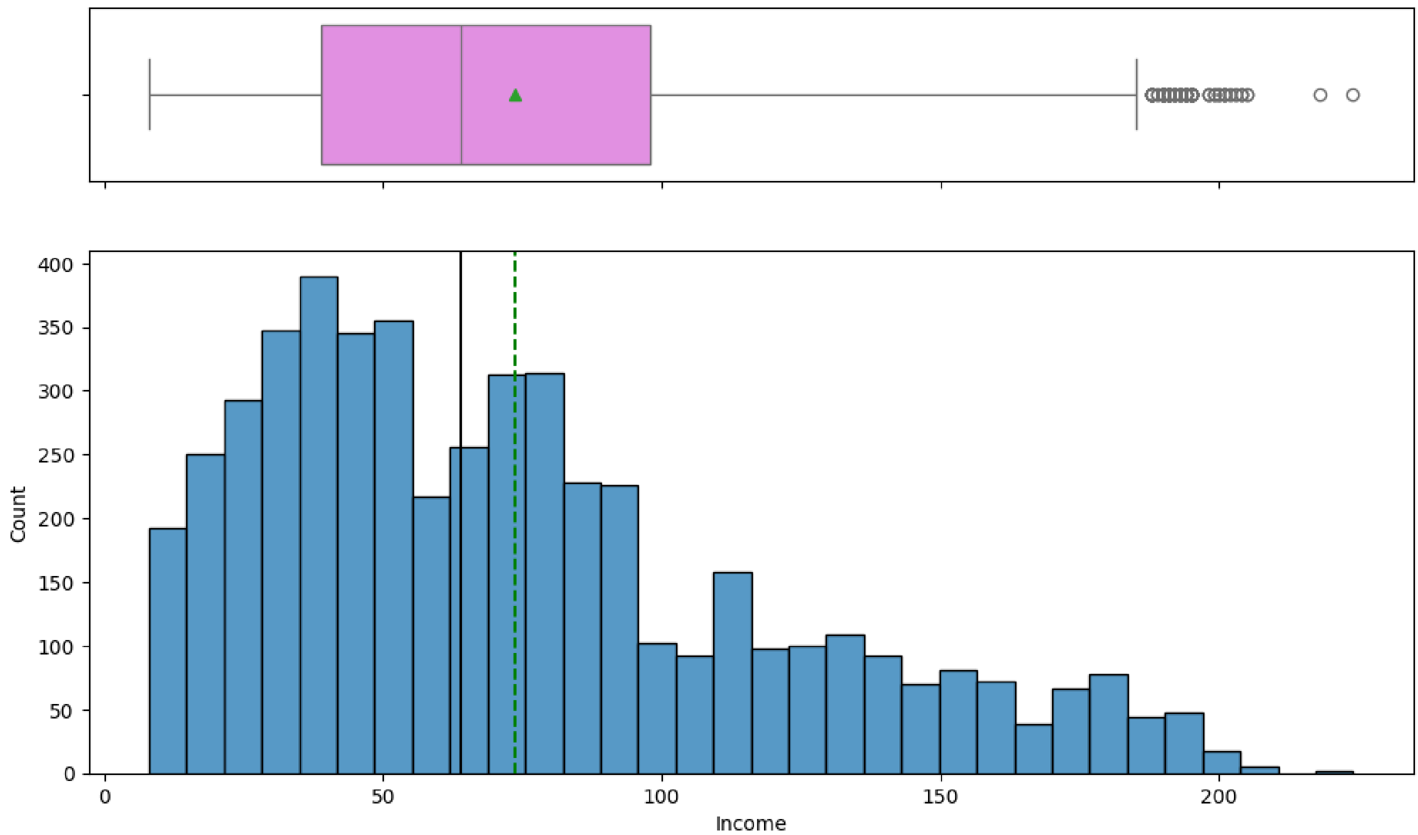
```
histogram_boxplot(data,"Experience") ## Complete the code to create histogram_boxplot for experience
```



Observations on Income

In [223]:

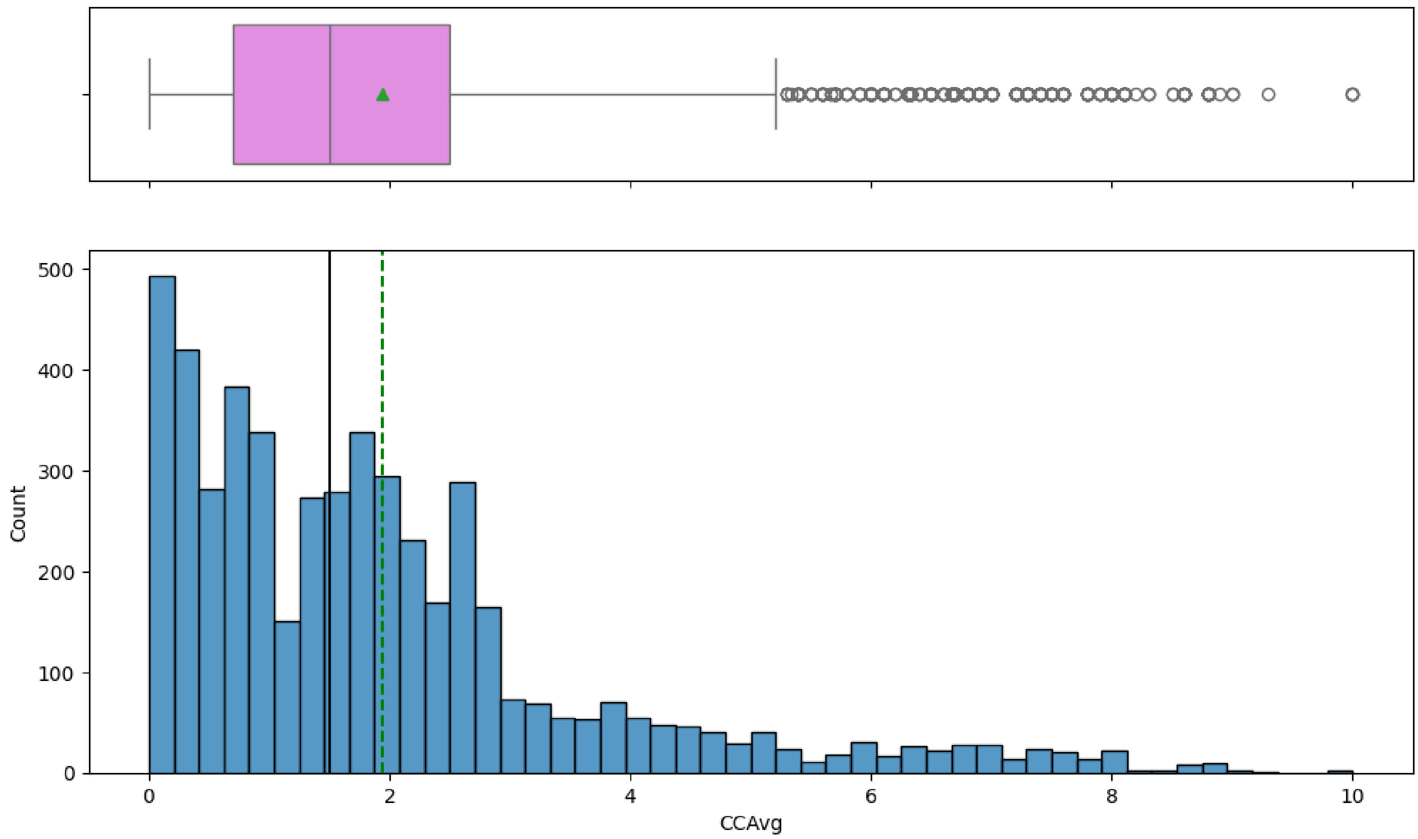
```
histogram_boxplot(data, "Income")  ## Complete the code to create histogram_boxplot for Income
```



Observations on CCAvg

In [224]:

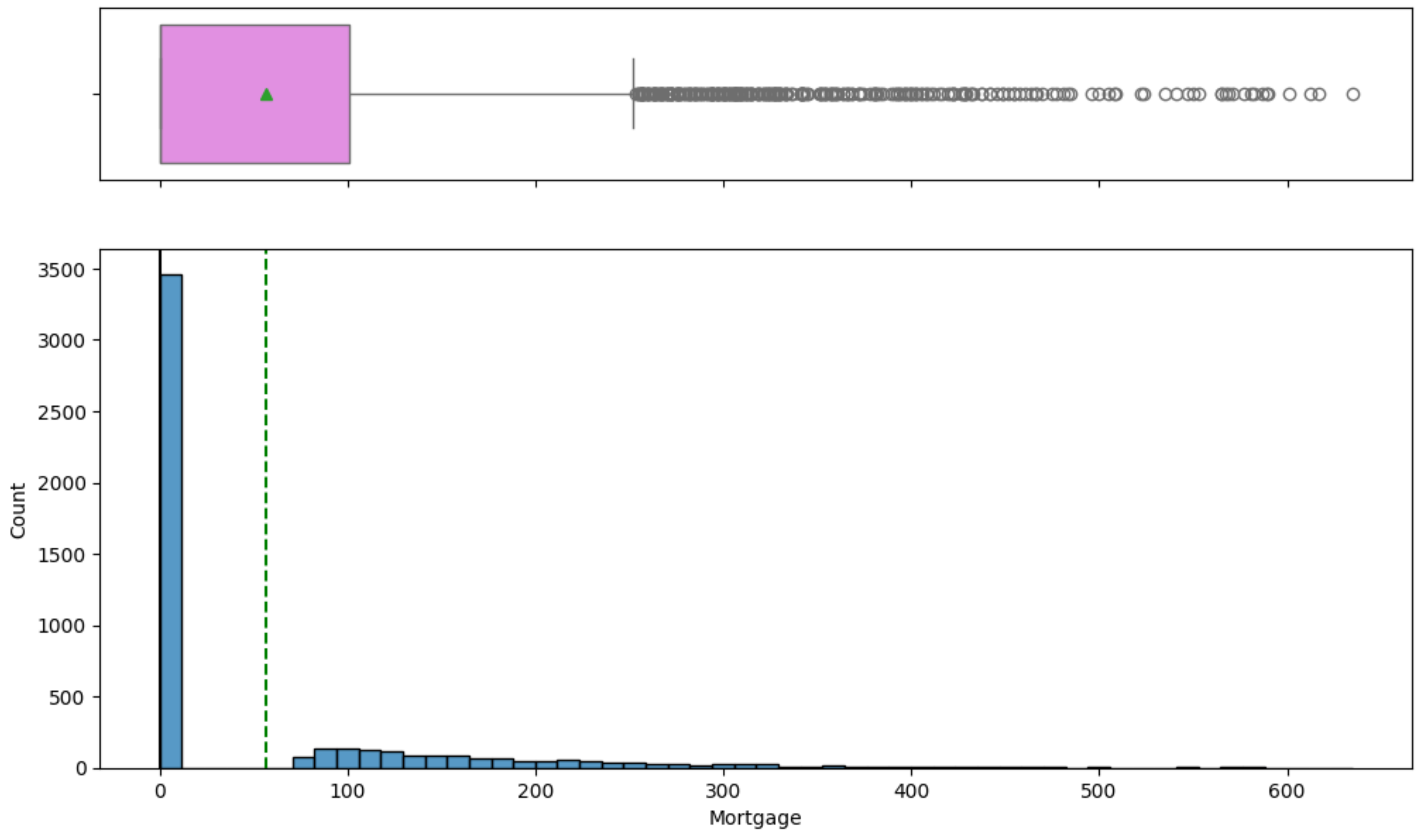
```
histogram_boxplot(data, "CCAvg")   ## Complete the code to create histogram_boxplot for CC
Avg
```



Observations on Mortgage

In [225]:

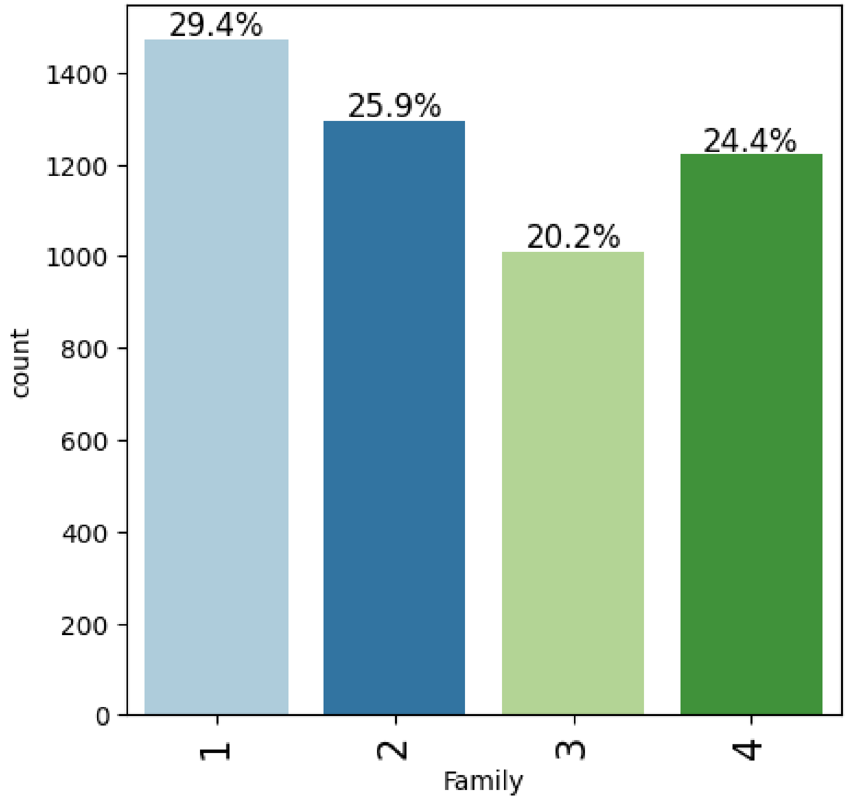
```
histogram_boxplot(data, "Mortgage")   ## Complete the code to create histogram_boxplot for
Mortgage
```



Observations on Family

In [226]:

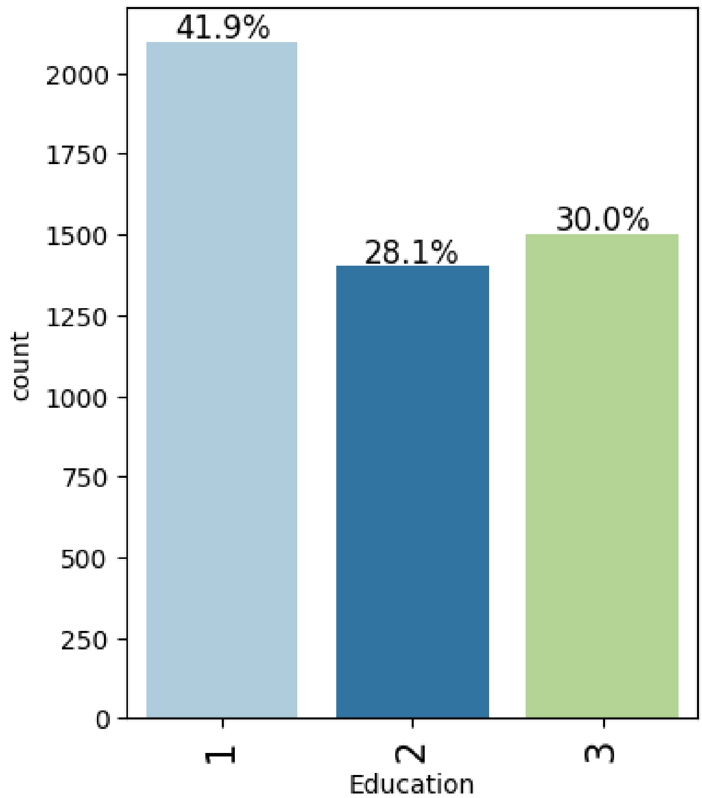
```
labeled_barplot(data, "Family", perc=True)
```



Observations on Education

In [227]:

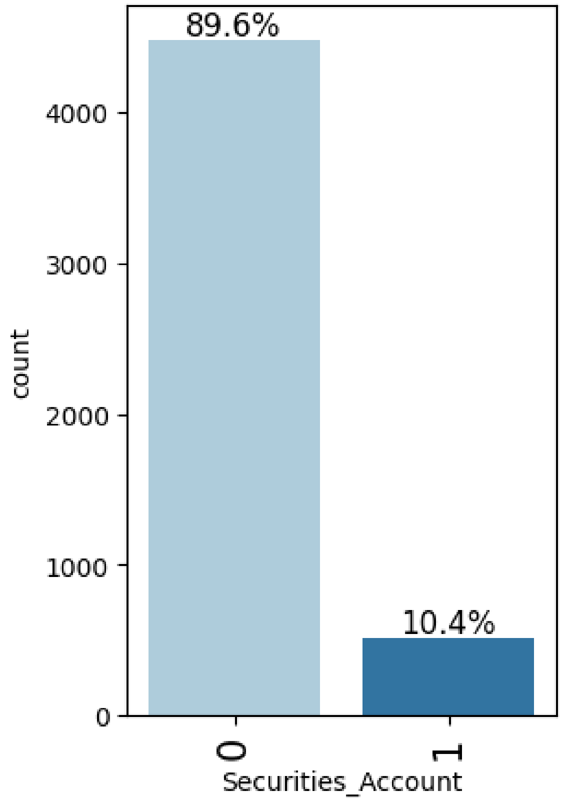
```
labeled_barplot(data, "Education", perc = True)   ## Complete the code to create labeled_b
arplot for Education
```



Observations on Securities_Account

In [228]:

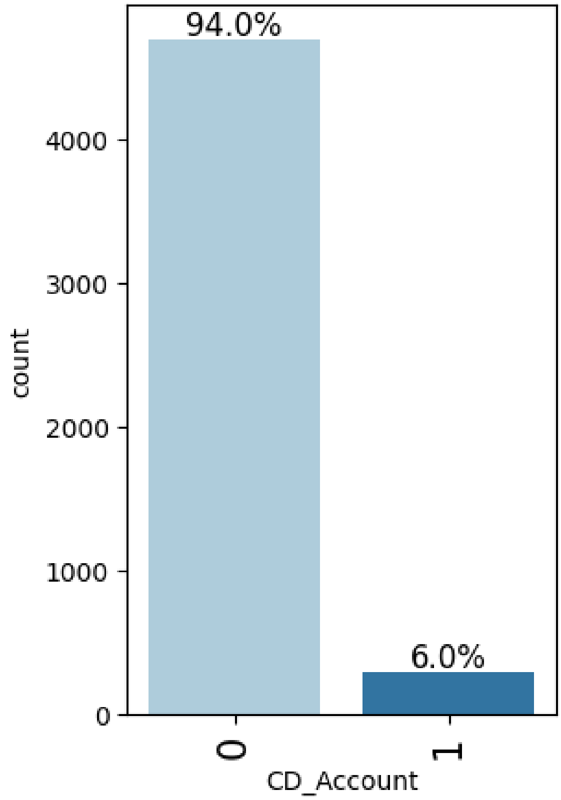
```
labeled_barplot(data, "Securities_Account", perc = True)   ## Complete the code to create labeled_barplot for Securities_Account
```



Observations on CD_Account

In [229]:

```
labeled_barplot(data, "CD_Account", perc = True)     ## Complete the code to create labeled_barplot for CD_Account
```

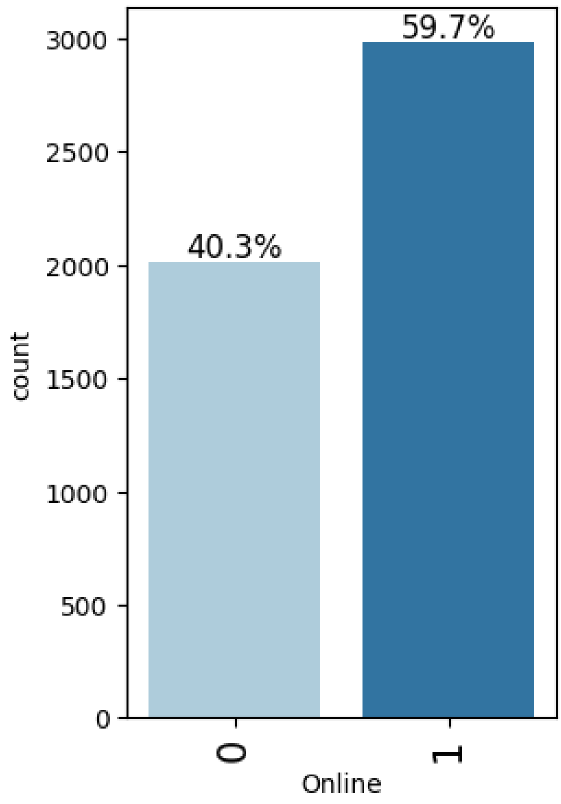


Observations on Online

In [230]:

In [230]:

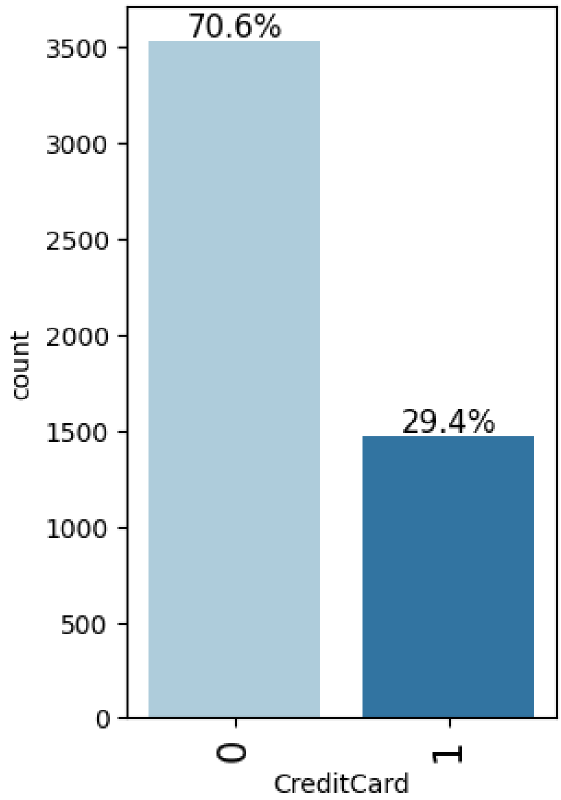
```
labeled_barplot(data, "Online", perc = True)    ## Complete the code to create labeled_bar
plot for Online
```



Observation on CreditCard

In [231]:

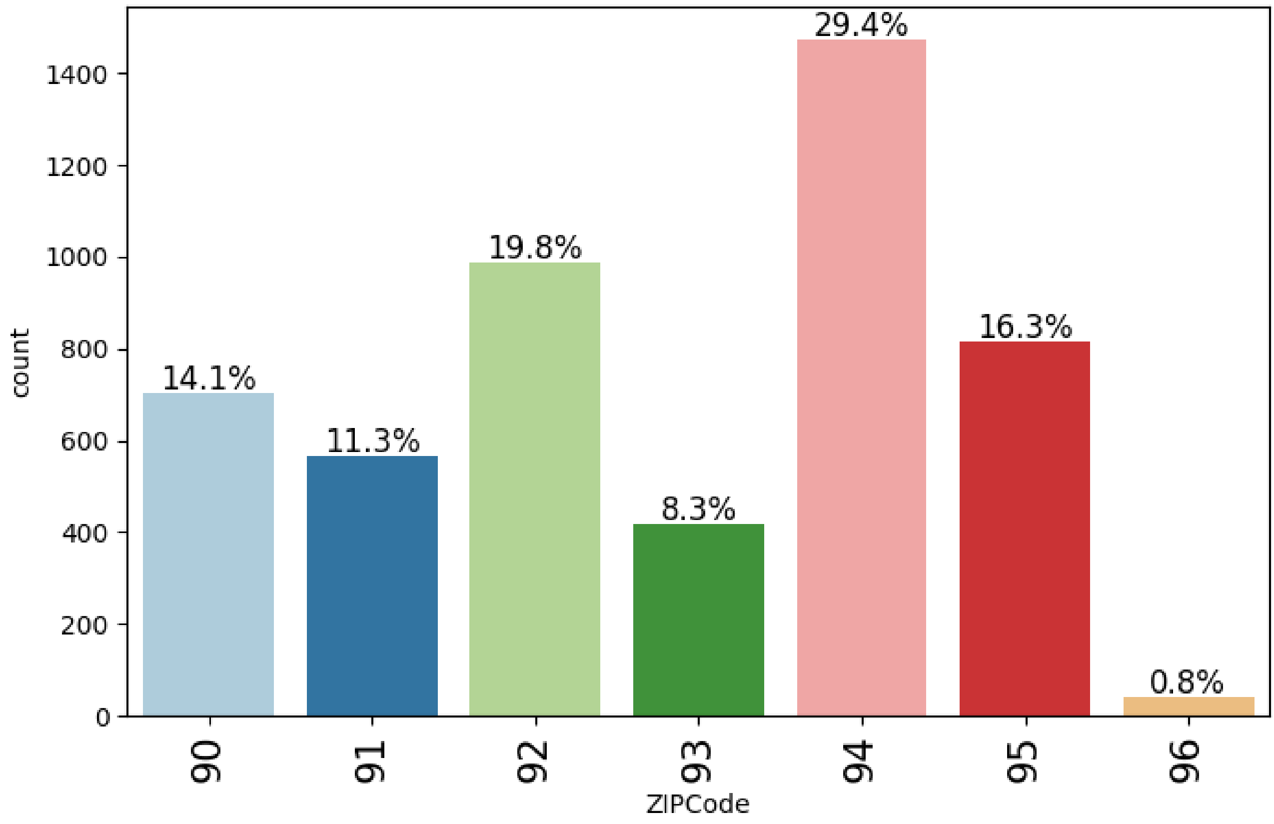
```
labeled_barplot(data, "CreditCard", perc = True)   ## Complete the code to create labeled_
barplot for CreditCard
```



Observation on ZIPCode

In [232]:

```
labeled_barplot(data, "ZIPCode", perc = True)   ## Complete the code to create labeled_bar
plot for ZIPCode
```



Bivariate Analysis

In [233]:

```
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()
```

In [234]:

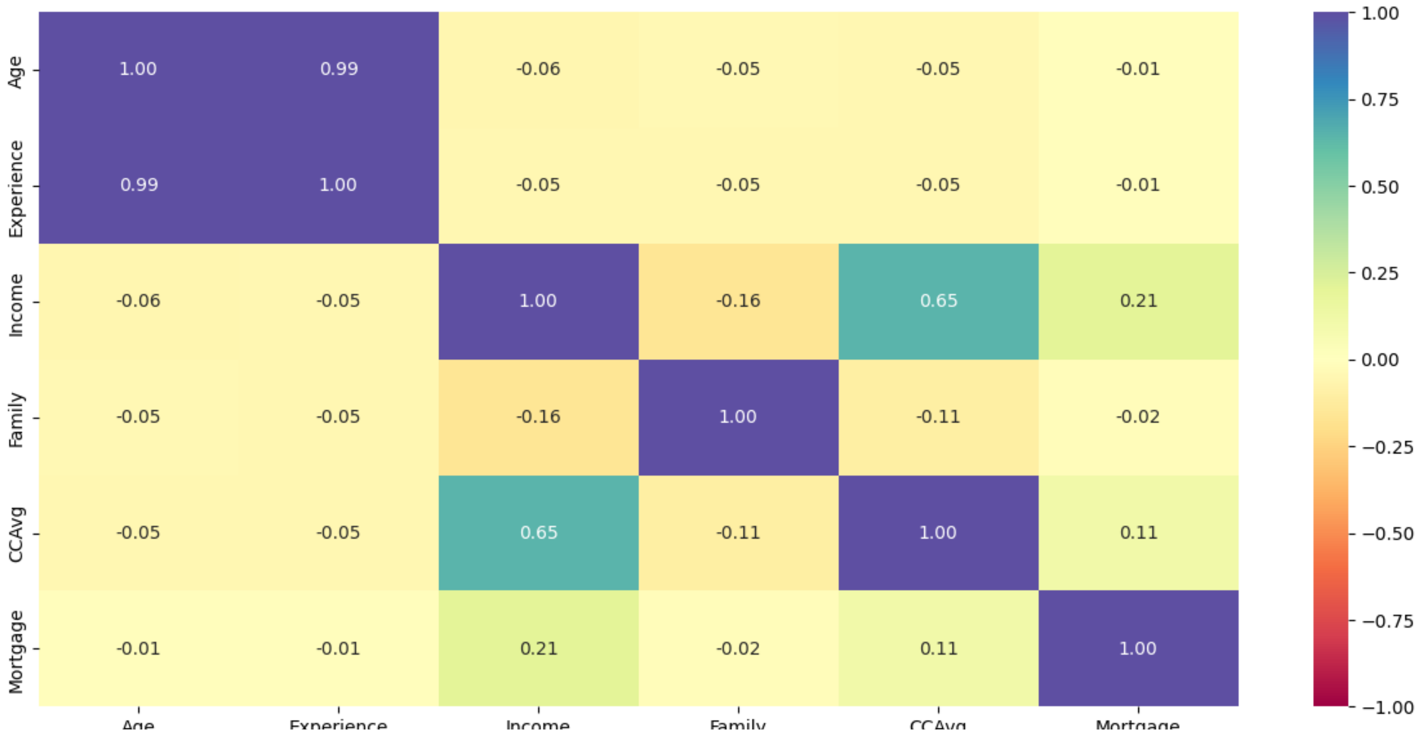
```
### function to plot distributions wrt target


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

In [235]:

```
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()
```

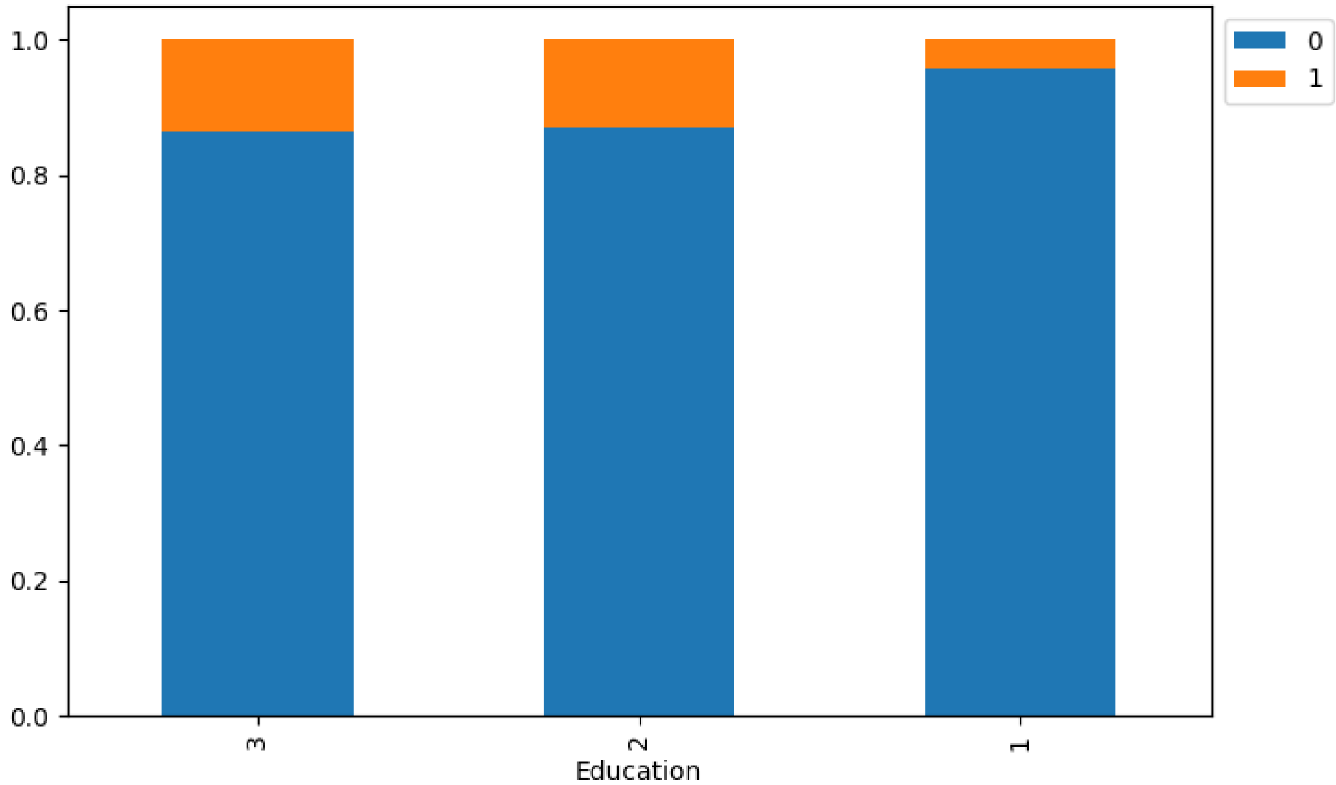


Let's check how a customer's interest in purchasing a loan varies with their education

In [236]:

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

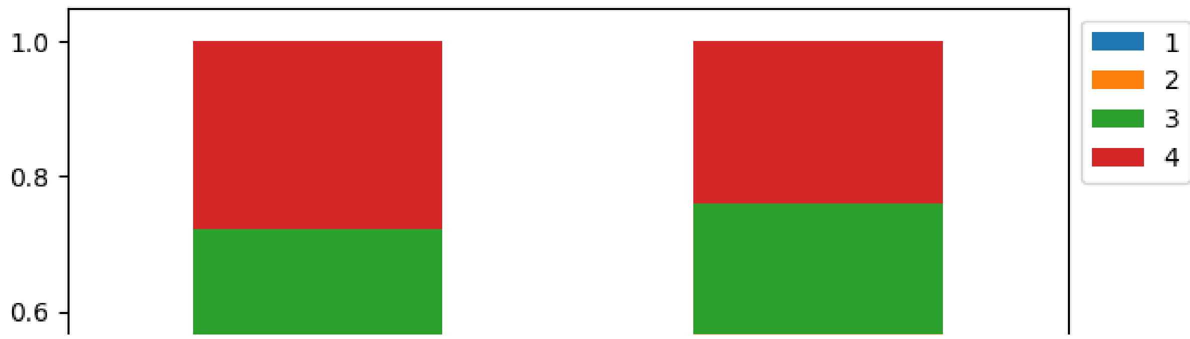


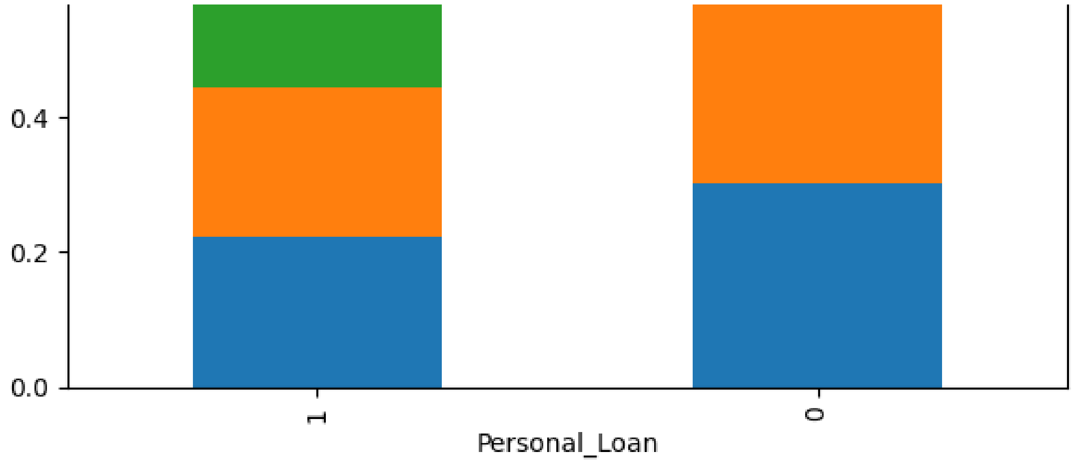
Personal_Loan vs Family

In [237]:

```
stacked_barplot(data, "Personal_Loan", "Family")  ## Complete the code to plot stacked ba
rplot for Personal Loan and Family
```

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



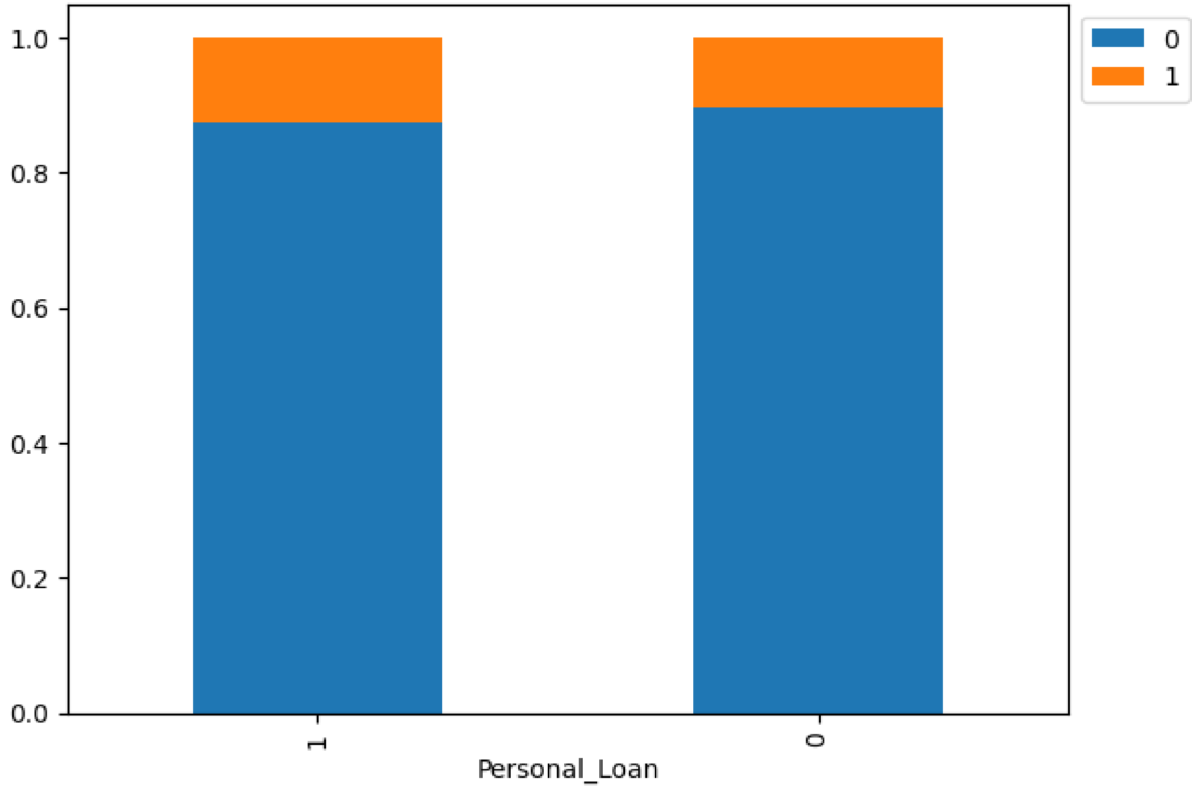


Personal_Loan vs Securities_Account

In [238]:

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

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



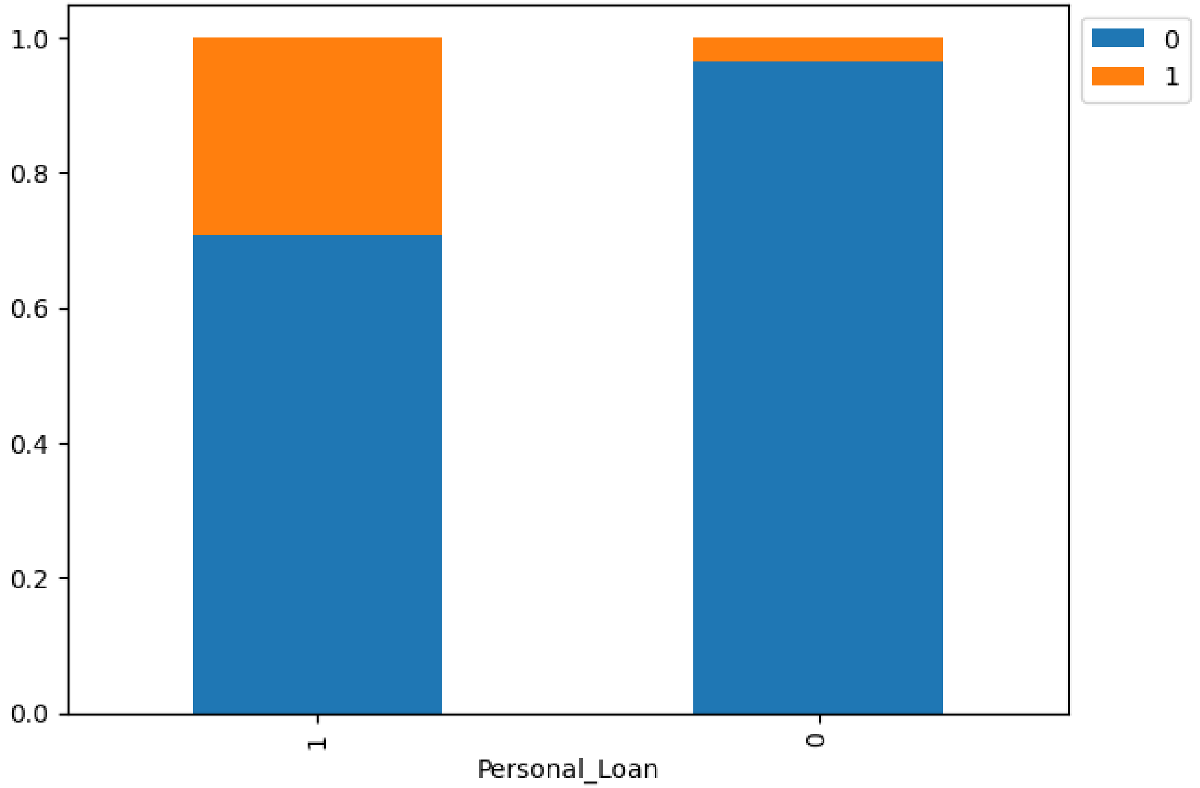
Personal_Loan vs CD_Account

In [239]:

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

```
CD_Account        0    1   All
Personal_Loan
All            4698  302  5000
0              4358  162  4520
```

```
1              340   140    480
------------------------------------------------------------------------------------------
----------------------------------
```

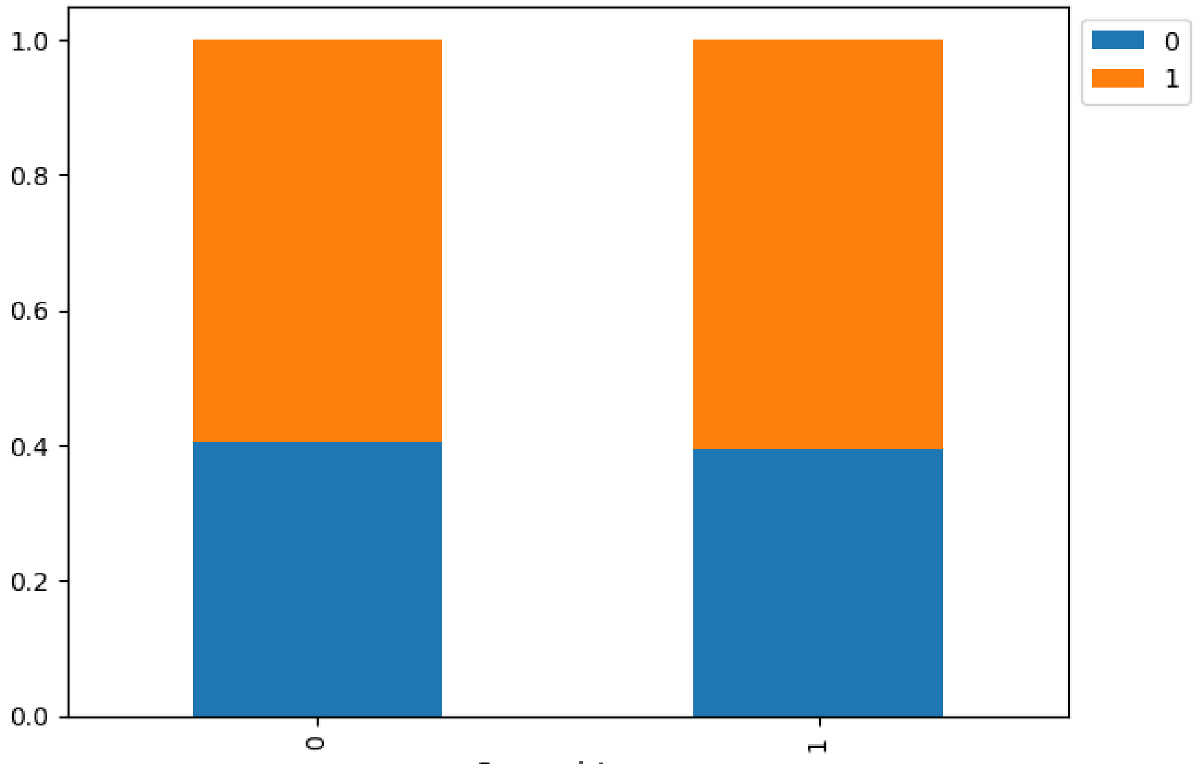


Personal_Loan vs Online

In [240]:

```
stacked_barplot(data, "Personal_Loan", "Online")## Complete the code to plot stacked barp
lot for Personal Loan and Online
```

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



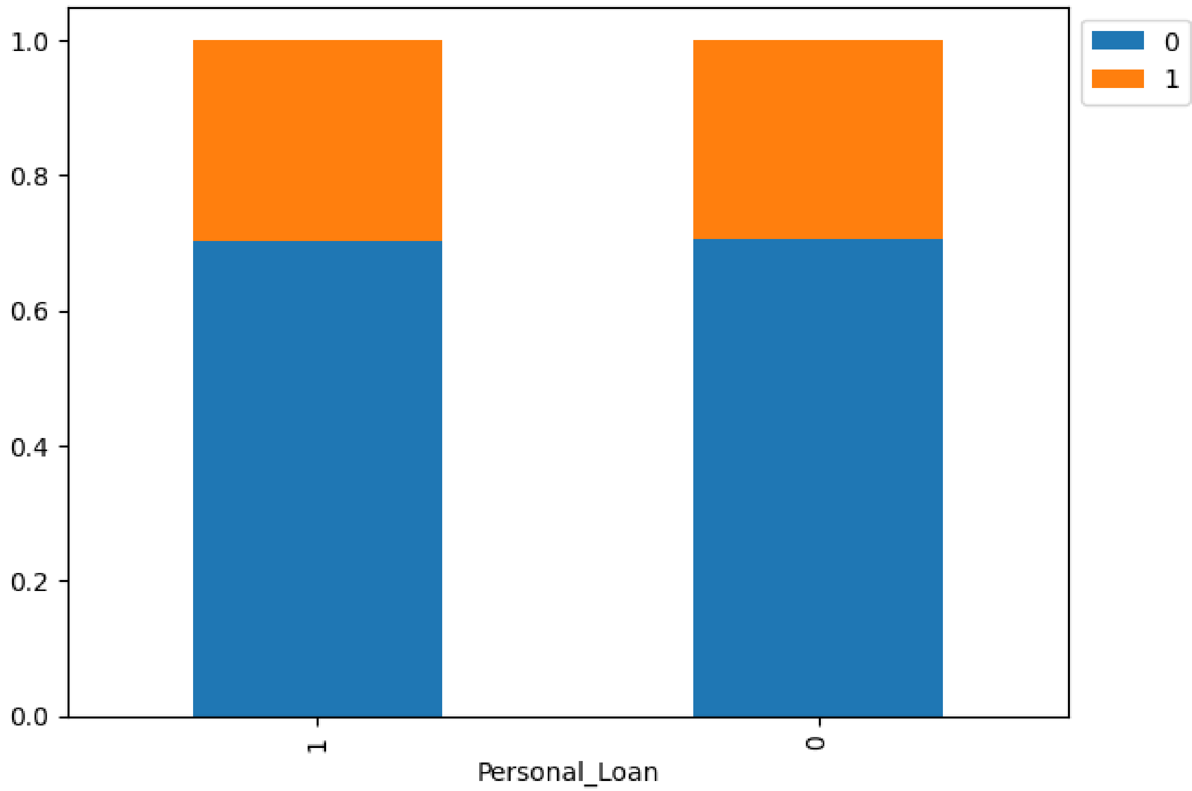
Personal_Loan

Personal_Loan vs CreditCard

In [241]:

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

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

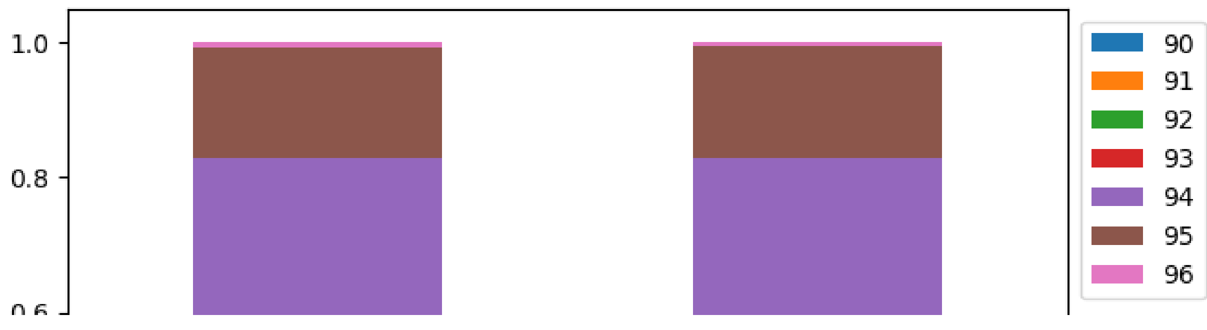


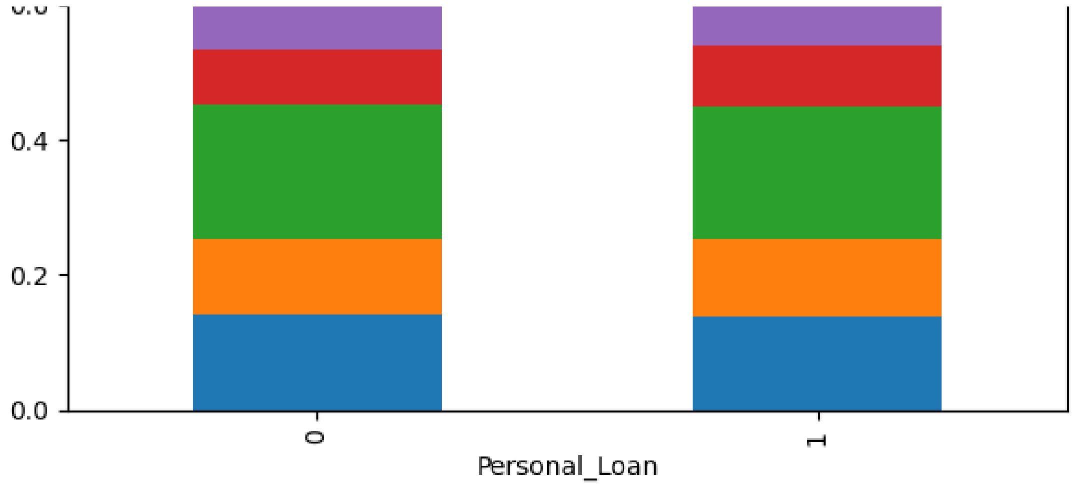
Personal_Loan vs ZIPCode

In [242]:

```
stacked_barplot(data, "Personal_Loan", "ZIPCode") ## Complete the code to plot stacked ba
rplot for Personal Loan and ZIPCode
```

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

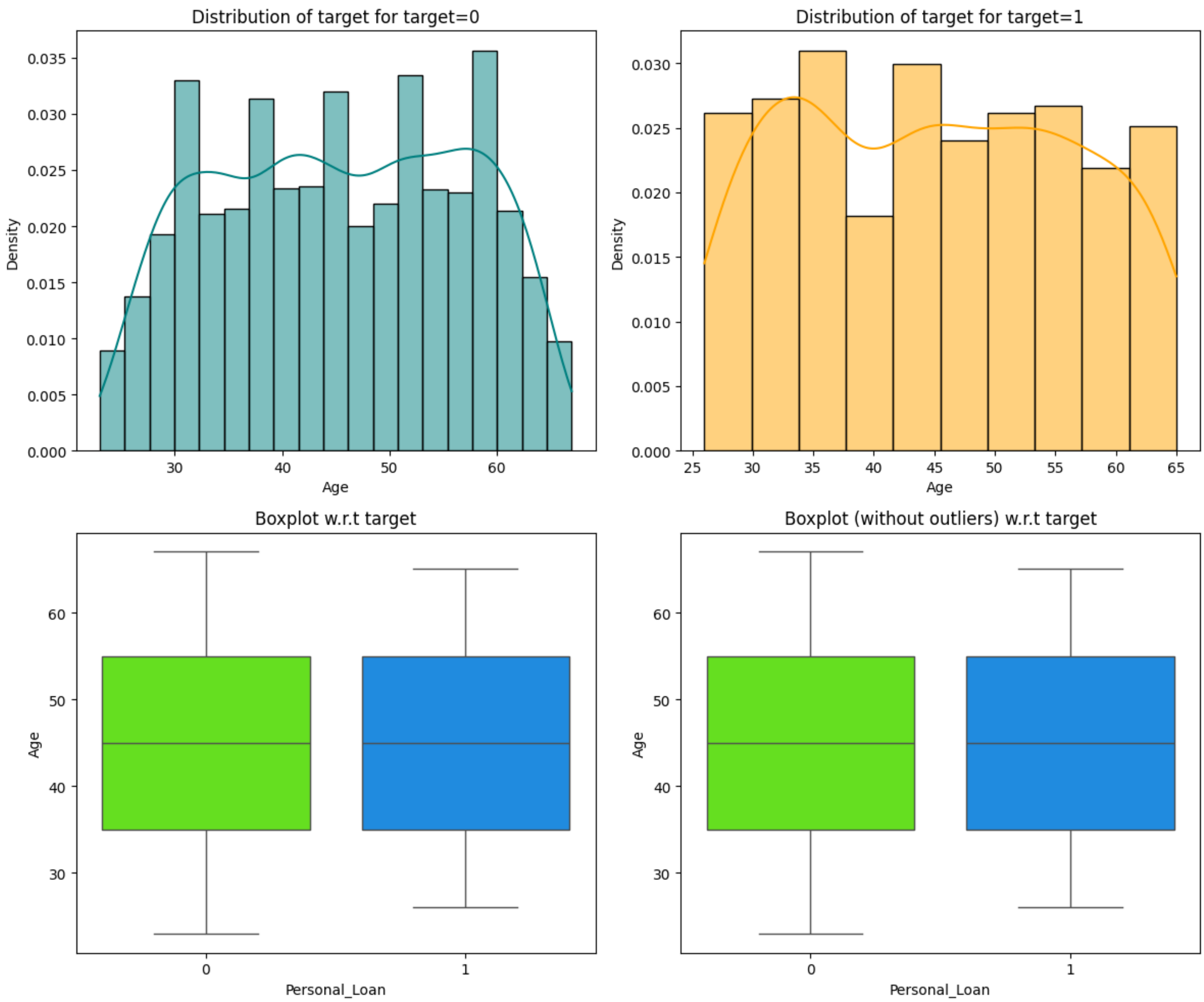




Let's check how a customer's interest in purchasing a loan varies with their age

In [243]:

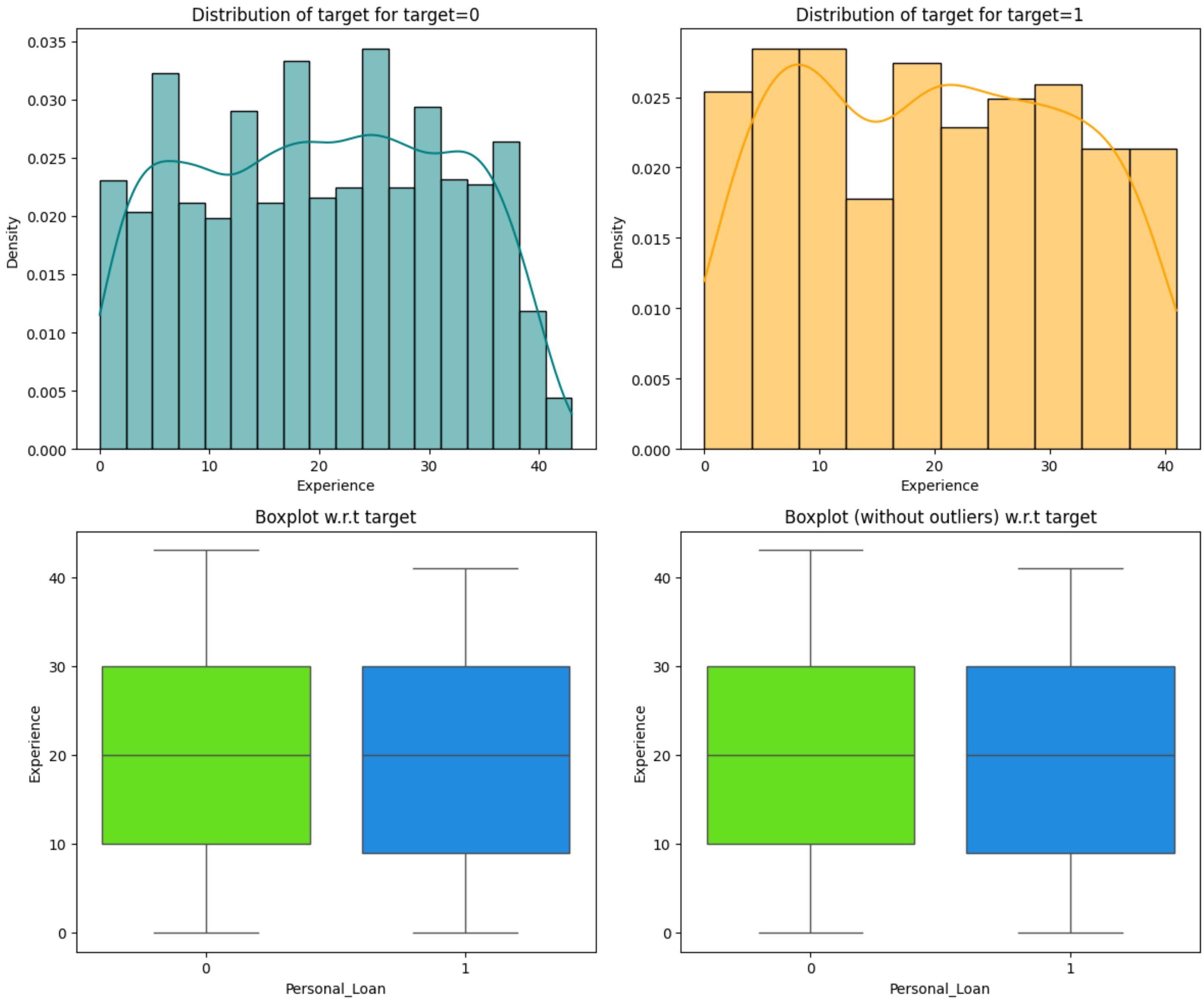
```
distribution_plot_wrt_target(data, "Age", "Personal_Loan")
```



Personal Loan vs Experience

In [244]:

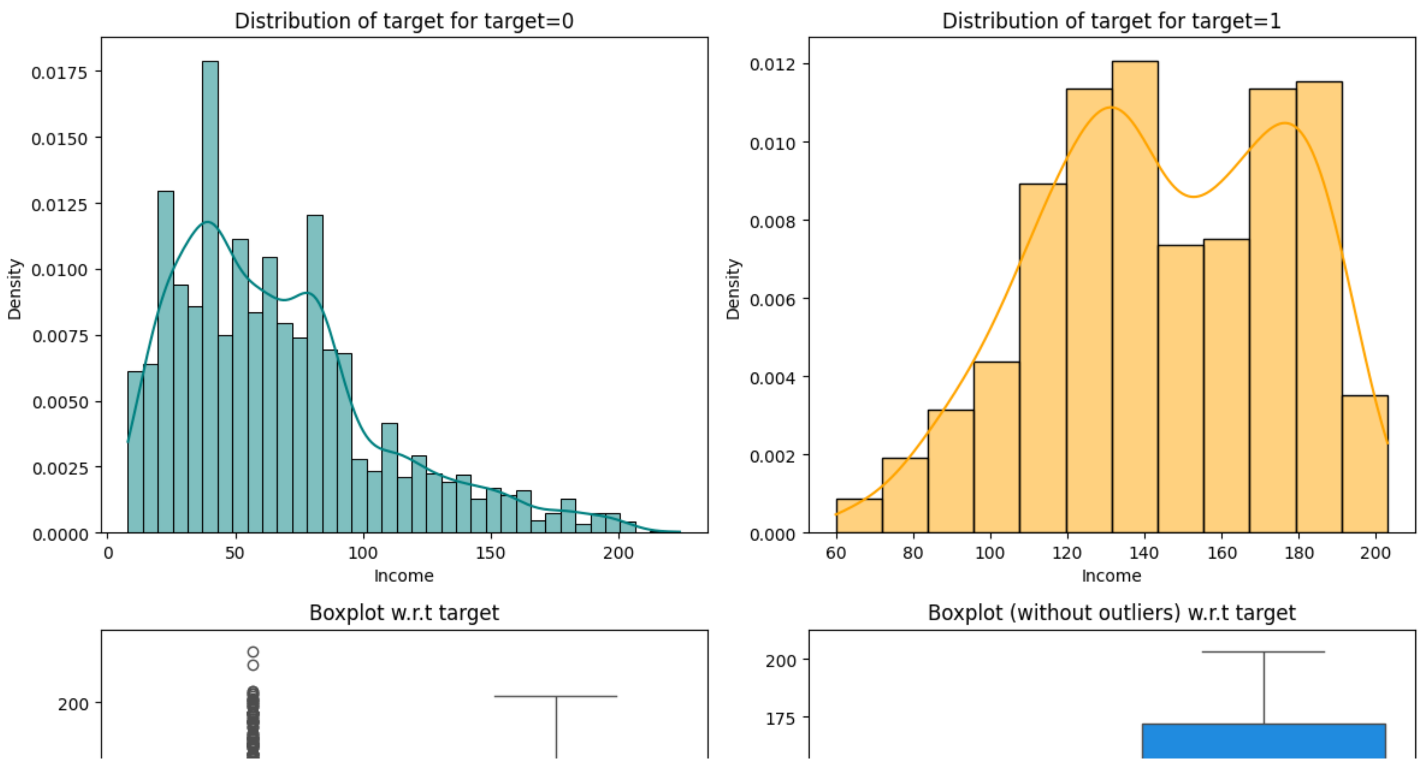
```
distribution_plot_wrt_target(data, "Experience","Personal_Loan") ## Complete the code to
plot stacked barplot for Personal Loan and Experience
```

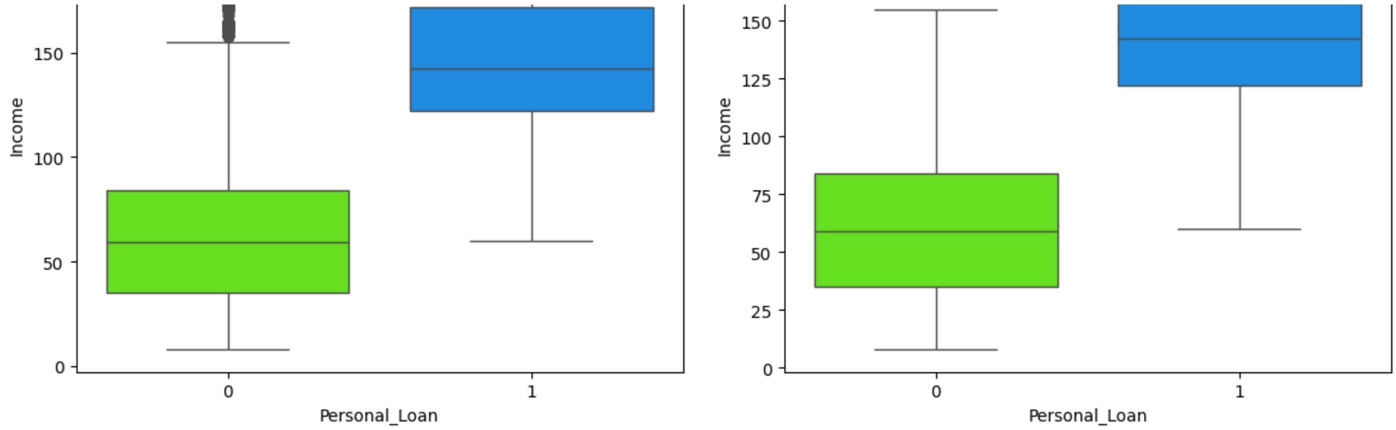


Personal Loan vs Income

In [245]:

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

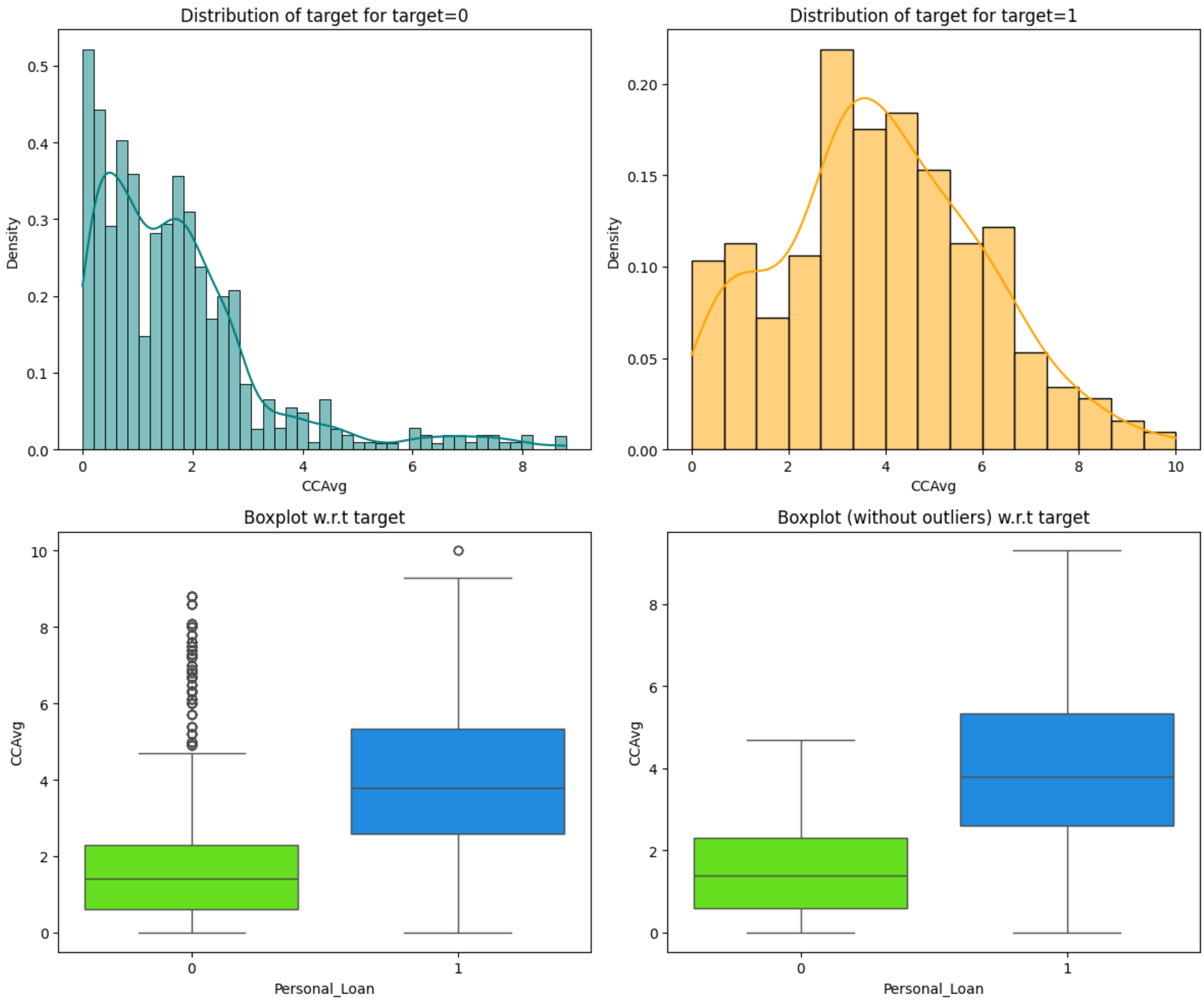




Personal Loan vs CCAvg

In [246]:

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



Data Preprocessing (contd.)

Outlier Detection

In [247]:

```
Q1 = data.equals(0.25)  # To find the 25th percentile and 75th percentile.
Q3 = data.equals(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 o
utliers
upper = Q3 + 1.5 * IQR
```

In [248]:

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

Out[248]:

	0
Age	100.00
Experience	98.68
Income	100.00
Family	100.00
CCAvg	97.88
Mortgage	30.76

dtype: float64

Data Preparation for Modeling

In [249]:

```
# 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
)
```

In [250]:

```
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
```

Model Building

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.**

In [251]:

```
# defining a function to compute different metrics to check performance of a classificati
on 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
```

In [252]:

```
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")
```

Decision Tree (sklearn default)

In [253]:

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

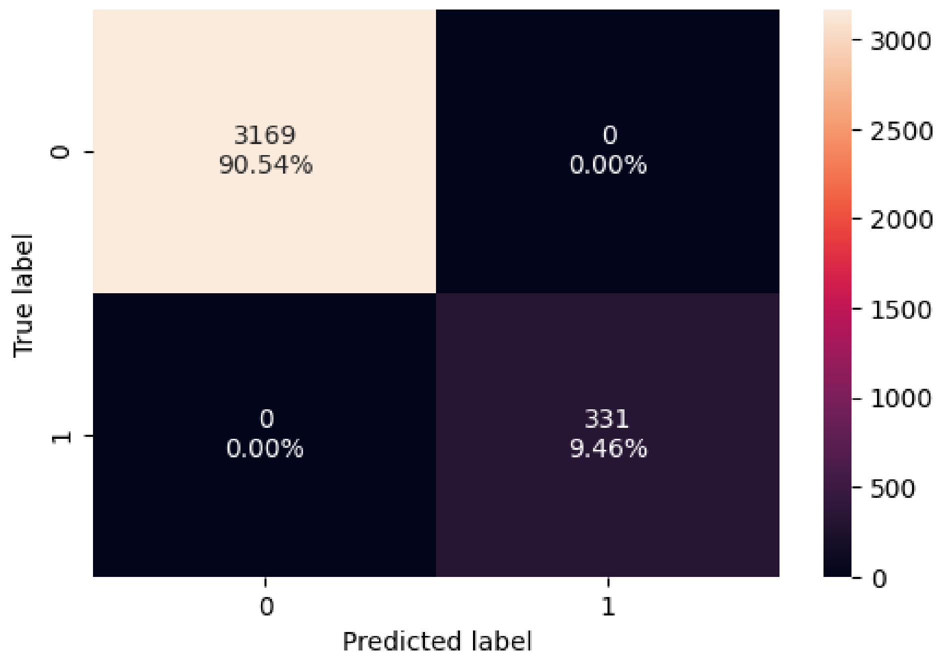
Out[253]:

```
▾    DecisionTreeClassifier    i ?

DecisionTreeClassifier(random_state=1)
```

Checking model performance on training data

In [254]:

```
confusion_matrix_sklearn(model, X_train, y_train)
```



In [255]:

```
decision_tree_perf_train = model_performance_classification_sklearn(
    model, X_train, y_train
)
decision_tree_perf_train
```

Out[255]:

	Accuracy	Recall	Precision	F1
0	1.0	1.0	1.0	1.0

Visualizing the Decision Tree

In [256]:

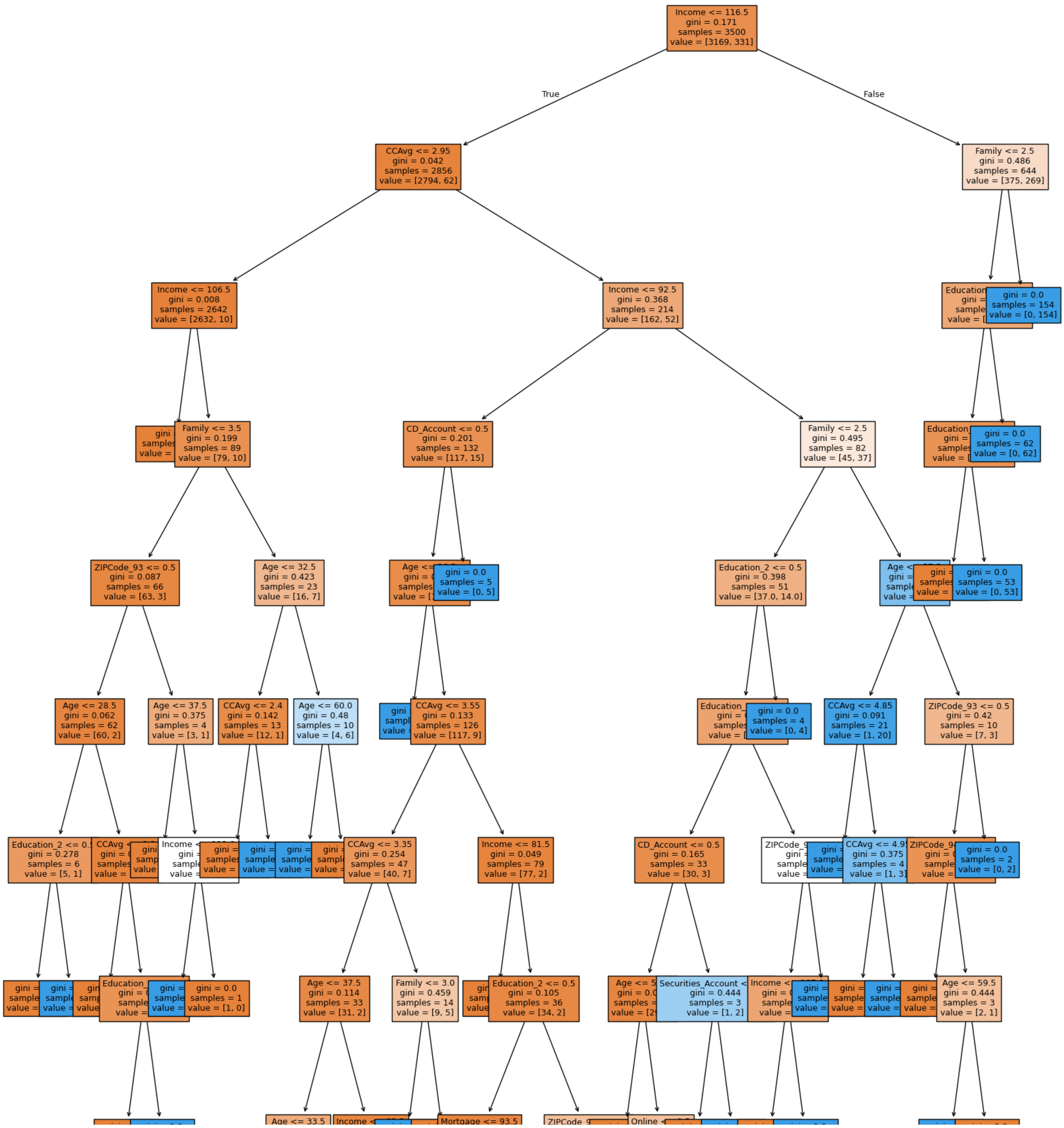
```
feature_names = list(X_train.columns)
print(feature_names)
```

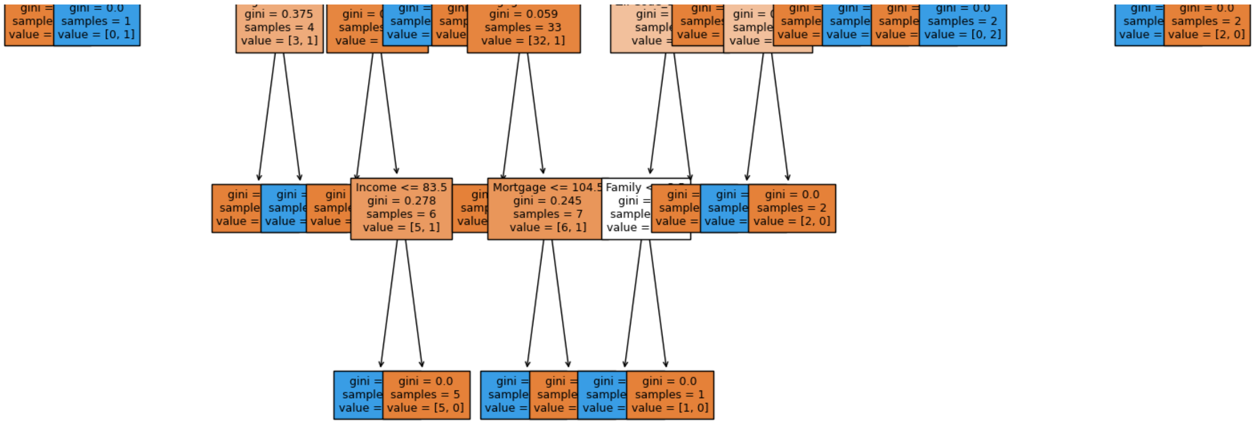
```
['Age', 'Income', 'Family', 'CCAvg', 'Mortgage', 'Securities_Account', 'CD_Account', 'Onl
ine', 'CreditCard', 'ZIPCode_91', 'ZIPCode_92', 'ZIPCode_93', 'ZIPCode_94', 'ZIPCode_95',
```

```
'ZIPCode_96', 'Education_2', 'Education_3']
```

In [257]:

```
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()
```





In [258]:

```
# 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
```

In [259]:

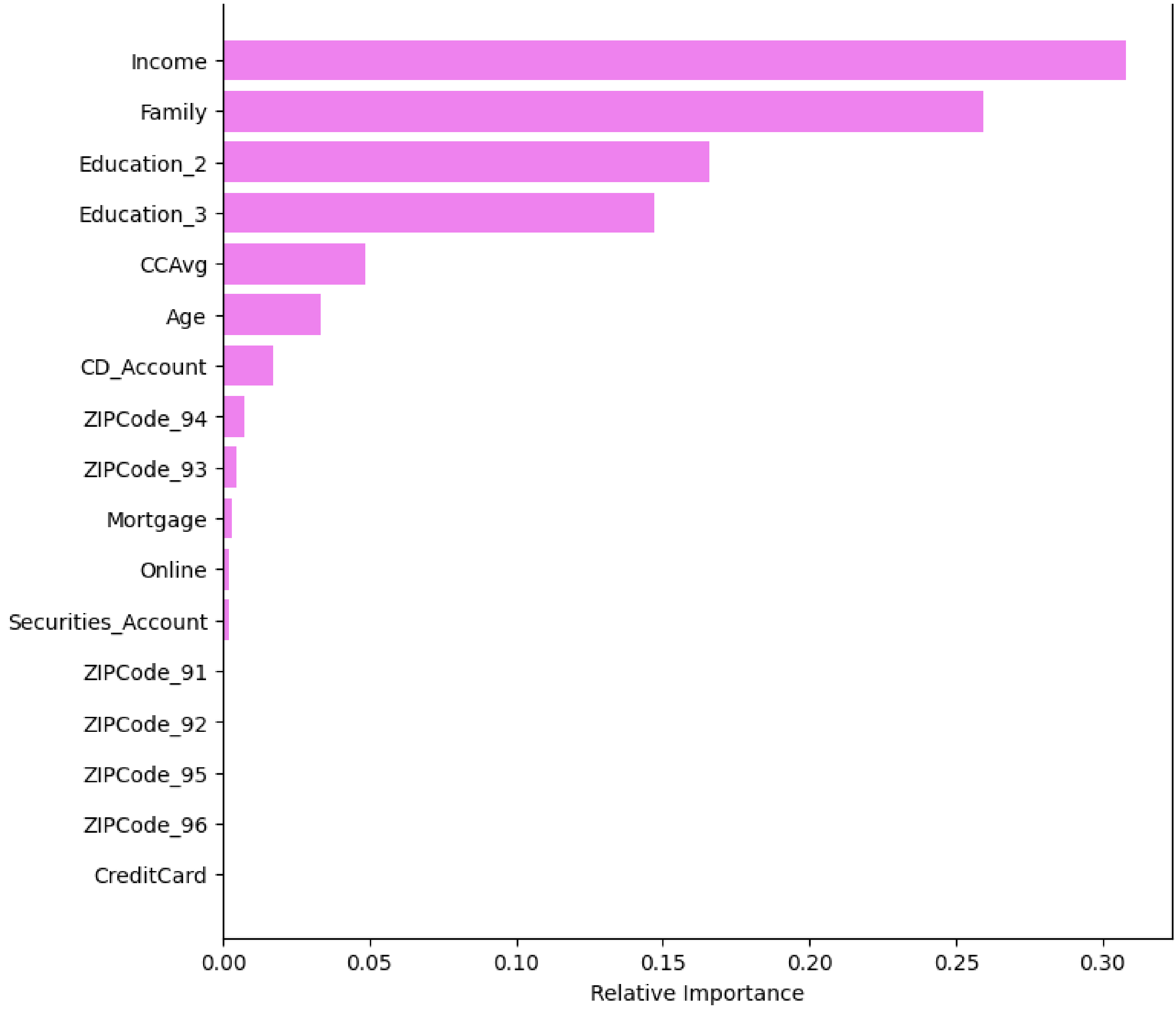
```
# importance of features in the tree building ( The importance of a feature is computed a
s the
# (normalized) total reduction of the criterion brought by that feature. It is also known
as the Gini importance )

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
```

In [260]:

```
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()
```

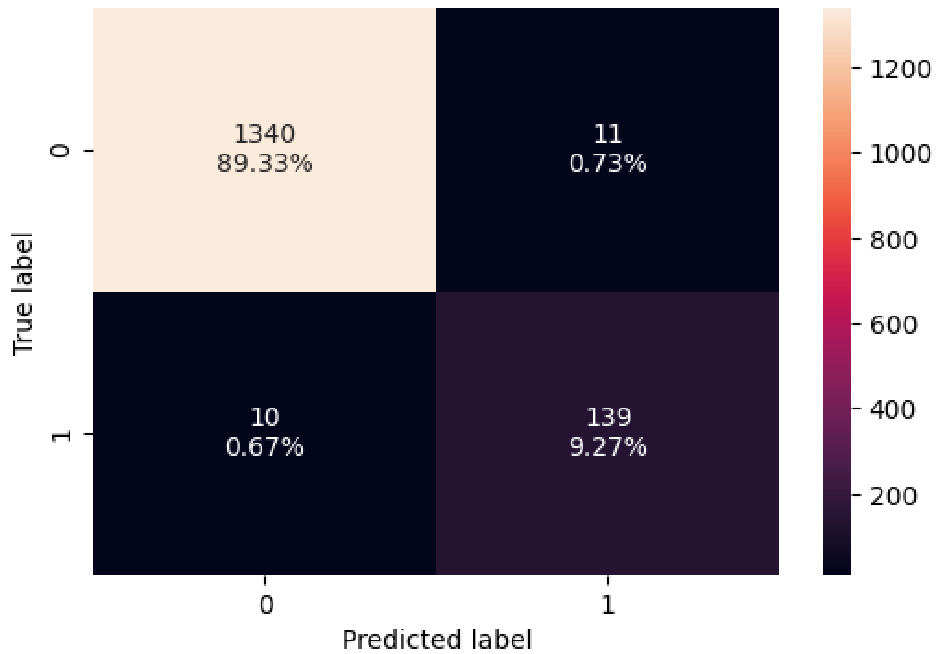
Feature Importances



Checking model performance on test data

In [261]:

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



In [262]:

```
decision_tree_perf_test = model_performance_classification_sklearn(model, X_test, y_test)
## Complete the code to check performance on test data
decision_tree_perf_test
```

Out[262]:

	Accuracy	Recall	Precision	F1
0	0.986	0.932886	0.926667	0.929766

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.

In [263]:

```
# 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 s
core 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
```

In [264]:

```
# 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
```

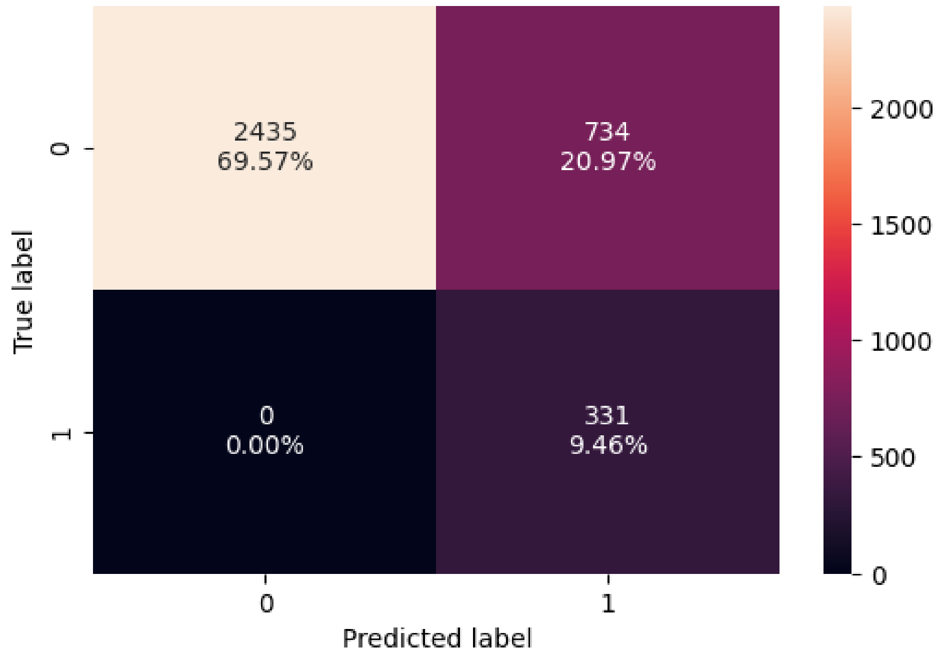
Out[264]:

```
▾                    DecisionTreeClassifier                    i ?

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

Checking performance on training data

In [265]:

```
confusion_matrix_sklearn(estimator, X_train, y_train) ## Complete the code to create conf
usion matrix for train data
```



In [266]:

```
decision_tree_tune_perf_train = model_performance_classification_sklearn(estimator, X_tra
in, y_train) ## Complete the code to check performance on train data
decision_tree_tune_perf_train
```

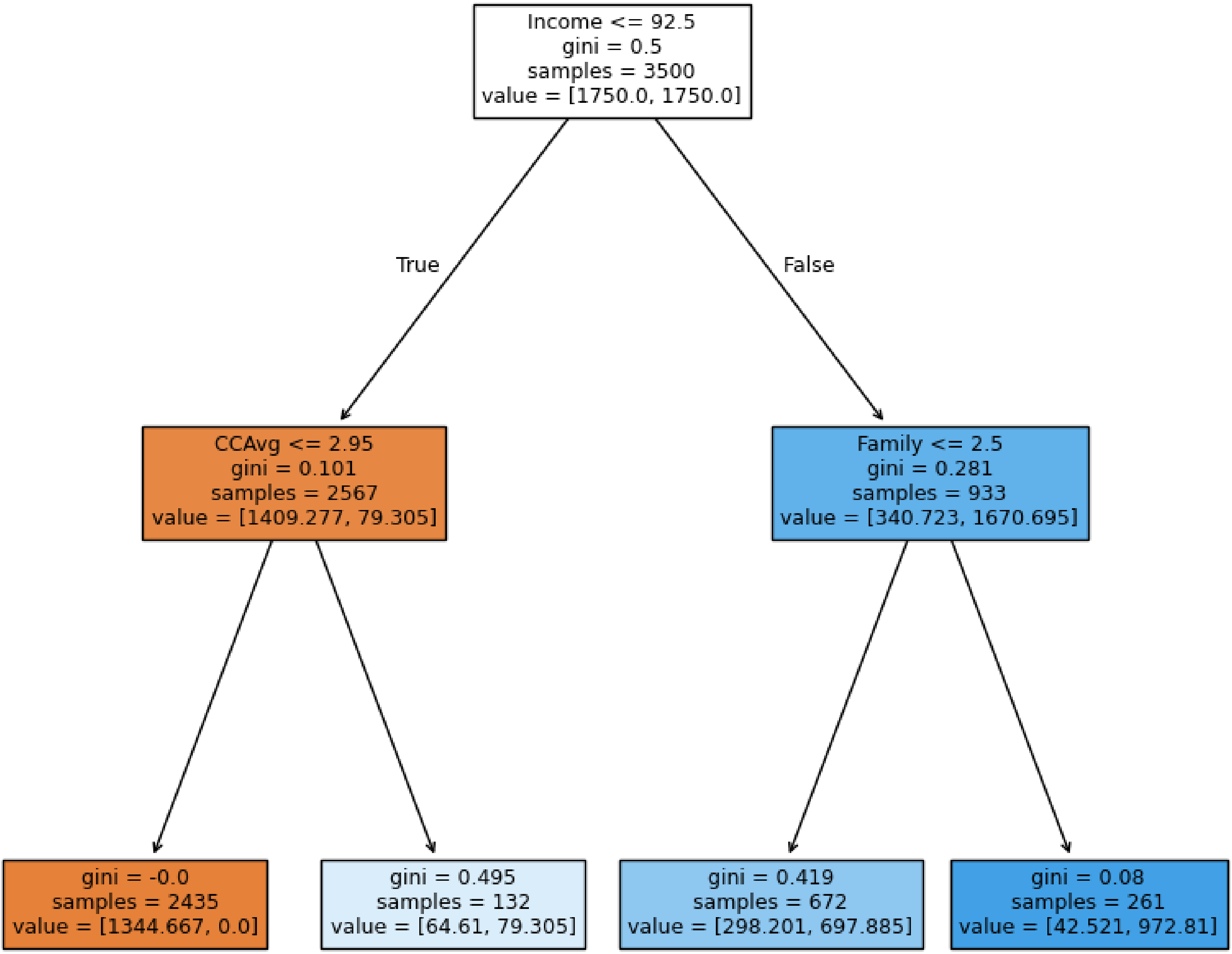
Out[266]:

	Accuracy	Recall	Precision	F1
0	0.790286	1.0	0.310798	0.474212

Visualizing the Decision Tree

In [267]:

```
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()
```



In [268]:

```
# 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
```

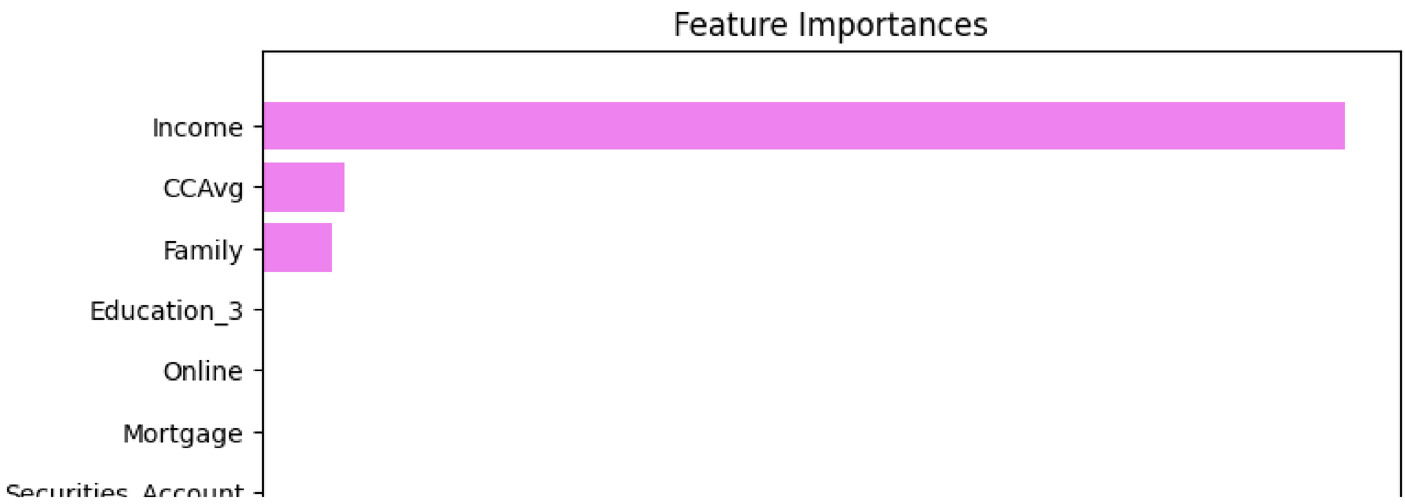
In [269]:

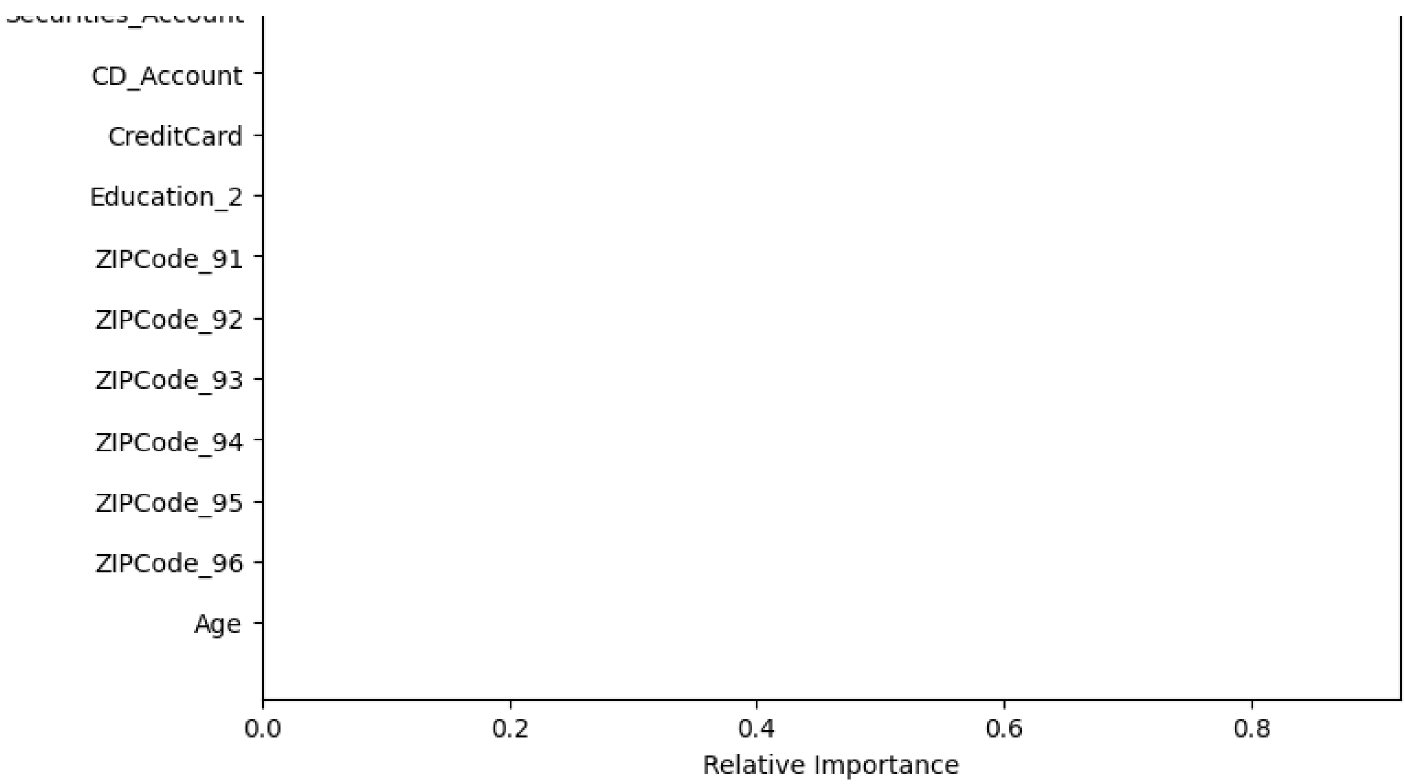
```
# importance of features in the tree building ( The importance of a feature is computed a
s the
# (normalized) total reduction of the criterion brought by that feature. It is also known
as the Gini importance )

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
```

In [270]:

```
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()
```

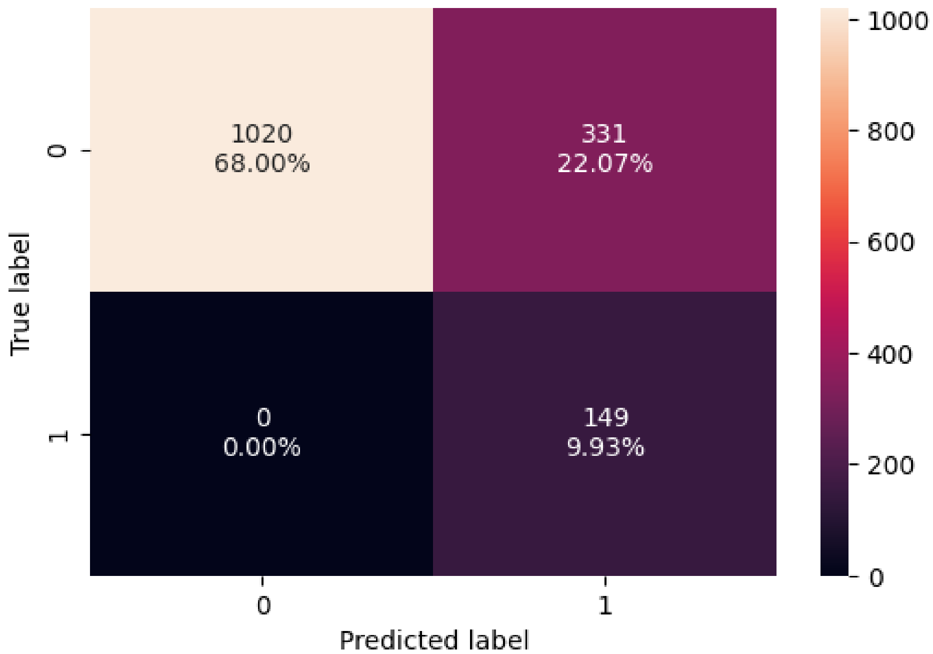




Checking performance on test data

In [271]:

```
confusion_matrix_sklearn(estimator, X_test, y_test)  # Complete the code to get the confu
sion matrix on test data
```



In [272]:

```
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
```

Out[272]:

	Accuracy	Recall	Precision	F1
0	0.779333	1.0	0.310417	0.473768

Post-pruning

In [273]:

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

In [274]:

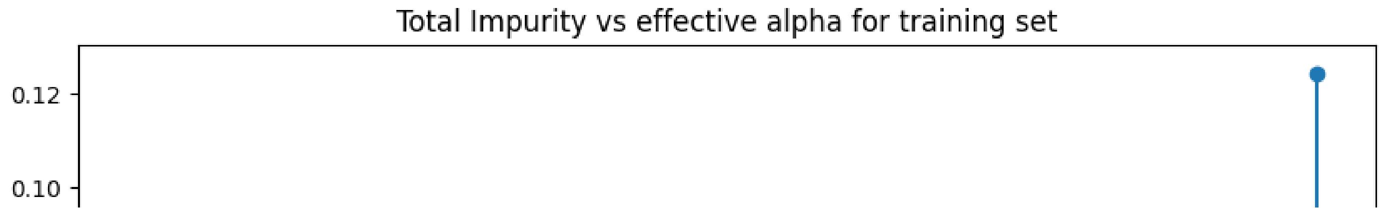
```
pd.DataFrame(path)
```

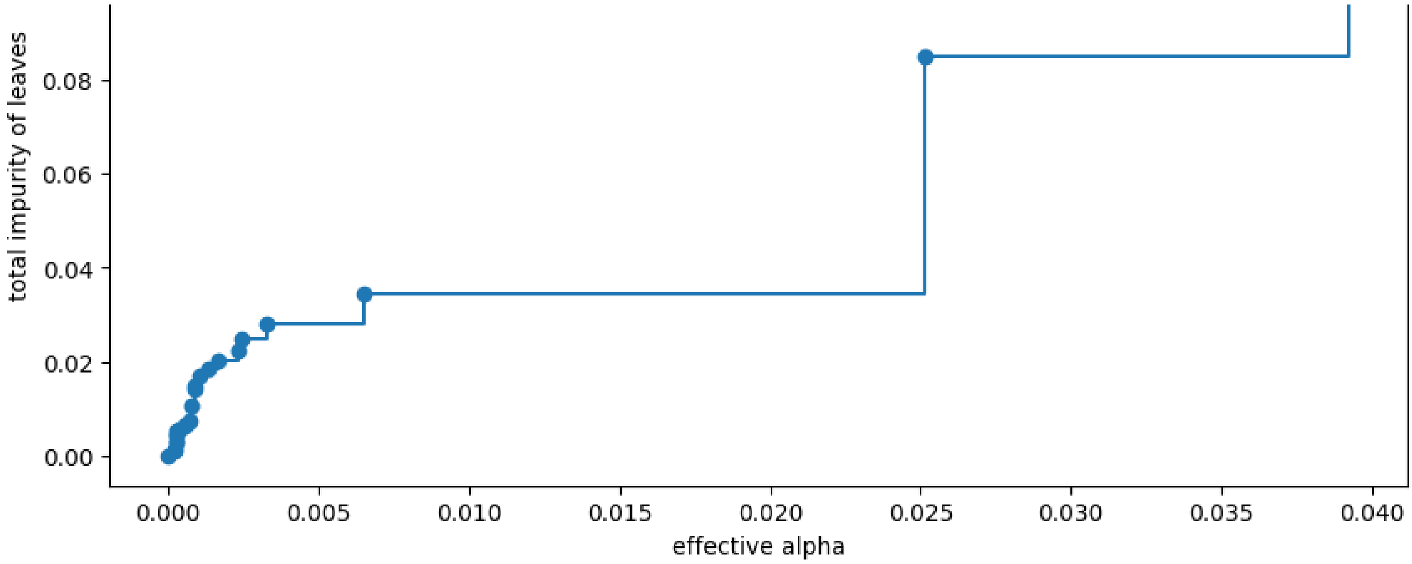
Out[274]:

	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

In [275]:

```
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.

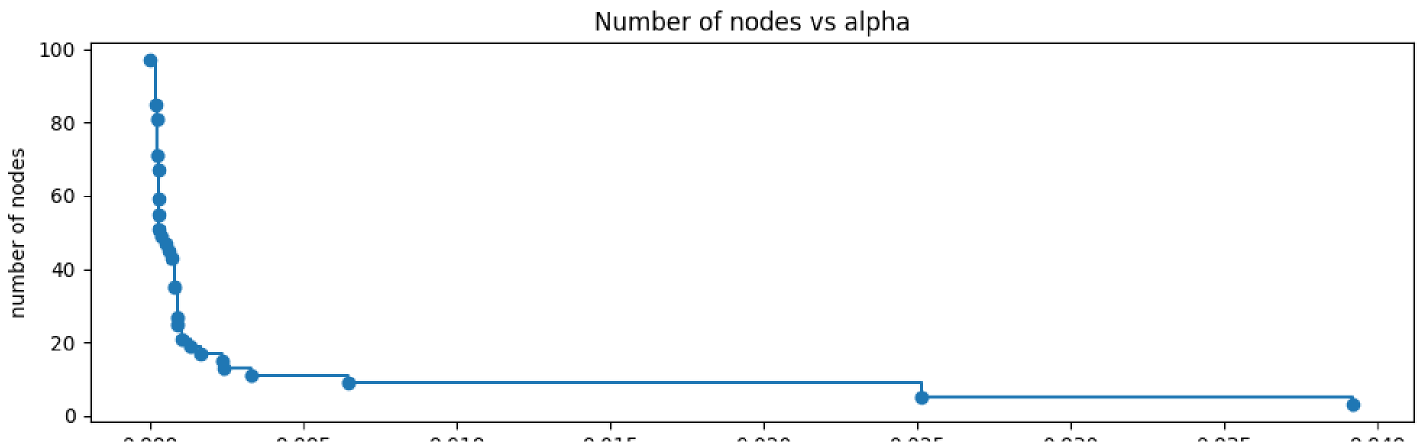
In [276]:

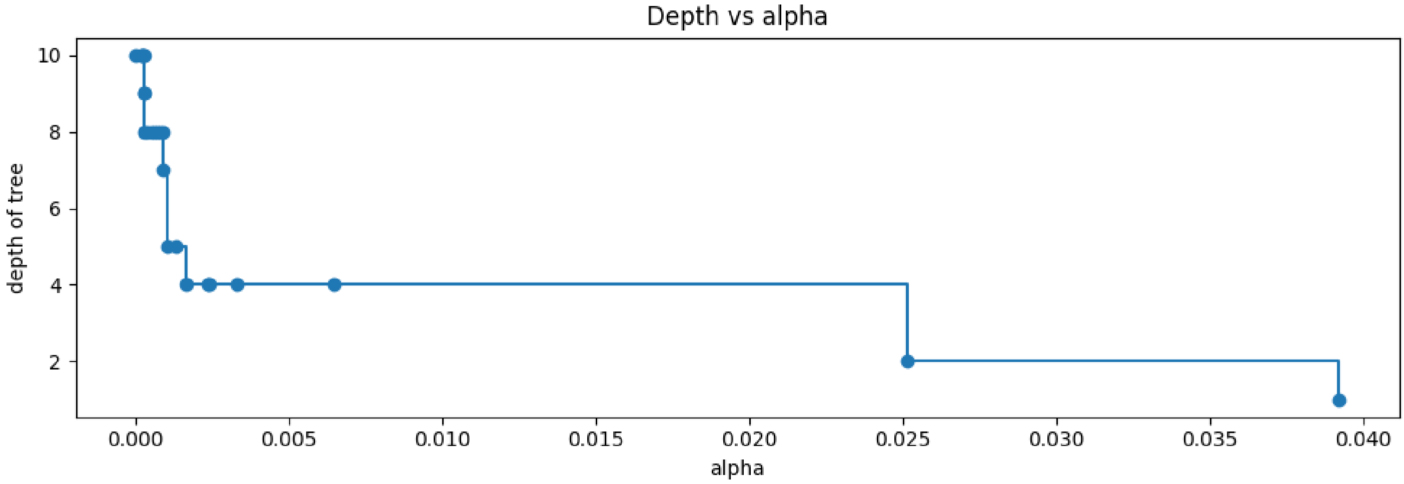
```
clfs = []
for ccp_alpha in ccp_alphas:
    clf = DecisionTreeClassifier(random_state=1, ccp_alpha=ccp_alpha)
    clf.fit(X_train, y_train)      ## Complete the code to fit decision tree on training d
ata
    clfs.append(clf)
print(
    "Number of nodes in the last tree is: {} with ccp_alpha: {}".format(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

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

In [277]:

```
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()
```





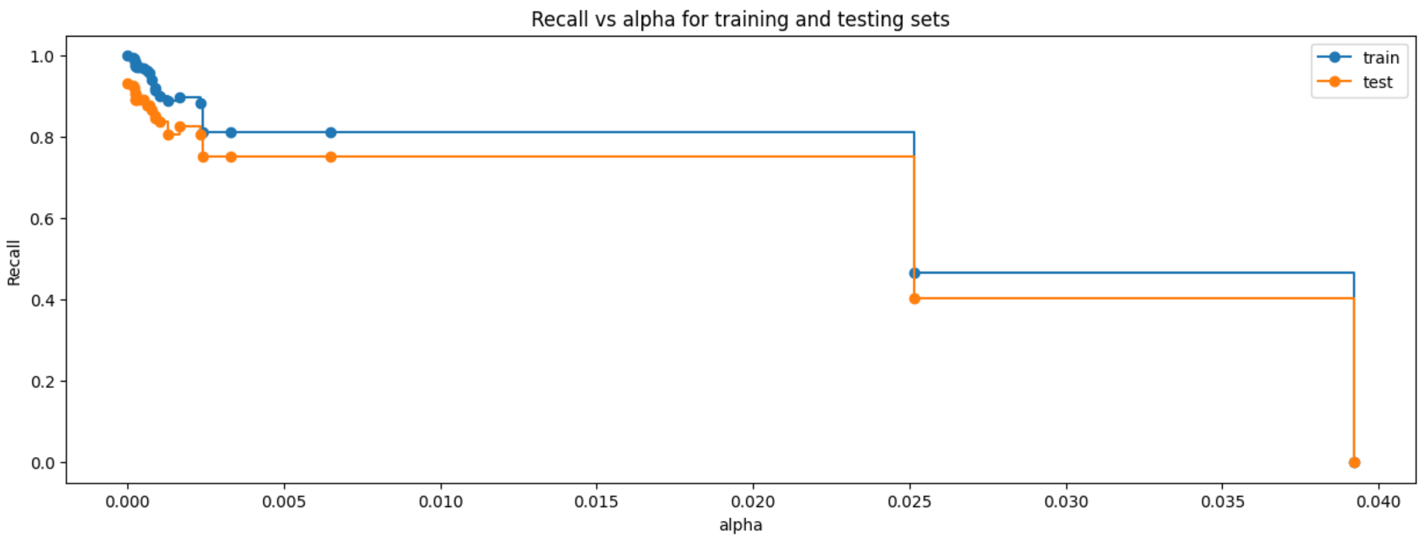
Recall vs alpha for training and testing sets

In [278]:

```
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)
```

In [279]:

```
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()
```



In [280]:

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

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

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

In [281]:

```
estimator_2 = DecisionTreeClassifier(
    ccp_alpha=ccp_alpha, class_weight={0: 0.15, 1: 0.85}, random_state=1          ## Comp
lete the code by adding the correct ccp_alpha value
)
estimator_2.fit(X_train, y_train)
```

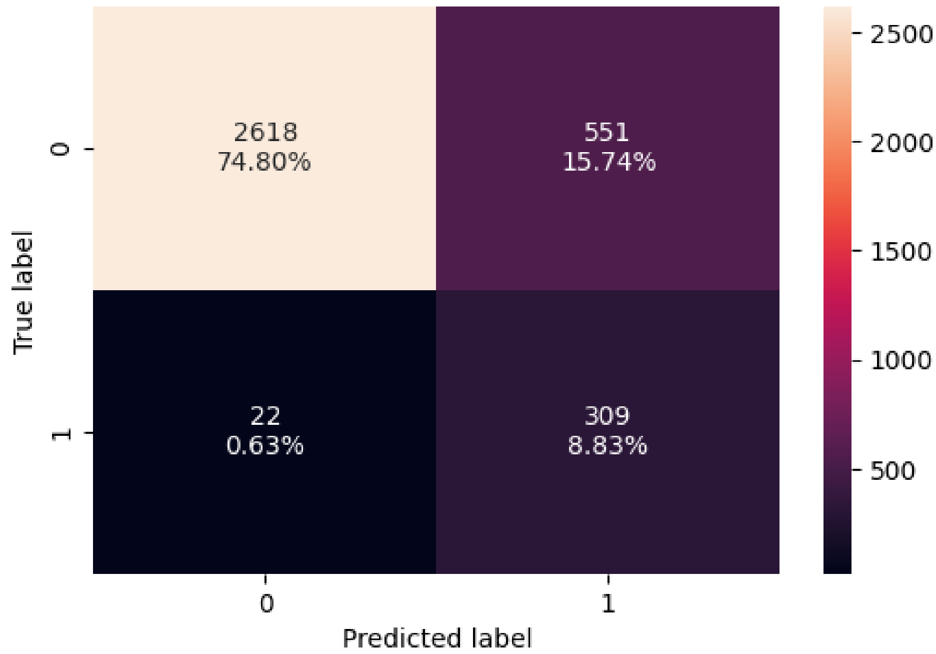
Out[281]:

```
▾                    DecisionTreeClassifier                    i ?

DecisionTreeClassifier(ccp_alpha=0.04708834100596766,
                       class_weight={0: 0.15, 1: 0.85}, random_state=1)
```

Checking performance on training data

In [282]:

```
confusion_matrix_sklearn(estimator_2, X_train, y_train) ## Complete the code to create co
nfusion matrix for train data
```



In [283]:

```
decision_tree_tune_post_train = model_performance_classification_sklearn(estimator_2, X_t
rain, y_train) ## Complete the code to check performance on train data
decision_tree_tune_post_train
```

Out[283]:

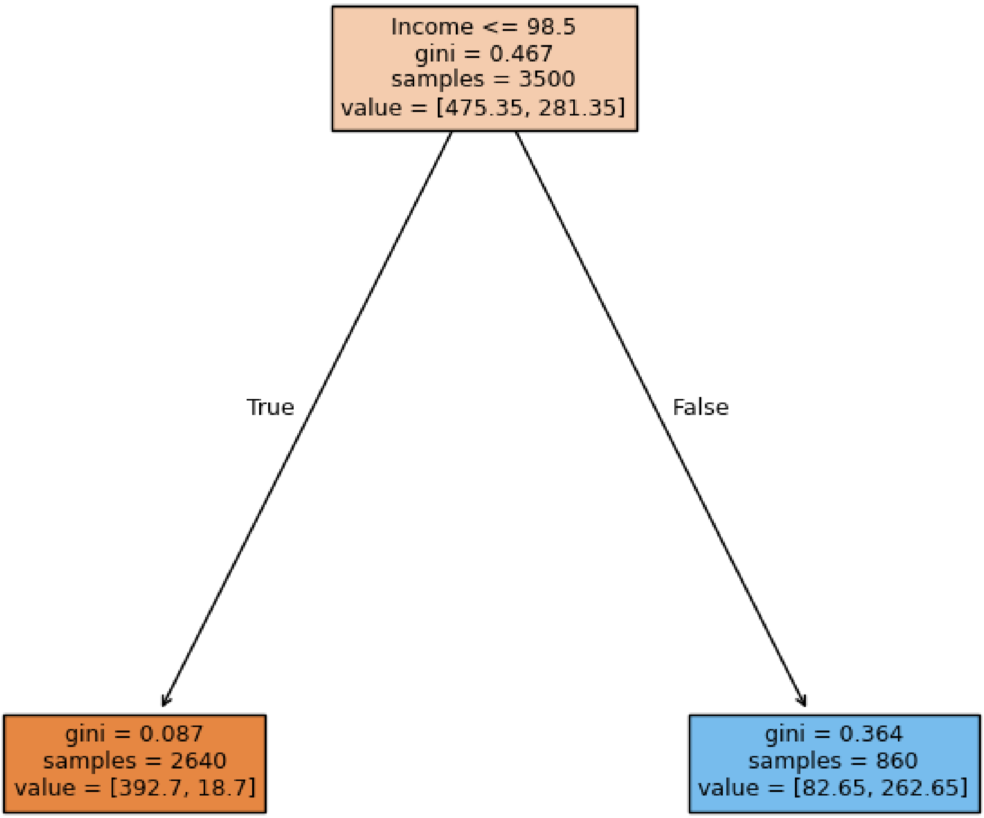
	Accuracy	Recall	Precision	F1
0	0.836286	0.933535	0.359302	0.518892

Visualizing the Decision Tree

In [284]:

```
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()
```



In [285]:

```
# 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
|   |--- weights: [392.70, 18.70] class: 0
|--- Income >  98.50
|   |--- weights: [82.65, 262.65] class: 1
```

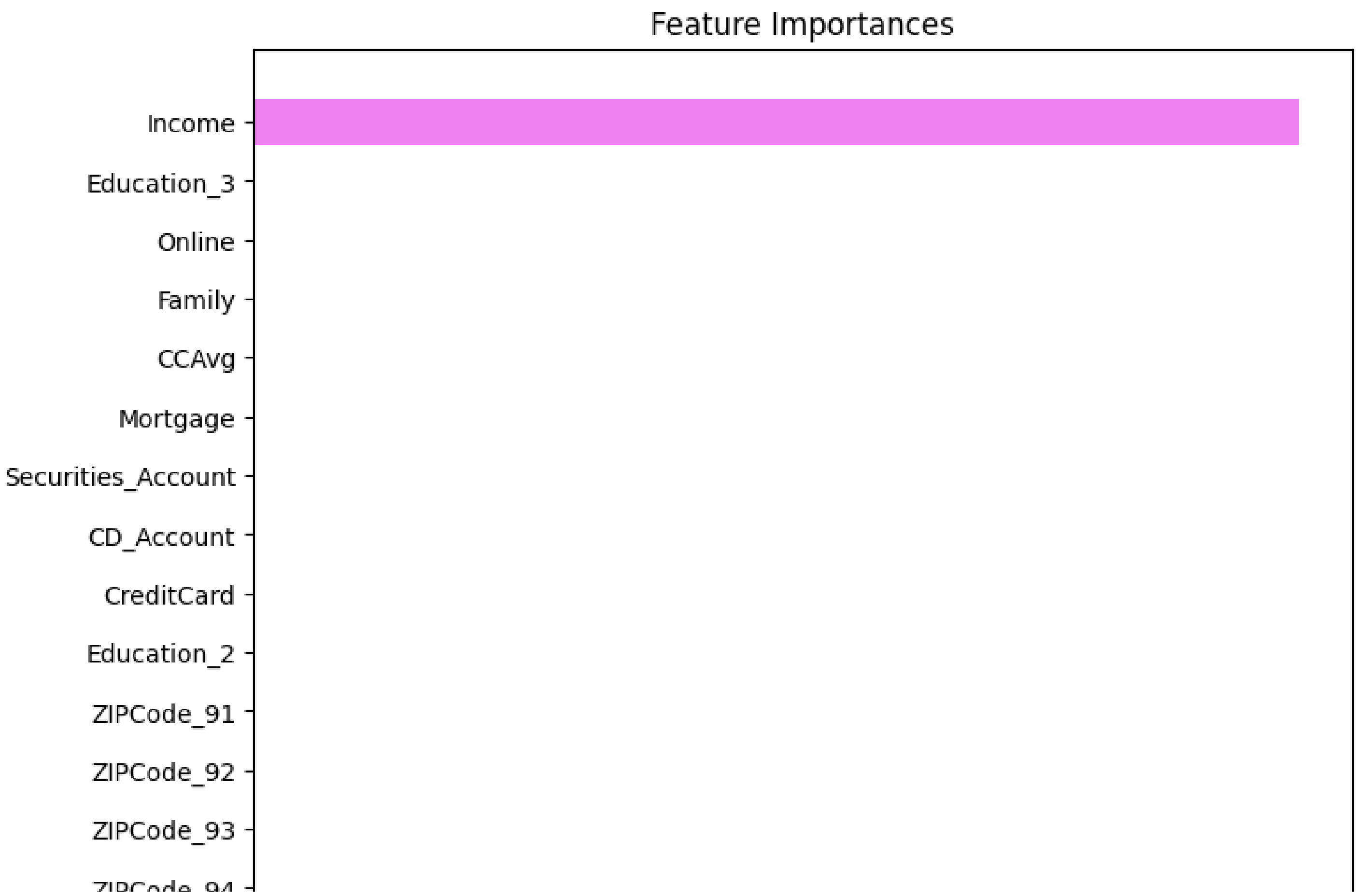
In [286]:

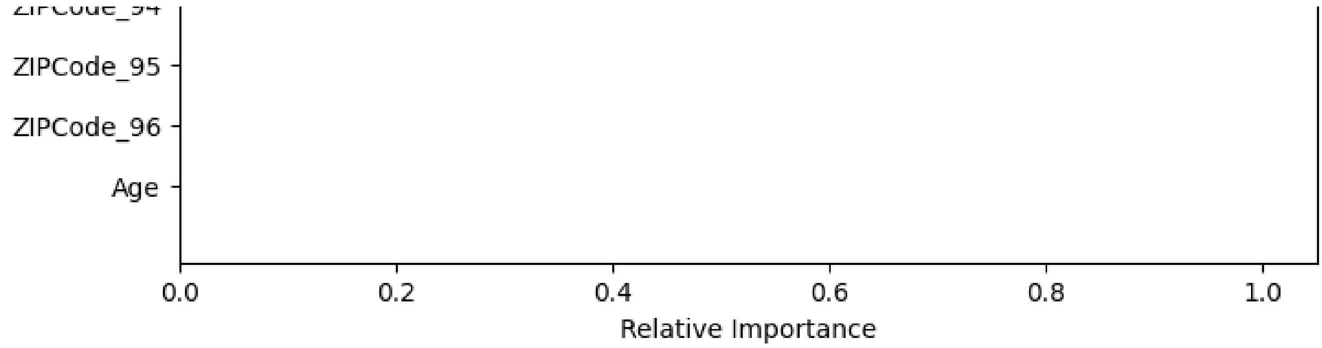
```
# importance of features in the tree building ( The importance of a feature is computed a
s the
# (normalized) total reduction of the criterion brought by that feature. It is also known
as the Gini importance )

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

```
                    Imp
Income              1.0
Age                 0.0
ZIPCode_91          0.0
Education_2         0.0
ZIPCode_96          0.0
ZIPCode_95          0.0
ZIPCode_94          0.0
ZIPCode_93          0.0
ZIPCode_92          0.0
CreditCard          0.0
Online              0.0
CD_Account          0.0
Securities_Account  0.0
Mortgage            0.0
CCAvg               0.0
Family              0.0
Education_3         0.0
```

In [287]:

```
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()
```

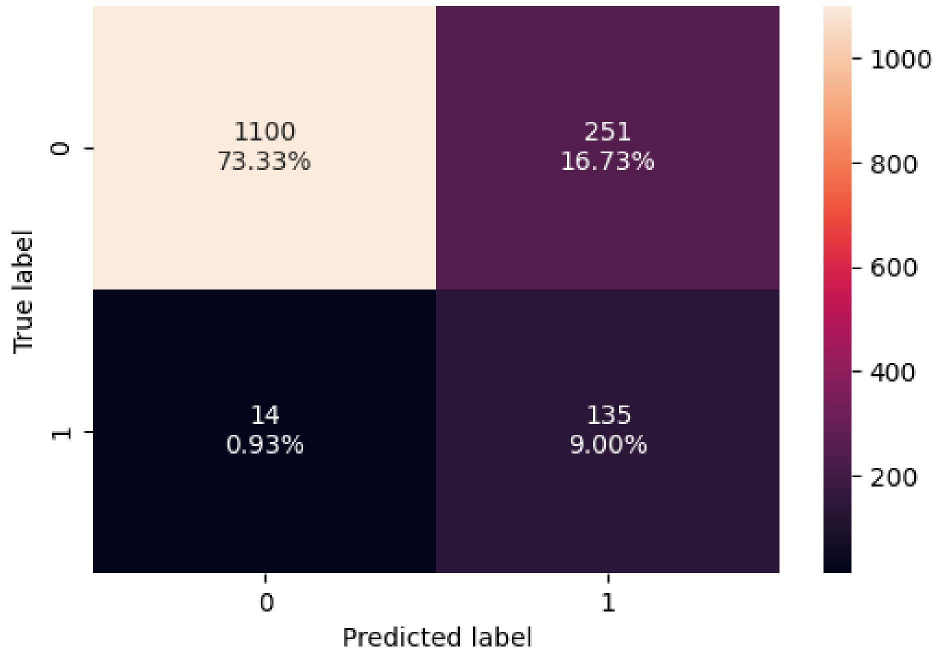




Checking performance on test data

In [288]:

```
confusion_matrix_sklearn(estimator_2, X_test, y_test)  # Complete the code to get the con
fusion matrix on test data
```



In [289]:

```
decision_tree_tune_post_test = model_performance_classification_sklearn(estimator_2, X_te
st, y_test) ## Complete the code to get the model performance on test data
decision_tree_tune_post_test
```

Out[289]:

	Accuracy	Recall	Precision	F1
0	0.823333	0.90604	0.349741	0.504673

Model Performance Comparison and Final Model Selection

In [290]:

```
# 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-Pr
uning)", "Decision Tree (Post-Pruning)"]
print("Training performance comparison:")
models_train_comp_df
```

```
Training performance comparison:
```

Out[290]:

	Decision Tree (sklearn default)	Decision Tree (Pre-Pruning)	Decision Tree (Post-Pruning)
Accuracy	1.0	0.790286	0.836286
Recall	1.0	1.000000	0.933535
Precision	1.0	0.310798	0.359302
F1	1.0	0.474212	0.518892

In [291]:

```
# testing performance comparison

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

```
Test set performance comparison:
```

Out[291]:

	Decision Tree (sklearn default)	Decision Tree (Pre-Pruning)	Decision Tree (Post-Pruning)
Accuracy	0.986000	0.779333	0.823333
Recall	0.932886	1.000000	0.906040
Precision	0.926667	0.310417	0.349741
F1	0.929766	0.473768	0.504673

Actionable Insights and Business Recommendations

What recommedations would you suggest to the bank?