Project Title:

Marketing Campaign for Banking Products

Data Description:

The file Bank_loan_project.csv contains data on 5000 customers. The data include customer demographic information (age, income, etc.), the customer's relationship with the bank (mortgage, securities account, etc.), and the customer response to the last personal loan campaign (Personal Loan).

Among these 5000 customers, only 480 (= 9.6%) accepted the personal loan that was offered to them in the earlier campaign.

Context:

The bank has a growing customer base. The bank wants to increase borrowers (asset customers) base to bring in more loan business and earn more through the interest on loans. So , the bank wants to convert the liability based 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. The department wants you to build a model that will help them identify the potential customers who have a higher probability of purchasing the loan. This will increase the success ratio while at the same time reduce the cost of the campaign.

Attribute Information:

● ID: Customer ID

● Age: Customer's age in completed years

● Experience: #years of professional experience

● Income: Annual income of the customer ($000)

● ZIP Code: Home Address ZIP code.

● Family: Family size of the customer

● CCAvg: Avg. spending on credit cards per month ($000)

● Education: Education Level. 1: Undergrad; 2: Graduate; 3: Advanced/Professional

● Mortgage: Value of house mortgage if any. ($000)

● Personal Loan: Did this customer accept the personal loan offered in the last campaign?

● Securities Account: Does the customer have a securities account with the bank?

● CD Account: Does the customer have a certificate of deposit (CD) account with the bank?

● Online: Does the customer use internet banking facilities?

● Credit card: Does the customer use a credit card issued by the bank?

1. Import the datasets and libraries, check datatype, statistical summary, shape, null values etc.

```
# Import necessary libraries
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

```
from sklearn.impute import SimpleImputer

import scipy.stats as stats

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn import metrics

from sklearn.ensemble import RandomForestClassifier

# Importing csv data and view data

data=pd.read_csv("/content/Bank_Personal_Loan_Modelling.csv")

data

# Checking the shape of data means no. of rows and columns.

data.shape

# Checking the first 5 rows

# by default the head() method gives the first 5 rows but if we need more rows then simply mention how many first rows you want.

# For example if we want first 10 rows then simply write data.head(10)

data.head()

# Checking the last 5 rows

# by default the tail() method gives the last 5 rows but if we need more rows then simply mention how many last rows you want.

# For example if we want last 10 rows then simply write data.tail(10)

data.tail()

# Checking the data types of each columns

data.dtypes

# Converting the data type of 'Personal Loan' from int to category

data['Personal Loan']=data['Personal Loan'].astype('category')

#checking that the data type of 'Personal Loan' is converted to category or not

data.dtypes

# Checking the count, mean, min, max, etc values of each columns of our data

data.describe()

# Checking the concise summary of our data

data.info()

# Checking the null values in our data
```

data.isnull().sum()

#**2. Check if you need to clean the data for any of the variables.**

Cleansing of data

Replacing all the negative values of experience column into nan values and then applied .describe method

data['Experience'].replace(to_replace= -1,value = np.nan,inplace = True)

data['Experience'].replace(to_replace= -2,value = np.nan,inplace = True)

data['Experience'].replace(to_replace= -3,value = np.nan,inplace = True)

data['Experience'].fillna(data['Experience'].median(),inplace=True)

data.describe()

Removing the 'ID' and 'Experience' column as it won't reqiured for determining accuracy of training and testing dataset because

'ID' is randomly generated number given to the customer and 'experience' is also not related with the 'Personal Loan'.

data=data.drop(['ID','Experience'],axis=1)

Checking the first 5 rows

by default the head() method gives the first 5 rows but if we need more rows then simply mention how many first rows you want.

For example if we want first 10 rows then simply write data.head(10)

data.head()

Checking the shape of data means no. of rows and columns.

Because we removed the 'ID' and 'Experience' therefore there are now total 12 columns remaining out of 14 columns.

data.shape

Checking the last 5 rows

by default the tail() method gives the last 5 rows but if we need more rows then simply mention how many last rows you want.

For example if we want last 10 rows then simply write data.tail(10)

data.tail()

3. EDA: Study the data distribution in each attribute and target variable, share your findings.

```python
##Number of unique in each column.

# .columns method is used to return the column labels of our data.

d_c=data.columns

# Applying 'for' loop to calculate no. of uniques in each columns of our data.

# This is helpful for us in determining which column of our data contains numerical data or categorical data.

for i in d_c:

  data[i].unique()

  print(i +" :   "+str(len(data[i].unique())))

# After calculating the no. of uniques in each column by above method, I found another method which does the same work as we did in above cell by applying for loop.

# This method is nunique() which gives us no. of unique in each column just by writing one line of code.

data.nunique()

##Number of people with zero mortgage.

# Calculating the no. of people with zero mortgage by using list and by applying for loop.

d=list(data['Mortgage'])

count=0

for i in d:

  if i==0:

    count=count+1

print(count)

##Number of people with zero credit card spending per month.

# Calculating the no. of people with zero credit card spending per month by using list and by applying for loop.

c=list(data['CCAvg'])

count1=0

for i in c:

  if i==0:

    count1=count1+1

print(count1)

##Value counts of all categorical columns.
```

Calculating value counts of all categorical coilumns by applying .value_counts() method.

print("Value count of Family : " + "\n" + str(data['Family'].value_counts()))

print("\n")

print("Value count of Education : " + "\n" + str(data['Education'].value_counts()))

print("\n")

print("Value count of Personal Loan : " + "\n" + str(data['Personal Loan'].value_counts()))

print("\n")

print("Value count of Securities Account : " + "\n" + str(data['Securities Account'].value_counts()))

print("\n")

print("Value count of CD Account : " + "\n" + str(data['CD Account'].value_counts()))

print("\n")

print("Value count of Online : " + "\n" + str(data['Online'].value_counts()))

print("\n")

print("Value count of CreditCard : " + "\n" + str(data['CreditCard'].value_counts()))

##Univariate and Bivariate analysis

Univariate Analysis

sns.distplot(data['Age'])

sns.distplot(data['Income'])

sns.distplot(data['CCAvg'])

sns.distplot(data['Mortgage'])

sns.countplot(x='CreditCard',data=data)

sns.countplot(x='Family',data=data)

sns.countplot(x='Securities Account',data=data)

sns.countplot(x='CD Account',data=data)

sns.countplot(x='Education',data=data)

sns.countplot(x='Online',data=data)

sns.countplot(x='Personal Loan',data=data)

Bivariate and Multivariate Analysis

sns.set_style('whitegrid')

sns.pairplot(data)

plt.show()

```
sns.FacetGrid(data,hue="Personal Loan",size=5).map(plt.scatter,"Education","Income").add_legend()
plt.show()
sns.countplot(x='Securities Account',data=data,hue='Personal Loan')
sns.countplot(x='CreditCard',data=data,hue='Personal Loan')
sns.countplot(x='Family',data=data,hue='Personal Loan')
sns.countplot(x='Online',data=data,hue='Personal Loan')

sns.countplot(x='CD Account',data=data,hue='Personal Loan')
# **4. Apply necessary transformations for the feature variables.**
# here I applied Boxcox transformation for the feature variables
# function to plot a histogram and Q-Q plot side by side , for a certain variable
def transform_plot(data_tr, variable):
  plt.figure(figsize=(15,6))
  plt.subplot(1,2,1)
  data_tr[variable].hist()

  plt.subplot(1,2,2)
  stats.probplot(data_tr[variable], dist="norm", plot=plt)

  plt.show()
# Boxcox transformation for 'income'
data['Income_boxcox'], param = stats.boxcox(data.Income+1)
print('Parameters/optimal lambda: ', param)

transform_plot(data,'Income_boxcox')
sns.distplot(data['Income_boxcox'])
# here by seeing Q-Q plot, I come to know that I need to apply Logistic Regression in further steps
# Boxcox transformation for 'CCAvg'
data['CCAvg_boxcox'], param = stats.boxcox(data.CCAvg+1)
print('Parameters/optimal lambda: ', param)
```

```
transform_plot(data,'CCAvg_boxcox')

sns.distplot(data['CCAvg_boxcox'])

# here by seeing Q-Q plot, I come to know that I need to apply Logistic Regression in further steps

# I also applied the Boxcox transformation for mortgage but I didn't got expected result

# That's why I choose to go with another transformation


#data['Mortgage_boxcox'], param = stats.boxcox(data_x.Mortgage+1)


#print('Parameters/optimal lambda: ', param)


#transform_plot(data,'Mortgage_boxcox')

#sns.distplot(data['Mortgage_boxcox'])

# In this cell, I have applied Binning tranformation for Mortgage

data['Mortgage_Int']=pd.cut(data['Mortgage'],bins=[0,100,200,300,400,500,600,700],labels=[0,1,2,3,
4,5,6],include_lowest=True)

data.drop(['Mortgage'],axis=1,inplace=True)

sns.distplot(data['Mortgage_Int'])

# defining the data_x and data_y for training and testing purpose

data_x = data.loc[:,data.columns != "Personal Loan"]

data_y = data[['Personal Loan']]

# removing the 'Income','ZIP Code','CCAvg' columns from the data_x as it is not required for further
steps

data_x=data_x.drop(['Income','ZIP Code','CCAvg'],axis=1)

data_x["Mortgage_Int"]=data_x["Mortgage_Int"].astype('int64')

# checking datatypes of each cloumns in data_x

data_x.dtypes

#data_x.head()

# **5. Normalise your data and split the data into training and test set in the ratio of 70:30
respectively.**

# splitting of data into training set and testing set in the ratio 70:30

# 70% training set is used to train the model and 30% testing set id used to test the model
```

```
train_X, test_X, train_Y, test_Y = train_test_split(data_x, data_y, test_size = 0.3, stratify = data_y, random_state=0)

# printing the shape of train_X, test_X, train_Y, test_Y

print("Shape of train_X: ",train_X.shape)

print("Shape of test_X: ",test_X.shape,"\n")


print("Shape of train_Y: ",train_Y.shape)

print("Shape of test_Y: ",test_Y.shape)

# here applying 'l2' normalisation for train_X, test_X, train_Y, test_Y

from sklearn import preprocessing

train_X = preprocessing.normalize(train_X,norm='l2')

test_X = preprocessing.normalize(test_X,norm='l2')

train_Y = preprocessing.normalize(train_Y,norm='l2')

test_Y = preprocessing.normalize(test_Y,norm='l2')

"""print(train_X)

print(test_X)

print(train_Y)

print(test_Y)"""

# here I comment the standard scaling technique because I just want to compare above 'l2' normalisation technique with standard scaling technique

# I got good result with 'l2' normalisation technique thats why I choose to go with 'l2' normalisation technique instead of going with StandardScaler technique

"""from sklearn.preprocessing import StandardScaler

scaling= StandardScaler()

scaling.fit_transform(train_X)

scaling.fit_transform(test_X)

scaling.fit_transform(train_Y)

scaling.fit_transform(test_Y)"""

# **6. Using the Logistic Regression model to predict the likelihood of a customer buying personal loans.**

#**7. Printing all the metrics related for evaluating the model performance.**

#**8. Building various other classification algorithms and comparing their performance.**
```

```
# importing necessary libraries
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import plot_confusion_matrix, plot_roc_curve, plot_precision_recall_curve
from sklearn.metrics import classification_report
# Fitting logistic regression to Training Set
class_names = ['wont take loan', 'take loan']
log_reg = LogisticRegression(C=1.0, max_iter=200)
log_reg.fit(train_X,train_Y)
# printing the results of Logistic regression
# printing the training accuracy, testing accuracy, precision value, recall value
# plotting the confusion matrix, ROC curve and Precision-recall curve for the logistic regression
print('Logistic Regression Results: ')

train_score = log_reg.score(train_X,train_Y)
print('Training Accuracy:', train_score.round(2))
test_score = log_reg.score(test_X,test_Y)
print('Testing Accuracy:', test_score.round(2))

y_pred_log = log_reg.predict(test_X)

precision_logi = precision_score(test_Y, y_pred_log, labels=class_names).round(2)
print('Precision:', precision_logi)
recall_logi = recall_score(test_Y, y_pred_log).round(2)
print('Recall:', recall_logi)

plot_confusion_matrix(log_reg,test_X,test_Y, display_labels=class_names)
plt.title('Confusion Matrix for Logistic Regression')

plot_roc_curve(log_reg,test_X,test_Y)
plt.title('ROC Curve for Logistic Regression')
```

```
plot_precision_recall_curve(log_reg,test_X,test_Y)
plt.title('Precision-Recall Curve for Logistic Regression')
print(classification_report(test_Y,y_pred_log))
# Fitting KNeighbors classifier to Training Set
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(train_X, train_Y)
# printing the results of KNeighbors classifier
# printing the training accuracy, testing accuracy, precision value, recall value
# plotting the confusion matrix, ROC curve and Precision-recall curve for the KNeighbors classifier
print('K Neighbors Classifier Results: ')

knntrain_score = knn.score(train_X,train_Y)
print('Training Accuracy:', knntrain_score.round(2))
knntest_score = knn.score(test_X,test_Y)
print('Testing Accuracy:', knntest_score.round(2))

y_pred_knn = knn.predict(test_X)

precision_knn = precision_score(test_Y, y_pred_knn, labels=class_names).round(2)
print('Precision:', precision_knn)
recall_knn = recall_score(test_Y, y_pred_knn).round(2)
print('Recall:', recall_knn)

plot_confusion_matrix(knn,test_X,test_Y, display_labels=class_names)
plt.title('Confusion Matrix for K Neighbors Classifier')

plot_roc_curve(knn,test_X,test_Y)
plt.title('ROC Curve for K Neighbors Classifier')

plot_precision_recall_curve(knn,test_X,test_Y)
```

```
plt.title('Precision-Recall for K Neighbors Classifier')
print(classification_report(test_Y,y_pred_knn))
#Fitting Decision Tree classifier to Training Set
from sklearn.tree import DecisionTreeClassifier
dt_clf= DecisionTreeClassifier()
dt_clf.fit(train_X,train_Y)
# printing the results of Decision Tree classifier
# printing the training accuracy, testing accuracy, precision value, recall value
# plotting the confusion matrix, ROC curve and Precision-recall curve for the Decision Tree classifier
print('Decision Tree Classifier Results: ')

trainscore = dt_clf.score(train_X,train_Y)
print('Training Accuracy:', trainscore.round(2))
testscore = dt_clf.score(test_X,test_Y)
print('Testing Accuracy:', testscore.round(2))

y_pred_dt = dt_clf.predict(test_X)

precision_dt = precision_score(test_Y, y_pred_dt, labels=class_names).round(2)
print('Precision:', precision_dt)
recall_dt = recall_score(test_Y, y_pred_dt).round(2)
print('Recall:', recall_dt)

plot_confusion_matrix(dt_clf,test_X,test_Y, display_labels=class_names)
plt.title('Confusion Matrix for Decision Tree Classifier')

plot_roc_curve(dt_clf,test_X,test_Y)
plt.title('ROC Curve for Decision Tree Classifier')

plot_precision_recall_curve(dt_clf,test_X,test_Y)
plt.title('Precision-Recall for Decision Tree Classifier')
```

```
print(classification_report(test_Y,y_pred_dt))
# Fitting Random Forest classifier to Training Set
rf_clf = RandomForestClassifier(n_estimators=300, max_depth=7,n_jobs=-1 )
rf_clf.fit(train_X,train_Y)
# printing the results of Random Forest classifier
# printing the training accuracy, testing accuracy, precision value, recall value
# plotting the confusion matrix, ROC curve and Precision-recall curve for the Random Forest classifier
print('Random Forest Classifier Results: ')

train_score = rf_clf.score(train_X,train_Y)
print('Training Accuracy:', train_score.round(2))
test_score = rf_clf.score(test_X,test_Y)
print('Testing Accuracy:', test_score.round(2))

y_pred_rf = rf_clf.predict(test_X)

precision_rf = precision_score(test_Y, y_pred_rf, labels=class_names).round(2)
print('Precision:', precision_rf)
recall_rf = recall_score(test_Y, y_pred_rf).round(2)
print('Recall:', recall_rf)

plot_confusion_matrix(rf_clf,test_X,test_Y, display_labels=class_names)
plt.title('Confusion Matrix for Random Forest Classifier')

plot_roc_curve(rf_clf,test_X,test_Y)
plt.title('ROC Curve for Random Forest Classifier')

plot_precision_recall_curve(rf_clf,test_X,test_Y)
plt.title('Precision-Recall for Random Forest Classifier')
print(classification_report(test_Y,y_pred_rf))
#**CONCLUSION**
```

**CONCLUSION**
##

We want to make a model which predicts whether the customer will take a personal loan or not.

1) I have imported all the necessary libraries which is required for our model.

2) From the data I get to know that our 'Age' and 'Experience' column is highly correlated, that's why I dropped the 'Experience' column. I also dropped the 'ID' column because it is randomly generated number given to the customer for identification purpose which has no relation with the personal loan.

3) Later in the further steps, after applying transformation I also removed the 'ZIP Code' column because it is not required for our model and also removed the original 'Income', 'CCAvg', 'Mortgage' columns because after applying transformation I have new transformed data for Income(Income_boxcox), CCAvg(CCAvg_boxcox) and Mortgage(Mortgage_Int).

4) Then after splitting the data into training set and testing set, I applied Logistic Regression, KNeighbors Classifier, Decision Tree Classifier and Random Forest Classifier and after comparing the results, I found that Random Forest Classifier and KNeighbors Classifier giving me the best accuracy as compared to logistic regression and Decision tree classifier. Here is the complete details:-

**///
//** **Logistic Regression**
**///
///**

Logistic Regression Results:

Training Accuracy: 0.9

Testing Accuracy: 0.9

Precision: 0.0

Recall: 0.0

	precision	recall	f1-score	support
0.0	0.90	1.00	0.95	1356
1.0	0.00	0.00	0.00	144
accuracy			0.90	1500
macro avg	0.45	0.50	0.47	1500
weighted avg	0.82	0.90	0.86	1500

**//
/ KNeighbors Classifier
//
**

K Neighbors Classifier Results:

Training Accuracy: 0.96

Testing Accuracy: 0.93

Precision: 0.69

Recall: 0.41

	precision	recall	f1-score	support
0.0	0.94	0.98	0.96	1356

1.0	0.69	0.41	0.52	144
accuracy			0.93	1500
macro avg	0.82	0.70	0.74	1500
weighted avg	0.92	0.93	0.92	1500

**//
Decision Tree Classifier
//**

Decision Tree Classifier Results:

Training Accuracy: 1.0

Testing Accuracy: 0.95

Precision: 0.77

Recall: 0.75

	precision	recall	f1-score	support
0.0	0.97	0.98	0.97	1356
1.0	0.77	0.75	0.76	144
accuracy			0.95	1500
macro avg	0.87	0.86	0.87	1500
weighted avg	0.95	0.95	0.95	1500

**//
Random Forest Classifier
//**

Random Forest Classifier Results:

Training Accuracy: 0.95

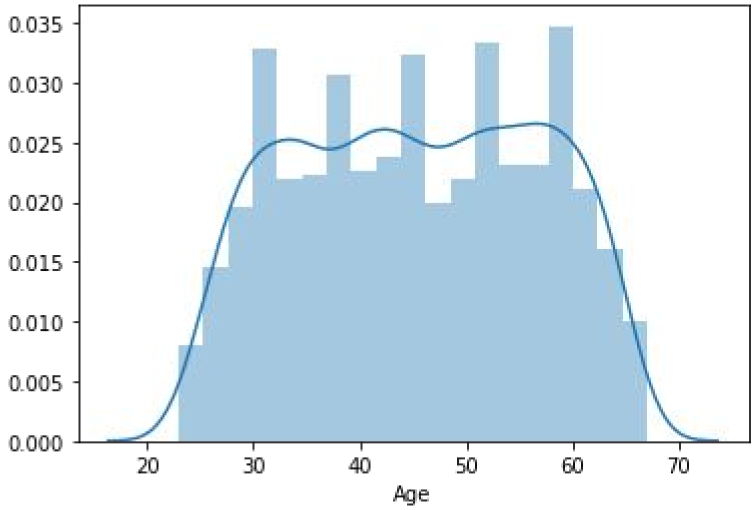
Testing Accuracy: 0.94

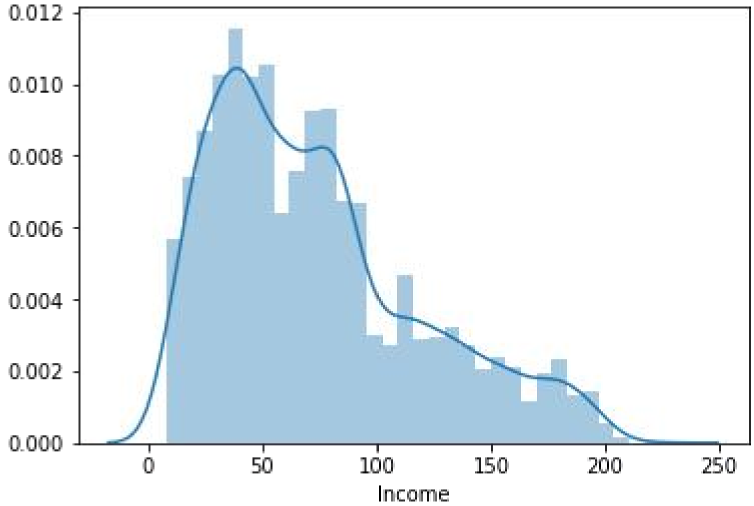
Precision: 0.95

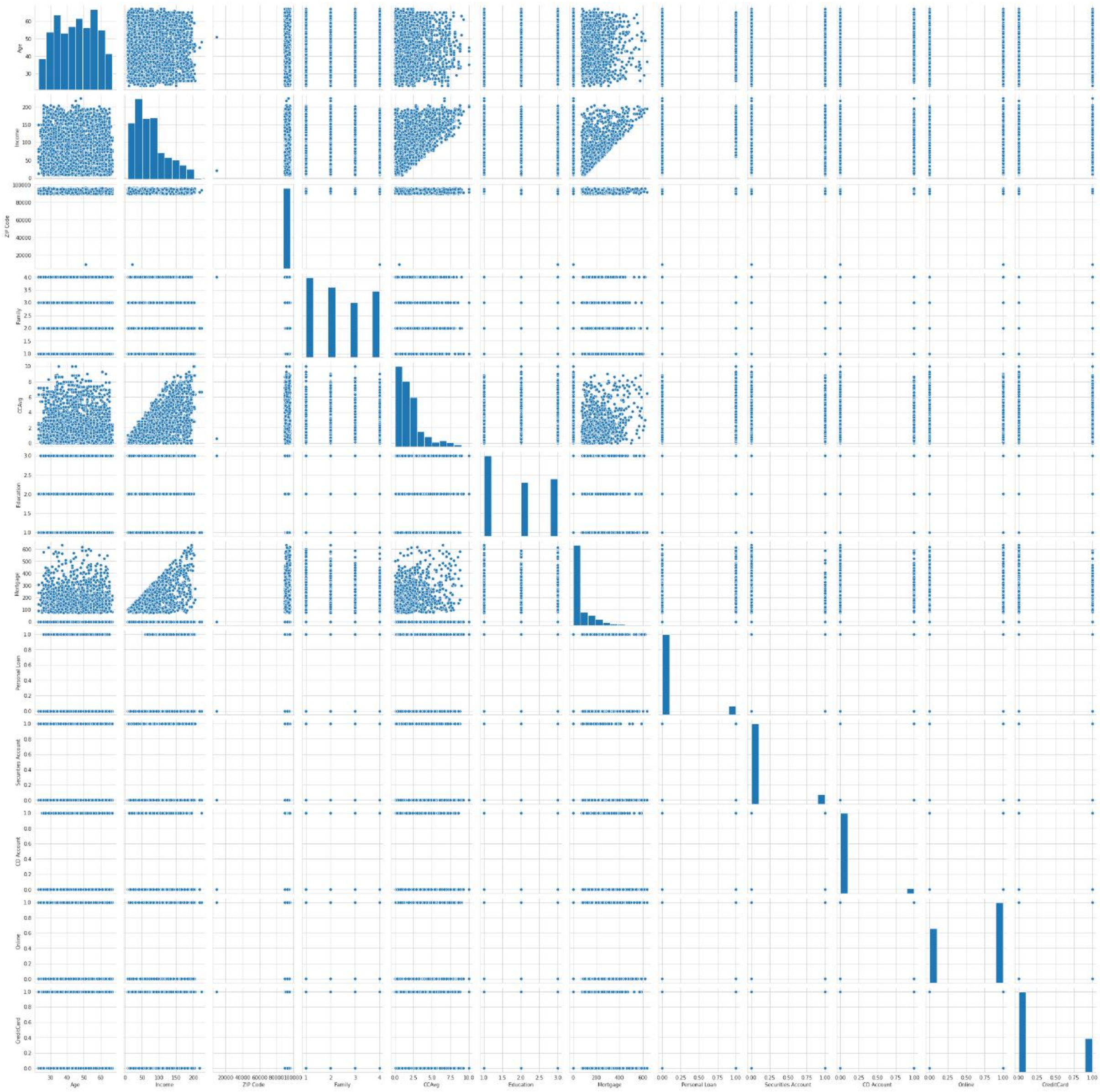
Recall: 0.4

	precision	recall	f1-score	support
0.0	0.94	1.00	0.97	1356
1.0	0.95	0.40	0.56	144
accuracy			0.94	1500
macro avg	0.94	0.70	0.76	1500
weighted avg	0.94	0.94	0.93	1500

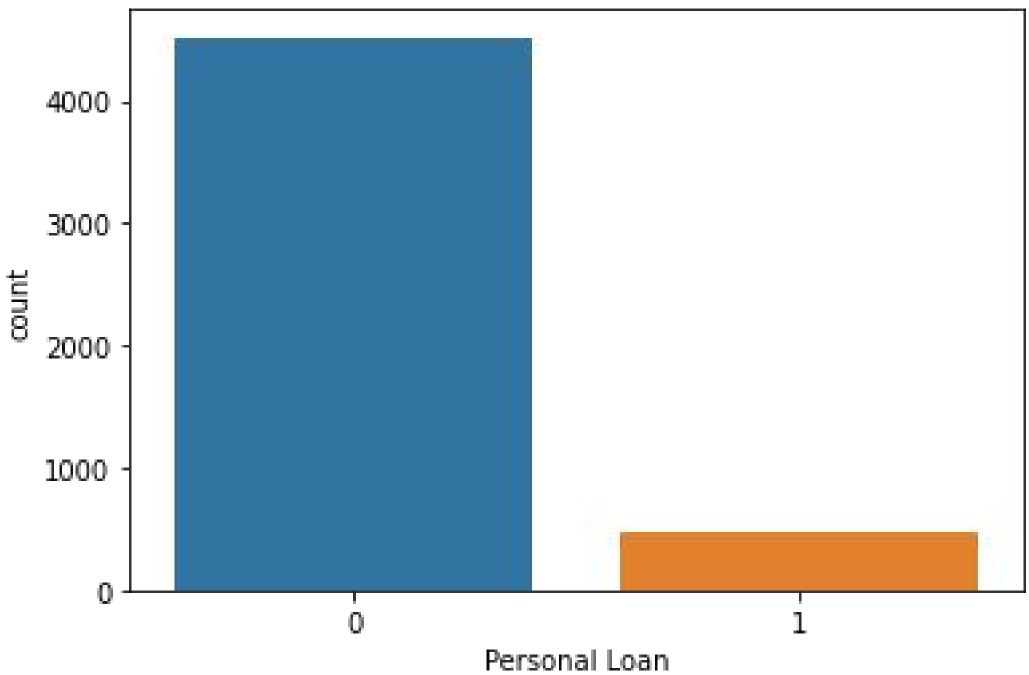
**##
##############################**


0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
20
30
40
50
60
70
Age

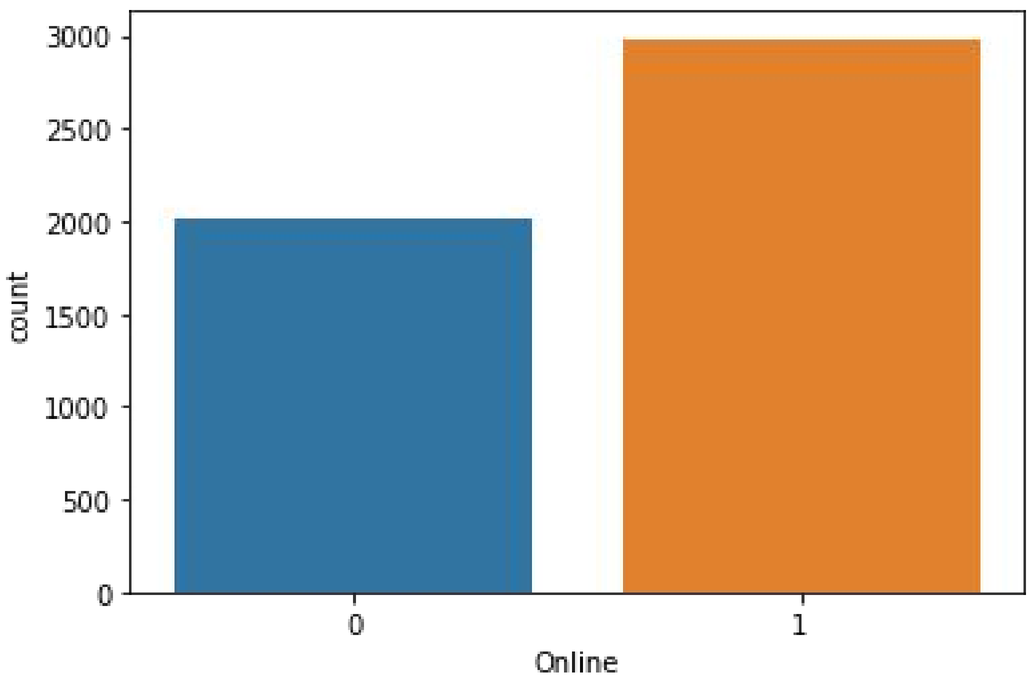

0.012
0.010
0.008
0.006
0.004
0.002
0.000
0
50
100
150
200
250
Income



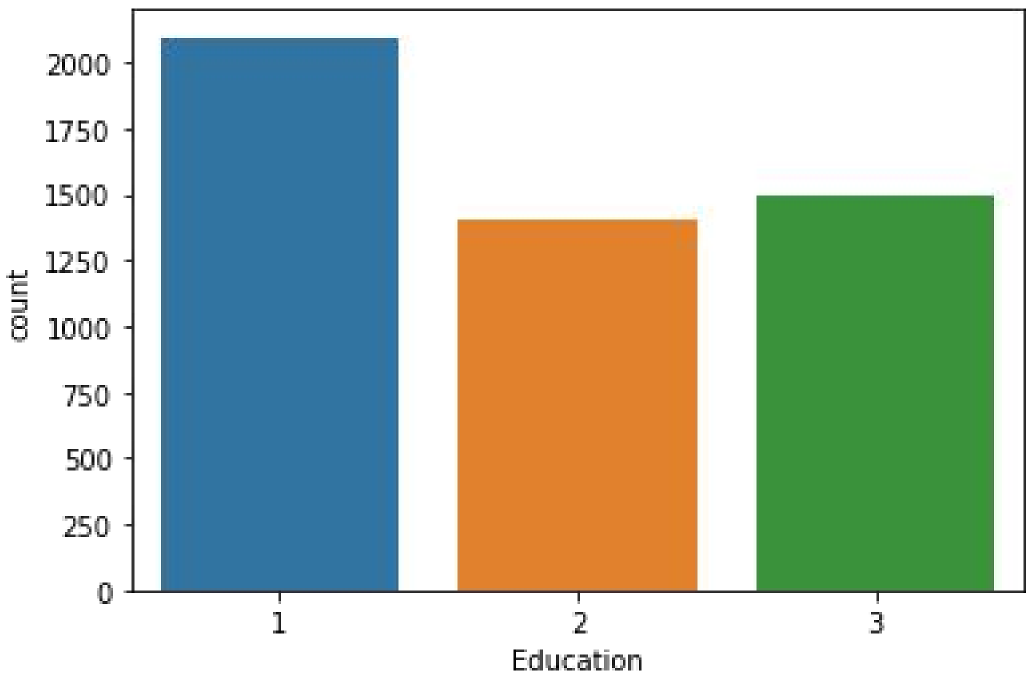
Age
Income
ZIP Code
Family
CCAvg
Education
Mortgage
Personal Loan
Securities Account
CD Account
Online
CreditCard

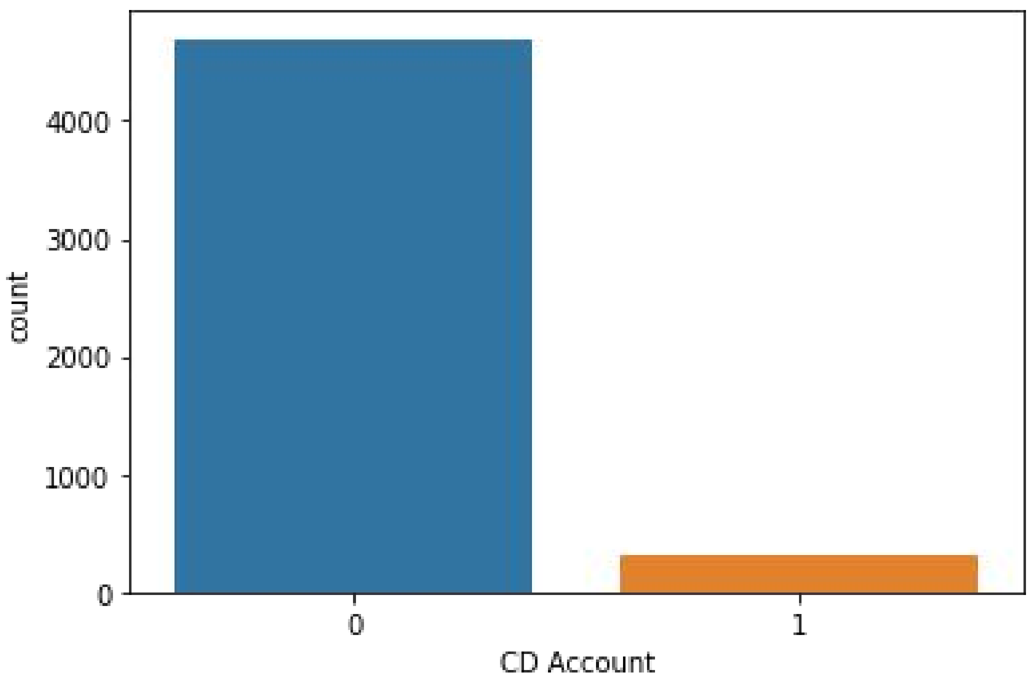


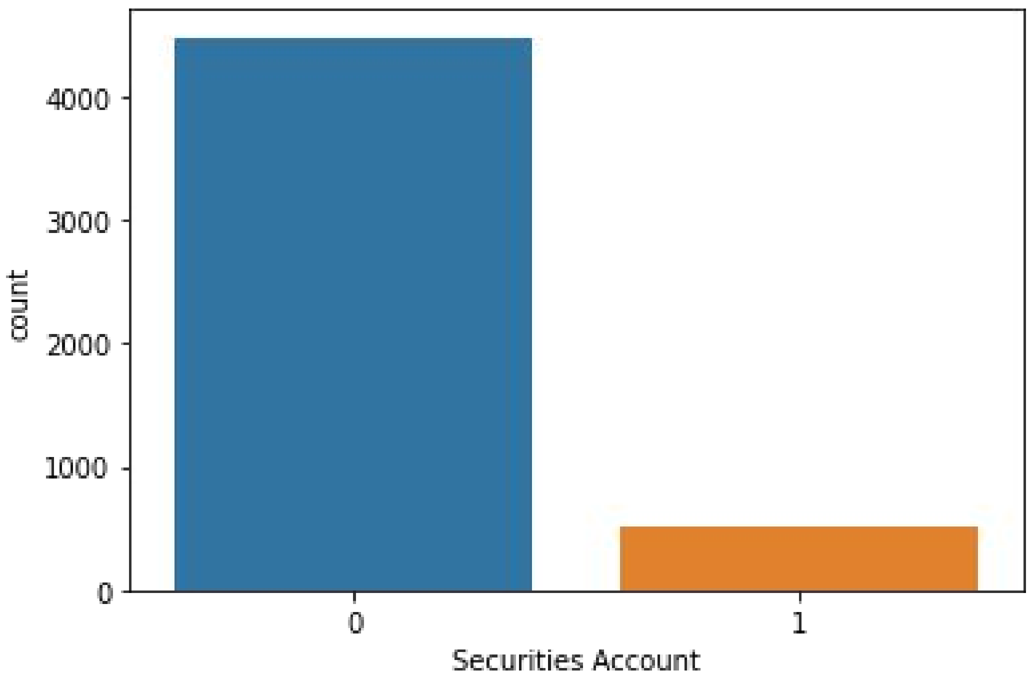
count
4000
3000
2000
1000
0
0
1
Personal Loan

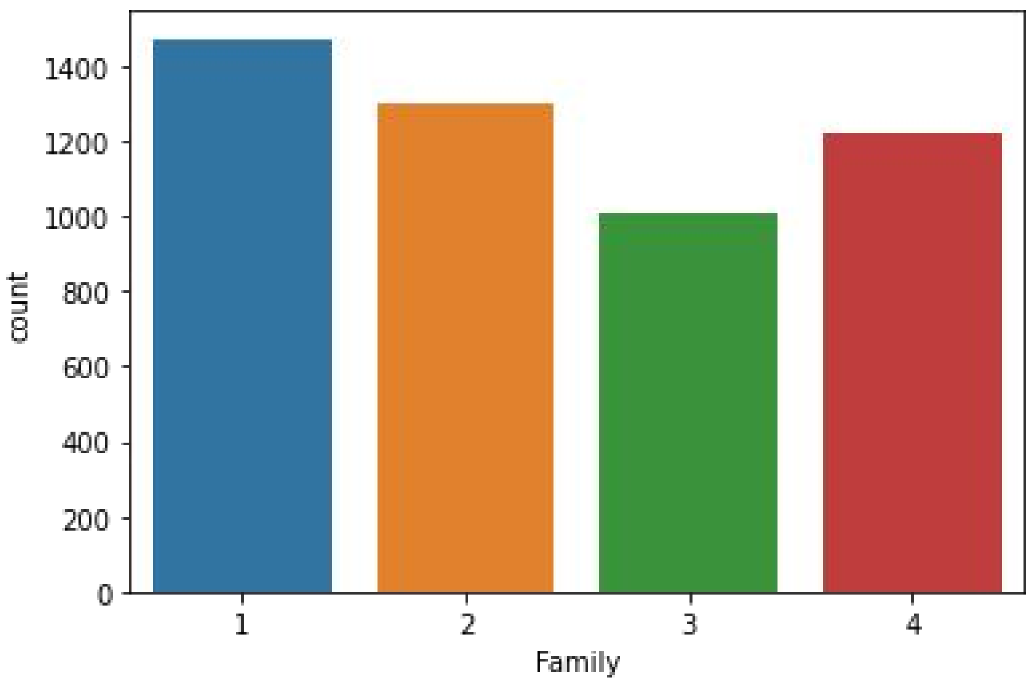


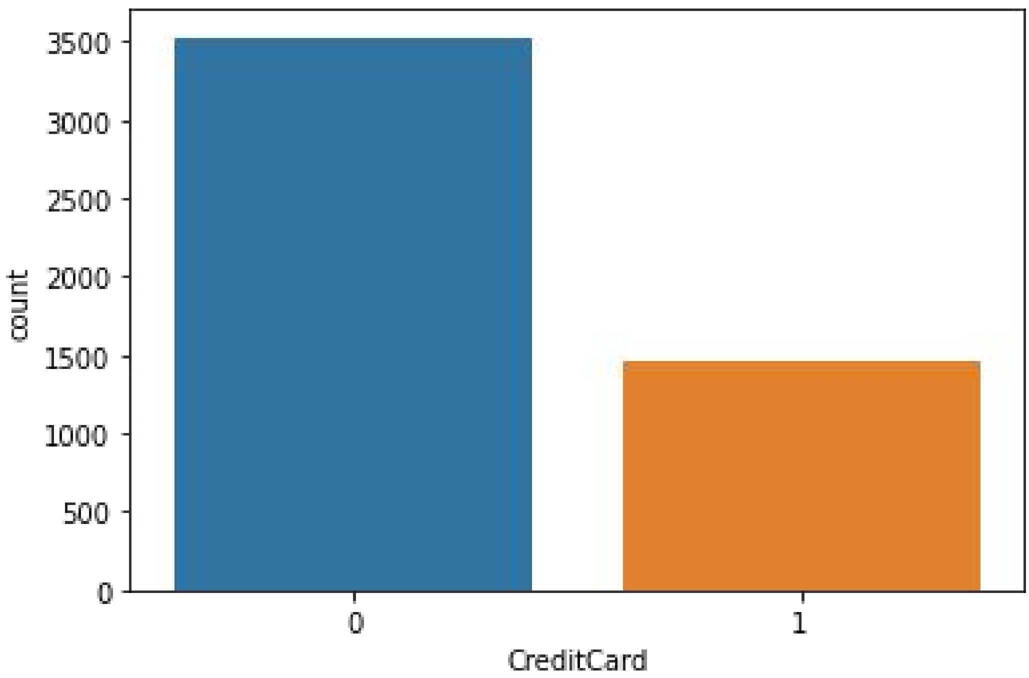
count
3000
2500
2000
1500
1000
500
0
0
1
Online


2000
1750
1500
1250
1000
750
500
250
0
count
1
2
3
Education

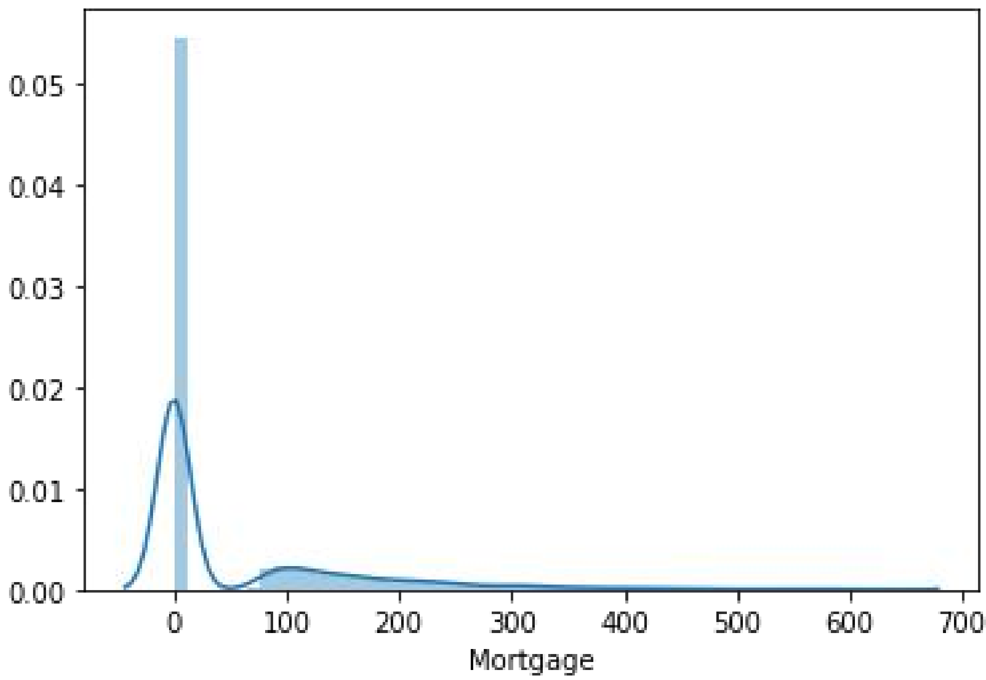

4000
3000
2000
1000
0
count
0
1
CD Account

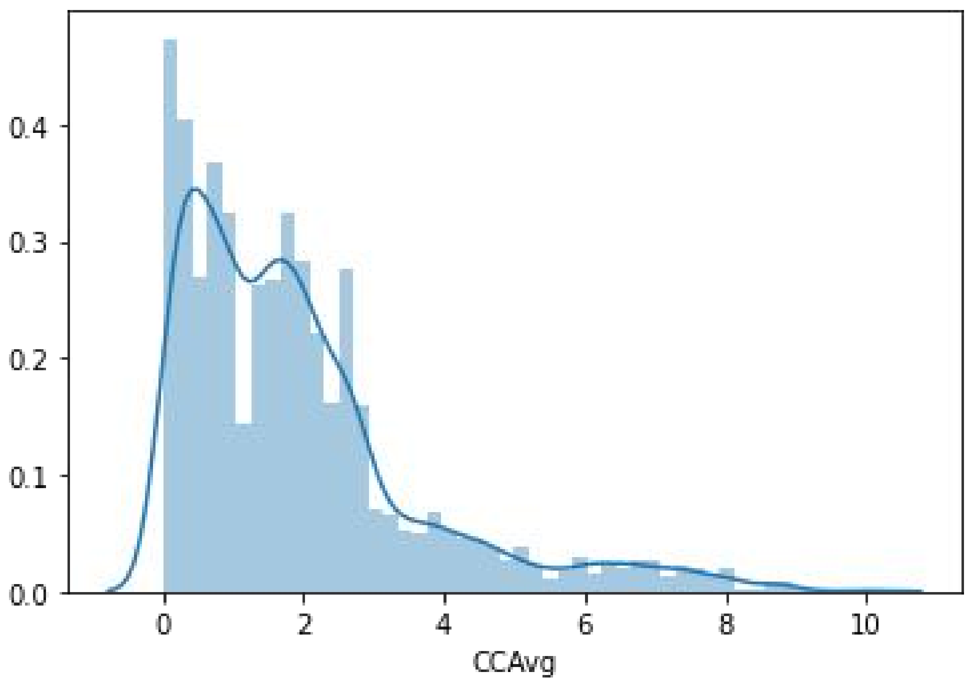

4000
3000
2000
1000
0
count
0
1
Securities Account

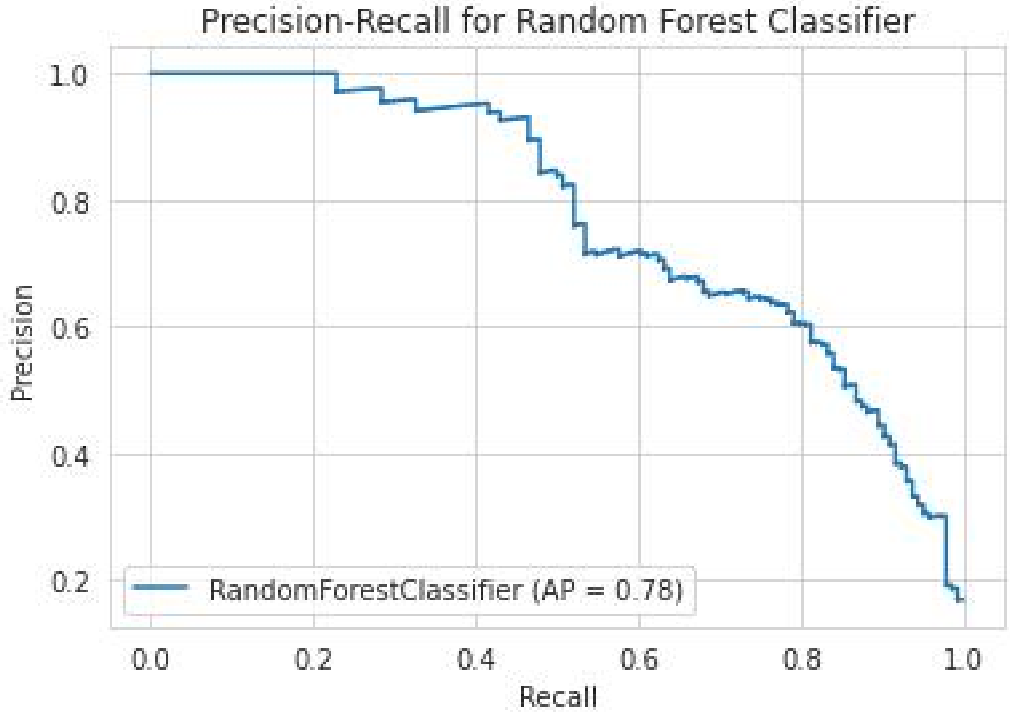

1400
1200
1000
800
600
400
200
0
count
1
2
3
4
Family

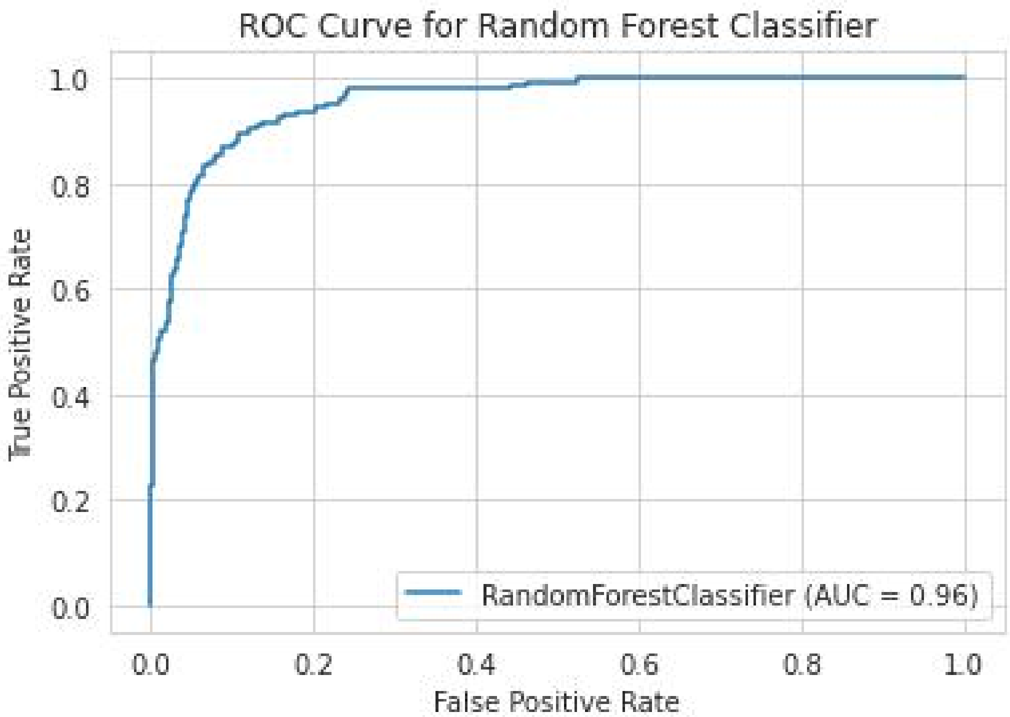


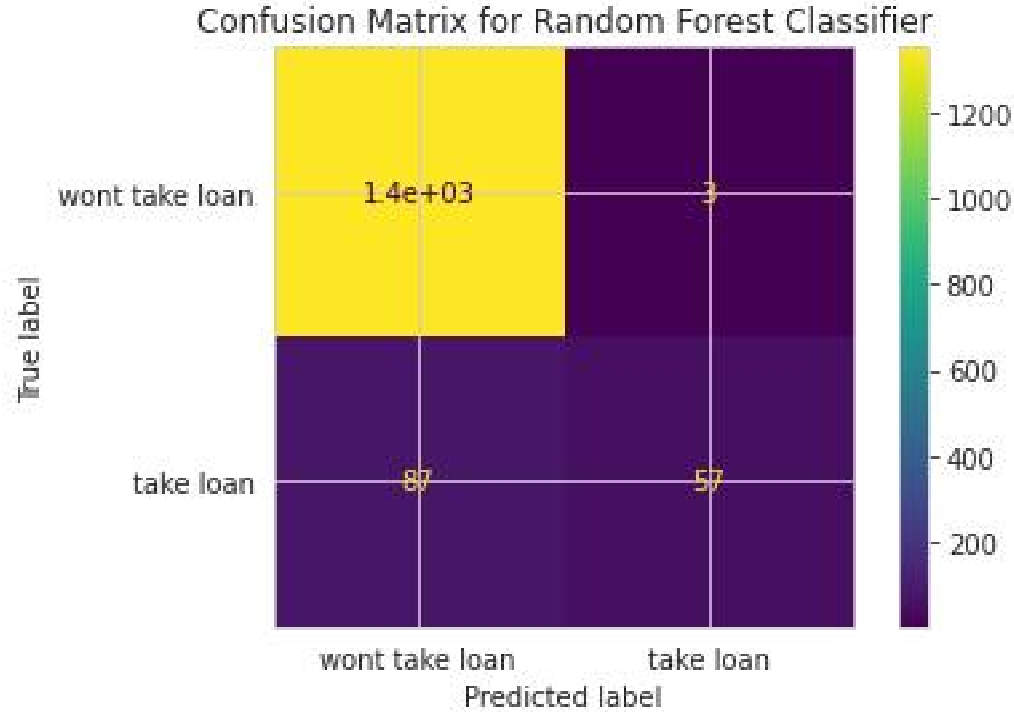
count
3500
3000
2500
2000
1500
1000
500
0
0
1
CreditCard

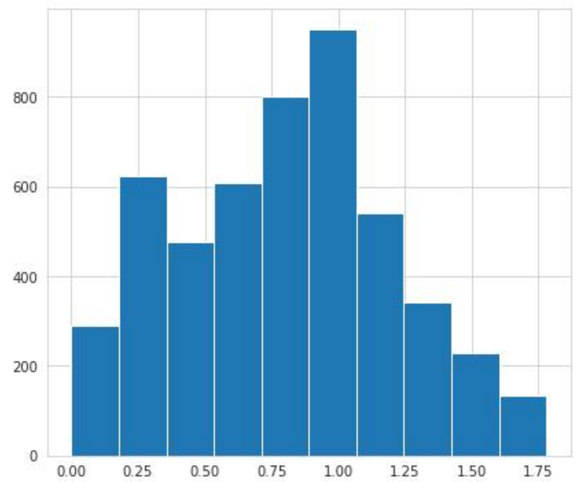

0.05
0.04
0.03
0.02
0.01
0.00
0
100
200
300
400
500
600
700
Mortgage

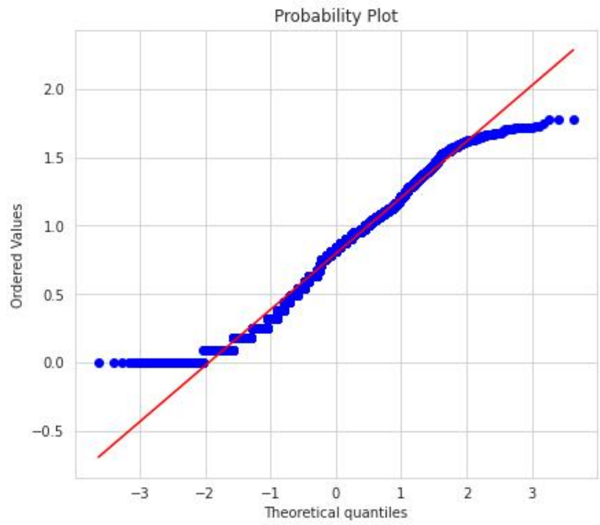

0.4
0.3
0.2
0.1
0.0
0
2
4
6
8
10
CCAvg

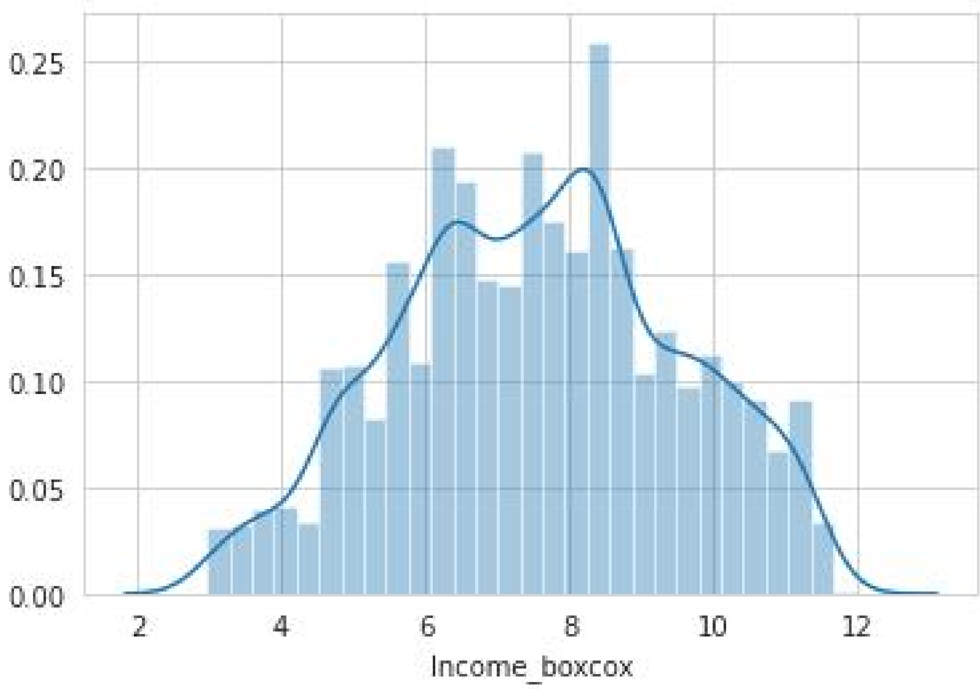

Precision-Recall for Random Forest Classifier
1.0
0.8
0.6
0.4
0.2
Precision
RandomForestClassifier (AP = 0.78)
0.0
0.2
0.4
0.6
0.8
1.0
Recall

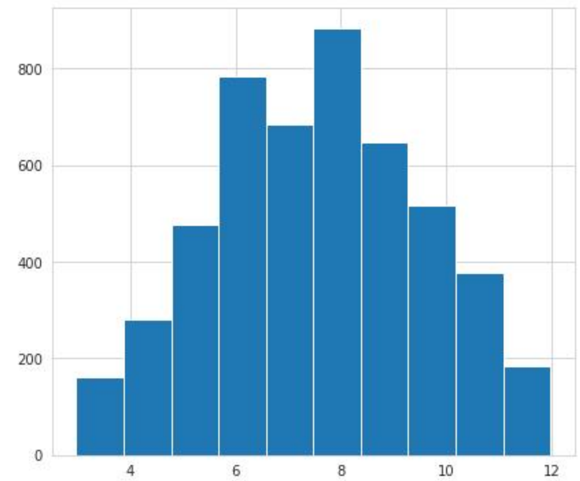

ROC Curve for Random Forest Classifier
1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
RandomForestClassifier (AUC = 0.96)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate

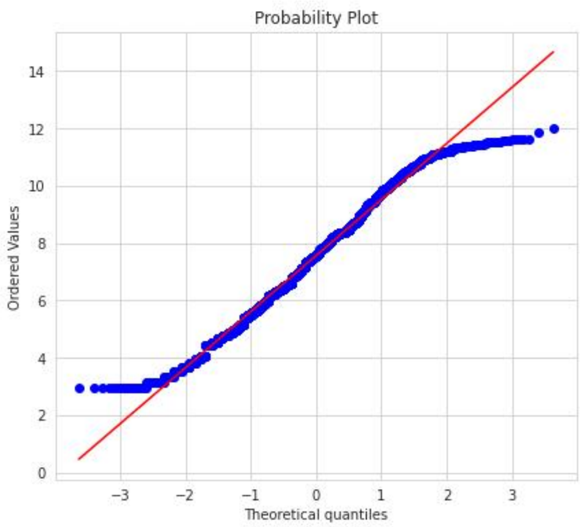

Confusion Matrix for Random Forest Classifier
wont take loan
take loan
1.4e+03
3
87
57
True label
Predicted label
1200
1000
800
600
400
200

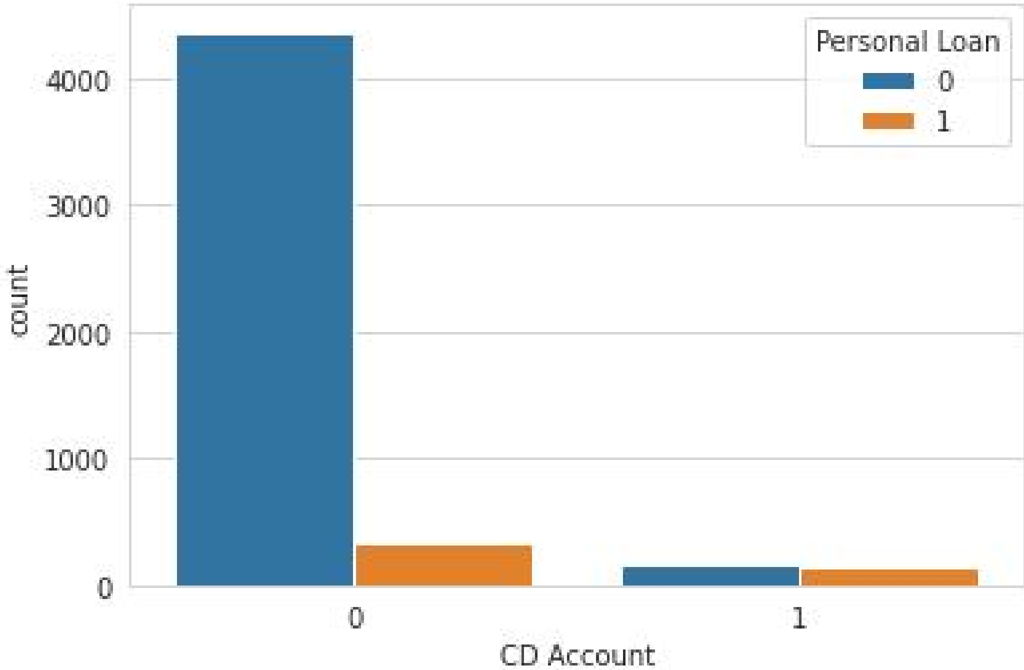

0
200
400
600
800
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75


Probability Plot
Ordered Values
Theoretical quantiles
2.0
1.5
1.0
0.5
0.0
−0.5
−3
−2
−1
0
1
2
3

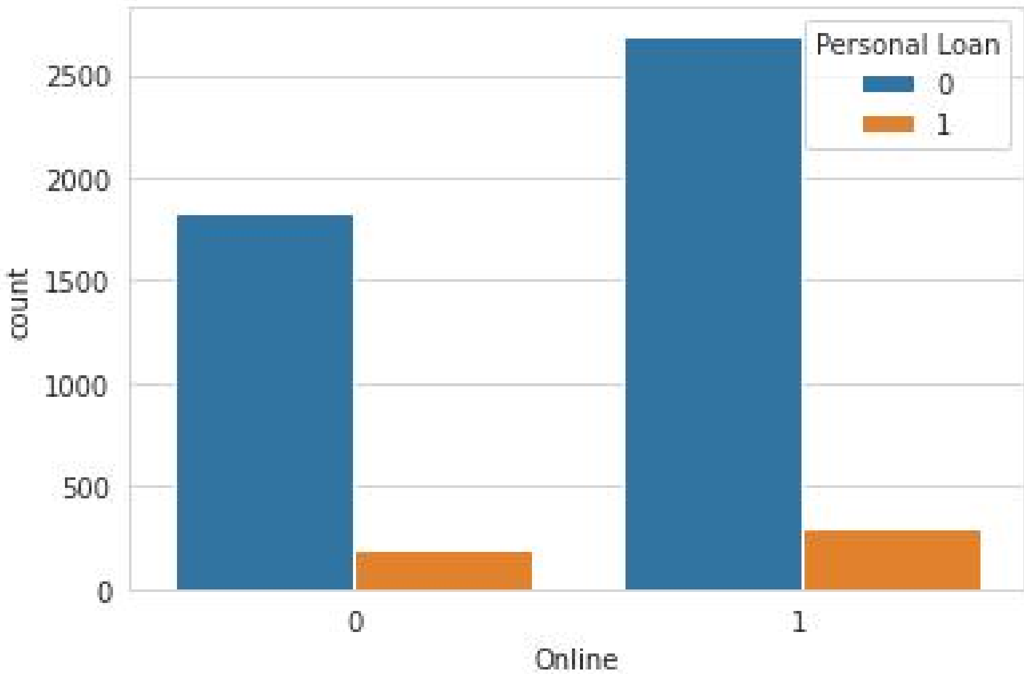

0.25
0.20
0.15
0.10
0.05
0.00
2
4
6
8
10
12
Income_boxcox


800
600
400
200
0
4
6
8
10
12

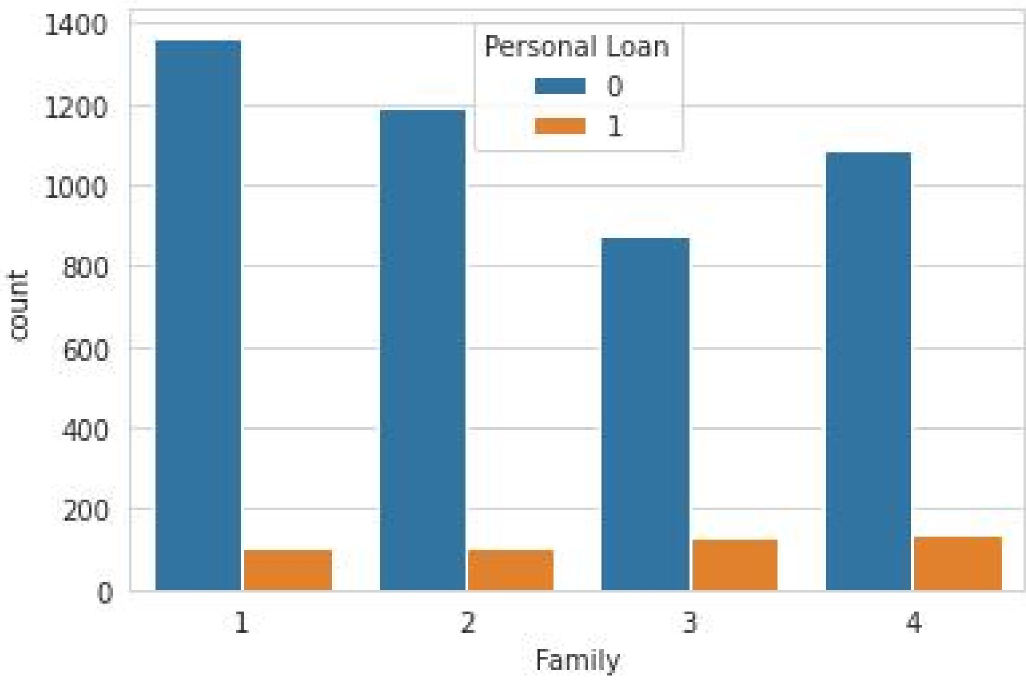

Probability Plot
14
12
10
8
6
4
2
0
Ordered Values
−3
−2
−1
0
1
2
3
Theoretical quantiles

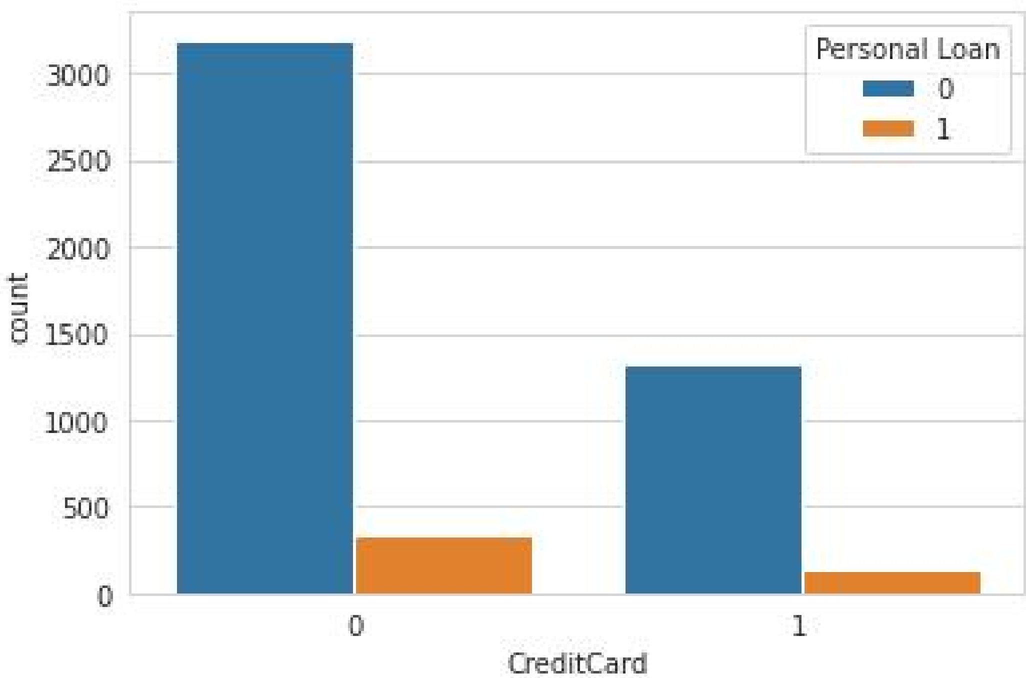


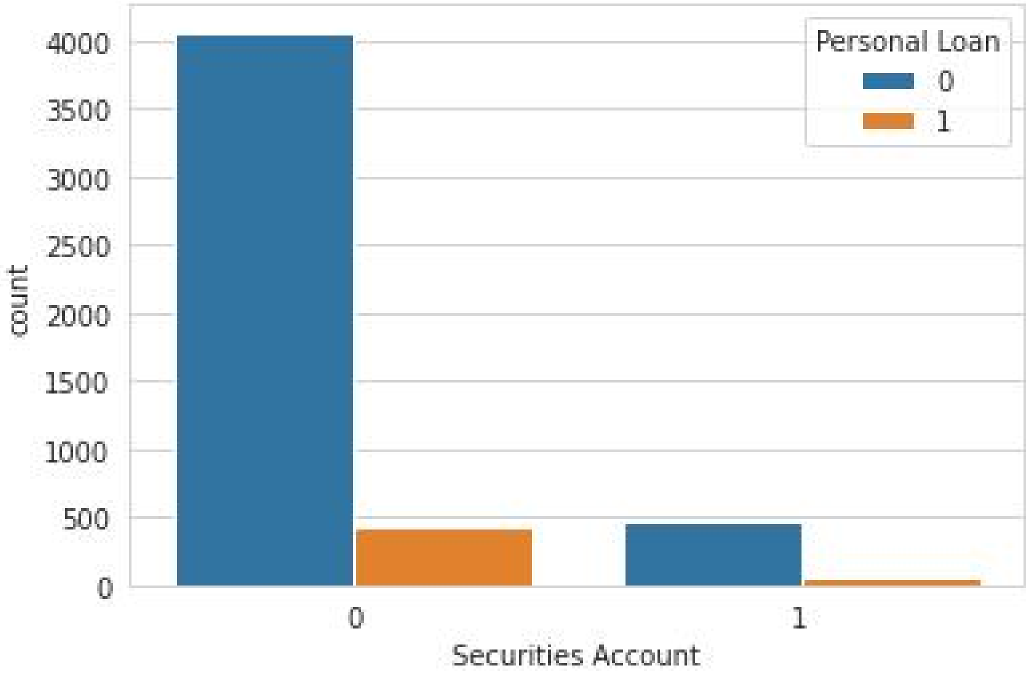
Personal Loan
0
1
4000
3000
2000
1000
0
count
0
1
CD Account

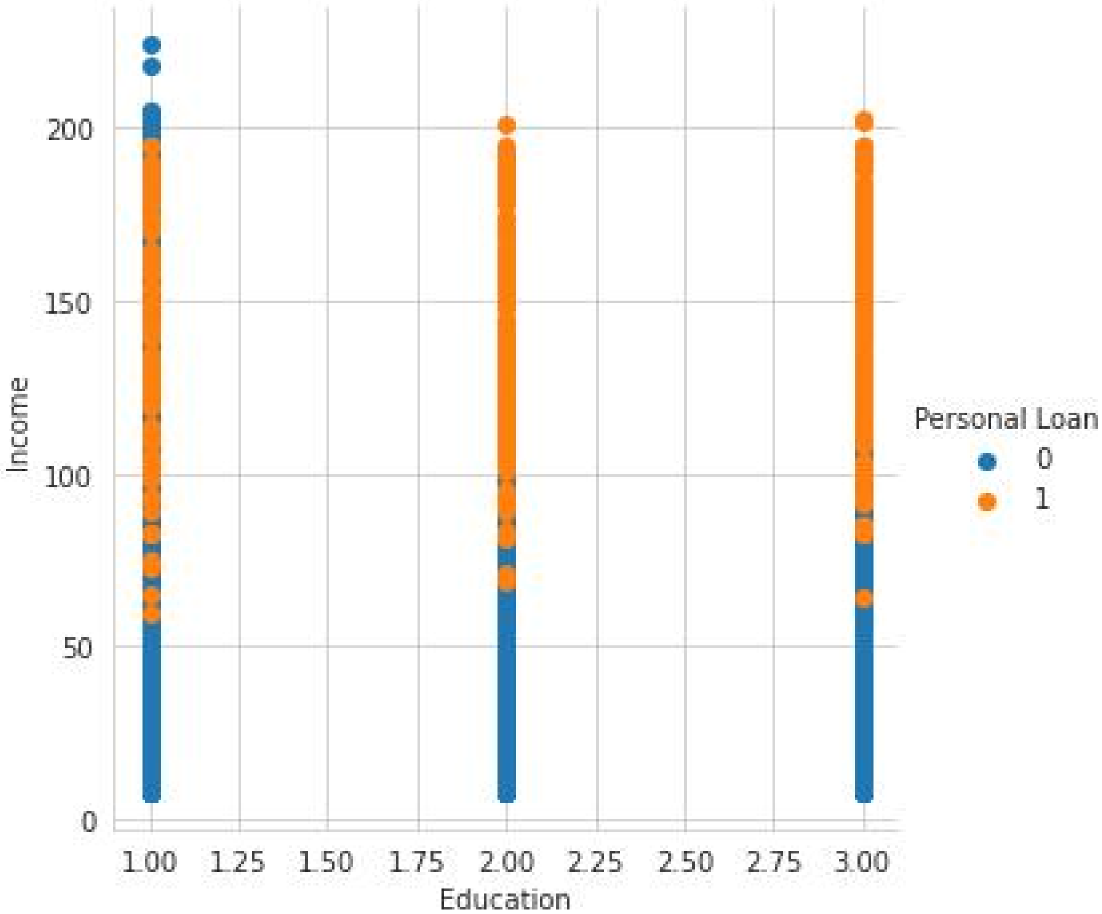


Personal Loan
0
1
2500
2000
1500
1000
500
0
count
0
1
Online


1400
1200
1000
800
600
400
200
0
count
Personal Loan
0
1
1
2
3
4
Family


3000
2500
2000
1500
1000
500
0
count
Personal Loan
0
1
0
1
CreditCard


Personal Loan
0
1
4000
3500
3000
2500
2000
1500
1000
500
0
count
0
1
Securities Account


200
150
100
50
0
Income
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Education
Personal Loan
0
1